UTILIZING CONSUMER PERSONALITY PROFILES AND KEYWORDS ASSOCIATED WITH PERSONALITY TYPES IN INFORMATION SYSTEMS FOR MOVIE RECOMMENDATIONS

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ABSTRACT

Field (2005) rightly stated that events in a movie are specifically designed to bring out the truth about the characters so that we, the audience, can transcend our ordinary lives and achieve a connection, or bond, between “them and us”; we see ourselves in them and enjoy a moment, perhaps, of recognition and understanding. The application of user ratings in making movie recommendations is implicitly detrimental to the user experience as they are deprived of the opportunity to experience movies with a storyline which they will find relatable to their present circumstances. This is because, such a movie was rated poorly by another user with similar taste to the user, or, such a movie had no ratings at all. Also, this research identified that the application of user ratings in making recommendations is also detrimental to movies with an unpopular cast list or/and movie production crew. This is because, for ratings to be predicted, initial ratings must exist, and predicted ratings are only based on existing ratings. Furthermore, the ability of a movie to have ratings is directly related to the level of popularity of the movie, because popularity enhances the visibility of the movie in the movie consumers market which in turn makes the movie available to receive a rating. If the consumers cannot see the movie, or know that the movie exists, they will not be able to provide any ratings.

The application of user ratings in movie recommender systems research has created the problem of ratings-based overspecialization where movies with high ratings are seemingly handed the advantage over movies with low ratings without allowing the user to decide for themselves if they like the movie based on the movie plot. The proposed personality-based movie recommender system aims to utilize the personality of the users to identify movies suitable for the personality group using the words associated with the subject matters in movies. This involved the creation of a list of keywords based on the favourite movies provided by 207 participants from the 16 MBTI personality types. The recommendation accuracy of the proposed model based on overall user satisfaction was 76.28% when the less popular movies were recommended to the users.

DECLARATION

No portion of the work referred to in the thesis has been submitted in support of an application for another degree or qualification of this or any other university or other institutes of learning.

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DEDICATION

This thesis is dedicated in loving memory of my mother, Mrs. Felicia M. Tuedor who was called to be with the Lord Jesus on the 26th of May 2017. She never stopped believing in me and always kept fighting on my behalf so I could have the best chance in life. She was a child of God, a Queen, a Warrior, and she will always be my hero.

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CHAPTER ONE - INTRODUCTION

1.1 RESEARCH CONTEXT

Nunes (2008) describes recommendation as a deliberative social process that is done by people when they want to describe their degree of appreciation about a product. The perception of recommendation as a *process* on its own implies that it consists of a variety of interdependent stages leading up to the recommendation output. Furthermore, the perception of recommendation as a *social process* implies that human interaction is a vital part of the original recommendation process. Therefore, if the process is going to be automated, there has to be some form of human interaction involved in the automated recommendation process for it to be successful. The art of making recommendations is fast becoming a common practice in several industries globally. O'Donovan & Smyth (2005) pointed out that the most successful recommendations are those which are influenced by friends or family as opposed to expert sources of advice. It can be assumed that recommendations made by friends and family members are better received because of the potentially high level of trust and understanding between them. Therefore, it is reasonable to say that if one wishes to make a successful recommendation, one would need to understand the recipients of the recommendation. This would involve the exploration of human psychology and the impact it has on the decision-making process.

Recommendations which are made based on the understanding of human psychology is a relatively new area of research. However, most of the research done so far in the exploration of the use of human psychology in making recommendations has been on movies (Song et al, 2009; Kompan & Bielkova, 2013; Cantador et al, 2013; Karumur et al, 2017). Karumur et al (2017) pointed out that the reason many researchers utilize movies in this kind of research is because of the data which is already made available online. Furthermore, O'Brien-Bours (2013) pointed out that movies have the power to inspire, to teach, to shape memories of events, and to create a shared narrative experience amongst a culture. This was supported by Field (2005) where it was indicated that movies that most consumers tend to rate highly are because of a connection which they were able to form with a character based on the subject matter of the movie. Also, Song et al (2009) and Hu & Pu (2011) also pointed out that movies tend to have a psychological impact on the consumer. Therefore, it only makes sense to explore that psychological connection with the intent of making future accurate recommendations. The psychological connection involved in making recommendations would be explored using the personality of the users and their favourite movie choices.

According to Tkalcic & Chen (2015), there has been an increase in research to find more oriented approaches in making recommendations where various psychological aspects such as personality have been investigated. John & Srivastava (1999) pointed out that personality accounts for the individual differences in our enduring emotional, interpersonal, experiential, attitudinal, and motivational styles. Therefore, the application of personality seems like the best-fit choice to personalize recommendations for users.

The research in the application of personality in recommendation systems has progressed to the point of identifying the potential in making recommendations to groups of individuals sharing similar personality profiles (Song et al., 2009; Hu & Pu, 2011; Karumur et al., 2017; Orestis & Christos, 2017). The approach of utilizing personality as a categorisation mechanism in recommender systems is based on the premise that people with similar personality profiles tend to like the same movies (Hu & Pu, 2011; Karumur et al., 2017). According to Quijano-Sanchez et al (2013), most of the work in the application of personality profiles in making movie recommendations provides recommendations for individual users based on their personality category. However, they further pointed out that many different activities can be performed by groups of people, like watching a movie, going to a restaurant, listening to a radio station, or traveling with friends. For these activities, they highlighted that recommender systems have to suggest items to groups based on the individual preferences of their members. Jameson & Smyth (2007), Recio-Garcia et al (2009), and Quijano-Sanchez et al (2013) further implied that a standard approach in the creation of group recommender systems involves the aggregation of the preferences of the members of the group where every individual is considered as equal to the others. They further pointed out that for group recommendations to be successful, it would involve merging the recommendations made for individuals, aggregating ratings for individuals, and constructing a group preference model. This simply means that to create a group preference model, one would need to understand what suits the individual members of the group and use the understanding of the similarities between the users' preferences and the potential recommendations to create the group preference model.

However, even though the application of user ratings is at the heart of every major movie recommender system such as MovieLens, Netflix, etc, it creates the problem of overspecialization whereby only movies which the user or users with similar tastes have given high ratings would always be recommended. This is the most appealing approach which bears a high propensity to be successful and has high recommendation accuracy values. However, this approach tends to leave out low rated movies or movies with no ratings at all, which is depriving the consumer of the chance to experience such movies and make a decision for themselves whether they like such movies or not. Therefore, the application of user ratings in making movie recommendations reduces the scope of movies available for making recommendations to a user to mainly those with high explicit and predicted ratings.

This research proposes that recommendations should be made based on the plot of the movie and not the user ratings. This is because the plot of the movie consists of a subject matter, and how it is interpreted through the characters in the movie propels the journey of the consumer throughout the movie. The application of user ratings in making movie recommendations implies that if there were two users with similar tastes in movies, an unrated movie by one of the users which has been rated highly by the other user would be seen as a fitting recommendation; while a movie which has been rated poorly will be seen as an unfitting recommendation. Therefore, the problem of overspecialization as it relates to the focus of recommender systems on movies with high user ratings is created. To this end, based on the steps identified by Quijano-Sanchez et al (2013), to build a group recommendation model for movies based on personality profiles which would help overcome the problem of overspecialization caused by the application of user ratings in making movie recommendations, this research would take the following steps:

1. Aggregation of the movie preferences for each personality group.
2. Aggregation of the words from the plots of the movies associated with possible subject matters in movies and associate them with the personality of the users.
3. Construction of the personality based group preference model.

1.2 PERSONALITY AND MOVIE CHOICES

Cantador et al (2013) describe personality as the psychological origins of the audience's needs which is a combination of characteristics or qualities that form an individual’s style of thinking, feeling, and behaving in different situations. Karumur et al (2017) further implied that the preferences of an individual with regards to movies can be explained by that individual’s personality. Existing literature has confirmed that personality plays a big role when selecting media content such as music and movies (Pennock et al., 2000; Hu & Pu, 2011; Karumur et al., 2017). Prior research by Jung (1971) pointed out that the decisions which individuals make are not random but are guided by their personalities. Jung (1971) and Smith (2007) further pointed out that our personalities consist of four dimensions which all play roles in how we act and react. They are:

- *Where do you prefer to focus your attention? – Extroversion (E) vs. Introversion (I)*
- *How do you take in information? – Sensing (S) vs. Intuition (N)*
- *How do you make decisions? - Thinking (T) vs. Feeling (F)*
- *How do you orient toward the outer world? - Judging (J) vs. Perceiving (P)*

Therefore, based on the premise implied in Jung (1971) that our decisions are not random but controlled by our personalities, it is assumed that each of the dimensions of the MBTI personality model mentioned above has a role to play in the decisions we make concerning the movies we watch. This was also spotted in Kallias (2012) where it was pointed out that extremely sensitive and empathetic people with the *Feeling* personality trait tend to gravitate towards light-hearted movies that are void of violence.

The two personality models which have been used consistently in recommender systems research are the Five-Factor Model of personality and the Myers Briggs Type Indicator (MBTI) (Song et al., 2009; Yi et al, 2016; Karumur et al., 2017). The ability of the MBTI model to place people into personality groups is what makes it the preferred option in terms of the choice of personality model in this research. Because this research is exploring the potential of making group recommendations to utilize the words associated with movie subject matters and personality profiles to make movie recommendations, it is reasonable to utilize a personality model with an in-built structure for grouping individuals.

1.3 AUTOMATING MOVIE RECOMMENDATIONS UTILIZING INFORMATION SYSTEMS

A recommender system is a type of information filtering system which attempts to predict the preferences of a user and make recommendations based on these preferences (Sappadla et al., 2017). For a recommender system to be effective, there must be enough data to make a prediction. Melville et al (2002) pointed out that recommender systems help overcome information overload by providing personalized suggestions from a vast amount of data based on the history of a user's likes and dislikes. Bell et al (2007) made it a point to note that automated information systems that make recommendations, attempt to profile user preferences, and model the interaction between the users and the products. Some examples of how recommendations have attempted to be automated include the application of demographic information and user ratings to make recommendations (Pazzani, 1999), the application of a user's lifestyle information for making recommendations (Lekakos & Giaglis, 2006), and the utilization of consumers' personality information to make recommendations (Pennock et al., 2000; Hu & Pu, 2011; Karumur et al., 2017). Adomavicius & Tuzhilin (2011), Cantador et al (2013), and Schafer et al (1999) also pointed out that recommendations can be made by utilizing the user's history and the user's ratings of the movies in addition to the above-mentioned attributes of location, demographic, and social companions (which includes other users with similar taste to the user in question). According to Ricci et al (2015), the application of recommender systems is still dominated by solutions recommending products like movies, music, news, and books. The application of personality profiles in recommender systems has so far been applied in the domains of books, music, and movies respectively (Pennock et al., 2000; Hu & Pu, 2009; Cantador et al., 2013; Golbeck & Norris, 2013; Karumur et al., 2017).

Because this research is utilizing movies and personality profiles in recommender systems, the following table will highlight some related literature on the area of movie recommendations and personality profiles in terms of their research contributions, the key findings of the research, and the personality model utilized in the research.

Reference	Research Contribution	Key Findings	Personality Model
Personality, User Preferences, and Behaviour in Recommender systems. (Karumur et al, 2017)	The application of personality in modelling newcomer retention, the intensity of engagement, activity preferences, user preferences toward categories, and nature of ratings provided by users in a recommender system.	- Different personality types exhibit different rating styles and there's also a difference in the magnitudes of ratings which could impact the performance of recommender algorithms. - Introverts and users with low agreeableness have higher customer retention potential than their personality traits counterparts in a recommender system environment. - Different personality types show a preference for different movie genres. - The knowledge of a user's personality can be used as a substitute for a user-ratings profile. User similarity in neighbourhood-based approaches can be computed between the personality vectors instead of user rating vectors, and appropriate recommendations can be made.	Five-Factor Model of Personality
The 50/50 Recommender: A method incorporating personality into movie	Examination of the role of personality in recommender systems utilizing a 50/50 recommendation	- In the application of personality profiles in movie recommender systems, there is a trade-off between	Five-Factor Model of Personality

recommender systems. (Nalmpantis & Tjortjis, 2018)	technique and an 80/20 recommendation technique versus the traditional k-NN recommendation method. For the 50/50, they took the predicted rating of the movie and number which represents the genre preference of the user and divided each of them by two. The addition of these figures produces a new predicted rating for the movie, where the k-NN scoring of the movie and the genre preferences of the user account for 50% each. For the 80/20, they took the predicted rating of the movie and multiplied it by 0.2 and the genre preference of the user and multiplied it by 0.8. That way, personality is now 80% and k-NN is 20%.	investing time to take the test and improving subsequent recommendation experience. - Top preferred method was the 50/50 recommendation technique with 36.92% of the total points, second came k-NN with 34.36%, while the 80/20 method received 28.72% of the points.	
Personalized Movie Recommendation System Combining Data Mining with the k-Clique Method. (Vilakone et al., 2019)	Combining data mining with the k-clique method to improve recommendation accuracy to the users in a movie recommender system environment. The method used the personal information of the users to classify users into several communities with the help of the k-clique process. After that, the system generates the recommended movies for the new users from the list of movies in the most suitable community for the new user by using the data mining method.	The best accuracy was found when the cost of k = 11.	Not Applicable
Personality and Hybrid Recommendation System for Social Networks. (Kethineni et al., 2020)	The combination of collaborative filtering techniques using personality tests to provide more personalised recommendations. The evaluation of a Friend Recommender System (FRS) is based on the big-five personality traits model and hybrid filtering, in which the friend recommended process is based on personality traits and users' harmony rating.	System accuracy was determined using user ratings. This was accomplished using a personality-based social network site that uses the proposed FRS named PersoNet. According to the users' rating results, PersoNet performs better than collaborative filtering (CF)-based FRS in terms of precision and recall	Five-Factor Model of Personality

Table 1. 1 Literature on the use of personality models in recommender systems

As indicated in Table 1.1, all contributions involving the application of personality in making recommendations discovered improvements in the performance of the movie recommender systems utilizing the Five-Factor Model of personality when they were measured against the results of the Traditional Collaborative Filtering recommendation technique. The following table shows the research works which utilize the application of personality in making group recommendations and their key findings.

Reference	Research Contribution	Key Findings	User Classification Model
Social Factors in Group Recommender Systems (Quijano-Sanchez et al, 2013)	The application of personality, trust, and memory in improving the group recommendation process by making a more exact representation of how group argumentations take place in real life.	- The strength of the recommendation technique is determined by the value of the two hit evaluation metrics. The higher the value, the stronger the recommendation technique. - The combination of trust and personality had the best recommendation results on both the one-hit evaluation metric and the two hit evaluation metric having a value of 30% using the two hits metric and therefore improved the base recommendations. - The use of personality alone in the recommendation process obtained a value of 20% using the two hit metrics and therefore improved the base recommendations. - The use of trust alone in the recommendation process did not improve the base recommendations.	The Thomas-Kilmann Conflict Mode Instrument.
Personality Aware Recommendations to Groups. (Recio-Garcia et al., 2009)	The introduction of a novel method of making recommendations to groups based on existing techniques of collaborative filtering and	- Results indicate that the accuracy of the recommendation correlates with higher values of the conflict mode weight (CMW).	The Thomas-Kilmann Conflict Mode Instrument.

	taking into account the group personality composition.	- The recommender algorithm used obtains better results for groups with people having heterogeneous conflict resolution personalities.	

Table 1. 2 Literature on group recommender systems

As indicated in Table 1.2, recommendations made to groups based on the personality of the users in the group improves the accuracy of the recommendations. However, new users to the group are still required to provide their user preferences which would be used in the generation of the group preference model. This simply implies that the personality group preference model has the propensity to change based on the preferences of the new users which are added to the personality group which in turn makes the recommendation model highly susceptible to the problem of scalability. Alharthi (2015) pointed out that there is a need for a common base when making recommendations. This raises the possibility of creating a personality group recommendation model that doesn't need to change with the addition of new members to the group.

To this end, this research will explore group movie recommendations based on personality profiles by identifying the words associated with movie subject matters which are in the plots of the movies and associating those words with the personality traits of the MBTI model to create a list of keywords which can be used in making movie recommendations. The list of keywords will serve as the common base for making recommendations. This implies that new users joining the personality group do not need to provide information about their movie preferences which would create a fixed structure for the personality group as it relates to recommendation preferences.

1.4 RECOMMENDER SYSTEMS AND CONSUMER PERSONALITY

Research on recommender systems in the movie industry is very valuable considering that Netflix used to offer the prize of $1 million to anyone who could help improve the accuracy of their recommender system (Bennett & Lanning, 2007). The movie industry is one of the most successful entertainment domains in the world with multiple products for the users to choose from, it makes sense that a recommender system will be applied to help deal with the information overload. Park et al (2012) further pointed out that recommender systems have more practical applications in movies and shopping than any other field. However, the recommender systems used to assist consumers in shopping are not as complicated as the ones used in a movie recommender system. The recommender systems used in shopping, such as Amazon and eBay, are the most popular examples, usually displaying related products/items which consumers who brought the same product/item also purchased. Such products are usually the same product from a different brand or an accessory to the product purchased. In a movie recommender system, Field (2005) indicated that movies can relate to people's real-life circumstances in terms of how they relate with others and how they react to various thoughts and feelings in life. Therefore, to make recommendations to movie consumers, one would need to understand how the consumers generally think, feel, and act.

1.5 RESEARCH GOALS

Prior research has already been able to establish a connection between the user's movie choices and their personality (Song et al., 2009; Cantador et al., 2013; Golbeck & Norris, 2013; Karumur et al., 2017) and therefore solidify its stance as a valuable component in a movie recommender system. However, the main driving force behind making recommendations in recommender systems research is user ratings. Existing recommendation models utilize predicted user ratings to make recommendations. However, this involves new users supplying the system with initial rating values which would be used to generate predicted rating values for unrated movies as evidenced via MovieLens (Chandrashekhar & Bhasker 2011). One thing common with all recommender systems is that they require new users to provide initial ratings of items such as in MovieLens or identification of favourite items such as in Netflix to enable the system to generate recommendations for the users. The initial ratings of the items provided by the users are used to calculate the predicted ratings for unrated items for individual users. The application of ratings in making recommendations functions on the premise that all the movies in the database have been rated at least once by a user. However, this creates the problem of overspecialization in terms of the continuous recommendation of only highly rated movies and the assumption that users with similar tastes in movies would give the same rating to the movie without knowing what the movie was about. According to Chandrashekhar & Bhasker (2011), this approach has shown to be successful in terms of having a 96.1% recommendation accuracy, however, it makes a certain section of movies un-recommendable because they are either completely unrated or are rated poorly by some users. This approach is detrimental to the movie industry and its investors as it relates to those associated with the making of movies with unpopular cast members or moviemakers in terms of earning profit from the movie.

According to Nunes (2008), due to the complexity of human behaviour, it cannot be adequately analyzed using scores such as ratings, therefore, the assumption of excluding certain movies for recommendation to a user on the premise that they were rated poorly by other users with similar tastes to the user deprives the user of the opportunity of watching a movie which they might like. Furthermore, such an approach significantly reduces the success of movies which can be categorised as unpopular due to their lack of ratings which in turn negatively impacts the jobs of those involved in making the movie because the success of the movie is highly dependent on the size of the consumer movie market which can access the movie. The research questions generated as a result of the identified problems above are:

1. *How can personality-based group recommendation models which make movie recommendations based on the words associated with the subject matter in movies help to overcome the problem of ratings-based overspecialization caused by the continuous recommendation of highly rated movies by existing recommendation models and also facilitate the expansion of the consumer movie market for unpopular movies?*
2. *What is the impact on the recommendation accuracy of a personality-based group movie recommendation model when user ratings are not used in making movie recommendations?*

1.6 RESEARCH METHODOLOGY – DESIGN SCIENCE RESEARCH

According to Osterwalder (2004), the choice of methodology is largely dependent on the problem which the research is trying to solve. The problem identified with the existing recommendation models is the problem of overspecialization as it relates to the continuous recommendation of movies with high consumer ratings, and the exclusion of unpopular movies which are not rated or have been rated very poorly by consumers thereby significantly reducing the size of consumers market who can access the movie. Recio-Garcia et al. (2009), Hu & Pu (2011), Quijano-Sanchez et al (2013), and Karumur et al (2017) indicated that making personality-based group recommendations improves recommendation accuracy through the application of predicted user ratings. The problem of overspecialization becomes apparent when users are just recommended movies which have been rated highly by them or other users with similar taste in movies. This approach of recommending movies with high user ratings or high predicted ratings would likely lead to a high recommendation accuracy because the movies which are least popular among the users with low ratings or no ratings at all are not being recommended. Therefore, it is reasonable to say that the art of making movie recommendations is the art of identifying the movies that will be satisfactory to the consumers based on their interpretation of the subject matter portrayed through the characters and events in the movie. This involves the development of an MBTI personality-based group recommendation model utilizing the design science research methodology.

1.7 THESIS STRUCTURE

THESIS CHAPTER	DESCRIPTION
Chapter One	Introduces the research by presenting the relevance of this research, the research methodology, research goals, and research questions.
Chapter Two	Explores the literature concerning recommender systems and the various drawbacks of recommender systems today. It also discusses the various similarity measures which have been applied in making recommendations. The chapter further highlights the need for group recommendations utilizing personality profiles.
Chapter Three	Discusses the research methods, data collection methods, and data analysis methods used in this research.
Chapter Four	Discusses the research process model design.
Chapter Five	Discusses the creation of the group recommendation model.
Chapter Six	Discusses the testing of the group recommendation model and the analysis of the consumer feedback and results.
Chapter Seven	Discusses the summary, conclusions, and future work

Table 1. 3 Thesis Structure

CHAPTER TWO - LITERATURE REVIEW

2.1 OVERVIEW ON RECOMMENDER SYSTEMS

Recommender systems are a subclass of information filtering system that seeks to predict 'rating' or 'preference' that a user would give to an item (such as music, books, or movies) or social element (e.g. people or group) they had not yet considered, using a model built from the characteristics of an item (content-based approaches) or the user's social environment (collaborative filtering approaches) (Madhukar, 2014). This is quite a comprehensive description of a recommender system; however, it is possible to break it down to a few keywords, these are, "information filtering", "predict preference", "model", "characteristics of an item", and "user's social environment". Resnick & Varian (1997) described the functionality of the recommender system as a means to augment the traditional social process of recommendation. According to Nunes (2008), the traditional social process of recommendation simply involves a friend meet friend situation where one friend suggests to the other friend an item which they found useful. Recommender systems are only necessary for situations where users have multiple potential preferences. Recommender systems that are used in online shopping for clothes, phones, jewellery, etc usually just focus on the items which a consumer buys and recommends items that other consumers who bought the same item also added to their purchase. However, recommender systems that are used in domains such as movies, music, and books require a more complex approach because these products tend to affect the personality of consumers in terms of how they feel, think, and act.

According to Rajpukar et al (2015), recommender systems were described as intelligent algorithms that are meant to generate recommendations for the consumers. This description simply implies that recommender systems are intelligent systems built to help satisfy our desires by recommending products that we need. The emphasis on this description would be on the recommendation of items that are needed. Recommender systems are software tools and techniques for suggesting items to users by considering their preferences in an automated fashion (Nilashi et al, 2013). Matthiesen et al (2019) rightly identified the mandatory requirement of the use of models in product development, since the original product does not exist until the development is completed. This suggests the separation of the processes involved in making recommendations into models. One of the models identified by Ricci et al (2015) is the user model. According to Ricci et al (2015), a user model is the user's profile which is made up of data that the recommender system could utilize in providing personalized recommendations to the user. Another model that can be applied in the development of a recommendation model is the product model. According to Hvam (1999), product models contain a formalized representation of product knowledge that is normally represented in the heads of skilled engineers. Furthermore, Krause et al (1993) pointed out that a central issue among these needed information technologies is product modeling, which generates an information reservoir of complete product data to support various activities at different product development phases. The product model is generated based on how the product is connected with the consumers. There is no recommendation model without a user model and a product model even though they may not be specifically identified in that manner. This is evident from the fact that the art of making recommendations relies solely on the ability of the recommender system to identify the right product for the right consumers. This is the core responsibility of any kind of recommender system and such a task is completely impossible to do without the use of a user model and a product model. The third model can be seen in Chandrashekhar & Bhasker (2011) as the recommendation model. This is the model within the overall recommendation model which contains the algorithm to predict recommendations based on the values associated with the user model and the product model. When we take a look at various recommendation models such as the collaborative filtering recommendation model and the content-based recommendation model, one would realise that they all function based on specific algorithms and if such an algorithm is taken out, it will not be able to make any recommendations. The recommendation model exists as a result of the data analysed in the collaborative filtering process or the content-based process. During the collaborative filtering process or the content-based process, the data about the user and the products are analysed to establish a relationship that can be used to make recommendations to the users. The relationship established between the product and the user is applied in an algorithm in the recommendation model phase of the recommendation process to make the most suitable recommendations to the users. Therefore, this research applies the services of the user model, product model, and the recommendation model in the development of the personality-based group recommendation model.

The automated approach to making recommendations using recommender systems is simply the automation of the processing of information concerning the users and the products in question. The main difference between recommender systems is in the kind of information which they choose to process in the user and product models which are fed into the algorithm in the recommendation model. According to Chandrashekhar & Bhasker (2011), two of the tests required to assess the performance of a recommendation model are the tests for prediction accuracy and the test for serendipitous recommendations which involves the recommendation of the movies which the user would not usually choose on their own. Kotkov et al (2016) rightly pointed out that recommender systems need to have the ability to suggest items to consumers which they probably would not have been able to suggest for themselves. According to Schafer et al (1999) and Rashid et al (2002), recommender systems are described in terms of e-commerce systems that portray them as decision-making systems that are utilized in environments where the information available is too much and the probability of making an unsatisfactory decision is high. This implies that the process of recommendation involves the processing of user and product information and the filtration of recommendable products based on the information processed. Therefore, it is reasonable to say that the process of recommendation is synonymous with the simple information processing model where input is received, the data is processed, and an output is generated and delivered. The input received represents the data that will be analysed from the user and product models to determine which items would be recommended; the decision-making stage is where the recommendation algorithm is applied, and the recommendations are generated as the output in the output stage. The users provide feedback on if they liked the recommendations or not and the feedback is fed back into the input stage to customise the recommendations according to the needs of the user.

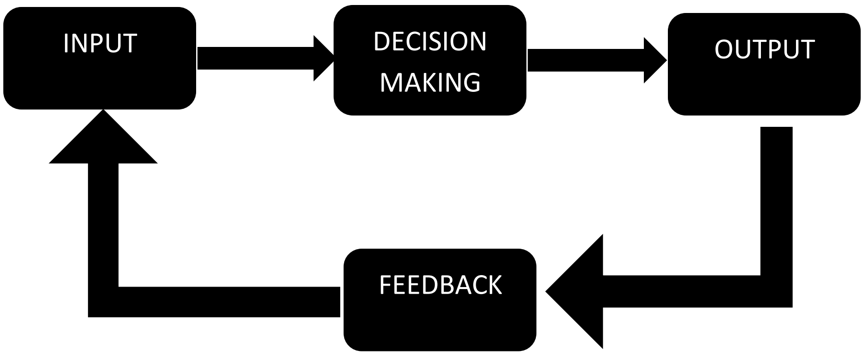

Fig. 2. 1 A Basic Information Processing Model

Now that a general overview of recommender systems has been provided, the next step is to understand the necessity of implementing personality in a movie recommendation model. The main difference between existing personality-based movie recommender systems research and the non-personality-based movie recommender systems research is in the presence or absence of the k-NN function in the creation of a personality based recommendation neighbourhood. The k-NN was selected to represent the traditional collaborative filtering technique due to it’s popularity and simplicity. In a personality-based movie recommendation model, the users are categorised based on their personalities which are determined through the use of a personality questionnaire. But with the non-personality-based movie recommendation model, the k-NN function is applied to determine the users with similar tastes in movies. According to Nalmpantis & Tjortjis (2018), in the application of personality profiles in movie recommender systems, there is a trade-off between investing time to take the test and improving subsequent recommendation experience.

The following table shows various kinds of recommender systems including their functionalities, key findings of the research, the domains they were applied, and the personality model utilized.

Research Paper	Recommender System and functionalities	Key Findings	Domain and Personality model
TWIN: Personality-based Recommender System (Roschina, 2012)	The TWIN personality-based recommender system produces recommendations by applying the results achieved in the personality from the text recognition research field to Personality-based Recommender System user profile modelling. The main components of the TWIN system are: - User Data Processor - this collects the data written by the user from the social media online resource, analyses it, calculates personality scores, and stores the results in the user profile following the constructed user ontology. - Similarity Estimator - this performs the general functionality of the RS by applying the k-NN algorithm to find the circle	- The effectiveness and usefulness of the TWIN system depend on the accuracy of the personality match. - The k-NN algorithm performs better when considering the mean vectors of reviews' scores that represent the overall personality of the author. - The combination of "Extraversion-Neuroticism-Consciousness-Openness to Experience" performs better than the combination of all the Big 5 Traits together. - The hypothesis concerning the use of the TWIN personality-based recommender system to provide accurate recommendations utilizing the predicted personality profile was inconclusive.	Domain – Travel Personality Model – Big Five Personality Model

	of people with a similar personality. - Results Visualiser – this is the Flash user interface that visualises the calculated personality of the user and presents the list of found recommendations.		
The Use of Items Personality Profiles in Recommender Systems. (Alharthi, 2015)	Proportion-based IPPs (Personality Profile for Items) CF recommendation system that develops a personality profile for each product and represents items by an aggregated vector of personality features of the people who have liked the items. It consists of 15 attributes that aggregate the number of fans who have high, average, and low Big Five values. The system functions like an item-based collaborative filtering recommender; that is, it recommends items similar to those the user liked.	- It focuses on users' personalities, and thus finds deeper associations between users and items. - The size of the matrix will not increase when new users join the community, and it will only grow vertically if the profiles of new items are added since each IPP vector consists of just 15 attributes. - The use of personality allows for serendipitous recommendations. - To have a personality profile developed, an item must receive enough positive ratings. Thus, similar to traditional CF, this system also encounters the cold start problem in the form of the new item problem. - Like regular content-based filtering and collaborative based filtering, the IPPs-based CF system requires a user to have already rated some items, before they can receive recommendations. This brings to light another cold start problem in the	Domain – Movies, Books. Personality Model – The Big Five Personality Model

		form of the new user problem.	
Recommender Systems based on Personality Traits (Nunes, 2008)	A recommender system which is used to give private recommendations considering the best choice of a presidential candidate for a person to vote for utilizing the individual reputation of each candidate in the form of their User Psychological Profile according to other users' view.	- The recommendation was very useful to provide evidence that the recommendation generated in this experiment was indeed very relevant, as people's effective vote was 100% compatible with the recommendation. - Users were resistant towards answering the NEO-IPIP questionnaire which would tell them about their personality for the research.	Domain – Online voting Personality Model – The Big 5 Personality Model
	Social Matching Recommender System - generation of recommendations about more compatible students considering their psychological aspects or, more precisely, their Personality Traits. Those recommendations might be used as an additional attribute to contribute to the students' decision-making process towards the selection of the best partner to be part of their effective workgroup.	- People prefer to interact with others who have a similar personality rather than with others who have personalities that are different from their own. - Inability to extract the pattern of behaviour considering only student's scores. The main reason is that human behaviour cannot be analyzed and extracted only from students' scores, it is much more complex than that. - Users were not motivated to fill out the NEO-IPIP questionnaire so that their personality trait values can be used in the research.	Domain – Academia Personality Model – The Big 5 Personality Model

Table 2. 1 Related Literature for Personality-based Recommender Systems

Considering Table 2.1 above, the following deductions can be made in facilitating the creation of the personality-based group movie recommender system for this research.

1. Human behaviour in movie recommender systems cannot be adequately analysed using user ratings due to the complexity of human behaviour. This implies that if we are going to try to recommend movies based on the consumer's personality which reflects on how they behave in the society, it's only reasonable to use words associated with the subject matter of movies which are based on societal issues such as abortion, abandonment, etc or events/actions associated with people such as murder, graduation, etc. Such information can be found in the plots of the movies and can be extracted using the process of text mining.
2. According to Nunes (2008), people prefer to interact with others with the same personality profiles. This implies that people can be grouped based on their personality profiles to virtually interact with others within the same personality group to make and receive recommendations.
3. People don't like filling out personality questionnaires. The Big 5 Personality model is a preferred model by psychologists as it has been confirmed as one which gives the best representation of a user's personality; however, it takes a long time to fill (about 20 - 30 minutes). On the other hand, the MBTI personality model takes just about 5-10 minutes to fill. The MBTI personality model has a lesser accuracy of predicting a user's personality than the Big 5 personality model. However, most people already know their MBTI personality types as evident in the various MBTI personality type Facebook groups with thousands of members relating and interacting with each other.
4. Social matching based on personality profiles can be used in a personality-based recommender system to match people with the same personality profiles to create a personality-based neighbourhood. According to Nunes & Hu (2012), the successful applications of personality-based recommendation technologies include social matching systems (e.g., online dating systems), gift recommenders, music recommenders, and movie recommenders.

The following sections discuss further types of recommendation techniques. This research will focus on the analysis of the content-based, collaborative filtering, and the application of deep learning and neural networks in developing recommender systems as these are the most used techniques in the development of recommendation models.

2.2 CONTENT-BASED FILTERING

According to Aggarwal (2016) and Gemmis et al (2015), in content-based recommender systems, the descriptive attributes of items are used to make recommendations. This was supported by prior research by Bobadilla et al. (2013) who pointed out that the user content used in making recommendations refers to the content of the items in the consumer's transaction history. This approach tends to limit the users within the scope of their transaction history thereby denying them the opportunity of exploring something new. According to Bell et al (2007) and Bobadilla et al (2013), the content-based approach uses the analysis of the content of the item in the user's transaction history to create a user profile that allows the recommender system to associate users with items which suit their preferences. In the content-based recommendation model, out of all the descriptive elements of the item, the main element which determines if the item would be recommended or not is the rating associated with the item. According to Gemmis et al (2015), the process adopted by the content-based recommender system is divided into three. This can also be described as the elements of the process model through which the content-based recommender system operates. These are analysed in the following subsections.

2.2.1 CONTENT ANALYSER

The first element of the content-based recommender system process model is the content analyser. The content analyser is used to determine the kind of information which would be processed to determine the most suitable item to be recommended to the consumer. The information collected at this stage is crucial to the efficiency of the recommender system and the accuracy of the recommendations provided. According to the descriptions of information retrieval and information filtering provided in Belkin & Croft (1992), one may postulate that the content analyser functions as information retrieval and filtration system. Retrieval simply refers to the selection of data from a fixed data set, whereas filtering typically refers to the selection of relevant information or rejection of irrelevant information from a data stream. In terms of the content analyser functioning in the capacity of information retrieval and filtration system, it retrieves the content of the items in the database and filters out the contents which are relevant in the determination of the items to recommend to the user. The deliverable or the output from the content analyser can be said to be the user model which according to Ricci et al (2015) is made up of data that the recommender system could utilize in providing personalized recommendations to the user.

2.2.2 PROFILE LEARNER

The profile learner receives the information from the content analyser and attempts to understand how the information in the user model is related to the information in the product model which in turn was developed based on the needs of the consumers. According to Aggarwal (2016), the data collected is used to create a user-specific model which will be used to determine if the user will like the recommended item or not. The profile learner takes the information from the user model and the information about the product to create the product model. Therefore, in the content-based recommendation process, the ratings of the product based on the user's rating history are the elements taken into consideration when recommendations are to be generated. The data analysed from the product model which is used in the creation of the user model will be based on the product information acquired from the user's transaction history. The user model is constantly updated with information about the user's preferences as it relates to the products in the database.

2.2.3 FILTERING COMPONENT

The filtering component takes the information provided in the product model which is now made up of data that relates the products to the user and filters out the items with the highest ratings for a recommendation. The recommendation model, the user model, and the product model are constantly changing due to the erratic nature of human behaviour. The recommendation model which is generated as a deliverable of the filtering component is generally a ranked list of potentially interesting items. This was supported by Gemmis et al (2015) and suggests that recommender systems can only generate items that are potentially interesting with no guarantees that they would be interesting to that specific user.

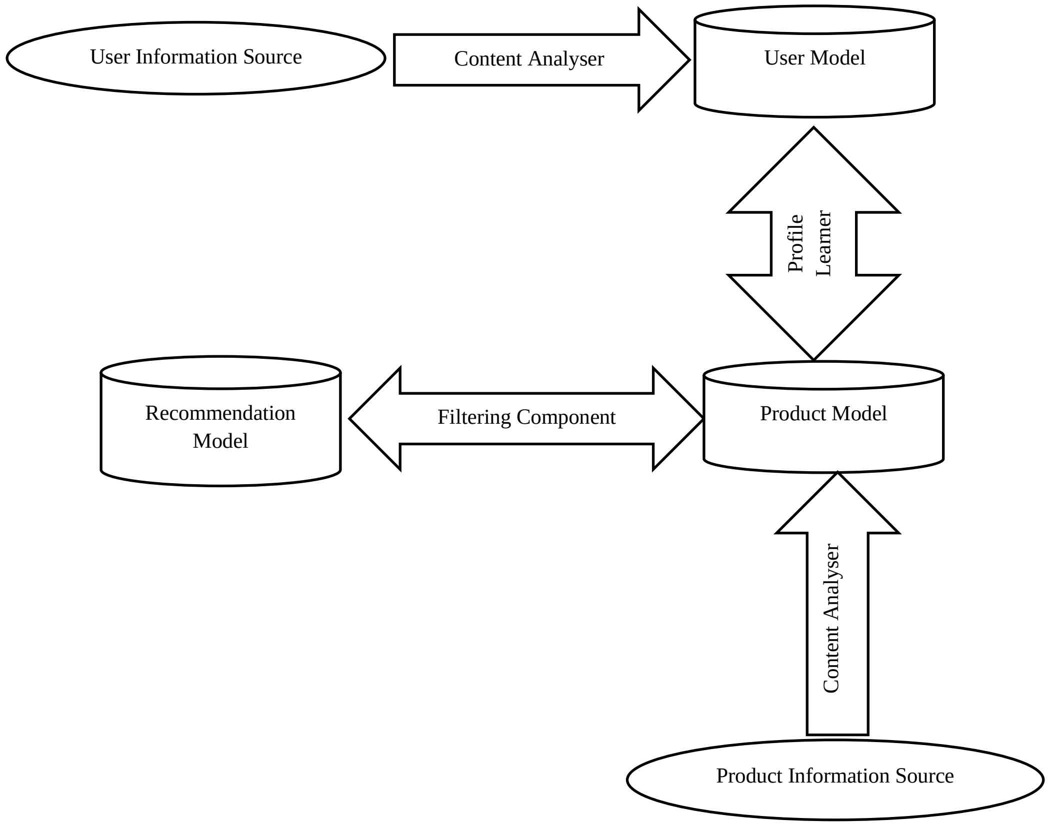

Fig. 2. 2 Architecture of a content-based recommender

2.2.4 DRAWBACKS OF CONTENT BASED RECOMMENDER SYSTEMS

So far it has been shown how the product model, user model, and recommendation model, which make up a recommender system can be applied in a content-based recommender system. This section will discuss the challenges which are associated with using the content-based recommender system. The major drawbacks are:

The Cold Start Problem - The cold start problem is typical in recommendation systems. Lika et al (2014) and Karumur et al (2017) rightly mentioned that the “cold start" problem happens in recommendation systems due to the lack of information, on users or items. In the case of a content-based recommender system, the cold start problem occurs because of a lack of information on the users and items. Content-based recommender systems typically rely on the ratings of an item to make recommendations to a user based on the ratings the user has provided for past items. The cold start problem refers to the situation when a new user or new item just enters the system. This exposes two kinds of cold start problems as applies to content-based recommender systems, they are new user problem and new item problem. In the case of a new user, there is no previous history for the recommender system to analyse to help in predicting the future choices for the user. In the case of a new item, there are no available ratings, therefore since ratings determine the items which will be recommended, the new items will not be recommended. This leads nicely to the next drawback of content-based filtering, which is, data sparsity.

Data Sparsity – Data sparsity occurs when there are not enough ratings on an item for it to be considered for recommendation. According to Al-Bakri & Hashim (2018), the data sparsity problem leads to generation of unreasonable recommendations for those users who provide no ratings. A typical content-based recommender system would usually request for explicit ratings to be provided by the new user on some of the movies of their choice for the recommendation model to understand the user's movie preferences. The content-based recommender uses the movie attributes such as the actors, directors, screenwriters in conjunction with the user ratings of the movies to make recommendations to the user. The problem of data sparsity is largely associated with the problem of overspecialization in terms of recommending only the movies in which the user has given a high rating or making recommendations based on similar movies to those movies which the user has given high ratings.

2.3 COLLABORATIVE FILTERING RECOMMENDATION SYSTEM

Collaborative filtering is the most widely used technique in movie recommendation systems. It is a method of making automatic recommendations of certain movies by creating profiles based on diverse kinds of information collected from multiple users, and subsequently making predictions based on these profiles, about the interests of a user who has preferences similar to other like-minded users. In a collaborative filtering system, users give preference ratings to items based on their taste. The system calculates preference similarities among users from such ratings and makes predictions about a user's rating for a product which the user has not rated yet. For the collaborative filtering recommender system to function effectively, it requires the users to provide ratings on many items. However, users are normally unable to assess all the items in the system, which always presents a fundamental problem of data sparsity to the collaborative filtering recommender systems. Despite the obvious problems of data sparsity, the collaborative filtering recommender system is known to be the most successful recommender system (Herlocker et al, 2000, Herlocker et al, 2004, Ronen et al, 2013). The main difference between content-based and collaborative filtering is that the content-based approach makes recommendations based on an item – item and user-item collaborations while the collaborative filtering approach makes recommendations based on an item – item, user – item, and user-user collaborations. According to Koren et al (2009), collaborative filtering produces user-specific recommendations of items based on patterns of ratings or usage. Prior research by Debnath et al (2008) pointed out that collaborative filtering recommender systems compute similarities between two users based on their rating profile and recommend movies that are highly rated by users with similar preferences. This means that as opposed to content-based recommender systems that take into consideration the ratings of one user, collaborative filtering recommender systems take into consideration the user in question as well as other users with similar preferences. This increases the possibility of serendipitous recommendations.

The general idea behind collaborative filtering recommender systems is to identify the user's nearest neighbours. The nearest neighbours are defined by their levels of similarities in item preferences to the user in question. Similarities can be defined in terms of the ratings which the user gives an item and the characteristics of the item. This approach can also be referred to as the neighbourhood based approach. Interestingly, the neighbourhood-based approach has been described by Vig et al (2009) and Koren et al (2009) as both user-based, and item-based. In an item-based collaboration, Koren et al (2009) indicated that it signified the evaluation of a user's preferences of an item based on ratings of neighbouring items rated by the same user then. An item-based collaboration creates a network of items with similar characteristics and similar ratings. Schafer et al (1999) referred to item-based collaboration as an ephemeral approach because the system does not recognise the user from one session to the next. This means that the system does not use information about the user's history to make recommendations, rather, recommendations are made based on the user's selections and ratings during an active session. In user-user collaboration, Rashid et al (2002) pointed out that the system recommends items to a user based on the ratings of that same item by other users with similar tastes. The user-based collaboration approach is the most similar to the traditional recommendation process because it involves two or more users. Rashid et al (2002) and Chandrashekhar & Bhasker (2011) further highlighted that the user-based collaboration approach increases the possibility of serendipitous recommendations.

The three main problems associated with collaborative filtering are:

1. Data Sparsity: This occurs when the recommender system doesn't have enough data to make valuable recommendations. The following problems fall under data sparsity.

   a) Cold Start: Lika et al (2014) pointed out that there are three types of cold start problems, they are:

      i. Recommendations for new users

ii. Recommendations for new items

iii. Recommendations on new items for new users. A problem occurs because new users will not receive proper recommendations. After all, they don't have any rating history and the items are also unrated.

b) Reduced coverage: A problem that occurs because not all the items in the system are rated.

2. The Grey Sheep: this occurs when a user does not have interests that follow those of a particular group and therefore is not able to receive valuable recommendations. Ghazanfar & Prugel-Bennett (2014) and Zheng et al (2017) pointed out that the grey sheep users have low correlation coefficients with other users, as they partially agree or disagree with other users. They further stated that the presence of these users in a small or medium community of users poses two problems:

    a. they may not receive an accurate recommendation, even after the initial start-up phase for users and the system.

    b. they may negatively affect the recommendations of the rest of the community.

Collaborative filtering recommender systems rely on users' ratings to provide recommendations. This approach allows the recommendation of items highly rated by similar individuals and does not require extensive knowledge about items themselves. The common similarity criteria used to determine the similarity between users is the Jaccard similarity or the cosine similarity. These will be demonstrated using the sample dataset below which consists of ratings of movies for 4 users, A, B, C, and D.

	Titanic	Inception	Shutter Island	Charlie's Angels
A	5	-	-	2
B	-	3	-	5
C	4	3	5	-
D	-	4	4	-

Table 2. 2 Sample Dataset to calculate similarity criteria

The Jaccard similarity coefficient compares members for two sets to see which members are shared and which are distinct. It's a measure of similarity for the two sets of data, with a range from 0% to 100%. The higher the percentage, the more similar the two populations. The formula for determining the Jaccard similarity between two users is as follows, where *sim* refers to similarity, x and y refers to the users, and R refers to the ratings of the users:

$$sim(x,y) = | R_x \cap R_y | / | R_x \cup R_y |$$

In the case of Table 2.2, the calculation would be as follows,:

$$sim(A,B) = | R_a \cap R_b | / | R_a \cup R_b |$$

$$\text{where } R_a \cap R_b = 1 \text{ and } R_a \cup R_b = 4$$

$$sim(A,B) = ¼ = 0.25$$

$$\text{Therefore, } sim(A,B) = 25\%$$

Following the same process, the following results were obtained in calculating the similarity between users A, B, C, and D using the Jaccard similarity criteria.

$$sim(A,C) = 20\%$$

$$sim(B,C) = 20\%$$

$$sim(B,D) = 20\%$$

$$sim(C,D) = 40\%$$

Therefore, using the Jaccard similarity criteria, the users with the highest similarity are users C and D. In a collaborative filtering recommender system, it is therefore expected that the movie “Titanic” would be recommended to user D since it was highly rated by user C. The problem with this method of similarity classification is that it doesn’t take into consideration the actual value of the ratings which the users gave the movies when calculating for the similarity between users. It only takes into consideration the fact that the users have watched the movie and provided ratings for the movie. For instance, users A and C may be more similar in preferences than the Jaccard similarity computation projects as they both gave high ratings for the same movie even though they only have one movie in common.

The cosine similarity is a measure of similarity between two non-zero vectors of an inner product space that measures the cosine of the angle between them. Cosine similarity is the cosine of the angle between two n-dimensional vectors in an n-dimensional space. It is the dot product of the two vectors divided by the product of the two vectors' lengths (or magnitudes). In the case of movies, unlike the Jaccard similarity computation, it utilizes the actual values of the ratings provided by users in computing the similarity between users. The cosine similarity is between -1 to +1 and is the calculation of the angle between the ratings of two users. The formula for cosine similarity is as indicated below.

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A}\cdot\mathbf{B}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2}\sqrt{\sum_{i=1}^{n} B_i^2}},$$

As indicated in the formula above, A and B are the users, n is the total number of ratings provided by the user. A_i represents the ratings provided by user A and B_i represents the ratings provided by user B. The numerator is the multiplication of the ratings of the movies the user's A and B have in common, while the denominator is the square root of the addition of the squares of all the ratings for user A multiplied by the square root of the addition of the squares of all the ratings for user B. Using Table 2.2, the cosine similarity for users A, B, C, and D have been computed as follows.

$$Sim(A,B) = \cos(r_a, r_b) = 0.3185$$

$$Sim(A,C) = \cos(r_a, r_c) = 0.5252$$

$$Sim(B,C) = \cos(r_b, r_c) = 0.2182$$

$$Sim(B,D) = \cos(r_b, r_d) = 0.3638$$

$$Sim(C,D) = \cos(r_b, r_d) = 0.8000$$

However, to determine the strength of the similarity between two users, the cosine distance has to be calculated. The higher the value of the cosine distance, the less similar the users are in terms of their movie preferences. The cosine distance is calculated by subtracting the cosine similarity value from 1. The formula is as stated below.

$$1 - \cos(r_a, r_b)$$

Therefore the cosine distances for the cosine similarities calculated above are:

Sim(A,B) = 0.6815

Sim(A,C) = 0.4748

Sim(B,C) = 0.7818

Sim(B,D) = 0.6362

Sim(C,D) = 0.2000

In the case of a collaborative filtering recommender system being applied to the data in Table 2.2 in the determination of the similarity between users utilizing cosine similarity and cosine distance, the most similar users are C and D. Therefore the collaborative filtering recommender system would recommend the movie "Titanic" to user D because user C gave the movie a high rating and is the most similar in terms of movie preferences to user D. The main drawback of utilizing the cosine similarity in determining the similarity between two users is that it treats null values as 0 which is wrong because it implies that the user provided a rating of 0 when the user has not provided a rating for the movie. An important difference between the Jaccard similarity and the cosine similarity is that the cosine similarity provides clearer similarity results because of its use of the user ratings in the determination of user similarity.

Now that an understanding concerning the similarity metrics utilized in collaborative filtering recommender systems has been provided, the following subsections will dive a bit deeper into the world of collaborative filtering recommender systems by categorising them based on how they operate.

2.3.1 MEMORY-BASED COLLABORATIVE FILTERING

According to Rafter (2010), a collaborative filtering recommender system is said to be memory based when the recommendation algorithm computes the similarities in-memory without the need to produce a model first. According to Yuan (2018), memory-based CF can be broadly divided into user-item CF and item-item CF. The common approach for user-item CF is to find users that are similar to the target user by leveraging the similarity of ratings. By contrast, item-item CF typically first focuses on users who like the particular item, and then recommend other items that those users also liked. In practice, memory-based CF techniques can be implemented by calculating the distance metric, such as cosine similarity (Linden et al., 2003), Pearson correlation (Sheugh and Alizadeh, 2015), and Jaccard coefficient.

A popular algorithm used in collaborative filtering recommender systems which are memory-based is the k-Nearest Neighbour (k-NN) algorithm. The k-NN is based on feature similarity, meaning that the nearest neighbour is determined by calculating the similarities in features of items selected by users. It’s one of the simplest machine learning algorithms used in the classification of items. The *k* in k-NN is a parameter that refers to the number of nearest neighbours to include in the prediction process. The value of k is determining by calculating the square root of the total number of data points to be classified. The k-NN algorithm is an instance-based learning algorithm; it operates on a subset of ratings when computing predicted values. The k-NN training phase consists of forming neighbourhoods for each user (or item). In determining the k-NN, the training dataset is stored and the similarity between the user ratings in the training dataset and the user ratings in the test dataset is calculated to predict ratings of movies not yet rated by the users within the collaborative network. The use of the k-NN overcomes the problem of null values identified in the calculation of the cosine similarity above. This phase entails selecting a subset of the user-item matrix for each of the predictions that the algorithm will subsequently be asked to make. The k-NN is also known as a lazy learner because it doesn’t learn much from the training data as most of the learning happens from the live data. The k-NN is determined by calculating the Euclidean distance between users by utilizing the ratings of the users. The smaller the value of the Euclidean distance *d*, the more similar the users. The formula for calculating the Euclidean distance is generated from the Pythagorean theorem and is indicated below.

$$d(\mathbf{p},\mathbf{q}) = \sqrt{(p_1-q_1)^2+(p_2-q_2)^2+\cdots+(p_i-q_i)^2+\cdots+(p_n-q_n)^2} = \sqrt{\sum_{i=1}^{n}(p_i-q_i)^2}.$$

Where p and q represent the users, n represents the total number of data points, and i represents the ratings of the users, therefore, p_1 represents the first rating of user p, and so on. The k-NN can be used when the dataset is not too large or too complicated. For recommender systems, the k-NN is not appropriate because the social relationship between the users is not taken into account. If the traditional process of making recommendations is to be computerised or automated, all the conditions which are involved in the traditional recommendation process have to be taken into consideration. The k-NN uses the similarities in user ratings to determine the similarity between users, but that does not account for the social relationship between users when making recommendations as that is a vital part of making successful recommendations. This was supported by Nielsen (2015) when it was pointed out that the most credible form of advertising comes straight from the people we know and trust. The report pointed out that eighty-three percent of online respondents in 60 countries say they trust the recommendations of friends and family. This highlights the fact that similarities in ratings are not sufficient to understand the social bond between the users. If the traditional process of recommendation is to be taken into account, the ability to understand the social connection between users supersedes the strength of the similarity in user ratings. The k-NN cannot understand the social connection between users because such data is not naturally quantitative but qualitative.

In recommender systems research, it’s not possible to automatically determine users who are related by blood and categorise them for recommendation purposes, unless the relationship is explicitly stated by the users. However, it is possible to categorise people based on their exhibition of similar social behaviours. The social behaviours of users is another way to identify the social connection between users to facilitate the social matching process in a recommender system. This qualitative data can be exploited by recommender systems to make similar recommendations to users who have similar social behavioural characteristics. To this end, the term which takes into account the social behavioural characteristics of a user in its description is ***“personality”***. Therefore, rather than using the k-NN as a method of classification, users can be categorised based on their personality profiles (Song et al., 2009; Yi et al., 2016).

2.3.2 MODEL-BASED COLLABORATIVE FILTERING

Yuan (2018) rightly described model-based CF as one which does not need to explicitly calculate the similarities between users and items. Instead, it usually relies on machine learning and data mining techniques to automatically learn the parameters by certain optimization framework. Examples of model-based methods include matrix factorization (Koren et al., 2009) and neural network models (He et al., 2017). Compared with the memory-based methods, model-based CF techniques are usually built based on low-dimensional models (e.g., factorization techniques). As a result, model-based models take less memory since they do not need to store the original rating matrix; moreover, they are usually much faster in the pre-processing phase as the quadratic complexity for calculating the similarity between users and items are omitted (Aggarwal, 2016). The following subsections provide some insight into model-based collaborative filtering via the analysis of the matrix factorization method and neural networks.

2.3.2.1 MATRIX FACTORIZATION (MF)

Srebro (2004) rightly pointed out that matrix factorization is used in an unsupervised learning setting to model structure in a data corpus. Each item in the data corpus corresponds to a row in the matrix, and columns correspond to item features. Matrix factorization is used to understand the relationship between items in the data corpus and the major modes of variation. MF methods learn a latent representation of users and items that, when combined in the dot-product, produce an approximation of the rating that a user would give to an item (Sarwar et al. 2001, Koren et al. 2009). Factorization is basically when you break a number down into smaller numbers that when multiplied together, give you that original number. Therefore, matrix factorization involves breaking down a bigger matrix into smaller ones such that when the smaller matrices are multiplied together they would produce the data in the bigger matrix. In a movie recommender system, the ratings utilized in matrix factorization are based on hidden latent semantic characteristics of the movies. For instance, if a user gives a rating value of 4 out of 5 to the movie *"Titanic"*, matrix factorization would involve identifying the hidden latent semantic characteristics of the movie which may have influenced the user to give a rating of 4 to the movie. This will be accomplished by identifying movies with similar characteristics to the *"Titanic"*, such as the movie genre, the actors, the directors, the producers, the screenwriters, etc. The process of matrix factorization is an attempt to understand the users thought process in selecting a movie that they have rated very highly so that ratings could be predicted for movies that the users have not yet watched. Simply put, matrix factorization is the multiplication of two matrices to produce a bigger matrix used in predictive analysis. The matrix factorization is model-based because it first attempts to understand the pattern of ratings by the user and creates a model based on the identified pattern which will be used in making recommendations. The following example will provide a basic understanding of what matrix factorization is all about.

Users	Comedy	Drama	Action
A	1	1	0
B	0	1	1
C	1	0	1
D	1	1	1

Table 2. 3 User Sample Data to Demonstrate Matrix Factorization

Considering Table 2.3 above, which contains the movie genres which the user prefers, where 1 is equivalent to *Yes* and 0 is equivalent to *No*.

Genres	M1	M2	M3	M4	M5
Comedy	4	3	1	5	2
Drama	3	4	5	3	3
Action	2	5	3	3	4

Table 2. 4 Movies Features Sample Data with Movie Genres

Table 2.4 shows the movies represented by M1, M2, M3, M4, and M5 and the genres associated with the movies which are rated on a scale of 1-5 based on how effectively they can represent the specified movie genre. Matrix factorization is calculated by using the dot product of one row in the user matrix in Table 2.3 and one column in the item matrix in Table 2.4, the higher the recommendation value in the new matrix, the higher the possibility that the user would like the movie. For instance, from Table 2.3, we know that user A has a preference for comedy and drama movies. The full table for the recommendation values for movies M1, M2, M3, M4, and M5 for users A, B, C, and D are indicated in Table 2.5 below.

Users	M1	M2	M3	M4	M5
A	7	7	6	8	5
B	5	9	8	6	7
C	6	8	4	8	6
D	6	8	6	11	10

Table 2. 5 Predicted Recommendation Values Table using Matrix Factorization

Based on the recommendation values in Table 2.5, user similarity can also be calculated using cosine similarity and cosine distance. The model created as a result of matrix factorization learned about the user's movie preferences based on the ratings of the movie features. The value of the ratings in Table 2.4 can either be obtained from the user explicitly by directly requesting for feedback from the user, or implicitly through the analysis of the user's viewing history.

2.3.2.2 ARTIFICIAL NEURAL NETWORKS

According to Mustafa (2018), artificial neural networks consist of artificial neurons that are interconnected and a computational model for processing on the inputs. Artificial neurons are designed to mimic the functionality of neurons, which are cells within the nervous system that transmit information to other nerve cells, muscle, or gland cells. The main function of artificial neurons is to transmit information within a system which would help in achieving a specific objective. Typically, artificial neural networks consist of three layers known as an input layer, hidden layer, and output layer. Michailidis (2017) and Mustafa (2018) pointed out that artificial neurons which are called perceptron from the input layer are used to provide the input to the artificial neural network while the hidden layer further assigns weights to the input. The output layer calculates the output based on the weights assigned as part of the hidden layer to provide final results based on the techniques chosen for the artificial neural network. Artificial neural networks can learn, memorize, and establish a relationship between the input data of different types. They are generally used to find trends, patterns, or anomalies in a set of data, and analysing large and complex datasets. This technology could either be used for grouping certain data points together, finding anomalies in data, or for predicting an attribute out of several known parameters, based on trends and patterns found in the training data. Predicting an unknown attribute of an object based on other known attributes and information about it is what is generally known as supervised machine learning. Different applications of artificial neural networks can be used for problems such as classification, pattern recognition, prediction, and modeling. According to Schmidhuber (2015), the advances in computing power and specifically the usage of Graphic Processing Units (GPUs) have allowed the previously slow neural network machine learning models to be run at greater speeds. The simplest artificial neural network model is the perceptron which consists of a single neuron. However, in the case of a multilayer perceptron, a complex model is formed which contains a large number of neurons. The neurons in a multilayer perceptron are structured into several layers, where each neuron is connected to all the neurons in the next layer.

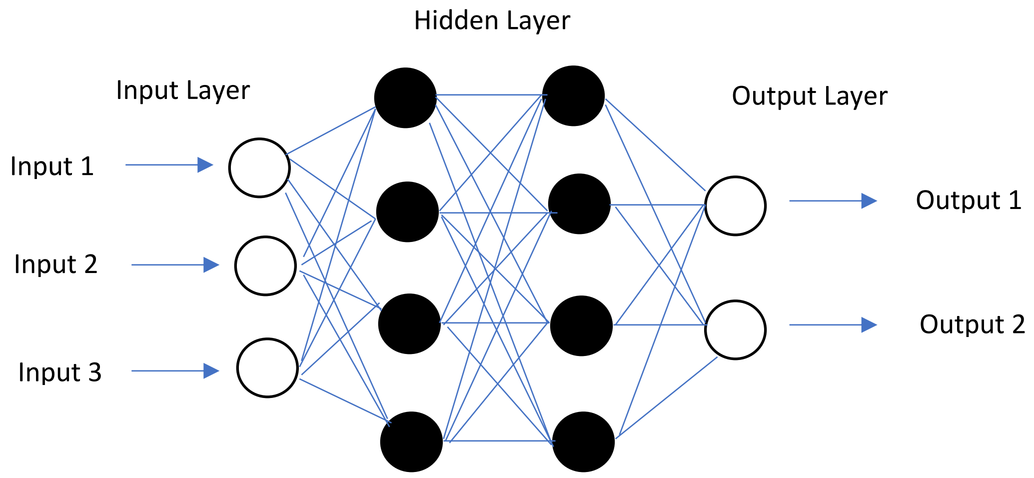

Fig. 2. 3 An Example of a Multilayer Perceptron Structure

As indicated in Fig. 2.2 above, the instances are inputted into the input layer. The values which are generated are transmitted to all the neurons in the hidden layer. The ability of the model to identify patterns and perform predictive functions is dependent on the work which is done in the hidden layers of the model. Schmidhuber (2015) pointed out that the term deep learning which is used in neural network modelling is connected to the fact that a multilayer perceptron has many hidden layers and therefore a high depth. Neural networks model user and item interactions in a latent space effectively. The matrix factorization technique can be embedded within the hidden layers of a multilayer perceptron structure. This gives the recommender system the space to test different variations of user and item interactions to come out with the best possible predicted ratings for a set of ranked items to recommend to the user. However, the problem associated with the application of user ratings is still prevalent in the case of artificial neural networks because recommendations are still made based on high ratings, and a movie that is given a low predictive rating or a low explicit user rating becomes unattractive to consumers.

The next section discusses the personality models associated with the development of personality-based group recommendation models which are the MBTI personality model, the Big 5 Personality model, and the relationship between the MBTI model and the Big 5 Personality model.

2.4 RESEARCH PERSONALITY MODELS

This section contains the literature concerning the personality models usually associated with the development of personality-based movie recommender systems.

2.4.1 THE MBTI PERSONALITY MODEL

The use of personality profiles in collaborative filtering recommender systems is a reasonable approach and was supported by Hu & Pu (2010) and Karumur et al (2017) when they indicated that people within the same personality category tend to like the same things. It's also important to remember that it's impossible to separate a user from the user's personality when it comes to recommending products capable of generating an emotional response from the user. This was confirmed in Song et al (2009) where users with the same Myers Briggs Type Indicator (MBTI) personality profiles gave similar emotional responses to movie choices. Prior research by McCrae & Costa (2004) pointed out that personality traits are often defined as long-term dimensions of individual differences in tendencies toward other patterns of thoughts, feelings, and actions. Further research by Funder (2004) and Pervin et al (2005) supported this by describing personality as an individual's characteristic patterns of thought, emotion, and behaviour, in addition to the psychological mechanisms which are responsible for the formation of those patterns. According to Fig. 4.1, the identification of the user's MBTI personality type is the first step after the recommendation process has started. According to Myers & Myers (1995), there are 4 dimensions of personality that ultimately constitute the 16 permutations of the MBTI personality model. The four dimensions are indicated below.

- *Where do you prefer to focus your attention? – Extroversion (E) vs. Introversion (I)*
- *How do you take in information? – Sensing (S) vs. Intuition (N)*
- *How do you make decisions? - Thinking (T) vs. Feeling (F)*
- *How do you orient toward the outer world? - Judging (J) vs. Perceiving (P)*

Introversion vs Extroversion **-** Baxter (2009) pointed out that two-thirds of any population is made up of extroverts while the remaining one third is made up of introverts. According to Alkan et al (2007), a typical introvert is described as a person who is usually silent and shy, cannot behave intimately, plans his/her future, does not rely on instant reactions, controls his/her emotions, and is concerned with ethical judgements. Alkan et al (2007) described an extrovert as someone who enjoys a social environment, not working alone, has many friends, is usually self-indulgent, can be aggressive, and whose emotions are not in control.

Sensing vs Intuition **-** Boyd & Brown (2005) described the individuals with a high level of sensing as those who are very objective and prefer to work with facts. This was supported by Kim & Han (2014) who pointed out that those with a high level of sensing collect information through what is happening and by focusing on observable facts, data, and phenomena. On the other hand, Kim & Han (2014) pointed out that intuitive-type learners assess information by their possibilities, focusing on the big picture and searching for connections, patterns, relationships, and insightful meaning.

Thinking vs Feeling* -** *Thinking* is an attitude that tends to decide by linking ideas together through logical connections, while *Feeling* is the function by which one comes to decisions by weighing relative values and merits of the issues and relies on an understanding of personal and group values (Kim & Han, 2014). Martin (1997) further highlighted that those with the ***thinking personality trait tend to analyse pros and cons and exhibit a certain consistency and logic in making decisions, while those with the ***feeling*** personality trait tend to be concerned with values and what is best for the people involved.

Judging vs Perceiving* -** According to Martin (1997), the ***judging or ***perception*** personality trait is the application of the ***thinking*** or ***feeling*** personality trait. It represents how decisions are made in the outside world. Boyd & Brown (2005) pointed out that the ***judging*** personality trait is concerned with seeking closure, planning operations, or organizing activities, while the ***perceiving*** personality trait is exhibited in those who are being attuned to incoming information, tend to thrive on spontaneity, prefer to leave things open, and require more information to make decisions.

The 16 permutations of the MBTI personality model which are based on the four dimensions of personality identified above are as follows:

Personality Classifications	
INTJ	ENTJ
INFJ	ENFJ
INFP	ENFP
INTP	ENTP
ISFJ	ESFJ
ISTJ	ESTJ
ISFP	ESFP
ISTP	ESTP

Table 2. 6 MBTI Personality Classifications

To determine which of the personality classifications a user belongs to, the user is required to take a personality test. The results of the personality test provide values for all the 8 personality traits. Therefore, it is important to note that even though an individual has four dominant personality traits as indicated in Table. 2.6, the recessive personality traits still form a part of the user's personality and should not be excluded when making movie recommendations to the user.

2.4.2 THE BIG 5 MODEL OF PERSONALITY

Hogan et al (1996) pointed out that personality traits are conceptualized as stable characteristics different for each person explaining individual predispositions to certain patterns of behaviour, cognition, and emotions. Briggs (1992) and Zhang (2006) agreed that after decades of factor analytical research, psychologists finally came up with what they claim to be a more reliable model for the determination of personality types known as the Big 5 model of personality. Zhang (2006) further pointed out that openness to experience, conscientiousness, extroversion, agreeableness, and neuroticism, also known as OCEAN, are known as the big five personality traits in psychology. According to Costa & McCrae (1992) and Cantador et al (2013), the NEO PI-R measures the five major domains of personality as well as the six facets that define each domain as indicated in the table below.

Personality Traits	Personality Facets
Openness to Experience	• Fantasy • Aesthetics • Feelings • Actions • Ideas • Values
Conscientiousness	• Competence • Order • Dutifulness • Achievement Striving • Self-Discipline • Deliberation
Extroversion	• Warmth • Gregariousness • Assertiveness

	• Active • Excitement Seeking • Positive Emotions
Agreeableness	• Trust • Straightforwardness • Altruism • Compliance • Modesty • Tender-Mindedness
Neuroticism	• Anxiety • Angry Hostility • Depression • Self-Consciousness • Impulsiveness • Vulnerability

Table 2. 7 The Five-Factor Model of Personality

Although the Big 5 personality model is widely acknowledged as providing the most consistent and accurate description of an individual's personality, it can't be used as a user classification tool because it's simply not structured to categorise people into groups.

Another problem with the Big 5 personality model is the questionnaire which the users would have to fill to understand their personality. The questionnaire is extremely long because it is measuring for 30 different facets of personality. The length of the questionnaire to determine the personality of a user using the Big 5 personality model has been identified as a discouraging factor in using the Big 5 personality model with recommender systems. The next section explores the possible relationship between the MBTI personality model and the Big 5 personality model.

2.4.3 EXPLORING MBTI AND THE BIG 5 INTER-RELATIONS

This section examines the possibility of interpreting the Big 5 personality results using the MBTI personality framework. According to McCrae et al (1989), *Sensing vs Intuition* and *Feeling vs Thinking* have similarities with *Openness to Experience (OTE).* To determine which of the MBTI personality traits have more in common with *OTE*, a comparison of their characteristics is required. This is shown in Table 2.8 below.

<table>
<tr><td>Sensing</td><td>Intuition</td><td>Thinking</td><td>Feeling</td><td>Openness to Experience</td></tr>
<tr><td>Facts</td><td>Ideas</td><td>Logic</td><td>Values</td><td rowspan="7">Fantasy: receptivity to the inner world of imagination.
Aesthetics: the appreciation of art and beauty
Feelings: openness to feelings and emotions
Actions: openness to new experiences on a practical level
Ideas: intellectual curiosity
Values: readiness to re-examine their values and those of authority figures</td></tr>
<tr><td>Down to earth</td><td>Dreams</td><td>Objective</td><td>Personal</td></tr>
<tr><td>Practical</td><td>Theory</td><td>Frankness</td><td>Tactfulness</td></tr>
<tr><td>Make</td><td>Create</td><td>Truth</td><td>Love</td></tr>
<tr><td>Five senses</td><td>Imagination</td><td>Justice</td><td>Mercy</td></tr>
<tr><td>Experience</td><td>Vision</td><td>Critique</td><td>Praise</td></tr>
<tr><td>Past & present</td><td>Future</td><td>Task-oriented</td><td>People-oriented</td></tr>
</table>

Table 2. 8 Sensing vs Intuition, Thinking vs Feeling, & OTE Characteristics (Bayne, 1997)

As indicated in Table 2.8, *OTE* has similar characteristics to *Intuition* and *Feeling* than *Sensing* and *Thinking*. *Thinking vs Feeling* personality dimension has been linked with *Agreeableness* in the Big 5 personality model.

<table>
<tr><th>Thinking</th><th>Feeling</th><th>Six Facets of Agreeableness</th></tr>
<tr><td>Logic</td><td>Values</td><td rowspan="7">Trust: belief in the sincerity and good intentions of others
Straightforwardness: frankness in expression
Altruism: active concern for the welfare of others
Compliance: response to interpersonal conflict
Modesty: the tendency to play down their achievements and be humble.
Tender-Mindedness: an attitude of sympathy for others.</td></tr>
<tr><td>Objective</td><td>Personal</td></tr>
<tr><td>Frankness</td><td>Tactfulness</td></tr>
<tr><td>Truth</td><td>Love</td></tr>
<tr><td>Justice</td><td>Mercy</td></tr>
<tr><td>Critique</td><td>Praise</td></tr>
<tr><td>Task-oriented</td><td>People-oriented</td></tr>
</table>

Table 2. 9 Characteristics of Thinking vs Feeling and 6 Facets of Agreeableness (Bayne, 1997; McCrae et al., 1989)

As indicated in Table 2.9, a higher percentage level in the *Feeling* trait over the *Thinking* trait suggests a high personality score in *Agreeableness*. *Judging vs Perceiving* has been linked with *Conscientiousness*.

<table>
<tr><th>Judging</th><th>Perceiving</th><th>Six Facets of Conscientiousness</th></tr>
<tr><td>Closure</td><td>Openness</td><td rowspan="2">Competence: belief in own self-efficacy
Order: personal organization</td></tr>
<tr><td>Decision</td><td>Options</td></tr>
</table>

Scheduled	Spontaneous	Dutifulness: emphasis placed on the importance of fulfilling moral obligations Achievement Striving: the need for personal achievement and sense of direction Self-Discipline: the capacity to begin tasks and follow through to completion despite boredom or distractions. Deliberation: the tendency to think things through before acting or speaking.
Organised	Disorganised	
Planned	Emergent	
Control	Flexible	
Now	Procrastinate	

Table 2. 10 Characteristics of the Judging vs Perceiving & 6 facets of Conscientiousness (Bayne, 1997; McCrae et al., 1989)

According to Table 2.10, a higher percentage level in the *Judging* trait over the *Perceiving* trait suggests a high personality score in *Conscientiousness*. This was previously confirmed in Conley (1985) where it was discovered that individuals who fall under the *Judging* personality trait have high levels of *Conscientiousness* and those who fall under the *Perceiving* personality trait have low levels of *Conscientiousness*. Furthermore, *Extraversion* in the Big 5 personality model can be linked with *Extroversion* in the *Extroversion vs Introversion* personality dimension as indicated in Table 2.11 below.

Introversion	**Extraversion**	**Six Facets of Extraversion**
Inhibited	Dominant	Warmth: interest in and friendliness towards others Gregariousness: preference for the company of others Assertiveness: social ascendancy and forcefulness of expression Activity: the pace of living Excitement Seeking: the need for environmental stimulation Positive Emotions: the tendency to experience positive emotions
Un-sparkling	Confident	
Deferent	Friendly	
Undemonstrative	Outgoing	
Reserved	Enthusiastic	
Hostile	Competitive	
Shy	Perky	
Submissive	Exhibitionist	

Table 2. 11 Extraversion vs Introversion and 6 Facets of Extraversion Characteristics (Bayne, 1997; McCrae et al., 1989)

To this end, a summary of the relationship between the MBTI personality model and the Big 5 personality model is indicated in Table 2.12 below.

MBTI personality Traits	**Big 5 Personality Traits**	**Big 5 Personality Score**
Introversion	Extraversion	Low

Extroversion	Extraversion	High
Sensing	Openness to Experience	Low
Intuition	Openness to Experience	High
Thinking	Agreeableness	Low
Feeling	Agreeableness	High
Judging	Conscientiousness	High
Perceiving	Conscientiousness	Low

Table 2. 12 Relationship Between the MBTI model and the Big 5 (Chausson et al., 2010; Cantador et al., 2013)

As indicated in Table 2.12, the Big 5 personality trait, Neuroticism, has not yet been directly linked with any of the personality traits in the MBTI model, although one may argue that their characteristics may have more in common with the *Feeling* personality trait. The application of this knowledge potentially gives consumers a broader perspective on their personality and expands the range of personality-based recommender systems in terms of the number of consumers that can be serviced.

To this end, the next section will explore the reasons in which personality is being linked with movies in recommender systems.

2.5 WHY THE INTEREST IN MOVIES?

The movie industry is a multi-billion dollar entertainment industry. Park et al (2012) pointed out that considering that test data was hard to acquire, the data made freely available to researchers within the entertainment domain is mostly associated with movies. The most popular dataset used as it relates to movies and recommender systems are the MovieLens datasets. The Internet Movie Database (IMDB) is a large database consisting of comprehensive information about past, present, and future movies. User statistics from the IMDB website pointed out that the website has more than 250 million unique visitors every month. IMDB data is made freely available to users for non-commercial purposes. Furthermore, movies can emotionally connect with the users through which they can influence the way the users think, feel, and act, which implies an influence on the user’s personality. Movies are quite popular because they are a unique form of art brought to life via the use of advanced forms of technology, through which audiences can make conscious connections between what they see in the movie and their experiences in the real world. Field (2005) indicated that movies portray fictional representations of real-life events and experiences and hence can connect emotionally with the audience. The following sections will discuss the reasons why people watch movies and the influence movies can have on consumers.

2.5.1 REASONS WHY PEOPLE WATCH MOVIES

2.5.1.1 ESCAPISM

According to Longeway (1990), escapism can simply be explained as an attempt to draw us away from the troubles and challenges we face every day and sometimes helps us to fantasize ourselves as better off and more important than we are. Escapism signifies the creation of a temporary safe space by our subconscious to help us escape from an unpleasant reality. Movies provide a means which enhances the creation of this temporary safe space as users find themselves immersed in the pseudo-reality which the movie has created. In the process of escapism, our imagination is stimulated and our perception of reality as well as reality itself can be redefined. Film narratives offer the opportunity to momentarily immerse in a different world in favour of narrative stories that lead to unknown worlds (Tesser et al., 1988).

2.5.1.2 EDUCATION

Movies also tend to serve as educational tools. This can be used in such a way as to inspire the viewer to attempt to attain a certain level of academic excellence or to educate the viewer on a subject matter highlighted by the movie. O'Brien-Bours (2013) supported this by pointing out that movies have the power to inspire, to teach, to shape memories of events, and to create a shared narrative experience amongst a culture. According to Pandey (2012), movies can be used to create a connection between educational topics and the current generation of learners. It is a tool that can be used to help the viewer to understand concepts that are relevant to their lives. Priming theory also holds that witnessing, reading, or hearing of an event or idea through movies can prime or stimulate related thoughts or ideas which can influence our reactions and behaviours in a consistent way (Sayre & King, 2010).

2.5.1.3 ENTERTAINMENT

According to Sayre & King (2010), entertainment comes in two forms, they are live entertainment and mass-mediated entertainment. Live entertainment takes place primarily on a stage in front of an audience while mass-mediated entertainment uses technological aid to bridge the gap between the performers and the audience. Mass mediated entertainment is usually easily accessible, cost-effective, and provides autonomy for the viewers in terms of where and when they want to be entertained. Movies fall in the category of mass-mediated entertainment and provide a mechanism through which people seek their self-identities and engage in actual or vicarious behaviours of everyday life. Movies are used as entertainment tools to shape and reflect the history, culture, beliefs, experiences, and concerns of the people of that society. Research has shown that drama is the main genre of all movies; other sub-genres are considered as just specialized forms of drama.

2.5.2 THE INFLUENCE OF MOVIES ON SOCIETY

2.5.2.1 POLITICAL INFLUENCE OF MOVIES ON CONSUMERS

Movies are also used as a means of promoting political ideas or the subtle unveiling of political agendas. Research conducted by Adkins & Castle (2013) pointed out that the political nature of messages embedded within movies is less likely to be recognised and hence reducing their capacity for resistance. Although the political messages embedded in movies are less likely to be recognized, the audience could potentially unknowingly conform to such political ideas or opinions because of the compelling way with which it was presented through the movie. Movies possess the ability to potentially sway political decisions and change governmental political strategies.

2.5.2.2 SOCIAL INFLUENCE OF MOVIES ON CONSUMERS

Vasan (2010) pointed out that movies are also a great influencing factor in youth ideas of fashion, their choices of clothing and accessories. Movies also have a way of influencing how we interact with other people and could easily lead to a certain race of people to be stereotyped. Good examples of such movies are those which tell of the slavery of Africans and their relentless and painful fight for freedom. Movies also tend to affect the ways we walk, talk, think, and carry out our job responsibilities at our places of employment, etc., one may argue that it has become increasingly difficult to separate movies from the social behaviour of the movie consumers as some movies tend to help the socially awkward to gain a certain degree of confidence, others help the individual in choosing the right career path.

2.5.2.3 CULTURAL INFLUENCE OF MOVIES ON CONSUMERS

In several American movies, one often hears statements like "*that's what it means to be a true American*" or "*that's the American way*" and several other statements that promote the American culture. Lule (2015) pointed out that movies mirror the culture of the country involved in the movie, although, at times their culture may be misrepresented in the movie which in turn could impact negatively the existing culture of the people. Lule (2015) further went on to say that not only do movies reflect the culture of the society that produces them, but they are a product of that society and a reflection of prevailing concerns, attitudes, and beliefs.

2.6 ANALYSIS OF RELATED WORK

2.6.1 Alleviating the New User Problem in Collaborative Filtering by Exploiting Personality Information

Early recommender systems struggled with the cold start problem which included the new user problem and the new item problem. It was a problem created by the fact that for recommender systems to function, they needed to have access to existing data of the user which would help them understand the user's preferences so that they could make the appropriate recommendations. Cantador et al (2016) proposed an interesting solution to the alleviation of the new user problem via the exploitation of personality information. Prior research by Nunes & Hu (2011) highlighted that personality influences how people make decisions. The research by Cantador et al (2016) was based on existing research by Hu & Pu (2011) and Tkalcic et al (2011) who have already confirmed that the application of personality in the collaborative filtering recommendation technique will resolve the new user problem, however, the challenge was in the accuracy of the recommendations based on personality data. Furthermore, the research by Cantador et al (2016) was also based on the confirmed hypothesis that people with similar personality profiles are likely to have similar preferences (Chausson, 2010; Hu & Pu, 2011; Cantador et al, 2013). The approach selected by Cantador et al (2016) was to exploit user personality information to identify the most useful user preference information (ratings or "likes") for the system to generate accurate recommendations for a new user. The proposed recommender system by Cantador et al (2016) further applies the knowledge acquired for the new user in related source domains, a method also referred to as cross-domain recommendation. The dataset applied in the research by Cantador et al (2016) consisted of 159,551 users and 16,303 items in the movie, music, and book domains.

According to Cantador et al (2016) and Ricci et al (2015), the methods applied in the data collection process to acquire the data which will help guide the recommender system to the most suitable items to recommend to the consumer included the explicit collection of data and the implicit collection of data. The explicit collection of data involved outrightly asking the users to provide ratings for items. The implicit collection of data involved exploiting auxiliary information about the user's preferences or other personal information that might be useful for the system to establish similarities between the user and other users. Explicitly collecting the data from the user provides the recommender system with data that could reduce the need for the system to make assumptions. Cantador et al (2016), Ricci et al (2015), and Karumur et al

(2017) pointed out that the problem with the explicit data collection method is that it requires some effort from the user to initially provide feedback on some recommended items. This has been seen as a discouraging element for the new users when it comes to using recommender systems. Cantador et al (2016) further pointed out that at the initial stage when the recommender system recommends an item for the new user to provide a rating, the system has to be careful when selecting the items to request the user to rate and it is of utmost importance that the user should be familiar with the proposed items. The downside of recommending unfamiliar items is that they could negatively impact the perception of the usefulness of the system to the new user. In contrast, the implicit data collection methods which exploit auxiliary information does not require the user to rate items. Nonetheless, a method to inject the additional user data into the CF framework has to be devised, and it may be hard to know in advance whether the auxiliary information will be helpful in the cold-start. The research concluded by pointing out that in terms of accuracy, personality proves useful for completely new users in the domains of movies, books, and music.

2.6.2 The 50/50 Recommender: A Method Incorporating Personality into Movie Recommender Systems

According to Orestis & Christos (2017), it was highlighted that the main motivation behind their work was the lack of personalisation in current recommender systems. This simply points out that recommendations are meant to be tailored to the individual who is the recipient of the recommendations This further pointed out that the main challenge which recommender systems faced was in how to effectively personalise recommendations for a consumer. Orestis & Christos (2017) proposed a movie recommender system that was based on a user model that takes into account 50% of the consumer’s personality traits and 50% of the existing content which can be applied in making movie recommendations. It was highlighted by the authors that the use of the consumer’s personality traits was for the recommender system to operate according to the user’s personality type. The personality model applied in the 50/50 recommender was the Big Five Personality model which consists of the following personality traits: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. The flow diagram of the system is as indicated below.

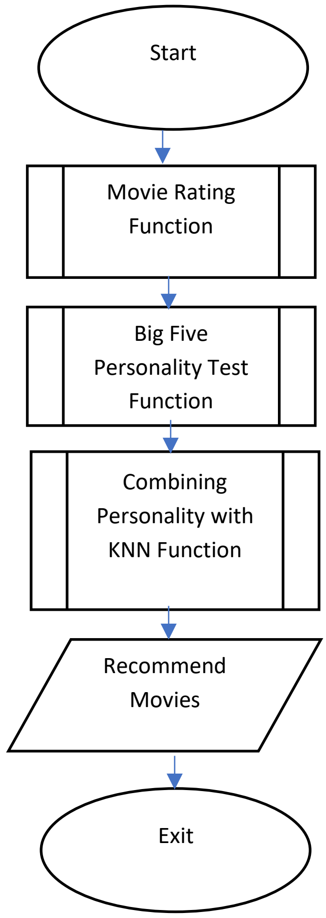

Fig. 2. 4 50/50 Recommender System Main Flow Chart (Orestis & Christos, 2017)

The 50/50 recommender further utilized the ratings of the movies by the user to learn about the user's preferences and combined the results with the collaborative filtering process via the k-NN function with the user's personality traits as a guiding tool through the recommendable items. In the 50/50 recommender, the k-NN function of the collaborative filtering recommendation technique was used to provide the predicted ratings of movies for the consumer. The formula utilized in providing recommendations in the 50/50 recommender involved taking the predicted rating of the movie and dividing it by 2, and also taking the number which represents the genre preference of the user and dividing it by 2, and finally adding these numbers to get a new predicted rating for the movie. In this case, the k-NN scoring of the movie which was used in conjunction with the user's personality profile, and the genre preferences account for 50% each of the final results. The results obtained via the 50/50 recommender were compared against the standard k-NN based recommendations to evaluate the performance of the system, and it was confirmed that personality plays a significant role in improving recommendations as indicated in Table 1.1.

According to Batista & Silva (2009), k-NN is a widely used technique, being successfully applied in a large number of domains. Although the k-NN is widely applied in the collaborative filtering process, it is computationally complex in the case of large datasets. The k-NN function faces a major challenge when it comes to choosing the optimal number of neighbours to consider while classifying new data entry. The personality model utilized in the 50/50 recommender cannot classify the consumers in terms of their personality profiles and hence the need for the k-NN function to help in providing a form of consumer classification. This, therefore, subjects the 50/50 recommender to the drawbacks of the k-NN algorithm.

Another aspect of the 50/50 recommender research to be taken into consideration is in the application of ratings. The use of ratings was supported by Ricci et al (2015) where it has been pointed out that ratings are the most popular form of transaction data which recommender systems collect. The 50/50 recommender uses the ratings which the user has provided to predict the ratings for similar movies. The use of ratings as a recommendation tool in a movie recommender system is deficient because it provides no context with regards to what the consumer liked or disliked about the movie. Predicted ratings are susceptible to error because the context associated with a poor rating or a good rating is unknown. Therefore, the need for ratings in a movie recommendation model makes it susceptible to the problem of data sparsity, because, it’s either there are not enough ratings provided by the user or there is no information on the reasons the user-provided such a rating. Furthermore, in the 50/50 recommendation model, if a movie doesn’t have a certain number of ratings, it will not be recommended, therefore, the consumers are not given the opportunity of deciding for themselves if they would like such a movie or not. This makes the system subject to overspecialization in terms of continuously recommending movies that have high rating values.

Considering the analysis of the related work above, the proposed group recommendation model in this research will apply the approach by Song et al. (2009) where the MBTI personality model was used as a user classification model instead of the k-NN algorithm. In this case, the nearest neighbours would be those with the same personality profiles. According to Hu & Pu (2011), people who share the same personality traits often tend to like the same things. This can potentially eliminate the need for similarity calculations between users through the creation of a personality-based neighbourhood.

2.6.3 MBTI-based Collaborative Recommendation System: A Case of Webtoon Contents

Yi et al (2016) proposed a solution to the two major problems of collaborative filtering which are, data sparsity and scalability, through the application of the Myers Briggs Type Indicator (MBTI). They rightly pointed out that the application of the 5 factor model of personality is not a solution to the problem of scalability because it measures personality on a dimensional scale, which means that similarities between users would have to be estimated. Yi et al (2016) justified the use of the MBTI model of personality in their research based on prior research by Song et al (2009). It was pointed out that in an experiment where the participants were classified according to their MBTI personality profiles, the participants were required to select emotional words which they would associate with specific movies. The results revealed that those with the same MBTI personality profile selected similar emotional words. This led to the conclusion that those with the same MBTI personality profile have similar movie preferences and similar interpretations of their emotions.

According to Yi et al (2016) and Hafshejani et al (2018), the application of personality factors in recommender systems solves the data sparsity problem in collaborative filtering via the building of personality-based neighbourhoods. The results achieved by Yi et al (2016) confirmed that the application of the MBTI model of personality does not improve the accuracy of recommendation but reduces the complexity of the computation of similarity between users. This was accomplished by normalizing ratings and grouping users by their MBTI, followed by computation of similarities between users in a neighbourhood using vector cosine similarity. Therefore, the similarity calculation was made easier because the users were already classified based on their personality and not based on their viewing/rating history which is required in the use of the k-NN. In the case of the k-NN, the calculation for the similarity between users involves grouping the users and finding those who are the most similar. However, with the use of the MBTI model as a user classification model, the computation required to group the users is eliminated.

Finally, Yi et al (2016) made it clear that in using the MBTI model as a user classification model there is a trade-off between recommendation accuracy and scalability. This implied that the recommendations made were not accurate, but the new user problem was solved, and it had the potential to handle multiple users since the need to calculate for users to be grouped has been eliminated. However, the problem of scalability may still arise because of the need to calculate for the similarity between users in the same personality group.

2.6.4 Enhancing Collaborative Filtering Systems with Personality Information

A personality-based recommendation model created by Hu & Pu (2011) was developed on the premise of creating personality-based neighbourhoods. They stated that people can be distinguished by their personalities, and people in the same personality segment are assumed to have similar behaviours or interests. They put the user's personality characteristics in a vector similar to the manner used in dealing with the rating data. The personality model used for their system was the Five-Factor Model of personality which is not naturally structured to classify users into neighbourhoods. However, they used the similarities in the values associated with the Big Five personality traits to create the personality-based neighbourhood. Their research implemented personality into the CF recommender system using the cascade hybrid approach. This simply utilizes the personality-based approach to make initial predictions on the unobserved ratings to densify the user-item matrix. The performance of the model was assessed against the traditional ratings based collaborative filtering (CF) using Mean Absolute Error (MAE) and Receiver Operating Characteristics (ROC) sensitivity. The traditional ratings-based CF approach involves the use of the k-NN to find the nearest neighbours instead of the personality characteristics, and the ratings.

The cascade hybrid approach was found to have outperformed the traditional ratings based CF approach in terms of prediction accuracy (MAE) and classification accuracy (ROC sensitivity). The research also took into consideration the problem of efficiency, in terms of the time required to generate the recommendations. The cascade hybrid approach was found to require more time than any other approach due to its extra computation for the pseudo-ratings. This is not surprising since the system also needs to calculate for the nearest neighbours using personality values. This simply implies that the fewer the amount of computation required in determining what to recommend to the users, the higher the efficiency of the recommender system.

Fig 2.5 below shows the collaborative filtering ratings based recommendations model which uses the user's personality in the recommendation process.

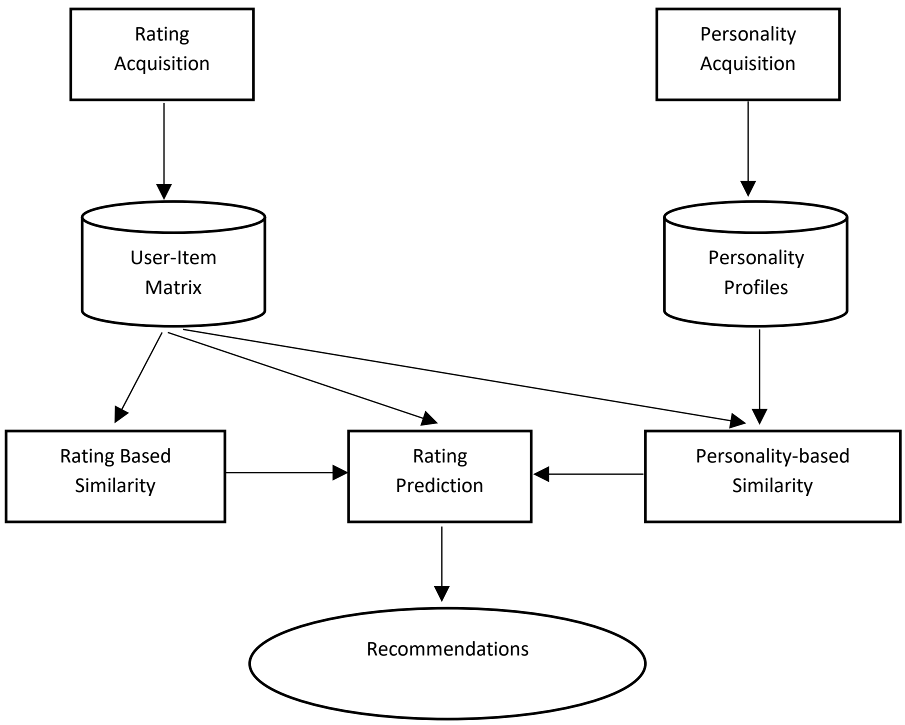

Fig. 2. 5 Collaborative Filtering Recommendation Model (Hu & Pu, 2011)

As indicated in Fig. 2.5 above, the process to generate recommendations involved the acquisition of the ratings from the users as well as the personality values associated with the users. The personality values acquired form the personality profiles of the users. The personality-based neighbourhood is formed in the personality-based similarity unit. The user-item matrix consists of users and the items which they have rated. The rating based similarity unit identifies users with similar ratings. Based on the existing ratings, pseudo-ratings for items that have not yet been rated will be calculated and used for making recommendations. The calculation for pseudo-ratings helps to prevent the problem of data sparsity. The use of personality also helps solve the new user problem as new users who join the personality-based neighbourhood can receive the same recommendations as to the existing members within that neighbourhood without the need for them to have a history of rating items. The use of a personality-based neighbourhood also increases the possibility of receiving serendipitous recommendations.

To this end, their research has pointed out the benefits associated with making recommendations using a personality-based neighbourhood. However, because of the amount of computation required in calculating personality similarity between users and the calculation for the pseudo-ratings, there is a trade-off between accuracy and efficiency.

2.6.5 The MovieLens Recommendation Model

In the MovieLens recommendation model, when a new user registers they have to rate some movies to get proper recommendations from the system. The users will have given ratings of some but not all of the items. The unrated items will contain predicted values based on the initial ratings provided by the users. The MovieLens system utilizes a ratings/recommendation approach in the sense that the ratings provided by the user will determine what would be recommended in the next page of the recommender system. Harper & Konstan (2015) pointed out that one disadvantage of placing an integral part of the recommendation process in the user ratings is that the MovieLens datasets only include data from users with at least 20 ratings, and therefore are inherently biased towards successful users. This simply means that the users who are less interested in rating movies were unable to find enough movies to rate or did not enjoy their initial experience in the system are not included in the datasets used in the prediction of rating values for movies. This could lead to users being recommended movies which they are not interested in because the prediction ratings associated with their recommendations are not based on their rating values but the ratings of another user with seemingly close similarities to the few movies rated by the user. In addition to using ratings as a means to provide movie recommendations, MovieLens also displays tags next to movies. Tags are short user-defined keywords that describe the movies. These tags are clickable to show a list of movies where that tag has been applied. Furthermore, the MovieLens interface has a feature called *Tag Expressions* which allows users to re-tag movies easily. This feature helped to increase tagging activity and tagging diversity. According to Harper & Konstan (2015), the MovieLens interface has always emphasized interacting with movies over interacting with other users. This implies that MovieLens was built on an item to item collaboration basis as opposed to a user-user or user – item collaboration.

2.6.6 A Personalised recommender system using Entropy-Based Collaborative Filtering (ECBF) technique.

Chandrashekhar & Bhasker (2011) tested for the recommendation accuracy of an Entropy-Based Collaborative Recommender system using the MovieLens dataset. The online operation begins when a user seeks a recommendation list from the system. The Entropy-Based Collaborative Filtering Algorithm (EBCFA) is used to predict the ratings of the active user's unrated items. These unrated items are then ranked based upon the predicted value in decreasing order from which the top N items are presented to the user as a recommendation list. This is indicated in Fig. 2.6 below.

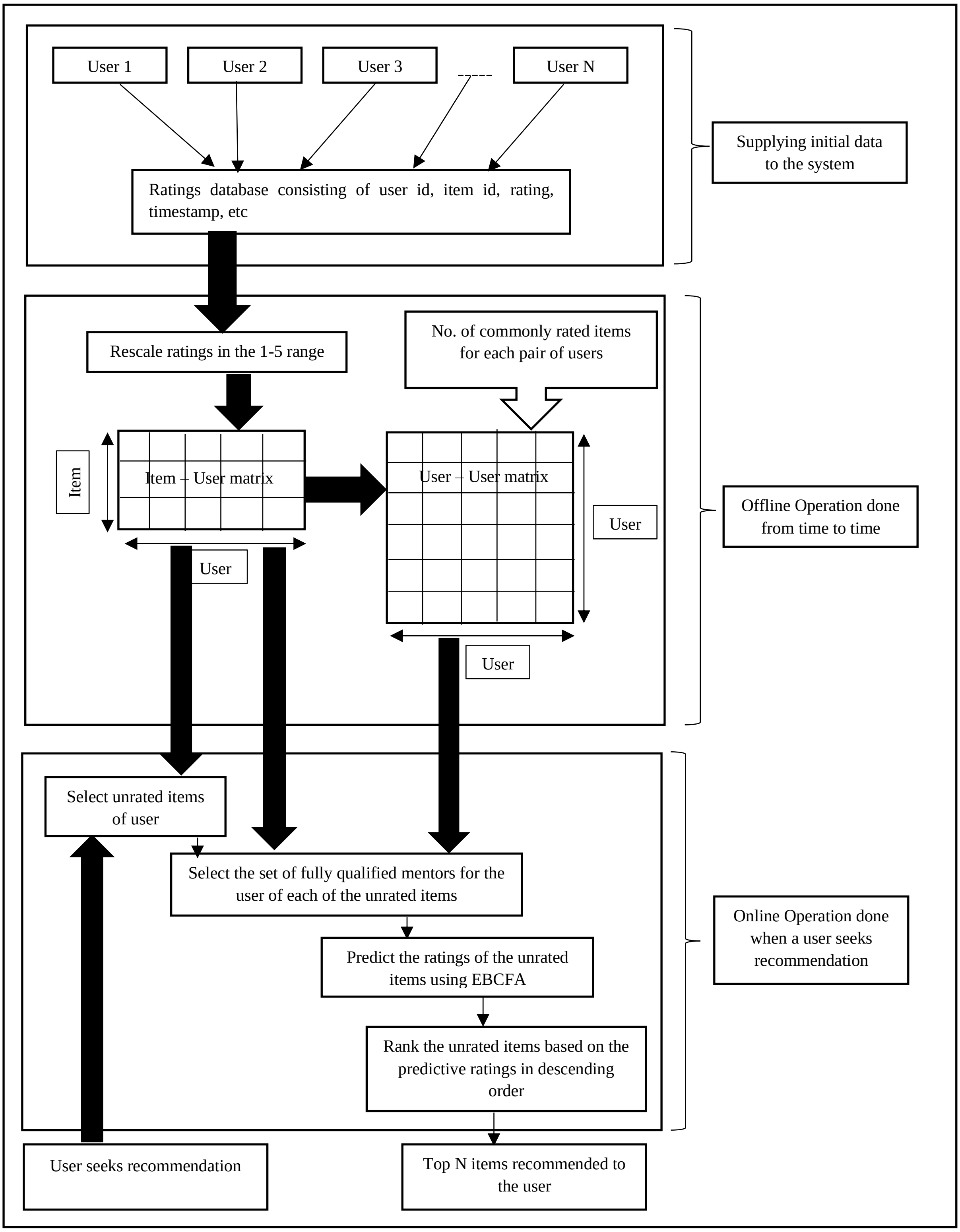

Fig. 2. 6 Architecture of the EBCF Recommender System (Chandrashekhar & Bhasker, 2011)

According to Chandrashekhar & Bhasker (2011), by testing the performance of the model above, they realised that the recommendation accuracy achieved using the MovieLens dataset was 96.1%. It was pointed out that while the EBCF approach seems to cope well with rating sparsity, it is computationally more intensive than the Traditional Collaborative Filtering (TCF) approach. They discovered via their research that while the TCF computes one similarity value between each pair of users, the EBCF has to constantly manage several computations between each pair of users in the determination of what items to recommend. This was found to utilize more memory and increased response time to generate recommendations as compared to the TCF approach.

As indicated in Fig. 2.6, just like Fig. 2.2, it can be seen that the recommendation process is divided into 3 sections, the first section provides information about the users and can therefore be referred to as the user model. The second section associates the product/items with the users to establish a connection between the users and the products/items; this can be referred to as the product model. The third section contains the algorithm for the recommendation of unrated items; this can be referred to as the recommendation model. The integration of all three models is what produced the EBCF recommendation model. To this end, this research will apply the approach utilized in Fig. 2.6 in terms of the effective use of the 3 models which make up the EBCF recommendation model in the development of the personality-based group recommendation model.

2.7 RESEARCH FINDINGS

Literature Source	Research Findings
Personality, User Preferences, and Behaviour in Recommender systems. (Karumur et al., 2017) The 50/50 Recommender: A Method Incorporating Personality into Movie Recommender Systems. (Orestis & Christos, 2017)	The application of personality in movie recommender systems improves movie recommendations.
MBTI-based Collaborative Recommendation System: A Case of Webtoon Contents. (Yi et al., 2016)	The use of the MBTI personality model as a classification model in a movie recommender system solves the new user problem and the scalability problem of collaborative filtering but at the risk of reducing recommendation accuracy.
Recommender Systems based on Personality Traits (Nunes, 2008)	Humans are complex emotional beings and the analysis of their behaviour is largely subjective.
Recommender Systems based on Personality Traits (Nunes, 2008) Personality, User Preferences, and Behaviour in Recommender systems. (Karumur et al., 2017)	Personality questionnaires are a pain for consumers to complete due to the time it takes to complete them.
Explaining collaborative filtering recommendations. (Herlocker et al., 2000) Evaluating Collaborative Filtering Recommender Systems. (Herlocker et al., 2004)	Collaborative filtering recommendation is the most popular recommendation technique used in conjunction with a consumer's personality in a personality-based recommender system.

Selecting content-based features for collaborative filtering recommenders. (Ronen et al., 2013)	
Personality, User Preferences, and Behaviour in Recommender systems. (Karumur et al., 2017)	All recommender systems require some form of consumer feedback to learn about user preferences.
The Use of Items Personality Profiles in Recommender Systems. (Alharthi, 2015)	The application of consumer personality in a movie recommender system allows for serendipitous recommendations.
MBTI-based Collaborative Recommendation System: A Case of Webtoon Contents. (Yi et al., 2016)	The use of the MBTI personality model as a user classification model in place of the k-NN classification model effectively eliminates the need to calculate for users to be grouped.
A Proposed Movie Recommendation Method Using Emotional Word Selection. (Song et al., 2009)	To use the MBTI personality model as a classification model in a recommender system to recommend movies utilizing keywords, one must identify the keywords which are associated with the personality types and the movies.
Personality, User Preferences, and Behaviour in Recommender systems. (Karumur et al., 2017) The 50/50 Recommender: A Method Incorporating Personality into Movie Recommender Systems. (Orestis & Christos, 2017)	Recommender systems make predictions. The recommender system requests for explicit user ratings at the initial stage and attempts to use the acquired ratings to predict the user ratings at the latter stages to make recommendations to the user.
Social Factors in Group Recommender Systems (Quijano-Sanchez et al, 2013)	Group recommendations based on personality profiles improve recommendation accuracy but the preferences of each user in the personality group need to be taken into consideration.
Enhancing Collaborative Filtering Systems with Personality Information. (Hu & Pu, 2011)	The use of personality-based neighbourhoods solves the new user problem and enhances scalability.
Enhancing Collaborative Filtering Systems with Personality Information. (Hu & Pu, 2011)	The application of personality in recommender systems increases the accuracy of recommender systems but reduces its efficiency.
A Personalised recommender system using Entropy-Based Collaborative Filtering (ECBF) technique. (Chandrashekhar & Bhasker, 2011) Recommender Systems Handbook. (Ricci et al. 2015) Product models in embodiment design: an investigation of challenges. (Matthiesen et al. 2019)	EBCF using the MovieLens dataset outperformed the traditional CF approaches for Prediction Accuracy, as well as recommendation quality through classification accuracy and novelty of recommendations. This approach utilized the ability of the system to predict user ratings to make the recommendations. The complete recommendation process can be divided into 3 models; the user model, the product model, and the recommendation model

Table 2. 13 Research Findings

2.8 RESEARCH GAPS

The existing recommendation models have been found to utilize the user ratings as the core element in making movie recommendations which tend to recommend movies with high ratings to the users. This becomes detrimental to the movies with an unpopular cast list or movie production crew as their movies will likely not be rated due to their unpopularity.

Furthermore, it enhances the problem of overspecialization based on the recommender system continuously recommending movies with high ratings. By so doing, such recommender systems are likely to have high recommendation accuracies in the light of the approach utilized. This creates a ratings-based overspecialization problem which is prevalent in existing recommender systems. Therefore how can movie recommendations be made to users using the words associated with the subject matters portrayed in movies which would identify and recommend the movies which are suitable to the users regardless of whether such movies have high, low, or no ratings?

Blinick (2019) attempted the use of keywords provided by users on movies on IMDB to develop a recommendation model, however, the main problem with this approach was that the keywords have to be provided by users and hence it is usually the popular movies which would have sufficient keywords to be recommended. Therefore, this creates a keywords-based data sparsity problem. Also, what would be the accuracy of the recommendation model if user ratings were excluded from the recommendation process and keywords utilized as the recommendation tool were directly extracted from the plots of the movies to be recommended?

CHAPTER THREE – RESEARCH METHODS

3.1 INTRODUCTION

The previous chapter discussed the various techniques which exist in making recommender systems. This included the identification of the three models which make up the proposed personality-based group recommendation model as the user model, the product model, and the recommendation model. This chapter presents the research methods applied in the determination of the content which would be used in the user model and the product model which would be used in the calculation of the values in the recommendation model. This involves the discussion of the identified problems leading up to the research questions which highlights the relevance of this research in terms of the problems it attempts to solve. Furthermore, it goes on to explain the research method applied to solve the identified problem, the data collection methods applied to provide content for the user and product models, and the collaborative filtering technique used in the development of the proposed personality-based group recommendation model.

3.2 IDENTIFIED PROBLEMS

The problem identified with the existing recommender systems as indicated in the literature review is the problem of overspecialization and data sparsity. According to Abassi et al (2009) and Jain et al (2015), overspecialization occurs when items with similar attributes are continuously recommended, while data sparsity in recommender systems is a result of insufficient data to make recommendations to the users. Yu et al (2009) pointed out that the solution for overspecialization is recommendation diversification. This involves the identification of movies which are dissimilar, but relevant to the user's interests. They further pointed out that the method mostly utilized in ensuring recommendation diversification are attribute-based. This simply means that the diversity of the recommended list is defined by how much each item in the list differs from the others in terms of their attribute values.

3.2.1 Ratings-Based Overspecialization

The most common element in existing recommender systems is their ability to predict ratings and associate those ratings with unrated items as evidenced in research by Chandrashekhar & Bhasker (2011), Karumur et al (2017), and Orestis & Christos (2017). However, the problem of ratings-based overspecialization occurs because the recommendations which are made based on ratings only use the high user ratings. The ratings-based approach excludes the recommendation of movies that have low predicted user ratings, low explicit user ratings, or no predicted or explicit ratings at all. This approach is detrimental to the movie industry as it relates to movies with unpopular cast members and movie production crew members as their movies will likely not be rated due to their unpopularity. There is a need to explore the validity of the recommendation of movies based on the plots of the movies to ensure that recommendations would not be made based on user ratings to enhance the visibility of the unpopular movies in the movie consumer market.

3.2.2 Keywords-Based Data Sparsity

Keywords-based data sparsity was highlighted via Blinick (2019) where a recommendation system was created utilizing the keywords provided by users for the movies on IMDB. These keywords were provided by the users to describe the content of the movies. However, these keywords were found not to be consistent across all the movies as some movies had up to 200 keywords while others had just 10 keywords and some movies didn't have any keywords associated with them at all. Therefore, according to Alharthi (2015), there is a need for a common base to exist from which recommendations can be made. This highlights the need for the creation of a list of keywords that can be applied to all movies as opposed to each movie having its list of keywords.

To this end, the research proposes the use of keywords extracted from the plots of the movies which are associated with users with specific MBTI personality types to facilitate the movie recommendation process in the personality-based group recommendation model. Therefore, the research questions as indicated in chapter 1 are as follows:

1. *How can personality-based group recommendation models which make movie recommendations based on the words associated with the subject matter in movies help to overcome the problem of ratings-based overspecialization caused by the continuous recommendation of highly rated movies by existing recommendation models and also facilitate the expansion of the consumer movie market for unpopular movies?*
2. *What is the impact on the recommendation accuracy of a personality-based group movie recommendation model when user ratings are not used in making movie recommendations?*

Based on the research questions above, the deliverable of this research is an artefact in the form of a personality-based group movie recommendation model that utilizes words associated with the movie subject matter and the personality of the user to make movie recommendations. The next section will discuss the research methodology used in the development of the proposed artefact.

3.4 DESIGN SCIENCE RESEARCH METHODOLOGY

Design science was used in this research because it provides a structured approach to addressing the research problem. Kuechler & Vaishnavi (2011) pointed out that design science research uses the construction of an information technology artifact and its evaluation as the research method. Furthermore, design science research seeks to extend the boundaries of human and organizational capabilities by creating new and innovative artifacts (Hevner et al, 2004). This simply indicates that design science research fosters the exploration of fresh perspectives on an existing theory or combination of theories. This method of research is usually accompanied by the design of an artefact to support the research. According to Crowston & Prestopnik (2013), design science research has two equally important outcomes:

- A prototype artifact that helps address a specific, challenging, and practical design problem within a given context.
- Meaningful scholarly contributions to a field of inquiry.

March & Smith (1995) highlighted a design science framework that enables the researcher to outline the research activities and the expected research output from that activity. The framework is illustrated below.

RESEARCH ACTIVITIES

RESEARCH OUTPUT

	Build	Evaluate	Theorize	Justify
Constructs				
Model				
Method				
Instantiation				

Table 3. 1 Design Science Research Framework (March & Smith, 1995)

According to Osterwalder (2004), *Constructs* constitute a conceptualization used to describe problems within a domain. A *model* represents a situation as a problem and solution statements. The *method* represents the set of steps used in performing a task; and *instantiation* is the realization of the artefact in its targeted environment. With regards to the research activities, according to March & Smith (1995) and Hevner et al (2004), *build* refers to the construction of models, methods, and artifacts; *evaluate* refers to the development of criteria and the assessment of the output's performance against those criteria. *Theorize* refers to the construction of theories that explain why and how an artefact works. *Justify* refers to the supporting or refuting of theories through the acquisition and assessment of scientific evidence.

The personality-based recommendation model research in this thesis is based on the design science framework specified above and essentially covers the build and evaluate research activities and has constructs, models, and instantiations as the research output. In Table. 3.2 depicted below, it is illustrated how the design science research framework by March & Smith (1995) will be applied in this research.

	RESEARCH ACTIVITIES				
		Build	Evaluate	Theorize	Justify
RESEARCH OUTPUT	Constructs	Identification of textual data and basic concepts that link movies with various personality profiles.	Investigate for keyword similarities with plots of popular movies on IMDB to expand the versatility of the keywords used in the lists across multiple movies.	The application of keywords associated with the subject matter in movies and the users will enhance the visibility of the unpopular movies and still provide user satisfaction.	
	Model	Definition of a personality-based model that can make movie recommendations to users based on their personality groups.	Investigate for completeness and understandability.	The creation of a personality-based neighbourhood to make movie recommendations to the personality group as a whole as opposed to making different recommendations to each individual in the group is an efficient and reliable approach.	
	Method	Matrix Factorization model in the development of the recommendation model to determine the recommendation values of the movies selected in the creation of the model. Identify the user model, the product model, and	Calculate the Average Recommendation Value for each personality type.	The Average Recommendation Value for each personality type represents the expected minimum recommendation value for the movies which would be expected to provide user satisfaction for the various personality types.	

		the recommendation model.			
	Instantiation	Creation of a prototype personality-based movie recommender system using movie keywords.	Calculate the Recommendation Accuracy of the model for each MBTI personality type by requesting for user feedback and using a confusion matrix.	The movies which achieve the minimum recommendation value for each personality type will likely provide user satisfaction while the movies which do not achieve the minimum recommendation value will likely lead to user dissatisfaction.	

Table 3. 2 Research Outline based on March & Smith (1995)

Furthermore, Palvia et al (2003) identified a set of methods that can be applied in information systems research. They are:

Speculation/Commentary – According to Palvia et al (2003), this method signals the arrival of new trends and directions in technology. In this thesis, this method has initiated the research on the development of a personality-based movie recommendation model that overcomes the problems of ratings-based overspecialization and keywords-based data sparsity.

Frameworks and Conceptual Models – According to Palvia et al (2003) represents the artifact which is a significant deliverable in design science research. The artifact in this research takes the form of a personality-based movie recommendation model.

Library Research – this research examines previous studies and literature concerning personality models and movie recommender systems and brings to light the problem created by utilizing user ratings in making movie recommendations. Furthermore, it highlights the potential problem of data sparsity in a keywords based recommender system caused by the use of keywords provided by users on the movies on the IMDB website.

Survey – To successfully create a personality-based movie recommendation model, one must have existing data consisting of personality profiles and movies to be used to build the model. This data can only be obtained from willing participants via structured surveys.

Qualitative Research – The qualitative methods applied in this research were text mining and interpretive studies. Text mining was used to extract the movie textual data, while interpretive studies were used to determine the words which can be considered as those associated with the subject matter of movies in the creation of the lists of keywords.

Table 3.3 below identifies the methods which were selected for this research to fulfill the research objectives.

Methodology	Definition
Speculation/commentary	Research that derives from thinly supported arguments or opinions with little or no empirical evidence.
Frameworks and Conceptual Models	Research that intends to develop a framework or a conceptual model.
Library Research	Research that is based mainly on the review of existing literature.
Survey	Research that uses predefined and structured questionnaires to capture data from individuals.
Qualitative Research	Qualitative research methods are designed to help understand people and the social and cultural contexts within which they live. These methods include ethnography, action research, case research, interpretive studies, and examination of documents and texts.

Table 3. 3 MIS Methodologies retained for this research (based on Palvia et al. (2003))

The next section discusses the collaborative filtering technique applied to ultimately deliver the design science artefact which is one of the deliverables of the design science research. The section will also discuss the rationale for selecting such a method.

3.5 MODEL-BASED COLLABORATIVE FILTERING

As indicated in chapter 2 of this research, collaborative filtering has been identified as the most effective technique when used in recommender systems. The model-based collaborative filtering method was seen as the most effective method of developing the proposed group recommendation model because it requires the use of machine learning and data mining techniques to learn the parameters involved in making recommendations. The art of making recommendations is the art of identifying the patterns in the user's product selections and utilizing those patterns to aid the users in making satisfactory decisions as it relates to the product in question. The model-based approach applied the following steps based on the information regarding the use of models in creating a product (Chandrashekhar & Bhasker, 2011; Quijano-Sanchez et al., 2013; Ricci et al., 2015; Matthiesen et al., 2019).

I. The creation of the user model – the merging of the recommendations made for individuals highlights the intent of the system to understand the common preferences of the group. The user model categorises individuals into groups based on their specific commonalities.
II. The creation of the product model – this involves the identification of the relationship between the group of users and the product. Therefore, to make recommendations to a group of people, a strong connection has to be established between the group and the recommended products, in this case, movies. A key component in the creation of the product model is the identification of the product attribute used to make the required connection between the product and the group of users.
III. The creation of a group recommendation model – the construction of a group preference model can only be accomplished using the data acquired from steps I and II. This can be accomplished using the matrix factorization of the contents in the user model and the product model.

These models have been identified as three vital components in the development of a personality-based group recommendation model for movies. The next section discusses the data collection methods applied in this research to acquire the content for each of the models identified above.

3.6 DATA COLLECTION METHODS

The data used in this research was the primary data. The primary data used was collected through the use of a questionnaire that was posted on Facebook MBTI personality groups. This included a request for the personality type of the user and a request for the top 10 favourite movies of the user. The data required for the development of the proposed model was the movie plot description of all the movies; this was extracted using a web scraper after the selected movies by the participants were identified on the IMDB website. The table below shows the number of people who responded to the questionnaire on Facebook and their personality types.

Personality Profiles	No. of Respondents
ENFJ	5

ENFP	5
ENTJ	3
ENTP	1
ESFJ	3
ESFP	3
ESTJ	3
ESTP	2
INFJ	36
INFP	65
INTJ	43
INTP	11
ISFJ	12
ISFP	4
ISTJ	8
ISTP	3
Total	207 Participants

Table 3. 4 Participants Table

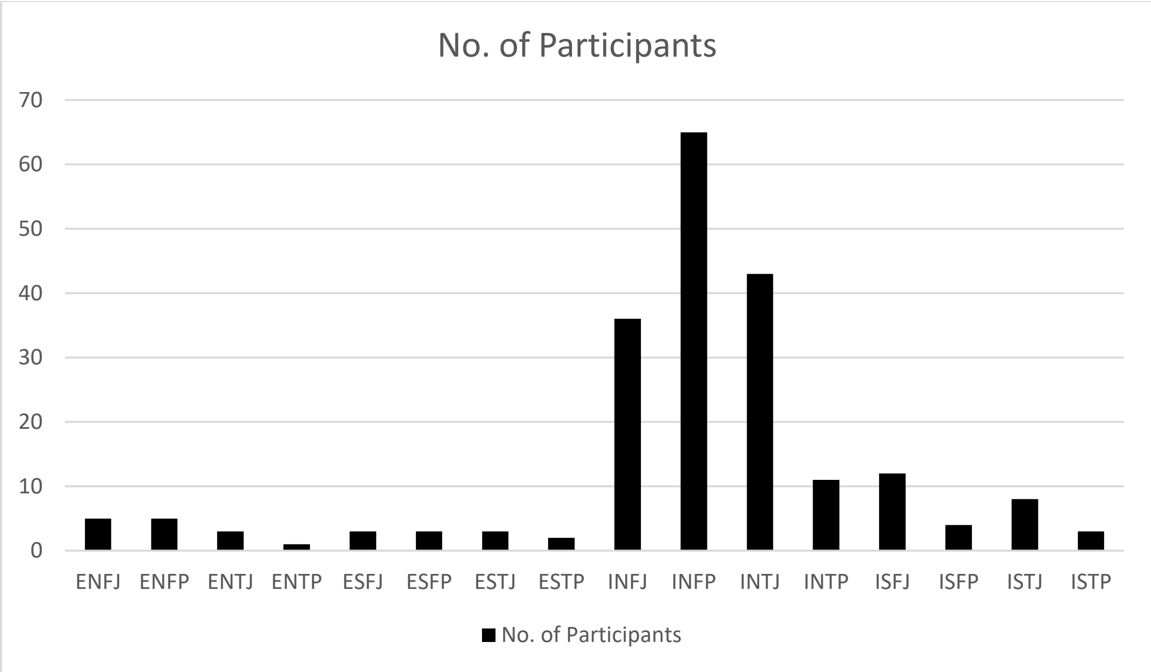

Fig. 3. 1 Bar Chart for Participants

A indicated in Fig. 3.1, the most responses from participants were obtained from the introverts. This is relevant because it identifies the consumer's market which is most likely to respond to online movie content. This is synonymous with their introvertive characteristics which were described by Myers & Myers (1995) as having a preference for their inner world than the outer world. This raises the notion that introverts are more likely to have a preference for watching movies online than extroverts thereby making online movie recommender systems a more valuable asset for introverts than extroverts.

The participants in Fig. 3.1 provided a total of 726 unique movie titles of which the movie plots were extracted from IMDB. The 726 movies can be separated based on MBTI personality traits in terms of the total amount of movies that were selected for personality types with the specified personality trait. This is indicated in Table 3.5 below.

Personality Traits	Total No. of Movies
Extroversion	709
Introversion	713
Intuition	716
Sensing	622

Feeling	718
Thinking	722
Judging	725
Perceiving	722

Table 3. 5 Personality Traits and Movies

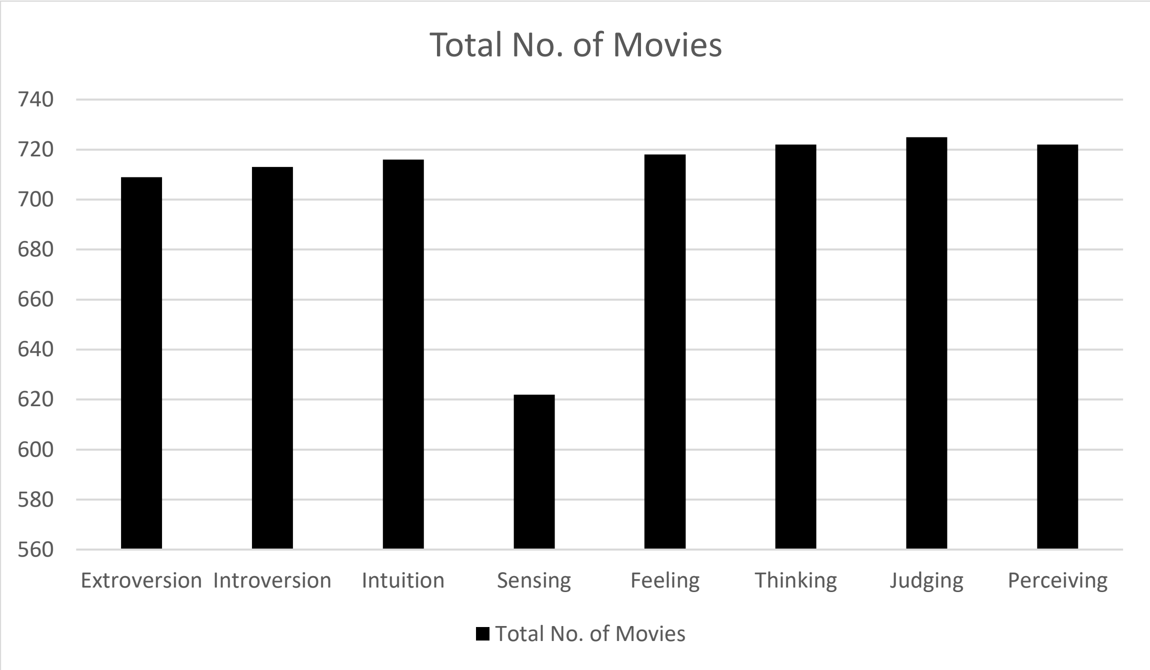

Fig. 3. 2 Movies Per Personality Trait

Fig. 3.2 indicates the total amount of movies identified for each personality trait. This revealed that users with the *Judging* personality trait provided more movies to use in the development of the personality-based group movie recommendation model. According to Stilwell et al (2000), it was pointed out that the judger prefers to live in a decisive, planned, and orderly way, to regulate and control events. Therefore based on Fig. 3.2, it is plausible to say that those with a high level of the *Judging* personality trait tend to make more decisions than other personality traits. Also, according to Martin (1997), the *Judging vs Perceiving* personality dimension represents how decisions are made in the outside world. Therefore, it makes sense that the *Judging vs Perceiving* personality dimension would contain the highest representation of movies as compared to the other personality dimensions. This is because the questionnaire asked the participants to provide 10 of their favourite movies which would require the use of the *Judging vs Perceiving* personality dimension in deciding which movies to provide. On the other hand, the *Sensing* personality trait was associated with the lowest number of movies. This can be attributed to the fact that those with the *Sensing* personality trait are associated with the gathering of sufficient information before a decision is made.

3.7 DATA ANALYSIS METHOD

3.7.1 THE WORD2VEC MODEL

A word embeddings model known as the Word2Vec model provides a better alternative to the bag of words approach in which words are mapped to the low-dimensional vectors of a continuous space. Mikolov et al (2013) pointed out that for a Word2Vec model to work, they need to be trained with a vast amount of data. The steps taken in the application of the Word2Vec model in this research involved the following steps.

1. Importing of the relevant python packages which include the following: codecs, glob, multiprocessing, os, pprint, re, nltk, gensim.models.word2vec, sklearn.manifold, numpy, matplotlib.pyplot, pandas, and seaborn.
2. Populating of the interactive namespace from the packages numpy and matplotlib specified above.
3. Downloading of the NLTK (Natural Language Tool Kit) tokenizer models by downloading the punkt and stopwords packages.
4. Starting the preparation of the corpus by first loading the movie plot summaries and the movie keywords text files for the specific personality traits using the glob package imported in step one.
5. Splitting the corpus into words. This is the point in the program where some basic pre-processing such as tokenization, lowercasing, etc. is performed on the content in the files loaded in step four. The program returns a list of tokens (words).
6. Training the Word2Vec model. Word2Vec simply implies the transformation of words into vectors. Word2Vec operates on the premise that the meaning of a word can be inferred by the company it keeps. If two words have very similar neighbours, then these words are probably quite similar in meaning or are at least related. Word2Vec can be used to find words that are related or have similar meanings. Word2Vec uses the tokens generated in step 5 to create a vocabulary of unique words. In this section of the program, behind the scenes, a neural network is being trained with a single hidden layer where the model is trained to predict the current word based on the context. The resulting learned vector is also known as the embeddings.

3.8 FLOW CHART ANALYSIS

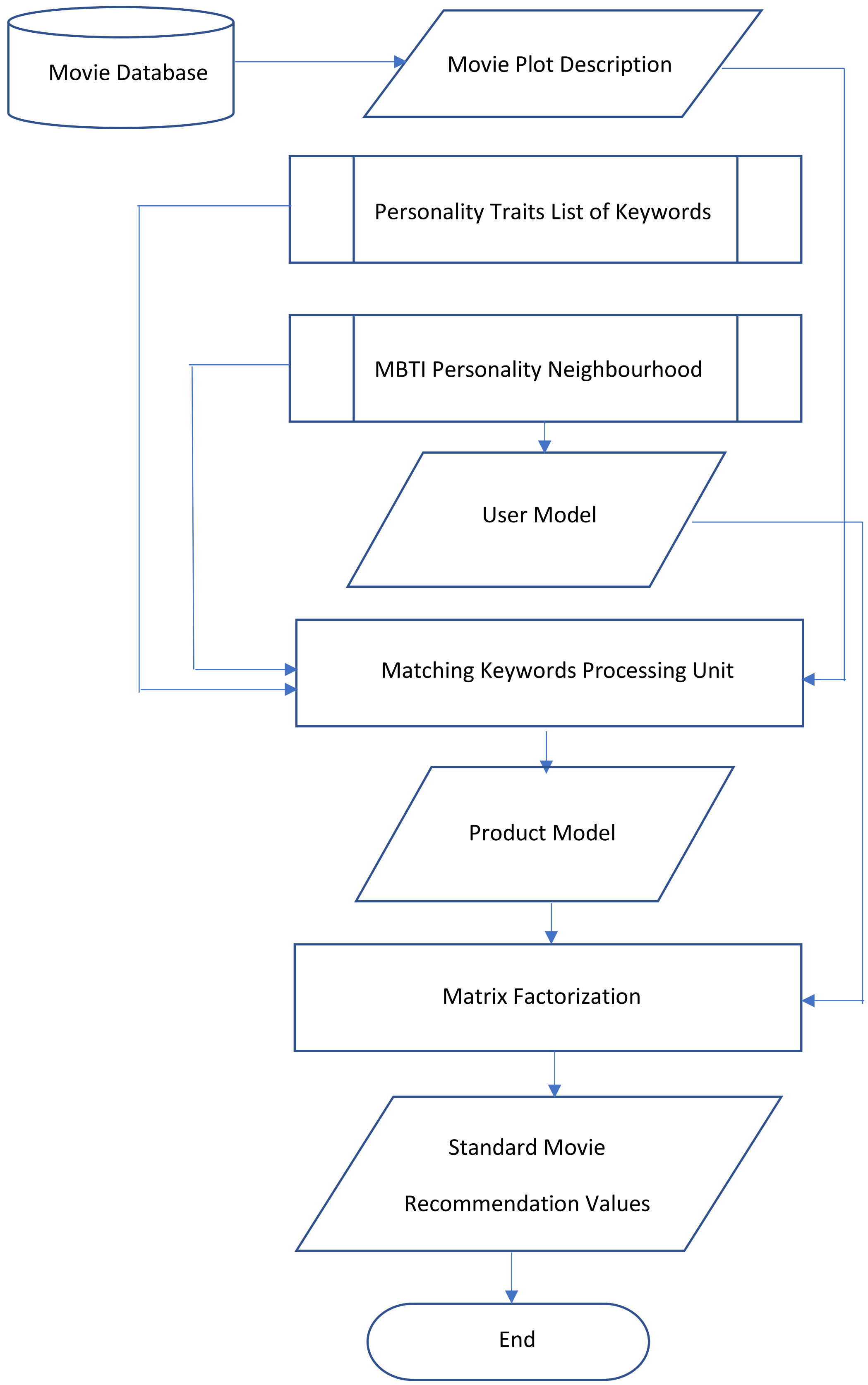

Fig. 3. 3 Flow Chart for developing a Personality Based movie recommendation model.

Fig. 3.3 above depicts the approach used to generate the standard recommendation values for movies per personality type. The steps can be explained as follows:

1. The movies in the database provide their plot descriptions to the recommendation model which is immediately fed into the Keywords Matching Processing Unit. In the keywords matching unit, they are met with the list of keywords created via this research.
2. The next phase is the identification of the 16 MBTI personality types which are formed through the integration of 4 dominant MBTI personality traits and 4 recessive MBTI personality traits. The MBTI personality neighbourhood created is also fed into the Keywords Matching Processing Unit to confirm the personality traits involved in the creation of the model so that only the relevant personality traits from the Personality Traits List of Keywords Unit will be used in the keywords matching process.
3. The MBTI Personality Neighbourhood Unit also creates an output called the User Model. The User Model unit consists of the 16 MBTI personality types and the respective percentage values for the 8 MBTI personality traits for each personality type. The value of 80% is associated with the dominant personality traits and the value of 20% is associated with the recessive personality traits.
4. The Keywords Matching Processing Unit is where the movies are matched with the personality traits based on the number of matching keywords which exist between the plots of the movies and the Personality Traits List of Keywords. The output created from this matching process is called the Product Model.
5. The next phase is for the Product Model and the User Model to be engaged in the Matrix Factorization process where the contents in the User Model matrix are multiplied by the contents in the Product Model matrix. This generates an output which is the standard recommendation values for movies for each personality type.

3.9 RELATED DATA ANALYSIS METHODS

3.9.1 THE WANG2VEC MODEL

According to Trask et al (2016), word embeddings in word2vec are insensitive to word order. The word2vec model uses two models called the skip-gram and the continuous bag-of-words models. These models discard word order information in how they account for context. Word embeddings that were built using these models have been shown to capture semantic information between words. Word embeddings built using these models are suboptimal for tasks involving syntax, such as part-of-speech tagging or dependency parsing. This is because syntax defines “*what words go where*”, while semantics tells us “*what words go together*”. In a model where word order is discarded, the many syntactic relations between words cannot be captured properly. For instance, while most words occur with the word “*the*”, only nouns tend to occur exactly afterward (e.g. *the cat*). Ling et al. (2015) proposed modifications to word2vec that incorporated word order which consisted of structured skip-gram and continuous window methods that are together called wang2vec. Ling et al (2015) discovered that the wang2vec model demonstrates a significant ability to model syntactic representations.

The word2vec model remains a popular choice due to its efficiency and simplicity. The proposed personality-based recommendation model was not concerned with the syntactic nature of words but rather the semantics, hence the wang2vec model was seen as not relevant to be used in this research. The word2vec model searches for words from the text which reveal some relatable information about a movie that can be associated with a specific personality profile.

3.9.2 THE CONTEXT2VEC MODEL

According to Melamud et al (2016), context2vec is an unsupervised model and toolkit for efficiently learning generic context embedding of wide sentential contexts, using bidirectional LSTM (Long Short-Term Memory). Unsupervised models are those which draw inferences from datasets consisting of input data without pre-existing labels. In context2vec, a large plain text corpus is used to learn a neural model that embeds entire sentential contexts and target words in the same low-dimensional space, which is optimized to reflect inter-dependencies between targets and their entire sentential context as a whole. The word2vec model had some drawbacks despite its effectiveness. As indicated in the previous section, the word2vec model cannot model syntactic representations of words, which simply means it doesn’t understand how to represent words in the order in which they appear. This specific drawback was corrected by the wang2vec model but at the cost of computation speed (Ling et al, 2015). According to Mikolov et al (2013), word2vec assigns a single vector representation to a word independent of the context in which it is used. In a word2vec model, the context representations used are commonly just a simple collection of the individual embeddings of the neighbouring words in a window around the target word. However, such approaches do not take into consideration the use of the word in the entire sentence as a whole, which is what the context2vec attempts to rectify. As pointed out by Melamud et al (2013), context2vec generates context-dependent representations.

The context2vec model would be effective in analysing a large corpus of consumer feedback regarding a product or service. However, as it relates to this research, the context2vec model was not used because the goal of this research was to identify the words associated with the subject matters in movies and not specifically how the identified words were used in the sentences from which they were extracted. The context2vec model would be the most appropriate in terms of interpreting consumer feedback, for instance, if consumer feedback contained the word *"good"*, the context2vec model would find out how the word was used in the sentence rather than assuming that the consumer's feedback was positive. A possible example of a sentence of that nature is, "*This movie was **good** for nothing"*. On the other hand, if a word such as "*unfortunate"* was used in consumer feedback, the context2vec model would be able to determine that if it was used positively or negatively by taking the whole sentence into context, which is, "*It is **unfortunate** that this movie is not getting the recognition it deserves, it is amazing!"*.

Therefore, in terms of the determination of the words which will be used in the recommendation process of this research, such in-depth analysis provided by the context2vec would create complexities such as the need to categorise words based on how they were used in the movie plots. However such methods can be explored in future research depending on the outcome of the results of this research based on the selected words associated with movie subject matters subjectively extracted from the plots of the movies provided by participants in Fig.3.1.

3.10 CHAPTER SUMMARY

This chapter started by identifying the problems associated with existing recommender systems as ratings-based overspecialization and keywords-based overspecialization. However, the most pressing of the two problems was the ratings-based overspecialization because existing recommender systems are powered by the use of user ratings. The chapter went on to discuss the design science methodology as the methodology which would best suit this kind of research since the end purpose is to generate an artefact and make a contribution to recommender systems research. The chapter also highlighted that the model-based approach will be utilized in the development of the proposed artefact and it will involve the identification of a user model, a product model, and a recommendation model. Furthermore, the chapter identified the approach utilized in collecting and analysing the data utilized in this research which can be summarised as, the use of a questionnaire, the use of a web scraper, and the use of a word2vec model. The next chapter will discuss how the data which has been collected will be used in the process of developing a personality-based group recommendation model for the recommendation of movies.

CHAPTER FOUR – RESEARCH PROCESS MODEL DESIGN

4.1 INTRODUCTION

The effectiveness of recommendation techniques is in their ability to efficiently utilize the user to item interaction to accurately predict the items which the user would like. To understand what a user needs, it is imperative to interpret the value of the product to the user. This was confirmed in Fig. 2.5 in the user-item matrix created after the users had supplied the recommendation model with rating information. This simply implies that the effective matching of the attributes associated with the user and the attributes associated with the product is what produces satisfactory recommendations. However, when it comes to making recommendations to a group of people within the same category, the preferences of the group need to be taken into consideration. Therefore, this research postulates that the first thing to identify when considering making recommendations to a group of people would be the attributes of the group followed by the preferences of the group. The identification of the attributes of the group creates the user model, and the identification of the group preferences associated with the group attributes creates the product model for the groups. The effective combination of the data in the user and product models generates the recommendation model.

As pointed out in the literature review by Field (2005), the ability of most consumers to connect with a movie character is what keeps them engaged throughout the movie as they follow the journey of their preferred character(s) through the story associated with the character until the point of disconnection. Therefore, since it's the story that determines the journey of the characters in the movie, it makes sense to use the words associated with the story of the movies to identify movies to recommend to users. Considering the structure applied in Fig. 2.5, the architecture of the personality-based group recommendation model is seen in Fig. 4.1 below.

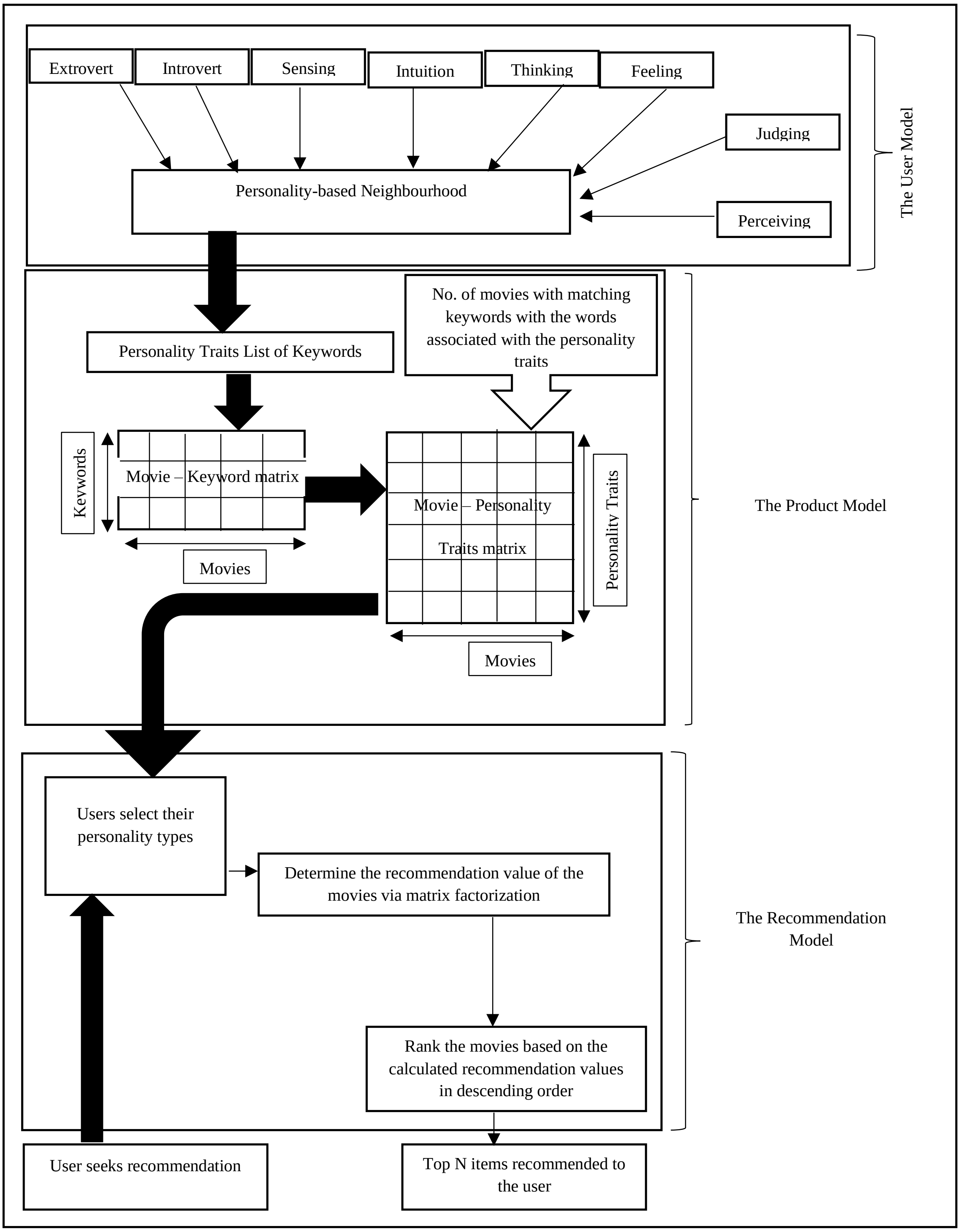

Fig. 4. 1 Architecture of a Personality-based Group Recommendation Model

As indicated in Fig. 4.1 above, the user model consists of the personality traits rather than the users represented in Fig. 2.5. This represents the personality-based neighbourhood created which creates a matrix in which its continuous increase in size will not affect the recommendation process for the community of users. This satisfies the need to have a common base for recommendations as it relates to the user model as recommended in Alharthi (2015). The common base in this scenario would be the personality types of the users.

This chapter will discuss the user and product models in terms of the kind of content they would contain to fulfill the recommendation needs of the personality groups.

4.2 THE USER MODEL

The user model consists of the user's personality types and the percentage values associated with the personality traits which make up the personality types. Considering that it is highly unlikely for users to know the percentage levels of the personality traits associated with their personality types, it is reasonable to find a way to standardize these values. Therefore, Pareto's 80/20 principle was employed to provide standard values for personality traits as it relates to the development of the personality-based recommendation model. According to Alecu (2010), Pareto's 80/20 principle states that, for many events, roughly 80% of the effects come from 20% of the causes. Furthermore, it was stated that the principle can be virtually applied in any area, like domestic behaviour, social activities, etc, for example – we may spend 80% of the time doing the most frequent 20% of activities. Alecu (2010) further pointed out that mathematically speaking, there is nothing special about the proportion of 80/20, but many real systems come across a ratio very closed by the Pareto's distribution. Therefore, as it relates to personality traits, it can be said that a personality trait is about 80% dominant because we only explore about 20% of the opposite side of a personality dimension thereby making the lesser personality trait recessive. Therefore, in this research, the dominant personality traits were given the percentage score of 80% and the recessive personality traits were given a percentage score of 20%.

4.3 THE PRODUCT MODEL

The development of the product model involves the development of a list of keywords associated with the personality traits which make up the personality types. The keywords which are generated are matched with the words in the plots of the movies selected from the user's favourite movies to build the recommendation model. Therefore, the product model consists of the total number of keywords that are associated with both the personality traits and the movies. The movies which were utilized in developing the list of keywords associated with the various personality traits were the movies that were provided by the participants in Table 3.4. The following subsection highlights how the keywords associated with the personality traits were generated.

4.3.1 THE MOVIE KEYWORDS GENERATION PHASE

The total number of movies from which the plot summaries were extracted using a web scraper was 726. The movie keywords were extracted from the movie plot summaries using a word2vec model. The keywords were extracted and stored based on the personality traits which make up the personality types. This resulted in 8 separate lists of keywords for the *Extrovert, Introvert, Intuition, Sensing, Thinking, Feeling, Judging, and Perceiving*. The method utilized in extracting the movie keywords from the movie plots was text mining using a word2vec model by following the steps highlighted in section 3.7.1. Using the word2vec model, a word vocabulary is created from the movie plot summaries. A 2D scatter plot is created with all the words in the vocabulary and the 2D scatter plot is text mined by manipulating the x and y coordinates of the scatter plot. The purpose of manipulating the x and y co-ordinates was to highlight specific areas of the 2D scatter plot to see the words located in that area. The x and y coordinates from which the keywords were extracted are also seen in Table 4.1 below with the co-ordinates of one axis staying constant while the other is manipulated to zoom in on the words in that location. The creation of the 2D scatter plot resulted in a snake-plot. This is significant because according to Weiss (2001), snake-plots are one of the techniques which are used to depict consumer perceptions. Weiss (2001) further pointed out that the concept of a snake plot involves the gathering of the benefits that customers use to judge the different products in the market and place each benefit on a scale with the appropriate endpoints. Consumer perceptions of this nature are usually unstructured and represented in large textual formats. Therefore, considering that the data used in the word2vec model were the movie plots which included large unstructured textual data, it makes sense that the resulting 2D scatter plot was a snake-plot.

To this end, considering the vast amount of data provided for the text mining process, the most concentrated part of the snake-plot was chosen for the keyword extraction process; this was located at the part of the plot which looked like the head of a snake. An example of the 2D scatter plot produced from the word2vec model is the one for the Extrovert personality trait seen in Fig. 4.2 below.

Personality Traits	Total No. of Movies	Word Vocabulary Length	Total No. of Keywords	X Bounds	Y Bounds	Constant Axis
Extroversion	709	11123	772	(-15, 15)	(0, 42)	X Axis
Introversion	713	25442	832	(-20, 15)	(-32, 0)	X Axis
Intuition	716	25539	1408	(-40, 0)	(-30, 0)	X Axis
Sensing	622	13501	1873	(-25, 0)	(-45, -20)	Y Axis
Feeling	718	21819	1307	(-40, -5)	(20, 36)	X Axis
Thinking	722	17923	1695	(-20, 0)	(-15, -20)	Y Axis
Judging	725	20936	2006	(0, 35)	(-37, -17)	X Axis
Perceiving	722	18983	2422	(-20, 0)	(0, 40)	Y Axis

Table 4. 1 Personality Traits and Associated Keywords

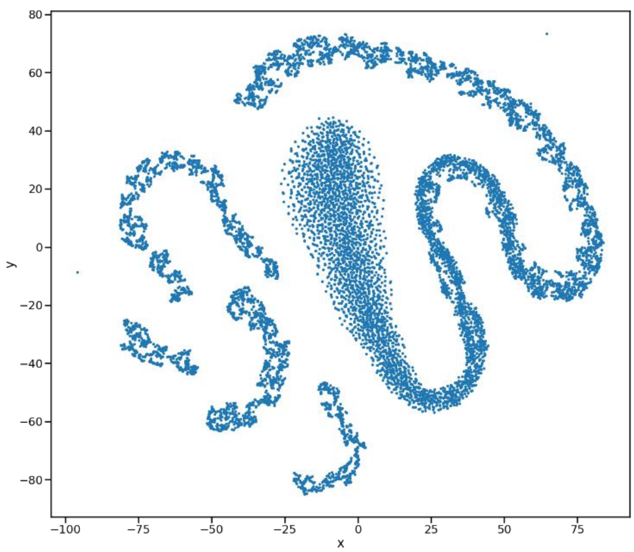

Fig. 4. 2 Scatter Plot for Extrovert Trait Movie Word Vocabulary

The manipulation of the x and y coordinates for the scatter plot in Fig 4.2 was from the range of between -15 to +15 on the x-axis and +42 to 0 on the y-axis as that is the region which covers what appears to be the head of a snake. After identifying the range of x and y coordinates from which the keywords would be extracted, to extract the keywords, one needs to zoom into the scatter plot by breaking down the x or y-axis coordinates as indicated below in Fig. 4.3. As indicated in Fig. 4.3, one is now able to have a clearer picture of the words which are located in the region of -15 to +15 on the x-axis, and +40 to +42 on the y-axis. The words are extracted and stored in an excel file and the process is repeated by gradually reducing the co-ordinates on the y-axis by 2 until it gets to plot_region(x_bounds = (-15, 15), y_bounds = (0, 2)). The total number of keywords extracted for those with the extroversion personality trait using this method was 772 as indicated in Table 4.1. The process was repeated for all the other personality traits and the range of x and y co-ordinates selected for text mining are indicated in Table 4.1.

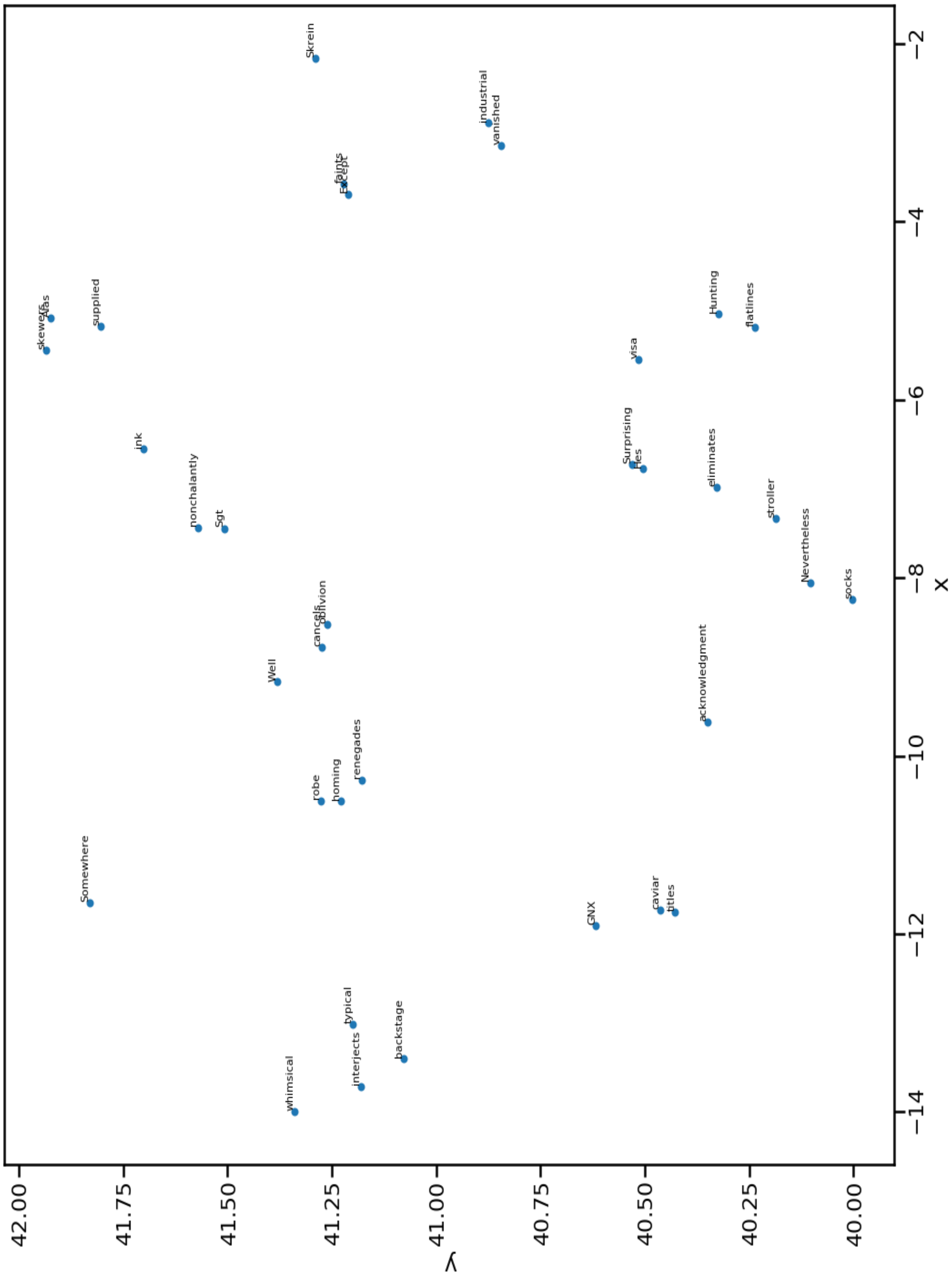

Fig. 4. 3 plot_region(x_bounds=(-15, 15), y_bounds=(40, 42))

The keywords extracted which were associated with the personality traits represent the query vector in the calculation of the semantic cosine similarity between words. A query term vector requires a document term vector to determine the semantic cosine similarity between the words. The document vector was represented by the combined corpus of the movie plots from 3,327 of the most popular movie titles on IMDB. Therefore by querying the words in the keywords list against the words associated with the movie plots in most popular movies on IMDB one would be able to identify the cosine similarities associated with words in movies which many consumers have provided high positive feedback. According to Rahutomo et al (2012), the higher similarity score between the document's term vector and query's term vector means more relevancy between document and query. Therefore, it was decided that for this research, only values that are greater than or equal to 0.990 would be considered as suitable keywords in the creation of the list of keywords. The semantic cosine similarity between words was calculated by using the *most similar* function in the word2vec model which automatically generates the results. An example is shown in Table 4.2 below. The table shows the *Extrovert* personality trait which has a keyword called *Vanished*. The neighbouring keywords are the words displayed when the *most similar* function is applied to the keyword *Vanished*.

Personality Trait	Original Keyword	Neighbouring Words	Cosine Similarity
Extrovert	Vanished	Stem	0.9962829351425171
		Dug	0.9960925579071045
		Nothing	0.9959673881530762
		Emerged	0.9959471821784973
		Outlook	0.995720624923706
		Crossed	0.9956353306770325
		Confessions	0.9955299496650696
		Wages	0.9955105781555176
		Marked	0.9954432845115662
		Equal	0.9954097867012024

Table 4. 2 Sample of Keywords and Neighbouring Words Data

As indicated in Table 4.2, the neighbouring words identified via the *most similar* function with cosine similarities greater than or equal to 0.990 were added to the *Extroversion* list of keywords in addition to the keyword *Vanished*. This is because the neighbouring words identified showed strong relevance to the word *Vanished* through their cosine similarity values. As can be seen in Table 4.2, one can identify the reasons why the neighbouring words had such high cosine similarity values as they can all be characterized in terms of revealing something, which is the opposite of *Vanished*.

To ensure that the list of keywords only contains document term vectors and query term vectors with very high levels of relevancy based on the values of their cosine similarities, words with cosine similarities less than 0.990 were discarded. Also, the purpose of discarding such words was mainly to create a list of keywords with consistent cosine similarity values which represents a stronger bond between the words selected to be in the list of keywords associated with the personality traits. Table 4.3 below shows an example of a word which was discarded because the cosine similarity values associated with the neighbouring keywords were less than 0.99.

Personality Trait	Keyword	Neighbouring Words	Cosine Similarity
Extrovert	Oblivion	Excruciating	0.9894995093345642
		Paralyzes	0.989260196685791
		Bathed	0.9889873266220093
		Sparazza	0.9888256192207336
		Slang	0.9886614680290222
		Mosely	0.9886406064033508
		Slur	0.9886369705200195
		Brahms	0.988632082939148
		Tucci	0.9885636568069458
		Hating	0.9885332584381104

Table 4. 3 Sample of Keywords and Neighbouring Words Data

As indicated in Table 4.3, the word *Oblivion* was discarded from the *Extrovert* list because there were no neighbouring words that had strong enough cosine similarity values to be associated with it. There is no clear relationship between the word *Oblivion* and the list of neighbouring words generated. Therefore, since the word *Oblivion* could not be associated with words from the document vectors having a cosine similarity of greater than or equal to 0.990, it implies that the word *Oblivion* and the neighbouring words generated were not suitable to be in the list of keywords created based on having a reduced level of relevancy. The total number of keywords for each personality trait after the *most similar* function was applied to the extracted keywords are indicated in Table 4.4 below.

Personality Traits	Total No. of keywords before calculating cosine similarity between keywords	Total No. of Keywords after calculating cosine similarity between keywords
Extroversion	772	742
Introversion	832	794
Intuition	1408	1281
Sensing	1873	3276
Feeling	1307	1148
Thinking	1695	1482
Judging	2006	1716
Perceiving	2422	1985

Table 4. 4 Personality Traits and Associated No. of Keywords.

According to Table 4.4, it can be deduced that the personality trait of sensing has the highest number of keyword representation; this could imply that the personality trait of *Sensing* could play a major role in the consumer movie selection process. Kim & Han (2014) pointed out that those with a high level of sensing collect information through what is happening and by focusing on observable facts, data, and phenomena. Therefore, considering Fig. 3.2 and Table 4.4, it is reasonable to postulate that those with the *Sensing* trait would require the highest number of keywords because they were associated with the lowest amount of movies. The list of keywords created fulfils the need to serve as a common base for the recommendation of movies as pointed out by Alharthi (2015).

4.4 CHAPTER SUMMARY

This chapter discussed the process involved in the creation of a personality-based group movie recommendation model. The chapter started by identifying the architecture of the proposed model. The architecture of the proposed model revealed how the proposed model will be able to make movie recommendations without the use of ratings. The architecture revealed that the recommendation process can be broken down into three models: the user model, the product model, and the recommendation model which contains the recommendation algorithm. The highlight of the chapter was in the explanation of the process used in the determination of the words which would be included in the list of keywords associated with the MBTI personality traits. The next chapter will show how the list of keywords generated in this chapter can be applied in the creation of a personality-based group recommendation model for movies.

CHAPTER FIVE – CREATING THE GROUP RECOMMENDATION MODEL

5.1 INTRODUCTION

According to Madhukar (2014), as highlighted in the literature review, recommender systems are a subclass of information filtering system that seeks to predict the user's preference for an item such as music, books, or movies which they had not yet considered using a model built from the characteristics of the item or the user's social environment. Therefore, this confirms that it is expedient to consider the characteristics of the movie as it relates to the user's social environment if one were to make successful recommendations. In the case of this research, the user's social environment is represented by the personality-based neighbourhoods created for the various MBTI personality types. This chapter explores the application of matrix factorization in the determination of the values generated in the recommendation model based on the content of the user and product models. The chapter will also qualitatively explore the content of the training data used in this research to confirm that there is a relationship between the MBTI personality types and the movies which were selected by the participants.

5.2 CRITICAL ANALYSIS OF THE TRAINING DATASET

The data used in the creation of the recommendation model was the data provided by the participants in Table 3.4 and can also be referred to as the training dataset. The purpose of the training dataset is to train the recommendation model, so it understands what is expected in terms of the recommendations made to consumers in a testing environment. The expected outcome is to identify the standard recommendation value for movies for each personality type. The benefit of using this data was based on the fact that there was no need to find out if the selected movies were suitable for the various personality types. This was because the participants with those personality types were the ones who provided the movie titles and confirmed via the questionnaire that the movies provided were in their top 10 favourite movies. The recommendation model created in this research is based on these participants and their movie choices and serves as a threshold from which future recommendations can be assessed per personality neighbourhood based on the standard recommendation value for movies per personality type.

However, before thinking about making movie recommendations utilizing the MBTI personality model and keywords associated with the plots of the movies and the list of keywords per personality trait, it is important to understand if there are specific movie genres which are associated with specific MBTI personality types. This will be accomplished by identifying the total number of matching movies between the personality traits which make up a personality type, after which the percentage value for all the movies associated with a specific movie genre is generated and the stand-out performers can be identified.

Table 3.5 has already shown the number of movies from the 726 movies selected by the participants which are associated with each personality trait. Table 5.1 below goes a step further to show the total number of movies the respective personality traits which make up the various personality types, have in common.

Personality Profiles	Matched Movie Titles
ENFJ	701
ENFP	701
ENTJ	702
ENTP	703
ESFJ	606
ESFP	605
ESTJ	607
ESTP	607
INFJ	705
INFP	705
INTJ	707
INTP	706
ISFJ	610
ISFP	610
ISTJ	613
ISTP	612

Table 5. 1 Matched movies between personality traits which make up the Personality Types

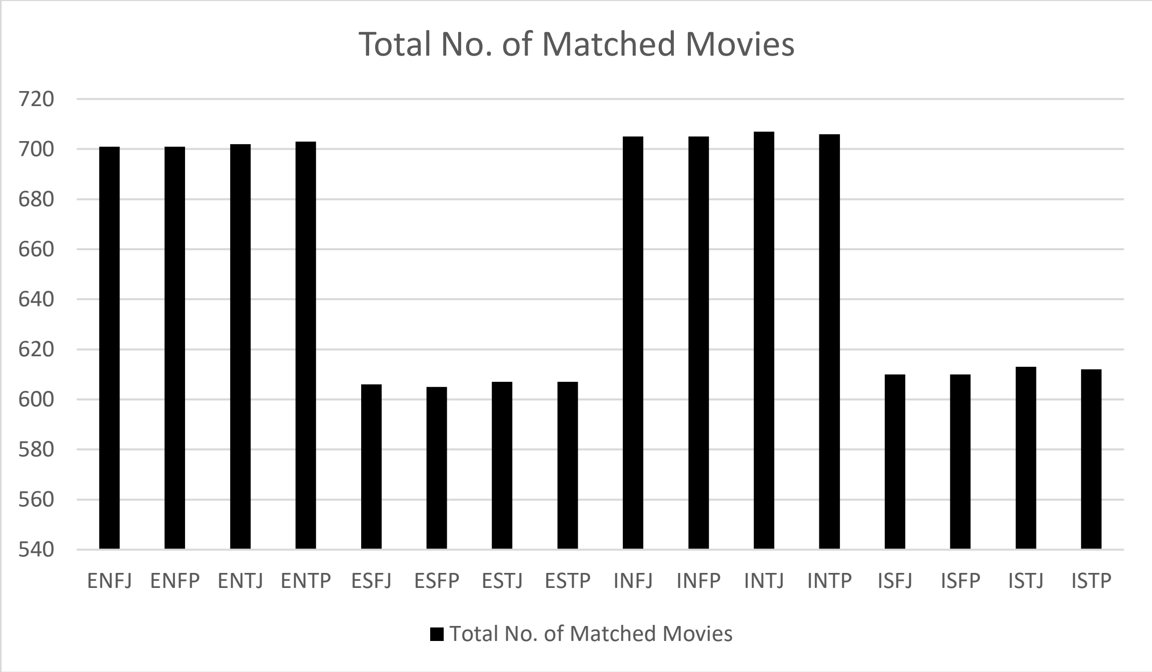

Fig. 5. 1 Matched movies between personality traits which make up the Personality Types

As indicated in Fig. 5.1 above, one can see the significance of the *Sensing* personality trait in the participants movie selections as it is only those personality types with the *Sensing* personality trait that are associated with the lower figures in terms of the movie titles provided.

Fig. 5.2 below shows the percentage representation for each movie genre per personality type. This was done to identify if there were any movie genres which are significantly associated with a specific personality type. The data clearly shows that the most popular movie genre associated with all personality types is the *Comedy* genre, and the least preferred genres are the *Western* & *Sport* genre. However, the data confirms the work by Karumur et al (2017) where it was pointed out that there was no significant connection between a specific movie genre and a specific personality profile. Their research was done utilizing the Big Five personality model which has now been further confirmed via this research utilizing the MBTI personality model. This was evident in the fact that none of the personality types distinctively stood out for any of the represented movie genres.

It can also be seen in Fig. 5.2 that the *Drama* genre was excluded from the analysis. According to Ullah (2020), the *Drama* genre can be defined as an adaptation, recreation, and reflection of reality on stage. Sir Alfred Joseph Hitchcock KBE, an English film director, producer, and screenwriter, once stated, "*Drama is life with the dull bits cut*". Therefore, it is reasonable to say that the *Drama* genre is a significant attribute of a movie while the other genres associated with the movie determine how the *Drama* will be delivered to the audience To this end, the *Drama* genre was excluded from the analysis due to the broad nature of the genre.

	Comedy	Adventure	Romance	Action	Sci-Fi	Fantasy	Crime	Thriller	Family	Animation	Mystery	Biography	Horror	Music	History	War	Western	Sport
ENFJ	45.79	37.38	31.53	25.68	16.69	14.41	12.7	12.41	10.41	9.84	9.84	8.56	7.56	6.56	3.42	3.14	1.43	1.28
ENFP	45.79	37.38	31.53	25.68	16.69	14.41	12.7	12.41	10.41	9.84	9.84	8.56	7.56	6.56	3.42	3.14	1.43	1.28
ENTJ	45.87	37.18	31.48	25.64	16.67	14.39	12.82	12.54	10.26	9.83	9.83	8.55	7.55	6.55	3.42	3.13	1.42	1.28
ENTP	45.95	37.27	31.44	25.6	16.64	14.37	12.8	12.52	10.24	9.96	9.82	8.53	7.54	6.54	3.41	3.13	1.42	1.28
ESFJ	45.05	41.42	30.69	28.71	18.98	15.51	13.86	14.03	10.89	10.23	11.06	8.75	8.09	6.77	3.63	3.63	1.32	1.16
ESFP	45.12	41.49	30.58	28.76	19.01	15.54	13.88	14.05	10.91	10.25	11.07	8.76	8.1	6.78	3.64	3.64	1.32	1.16
ESTJ	45.14	41.35	30.48	28.67	18.95	15.49	14	14.17	10.87	10.21	11.04	8.73	8.07	6.75	3.62	3.62	1.32	1.15
ESTP	45.14	41.35	30.48	28.67	18.95	15.49	14	14.17	10.87	10.21	11.04	8.73	8.07	6.75	3.62	3.62	1.32	1.15
INFJ	45.82	37.02	31.49	25.53	16.6	14.33	12.62	12.34	10.5	9.65	9.79	8.51	7.38	6.67	3.55	3.12	1.42	1.28
INFP	45.82	37.02	31.49	25.53	16.6	14.33	12.62	12.34	10.5	9.65	9.79	8.51	7.38	6.67	3.55	3.12	1.42	1.28
INTJ	45.97	36.78	31.4	25.46	16.55	14.29	12.73	12.45	10.33	9.62	9.76	8.49	7.36	6.65	3.54	3.25	1.41	1.27
INTP	45.89	36.83	31.44	25.5	16.57	14.31	12.75	12.46	10.34	9.63	9.77	8.5	7.37	6.66	3.54	3.12	1.42	1.27
ISFJ	45.08	40.98	30.49	28.52	18.85	15.41	13.77	13.93	10.98	10	10.98	8.69	8.03	6.89	3.77	3.61	1.31	1.15
ISFP	45.08	40.98	30.49	28.52	18.85	15.41	13.77	13.93	10.98	10	10.98	8.69	8.03	6.89	3.77	3.61	1.31	1.15
ISTJ	44.86	40.78	30.34	28.38	18.76	15.33	13.87	14.03	10.93	9.95	10.93	8.65	7.99	6.85	3.75	3.75	1.31	1.14
ISTP	45.1	40.85	30.39	28.43	18.79	15.36	13.89	14.05	10.95	9.97	10.95	8.66	8.01	6.86	3.76	3.59	1.31	1.14

Fig. 5. 2 Percentage representation of movie genres for movies per personality type

5.2.1 ADVANTAGES AND LIMITATIONS

The advantages of using the training dataset includes the following:

1. It provides the opportunity to create a standard recommendation model for other users with the same personality types as those mentioned in Table 3.4.
2. It provides the opportunity to extract the words associated with various subject matters in movies from the plots of the 726 movies already identified as favourites to the participants.

The limitations associated with using the training dataset include:

1. There were very few responses from the *Extrovert-related* personality types and therefore the research was unable to explore the relationship between *Extrovert* related personality types and their movie selections as the data provided was insufficient to draw any reasonable conclusions.
2. The 726 movies provided by the 207 participants implies an estimated average of 4 movies provided per participant. However, this was because there were some participants who did not provide up to 10 movies as requested in the questionnaire.

5.2.2 DATA SAMPLE DETERMINATION

Considering the fact that it will be unrealistic to fit 726 movies in a matrix in this report, it becomes imperative that a section of the movies has to be selected which can effectively represent all the movies in the dataset. According to Dibley (2011) and Burmeister & Aitken (2012), it may be best to think of data in terms of rich and thick rather than the size of the sample. Fusch & Ness (2015) pointed out that the easiest way to differentiate between rich and thick data is to think of rich in terms of quality and thick in terms of quantity. They also highlighted the fact that thick data is a lot of data while rich data is many-layered, intricate, detailed, nuanced, and more. Also, because the selected movies will be applied in a matrix in this study, it was considered reasonable to limit the number of movies that will be used in the creation of the recommendation model to 20 movies.

To this end, the criteria for selecting 20 movies that would represent the whole dataset in the recommendation model was based on the richness of the selected movies based on Dibley (2011) and Burmeister & Aitken (2012). Also, Vasileiou et al (2018) also stated that samples in qualitative research tend to be small to support the depth of case-oriented analysis that is fundamental to this mode of inquiry. They further stated that qualitative samples are purposive, that is, selected by their capacity to provide richly-textured information, relevant to the phenomenon under investigation. The richness was determined firstly in terms of the movies being associated with all the MBTI personality traits. Secondly, considering that we have already started with the value of 20 to represent the number of movies selected, the research will also use the number 20 to represent the minimum number of words in the plots of these movies which match with the words in the list of keywords for each personality trait. Thirdly, the 20 movies selected had to be diverse in terms of their movie genres. The selected list of 20 movies is indicated in Table 5.1 below.

Movie ID	IMDB_ID	Movie Titles	Genres	Movie Plot Word Count
M12	tt0457430	Pan's Labyrinth	Drama Fantasy War	3090
M8	tt1375666	Inception	Action Adventure Sci-Fi	5271
M6	tt0031381	Gone with the Wind	Drama History Romance	4343
M10	tt0071853	Monty Python and the Holy Grail	Adventure Comedy Fantasy	4148
M18	tt0434409	V for Vendetta	Action Drama Sci-Fi	4597
M9	tt0816692	Interstellar	Adventure Drama Sci-Fi	4603
M2	tt0078748	Alien	Horror Sci-Fi	4509
M5	tt0087332	Ghostbusters	Action Comedy Fantasy	3379
M3	tt0090605	Aliens	Action Adventure Sci-Fi	5076
M14	tt2084970	The Imitation Game	Biography Drama Thriller	4294
M19	tt2948356	Zootopia	Adventure Animation Comedy	4396
M13	tt0120815	Saving Private Ryan	Drama War	3751
M20	tt0068646	The Godfather	Crime Drama	3129
M7	tt0119217	Good Will Hunting	Drama Romance	1358
M15	tt0093779	The Princess Bride	Adventure Family Fantasy	2432
M16	tt0081505	The Shining	Drama Horror	1904
M4	tt0947798	Black Swan	Drama Thriller	4089
M17	tt0993846	The Wolf of Wall Street	Biography Crime Drama	4040
M1	tt0183790	A Knight's Tale	Action Adventure Romance	2810
M11	tt0073486	One Flew Over the Cuckoo's Nest	Drama	1358

Table 5. 2 Movies and Total No. of matching keywords

To determine the minimum number of words in a movie plot description for this approach to function, the range would have to be determined. This involves the subtraction of the lowest movie plot word count from the highest movie plot word count.

$$\text{Range }(X) = \text{Max }(X) - \text{Min }(X)$$

$$\text{Range }(X) = 5271 - 1358 = 3913$$

To this end, the movies which will be used in the creation of a recommendation model which will in turn be used to set standards for making movie recommendations to each personality type have now been identified. Also, the list of keywords which serves as a common base for making recommendations has been created in chapter 4, section 4.3.1. The next step would be to apply the data in the creation of the personality-based group recommendation model. The aim of creating the personality based group recommendation model are:

1. To identify the standard movie recommendation values for the 16 MBTI personality types to serve as a threshold for future movie recommendations to each personality type.
2. To provide a guide on how to make movie recommendations utilising keywords associated with the plots of the movies and the 8 MBTI personality traits which constitute the 16 MBTI personality types when they are integrated together.

5.3 CREATING THE USER MODEL

As indicated in section 4.2, the user model is where all the users are classified into the various personality categories and where the 80/20 principle according to Alecu (2011) is applied to the assignment of values to the percentage levels of each of the personality traits. The user model represents the personality-based neighbourhood based on social matching which was indicated in the literature as an essential component of using personality in the development of a recommendation model (Nunes & Hu, 2012). The user model will consist of 16 personality types which are represented by the percentage values of their dominant and recessive personality traits. The application of the 16 MBTI personality types was necessary due to the fact that one of the aims of creating the personality based group movie recommendation model was to generate standard recommendation values for each personality type to serve as a threshold for measuring the accuracy of the recommender system in relation to the various personality types. The user model is represented using Table 5.3 below.

	E	I	N	S	T	F	J	P
ENFJ	80	20	80	20	20	80	80	20
ENFP	80	20	80	20	20	80	20	80
ENTJ	80	20	80	20	80	20	80	20
ENTP	80	20	80	20	80	20	20	80
ESFJ	80	20	20	80	20	80	80	20
ESFP	80	20	20	80	20	80	20	80
ESTJ	80	20	20	80	80	20	80	20

ESTP	80	20	20	80	80	20	20	80
INFJ	20	80	80	20	20	80	80	20
INFP	20	80	80	20	20	80	20	80
INTJ	20	80	80	20	80	20	80	20
INTP	20	80	80	20	80	20	20	80
ISFJ	20	80	20	80	20	80	80	20
ISFP	20	80	20	80	20	80	20	80
ISTJ	20	80	20	80	80	20	80	20
ISTP	20	80	20	80	80	20	20	80

Table 5. 3 The User Model.

5.4 CREATING THE PRODUCT MODEL

Hvam (1999) pointed out that product models contain a formalized representation of product knowledge which can be defined based on the consumer's need the designer is trying to satisfy. Also, Alharthi (2015) pointed out the need for a common base to be provided from which recommendations can be made. Therefore, the product model will contain the representation of a common base between the personality traits and the selected 20 movies. This involves the identification of the number of exact matching keywords between the words in the plots of the movies and the list of keywords created in section 4.3.1. As a reminder, the total number of keywords associated with each of the personality traits are shown in Table 5.4 below.

Personality Traits	Total No. of Keywords
Extroversion	742
Introversion	794
Intuition	1281
Sensing	3276
Feeling	1148
Thinking	1482
Judging	1716
Perceiving	1985

Table 5. 4 No. of Keywords with Personality Traits

To determine the number of words in the plots of the movies which were an exact match to the words identified in Table 5.4 for each personality trait for each movie, the movies and the movie plots were imported into the SQL Server database. The list of keywords for each personality trait was also imported into the SQL Server database. A full-text index was defined on the column containing the movie plots in the SQL table created for movies. This enabled the use of SQL statements to search through the movie plots to search for specific words in the movie plots. This made it easier to query the data and eventually obtain the total number of words associated with the personality traits keywords and the movies. The SQL statement utilized to search for the number of matching keywords between the list of keywords associated with the *Intuition* personality trait and the 20 movies selected to build the recommendation model is indicated below. The same SQL statement is utilized to identify the matching keywords between the 20 movies selected to build the recommendation model and the list of keywords for the other personality traits by substituting the name of the keywords list in the SQL statement.

```
Select IMDB_ID, Movie_Title, Year_of_Release, IMDB_Ratings, Genres, COUNT(Keywords) AS 'Intuition'
From sys.dm_fts_index_keywords_by_document(DB_ID(), OBJECT_ID('original_movies')) As X
   Inner Join intuition_keys On X.display_term = intuition_keys.Keywords
   Inner Join original_movies On X.document_id = original_movies.ID
   Where Movie_Title IN ('The Princess Bride', 'The Imitation Game', 'Aliens', 'Inception', 'Interstellar', 'Monty Python and the Holy Grail', 'Black Swan', 'The Wolf of Wall Street', 'Zootopia', 'Saving Private Ryan', 'Good Will Hunting', 'One Flew Over the Cuckoo''s Nest', 'Pan''s Labyrinth', 'A Knight''s Tale', 'Dead Poet''s Society', 'Gone with the Wind', 'Alien', 'V for Vendetta', 'Ghostbusters', 'The Shining', 'The Godfather')
   GROUP BY IMDB_ID, Movie_Title, Year_of_Release, IMDB_Ratings, Genres
   ORDER BY COUNT(Keywords) DESC
```

The resulting matrix is the product model and it is indicated in Fig. 5.3 below.

	E	I	N	S	T	F	J	P
M1	36	63	63	234	114	96	102	129
M2	62	62	98	276	118	82	154	144
M3	64	88	90	324	110	110	164	184
M4	36	40	68	260	110	72	118	138
M5	69	81	96	330	162	108	141	192
M6	108	105	132	432	198	132	222	252
M7	69	30	72	210	54	60	60	81
M8	57	84	135	396	168	123	216	237
M9	63	78	111	396	153	126	195	267
M10	62	56	122	332	158	110	186	188
M11	21	27	39	174	57	78	81	87
M12	72	54	135	336	123	84	159	213
M13	38	40	82	208	98	66	106	138
M14	72	60	90	312	102	96	135	153
M15	78	75	69	252	120	75	141	129
M16	30	57	69	228	63	66	99	141
M17	32	34	68	280	122	68	132	124
M18	72	105	117	426	210	180	231	246
M19	56	52	90	224	120	94	138	140
M20	78	60	75	366	132	93	174	183

Fig. 5. 3 The Product Model

Fig. 5.3 above represents the product model, which is the matrix representation of the total number of words in the plots of the selected movies which match the keywords identified for each personality trait in Table 5.4.

Based on Fig. 5.3 above, the average number of matching words per personality traits are listed in the table below. The ability of a movie plot description to have matching keywords which are greater than or equal to the values associated with the personality traits in Table 5.5 below will indicate if the eventual recommendation value of the movie will reach the standard recommendation value for the personality type in question.

MBTI Personality Traits	Average Number of Matching Keywords
E	59
I	63
N	91
S	300
T	125
F	96
J	148
P	168

Table 5. 5 Average Number of Matching Keywords Per MBTI Personality Trait

Now that the user model and the product model have been identified, the recommendation model can be created through the matrix factorization of the user model and product model as seen in the next section.

5.5 CREATING THE GROUP RECOMMENDATION MODEL

The approach used in the creation of the recommendation model was matrix factorization and this involved the multiplication of the matrix generated for the users in the user model by the values generated in the product model for each of the personality traits. The formula used in the multiplication of the two matrices is indicated below.

$$(\mathbf{AB})_{ij} = \sum_{k=1}^{m} A_{ik} B_{kj}$$

Where A = user model matrix, B = product model matrix, *i* = value in the row, *j* = value in the column

Therefore, by utilizing the formula above, the recommendation value for the movies as it relates to each personality type can be calculated. For the first movie represented by M1, the first value in the first row of the user model matrix is multiplied by the first value in the first column of the product model matrix. This is repeated for all the rows and columns as it relates to M1. The values for the product of all the rows and columns as it relates to M1 are added together to generate the recommendation value for M1 as it relates to the specific personality type. The same process is repeated for all the movies from M1 to M20. The results are represented in Fig. 5.4 below.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	M13	M14	M15	M16	M17	M18	M19	M20	ARV
ENFJ	34560	43680	48360	34480	48420	67260	28380	60180	57480	53080	24420	50520	33040	43980	40560	36360	35200	67740	40960	48420	44854
ENFP	36180	43080	49560	35680	51480	69060	29640	61440	61800	53200	24780	53760	34960	45060	39840	33420	34720	68640	41080	48960	45817
ENTJ	35640	45840	48360	36760	51660	71220	28020	62880	59100	55960	23160	52860	34960	44340	43260	30720	38440	69540	42520	50760	46300
ENTP	37260	45240	49560	37960	54720	73020	29280	64140	63420	56080	23520	56100	36880	45420	42540	33240	37960	70440	42640	51300	47536
ESFJ	44820	54360	62400	46000	62460	85260	36660	75840	74580	65680	32520	62580	40600	57300	51540	40440	47920	86280	49000	65880	57106
ESFP	46440	53760	63600	47200	65520	87060	37920	77100	78900	65800	32880	65820	42520	58380	50820	42960	47440	87180	49120	66420	58342
ESTJ	45900	56520	62400	48280	65700	89220	36300	78540	76200	68560	31260	64920	42520	57660	54240	40260	51160	88080	50560	68220	58825
ESTP	47520	55920	63600	49480	68760	91020	37560	79800	80520	68680	31620	68160	44440	58740	53520	42780	50680	88980	50680	68760	60061
INFJ	36180	43680	49800	34720	49140	67080	26040	61800	58380	52720	24780	49440	33160	43260	40380	32520	35320	69720	40720	47320	44808
INFP	37800	43080	51000	35920	52200	68880	27300	63060	62700	52840	25140	52680	35080	44340	39660	35040	34840	70620	40840	47880	46045
INTJ	37260	45840	49800	37000	52380	71040	25680	64500	60000	55600	23520	51780	35080	43620	43080	32340	38560	71520	42280	49680	46528
INTP	38880	45240	51000	38200	55440	72840	26940	65760	64320	55720	23880	55020	37000	44700	42360	34860	38080	72420	42400	50220	47764
ISFJ	46440	54360	63840	46240	63180	85080	34320	77460	75480	65320	32880	61500	40720	56580	51360	42060	48040	88260	48760	64800	57334
ISFP	48060	53760	65040	47440	66240	86880	35580	78720	79800	65440	33240	64740	42640	57660	50640	44580	47560	89160	48880	65340	58570
ISTJ	47520	56520	63840	48520	66420	89040	33960	80160	77100	68200	31620	63840	42640	56940	54060	41880	51280	90060	50320	67140	59053
ISTP	49140	55920	65040	49720	69480	90840	35220	81420	81420	68320	31980	67080	44560	58020	53340	44400	50800	90960	50440	67680	60289

Fig. 5. 4 The Recommendation Model

Where ARV = Average Recommendation Value and M(n) = Movie title

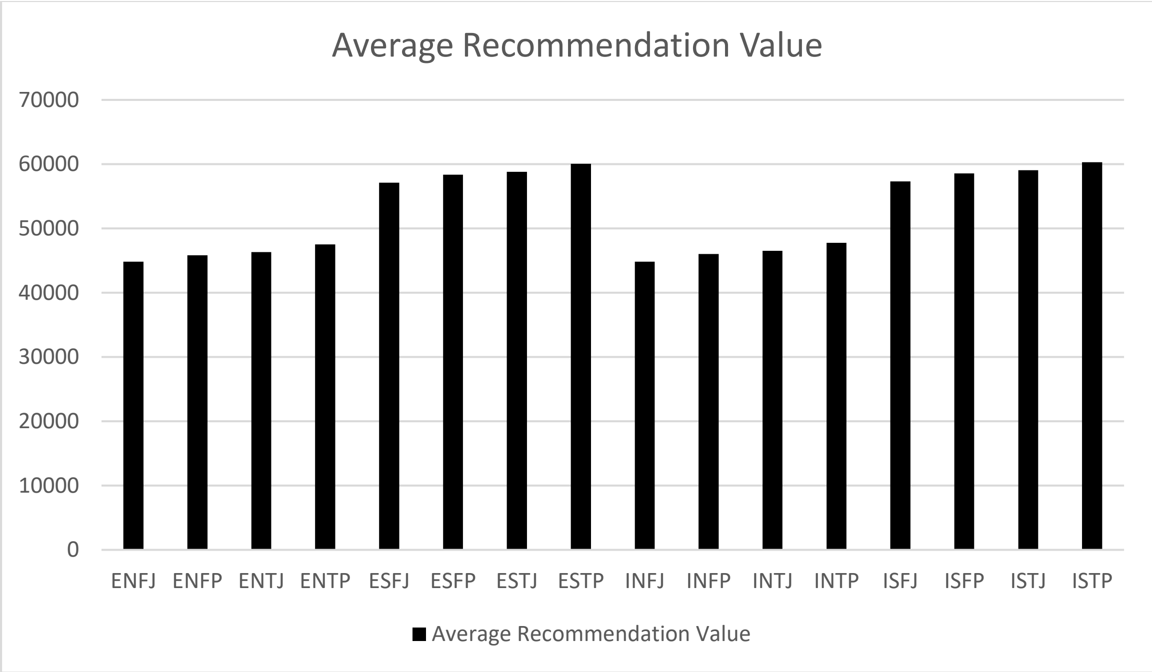

Fig. 5. 5 ARV Distribution for MBTI Personality Types

A high ARV implies that the personality type requires a high number of matching keywords between the movie plot and the list of keywords associated with the personality traits to be able to satisfy the movie needs of the members of the associated personality-based neighbourhood. On the other hand, a low ARV implies the exact opposite. Therefore, based on Fig. 5.5, one can deduce that it would be quite difficult to make movie recommendations which would be satisfactory to the *ESTPs* and *ISTPs* because they have the highest ARVs. This could seemingly be explained by the presence of the personality traits of *Sensing*, *Thinking,* and *Perceiving* which involves the gathering of large volumes of data before deciding on how to act. On the other hand, Fig. 5.5 shows that the *INFJs* would be the easiest personality group to provide movie recommendations because of their low ARVs. The ARVs identified can be applied as the standard recommendation value for every movie recommended to each personality type. This further satisfies the need for a common base (Alharthi, 2015) from which recommendations can be assessed to determine their suitability and accuracy for that personality-based neighbourhood. Therefore, the expected minimum recommendation value for movies for each of the personality types are summarised in Table 5.6 below.

Personality Type	Standard Movie Recommendation Value
ENFJ	44854
ENFP	45817
ENTJ	46300
ENTP	47536
ESFJ	57106
ESFP	58342
ESTJ	58825
ESTP	60061
INFJ	44808
INFP	46045
INTJ	46528
INTP	47764
ISFJ	57334
ISFP	58570
ISTJ	59053
ISTP	60289

Table 5. 6 Personality Types and their Standard Movie Recommendation Values

To this end, it has been deduced that for the recommendation model to be accurate, the recommendation value for the movie has to be greater than or equal to the value associated with the personality type in Table 5.6 otherwise the recommendation would be considered inaccurate and there is a risk of the consumer not being satisfied with the movie if they select it. In addition, it has been deduced that the minimum word count expected in a movie plot description which is fed into the recommendation model to identify the words which match with the movie plot from the list of keywords created should be **3913** words. The fewer the words in the movie plot description, the lower the recommendation accuracy of the model. Table 5.5 shows the expected minimum number of matching keywords per personality trait in order to achieve recommendation accuracy for both the model and the user. The movie plot description is not provided by the user, but by the creators of the movie or the uploader of the movie content into the recommender system.

5.6 CHAPTER SUMMARY

This chapter aimed to create a personality-based group recommendation model by utilizing the list of keywords generated in section 4.3.1. This was necessary for the process of providing an answer to the first research question in terms of determining how a personality-based group recommendation model can overcome the problem associated with ratings-based overspecialization. The data used in the creation of the proposed recommendation model was first critically qualitatively assessed to confirm a link between the movies selected by the various personality types and their personality types. The data confirmed a link between the personality types and their movie selections in terms of their movie genre preferences. The chapter went on to identify the contents of the user and product models used in the determination of the recommendation model. The recommendation model contained recommendation values which can be used as a standard for making movie recommendations for each personality type. The creation of the recommendation model involved the matrix factorization of the contents in the user model and the contents in the product model. The results revealed that the *INFJ* would be the easiest personality neighbourhood to provide movie recommendations due to their low standard recommendation values. On the other hand, it was also revealed that the *ESTP* and *ISTP* would be the most demanding personality groups to provide movie recommendations due to their high standard recommendation values. The next chapter will test the recommendation accuracy of this recommendation model.

CHAPTER SIX – TESTING THE GROUP RECOMMENDATION MODEL

6.1 INTRODUCTION

To test the validity of the recommendation values for each personality type as indicated in Table 5.6, a personality-based movie recommendation test model was developed which gave a new set of participants access to a new selection of 1273 movies. Considering that one of the main purposes of this research as seen in the research questions was to provide a way to enhance the visibility of movies regardless of the level of the popularity associated with them, the movies selected for this test were movies which were a bit further down the list in terms of popularity among users on IMDB. The flow diagram for the personality-based movie recommendation test model is seen in Fig. 6.1 below.

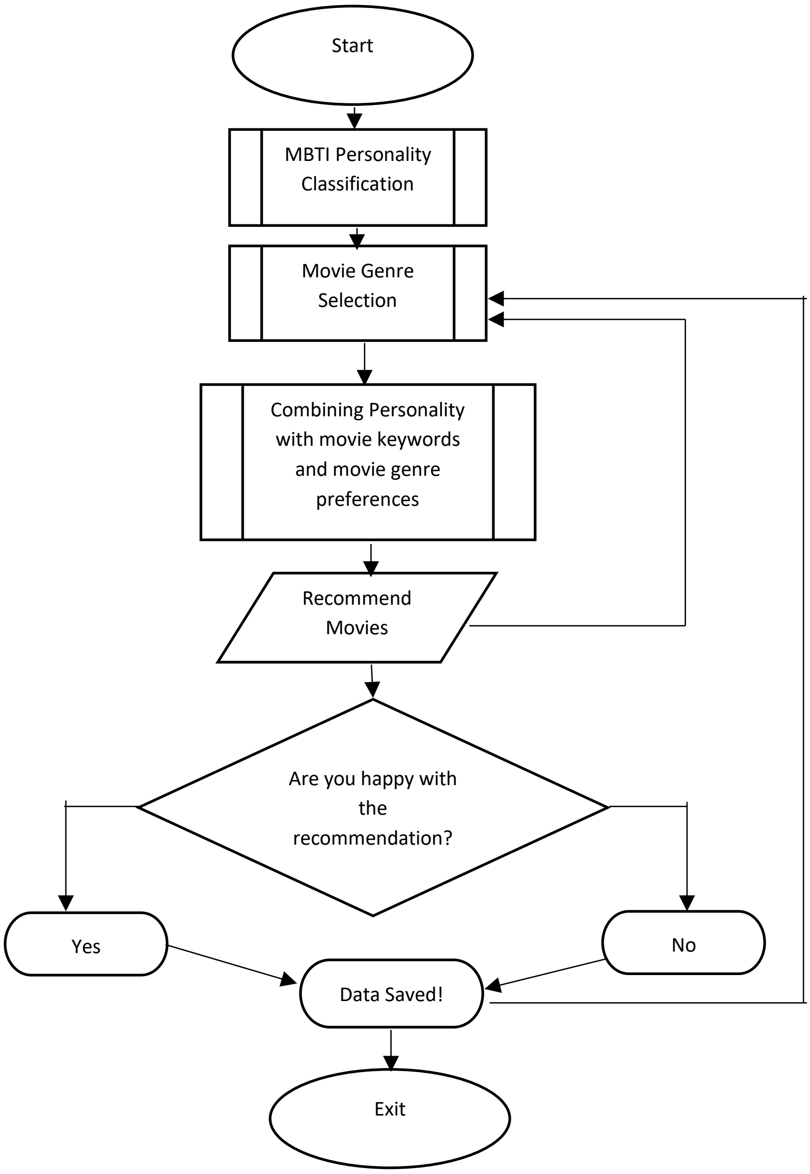

Fig. 6. 1 Personality-based Movie Recommendation Test Model

The movies recommended to the users through the personality-based movie recommendation test model were not recommended based on their recommendation values but based on the number of matching keywords existing between their movie plots and the list of keywords generated in this research. This test model aimed to identify the following:

1. What is the impact on user satisfaction considering the low popularity status of the selected movies available for recommendation to participants? This was necessary to identify the possibility of recommender systems being able to achieve user satisfaction regardless of the popularity status of the movies considering that one of the main drivers for user ratings is the popularity of the movie among users. This was made evident in recommender systems research such as Chandrashekhar & Bhasker (2011) and Orestis & Christos (2017) where high user satisfaction was achieved because the movies recommended through the recommendation model were ranked based on the value of their predicted user ratings. The ratings-based approach has been found to create a problem termed in this research as ratings-based overspecialization because of the continuous recommendation of highly rated movies generated using this approach.
2. What is the impact on the recommendation accuracy of the model when user satisfaction is assessed based on if the recommended movie achieved the expected minimum recommendation value for that specific personality type? This was necessary to test for a common base for making recommendations (Alharthi, 2015) by confirming the validity of the recommended standards for each personality type indicated in Table 5.6.
3. Can the list of keywords created in this research using the movie plots of popular movies be successfully applied in recommending the less popular movies on IMDB? This was necessary to test the potential of recommendation tool in the form of the list keywords per personality trait which can be used as a common base for making recommendations (Alharthi, 2015).

A total of 15 participants from 7 personality types provided a total of 88 recommendation feedback on 62 movies through the Personality-based Recommendation Test Model. Because this personality-based group recommendation focuses on making recommendations to groups and not individuals, the data taken into consideration was not that of the users but that of the recommendation feedback associated with the personality type. The users responded with *Yes* if they liked the recommendation, *No* if they didn’t like the recommendation, and *Undecided* if they were not sure about their decision. The movies selected and the feedback provided is shown in Table 6.1 below.

	IMDB_ID	Movie Title	Plot Word Count	User Feedback	MBTI Type
1	tt5719700	Home Again	1562	Yes	ISFJ
2	tt4701724	Early Man	3728	Yes	ISFJ
3	tt2139881	Long Shot	1487	Yes	ISFJ
4	tt1753496	Resident Evil: Damnation	1661	Yes	ISFJ
5	tt1395054	Once Upon a Time in Mumbai	824	Yes	ISFJ
6	tt0324127	Suspect Zero	206	Yes	ISFJ
7	tt0095179	Friday the 13th Part VII: The New Blood	917	Yes	ISFJ
8	tt0093936	The Secret of My Success	1261	Yes	ISFJ
9	tt0093677	Opera	1173	No	ISFJ
10	tt0091278	Iron Eagle	1175	No	ISFJ
11	tt0088117	Silent Night Deadly Night	2282	Yes	ISFJ
12	tt0086361	Staying Alive	992	Yes	ISFJ
13	tt0083943	Firefox	3387	Undecided	ISFJ
14	tt0082817	Nighthawks	1607	Yes	ISFJ
15	tt0077713	I Spit on Your Grave	1055	Yes	ISFJ
16	tt0077713	I Spit on Your Grave	1055	Undecided	ISFJ
17	tt0077663	Heaven Can Wait	1407	Yes	ISFJ
18	tt0076740	Sorcerer	861	Yes	ISFJ
19	tt0063688	The Thomas Crown Affair	1710	Yes	ISFJ
20	tt0059749	The Spy Who Came In from the Cold	1401	No	ISFJ
21	tt0056937	Cleopatra	1172	Yes	ISFJ
22	tt1753496	Resident Evil: Damnation	1661	No	INTJ
23	tt0104009	Cool World	398	No	INTJ
24	tt0104009	Cool World	398	No	INTJ
25	tt0082509	Heavy Metal	3190	No	INTJ
26	tt0057197	Jason and the Argonauts	845	Yes	INTJ
27	tt2620590	Leatherface	890	No	INFJ
28	tt2581244	Life After Beth	1112	No	INFJ
29	tt2139881	Long Shot	1487	Yes	INFJ
30	tt1753496	Resident Evil: Damnation	1661	Yes	INFJ
31	tt0910905	In the Electric Mist	758	Yes	INFJ
32	tt0465502	Igor	904	Yes	INFJ
33	tt0465502	Igor	904	Yes	INFJ
34	tt0360556	Fahrenheit 451	425	Yes	INFJ
35	tt0360556	Fahrenheit 451	425	Yes	INFJ
36	tt0351817	The Twilight Samurai	1018	Yes	INFJ
37	tt0338097	Head in the Clouds	592	Yes	INFJ
38	tt0324127	Suspect Zero	206	Yes	INFJ
39	tt0279111	Gods and Generals	371	Yes	INFJ

40	tt0274117	Read My Lips	409	Yes	INFJ
41	tt0274117	Read My Lips	409	Yes	INFJ
42	tt0274117	Read My Lips	409	Yes	INFJ
43	tt0263975	The Girl with the Red Scarf	288	Yes	INFJ
44	tt0214388	100 Girls	874	Yes	INFJ
45	tt0155776	Jawbreaker	996	No	INFJ
46	tt0119942	Primary Colors	852	Yes	INFJ
47	tt0119942	Primary Colors	852	Yes	INFJ
48	tt0119942	Primary Colors	852	Yes	INFJ
49	tt0119861	Pardes	1620	No	INFJ
50	tt0118798	Bulworth	834	Yes	INFJ
51	tt0118798	Bulworth	834	Yes	INFJ
52	tt0118798	Bulworth	834	No	INFJ
53	tt0118751	Border	1480	No	INFJ
54	tt0116000	D3: The Mighty Ducks	1038	Yes	INFJ
55	tt0113419	The Indian in the Cupboard	1381	Undecided	INFJ
56	tt0113419	The Indian in the Cupboard	1381	Yes	INFJ
57	tt0111693	When a Man Loves a Woman	150	Yes	INFJ
58	tt0111693	When a Man Loves a Woman	150	No	INFJ
59	tt0110907	Ready to Wear	1113	Yes	INFJ
60	tt0110725	On Deadly Ground	1150	Yes	INFJ
61	tt0110527	Miracle on 34th Street	540	Yes	INFJ
62	tt0110081	To Live	889	Yes	INFJ
63	tt0108101	Shadowlands	968	Yes	INFJ
64	tt0108101	Shadowlands	968	No	INFJ
65	tt0101640	Raise the Red Lantern	760	Undecided	INFJ
66	tt0101640	Raise the Red Lantern	760	Yes	INFJ
67	tt0101640	Raise the Red Lantern	760	No	INFJ
68	tt0100419	Problem Child	935	Yes	INFJ
69	tt0100419	Problem Child	935	Yes	INFJ
70	tt0099165	The Bonfire of the Vanities	1931	Yes	INFJ
71	tt0086993	The Bounty	871	Yes	INFJ
72	tt0084412	Night Shift	1455	Yes	INFJ
73	tt0082089	Body Heat	1142	Undecided	INFJ
74	tt0077663	Heaven Can Wait	1407	Yes	INFJ
75	tt0066473	Tora! Tora! Tora!	2458	Yes	INFJ
76	tt0061619	El Dorado	2007	Undecided	INFJ
77	tt0059749	The Spy Who Came In from the Cold	1407	Yes	INFJ
78	tt0056937	Cleopatra	1172	Yes	INFJ
79	tt0046672	20 000 Leagues Under the Sea	1160	Yes	INFJ
80	tt0004972	The Birth of a Nation	128	Yes	INFJ
81	tt0004972	The Birth of a Nation	128	Yes	INFJ
82	tt1753496	Resident Evil: Damnation	1661	Yes	ESTP
83	tt1699231	Quarantine 2: Terminal	1874	Yes	ESFJ

84	tt0282209	Darkness Falls	814	Yes	ESFJ
85	tt0080319	9 to 5	1673	Yes	ESFJ
86	tt0106950	Fortress	1140	Yes	ENTJ
87	tt0071141	Ali: Fear Eats the Soul	4367	Yes	ENFP
88	tt0071141	Ali: Fear Eats the Soul	4367	Undecided	ENFP

Table 6. 1 Recommended movies and User Feedback

As indicated in Table 6.1 above, all the movies apart from *Ali: Fear Eats the Soul* had movie plot descriptions which were greater than or equal to 3913, therefore it would be expected that the movie recommendation values would be too low to provide recommendation accuracy for the recommendation model. Therefore, they would definitely be less than the standard movie recommendation values for the personality types who responded to the questionnaire. To this end, considering the fact that the recommendation accuracy of the model would fail based on the predicted recommendation value of the movies, it would be beneficial to calculate for user satisfaction to confirm the validity of the proposed keyword based recommendation approach.

Therefore, this chapter will analyse the feedback provided by the personality types concerning the recommended movies. This will involve the identification of the user and product models, the determination of the recommendation values for the movies, and the test for recommendation accuracy and user satisfaction.

6.2 IDENTIFYING THE MODELS

As indicated in Table 6.1, the 7 personality types represented in the consumer's feedback data are *ENFP, ENTJ, ESFJ, ESTP, INFJ, INTJ, and ISFJ*. Table 6.2 below shows a summary of the responses from each personality type.

Personality Type	Total Number of Recommendation Feedback	Total No. of Participants
ENFP	2	2
ENTJ	1	1
ESFJ	3	1
ESTP	1	1
INFJ	55	5
INTJ	5	2
ISFJ	21	3

Table 6. 2 Personality Type Feedback

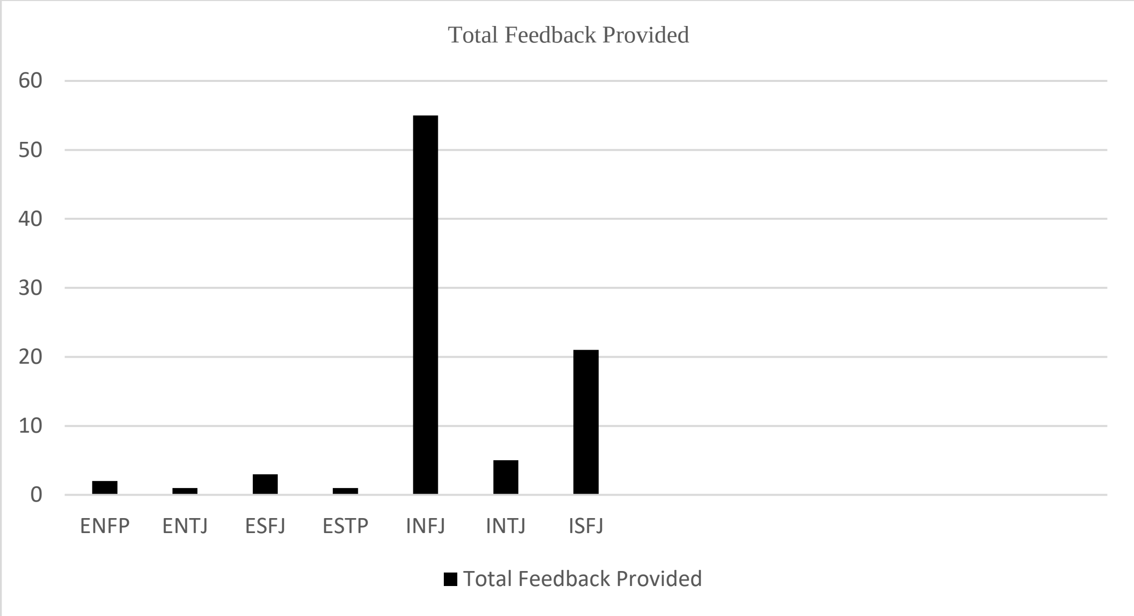

Fig. 6. 2 Frequency Distribution for Recommendation Feedback

As indicated in Fig. 6.2, the *INFJs* provided the highest number of recommendation feedback. This further confirms that the *INFJs* are the easiest personality group to provide movie recommendations as indicated in Fig. 5.5. Based on the data in Fig. 6.2 above, only the responses from the *INFJ* and *ISFJ* will be analysed since the data provided by the other personality types were too small to come to any kind of statistical conclusions.

To understand the user feedback in terms of the recommendation model developed in Fig. 5.4, one would need to know the recommendation value for each of the movies for which recommendation feedback was provided. There were 62 distinct movies for which recommendation feedback was provided as indicated in Table 6.1 above, the data analysis will begin by identifying the user model and the product model.

6.2.1 THE USER MODEL

Personality Type	E	I	N	S	T	F	J	P
INFJ	20	80	80	20	20	80	80	20
ISFJ	20	80	20	80	20	80	80	20

Table 6. 3 Feedback User Model

Based on the personality types who responded to the request to provide feedback, Table 6.3 above shows the personality types and the associated percentage levels applied to the personality traits as per the 80/20 principle (Alecu, 2011).

6.2.2 THE PRODUCT MODEL

The product model consists of the total number of words associated with the plots of the 62 movies chosen by the various personality types and the list of keywords associated with the personality traits. This was accomplished using SQL queries to identify the words in the personality traits keywords list which were an exact match with the words in the movie plots of the selected movies.

	IMDB ID	Movie Title	E	I	N	S	T	F	J	P
M1	tt0004972	The Birth of a Nation	2	2	2	14	2	6	4	2
M2	tt0046672	20 000 Leagues Under the Sea	9	15	14	52	22	19	30	34
M3	tt0056937	Cleopatra	7	12	20	50	20	17	21	30
M4	tt0057197	Jason and the Argonauts	7	6	11	28	17	7	20	19
M5	tt0059749	The Spy Who Came In from the Cold	6	9	16	52	15	13	28	26
M6	tt0061619	El Dorado	3	12	18	38	17	15	21	29
M7	tt0063688	The Thomas Crown Affair	6	13	15	54	20	20	25	34
M8	tt0066473	Tora! Tora! Tora!	22	22	36	106	37	34	44	56
M9	tt0071141	Ali: Fear Eats the Soul	9	8	13	58	30	16	32	42
M10	tt0076740	Sorcerer	6	11	9	26	15	13	14	17
M11	tt0077663	Heaven Can Wait	12	14	15	40	23	16	26	25
M12	tt0077713	I Spit on Your Grave	2	9	17	34	10	12	21	16
M13	tt0080319	9 to 5	12	22	26	62	38	18	34	30
M14	tt0082089	Body Heat	9	9	16	32	12	16	19	17
M15	tt0082509	Heavy Metal	27	25	41	100	35	32	55	64
M16	tt0082817	Nighthawks	10	11	18	44	17	22	28	24
M17	tt0083943	Firefox	23	24	31	78	46	26	50	51
M18	tt0084412	Night Shift	3	14	9	54	29	17	31	24
M19	tt0086361	Staying Alive	10	9	13	30	18	11	21	21
M20	tt0086993	The Bounty	6	3	7	20	11	11	18	15
M21	tt0088117	Silent Night Deadly Night	3	10	10	28	25	17	35	31
M22	tt0091278	Iron Eagle	9	9	13	26	21	16	21	17
M23	tt0093677	Opera	8	9	17	36	15	14	22	18
M24	tt0093936	The Secret of My Success	5	9	20	32	23	15	23	22
M25	tt0095179	Friday the 13th Part VII: The New Blood	4	11	6	28	12	10	22	16
M26	tt0099165	The Bonfire of the Vanities	11	12	17	54	32	14	36	39
M27	tt0100419	Problem Child	3	5	11	20	16	18	15	23
M28	tt0101640	Raise the Red Lantern	8	5	17	46	18	13	21	21
M29	tt0104009	Cool World	6	3	3	20	5	8	6	7
M30	tt0106950	Fortress	11	9	8	32	15	13	20	17
M31	tt0108101	Shadowlands	8	4	6	34	15	11	20	19
M32	tt0110081	To Live	7	8	12	36	12	17	23	30
M33	tt0110527	Miracle on 34th Street	1	3	4	18	8	3	14	9
M34	tt0110725	On Deadly Ground	9	9	14	22	10	11	17	22

M35	tt0110907	Ready to Wear	4	8	11	42	22	13	21	27
M36	tt0111693	When a Man Loves a Woman	9	2	3	8	1	3	5	2
M37	tt0113419	The Indian in the Cupboard	7	3	13	40	18	7	24	23
M38	tt0116000	D3: The Mighty Ducks	9	9	13	48	22	13	15	24
M39	tt0118751	Border	9	8	17	58	19	16	31	34
M40	tt0118798	Bulworth	21	13	15	50	23	13	21	28
M41	tt0119861	Pardes	5	13	29	68	36	17	28	34
M42	tt0119942	Primary Colors	12	6	16	50	10	9	23	24
M43	tt0155776	Jawbreaker	8	16	17	78	31	13	30	31
M44	tt0214388	100 Girls	3	5	10	28	14	11	12	17
M45	tt0263975	The Girl with the Red Scarf	2	3	5	16	5	4	10	7
M46	tt0274117	Read My Lips	1	5	1	18	4	5	4	9
M47	tt0279111	Gods and Generals	9	5	3	28	11	10	11	8
M48	tt0282209	Darkness Falls	1	8	12	30	10	13	19	19
M49	tt0324127	Suspect Zero	4	3	1	8	19	4	2	6
M50	tt0338097	Head in the Clouds	11	8	9	14	23	12	12	13
M51	tt0351817	The Twilight Samurai	2	13	12	38	6	13	19	18
M52	tt0360556	Fahrenheit 451	5	3	7	16	15	9	7	8
M53	tt0465502	Igor	6	15	15	40	12	13	18	20
M54	tt0910905	In the Electric Mist	12	10	12	32	21	12	10	16
M55	tt1395054	Once Upon a Time in Mumbai	11	6	7	38	21	12	17	12
M56	tt1699231	Quarantine 2: Terminal	11	8	14	50	28	14	28	28
M57	tt1753496	Resident Evil: Damnation	10	21	19	62	25	15	34	41
M58	tt2139881	Long Shot	8	19	13	54	20	16	22	23
M59	tt2581244	Life After Beth	7	12	7	32	11	15	9	15
M60	tt2620590	Leatherface	7	8	12	22	10	6	15	16
M61	tt4701724	Early Man	30	33	48	134	51	34	71	73
M62	tt5719700	Home Again	8	7	11	32	23	14	21	18

Table 6. 4 The Product Model

6.3 THE FEEDBACK ANALYSIS

According to Chandrashekhar & Bhasker (2011), the test for the performance of the recommendation model is based on the ability of the recommendation model to accurately predict movies. The test for recommendation accuracy will be based on the following:

- The recommendation accuracy based on the recommendation values
- The recommendation accuracy based on user satisfaction

6.3.1 The Recommendation Accuracy Based on Recommendation Values

Upon the successful identification of the content for the user model and the product model, this section will analyse the feedback for each of the personality types who provided the feedback. The feedback analysis for the personality types will only take into account the positive and negative values to identify the True Positive (TP), True Negative (TN), False Positive (FP), False Negative (FN) values in the determination of the recommendation accuracy of the recommendation values for each personality type using the confusion matrix. Therefore, the *Undecided Feedback* and the *Negative Feedback* values will be categorised as failed recommendations because the recommendation model is supposed to help the user to decide what they want and not leave them in an *Undecided* state. *Positive Feedback* values will be categorised as successful recommendations. The confusion matrix will be arranged as indicated in Table 6.5 below.

Actual Response

Predicted Response

	Successful Recommendations	Failed Recommendations
Successful Recommendations	TP	FP
Failed Recommendations	FN	TN

Table 6. 5 Confusion Matrix

The formula for calculating the recommendation accuracy is as follows:

Recommendation Accuracy = (TP + TN)/(TP + TN + FP + FN)

6.3.1.1 INFJ

	Recommendation Value	Total Positive Feedback	Total Negative Feedback	Total Undecided Feedback
M1	1520	2	0	0
M2	8580	1	0	0
M3	7740	1	0	0
M5	7260	1	0	0
M6	7020	0	0	1
M8	15300	1	0	0
M11	7680	1	0	0
M14	6200	0	0	1
M18	7880	1	0	0
M20	4160	1	0	0
M26	9040	1	0	0
M27	5160	2	0	0
M28	6340	1	1	1
M31	4800	1	1	0
M32	6500	1	0	0
M33	2640	1	0	0
M34	5340	1	0	0
M35	6140	1	0	0
M36	1440	1	1	0

M37	5520	1	0	1
M38	6060	1	0	0
M39	8160	0	1	0
M40	7400	2	0	1
M41	9820	0	1	0
M42	6240	3	0	0
M43	9040	0	1	0
M44	4280	1	0	0
M45	2360	1	0	0
M46	1840	3	0	0
M47	3440	1	0	0
M49	1540	1	0	0
M50	4500	1	0	0
M51	5840	1	0	0
M52	2960	2	0	0
M53	6440	2	0	0
M54	5140	1	0	0
M57	9880	1	0	0
M58	7700	1	0	0
M59	4740	0	1	0
M60	4380	0	1	0

Table 6. 6 INFJ Recommendation Feedback

INFJ	Successful Recommendations	Failed Recommendations
Successful Recommendations	0	42
Failed Recommendations	0	13

Table 6. 7 INFJ Confusion Matrix

Recommendation Accuracy = (TP + TN)/(TP + TN + FP + FN)

Recommendation Accuracy (RA) = 13/55 = 0.2363 = 23.64%

Error Rate = 1 – RA = 1 – 0.2363 = 0.7637 = 76.37%

According to Table 5.6, the standard recommendation value for INFJs is 44808. Therefore, since all the recommendation values fall short of 44808, it implies that all the positive values were *False Positives*.

6.3.1.2 ISFJ

Movie	Recommendation Value	Total Positive Feedback	Total Negative Feedback	Total Undecided Feedback
M3	9540	1	0	0
M5	9420	0	1	0
M7	10460	1	0	0
M10	6060	1	0	0
M11	9180	1	0	0

M12	6980	1	0	1
M16	9780	1	0	0
M17	17260	0	0	1
M19	6920	1	0	0
M21	8580	1	0	0
M22	6960	0	1	0
M23	7640	0	1	0
M24	7720	1	0	0
M25	6440	1	0	0
M49	1960	1	0	0
M55	6860	1	0	0
M57	12460	1	0	0
M58	10160	1	0	0
M61	25800	1	0	0
M62	7120	1	0	0

Table 6. 8 ISFJ Recommendation Feedback

ISFJ	Successful Recommendations	Failed Recommendations
Successful Recommendations	0	16
Failed Recommendations	0	5

Table 6. 9 ISFJ Confusion Matrix

Recommendation Accuracy = (TP + TN)/(TP + TN + FP + FN)

Recommendation Accuracy (RA) = 5/21 = 0.2380 = 23.80%

Error Rate = 1 – RA = 1 – 0.2380 = 0.7620 = 76.20%

According to Table 5.6, the expected minimum recommendation value for ISFJs is 57334. Therefore, the positive feedback provided is categorised as a *False Positive*, while the negative feedback and undecided feedback are categorised as *True Negative*.

6.3.2 The Recommendation Accuracy Based on User Satisfaction

The summary of the participant's responses are indicated in Table 6.10 below, the *Undecided* responses are also categorised as negative feedback in addition to the *No* responses.

Personality Type	Total Percentage of Positive Feedback	Total Percentage of Negative Feedback
INFJ	76.36%	23.64%
ISFJ	76.19%	23.81%
Total Average Percentage Feedback	76.28%	23.73%

Table 6. 10 Total Percentage Feedback Per Personality Type

As indicated in Table 6.10 above, the user satisfaction based on the individual personality neighbourhoods for the *INFJs* and the *ISFJs* achieved relatively decent values in terms of user satisfaction.

6.4 DISCUSSION

The research started by identifying the problems with existing movie recommendation models where recommendations were made based on the initial ratings provided by the users. These initial ratings were used in the calculation of the predicted ratings for unrated items as seen in Chandrashekhar & Bhasker (2011), Karumur et al (2017), and Orestis & Christos (2017). The predicted ratings for the movie in these recommendation models are calculated and the recommendations are made based on the similarities to the ratings of the movies which the user has watched in the past. In the scenario where the ratings associated with a movie were poor, the movie is either ranked very low on the list of recommended items or does not make it to the list at all. The unfortunate thing about predicted ratings is that poor ratings can be given to movies which the user has not yet seen because it was rated poorly by someone with similar movie tastes to the user. This deprives the user of the opportunity of making such decisions on their own and significantly reduces the ability of the less popular movies to capture the attention of the consumers in the movie industry.

The first aim of testing the recommendation model developed for this research was to identify the level of user satisfaction achieved when the less popular movies are recommended to the users. The personality-based group movie recommendation model created through this research confirmed that the recommendation of the less popular movies to users utilizing the list of keywords created via this research provided an overall average user satisfaction of 57.51%. However, the performance of the recommendations differed for each personality neighbourhood with the *INFJ* and the *ISFJ* personality neighbourhoods achieving 76.36% and 76.19% user satisfaction respectively. Therefore, considering that these personality types where the ones who provided sufficient feedback about the recommendations provided, it would be more reasonable to assess the overall average user satisfaction based on them. Therefore, based on the premise of the feedback provided by the *INFJ* and the *ISFJ*, the recommendation accuracy based on user satisfaction is 76.28%. To this end, it is reasonable to come to a statistical conclusion that making recommendations of the less popular movies can still provide a decent amount of user satisfaction.

The second aim of testing the recommendation model developed for this research was to identify the impact on the recommendation accuracy of the model when user satisfaction is assessed based on if the recommended movie achieved the standard recommendation value for that specific personality type. The recommendation accuracy failed in this instance because none of the movies were able to reach the standard recommendation value for that personality type as seen in Table 5.6. As can be seen in Table 6.1, the recommendation accuracy failed because of the data sparsity associated with the movies selected for recommendation because their movie plots contained less than 3913 words. This can arguably be interpreted as a direct impact of the popularity status of the movies used in each instance. However, this can be rectified by the movie industry by creating an extensive movie plot description for use in making recommendations that will be invisible to the users as it will contain spoilers; and creating a shorter version without spoilers for the users to read. This could potentially convert all the *False Positives* to *True Positives* thereby improving the recommendation accuracy of the model.

The third aim of testing the recommendation model developed for this research was to confirm if the list of keywords created in this research is successfully applied across the popular and the unpopular or the less popular movies. The list of keywords did not find too many matching keywords with the movies used to test the recommendation model, however, the application of the list of keywords in the recommendation process still returned an average user satisfaction of 76.28%. This served as a confirmation of the reliability of the application of the list of keywords in making movie recommendations. Furthermore, even though the list of keywords did not find too many matching keywords with the plots of the movies used in testing the model, there was at least one keyword matched per personality trait for all the movies for which feedback was provided. This served as a confirmation that even though the list of keywords was created using popular movies because the words selected to create the list of keywords were based on the various subject matters associated with movies, it has opened the possibility for the less popular or the unpopular movies to be visible and given the same chance as the popular movies in the consumer market to make a positive impression on the consumer depending on their personality profiles. Also, it further confirms that the art of making movie recommendations is the art of predicting consumer behaviour as it relates to movies which cannot be summed up by a score or numerical value (Nunes & Hu, 2012), as all that could be required to make a difference between a consumer liking or disliking a movie can just be one matching keyword with a personality trait. However, to increase the possibility of achieving user satisfaction, it is recommended via this research that the recommendation values of the movies reach or exceed the standard recommendation value for that personality type as indicated in Table 5.6. For this to be implemented successfully, the data sparsity associated with the plots of the movies provided on IMDB has to be corrected as recommended above.

6.4.1 THE RATINGS-BASED APPROACH VS THE PROPOSED APPROACH

The ratings-based approach may prove useful in domains like Amazon or eBay where products and sellers are rated based on the service which they provide. However, it is worth noting that in such systems, the customers are expected to rate products which they have used rather than products which they are thinking about using. As it relates to movies, recommender systems have created an unfair approach with the ability to automatically assign poor predicted ratings to movies which the consumer has not yet watched. In the simplest of terms, the ratings-based approach in a movie recommender system gives the consumer a reason to bypass a movie based on calculated assumptions made by the recommender system thereby denying themselves of the opportunity to watch something which might have meant something meaningful to them. This is because, the ratings-based approach does not recommend movies to consumers based on the value of the movie which is embedded within the plot of the movie but rather based on the opinion of other users with similar taste in movies. The value associated with a movie cannot be quantified using user ratings because it is a product with the potential to impact the consumers both mentally and emotionally. The ratings-based approach creates a situation which is harmful to the workers in the movie industry because some movies may never get recommended due to the fact that they have been assigned a poor rating, a poor predicted rating, or no rating at all. The ratings-based approach will always suffer from the data sparsity problem which in turn tends to create the overspecialization problem followed by the lack of serendipitous recommendations. The movie database is too large to develop a fair approach in making recommendations to the consumers using the ratings-based approach in a movie recommender system. Finally, with the ratings-based approach consumers are constantly tasked with the burden of feeding the recommender system with ratings data which is highly susceptible to bias and therefore detrimental to some movies.

The proposed approach eliminates the need for users to provide initial data for the recommender system to learn about the user's preferences. Through the use of the MBTI personality type and 207 volunteers, a list of keywords has been created which encapsulates a large amount of movie plot lines. The users only need to inform the recommendation model of their personality type and they will be taken to their respective personality based neighbourhood ready to receive recommendations immediately. The proposed approach promotes a balanced movie recommendation platform such that the movies are recommended based on the value which the movie has been designed to give to the consumers which is embedded within the plot of the movie. In addition, the proposed approach is not susceptible to bias because the keywords are not user defined, rather they are pre-defined for each personality trait which make up the personality types based on prior movie plot data provided which were extracted from movie choices of volunteers from all the personality types. The proposed approach also suffers from the problem of data sparsity which can easily be fixed by providing more content in the plot summary. The ratings based approach relies on the users to help solve the data sparsity problem associated with user ratings by encouraging them to continually rate movies. However, the data sparsity problem with the proposed approach projects a one-time fix through the provision of an extensive plot summary by the uploader of the movie. It is also worth noting that even with the problem of data sparsity experienced with the movies recommended during this testing phase, the keyword-based recommendation approach still achieved an average user satisfaction of 76.28%.

CHAPTER SEVEN – SUMMARY, CONCLUSIONS, AND FUTURE WORK

7.1 RESEARCH SUMMARY

This research started by identifying the main problem associated with recommender systems as ratings-based overspecialization which occurs as a result of recommendation of movies based on user ratings which lead to users having a preference for the highly-rated movies due to the recommended movies being displayed in descending order. This makes it increasingly unlikely for users to choose or see movies with low ratings. Furthermore, the research identified that ratings-based overspecialization is detrimental to the consumer's movie experience as well as the movie industry. It negatively impacts the consumer's movie experience implicitly because there will be some movies that consumers might like but will never have the opportunity to watch because of the poor rating associated with the movie. On the other hand, it negatively impacts the movie industry because some movies will not return any profit, and investors in the movie will lose out on their investments because the movie was not rated or was poorly rated by users. An initial poor rating on a movie by a user will generate a poor predicted rating on the same movie for another user with similar tastes to the initial user which will make the movie less appealing to recommend to the consumers. To this end, it was concluded that the application of ratings in making movie recommendations was not an effective way to ensure that the consumers have the opportunity to connect with the story of a movie and make a decision on if they enjoyed it based on the story and not the ratings associated with the movie. Furthermore, it's only fair that every movie needs to get the same opportunity through recommender systems to capture the attention of the consumers based on the plots of the movies as opposed to using the ratings assigned to them. This was accomplished through the development of a personality-based group recommendation model.

The development of a personality-based group recommendation model is divided into three models, the user model, the product model, and the recommendation model. The research further pointed out that personality-based recommendations involve the use of a personality-based neighbourhood where those with similar personalities are grouped. The personality-based neighbourhood was made easier to create through the use of the MBTI personality model. The research identified gaps in the recommender system's literature which involved solving the problems of scalability through the use of a personality-based neighbourhood and the calculation for the recommendation value for new movies. Through the use of the MBTI personality model for user classification, scalability is not an issue because recommendations are not made based on the individual users but based on the personality types which are fixed at 16 personality types. Therefore, an increase in the number of users will not be a problem because the users are added to their respective personality groups. However, this was achieved at the cost of recommendation accuracy as solving the problem of scalability involved treating group recommendations as a group rather than focusing on the individual recommendation needs of the members of the group. A comprehensive list of keywords was generated from the plots of movies selected by specific personality types for all the personality traits which make up the personality types. These keywords were associated with the 8 personality traits which make up the 16 MBTI personality types and can be universally applied across all movies regardless of the time in which the movie was created.

Movie content is based on real-life scenarios and circumstances that people can relate with through empathy. Nuwer (2013) and Dempsey (2018) provided some insight into how humans connect with movies through empathy. In movie genres such as comedy and drama, it may be obvious how we can see some elements of our own lives in them; however, this is not the case for more obscure genres of sci-fi, fantasy, and adventure. These genres may present less realistic worlds to us, ones that may only present themselves to us otherwise in our wildest dreams. Movies such as Harry Potter, The Lord of the Rings, the Marvel superheroes. How can we empathize with this? How do we connect to real-life through these fantasy lands? Is it through the fantastical characters that share our human emotions, or does it come down to the common desire that each of us may share: to be the heroes of our own stories? Therefore, consumers watch movies for different reasons, it might be purely for escapism or to connect with a movie character in a situation that relates to theirs in real life such as domestic violence, sexual abuse, bullying, etc. The important thing to note about movies is that they have the powerful ability to connect with people which is being exploited in movies through the insertion of various slots for product placements for the conditioning of the minds of the viewers. The effects of the application of product placement in movies is another area of research that is yet to be explored in depth.

The research applied Pareto's 80/20 principle to set standard scores for dominant and recessive personality traits. The proposed personality-based movie recommendation model was eventually generated using matrix factorization. The test for recommendation accuracy revealed that group recommendations utilizing the recommendation methods in the group recommendation model provided 76.28% user satisfaction. This was achieved without the application of user ratings but rather with the use of the list of keywords associated with the various personality traits. This successfully expanded the scope of the movies being recommended to cover both the popular and the less popular movies thereby increasing the possibility for consumers to see movies which they would likely not have been recommended using the ratings-based approach. However, the data sparsity associated with the plots of the movies used in testing the recommendation model significantly reduced the number of matched words between the plots of the movies and the personality traits keywords lists. This caused the group recommendation model to fail in terms of recommendation accuracy based on the generated recommendation values of the recommended movies as it relates to the specific personality types because none of the recommended movies achieved the minimum expected recommendation value for the personality types in Table 5.6. The research outline in Table 3.2 can be updated with the justifications based on the research results as indicated in Table 7.1 below.

		RESEARCH ACTIVITIES			
		Build	Evaluate	Theorize	Justify
RESEARCH OUTPUT	Constructs	Identification of textual data and basic concepts that link movies with various personality profiles.	Investigate for keyword similarities with plots of popular movies on IMDB to expand the versatility of the keywords used in the lists across multiple movies.	The application of keywords associated with the subject matter in movies and the users will enhance the visibility of the unpopular movies and still provide user satisfaction.	The lists of keywords created of each personality trait and the 76.28% positive feedback received from using them to make movie recommendations are sufficient evidence to validate the use of this approach.
	Model	Definition of a personality-based model that can make movie recommendations to users based on their personality groups.	Investigate for completeness and understandability.	The creation of a personality-based neighbourhood to make movie recommendations to the personality group as a whole as opposed to making different recommendations to each individual in the group is an efficient and reliable approach.	The total average user satisfaction for the INFJ and ISFJ personality types using the personality-based neighbourhood was 76.28%.
	Method	Matrix Factorization model in the development of the recommendation model to determine the recommendation values	Calculate the Average Recommendation Value for each personality type.	The Average Recommendation Value for each personality type represents the expected minimum recommendation value for the movies which	To create a common base from which recommendations can be made by setting a standard recommendation

		of the movies selected in the creation of the model. Identify the user model, the product model, and the recommendation model.		would be expected to provide user satisfaction for the various personality types.	value for each personality type.
	Instantiation	Creation of a prototype personality-based movie recommender system using movie keywords.	Calculate the Recommendation Accuracy of the model for each MBTI personality type by requesting for user feedback and using a confusion matrix.	The movies which achieve the minimum recommendation value for each personality type will likely provide user satisfaction while the movies which do not achieve the minimum recommendation value will likely lead to user dissatisfaction.	The movies which did not achieve the minimum recommendation value still provided user satisfaction. This implied that even though the minimum recommendation value was not reached, user satisfaction utilizing keywords and personality types can still be achieved. Further research needs to be conducted to confirm that the movies which achieved the minimum recommendation values meet user satisfaction.

Table 7. 1 Research Output and Justifications

7.2 RESEARCH DELIVERABLE

This section discusses the deliverables of this research in terms of the artefact produced using the design science methodology. A key outcome of design science research is that there should be a contribution to knowledge that either provides a better understanding of a problem, or that can be used to provide or design a solution or to improve an artefact's design (Hevner et al. 2004). The artefact of this research is in the form of a conceptual model and it is described in the following subsections below.

7.2.1 THE PERSONALITY-BASED GROUP RECOMMENDATION MODEL

Fig. 7.1 below depicts the personality-based group recommendation model as the prototype artefact which represents one of the essential outcomes of design science research. This artefact also serves as part of the original contribution to knowledge in this research. The following subsections will briefly discuss the units of the model.

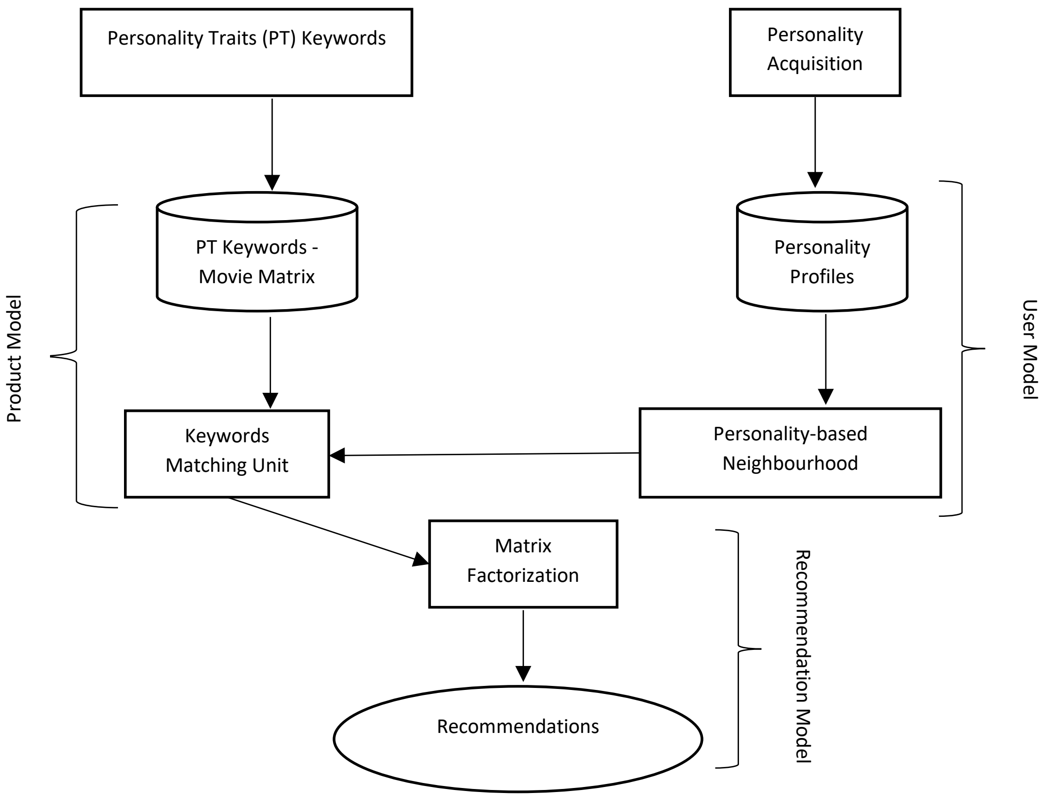

Fig. 7. 1 Personality-based Group Recommendation Model

7.2.1.1 PERSONALITY TRAITS (PT) KEYWORDS UNIT

This consists of the full list of movie keywords which can be found in Appendix F. The use of movie keywords instead of user ratings as indicated in Fig. 2.4 implies that recommendations are being made based on the content of the movie in question and not the user's opinion which is based on a related movie. The application of a broad range of movie keywords makes it possible to reuse the list of keywords continuously in making recommendations. Because the movie keywords were extracted from the plot of various movies, and movie plots are usually based on real-life scenarios which keep recurring over time, this implies the reusability potential of the list of keywords over a long period. The list of keywords can be said to be the common base (Alharthi, 2015) through which recommendations based on the MBTI personality model can be made. The process involved in generating these lists of keywords for each of the personality traits which make up the personality types is indicated in chapter 4 in section 4.3.1.

7.2.1.2 PERSONALITY-BASED NEIGHBOURHOOD

The research contributes to the concept of social matching in recommender systems as described by Nunes (2008) and Nunes & Hu (2012). The personality-based neighbourhood consists of the user models for each personality type and it creates the environment for users within the same personality neighbourhood to receive the same movie recommendations as opposed to making different movie recommendations to each individual within the specific personality neighbourhood. The personality profiles unit works closely with the personality-based neighbourhood because it is the personality profiles that are used to create the personality-based neighbourhood. types. Upon the acquisition of the user's personality types, all the users with the same MBTI type are integrated in preparation for receiving group recommendations. The integration of all the users with the same MBTI type creates the personality-based neighbourhood for that specific personality type.

7.2.1.3 PT KEYWORDS – MOVIE MATRIX UNIT

The personality traits keywords – movie matrix unit is where the keywords associated with the various personality traits are matched with specific words associated with the movie plots of the movies to be recommended. This would usually be the ratings – movie matrix unit as indicated in Fig. 2.4; however, the use of keywords instead of ratings made it possible to enhance the visibility of the less popular movies which are mostly un-recommendable due to poor ratings or no ratings at all. Furthermore, the users don’t have to provide the keywords like they have to provide ratings as indicated in Fig. 2.4 and Fig. 2.5. This was made possible due to the creation of the personality traits keyword lists. Also, the personality traits keywords lists can be applied across multiple movies. This implies that one keyword can apply to multiple movies even though the user has not yet watched the movie because the keyword is associated with the content of the movies. The PT keywords – movie matrix unit connects with the personality-based neighbourhood in the Keywords Matching Unit.

7.2.1.4 KEYWORDS MATCHING UNIT

The concept of keywords matching utilized in this model is similar to the concept of social matching where people are matched together based on their personality traits. In this case, the words in movies which are matched with the words in the personality traits lists of keywords are identified and matched together. This creates the product model which involves the generation of product knowledge in terms of how it relates to the targeted consumers. The user model matrix is multiplied by the product model matrix to generate the recommendation values for each movie in the process known as matrix factorization. This research further contributes the minimum recommendation values for each personality type which was generated using the personality traits keywords list. If the recommendation values for each of the personality types are less than the values indicated in Table 5.6, then the accuracy of the recommendation model in terms of the recommendation values would be negatively affected even if the feedback from the users were positive.

7.3 OTHER RECOMMENDATION PROBLEMS VS SOLUTIONS

In the attempt to resolve the problem caused by the ratings-based approach in recommender systems, this research provided additional solutions to the common problems associated with movie recommender systems. This section highlights those problems and the solutions provided by the proposed model.

Literature	Existing Recommender System Problems	Solutions by New Recommendation Model
Facing the cold start problem in recommender systems. (Lika et al., 2014)	Data Sparsity - Cold Start Problem (new movie, new user, new movie-new user problem) - Reduced coverage	The new movie problem – the use of the list of keywords in making recommendations means that as long as there is enough information in the movie plots fed into the recommendation model, the movies will have a fair chance of being recommended to the users. The new user problem – The creation of a personality-based neighbourhood utilizing the MBTI personality model creates a platform for new users to join the neighbourhood and still be integrated successfully into the recommendation process. This was made possible because the model doesn't make recommendations based on individual users but based on the personality type of the specified personality-based neighbourhood. The new movie – new user problem – the combination of the personality-based neighbourhood and the list of keywords created in this research has made it possible for the new users to be able to connect with new movies easily

		if the movies are suitable for that specific personality group. Reduced Coverage – reduced coverage is a ratings-based approach problem and the use of keywords to make recommendations instead of ratings has overcome this problem. This is because the recommendations were located by matching words associated with various movie subject matters between the plots of the movies to be recommended and the list of keywords.
Identification of Grey Sheep Users By Histogram Intersection In Recommender Systems. (Zheng et al., 2017) Fulfilling the Needs of Gray-Sheep Users in Recommender Systems, A Clustering Solution. (Ghazanfar & Prugel-Bennett, 2014)	The Grey Sheep	The keywords list created cuts across a vast amount of movies that are recommended to the personality group based on the assessment of previous movies associated with that specific personality type. Based on the results for the *INFJ* and the *ISFJ*, just 5 out of the 55 recommendation feedback provided for the *INFJ* were *Undecided*, while for the *ISFJ*, just 2 out of the 21 recommendation feedback came back as *Undecided*. This shows that the recommended approach utilized in this research can have a positive impact on limiting the amount of Grey sheep users in the personality neighbourhood because recommendations are made based on the words related to subject matters associated with movies and not user ratings. Therefore, the users have a greater range of movies to choose from based on words associated with subject matters in movies that are associated with their personality type.
MBTI-based Collaborative Recommendation System: A Case of Webtoon Contents. (Yi et al., 2016)	Scalability	The recommendation model developed in this research solves the problem of scalability by effectively restricting the provision of service to 16 types of users in line with the MBTI personality model. This potentially enhances the

Enhancing Collaborative Filtering Systems with Personality Information. (Hu & Pu, 2011)		efficiency of the model because of its ability to manage multiple users at once.

Table 7. 2 Research Problems vs Solutions

7.4 RESEARCH CONTRIBUTION SUMMARY

This research has a number of design implications for recommender systems research. This section will summarise the research contributions for the purpose of further clarity.

First, the research makes a contribution to knowledge by creating an extensive list of keywords which can be used in making movie recommendations based on the plots of the movies. The list of keywords created are associated with each of the 8 MBTI personality traits and were extracted from existing movie plots. The list of keywords are associated with real-life scenarios because movies simply provide fictional representations of real-life scenarios. This implies that it is a sustainable and long-lasting recommendation approach which eliminates the need for requesting the user to feed the recommender system with ratings data for the sake of getting movie recommendations. The keywords are already associated with movie plot lines which have been identified as satisfactory for users with a specific personality trait. This approach has been confirmed as acceptable by movie consumers as the application of keywords, movie plots, and MBTI personality traits in the movie recommendation process produced an average of 76.28% user satisfaction.

Second, the research makes a contribution to the understanding of the conceptual view of recommender systems design by redirecting the focus of making movie recommendations from the application of user ratings to the application of keywords associated with the plots of the movies and the user's personality type. This ensures that movies are recommended based solely on the value they are designed to give to the consumers and not a calculated assumption determined by the application of user ratings which have no connection with the value of the movie. Furthermore, it serves as a guide on how to make movie recommendations utilizing keywords associated with personality profiles. The basic steps are as follows:

1. Identification of the contents for the user model matrix – this is basically the standard percentage values for the personality traits which are 80% for the dominant MBTI personality traits and 20% for the recessive MBTI personality traits.
2. Identification of the contents of the product model matrix – this is basically the identification of the total number of matching keywords between the list of keywords

created in this research, and the plots of the movies being considered for recommendation to the personality group.

3. Determination of the recommendation value of the movie – this is determined by multiplying the data in the user model matrix by the data in the product model matrix in a process known as matrix factorization.

The recommendation value which is associated with the movie through the matrix factorization process serves as a replacement to the application of user ratings. The difference is that the recommendation value is directly associated to the plot of the movie while the user rating is not. The recommendation value associated with the movie would only suffer if the movie creators or the uploader of the movie to the recommender system failed to provide a movie plot description of at least 3913 words.

Third, the research contributes the standard recommendation values for each personality neighbourhood as indicated in Table 5.6 and what is required to decrease the possibility of the recommendation value of the movies for recommendation falling short of the standard movie recommendation value for the personality neighbourhood. The matrix factorization process will come up with various values for the movies to be recommended to the users in the personality neighbourhood. However, the standard recommendation values provided in Table 5.6 serves as the threshold in the confirmation of what is acceptable to such a personality neighbourhood. In addition, a movie recommendation value which is lower than the threshold for that personality type will definitely have a negative impact on the recommendation accuracy of the model and such a movie stands the risk of not attaining user satisfaction.

7.5 IMPLICATIONS OF THE THESIS

The personality based group movie recommendation model artefact presents the standard movie recommendation values for each personality type and at the same time serves as a guide on what is required to make movie recommendations utilizing keywords associated with user MBTI personality traits and movie plots. This thesis proposes a change on how researchers think concerning movie recommender systems and highlights the benefit it can add to both the consumers and the movie industry by proposing the elimination of the application of user ratings during the movie recommendation process and applying keywords from the movie plots in its place.

Movies are motion pictures that have been a part of our lives for centuries for entertainment. According to an article on the Science & Media Museum website, the first to present projected moving pictures to a paying audience were the Lumière brothers in December 1895 in Paris. The movie industry has rapidly evolved over the years and has become an integral part of society due to the extensive amount of influence it exerts on the human personality. This influence is demonstrated in the reaction of the consumer to the events which occur in the movie. It is fascinating just how a movie can effectively take consumers on an emotional roller coaster ride throughout its lifecycle; at some point in the movie, the consumers may feel happy, not long after that, they may feel sad, and then, later on, they may feel anger and hate, and it just goes on and on until the end. The fact that a movie can instigate such a reaction from the consumer indicates that there is some form of relationship between the consumer and the movie. Field (2005) rightly stated that events in a movie are specifically designed to bring out the truth about the characters so that we, the audience, can transcend our ordinary lives and achieve a connection, or bond, between "them and us". We see ourselves in them and enjoy a moment, perhaps, of recognition and understanding. Therefore, the user ratings should not define what we watch when it comes to movies because the connection of a consumer with a movie cannot be defined by the ratings associated with the movie, especially when that rating is a predicted rating and the consumer has not even watched the movie. The connection of a consumer with a movie can only be defined by the connection of the consumer with the story of the movie.

This research identified that the application of user ratings in making movie recommendations is implicitly detrimental to the user experience as they are deprived of the opportunity to experience movies with a storyline which they will find relatable to their present circumstances. This is because, such a movie was rated poorly by another user with similar taste to the user, or, such a movie had no ratings at all. Also, this research identified that the application of user ratings in making recommendations is also detrimental to movies with an unpopular cast list or/and movie production crew. This is because, for ratings to be predicted, initial ratings must exist, and predicted ratings are only based on existing ratings. Furthermore, the ability of a movie to have ratings is directly related to the level of popularity of the movie, because popularity enhances visibility in the movie consumers market which in turn makes the movie available to receive a rating. If the consumers cannot see the movie, or know that the movie exists, they will not be able to provide any ratings. Also, Chandrashekhar & Bhasker (2011) and Orestis & Christos (2017) pointed out that at the initial stage when requesting for the user to provide initial ratings which will be used in the prediction of future ratings, consumers would likely be put off from the system if they are given movies to rate which they don't know at the initial stage. This was confirmed in this research where it was discovered that the *Sensing* personality trait returned the highest number of keywords and was associated with the lowest number of movies. According to Boyd & Brown (2005), the *Sensing* personality trait is associated with objective thinking and working with facts. Therefore, at the initial stage, when the recommender system requests the user to provide a rating for a movie, it makes sense that they would utilize movies with a reasonably high level of popularity to them since it's likely the *Sensing* personality trait in the consumer at work at that moment. Therefore, based on the ratings-based approach, it seems like the movies with popular cast members or/and movie production crew are given an unfair advantage over the movies deemed as unpopular through the ratings-based recommendation approach.

To this end, this research explored the concept of identifying words in plots of movies associated with a diverse range of subject matters usually explored in movies to utilize in making movie recommendations to the consumers as opposed to the use of the user ratings. The application of the list of keywords created in this research to facilitate the recommendation of movies to consumers based on the movie plots returned a total average user satisfaction rate of 76.28% per personality neighbourhood. The movies selected for recommendation were movies with low levels of popularity among users on the IMDB website. Furthermore, this research discovered the need for the creation of an extensive movie plot description with a minimum of 3913 words for all movies recommended to all personality types. This is fed into the recommender system to allow the matching of as many words as possible from the list of keywords associated with the MBTI personality traits and to ensure recommendation accuracy is achieved.

7.3 RESEARCH LIMITATIONS

The research challenges will be discussed based on the phase of the research where that challenge occurred.

7.3.1. CHOOSING A PERSONALITY MODEL

The choice of a personality model was a challenge because the MBTI personality model has received heavy scrutiny from psychologists globally as an ineffective tool in the determination of a user's personality. This was because, in some cases, they discovered that the MBTI personality test provided two different results to a user when the user takes the test twice. This was a result of the users in this scenario answering the same questions differently than they did when they were asked the first time. This could further point to the problem of the user not understanding the question being asked in the determination of their MBTI personality type or a deliberate attempt by the users to sabotage their MBTI personality test results. However, the MBTI model was eventually selected because of its ability to categorise users into groups which is an essential part of this research. Furthermore, one of the identified advantages of the FFM over the MBTI personality model is the focus on personality traits while the MBTI personality model focuses on personality types. Therefore, this research did not just focus on the personality types, but also on the traits which make up the personality types, which include both the dominant and recessive traits.

7.3.2 DATA COLLECTION

The challenge encountered in the data collection phase was in the extraction of the movie plot summaries from the IMDB website. This was challenging because the process of web scraping requires a stable internet connection throughout the web scraping process. If there is a break in the internet connection, the web scraping will return as failed. Furthermore, it was discovered that some movies don’t have movie plot summaries. At the testing phase, there was also the problem of data collection through the web application. The testing phase involved the use of participants to test the proposed personality-based movie recommendation model by providing feedback on the recommendations made to them in their personality neighbourhoods. The challenge involved in acquiring the data required for the testing phase was in the recruitment of participants to test the model. The data collection was done through the use of a web application developed specifically to recommend movies based on the proposed recommendation model. In the end, the research had to settle with responses from participants from 2 personality groups, *INFJ* and *ISFJ*. This feedback was used to determine the recommendation accuracy of the recommendation model as it relates to the personality types in question-based on the recommendation values of the movies and based on overall user satisfaction. However, in the face that there was more time, a social media campaign would have commenced requesting users to provide feedback on selected recommended items using a questionnaire and not a web application. The error made in this research was the attempt to build a substantial set of subscribers through the development of the web application. Such a feat requires time to build unless one already has access to a group of subscribers. The use of a web application to collect the feedback would work if it was through an already established platform with existing subscribers, such as Netflix or MovieLens, otherwise, it is best to stick with the use of standard questionnaires and vigorous social media campaigns to solicit for participants.

7.4 FUTURE RECOMMENDATIONS

According to Song et al (2015), currently, based on users' listening behaviour and historical ratings, collaborative filtering algorithm has been found to perform well for making music recommendations. They further pointed out that when collaborative filtering is combined with the use of a content-based model, the user can get a list of similar songs by low-level acoustic features such as rhythm, pitch, or high-level features like genre, instrument, etc. According to Feng & Zhuang (2003), music is subjective and universal. It not only can convey emotion but also can modulate a listener's mood. The tastes in music are varied from person to person, therefore, the previous approaches cannot always meet the users' needs. Kleć (2017) pointed out that to deliver better recommendations, music information systems need to go beyond standard methods for the prediction of musical taste. Kleć (2017) further stated that tracking the listener's emotions is one way to improve the quality of recommendations. According to Kleć (2017), this can be achieved explicitly by asking the listener to report his/her emotional state or implicitly by tracking the context in which the music is heard. The research by Kleć (2017) concluded that music is characterized by its emotional charge, which is primarily dictated by the chord (pitch-class) progression. This progression determines the style, mood, and final perception of a song. Listeners judge these things subconsciously when deciding whether they like a piece of music or not. In this context, the chromagram is a very good candidate for music representation, especially for predicting the musical tastes of individuals with different personality types. However, there is still a research gap to determine if music can be recommended based on the lyrics of the song utilizing an MBTI personality-based neighbourhood. Do the lyrics of a song have any impact on the consumer's music preferences?

The list of keywords generated via this research can be tested for a cross-domain recommendation for music. The music consumers can be requested to provide their top 10 songs. The users are categorised based on their MBTI personality neighbourhoods and a critical assessment of the data acquired can be conducted to qualitatively determine the relationship between the song selections and the personality neighbourhood. The lyrics of the selected songs are extracted from the respective online providers and stored in a database. An initial test of the list of keywords can be carried out against the extracted song lyrics per personality type. This test would involve the determination of the number of words in the song lyrics which are an exact match with the words in the list of keywords per personality trait created in this research. The expectation would be to have a high number of matching keywords for the dominant personality traits of the specified personality type. This assessment would help to determine the words from the list of keywords that can be associated with consumer music choices. If there are no matching keywords, or the number of keywords identified is too small to draw any kind of statistical conclusions, that implies that the list of keywords would need to be updated to suit the music industry.

To this end, the lyrics of the selected songs need to be imported into a word2vec model as a combined corpus to serve as the document vector which will be queried by the list of keywords for each personality trait that would serve in the capacity of the query vector. The words in the list of keywords per personality trait would serve as the query term vector in the determination of the relevancy between the list of keywords and the lyrics of the selected songs. The relevancy would be determined through the identification of the most similar words found between the query term vector and the document vector. The relevancy of the query term vector against the document vector is determined by the strength of the cosine similarity of the words produced from the document vector when queried with the query term vector from the personality traits keywords lists. If the words generated have a cosine similarity of not less than 0.990, they can be added to the list of keywords being assessed as they would be deemed as relevant to that specific list as it relates to the music selections for that personality type. Upon the successful completion of the update process carried out on the existing list using the *most similar* function in the word2vec model, the user model and the product model can be created to determine the recommendation model for music users based on their personality types. The recommendation value for the selected songs is calculated and the average recommendation value for each personality type is calculated. The new personality-based music recommendation model will utilize the average recommendation value determined for each personality type as a guide to the determination of the best kind of music to recommend to the music consumers within the personality neighbourhood. The same process can be applied to test the list of keywords for the recommendation of books to consumers.

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APPENDIX A – RESEARCH QUESTIONNAIRE

The following questions were used in the questionnaire posted on various MBTI personality type related Facebook groups. 207 responses were recorded.

Question 1 - Please Enter your email address.

Question 2 – Do you know your MBTI Personality Type? If No, please follow this link:- https://www.16personalities.com/free-personality-test. Otherwise, just proceed to the next question.

Question 3 - Please select your personality type.

Question	Movies
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 1
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 2
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 3
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 4
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 5
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 6
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 7
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 8
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 9
Type in your favourite movies (NOT TV SHOWS) or movies you watched and really liked.	Movie Title 10

APPENDIX B – PARTICIPANT'S MOVIE CHOICES

ENFJ	Antman	Ironman 3	Lucy	Kingsman: The Secret Service	Batman VS Superman	Cinderella	Minions	Inside Out	The Martian	Pitch Perfect 2
ENFJ	Ride Along	Brown Sugar	Love and Basketball	With this ring	Bestman	Diary of a mad black woman	Good deeds	The Perfect Guy	The Perfect Match	Temptation: Confession of a Marriage Counsellor
ENFJ	Sleepless in Seattle	Lord of the Rings	Crash	Pursuit of Happyness	It's a Wonderful Life	Sunset Boulevard	Woman of the Year	Casablanca	Dead Poets Society	Patch Adams
ENFJ	Man of steel	Law abiding citizen	Kung Fu panda	Finding nemo	Lion king	Toy story	Inception	Forrest Gump	Titanic	rocky
ENFJ	the Gods are not dead	let the light shine	the independence day	London has fallen	the hit list	Akeelah and the Bee	bending the rules	fireproof	courageous	facing the giants
ENFP	Wizard of oz	Shawshank Redemption	The green mile	The help	The Colorado purple	Gone with wind	Calamity jane	The holiday	Enchanted	School of rock
ENFP	The 3 musketeers	Kungfu hustle	V for vendetta	Kingsman; the secret service	The aggression scale	Chinese zodiac	Focus	Blended	Draft day	Now you see me
ENFP	Shawshank redemption	Goonies	Fight club	Clerks	Snow piercer	Step Brothers	The Princess Bride	The Big Lebowski	Inception	Trading Places
ENFP	Forest Gump	A beautiful mind	Mulan	Harry Potter	Holy Ghost	Lord of the rings	Chocolate	Chicago	Narnia	The 100 Year-Old Man Who Climbed Out the Window and Disappeared
ENFP	The matrix	Star wars	The usual suspects	Dodge ball	Dead pool	Total recall	4 weddings and a funeral	Back to the future	Fight club	The Martian
ENTJ	Bad Teacher	Think Like a man	Think Like a man too	I am legend	Mean girls	Diary of a mad black woman	Avatar	Beyond the lights	Baby boy	10 years a Slave
ENTJ	The Notebook	The Wedding Singer	The Princess Bride	Just Friends	The Nightmare Before Christmas	My Big Fat Greek Wedding	She's The Man	The Emperor's New Groove	The Proposal	Braveheart
ENTJ	The Prestige	O Brother Where Art Thou	Beginners	The Royal Tenenbaums	Amelie	Goodfellas	Doubt	Birdman	Reservoir Dogs	Eternal Sunshine of the Spotless Mind
ENTP	Good Will Hunting	Gatsby	To Catch a Thief	The Philadelphia Story	A Beautiful Mind	Shawshank Redemption	Memento	Mulholland Drive	Shutter Island	Eternal sunshine of the spotless mind
ESFJ	Shawshank Redemption	Deadpool	Captain America: Winter Soldier	Captain America:	Italian Job	007: Die Another Day	American Gangster	Olympus Has Fallen	Kingsmen: Secret Service	The Prestige

				Civil War						
E S F J	The parent trap	The nightma re before christm as	Tarzan (2016)	The page maste r	How to train your dragon	Hotel Transylv ania	Deep blue sea	The Dark knight rises	The hope	The bone collector
E S F J	Sixteen Candles	The Note book	Family Man	When a man loves a woma n	National lampoons Christmas vacation	Time travelers wife	The little mermai d	Bridesmaids	Fast and furious movies	Pitch perfect
E S F P	The Dark Knight	Sicario	Captain Phillips	Ameri can Ultra	I Am Number Four	Star Wars	No Country for Old Men	Guardians of the Galaxy	The Matrix	Lord of the Rings
E S F P	Avatar	Titanic	Good Will Hunting	The Hunge r Game s	Bourne Identity	Pride and Prejudic e	Save the Last Dance	Harry Potter	Eagle Eye	The Dark Knight
E S F P	Pulp Fiction	Reservo ir Dogs	Hateful 8	Star Wars: A New Hope	Star Wars: Empire Strikes Back	Star Wars: Return of the Jedi	Despera do	Guardians of the Galaxy	Titanic	Avengers
E S T J	The Martian	The Imitatio n Game	The Road	10 Clover field lane	The last days on Mars	Joy	The fault in our stars	Fatal Attraction	Transce ndence	Gone girl
E S T J	Up	Gods Not Dead	Parenta l Guidanc e	Findin g Nemo	Finding Dory	Despica ble Me	Hop	Hannah Montana The Movie	Santa Paws	Air Buddies
E S T J	Love Actually	The Usual Suspect s	Crazy Stupid Love	Ameri can Hustle	Heat	Primal Fear	Good Will Hunting	American President	Prime	Postcards from the Edge
E S T P	American beauty	A very long engage ment	Space odyssey	Mulho lland drive	Bad Education	Youth	The basic instinct	Talk to her	Interstel lar	There will be blood
E S T P	Avengers 1 & 2	Thor 1 & 2	Iron Man 1, 2 & 3	Captai n Ameri ca 1, 2 & 3	Sherlock Holmes 1 & 2	The Imitatio n Games	Interstel lar	The Man from UNCLE	James Bond (all of them)	Deadpool
I N F J	Dirty Dancing	Jurassic Park	Transfo rmers	Fast and Furiou s	X men	Avenger s	Cutting Edge	Captain America	The diary of a mad black woman	Our family wedding
I N F J	Thor	Avenge rs	Avenge rs: Age of Ultron	Thor: The Dark World	Ant Man	Captain America: Civil War	Frozen	Deadpool	Coming to America	Men in Black
I N F J	Think like a man	Think like a man two	Norbit	Indep enden ce Day	Annie	Woman on top	Just my luck	Cheaper by the dozen	War room	Wild Wild west
I N F J	Eternal Sunshine of the Spotless Mind	You've got Mail	Lost in Translat ion	Into the Wild	Maleficen t	How to Train your Dragon	Singing in the Rain	Star Wars	Monste rs Inc.	The Science of Sleep
I N F J	Dazed and Confused	The Sandlot	Mr. Deeds	The Age of Adelin e	Sisters	The Secret Life of Pets	The Other Woman	Pitch Perfect	Sliver	Dirty Dancing

INFJ	V for Vendetta	Immortal Beloved	Perfume: The story of a murderer	Another Earth	Only Lovers Left Alive	One Flew Over The Cuckoo's Nest	Inglourious Basterds	Pan's Labyrinth	Into the Wild	Bram Stoker's Dracula
INFJ	Old Yeller	X-Men	The Notebook	Mrs Doubtfire	Willy Wonka	The Choice	The Little Mermaid	Flicka	The Lion King	Captive
INFJ	Peaceful Warrior	V for Vendetta	Australia	Life of PI	Eat Pray Love	As Good As It Gets	Best Exotic Marigold Hotel.	Something's Gotta Give	First Wives Club	Footloose
INFJ	10 Things I Hate About You	School of Rock	The Breakfast Club	Say Anything	The Sandlot	Pitch Perfect	Napoleon Dynamite	The Secret Life of Walter Mitty	The Big Year	The Silence of the Lambs
INFJ	Notting Hill	Wall-e	The Interpreter	ET	The Constant Gardener	Music & Lyrics	Harry Potter	Back to the Future	Lost in Translation	Amélie
INFJ	Clueless	Titanic	Halloween	Scream	Romy and Michelle's High School Reunion	The Goonies	Hairspray	The Care Bears Movie	Beautiful Thing	My Best Friend's Wedding
INFJ	Before Sunrise	Before Sunset	(500) days of Summer	Cast away	Saving Private Ryan	Passion of the Christ	King Kong,2005	Bridges of Madison County	Titanic	Avatar
INFJ	The Godfather	Gone with the Wind	Top Gun	Grease	40 Year Old Virgin	The Notebook	West Side Story	Dodgeball	Step Brothers	Dirty Dancing
INFJ	Harry Potter (all)	Gone With the Wind	Forrest Gump	Phantom of the Opera	Frozen	O Brother Where Art Thou	Sound of Music	Mary Poppins	Pirates of the Caribbean (all)	The Hobbit (all)
INFJ	Pride and Prejudice	The Notebook	The Green Mile	Seven Pounds	Soul Food	Ghost	Cold Mountain	P.S. I Love You	Ladder 49	Backdraft
INFJ	The Color purple	Fried green tomatoes	The aviator	Mean girls	Legally blonde	Gravity	Escape from LA	Gattaca	The big short	The Hateful Eight
INFJ	Dances with wolves	Twister	Color Purple	Ghost	Corina Corina	Poltergeist	Last of the Mohicans	Alice in Wonderland	The Breakfast Club	The Hurt Locker
INFJ	The Emperor's Club	Castaway	Pride and Prejudice	Mansfield Park	Sense and Sensibility	White Christmas	Sherlock Holmes	A Christmas Story	The Corpse Bride	The Pianist
INFJ	Anne of green gables/Anne of Avonlea	Dead poets society	13 going on 30	Young guns/young guns 2	Superman	Pitch perfect	A walk to remember	Rudy	A knight's tale	My girl
INFJ	Friday	Beyond the stars	Inside man	Why did I get married	Friday	Hunger games	Planet of the apes	Man on fire	The equalizer	Inception
INFJ	The Wizard of Oz	Ghostbusters	Teenage Mutant Ninja Turtles	Happy Feet	Finding Nemo	LOTR: The Fellowship of the Ring	The Tale of Two Towers	The Return of the King	28 Days	13 Going on 30

INFJ	The Princess Bride	Ghostbusters (the original one!)	Monty Python and the Holy Grail	Face Off	Footloose	Dirty Dancing	Mr. Popper's Penguins	National Treasure	Field of Dreams	Sabrina
INFJ	Matilda	Hugo	The Little Tree	The Little Prince	Rurouni Kenshin (Kyoto Inferno, The Legend Ends)	The Girl Who Leaps Through Time	A Walk To Remember	The Grave of the Fireflies	The Blind Swordsman: Zatoichi	The Olympus Has Fallen
INFJ	Harry Potter	Vacation	Good Will Hunting	Inception	The Imitation Game	Finding Nemo	Back to the Future	Hustle & Flow	Airplane	White Noise
INFJ	99 Homes	Love Actually	You Can Count on Me	The Martian	Wild	A Walk in the Woods	Notting Hill	The Big Chill	Babe	Four Weddings and a Funeral
INFJ	Drive	Short Term 12	Happythankyoumorepleaselease	Blue Valentine	Liberal Arts	The Giant Mechanical Man	Mud	What Maisie Knew	Lars And The Real Girl	The Spectacular Now
INFJ	Singin' In The Rain	Eternal Sunshine of the Spotless Mind	The Matrix	Jerry Maguire	Lost In Translation	Atonement	Moulin Rouge	Cloud Atlas	Vanilla Sky	Inception
INFJ	Fargo	Dogma	American Beauty	Jupiter Ascending	Star Trek	Howard's End	Apollo 13	Fifth Element	Keeping Mum	The Score
INFJ	The Fundamentals of Caring	The Shallows	Divergent	Theory of Everything	Me Before You	A Walk to Remember	Interstellar	The Fault In Our Stars	The Hangover	The Sixth Sense
INFJ	Usual suspects	Mighty	Why you were sleeping	Jane Eyre	Becoming Jane	X-Men, Past is Future	Gladiator	Duff	L.A. Confidential	P.S. I love you
INFJ	Avengers	Iron Man	The Martian	Book of Eli	World war z	Mad Max	Guardians of the Galaxy	Star Trek	Interstellar	Star wars
INFJ	The Pianist	Titanic	School of Rock	I Love You, Man	The Help	Milk	Downfall	Inglourious Basterds	Shrek Forever After	Amelie
INFJ	Men in black	The never-ending story	Harry potter	the turning point	My fair lady	Seven brides for seven brothers	Steel magnolias	Firefly the movie	Contact	Star trek
INFJ	Despicable Me	The Matrix	Star Wars	Kung Fu Panda	Shrek	Mulan	Last Samurai	The conjuring	The Ring	American Pie
INFJ	Jane Eyre	Pride & Prejudice	Django Unchained	Dirty Dancing	Titanic	Last of the Mohicans	Vanity Fair	The Other Boleyn Girl	Tristan & Isolde	District 9
INFJ	Gone with the wind	Atonement	Star Trek - into darkness	The shining	Alien	Interstellar	Gravity	The seventh seal	Back to broke mountain	Star wars

INFJ	You've Got Mail	He's Just Not That into You	A Walk to Remember	Second Best Marigold Hotel	When Harry Met Sally	A Beautiful Mind	..	..	..	..
INFP	le fabuleux destin d'amelie poulain	fight club	into the wild	requiem for a dream	Mr nobody	shutter island	detachment	the butterfly effect	lord of the rings	Dumbo
INFP	Harry potter	Star wars	Kill bill	Shutter island	Home alone	Inception	Big bang theory	Vampires diaries	Homeland	E.t
INFP	A Walk To Remember	Midnight in Paris	Hangover 2	Requiem for a dream	The Lego Movie	The Conjuring	Inside Out	Toy Story 3	Step Up 2	Bad Boys 2
INFP	American History X	Fight Club	Lock, Stock, and Two Smoking Barrels	LOTR Trilogy	Control	About Time	Gangster No. 1	Back to the Future	P.S. I Love You	500 Days of Summer
INFP	Verona mars	dead poets society	Muppets Christmas Carol	inside out	you've got mail	Harry potter series	snow piercer	becoming Jane	the intern	a monster in Paris
INFP	Les Misérables	Schindler's List	Interstellar	The Imitation Game	Up	Howl's Moving Castle	WALL-E	The Lord of the Rings Trilogy	The Princess Bride	The Giver
INFP	Color of paradise	Where is my friend's home?	I origins	Seconds	Taste of cherry	Palindromes	Kytice	Amelie	Pi	Lepa sela lepo gore
INFP	Aliens	Amelie	Kenny	The Castle	Mary & Max	The English Patient	Wall-e	Iron Giant	Galaxy Quest	The Fountain
INFP	The Lion King	The Perks of being a wallflower	Like Crazy	Sleuth	Gamer	S. Darko	The lovely bones	Ps: i love you	Silver linings	Up in the air
INFP	French Kiss	Leap Year	Pride and Prejudice	Song of the Sea	Nemo	Cars	Emma	Lake house	Baby Boom	Kungfu Panda 1,2,3,
INFP	What's Eating Gilbert Grape	Edward Scissorhands	Volver	Adventures in Babysitting	Rushmore	The Royal Tenenbaums	The Goonies	Punch Drunk Love	Eternal Sunshine of the Spotless Mind	June bug
INFP	The Color purple	Oh brother where art though	Grease	Legends of the fall	The notebook	Dirty Dancing	Finding nemo	Lord of the rings trilogy	Napoleon dynamite	Superb bad
INFP	Mood Indigo	Amelie	Singin' in the Rain	V for Vendetta	Dirty dancing	Killing fields	Leon	Dead Poets Society	District 9	The Grand Budapest Hotel
INFP	Up	Brave	Hero (Chinese movie, 2003)	Amelie	Beauty and the Beast	Mulan	Eternal Sunshine of the Spotless Mind	Harry Potter movies	Sound of Music	You've Got Mail

INFP	pretty woman	harry potter	lost in translation	star wars	the doors	Innocence	dirty dancing	Fakat Müzeyyen Bu Derin Bir Tutku	Arizona dream	pride and prejudice
INFP	Digimon The Movie	Unbreakable	Inside Out	The Avengers	Princess Bride	Freak The Mighty	Cloudy With a Chance of Meatballs	Kung Fu Hustle	Ip Man: The Legend Is Born	Alice In Wonderland
INFP	The Station Agent	Rosemary's Baby	Casablanca	The Virgin Suicides	The Boat That Rocked	Silence of the Lambs	Benny & Joon	Close Encounters of the Third Kind	City Lights	Modern Times
INFP	The Breakfast Club	The Dead Poets Society	The Scarlet Pimpernel	The Avengers	The Princess Bride	Iron Man	Inside Out	Zootopia	The Lord of the Rings trilogy	Silver Linings Playbook
INFP	The Dark Crystal	Seventh Son	Legend	Dracula	Dorian Grey	The Shining	Labyrinth	Footloose	X-Men	Gremlins
INFP	The Notebook	Titanic	Interstellar	Seven Pounds	How to be Single	Mean Girls	Back to the Future	The Goonies	What’s Eating Gilbert Grape	Harry Potter and the Sorcerer’s Stone
INFP	Star Wars (The Original Trilogy)	Kingsman the Secret Service	Avatar (The James Cameron one)	Monty Python and the Holy Grail	Mel Brooks' "History of the World Part I"	Star Wars (The Prequels)	Spaceballs	Get Smart	Airplane!	The Garden of Words
INFP	Lord of the rings	Dr Zhivago	Pride and prejudice	Silence of the lambs	Skyfall	Hobbit	Pirates of the Caribbean	The others	The bridges of Maddison country	Out of Africa
INFP	Schindler's List	Shining	28 Days Later	Se7en	Reservoir Dogs	The Virgin Suicides	Trainspotting	Sucker Punch	Fight Club	The Hunger Games
INFP	The Avengers: Earth's Mightiest Heroes	Guardians of the Galaxy	Star Wars IV	Star Wars V	Star Wars VI	Star Wars III	Star Wars VII	X-Men: Apocalypse	Captain America: Civil War	Back to the Future
INFP	The Purge	The Notebook	About Time	Shawshank Redemption	My Best Friend's Wedding	The Runaway Bride	Me Before You	The Heat	The Proposal	Premonition
INFP	Pay it off	Casablanca	Godfather	Epic	Life is beautiful	It's a wonderful life	Troy	One day	Before series	Dark Knight
INFP	Dead Poet Society	Inside Out	Megamind	As good as it gets	Pather panchali	Forrest Gump	Philadelphia	Magic in the Moonlight	Fading Gigolo	Trumbo
INFP	Pretty Woman	Dirty Dancing	Beauty and the Beast	Lady and the Tramp	Camelot	Phantom of the Opera	Sound of Music	Rain Man	One Flew Over the Cuckoo’s Nest	The Birdcage
IN	love actually	you've got mail	a good year	a beauti	crazy, stupid, love	He's just NOT	pride and	letter to Juliette	valentine's day	legend of the fall

F P				ful mind		That into you	prejudice			
I N F P	Amelie	The Secret Life of Walter Mitty	Inherent Vice	The Revenant	Mad Max: Fury Road	The Harry Potter Series	We Are Your Friends	American Beauty	The Thin Red Line	A Scanner Darkly
I N F P	Forest Gump	Eternal Sunshine of the Spotless Mind	The Danish Girl	Our Idiot Brother	Cake	The Age of Adaline	About Time	The Time traveler's Wife	Me and Earl and The Dying Girl	The Notebook
I N F P	Everything is illuminated	Silver linings playbook	Pineapple Express	Avatar	Talladega Nights: Ballad of Ricky Bobby	Year One	Stardust	Warcraft	Star Wars: The Force Awakens	The Departed
I N F P	Harry Potter and the philosopher stone	Harry Potter and the chamber of secret	Harry Potter and the prisoner of Azkaban	Harry Potter and the goblet of fire	Harry Potter and the half-blood prince	Harry Potter and the deathly hollow part 1	Harry Potter and the deathly hollow part 2	Warm Bodies	Divergent	The rise of guardian
I N F P	Interstellar	The Mummy	Ghost Busters (original)	Back to the future	The Fifth Element	Aladdin	Hellboy 2	The Fountain	Pocahontas	Constantine
I N F P	Amelie	Princess Mononoke	Spirited Away	Allerleirauh	Nausicaä of the Valley of the Wind	The Fellowship of the Ring	The Two Towers	The Return of the King	Hamlet	Howl's Moving Castle
I N F P	Song of the Sea	Le grand bleu	I am Dina	Everything Is Illuminated	The Help	Secret Life of Walter Mitty	Lost in Translation	Whale Rider	Inside Out	Hector and the Search for Happiness
I N F P	Once	A Room With A View	Emma	Groundhog Day	Monty Python's Life of Brian	Star Trek 2009	Love Actually	The Best Exotic Marigold Hotel	Mama Mia	Pride And Prejudice 2005
I N F P	Inside Out	Jurassic Park	That Thing You Do	Big Hero 6	Remember Me	Finding Nemo	Monsters Inc.	The Last Five Years	Singin' in the Rain	Into the Woods
I N F P	The Hateful 8	Constantine	Days of Thunder	Happy Gilmore	A beautiful mind	Patch Adams	Back to the future	Good will hunting	Doc Hollywood	Dante's Peak
I N F P	beautiful mind	titanic	the great Gatsby	harry potter series	the boy in striped pyjamas	miracle in cell no. 7	my sassy girl	lovely bones	Notting hill	sherlock Holmes: game of the shadows
I N F P	Captain America The Winter Soldier	Captain America The First Avenger	The Avengers (Assemble)	The Avengers Age of Ultron	Captain America Civil War	Finding Nemo	Toys story	Maleficent	G.I Joe Rise of Cobra	Harry Potter
I N F P	Harry Potter	Lord of the Rings	Star Wars	Moulin Rouge	Hunger Games	Looper	The Butterfly Effect	Project Almanac	Eternal Sunshine of the Spotless Mind	DejaVu
I N F P	beautiful mind	shutter island	exam	Mr nobody	solace	don't say a word	Jessabelle	black swan	inside out	the fault in our stars

INFP	The Lakehouse	The Great Gatsby	A Walk In The Clouds	Avatar	How To Train Your Dragon	A Knights Tale	Two Week's Notice	Moulin Rouge	Big Hero 6	The Holiday
INFP	Virgin Suicides	The Godfather	Kramer vs Kramer	Larry Flynt VS the People	4 Weddings and a Funeral	Once Upon a Time in the West	Black Swan	Across the Universe	Silence of the Lambs	Lord of the Rings
INFP	Lord Of The Rings	Amelie	The Illusionist	The Secret Life of Walter Mitty	Wolf Children	Departures	Interstellar	All Studio Ghibli movies	Moonrise Kingdom	All Kusturica's movies
INFP	8 Mile	Borat	The Wolf of Wall Street	Pulp Fiction	The Big Lebowski	The Room	Wall-e	Bruno	Ali G Indahouse	The Dictator
INFP	Hachiko	Home alone	Purge 2	Purge 3	The Conjuring	Maleficent	Up	Wall-E	Ratatouille	How to train your Dragon
INFP	GATTACA	The Labyrinth	Silver Linings Playbook	The Mothman Prophecies	The Interpreter	Lord of the Rings trilogy	Harry Potter series	The Big Short	The Hunger Games trilogy	The Lion King
INFP	Lord of the Rings	Braveheart	Juno	Into the Wild	Requiem for a Dream	Memento	Napoleon Dynamite	The Matrix	Ella Enchanted	The Princess Diaries
INFP	Forrest Gump	Shawshank redemption	Memento	Prestige	Inception	Batman begins	Batman dark knight	Batman dark night rises	The conjuring	Cast away
INFP	The Color purple	The ten commandments	Ben Hur	Doubt	Amistad	Les miserable	The gladiator	Road to perdition	A Christmas carol	Pride and prejudice
INFP	What Ever Happened to Baby Jane	Mommy Dearest	Night of the Iguana	Forrest Gump	The Sixth Sense	American History X	Apocalypto	Dead Man's Chest	Empire Records	March of the Penguins
INFP	Pride and prejudice	Speed racer	North and south	12 angry men	Star wars	Now you see me	Inception	The young Victoria	Avengers	Lord of the rings
INFP	Lord of the Rings trilogy	The Hobbit	Inside out	Gods of Egypt	The Matrix	Aladdin	The Age of Adeline	The Dark Knight Rises	Nova Zembla	Spirited Away
INFP	Blue Velvet	Mulholland Drive	2001: The Space Odyssey	Dead Man	Pink Floyd: The Wall	Donnie Darko	The Fight Club	Apocalypse Now	Eraser head	The Big Lebowski
INFP	The Adventures of Buckaroo Banzai Across the Eighth Dimension	Fight Club	Buffalo 66	Memento	Gattaca	Raising Arizona	Monty Python and the Holy Grail	Being Malkovich	Singing in the Rain	Accidental Tourist
INFP	Gone with the wind	Grease	Grace of my heart	Apocalypse now	The sound of music	Mary Poppins	Star wars	The lord of the rings	Maleficent	It's a wonderful life
IN	Big	Star Trek IV: The	Zootopia	Big Hero 6	Despicable Me	Up	Bridge Over the	Ant-Man	The Railrodder	North of Superior

FP		Voyage Home					River Kwai			
INFP	Cry-baby (1995)	moulin rouge	juno	airplane	house of 1,000 corpses	harry potter	the little mermaid (Disney)	a nightmare on elm street	IT	holes
INFP	The colour of pomegranates	The Darjeeling limited	The Grand Budapest hotel	A short film about killing	Only lovers left alive	Flashbacks of a fool	The double life of Veronique	Vodka lemon	Christiane F	Wings of desire
INFP	Eternal Sunshine of the Spotless Mind	Her	American Movie	Anchorman	Drive	Predator	The Big Picture	Vacation	The Master	There Will Be Blood
INFP	The fall	The Intouchables	The lives of others	Me before you	Before sunrise	Before sunset	Before midnight	Cinema Paradiso	The pianist	Life is beautiful
INFP	Wings of Desire	The Way We Were	As Good As It Gets	Cool Hand Luke	When Harry Met Sally	Sound of Music	Gone With The Wind	Magnolia	Love Actually	My Fair Lady
INFP	Legend	Indiana Jones	Star Wars	Atlas Rising	Ghostbusters	Last of the Mohicans	Dangerous Liaisons	Never ending Story	Tombstone	Bridesmaids
INTJ	Dead pool	Hunger games catching fire	Mocking jay 1	Mocking jay 2	Antman	Spectre	Ride along	Independence day resurgence	Central intelligence	Ride along 2
INTJ	Lost in space	Predator	The spy who loved me	The Rock	Die Another Day	Lion King	Home Alone	Iron man	Despicable me	Minions
INTJ	Hannibal Rising	The pursuit of happyness	My name is Khan	Table 21	Saw	Hatchiko	Up	Wall-E	The hunger games	Hide and seek
INTJ	The Watchmen	Mr Nobody	Seven Pounds	Pursuit of Happyness	The Dark Knight	The Lobster	Zombieland	Interstellar	Dallas Buyers Club	Lord of The Rings Trilogy
INTJ	Sherlock: The Abominable Bride	Inside Out	Gone with the wind	Inception	Internal Affairs	Spirited away	Schindler's List	Forest Gump	Interstellar (Favourite)	Wall E
INTJ	Prison Break	Silence of the Lambs	Orange is the new black	Dexter	Law Abiding Citizen	Derailed	Sideways	Saw	Hostel	The Guardian
INTJ	The Departed	Mystery Science Theatre 3000 The Movie	O Brother Where Art Thou	Sleepless In Seattle	Black Hawk Down	Tears Of The Sun	Saving Private Ryan	Lorna Doone	The Count Of Monte Cristo	Tommy Boy
INTJ	Persona	Manhattan	The seventh seal	Crimes and misdemeanours	2001 A space odyssey	The white ribbon	Ran	Zelig	Tokyo Monogatari	The dark knight rises
INTJ	Clue	Natural Born Killers	Stand By Me	The Princess Bride	The Cure	Good Will Hunting	Old Boy	Martyrs	Heathers	The Breakfast Club
IN	Fight Club	The Matrix Trilogy	The Falling	Ghostbusters	Pulp Fiction	V For Vendetta	Captain America	Deadpool	X-Men: Apocalypse	The Butterfly Effect

T J							: Civil War			
I N T J	The Devil Wears Prada	Now & Then	The Birdcage	Steel Magnolias	Fahrenheit 911	Religulous	The Broken Hearts Club	The Family Stone	Hocus Pocus	Mean Girls
I N T J	Titanic	Arsenic and Old Lace	Mr. Blanding Builds a House	The Hunger Games	The Other Woman	Jaws	Mockingjay	Kingsman: The Secret Service	Jurassic World	Renaissance Man
I N T J	Contact	Alien	Riddick	The Bourne Identity	Life of Brian	Fiddler on the Roof	Dr. Zhivago	Gallipoli	The 40 Year Old Virgin	Funny Girl
I N T J	Forrest Gump	Now you see me	The Martian	I am Sam	One flew over cuckoo's nest	Little Ashes	The Shining	The perks of being a wallflower	I origins	Spotlight
I N T J	Green Lantern	Deadpool	Fault in our Stars	Notting hill	Lion King	Pretty Woman	Zootopia	X-Men	Star Wars IV, V, VI and The Force Awakens	The Martian
I N T J	Star Wars (all)	Ghostbusters (all)	The Big Short	Vacation	Goonies	Say Anything	Ant-Man	Guardians of the Galaxy	The Avengers	Iron Man
I N T J	Life is Beautiful	Spirited Away	The Woman in Black	One Flew Over the Cuckoo's Nest	Pulp Fiction	Schindler's list	The Silence of the Lambs	Inception	Forrest Gump	Interstellar
I N T J	Evil Dead	Seven Samurai	Wolf of wall street	Goodfellas	The Shining	8mm	The Departed	Jaws	The Lobster	Beyond the valley of the dolls
I N T J	The Lord of the Rings Trilogy	Braveheart	Dances With Wolves	The Matrix Trilogy	Grease	Star Wars	Star Trek	Avatar	Transformers (all of them)	Pirates of the Caribbean (all of them)
I N T J	Hitchhiker's Guide to the Universe	Shaun of the Dead	Shawshank Redemption	Tomb Raider	Star Trek Series	Harry Potter Series	What Dreams May Come	A Knights Tale	Evolution	Big Fish
I N T J	Natural Born Killers	True Romance	Lock, Stock & 2 Smoking Barrels	Aliens	Moulin Rouge	Blazing Saddles	Flash Gordon	Stealing Home	Wolf Creek	The Usual Suspects
I N T J	Stand by me	Alien	27 Dresses	Fifty Shades	I've	Chosen	Enough	Films	Now	Thanks
I N T J	Pretty in Pink	Christmas Land	Four Christmases	Tangled	Pride and Prejudice and Zombies	Sleepy Hollow	Saw	Vampire Academy	A Prince for Christmas	Me Before You
I N T J	American Beauty	Mr. Nobody	Primer	Pulp Fiction	The Princess Bride	Butch Cassidy and the Sundance Kid	The Truman Show	Dr. Strangelove or: How I Learned to Stop Worrying and	The Matrix	There Will be Blood

								Love the Bomb		
INTJ	The Godfather	Fear and loathing in Las Vegas	Inception	Pulp Fiction	The prestige	Half Baked	Don't legalize it	Star wars empire strikes back	Blow	Pineapple express
INTJ	Star Wars IV The Empire Strikes Back	Back to the Future II	Inception	Interstellar	Man of Steel	The Man From Earth	The Dark Crystal	Idiocracy	A.I. Artificial Intelligence	Her
INTJ	Harold and Maude	Welcome to the Dollhouse	Long Hot Summer	Leaves of Grass	Cool Hand Luke	Zeitgeist	Far and Away	Back to the Future	Chasing Amy	Wargames
INTJ	Star Wars	Star Trek	Harry Potter	The princess bride	Guardians of the Galaxy	Iron man (1)	The incredible spider man	The labyrinth	Love actually	Erin Brockovich
INTJ	Terminator series	Rocky series	Halloween 1,2,6,7	The Fog	Rear Window	Shadow of a Doubt	Psycho	The Birds	Shawshank Redemption	Love Actually
INTJ	Lonesome Dove	Django	True Grit	Annie	Chicago	Meet the millers	Tammy	Identity thief	Silence of the lambs	The devils rejects
INTJ	Jason Bourne	Easy a	Pitch perfect	Dead pool	Star Trek (recent ones)	How to train your dragon	Ever after	Top gun	Lord of the rings	Count of Monte Carlo
INTJ	Shawshank Redemption	The Martian	Interstellar	The Color Purple	Captain America	The Hunger Games	The Book Thief	Avengers	X-men	The Mechanic
INTJ	Lost Highway	Sex, Lies, and Videotape	The Ninth Gate	Altered States	Rosemary's Baby	The Omen	The Dunwich Horror (1970)	The Waking Life	Dune (1984)	The Royal Tenenbaums
INTJ	Terminator 2	The Breakfast Club	Ex Machina	Goodfellas	Step Brothers	Feris Bueller's Day Off	Her	Crows Zero	Silver Linings Playbook	Coming to America
INTJ	Cake Boss	48 hours mystery	Case files	The first 48	Making of a murderer	Death row stories	Deep sea	Planet earth	HR griger	The marvelous misadventures of flapjack
INTJ	Star Wars: a new hope	The crow	Dead pool	The Shawshank redemption	Avengers assemble	Pulp fiction	The good, the bad and the ugly	The Battle of Britain	Excalibur	Grand Budapest hotel
INTJ	independence day	star wars 4	star wars 5	star wars 6	war of the worlds	star trek (all)	virus	Erin Brockovich	taken	planet of the apes
INTJ	Lord of the rings	How to train your Dragon	Dead Poets' Society	Oh brother, where art thou?	Harry Potter series	Sherlock Holmes	No additional titles	No additional titles	No additional titles	No additional titles
INTJ	Wuthering heights	How to steal a million	Gone with the wind	The English patient	Schindler's list	Dirty dancing	Gran Torino	Persepolis	Life is Beautiful	Arsenic and old lace

INTJ	The God Father	Bridge to Terabithia	The imitation game	The theory of everything	A Brilliant Young Mind	Steve Jobs	A beautiful mind	Before sunrise	Before midnight	Road to Eldorado
INTJ	Transformers	Matrix	The fall	What lies beneath	The others	The forgotten	Lord of the rings	Harry potter	The fifth element	Priest
INTJ	Juno	Eternal Sunshine of the Spotless Mind	Kill Bill 1/2	Fight Club	The Curious Case of Benjamin Button	The Bone Collector	The Silence of the Lambs	The Intouchables	Forrest Gump	Black Swan
INTJ	original Lord of the Rings trilogy (not The Hobbit)	Star Wars (most)	Ip Man (prequel, 1 and 2)	Inception	Braveheart	The Shawshank Redemption	The Illusionist	Ender's Game	The Sting	the Bourne trilogy
INTP	Shawshank Redemption	Spider man	Green Mile	Avengers	Ride Along 1	Bad Boys 1	Bad Boys 2	The Passion Of the Christ	Shrek	Hook
INTP	Deathgasm	You don't know jack	Wild at the heart	Lord of war	The serpent and the rainbow	Straight outta Compton	Deadpool	Desperado	Chained	The butterfly effect
INTP	PRIDE AND PREJUDICE	MASH	LOVE ACTUALLY	WHAT ABOUT BOB?	GOOD WILL HUNTING	HARRY POTTER AND THE DEATHLY HALLOWS	STAR WARS A NEW HOPE	STAR WARS THE FORCE AWAKENS	NETWORK	THE BOURNE IDENTITY
INTP	the english patient	batman begins	wedding crashers	the saint	the notebook	point of no return	matrix	pride & prejudice	the passion of the Christ	two moon junction
INTP	Blade Runner	The Killing Fields	Monty Python and the Holy Grail	Serenity	Lord of the Rings	The Matrix	Blue Brothers	Rocky Horror Picture Show	Deadpool	Singing in the Rain
INTP	Legend	The Dark Crystal	The Fifth Element	Serenity	The Avengers	Clerks	Hackers	Labyrinth	Clueless	Independence Day
INTP	Neverending Story	Same Time Next Year	Fierce Creatures	AVP	Dogma	Boondock Saints	Blazing Saddles	To Have and Have Not	The Cheap Detective	Piranha DD
INTP	Fargo	Holiday	Usual Suspects	There's something about Mary	Raise the Red Lantern	Chunking Express	Vicky Christina Barcelona	Spirited Away	Shining	Amelie
INTP	The Notebook	Tangled	Inside Out	Divergent	Coyote Ugly	Diary of a Mad Black Woman	Shark Tale	The Truman Show	Matilda	Barbershop
INTP	V for Vendetta	Black Swan	Fault In Our Stars	My Sister's Keeper	Gone Girl	Gone with the Wind	Spotlight	Angels and Demons	Monty Python and the Holy Grail	Amadeus
INTP	Avatar	ice age	lord of the rings	brave heart	the three idiots	the Antman	Harry Potter	catch me if u can	the A team	Italian job

ISFJ	Donnie Darko	Frozen (2010)	Silence of the Lambs	In the Mood for Love	The Piano	The Godfather	American Beauty	Possession (1981)	Blue Velvet	Gloomy Sunday
ISFJ	Wedding crashers	Identity theft	The little mermaid	Finding Nemo	Bridesmaids	Monsters Inc.	Scream	Beauty and the beast	The mask	Big daddy
ISFJ	Star Wars	Lord of the Rings	Pacific Rim	The Road to El Dorado	The Fugitive	Prince of Egypt	Tangled	Beauty and the Beast	Indiana Jones	Jurassic Park
ISFJ	Silver linings playbook	Snatch	Pride and prejudice	The fifth element	Fight club	Seven pounds	True grit	Arsenic and old lace	Father goose	Hunger games
ISFJ	The Shawshank Redemption	Wedding Crashers	Kill Bill	Deadpool	Swingers	Transporter	Ghostbusters II	The Replacements	The Green Mile	Bad Boys II
ISFJ	The Notebook	Inside Out	My Sassy Girl (Korean Movie)	Titanic	Despicable Me	Wedding Dress (Korean Movie)	Azumi (Japanese Movie)	Fifty First Dates	300 Pounds Beauty (Korean Movie)	High School Musical
ISFJ	Pride and Prejudice	Sense and Sensibility	Anne of Green Gables	So I Married an Axe Murderer	Twilight	Love Actually	P.S. I Love You	Finding Nemo	An Affair to Remember	Titanic
ISFJ	Legends of the Fall	A knight's Tale	Ever After	Land before time	Sassy Girl (Korean Version)	Les Misérables	Titanic	The Hobbit	Harry Potter and the Sorcerer's Stone	The Sound of Music
ISFJ	Braveheart	Shawshank Redemption	Twilight	Steel Magnolias	Elizabeth	The Hunger Games	Spotlight	Divergent	The Fault In Our Stars	Shakespeare In Love
ISFJ	Star Wars	Lord of the Rings	Beauty and the Beast	Titanic	The Principal	The Holiday	The Princess bride	Jane Eyre	Roman Holiday	White Christmas
ISFJ	A Walk to Remember	Cinderella (2015)	The Bourne series	Gladiator	While You Were Sleeping	It's A Wonderful Life	Hoodwinked	Home Alone movies	Jurassic Park	August Rush
ISFJ	The usual suspects	Gladiator	Matrix	Rush hour	Kill Bill	Sound of music	Ben Hur	Goodfellas	Scarface	Lion king
ISFP	The Color Purple	Finding Dory	Wall-E	District 9	Spirited Away	Pan's Labyrinth	Donnie Darko	Brokeback Mountain	Requiem For a Dream	Frances Ha
ISFP	Jobs (with Ash Kutcher)	Limitless	Wangan Midnight	Straight outta Compton	Initial D 3rd stage	Most of anime	-	-	-	-
ISFP	P.S I love you	Divergent	Insurgent	The hunger games	The holiday	Dirty dancing 2	Four Christmases	Sweet home Alabama	I'm just not that into you	The proposal
IS	Interstellar	Blue is the	Pulp fiction	A clockwork	Jesus is magic	Black swan	Pirates of the	Into the wild	Trainspotting	Drugstore cowboy

FP		warmest colour		orange			Caribbean			
ISTJ	Iron Man	Avengers	The Lion King	Now you see me	Captain America	The Dark Knight	Avatar	Transformers	The King's Speech	Lincoln
ISTJ	Megamind	To Sir with Love	The Lorax	High Society	Calamity Jane	Despicable Me	Django	Tangled	Princess and the Frog	Hotel Transylvania
ISTJ	Titanic	London has fallen	Nemo	Cars	Avatar	Dirty dancing	Independence day	Harry Potter- all movies	The hunger games	Sixth sense
ISTJ	Taxi Driver	The Godfather	The Godfather 2	Shawshank Redemption	The Italian Job	Ace Ventura: When Nature Calls	The Machinist	Scarface	500 Days of Summer	Shame
ISTJ	you got mail	pride and prejudice	while you were sleeping	the heat	Turner and hooch	bridges of Madison county	parent trap	Silverado	yours mine and ours	mr Roberts
ISTJ	Shawshank redemption	Monsters inc	Beauty and the beast	Jazz singer	Sound of music	American president	Top Gun	Marley and me	Beethoven	Speed
ISTJ	Gone with the Wind	Sound of Music	Dead Poet Society	Titanic	Die Hard 1	Die Hard 2	Ghost	Fifth Element	Air Force One	X-Men movies
ISTJ	Jaws	Amadeus	The War of the Worlds (remake)	Planet of the Apes (original)	The Day After Tomorrow	Green card	Jurassic Park	The Woman in Black	Logan's Run	Only You
ISTP	Die Hard	Bring Me The Head of Alfredo Garcia	The Godfather	The Seven Samurai	The Third Man	Wings of Desire	Repo Man	The Conversation	John Wick	HEAT
ISTP	Fight Club	Pitch Black	Chronicles of Riddick	The Last Samurai	The Lord of the Rings	Point Break	Kingsmen	Fast and Furious	The Amazing Spiderman	Guardians of the Galaxy
ISTP	Save The Last Dance	The Lion King	The Princess Diaries	Rush Hour	Transformers	London Has Fallen	Inception	Get Hard	Ride Along	Kingsman: The Secret Service
ISTP	Matrix	Burnt	Starter for 10	Sherlock	Godfather	Inception	Psycho	The pianist	Gummo	Lion king

APPENDIX C – FULL LIST OF MOVIES USED IN INITIAL KEYWORD EXTRACTION PROCESS FROM QUESTIONNAIRE IN APPENDIX B

IMDB_ID	Movie Title	Genres
tt0021749	City Lights	Comedy Drama Romance
tt0027977	Modern Times	Comedy Drama Family
tt0031381	Gone with the Wind	Drama History Romance
tt0032138	The Wizard of Oz	Adventure Family Fantasy
tt0033563	Dumbo	Animation Drama Family
tt0034583	Casablanca	Drama Romance War
tt0036342	Shadow of a Doubt	Thriller
tt0036613	Arsenic and Old Lace	Comedy Crime Thriller
tt0038650	It's a Wonderful Life	Drama Family Fantasy
tt0040613	Mr. Blandings Builds His Dream House	Comedy Romance
tt0045152	Singin' in the Rain	Comedy Musical Romance
tt0046438	Tokyo Story	Drama
tt0047396	Rear Window	Mystery Thriller
tt0047437	Sabrina	Comedy Drama Romance
tt0047472	Seven Brides for Seven Brothers	Comedy Drama Musical
tt0047478	Seven Samurai	Adventure Drama
tt0047673	White Christmas	Comedy Musical Romance
tt0048280	Lady and the Tramp	Adventure Animation Comedy
tt0048473	Pather Panchali	Drama
tt0049833	The Ten Commandments	Adventure Drama
tt0050083	12 Angry Men	Drama
tt0050212	The Bridge on the River Kwai	Adventure Drama War
tt0050798	Old Yeller	Adventure Drama Family
tt0051878	The Long Hot Summer	Drama
tt0052618	Ben-Hur	Adventure Drama History
tt0054215	Psycho	Horror Mystery Thriller
tt0055614	West Side Story	Crime Drama Musical
tt0056687	What Ever Happened to Baby Jane?	Drama Horror Thriller
tt0056869	The Birds	Drama Horror Mystery
tt0057012	Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb	Comedy
tt0058331	Mary Poppins	Comedy Family Fantasy
tt0058385	My Fair Lady	Drama Family Musical
tt0058404	The Night of the Iguana	Drama
tt0059113	Doctor Zhivago	Drama Romance War
tt0059742	The Sound of Music	Biography Drama Family
tt0060196	The Good the Bad and the Ugly	Western
tt0060315	Django	Action Western
tt0060522	How to Steal a Million	Comedy Crime Romance
tt0060827	Persona	Drama Thriller
tt0060955	Seconds	Sci-Fi Thriller
tt0061439	Camelot	Adventure Fantasy Musical

tt0061512	Cool Hand Luke	Crime Drama
tt0062622	2001: A Space Odyssey	Adventure Sci-Fi
tt0063522	Rosemary's Baby	Drama Horror
tt0063555	The Color of Pomegranates	Biography Drama History
tt0064072	Battle of Britain	Action Drama History
tt0064115	Butch Cassidy and the Sundance Kid	Biography Crime Drama
tt0064116	Once Upon a Time in the West	Western
tt0065466	Beyond the Valley of the Dolls	Comedy Drama Music
tt0065669	The Dunwich Horror	Horror
tt0067093	Fiddler on the Roof	Drama Family Musical
tt0067185	Harold and Maude	Comedy Drama Romance
tt0067992	Willy Wonka & the Chocolate Factory	Family Fantasy Musical
tt0068646	The Godfather	Crime Drama
tt0069281	Sleuth	Mystery Thriller
tt0070735	The Sting	Comedy Crime Drama
tt0070903	The Way We Were	Drama Romance
tt0071230	Blazing Saddles	Comedy Western
tt0071853	Monty Python and the Holy Grail	Adventure Comedy Fantasy
tt0073195	Jaws	Adventure Drama Thriller
tt0073486	One Flew Over the Cuckoo's Nest	Drama
tt0074486	Eraserhead	Horror
tt0074937	Murder by Death	Comedy Crime Mystery
tt0075005	The Omen	Horror
tt0075148	Rocky	Drama Sport
tt0075860	Close Encounters of the Third Kind	Drama Sci-Fi
tt0076752	The Spy Who Loved Me	Action Adventure Thriller
tt0076843	The Turning Point	Drama Romance
tt0077631	Grease	Musical Romance
tt0077651	Halloween	Horror Thriller
tt0078346	Superman	Action Adventure Drama
tt0078748	Alien	Horror Sci-Fi
tt0078788	Apocalypse Now	Drama War
tt0079417	Kramer vs. Kramer	Drama
tt0079470	Monty Python's Life of Brian	Comedy
tt0079522	Manhattan	Comedy Drama Romance
tt0080339	Airplane!	Comedy
tt0080745	Flash Gordon	Action Adventure Sci-Fi
tt0080749	The Fog	Horror Thriller
tt0081505	The Shining	Drama Horror
tt0082176	Christiane F.	Biography Drama
tt0082348	Excalibur	Adventure Drama Fantasy
tt0082432	Gallipoli	Adventure Drama History
tt0082517	History of the World: Part I	Comedy History
tt0082766	Mommie Dearest	Biography Drama

tt0083564	Annie	Comedy Drama Family
tt0083791	The Dark Crystal	Adventure Family Fantasy
tt0083866	E.T. the Extra-Terrestrial	Family Sci-Fi
tt0083907	The Evil Dead	Horror
tt0084503	Pink Floyd: The Wall	Animation Drama Fantasy
tt0084516	Poltergeist	Horror Thriller
tt0085244	The Big Chill	Comedy Drama
tt0085334	A Christmas Story	Comedy Family
tt0086567	WarGames	Sci-Fi Thriller
tt0086637	Zelig	Comedy
tt0086856	The Adventures of Buckaroo Banzai Across the 8th Dimension	Adventure Comedy Romance
tt0087182	Dune	Action Adventure Sci-Fi
tt0087277	Footloose	Drama Music Romance
tt0087332	Ghostbusters	Action Comedy Fantasy
tt0087363	Gremlins	Comedy Fantasy Horror
tt0087469	Indiana Jones and the Temple of Doom	Action Adventure
tt0087544	NausicaÃ¤ of the Valley of the Wind	Adventure Animation Fantasy
tt0087553	The Killing Fields	Biography Drama History
tt0087800	A Nightmare on Elm Street	Horror
tt0088323	The NeverEnding Story	Adventure Drama Family
tt0088847	The Breakfast Club	Comedy Drama
tt0088885	The Care Bears Movie	Adventure Animation Comedy
tt0088930	Clue	Comedy Crime Mystery
tt0088939	The Color Purple	Drama
tt0089218	The Goonies	Adventure Comedy Family
tt0089755	Out of Africa	Biography Drama Romance
tt0089881	Ran	Action Drama
tt0090605	Aliens	Action Adventure Sci-Fi
tt0090756	Blue Velvet	Drama Mystery Thriller
tt0091042	Ferris Bueller's Day Off	Comedy
tt0091790	Pretty in Pink	Comedy Drama Romance
tt0091867	A Room with a View	Drama Romance
tt0092005	Stand by Me	Adventure Drama
tt0092007	Star Trek IV: The Voyage Home	Adventure Comedy Sci-Fi
tt0092099	Top Gun	Action Drama
tt0092513	Adventures in Babysitting	Adventure Comedy Crime
tt0092605	Baby Boom	Comedy Drama Romance
tt0092890	Dirty Dancing	Drama Music Romance
tt0093132	Hachi-ko	Drama Family
tt0093191	Wings of Desire	Drama Fantasy Romance
tt0093342	Where Is the Friend's House?	Drama Family
tt0093773	Predator	Action Adventure Sci-Fi
tt0093779	The Princess Bride	Adventure Family Fantasy
tt0093822	Raising Arizona	Comedy Crime

tt0094012	Spaceballs	Adventure Comedy Sci-Fi
tt0094606	The Accidental Tourist	Drama Romance
tt0094737	Big	Comedy Drama Fantasy
tt0094898	Coming to America	Comedy Romance
tt0094947	Dangerous Liaisons	Drama Romance
tt0095250	The Big Blue	Adventure Drama Sport
tt0095327	Grave of the Fireflies	Animation Drama War
tt0095468	A Short Film About Killing	Crime Drama
tt0095765	Cinema Paradiso	Drama
tt0095953	Rain Man	Drama
tt0096487	Young Guns	Action Western
tt0096921	Beyond the Stars	Drama Sci-Fi
tt0096926	The Big Picture	Comedy Drama Romance
tt0097165	Dead Poets Society	Comedy Drama
tt0097351	Field of Dreams	Drama Family Fantasy
tt0097493	Heathers	Comedy Crime
tt0097757	The Little Mermaid	Animation Family Fantasy
tt0098090	The Phantom of the Opera	Drama Horror Music
tt0098258	Say Anything...	Comedy Drama Romance
tt0098384	Steel Magnolias	Comedy Drama Romance
tt0098635	When Harry Met Sally...	Comedy Drama Romance
tt0098724	Sex Lies and Videotape	Drama
tt0099329	Cry-Baby	Comedy Musical
tt0099348	Dances with Wolves	Adventure Drama Western
tt0099371	Days of Thunder	Action Drama Sport
tt0099487	Edward Scissorhands	Drama Fantasy Romance
tt0099653	Ghost	Drama Fantasy Romance
tt0099685	Goodfellas	Biography Crime Drama
tt0099785	Home Alone	Comedy Family
tt0099850	Internal Affairs	Crime Drama Thriller
tt0100405	Pretty Woman	Comedy Romance
tt0100758	Teenage Mutant Ninja Turtles	Action Adventure Comedy
tt0101393	Backdraft	Action Crime Drama
tt0101414	Beauty and the Beast	Animation Family Fantasy
tt0101745	Doc Hollywood	Comedy Drama Romance
tt0101761	The Doors	Biography Drama Music
tt0101765	The Double Life of VÃ©ronique	Drama Fantasy Music
tt0101921	Fried Green Tomatoes	Drama
tt0102492	My Girl	Comedy Drama Family
tt0102603	Oscar	Comedy Crime
tt0102926	The Silence of the Lambs	Crime Drama Thriller
tt0103639	Aladdin	Adventure Animation Comedy
tt0103874	Bram Stoker's Dracula	Horror
tt0104040	The Cutting Edge	Comedy Drama Romance

tt0104231	Far and Away	Adventure Drama Romance
tt0104454	Howards End	Drama Romance
tt0104691	The Last of the Mohicans	Action Adventure Drama
tt0104940	The Muppet Christmas Carol	Comedy Drama Family
tt0105236	Reservoir Dogs	Crime Drama Thriller
tt0106307	Arizona Dream	Comedy Drama Fantasy
tt0106387	Benny & Joon	Comedy Drama Romance
tt0106677	Dazed and Confused	Comedy
tt0107048	Groundhog Day	Comedy Fantasy Romance
tt0107120	Hocus Pocus	Comedy Family Fantasy
tt0107290	Jurassic Park	Action Adventure Sci-Fi
tt0107614	Mrs. Doubtfire	Comedy Drama Family
tt0107818	Philadelphia	Drama
tt0108002	Rudy	Biography Drama Sport
tt0108037	The Sandlot	Comedy Drama Family
tt0108052	Schindler's List	Biography Drama History
tt0108160	Sleepless in Seattle	Comedy Drama Romance
tt0108162	Sliver	Drama Thriller
tt0108358	Tombstone	Action Biography Drama
tt0108399	True Romance	Crime Drama Romance
tt0108442	Undercover Blues	Comedy Crime
tt0108550	What's Eating Gilbert Grape	Drama
tt0109484	Corrina Corrina	Comedy Drama Romance
tt0109506	The Crow	Action Drama Fantasy
tt0109830	Forrest Gump	Drama Romance
tt0109831	Four Weddings and a Funeral	Comedy Drama Romance
tt0110116	Immortal Beloved	Biography Drama Music
tt0110322	Legends of the Fall	Drama Romance War
tt0110357	The Lion King	Adventure Animation Drama
tt0110413	LÃ©on: The Professional	Action Crime Drama
tt0110632	Natural Born Killers	Crime Drama
tt0110912	Pulp Fiction	Crime Drama
tt0111161	The Shawshank Redemption	Drama
tt0112384	Apollo 13	Adventure Drama History
tt0112431	Babe	Comedy Drama Family
tt0112471	Before Sunrise	Drama Romance
tt0112573	Braveheart	Biography Drama History
tt0112579	The Bridges of Madison County	Drama Romance
tt0112697	Clueless	Comedy Romance
tt0112757	The Cure	Drama
tt0112817	Dead Man	Drama Fantasy Western
tt0112950	Empire Records	Comedy Drama Music
tt0113117	French Kiss	Comedy Drama Romance
tt0113118	Friday	Comedy Drama

tt0114148	Pocahontas	Adventure Animation Drama
tt0114369	Se7en	Crime Drama Mystery
tt0114388	Sense and Sensibility	Drama Romance
tt0114694	Tommy Boy	Adventure Comedy
tt0114709	Toy Story	Adventure Animation Comedy
tt0114814	The Usual Suspects	Crime Mystery Thriller
tt0114887	A Walk in the Clouds	Drama Romance
tt0114906	Welcome to the Dollhouse	Comedy Drama
tt0114924	While You Were Sleeping	Comedy Drama Romance
tt0115640	Beautiful Thing	Comedy Drama Romance
tt0115685	The Birdcage	Comedy
tt0116191	Emma	Comedy Drama Romance
tt0116209	The English Patient	Drama Romance War
tt0116225	Escape from L.A.	Action Adventure Sci-Fi
tt0116313	The First Wives Club	Comedy
tt0116442	Grace of My Heart	Comedy Drama Music
tt0116477	Hamlet	Drama
tt0116483	Happy Gilmore	Comedy Sport
tt0116629	Independence Day	Action Adventure Sci-Fi
tt0116695	Jerry Maguire	Comedy Drama Romance
tt0116922	Lost Highway	Mystery Thriller
tt0117008	Matilda	Comedy Family Fantasy
tt0117128	Mystery Science Theater 3000: The Movie	Comedy Sci-Fi
tt0117318	The People vs. Larry Flynt	Biography Drama
tt0117500	The Rock	Action Adventure Thriller
tt0117571	Scream	Horror Mystery
tt0117887	That Thing You Do!	Comedy Drama Music
tt0117951	Trainspotting	Drama
tt0117998	Twister	Action Adventure Thriller
tt0118607	Amistad	Drama History
tt0118715	The Big Lebowski	Comedy Crime
tt0118789	Buffalo '66	Comedy Crime Drama
tt0118799	Life Is Beautiful	Comedy Drama Romance
tt0118826	The Castle	Comedy Drama
tt0118842	Chasing Amy	Comedy Drama Romance
tt0118884	Contact	Drama Mystery Sci-Fi
tt0118928	Dante's Peak	Action Adventure Thriller
tt0119116	The Fifth Element	Action Adventure Sci-Fi
tt0119177	Gattaca	Drama Sci-Fi Thriller
tt0119217	Good Will Hunting	Drama Romance
tt0119488	L.A. Confidential	Crime Drama Mystery
tt0119670	The Mighty	Comedy Drama
tt0119738	My Best Friend's Wedding	Comedy Drama Romance
tt0119822	As Good as It Gets	Comedy Drama Romance

tt0120032	Romy and Michele's High School Reunion	Comedy
tt0120169	Soul Food	Comedy Drama
tt0120265	Taste of Cherry	Drama
tt0120338	Titanic	Drama Romance
tt0120363	Toy Story 2	Adventure Animation Comedy
tt0120382	The Truman Show	Comedy Drama Sci-Fi
tt0120586	American History X	Drama
tt0120601	Being John Malkovich	Comedy Drama Fantasy
tt0120631	Ever After: A Cinderella Story	Comedy Drama Romance
tt0120655	Dogma	Adventure Comedy Drama
tt0120689	The Green Mile	Crime Drama Fantasy
tt0120693	Half Baked	Comedy Crime
tt0120735	Lock Stock and Two Smoking Barrels	Comedy Crime
tt0120737	The Lord of the Rings: The Fellowship of the Ring	Adventure Drama Fantasy
tt0120762	Mulan	Adventure Animation Family
tt0120815	Saving Private Ryan	Drama War
tt0120863	The Thin Red Line	Drama War
tt0120889	What Dreams May Come	Drama Fantasy Romance
tt0120891	Wild Wild West	Action Comedy Sci-Fi
tt0121164	Corpse Bride	Animation Drama Family
tt0125439	Notting Hill	Comedy Drama Romance
tt0126029	Shrek	Adventure Animation Comedy
tt0128332	Innocence	Drama
tt0128445	Rushmore	Comedy Drama
tt0128853	You've Got Mail	Comedy Drama Romance
tt0129167	The Iron Giant	Action Adventure Animation
tt0129290	Patch Adams	Biography Comedy Drama
tt0133152	Planet of the Apes	Action Adventure Sci-Fi
tt0134273	8MM	Mystery Thriller
tt0137523	Fight Club	Drama
tt0138704	Pi	Drama Horror Mystery
tt0138749	The Road to El Dorado	Adventure Animation Comedy
tt0142688	The Ninth Gate	Mystery Thriller
tt0145681	The Bone Collector	Crime Drama Mystery
tt0146316	Lara Croft: Tomb Raider	Action Adventure Fantasy
tt0147800	10 Things I Hate About You	Comedy Drama Romance
tt0159097	The Virgin Suicides	Drama Romance
tt0159365	Cold Mountain	Adventure Drama History
tt0161081	What Lies Beneath	Drama Fantasy Horror
tt0162222	Cast Away	Adventure Drama Romance
tt0162661	Sleepy Hollow	Fantasy Horror Mystery
tt0163187	Runaway Bride	Comedy Romance
tt0163651	American Pie	Comedy
tt0166924	Mulholland Dr.	Drama Mystery Thriller

tt0167404	The Sixth Sense	Drama Mystery Thriller
tt0169547	American Beauty	Drama
tt0172156	Bad Boys II	Action Comedy Crime
tt0172495	Gladiator	Action Adventure Drama
tt0175880	Magnolia	Drama
tt0177789	Galaxy Quest	Adventure Comedy Sci-Fi
tt0178737	Mansfield Park	Comedy Drama Romance
tt0180093	Requiem for a Dream	Drama
tt0181288	American Movie	Comedy Documentary
tt0183790	A Knight's Tale	Action Adventure Romance
tt0190590	O Brother Where Art Thou?	Adventure Comedy Crime
tt0191043	The Color of Paradise	Drama Family
tt0191754	28 Days	Comedy Drama
tt0195685	Erin Brockovich	Biography Drama
tt0198021	Where the Heart Is	Comedy Drama Romance
tt0198781	Monsters Inc.	Adventure Animation Comedy
tt0203009	Moulin Rouge!	Drama Musical Romance
tt0203230	You Can Count on Me	Drama
tt0206420	Woman on Top	Comedy Fantasy Romance
tt0209144	Memento	Mystery Thriller
tt0210065	Gangster No. 1	Crime Drama Thriller
tt0211915	AmÃ©lie	Comedy Romance
tt0212720	A.I. Artificial Intelligence	Adventure Drama Sci-Fi
tt0217869	Unbreakable	Drama Mystery Sci-Fi
tt0221027	Blow	Biography Crime Drama
tt0222850	The Broken Hearts Club: A Romantic Comedy	Comedy Drama Romance
tt0230600	The Others	Horror Mystery Thriller
tt0232500	The Fast and the Furious	Action Crime Thriller
tt0239102	Wild Flowers	Drama Fantasy Horror
tt0241025	Vanity Fair	Drama
tt0241527	Harry Potter and the Sorcerer's Stone	Adventure Family Fantasy
tt0245429	Spirited Away	Adventure Animation Family
tt0245844	The Count of Monte Cristo	Action Adventure Drama
tt0246460	Die Another Day	Action Adventure Thriller
tt0246578	Donnie Darko	Drama Sci-Fi Thriller
tt0247638	The Princess Diaries	Comedy Family Romance
tt0250494	Legally Blonde	Comedy Romance
tt0251075	Evolution	Comedy Sci-Fi
tt0251736	House of 1000 Corpses	Horror
tt0253474	The Pianist	Biography Drama Music
tt0257044	Road to Perdition	Crime Drama Thriller
tt0258463	The Bourne Identity	Action Mystery Thriller
tt0259711	Vanilla Sky	Fantasy Mystery Romance
tt0259974	Digimon: The Movie	Action Adventure Animation

tt0260866	Don't Say a Word	Drama Mystery Thriller
tt0265086	Black Hawk Down	Drama History War
tt0265349	The Mothman Prophecies	Drama Horror Mystery
tt0265666	The Royal Tenenbaums	Comedy Drama
tt0266543	Finding Nemo	Adventure Animation Comedy
tt0266697	Kill Bill: Vol. 1	Action Crime Thriller
tt0268978	A Beautiful Mind	Biography Drama
tt0272338	Punch-Drunk Love	Comedy Drama Romance
tt0277027	I Am Sam	Drama
tt0280590	Mr. Deeds	Comedy Romance
tt0281358	A Walk to Remember	Drama Romance
tt0281924	I Am Dina	Drama
tt0283530	The Emperor's Club	Drama
tt0284837	Ali G Indahouse	Comedy
tt0289043	28 Days Later...	Drama Horror Sci-Fi
tt0289879	The Butterfly Effect	Drama Sci-Fi Thriller
tt0293508	The Phantom of the Opera	Drama Musical Romance
tt0298130	The Ring	Horror Mystery
tt0298203	8 Mile	Drama Music
tt0298228	Whale Rider	Drama Family
tt0299977	Hero	Action Adventure History
tt0311289	Holes	Adventure Comedy Drama
tt0313737	Two Weeks Notice	Comedy Romance
tt0314331	Love Actually	Comedy Drama Romance
tt0314353	Tears of the Sun	Action Drama Thriller
tt0317219	Cars	Animation Family Sport
tt0319061	Big Fish	Adventure Drama Fantasy
tt0325710	The Last Samurai	Action Drama War
tt0325980	Pirates of the Caribbean: The Curse of the Black Pearl	Action Adventure Fantasy
tt0327679	Ella Enchanted	Comedy Family Fantasy
tt0328107	Man on Fire	Action Crime Drama
tt0332280	The Notebook	Drama Romance
tt0332379	School of Rock	Comedy Music
tt0332452	Troy	Drama History
tt0335266	Lost in Translation	Drama
tt0335345	The Passion of the Christ	Drama
tt0337563	13 Going on 30	Comedy Fantasy Romance
tt0337741	Something's Gotta Give	Comedy Drama Romance
tt0338013	Eternal Sunshine of the Spotless Mind	Drama Romance Sci-Fi
tt0338751	The Aviator	Biography Drama
tt0340377	The Station Agent	Comedy Drama
tt0349205	Cheaper by the Dozen	Comedy Family
tt0349710	Ladder 49	Action Drama Thriller
tt0354899	The Science of Sleep	Comedy Drama Fantasy

tt0356618	The Forgotten	Drama Horror Mystery
tt0356680	The Family Stone	Comedy Drama Romance
tt0357413	Anchorman: The Legend of Ron Burgundy	Comedy
tt0359950	The Secret Life of Walter Mitty	Adventure Comedy Drama
tt0360486	Constantine	Action Fantasy Horror
tt0360717	King Kong	Action Adventure Drama
tt0361596	Fahrenheit 9/11	Documentary Drama War
tt0361748	Inglourious Basterds	Adventure Drama War
tt0362004	Palindromes	Comedy Drama
tt0363226	The Blind Swordsman: Zatoichi	Action Comedy Crime
tt0364569	Oldboy	Action Drama Mystery
tt0364725	Dodgeball: A True Underdog Story	Comedy Sport
tt0365748	Shaun of the Dead	Comedy Horror
tt0366548	Happy Feet	Adventure Animation Comedy
tt0367959	Hannibal Rising	Adventure Crime Drama
tt0368226	The Room	Drama
tt0368891	National Treasure	Action Adventure Mystery
tt0369436	Four Christmases	Comedy Drama Romance
tt0369610	Jurassic World	Action Adventure Sci-Fi
tt0371724	The Hitchhiker's Guide to the Galaxy	Adventure Comedy Sci-Fi
tt0371746	Iron Man	Action Adventure Sci-Fi
tt0373074	Kung Fu Hustle	Action Comedy Fantasy
tt0373926	The Interpreter	Crime Mystery Thriller
tt0374900	Napoleon Dynamite	Comedy
tt0375063	Sideways	Comedy Drama Romance
tt0375154	Tristan + Isolde	Action Drama Romance
tt0375210	White Noise	Drama Horror Mystery
tt0377092	Mean Girls	Comedy
tt0379577	Vodka Lemon	Comedy Drama
tt0380510	The Lovely Bones	Drama Fantasy Thriller
tt0381681	Before Sunset	Drama Romance
tt0382077	Hide and Seek	Drama Horror Mystery
tt0382932	Ratatouille	Adventure Animation Comedy
tt0383574	Pirates of the Caribbean: Dead Man's Chest	Action Adventure Fantasy
tt0387131	The Constant Gardener	Drama Mystery Romance
tt0387564	Saw	Horror Mystery Thriller
tt0387808	Idiocracy	Adventure Comedy Sci-Fi
tt0388795	Brokeback Mountain	Drama Romance
tt0390384	Primer	Drama Sci-Fi Thriller
tt0395584	The Devil's Rejects	Horror
tt0396171	Perfume: The Story of a Murderer	Crime Drama
tt0397078	Just My Luck	Comedy Fantasy Romance
tt0398286	Tangled	Adventure Animation Comedy
tt0398808	Bridge to Terabithia	Adventure Drama Family

tt0401445	A Good Year	Comedy Drama Romance
tt0404030	Everything Is Illuminated	Comedy Drama
tt0404254	My Sassy Girl	Comedy Drama Romance
tt0405094	The Lives of Others	Drama Thriller
tt0405296	A Scanner Darkly	Animation Crime Drama
tt0405422	The 40-Year-Old Virgin	Comedy Romance
tt0406816	The Guardian	Action Adventure Drama
tt0407304	War of the Worlds	Adventure Sci-Fi Thriller
tt0407887	The Departed	Crime Drama Thriller
tt0409459	Watchmen	Action Drama Mystery
tt0410097	Hustle & Flow	Crime Drama Music
tt0410297	The Lake House	Drama Fantasy Romance
tt0411477	Hellboy II: The Golden Army	Action Adventure Fantasy
tt0413879	Cake	Comedy Romance
tt0414387	Pride & Prejudice	Drama Romance
tt0414993	The Fountain	Drama Sci-Fi
tt0415306	Talladega Nights: The Ballad of Ricky Bobby	Comedy Sport
tt0416315	Wolf Creek	Horror Thriller
tt0416508	Becoming Jane	Biography Drama Romance
tt0418279	Transformers	Action Adventure Sci-Fi
tt0418773	Junebug	Comedy Drama
tt0421082	Control	Biography Drama Music
tt0421715	The Curious Case of Benjamin Button	Drama Fantasy Romance
tt0422093	Diary of a Mad Black Woman	Comedy Drama Romance
tt0425061	Get Smart	Action Adventure Comedy
tt0427327	Hairspray	Comedy Drama Musical
tt0428803	March of the Penguins	Documentary Family
tt0431308	P.S. I Love You	Comedy Drama Romance
tt0434215	Flicka	Adventure Drama Family
tt0434409	V for Vendetta	Action Drama Sci-Fi
tt0435651	The Giver	Drama Romance Sci-Fi
tt0438315	Peaceful Warrior	Drama Romance Sport
tt0441773	Kung Fu Panda	Action Adventure Animation
tt0441909	Volver	Comedy Drama
tt0443543	The Illusionist	Drama Mystery Romance
tt0444653	Keeping Mum	Comedy Crime
tt0445922	Across the Universe	Drama Fantasy History
tt0450278	Hostel	Horror
tt0452694	The Time Traveler's Wife	Drama Fantasy Romance
tt0453467	Deja Vu	Action Crime Sci-Fi
tt0454876	Life of Pi	Adventure Drama Fantasy
tt0454921	The Pursuit of Happyness	Biography Drama
tt0455824	Australia	Adventure Comedy Drama
tt0455944	The Equalizer	Action Crime Thriller

tt0457430	Pan's Labyrinth	Drama Fantasy War
tt0457939	The Holiday	Comedy Romance
tt0458352	The Devil Wears Prada	Comedy Drama
tt0460791	The Fall	Adventure Drama Fantasy
tt0467200	The Other Boleyn Girl	Biography Drama History
tt0467406	Juno	Comedy Drama
tt0469494	There Will Be Blood	Drama
tt0470752	Ex Machina	Drama Mystery Sci-Fi
tt0472043	Apocalypto	Action Adventure Drama
tt0472399	The Mechanic	Action Thriller
tt0477051	Norbit	Comedy Romance
tt0477071	Premonition	Drama Fantasy Mystery
tt0478970	Ant-Man	Action Adventure Comedy
tt0482571	The Prestige	Drama Mystery Sci-Fi
tt0485947	Mr. Nobody	Drama Fantasy Romance
tt0486655	Stardust	Adventure Family Fantasy
tt0499549	Avatar	Action Adventure Fantasy
tt0756683	The Man from Earth	Drama Fantasy Sci-Fi
tt0758758	Into the Wild	Adventure Biography Drama
tt0758766	Music and Lyrics	Comedy Music Romance
tt0770828	Man of Steel	Action Adventure Sci-Fi
tt0780504	Drive	Crime Drama
tt0783233	Atonement	Drama Mystery Romance
tt0790636	Dallas Buyers Club	Biography Drama
tt0795421	Mamma Mia!	Comedy Musical Romance
tt0800369	Thor	Action Adventure Fantasy
tt0803096	Warcraft	Action Adventure Fantasy
tt0805564	Lars and the Real Girl	Comedy Drama Romance
tt0808417	Persepolis	Animation Biography Drama
tt0808506	The Girl Who Leapt Through Time	Adventure Animation Comedy
tt0810819	The Danish Girl	Biography Drama Romance
tt0811080	Speed Racer	Action Adventure Comedy
tt0814314	Seven Pounds	Drama Romance
tt0815241	Religulous	Comedy Documentary War
tt0816442	The Book Thief	Drama War
tt0816692	Interstellar	Adventure Drama Sci-Fi
tt0816711	World War Z	Action Adventure Horror
tt0817230	Valentine's Day	Comedy Romance
tt0822389	Kenny	Comedy
tt0822847	Priest	Action Adventure Fantasy
tt0829482	Superbad	Comedy
tt0838221	The Darjeeling Limited	Adventure Comedy Drama
tt0838283	Step Brothers	Comedy
tt0844471	Cloudy with a Chance of Meatballs	Adventure Animation Comedy

tt0848228	The Avengers	Action Adventure Sci-Fi
tt0848537	Epic	Adventure Animation Family
tt0879870	Eat Pray Love	Drama Romance
tt0887912	The Hurt Locker	Drama Thriller War
tt0889583	BrÃ¼no	Comedy
tt0892318	Letters to Juliet	Adventure Comedy Drama
tt0892769	How to Train Your Dragon	Action Adventure Animation
tt0892791	Shrek Forever After	Adventure Animation Comedy
tt0903624	The Hobbit: An Unexpected Journey	Adventure Family Fantasy
tt0906108	Why Did I Get Married?	Comedy Drama
tt0907657	Once	Drama Music Romance
tt0910936	Pineapple Express	Action Comedy Crime
tt0910970	WALLÂ·E	Adventure Animation Family
tt0914798	The Boy in the Striped Pajamas	Drama War
tt0918927	Doubt	Drama Mystery
tt0936501	Taken	Action Thriller
tt0947798	Black Swan	Drama Thriller
tt0948470	The Amazing Spider-Man	Action Adventure Sci-Fi
tt0961097	A Monster in Paris	Adventure Animation Comedy
tt0962736	The Young Victoria	Biography Drama History
tt0970179	Hugo	Adventure Drama Family
tt0978762	Mary and Max	Animation Comedy Drama
tt0978764	Sucker Punch	Action Adventure Fantasy
tt0988595	27 Dresses	Comedy Romance
tt0993846	The Wolf of Wall Street	Biography Crime Drama
tt1001508	He's Just Not That Into You	Comedy Drama Romance
tt1001526	Megamind	Action Animation Comedy
tt1014759	Alice in Wonderland	Adventure Family Fantasy
tt1016290	Crows Zero	Action Thriller
tt1022603	500 Days of Summer	Comedy Drama Romance
tt1023481	Step Up 2: The Streets	Drama Music Romance
tt1029234	Martyrs	Horror
tt1034032	Gamer	Action Sci-Fi Thriller
tt1037218	Flashbacks of a Fool	Drama
tt1037705	The Book of Eli	Action Adventure Drama
tt1041829	The Proposal	Comedy Drama Romance
tt1045658	Silver Linings Playbook	Comedy Drama Romance
tt1045778	Year One	Adventure Comedy
tt1046173	G.I. Joe: The Rise of Cobra	Action Adventure Sci-Fi
tt1049413	Up	Adventure Animation Comedy
tt1053810	The Big Year	Comedy
tt1067106	A Christmas Carol	Animation Drama Family
tt1069238	Departures	Drama Music
tt1074638	Skyfall	Action Adventure Thriller

tt1104083	Little Ashes	Biography Drama Romance
tt1119646	The Hangover	Comedy
tt1120985	Blue Valentine	Drama Romance
tt1121096	Seventh Son	Action Adventure Fantasy
tt1130884	Shutter Island	Mystery Thriller
tt1133985	Green Lantern	Action Adventure Sci-Fi
tt1136608	District 9	Action Sci-Fi Thriller
tt1149362	The White Ribbon	Drama History Mystery
tt1155056	I Love You Man	Comedy Romance
tt1156398	Zombieland	Adventure Comedy Horror
tt1178665	A Walk in the Woods	Adventure Biography Comedy
tt1181614	Wuthering Heights	Drama Romance
tt1188996	My Name Is Khan	Drama
tt1193138	Up in the Air	Comedy Drama Romance
tt1197624	Law Abiding Citizen	Action Crime Drama
tt1205489	Gran Torino	Drama
tt1216492	Leap Year	Comedy Romance
tt1217209	Brave	Adventure Animation Comedy
tt1229822	Jane Eyre	Drama Romance
tt1231277	S. Darko	Mystery Sci-Fi Thriller
tt1235124	Dorian Gray	Drama Fantasy Thriller
tt1258197	Exam	Mystery Thriller
tt1276104	Looper	Action Crime Drama
tt1282140	Easy A	Comedy Drama Romance
tt1291570	Solace	Crime Drama Mystery
tt1292566	How to Be Single	Comedy Drama Romance
tt1305583	Our Family Wedding	Comedy Romance
tt1323594	Despicable Me	Animation Comedy Family
tt1343092	The Great Gatsby	Drama Romance
tt1371111	Cloud Atlas	Action Drama Mystery
tt1374989	Pride and Prejudice and Zombies	Action Comedy Fantasy
tt1375666	Inception	Action Adventure Sci-Fi
tt1392170	The Hunger Games	Action Adventure Sci-Fi
tt1392190	Mad Max: Fury Road	Action Adventure Sci-Fi
tt1396218	Mr. Popper's Penguins	Comedy Family Fantasy
tt1403865	True Grit	Adventure Drama Western
tt1403981	Remember Me	Drama Romance
tt1408101	Star Trek Into Darkness	Action Adventure Sci-Fi
tt1411250	Riddick	Action Adventure Sci-Fi
tt1411697	The Hangover Part II	Comedy Mystery
tt1412386	The Best Exotic Marigold Hotel	Comedy Drama Romance
tt1431045	Deadpool	Action Adventure Comedy
tt1446192	Rise of the Guardians	Action Adventure Animation
tt1454029	The Help	Drama

tt1454468	Gravity	Drama Sci-Fi Thriller
tt1457767	The Conjuring	Horror Mystery Thriller
tt1478338	Bridesmaids	Comedy Romance
tt1481572	Happythankyoumoreplease	Comedy Drama Romance
tt1489889	Central Intelligence	Action Comedy Crime
tt1490017	The Lego Movie	Action Adventure Animation
tt1515091	Sherlock Holmes: A Game of Shadows	Action Adventure Crime
tt1524930	Vacation	Adventure Comedy
tt1549572	Another Earth	Drama Romance Sci-Fi
tt1560747	The Master	Drama
tt1563738	One Day	Drama Romance
tt1570728	Crazy Stupid Love.	Comedy Drama Romance
tt1587310	Maleficent	Action Adventure Family
tt1588173	Warm Bodies	Comedy Horror Romance
tt1596363	The Big Short	Biography Comedy Drama
tt1596365	The Woman in Black	Drama Fantasy Horror
tt1605783	Midnight in Paris	Comedy Fantasy Romance
tt1617661	Jupiter Ascending	Action Adventure Sci-Fi
tt1621045	Think Like a Man	Comedy Romance
tt1626146	Hector and the Search for Happiness	Adventure Comedy Drama
tt1637706	Our Idiot Brother	Comedy Drama
tt1641638	The Legend Is Born: Ip Man	Action Biography Drama
tt1645170	The Dictator	Comedy
tt1655441	The Age of Adaline	Drama Fantasy Romance
tt1659337	The Perks of Being a Wallflower	Drama
tt1663202	The Revenant	Action Adventure Biography
tt1666801	The Duff	Comedy Romance
tt1670345	Now You See Me	Crime Mystery Thriller
tt1675434	The Intouchables	Biography Comedy Drama
tt1683526	Detachment	Drama
tt1706620	Snowpiercer	Action Drama Sci-Fi
tt1707386	Les MisÃ©rables	Drama History Musical
tt1714206	The Spectacular Now	Comedy Drama Romance
tt1714915	Only Lovers Left Alive	Comedy Drama Fantasy
tt1723121	We're the Millers	Comedy Crime
tt1731141	Ender's Game	Action Adventure Fantasy
tt1748122	Moonrise Kingdom	Adventure Comedy Drama
tt1754656	The Little Prince	Adventure Animation Drama
tt1758692	Like Crazy	Drama Romance
tt1769363	The Giant Mechanical Man	Comedy Drama Romance
tt1791528	Inherent Vice	Comedy Crime Drama
tt1798709	Her	Drama Romance Sci-Fi
tt1840309	Divergent	Action Adventure Mystery
tt1850457	Sisters	Comedy

tt1853728	Django Unchained	Drama Western
tt1865505	Song of the Sea	Adventure Animation Drama
tt1872818	Liberal Arts	Comedy Drama Romance
tt1877832	X-Men: Days of Future Past	Action Adventure Sci-Fi
tt1895587	Spotlight	Biography Crime Drama
tt1911607	Nova Zembla	Drama History
tt1932767	What Maisie Knew	Drama
tt1935179	Mud	Drama
tt1981677	Pitch Perfect	Comedy Music Romance
tt2015381	Guardians of the Galaxy	Action Adventure Comedy
tt2024432	Identity Thief	Adventure Comedy Crime
tt2080374	Steve Jobs	Biography Drama
tt2084970	The Imitation Game	Biography Drama Thriller
tt2096673	Inside Out	Adventure Animation Comedy
tt2103254	Tammy	Comedy Romance
tt2180411	Into the Woods	Adventure Comedy Drama
tt2194499	About Time	Comedy Drama Fantasy
tt2203939	The Other Woman	Comedy Romance
tt2209418	Before Midnight	Drama Romance
tt2229842	Table No. 21	Adventure Thriller
tt2239832	Think Like a Man Too	Comedy Romance
tt2245084	Big Hero 6	Action Adventure Animation
tt2258345	Fading Gigolo	Comedy
tt2278388	The Grand Budapest Hotel	Adventure Comedy Crime
tt2293640	Minions	Adventure Animation Comedy
tt2294629	Frozen	Adventure Animation Comedy
tt2300975	Jessabelle	Horror Thriller
tt2302755	Olympus Has Fallen	Action Thriller
tt2305051	Wild	Adventure Biography Drama
tt2326612	The Captive	Crime Drama Mystery
tt2345759	The Mummy	Action Adventure Fantasy
tt2361509	The Intern	Comedy Drama
tt2370248	Short Term 12	Drama
tt2404233	Gods of Egypt	Action Adventure Fantasy
tt2404463	The Heat	Action Comedy Crime
tt2436386	Project Almanac	Drama Mystery Sci-Fi
tt2452386	The Fundamentals of Caring	Comedy Drama
tt2474024	The Last Five Years	Comedy Drama Musical
tt2488496	Star Wars: Episode VII - The Force Awakens	Action Adventure Sci-Fi
tt2555736	The Second Best Exotic Marigold Hotel	Comedy Drama
tt2582496	Me and Earl and the Dying Girl	Comedy Drama Romance
tt2582846	The Fault in Our Stars	Drama Romance
tt2591814	The Garden of Words	Animation Drama Romance
tt2659414	Miracle in Cell No. 7	Comedy Drama

tt2709768	The Secret Life of Pets	Adventure Animation Comedy
tt2802144	Kingsman: The Secret Service	Action Adventure Comedy
tt2869728	Ride Along 2	Action Comedy Crime
tt2870756	Magic in the Moonlight	Comedy Romance
tt2884206	I Origins	Drama Romance Sci-Fi
tt2891174	99 Homes	Drama
tt2948356	Zootopia	Adventure Animation Comedy
tt2975578	The Purge: Anarchy	Action Horror Sci-Fi
tt2980516	The Theory of Everything	Biography Drama Romance
tt3029558	Rurouni Kenshin Part II: Kyoto Inferno	Action Adventure Drama
tt3203606	Trumbo	Biography Drama
tt3244992	Trailer Park Boys: Don't Legalize It	Comedy Crime Drama
tt3294200	The Falling	Drama Mystery Thriller
tt3385516	X-Men: Apocalypse	Action Adventure Sci-Fi
tt3460252	The Hateful Eight	Crime Drama Mystery
tt3464902	The Lobster	Comedy Drama Romance
tt3498820	Captain America: Civil War	Action Adventure Sci-Fi
tt3569230	Legend	Biography Crime Drama
tt3659388	The Martian	Adventure Drama Sci-Fi
tt3787590	We Are Your Friends	Drama Music Romance
tt3797868	The Choice	Drama Romance
tt3832914	War Room	Drama
tt4052882	The Shallows	Drama Horror Thriller
tt6105098	The Lion King	Adventure Animation Drama
tt6476140	Serenity	Drama Mystery Sci-Fi

APPENDIX D – FULL LIST OF MOVIES USED TO IDENTIFY ASSOCIATED WORDS TO THE INITIAL KEYWORDS EXTRACTED USING THE MOVIES IN APPENDIX C

IMDB ID	Movie Title
tt0183649	Phone Booth (2002)
tt0075686	Annie Hall (1977)
tt1213663	The World's End (2013)
tt0118884	Contact (1997)
tt2302755	Olympus Has Fallen (2013)
tt0438097	Ice Age: The Meltdown (2006)
tt0429493	The A-Team (2010)
tt1340138	Terminator Genisys (2015)
tt1401152	Unknown (2011)
tt0181875	Almost Famous (2000)
tt2024469	Non-Stop (2014)
tt1343727	Dredd (2012)
tt0452623	Gone Baby Gone (2007)
tt0259711	Vanilla Sky (2001)
tt2140479	The Accountant (2016)
tt4633694	Spider-Man: Into the Spider-Verse (2018)
tt0105323	Scent of a Woman (1992)
tt4649466	Kingsman: The Golden Circle (2017)
tt0094721	Beetlejuice (1988)
tt2798920	Annihilation (2018)
tt0120804	Resident Evil (2002)
tt0289765	Red Dragon (2002)
tt0322259	2 Fast 2 Furious (2003)
tt0196229	Zoolander (2001)
tt0414387	Pride & Prejudice (2005)
tt1790809	Pirates of the Caribbean: Dead Men Tell No Tales (2017)
tt3778644	Solo: A Star Wars Story (2018)
tt1077368	Dark Shadows (2012)
tt4975722	Moonlight (2016)
tt1302011	Kung Fu Panda 2 (2011)
tt0338526	Van Helsing (2004)
tt1959490	Noah (2014)
tt1706593	Chronicle (2012)

tt0298203	8 Mile (2002)
tt0443272	Lincoln (2012)
tt0783233	Atonement (2007)
tt1601913	The Grey (2011)
tt2316204	Alien: Covenant (2017)
tt1386703	Total Recall (2012)
tt0257044	Road to Perdition (2002)
tt0368447	The Village (2004)
tt0497465	Vicky Cristina Barcelona (2008)
tt0151804	Office Space (1999)
tt1817273	The Place Beyond the Pines (2012)
tt0120611	Blade (1998)
tt3521164	Moana (2016)
tt2397535	Predestination (2014)
tt0803096	Warcraft: The Beginning (2016)
tt3076658	Creed (2015)
tt0252866	American Pie 2 (2001)
tt0215750	Enemy at the Gates (2001)
tt1440129	Battleship (2012)
tt2737304	Bird Box (2018)
tt0120762	Mulan (1998)
tt1028532	Hachi: A Dog's Tale (2009)
tt0221027	Blow (2001)
tt0121164	Corpse Bride (2005)
tt1931533	Seven Psychopaths (2012)
tt4881806	Jurassic World: Fallen Kingdom (2018)
tt1033575	The Descendants (2011)
tt0113189	GoldenEye (1995)
tt0824747	Changeling (2008)
tt1386588	The Other Guys (2010)
tt0053291	Some Like It Hot (1959)
tt0479884	Crank (2006)
tt6966692	Green Book (2018)
tt0107614	Mrs. Doubtfire (1993)
tt0070735	The Sting (1973)
tt0099348	Dances with Wolves (1990)
tt0120812	Rush Hour (1998)
tt1092026	Paul (2011)
tt0363547	Dawn of the Dead (2004)
tt0457939	The Holiday (2006)
tt0112462	Batman Forever (1995)
tt0448134	Sunshine (2007)
tt0463985	The Fast and the Furious: Tokyo Drift (2006)
tt0118749	Boogie Nights (1997)
tt1032755	RocknRolla (2008)

tt0396171	Perfume: The Story of a Murderer (2006)
tt0093409	Lethal Weapon (1987)
tt0072890	Dog Day Afternoon (1975)
tt0118688	Batman & Robin (1997)
tt0089218	The Goonies (1985)
tt0978764	Sucker Punch (2011)
tt0432348	Saw II (2005)
tt0976051	The Reader (2008)
tt3110958	Now You See Me 2 (2016)
tt1464540	I Am Number Four (2011)
tt1655442	The Artist (2011)
tt0144117	The Boondock Saints (1999)
tt0185937	The Blair Witch Project (1999)
tt1192628	Rango (2011)
tt2229499	Don Jon (2013)
tt0414993	The Fountain (2006)
tt4034228	Manchester by the Sea (2016)
tt1673434	The Twilight Saga: Breaking Dawn - Part 2 (2012)
tt2277860	Finding Dory (2016)
tt0175142	Scary Movie (2000)
tt0104257	A Few Good Men (1992)
tt0093870	RoboCop (1987)
tt0097757	The Little Mermaid (1989)
tt0102057	Hook (1991)
tt0765443	Eastern Promises (2007)
tt0825232	The Bucket List (2007)
tt0364725	Dodgeball: A True Underdog Story (2004)
tt3079380	Spy (2015)
tt1212450	Lawless (2012)
tt0985699	Valkyrie (2008)
tt0134847	Pitch Black (2000)
tt1823672	Chappie (2015)
tt0478087	21 (2008)
tt0120660	Enemy of the State (1998)
tt0315733	21 Grams (2003)
tt1211956	Escape Plan (2013)
tt1855199	End of Watch (2012)
tt1731141	Ender's Game (2013)
tt0195714	Final Destination (2000)
tt1375670	Grown Ups (2010)
tt0118583	Alien: Resurrection (1997)
tt0077631	Grease (1978)
tt0082096	Das Boot (1981)
tt0430922	Role Models (2008)
tt0399146	A History of Violence (2005)

tt2660888	Star Trek Beyond (2016)
tt0183505	Me Myself & Irene (2000)
tt0309698	Identity (2003)
tt0259324	Ghost Rider (2007)
tt0381681	Before Sunset (2004)
tt3606756	Incredibles 2 (2018)
tt1210819	The Lone Ranger (2013)
tt0448011	Knowing (2009)
tt0163978	The Beach (2000)
tt1324999	The Twilight Saga: Breaking Dawn - Part 1 (2011)
tt1588173	Warm Bodies (2013)
tt1001526	Megamind (2010)
tt1179904	Paranormal Activity (2007)
tt0898367	The Road (2009)
tt0059578	For a Few Dollars More (1965)
tt0083987	Gandhi (1982)
tt0486822	Disturbia (2007)
tt0112442	Bad Boys (1995)
tt0245712	Amores Perros (2000)
tt0243155	Bridget Jones's Diary (2001)
tt1124035	The Ides of March (2011)
tt1243957	The Tourist (2010)
tt0107818	Philadelphia (1993)
tt0420223	Stranger Than Fiction (2006)
tt0172156	Bad Boys II (2003)
tt4550098	Nocturnal Animals (2016)
tt0077651	Halloween (1978)
tt1234721	RoboCop (2014)
tt0427944	Thank You for Smoking (2005)
tt0057115	The Great Escape (1963)
tt0465234	National Treasure: Book of Secrets (2007)
tt0837562	Hotel Transylvania (2012)
tt1080016	Ice Age: Dawn of the Dinosaurs (2009)
tt3263904	Sully (2016)
tt2209764	Transcendence (2014)
tt0145660	Austin Powers: The Spy Who Shagged Me (1999)
tt0296572	The Chronicles of Riddick (2004)
tt0302886	Old School (2003)
tt3450958	War for the Planet of the Apes (2017)
tt0083944	First Blood (1982)
tt0095765	Cinema Paradiso (1988)
tt0384537	Silent Hill (2006)
tt0983193	The Adventures of Tintin (2011)
tt0373469	Kiss Kiss Bang Bang (2005)
tt1564367	Just Go with It (2011)

tt0462499	Rambo (2008)
tt4046784	Maze Runner: The Scorch Trials (2015)
tt0052618	Ben-Hur (1959)
tt1485796	The Greatest Showman (2017)
tt1598778	Contagion (2011)
tt0133152	Planet of the Apes (2001)
tt0109445	Clerks (1994)
tt0335345	The Passion of the Christ (2004)
tt0138097	Shakespeare in Love (1998)
tt0333766	Garden State (2004)
tt0080678	The Elephant Man (1980)
tt1798684	Southpaw (2015)
tt0110632	Natural Born Killers (1994)
tt2908446	Insurgent (2015)
tt1424381	Predators (2010)
tt0758774	Body of Lies (2008)
tt1922777	Sinister (2012)
tt0095327	Grave of the Fireflies (1988)
tt0408306	Munich (2005)
tt1832382	A Separation (2011)
tt0120655	Dogma (1999)
tt0045152	Singin' in the Rain (1952)
tt1411238	No Strings Attached (2011)
tt1132620	The Girl with the Dragon Tattoo (2009)
tt0485947	Mr. Nobody (2009)
tt0108550	What's Eating Gilbert Grape (1993)
tt0287978	Daredevil (2003)
tt3065204	The Conjuring 2 (2016)
tt0116996	Mars Attacks! (1996)
tt1220719	Ip Man (2008)
tt1189340	The Lincoln Lawyer (2011)
tt0409847	Cowboys & Aliens (2011)
tt0117509	Romeo + Juliet (1996)
tt0119643	Meet Joe Black (1998)
tt1321870	Gangster Squad (2013)
tt1139797	Let the Right One In (2008)
tt2293640	Minions (2015)
tt0795421	Mamma Mia! (2008)
tt2126355	San Andreas (2015)
tt0123755	Cube (1997)
tt1599348	Safe House (2012)
tt2381941	Focus (2015)
tt1605630	American Reunion (2012)
tt2361509	The Intern (2015)
tt1291150	Teenage Mutant Ninja Turtles (2014)

tt2334879	White House Down (2013)
tt0246460	Die Another Day (2002)
tt0305224	Anger Management (2003)
tt1623205	Oz the Great and Powerful (2013)
tt0319343	Elf (2003)
tt0416320	Match Point (2005)
tt0431308	P.S. I Love You (2007)
tt4196776	Jason Bourne (2016)
tt0080339	Airplane! (1980)
tt0479143	Rocky Balboa (2006)
tt1046173	G.I. Joe: The Rise of Cobra (2009)
tt0376541	Closer (2004)
tt0308644	Finding Neverland (2004)
tt0265208	The Girl Next Door (2004)
tt1142988	The Ugly Truth (2009)
tt0425061	Get Smart (2008)
tt0311113	Master and Commander: The Far Side of the World (2003)
tt4160708	Don't Breathe (2016)
tt1077258	Planet Terror (2007)
tt0108399	True Romance (1993)
tt1606378	A Good Day to Die Hard (2013)
tt0281358	A Walk to Remember (2002)
tt0112281	Ace Ventura: When Nature Calls (1995)
tt1980209	Pain & Gain (2013)
tt1289401	Ghostbusters (2016)
tt0452608	Death Race (2008)
tt0064115	Butch Cassidy and the Sundance Kid (1969)
tt0187738	Blade II (2002)
tt0844471	Cloudy with a Chance of Meatballs (2009)
tt0050212	The Bridge on the River Kwai (1957)
tt0949731	The Happening (2008)
tt0181865	Traffic (2000)
tt0146316	Lara Croft: Tomb Raider (2001)
tt0106519	Carlito's Way (1993)
tt0087800	A Nightmare on Elm Street (1984)
tt1155056	I Love You Man (2009)
tt0435625	The Descent (2005)
tt0479952	Madagascar: Escape 2 Africa (2008)
tt0339291	Lemony Snicket's A Series of Unfortunate Events (2004)
tt0374900	Napoleon Dynamite (2004)
tt0295178	Austin Powers in Goldmember (2002)
tt0210945	Remember the Titans (2000)
tt2184339	The Purge (2013)
tt0481369	The Number 23 (2007)
tt3464902	The Lobster (2015)

tt3235888	It Follows (2014)
tt0119282	Hercules (1997)
tt1428538	Hansel & Gretel: Witch Hunters (2013)
tt0170016	How the Grinch Stole Christmas (2000)
tt0120855	Tarzan (1999)
tt0059742	The Sound of Music (1965)
tt3741834	Lion (2016)
tt0328828	American Wedding (2003)
tt0158983	South Park: Bigger Longer & Uncut (1999)
tt0032553	The Great Dictator (1940)
tt1272878	2 Guns (2013)
tt1815862	After Earth (2013)
tt2719848	Everest (2015)
tt1284575	Bad Teacher (2011)
tt0116483	Happy Gilmore (1996)
tt0207201	What Women Want (2000)
tt0043014	Sunset Blvd. (1950)
tt4925292	Lady Bird (2017)
tt0401855	Underworld: Evolution (2006)
tt3402236	Murder on the Orient Express (2017)
tt0388482	Transporter 2 (2005)
tt0499448	The Chronicles of Narnia: Prince Caspian (2008)
tt2234155	The Internship (2013)
tt0099653	Ghost (1990)
tt0094737	Big (1988)
tt2334873	Blue Jasmine (2013)
tt0993842	Hanna (2011)
tt0130827	Run Lola Run (1998)
tt0327597	Coraline (2009)
tt0959337	Revolutionary Road (2008)
tt1649419	The Impossible (2012)
tt0058461	A Fistful of Dollars (1964)
tt0087363	Gremlins (1984)
tt1636826	Project X (2012)
tt1219827	Ghost in the Shell (2017)
tt0960144	You Don't Mess with the Zohan (2008)
tt2582782	Hell or High Water (2016)
tt0128853	You've Got Mail (1998)
tt0098635	When Harry Met Sally... (1989)
tt0371724	The Hitchhiker's Guide to the Galaxy (2005)
tt0432283	Fantastic Mr. Fox (2009)
tt0118929	Dark City (1998)
tt0079501	Mad Max (1979)
tt0481499	The Croods (2013)
tt1127180	Drag Me to Hell (2009)

tt1667889	Ice Age: Continental Drift (2012)
tt0143145	The World Is Not Enough (1999)
tt0092890	Dirty Dancing (1987)
tt1148204	Orphan (2009)
tt0088846	Brazil (1985)
tt0318627	Resident Evil: Apocalypse (2004)
tt0117665	Sleepers (1996)
tt2883512	Chef (2014)
tt0397892	Bolt (2008)
tt1340800	Tinker Tailor Soldier Spy (2011)
tt0103874	Bram Stoker's Dracula (1992)
tt0079817	Rocky II (1979)
tt1606389	The Vow (2012)
tt0370263	Alien vs. Predator (2004)
tt1111422	The Taking of Pelham 123 (2009)
tt1305806	The Secret in Their Eyes (2009)
tt0432021	Resident Evil: Extinction (2007)
tt0477080	Unstoppable (2010)
tt2321549	The Babadook (2014)
tt4846340	Hidden Figures (2016)
tt1646987	Wrath of the Titans (2012)
tt0366551	Harold & Kumar Go to White Castle (2004)
tt0120685	Godzilla (1998)
tt1723811	Shame (2011)
tt0914798	The Boy in the Striped Pajamas (2008)
tt5362988	Wind River (2017)
tt0063522	Rosemary's Baby (1968)
tt0212346	Miss Congeniality (2000)
tt1120985	Blue Valentine (2010)
tt0083907	The Evil Dead (1981)
tt0363988	Secret Window (2004)
tt1972591	King Arthur: Legend of the Sword (2017)
tt0089927	Rocky IV (1985)
tt1013743	Knight and Day (2010)
tt0375063	Sideways (2004)
tt0488120	Fracture (2007)
tt2404435	The Magnificent Seven (2016)
tt0139134	Cruel Intentions (1999)
tt4123430	Fantastic Beasts: The Crimes of Grindelwald (2018)
tt0096438	Who Framed Roger Rabbit (1988)
tt0244244	Swordfish (2001)
tt0120347	Tomorrow Never Dies (1997)
tt2053463	Side Effects (2013)
tt1458175	The Next Three Days (2010)
tt0241303	Chocolat (2000)

tt0892791	Shrek Forever After (2010)
tt0097428	Ghostbusters II (1989)
tt0080455	The Blues Brothers (1980)
tt0758752	Love & Other Drugs (2010)
tt0075860	Close Encounters of the Third Kind (1977)
tt2094766	Assassin's Creed (2016)
tt0385752	The Golden Compass (2007)
tt0974661	17 Again (2009)
tt0118571	Air Force One (1997)
tt1596350	This Means War (2012)
tt0114898	Waterworld (1995)
tt0881320	Sanctum (2011)
tt0218839	Best in Show (2000)
tt4680182	Colossal (2016)
tt0119874	The Peacemaker (1997)
tt0029947	Bringing Up Baby (1938)
tt1226774	In the Loop (2009)
tt0053221	Rio Bravo (1959)
tt0403508	The Sisterhood of the Traveling Pants (2005)
tt1179891	My Bloody Valentine (2009)
tt0114787	Underground (1995)
tt1971325	Automata (2014)
tt0060176	Blow-Up (1966)
tt0365376	A Tale of Two Sisters (2003)
tt0099329	Cry-Baby (1990)
tt0787474	The Boxtrolls (2014)
tt7401588	Instant Family (2018)
tt1800302	Gold (2016)
tt4624424	Storks (2016)
tt0139414	Lake Placid (1999)
tt0108002	Rudy (1993)
tt0452598	Cheaper by the Dozen 2 (2005)
tt0218922	Original Sin (2001)
tt0185371	House on Haunted Hill (1999)
tt0403358	Night Watch (2004)
tt1389096	Stand Up Guys (2012)
tt1185834	Star Wars: The Clone Wars (2008)
tt1043726	The Legend of Hercules (2014)
tt0203119	Sexy Beast (2000)
tt0102536	Night on Earth (1991)
tt0116830	Last Man Standing (1996)
tt0088680	After Hours (1985)
tt4560436	Mile 22 (2018)
tt0010323	The Cabinet of Dr. Caligari (1920)
tt0042546	Harvey (1950)

tt0093260	Innerspace (1987)
tt0237572	The Pledge (2001)
tt0089885	Re-Animator (1985)
tt0271367	Eight Legged Freaks (2002)
tt1190539	The Chaser (2008)
tt0071877	Murder on the Orient Express (1974)
tt0261983	Session 9 (2001)
tt0103939	Chaplin (1992)
tt0268995	The Majestic (2001)
tt0338459	Spy Kids 3-D: Game Over (2003)
tt0254686	The Piano Teacher (2001)
tt0238546	Queen of the Damned (2002)
tt0377062	Flight of the Phoenix (2004)
tt0460829	Inland Empire (2006)
tt0382992	Stealth (2005)
tt1176740	Away We Go (2009)
tt0105151	The Player (1992)
tt5657846	Daddy's Home Two (2017)
tt0377981	Gnomeo & Juliet (2011)
tt0086425	Terms of Endearment (1983)
tt2788732	Pete's Dragon (2016)
tt3416828	Ice Age: Collision Course (2016)
tt5886046	Escape Room (2019)
tt0082158	Chariots of Fire (1981)
tt0079367	The Jerk (1979)
tt0355702	Lords of Dogtown (2005)
tt0089907	The Return of the Living Dead (1985)
tt0111742	Wolf (1994)
tt0105265	A River Runs Through It (1992)
tt0180073	Quills (2000)
tt0120877	Vampires (1998)
tt2223990	Draft Day (2014)
tt1334512	Arthur (2011)
tt2869728	Ride Along 2 (2016)
tt0821642	The Soloist (2009)
tt0402910	Chaos (2005)
tt0375154	Tristan + Isolde (2006)
tt2404425	Woman in Gold (2015)
tt0102070	Hudson Hawk (1991)
tt0102803	The Rocketeer (1991)
tt0125022	Heartbreakers (2001)
tt0242519	Hera Pheri (2000)
tt0032599	His Girl Friday (1940)
tt0398375	Rumor Has It... (2005)
tt0810922	Take Me Home Tonight (2011)

tt2268016	Magic Mike XXL (2015)
tt1567437	The Voices (2014)
tt4387040	Airlift (2016)
tt0327137	Secondhand Lions (2003)
tt0251114	Hart's War (2002)
tt1403177	Hesher (2010)
tt3848892	Baby (2015)
tt0046268	The Wages of Fear (1953)
tt2176013	Jab Tak Hai Jaan (2012)
tt0119223	Great Expectations (1998)
tt0112346	The American President (1995)
tt0427312	Grizzly Man (2005)
tt0144120	Bride of Chucky (1998)
tt0015648	Battleship Potemkin (1925)
tt0375173	Alfie (2004)
tt1703199	Grave Encounters (2011)
tt0837563	Pet Sematary (2019)
tt0228333	Ghosts of Mars (2001)
tt2463288	Walk of Shame (2014)
tt0046359	Stalag 17 (1953)
tt0795493	Cassandra's Dream (2007)
tt3203616	The Cobbler (2014)
tt0115964	Crash (1996)
tt0130623	Dinosaur (2000)
tt0103060	Teenage Mutant Ninja Turtles II: The Secret of the Ooze (1991)
tt0096463	Working Girl (1988)
tt2937696	Everybody Wants Some!! (2016)
tt0800241	Transsiberian (2008)
tt0093693	Overboard (1987)
tt0811138	The Love Guru (2008)
tt0245686	Joe Dirt (2001)
tt0074812	Logan's Run (1976)
tt0119715	Mousehunt (1997)
tt3960412	Popstar: Never Stop Never Stopping (2016)
tt1976009	Victor Frankenstein (2015)
tt0107302	Kalifornia (1993)
tt0087553	The Killing Fields (1984)
tt0292644	The Rules of Attraction (2002)
tt4361050	Ouija: Origin of Evil (2016)
tt0087985	Red Dawn (1984)
tt0421238	The Proposition (2005)
tt0065207	Where Eagles Dare (1968)
tt0762125	Planet 51 (2009)
tt0096764	The Adventures of Baron Munchausen (1988)
tt0104036	The Crying Game (1992)

tt2361317	Live by Night (2016)
tt4468740	Paddington 2 (2017)
tt0347048	Head-On (2004)
tt0115736	Bound (1996)
tt0089822	Police Academy 2: Their First Assignment (1985)
tt0118843	Black Cat White Cat (1998)
tt1850397	The Loft (2014)
tt4225622	The Babysitter (2017)
tt1139668	The Unborn (2009)
tt2771372	Veronica Mars (2014)
tt4547056	The Girl with All the Gifts (2016)
tt0058946	The Battle of Algiers (1966)
tt0119558	Lolita (1997)
tt2718492	Ida (2013)
tt0115956	Courage Under Fire (1996)
tt0070909	Westworld (1973)
tt0026029	The 39 Steps (1935)
tt0108333	The Three Musketeers (1993)
tt3169706	Pride (2014)
tt6265828	A Ghost Story (2017)
tt1764183	Arbitrage (2012)
tt0086837	2010: The Year We Make Contact (1984)
tt0068182	Aguirre the Wrath of God (1972)
tt1414382	You Again (2010)
tt0211443	Jason X (2001)
tt0089370	The Jewel of the Nile (1985)
tt2547584	The Light Between Oceans (2016)
tt0294870	Rent (2005)
tt2481498	Extremely Wicked Shockingly Evil and Vile (2019)
tt0089791	Pee-wee's Big Adventure (1985)
tt0077745	Invasion of the Body Snatchers (1978)
tt0362225	Tell No One (2006)
tt0095497	The Last Temptation of Christ (1988)
tt1285241	Don 2 (2011)
tt0111686	Wes Craven's New Nightmare (1994)
tt0120399	U Turn (1997)
tt0073707	Sholay (1975)
tt0430304	Little Man (2006)
tt0181984	Boiler Room (2000)
tt0063462	The Producers (1967)
tt1374989	Pride and Prejudice and Zombies (2016)
tt0179626	15 Minutes (2001)
tt0078935	Cannibal Holocaust (1980)
tt0297181	I Spy (2002)
tt3553442	Whiskey Tango Foxtrot (2016)

tt0312528	The Cat in the Hat (2003)
tt0844286	The Brothers Bloom (2008)
tt3829920	Only the Brave (2017)
tt0419677	Dead Man's Shoes (2004)
tt0947802	Lakeview Terrace (2008)
tt2614684	71 (2014)
tt1212436	The Back-up Plan (2010)
tt2066051	Rocketman (2019)
tt3390572	Haider (2014)
tt0227984	Formula 51 (2001)
tt6679794	Outlaw King (2018)
tt0091541	The Money Pit (1986)
tt0077405	Days of Heaven (1978)
tt0080745	Flash Gordon (1980)
tt0106673	Dave (1993)
tt0247586	Nine Queens (2000)
tt0443632	The Sentinel (2006)
tt6998518	Mandy (2018)
tt0260866	Don't Say a Word (2001)
tt1410063	The Flowers of War (2011)
tt1531663	Everything Must Go (2010)
tt4765284	Pitch Perfect 3 (2017)
tt1320244	The Last Exorcism (2010)
tt0362269	Kinsey (2004)
tt0088000	Revenge of the Nerds (1984)
tt0243585	Stuart Little 2 (2002)
tt0096933	Black Rain (1989)
tt0109117	Andaz Apna Apna (1994)
tt8108198	Andhadhun (2018)
tt0112950	Empire Records (1995)
tt2377938	Special 26 (2013)
tt1430607	Arthur Christmas (2011)
tt1024255	Wild Child (2008)
tt0891527	Lions for Lambs (2007)
tt0056687	What Ever Happened to Baby Jane? (1962)
tt1124037	Free State of Jones (2016)
tt2461150	Masterminds (2016)
tt0068699	High Plains Drifter (1973)
tt0095174	Frantic (1988)
tt0375210	White Noise (2005)
tt1135487	Duplicity (2009)
tt1313104	The Cove (2009)
tt0095742	A Nightmare on Elm Street 4: The Dream Master (1988)
tt0070849	Last Tango in Paris (1972)
tt0880578	Untraceable (2008)

tt4226388	Victoria (2015)
tt4532826	Robin Hood (2018)
tt4136084	Florence Foster Jenkins (2016)
tt1321860	The Beaver (2011)
tt7014006	Eighth Grade (2018)
tt0420332	Veer-Zaara (2004)
tt0090633	An American Tail (1986)
tt0304669	The Santa Clause 2 (2002)
tt1084950	Rachel Getting Married (2008)
tt2112124	Chennai Express (2013)
tt0165982	Sinbad: Legend of the Seven Seas (2003)
tt0098724	Sex Lies and Videotape (1989)
tt2967224	Hot Pursuit (2015)
tt2283748	OMG: Oh My God! (2012)
tt0066434	THX 1138 (1971)
tt1294688	Last Night (2010)
tt1311067	Halloween II (2009)
tt3064298	Man Up (2015)
tt4477536	Fifty Shades Freed (2018)
tt0057413	The Pink Panther (1963)
tt0084434	An Officer and a Gentleman (1982)
tt2452244	Isn't It Romantic (2019)
tt0098621	The War of the Roses (1989)
tt0098627	Weekend at Bernie's (1989)
tt0299930	Gigli (2003)
tt0118771	Breakdown (1997)
tt1270761	Don't Be Afraid of the Dark (2010)
tt2103254	Tammy (2014)
tt0475944	The Covenant (2006)
tt0433386	The Grudge 2 (2006)
tt0097647	The Karate Kid Part III (1989)
tt0101587	City Slickers (1991)
tt1175491	W. (2008)
tt1931435	The Big Wedding (2013)
tt1204977	Ouija (2014)
tt0046438	Tokyo Story (1953)
tt0848557	Diary of the Dead (2007)
tt0983213	5 Centimeters Per Second (2007)
tt1825157	The Double (2013)
tt1205535	The Rebound (2009)
tt2170299	Bad Words (2013)
tt0113117	French Kiss (1995)
tt1666186	Vampires Suck (2010)
tt0093565	Moonstruck (1987)
tt1767354	Odd Thomas (2013)

tt0089155	Fletch (1985)
tt2106651	Spectral (2016)
tt2279373	The SpongeBob Movie: Sponge Out of Water (2015)
tt0110367	Little Women (1994)
tt0977855	Fair Game (2010)
tt0240515	Freddy Got Fingered (2001)
tt0059646	Repulsion (1965)
tt0068327	Cabaret (1972)
tt1017451	The Runaways (2010)
tt0094812	Bull Durham (1988)
tt0104684	Hard Boiled (1992)
tt4622512	Battle of the Sexes (2017)
tt5220122	Hotel Transylvania 3: Summer Vacation (2018)
tt0090967	Down by Law (1986)
tt0815244	Sydney White (2007)
tt5592248	The Beguiled (2017)
tt0018455	Sunrise (1927)
tt4244998	Alpha (2018)
tt0172684	Kuch Kuch Hota Hai (1998)
tt0331632	Scooby-Doo 2: Monsters Unleashed (2004)
tt0349825	Miracle (2004)
tt1068242	Footloose (2011)
tt0069995	Don't Look Now (1973)
tt0094137	3 Men and a Baby (1987)
tt0081455	Scanners (1981)
tt4853102	Batman: The Killing Joke (2016)
tt5726086	Insidious: The Last Key (2018)
tt0124198	Very Bad Things (1998)
tt0085549	Flashdance (1983)
tt0118789	Buffalo '66 (1998)
tt0155975	Psycho (1998)
tt6133466	The First Purge (2018)
tt0119707	Mortal Kombat: Annihilation (1997)
tt0102511	Naked Lunch (1991)
tt2382396	Joe (2013)
tt0073802	Three Days of the Condor (1975)
tt0119675	Mimic (1997)
tt0087050	Children of the Corn (1984)
tt0082517	History of the World: Part I (1981)
tt2350496	The Lunchbox (2013)
tt1214962	Seeking Justice (2011)
tt0030341	The Lady Vanishes (1938)
tt0104940	The Muppet Christmas Carol (1992)
tt0108330	This Boy's Life (1993)
tt0109635	Disclosure (1994)

tt0365485	The Matador (2005)
tt1093370	Jab We Met (2007)
tt0457433	Perfect Stranger (2007)
tt0460989	The Wind that Shakes the Barley (2006)
tt0293715	My Sassy Girl (2001)
tt1321509	Death at a Funeral (2010)
tt0331811	11:14 (2003)
tt1748227	The Collection (2012)
tt0107616	Much Ado About Nothing (1993)
tt0460780	In the Name of the King: A Dungeon Siege Tale (2007)
tt0367479	After the Sunset (2004)
tt2752772	Sinister 2 (2015)
tt0242527	The Hole (2001)
tt0416044	Mongol: The Rise of Genghis Khan (2007)
tt2333804	The Zero Theorem (2013)
tt0105104	Passenger 57 (1992)
tt0400497	Herbie Fully Loaded (2005)
tt0421206	Gridiron Gang (2006)
tt5610554	Tully (2018)
tt0141369	Inspector Gadget (1999)
tt0283509	No Man's Land (2001)
tt0054953	The Guns of Navarone (1961)
tt0127723	Can't Hardly Wait (1998)
tt4005402	The Colony (2015)
tt1430626	The Pirates! Band of Misfits (2012)
tt5688932	Sorry to Bother You (2018)
tt1626146	Hector and the Search for Happiness (2014)
tt0424993	Employee of the Month (2006)
tt0418455	Adam's Apples (2005)
tt0069281	Sleuth (1972)
tt7043012	Velvet Buzzsaw (2019)
tt1480656	Cosmopolis (2012)
tt1572315	Texas Chainsaw 3D (2013)
tt0090142	Teen Wolf (1985)
tt4139124	Keanu (2016)
tt0083972	Friday the 13th Part III (1982)
tt0160797	Rules of Engagement (2000)
tt1640459	Hobo with a Shotgun (2011)
tt1596346	Soul Surfer (2011)
tt2091935	Mr. Right (2015)
tt0473308	Waitress (2007)
tt0233142	3000 Miles to Graceland (2001)
tt0398913	DOA: Dead or Alive (2006)
tt0364751	Without a Paddle (2004)
tt0240468	Kung Pow: Enter the Fist (2002)

tt1416801	Kill the Irishman (2011)
tt1182350	You Will Meet a Tall Dark Stranger (2010)
tt2592910	CM101MMXI Fundamentals (2013)
tt0425637	Red Cliff (2008)
tt0049223	Forbidden Planet (1956)
tt0092610	Bad Taste (1987)
tt0021814	Dracula (1931)
tt1656186	Stolen (2012)
tt0124718	He Got Game (1998)
tt0102034	Highlander II: The Quickening (1991)
tt0114781	Under Siege 2: Dark Territory (1995)
tt1181791	Black Death (2010)
tt1247640	District 13: Ultimatum (2009)
tt2375559	1 - Nenokkadine (2014)
tt0098067	Parenthood (1989)
tt0076729	Smokey and the Bandit (1977)
tt0113198	A Goofy Movie (1995)
tt0322589	Honey (2003)
tt6452574	Sanju (2018)
tt1621045	Think Like a Man (2012)
tt0377107	Proof (2005)
tt3099498	Tusk (2014)
tt0019254	The Passion of Joan of Arc (1928)
tt0813547	The Counterfeiters (2007)
tt0107076	Hard Target (1993)
tt0090056	Spies Like Us (1985)
tt0113824	Whisper of the Heart (1995)
tt0073341	The Man Who Would Be King (1975)
tt0049366	Invasion of the Body Snatchers (1956)
tt1160996	The Colony (2013)
tt1046163	My Best Friend's Girl (2008)
tt0446013	Pathfinder (2007)
tt0424880	Candy (2006)
tt0875034	Nine (2009)
tt3411444	Ferdinand (2017)
tt0191754	28 Days (2000)
tt0051459	Cat on a Hot Tin Roof (1958)
tt5390504	Detroit (2017)
tt6791096	I Feel Pretty (2018)
tt0444682	The Reaping (2007)
tt1727776	Scouts Guide to the Zombie Apocalypse (2015)
tt0450405	Cirque du Freak: The Vampire's Assistant (2009)
tt0099253	Child's Play 2 (1990)
tt0058329	Marnie (1964)
tt1083456	Fired Up! (2009)

tt0091149	The Great Mouse Detective (1986)
tt1833673	Dhoom 3 (2013)
tt0369226	Alone in the Dark (2005)
tt0457419	Mr. Magorium's Wonder Emporium (2007)
tt0091059	Flight of the Navigator (1986)
tt1182937	Rab Ne Bana Di Jodi (2008)
tt0089092	Enemy Mine (1985)
tt0248126	Kabhi Khushi Kabhie Gham... (2001)
tt0473444	Curse of the Golden Flower (2006)
tt1421051	Somewhere (2010)
tt1034415	Suspiria (2018)
tt0455857	When a Stranger Calls (2006)
tt4799050	Rough Night (2017)
tt0074896	The Message (1976)
tt0857191	The Visitor (2007)
tt1073105	The Descent: Part 2 (2009)
tt0385726	Glory Road (2006)
tt0107050	Grumpy Old Men (1993)
tt0087781	The Natural (1984)
tt1691917	Planes (2013)
tt0050613	Throne of Blood (1957)
tt1470023	MacGruber (2010)
tt0300140	Lilya 4-Ever (2002)
tt0089457	Ladyhawke (1985)
tt0434139	The Last Kiss (2006)
tt0091225	Howard the Duck (1986)
tt0091217	Hoosiers (1986)
tt1244754	Conviction (2010)
tt0091209	The Hitcher (1986)
tt1691916	Before I Fall (2017)
tt0108122	Short Cuts (1993)
tt0131369	Edtv (1999)
tt2932536	47 Meters Down (2017)
tt0094074	Superman IV: The Quest for Peace (1987)
tt1716777	People Like Us (2012)
tt0095776	Oliver & Company (1988)
tt4080728	A Man Called Ove (2015)
tt1232207	Capitalism: A Love Story (2009)
tt0347618	The Cat Returns (2002)
tt0045793	From Here to Eternity (1953)
tt1053810	The Big Year (2011)
tt0454824	Flyboys (2006)
tt1838544	Gone (2012)
tt0309377	Blood Work (2002)
tt1674784	Trespass (2011)

tt0074156	Assault on Precinct 13 (1976)
tt0324133	Swimming Pool (2003)
tt1231580	Alvin and the Chipmunks: The Squeakquel (2009)
tt0038109	Spellbound (1945)
tt1529572	Trust (2010)
tt0062229	Le SamouraÃ¯ (1967)
tt0871426	Baby Mama (2008)
tt0112715	Congo (1995)
tt0838232	The Pink Panther 2 (2009)
tt1967545	Labor Day (2013)
tt2702724	The Boss (2016)
tt0436339	G-Force (2009)
tt0088172	Starman (1984)
tt0095271	Halloween 4: The Return of Michael Myers (1988)
tt1720616	Friends with Kids (2011)
tt0780622	Teeth (2007)
tt0026138	Bride of Frankenstein (1935)
tt0087298	Friday the 13th: The Final Chapter (1984)
tt2452042	The Peanuts Movie (2015)
tt0060107	Andrei Rublev (1966)
tt3495026	Fan (2016)
tt0490086	Big Stan (2007)
tt0139699	Varsity Blues (1999)
tt6292852	I Am Mother (2019)
tt0091777	Police Academy 3: Back in Training (1986)
tt2479478	The Ridiculous 6 (2015)
tt0298845	In America (2002)
tt0065462	Beneath the Planet of the Apes (1970)
tt2034031	Laggies (2014)
tt1639426	Udaan (2010)
tt0065126	True Grit (1969)
tt0050783	The Nights of Cabiria (1957)
tt0202470	Rock Star (2001)
tt1881002	Maggie (2015)
tt1067774	Monte Carlo (2011)
tt0088794	Better Off Dead... (1985)
tt5710514	I Don't Feel at Home in This World Anymore. (2017)
tt1535438	Hope Springs (2012)
tt1082807	The Belko Experiment (2016)
tt0395251	The Producers (2005)
tt1584016	Catfish (2010)
tt1423995	Stone (2010)
tt0037008	Laura (1944)
tt0106364	Batman: Mask of the Phantasm (1993)
tt0455960	The Hitcher (2007)

tt0117038	Michael (1996)
tt0085636	Halloween III: Season of the Witch (1982)
tt1402488	Happy Feet Two (2011)
tt3097204	The Inbetweeners 2 (2014)
tt1598828	One for the Money (2012)
tt0114287	Rob Roy (1995)
tt3205376	Slow West (2015)
tt0798817	13 (2010)
tt0376968	The Return (2003)
tt0110997	The River Wild (1994)
tt4048272	Toni Erdmann (2016)
tt2402101	Dark Places (2015)
tt1369706	The Ward (2010)
tt0210070	Ginger Snaps (2000)
tt0338094	The Haunted Mansion (2003)
tt0472198	Notorious (2009)
tt1226271	The Damned United (2009)
tt0070510	Paper Moon (1973)
tt0219854	The Kid (2000)
tt0097027	Casualties of War (1989)
tt0808510	Tooth Fairy (2010)
tt0387514	Prime (2005)
tt2638144	Ben-Hur (2016)
tt2528814	God's Not Dead (2014)
tt0074483	The Enforcer (1976)
tt0067328	The Last Picture Show (1971)
tt0762073	Thirst (2009)
tt2318092	Endless Love (2014)
tt1291580	Behind the Candelabra (2013)
tt2918436	The Lazarus Effect (2015)
tt0421729	Big Momma's House 2 (2006)
tt0069113	The Poseidon Adventure (1972)
tt0881891	All About Steve (2009)
tt1216496	Mother (2009)
tt0104437	Honey I Blew Up the Kid (1992)
tt0083767	Creepshow (1982)
tt0189998	Shadow of the Vampire (2000)
tt2199711	Vishwaroopam (2013)
tt0070707	Sleeper (1973)
tt0082186	Clash of the Titans (1981)
tt0082085	Blow Out (1981)
tt0101917	Freddy's Dead: The Final Nightmare (1991)
tt3861390	Dumbo (2019)
tt0093886	Roxanne (1987)
tt0298228	Whale Rider (2002)

tt0095294	Hellbound: Hellraiser II (1988)
tt0093300	Jaws: The Revenge (1987)
tt0064505	The Italian Job (1969)
tt0779982	Black Sheep (2006)
tt0493405	CHIPS (2017)
tt1698641	Alexander and the Terrible Horrible No Good Very Bad Day (2014)
tt6850820	Peppermint (2018)
tt4781612	Imperium (2016)
tt0482527	It's a Boy Girl Thing (2006)
tt0093756	Police Academy 4: Citizens on Patrol (1987)
tt0086383	Sudden Impact (1983)
tt0084707	Sophie's Choice (1982)
tt0068611	Frenzy (1972)
tt2473682	Paranormal Activity: The Marked Ones (2014)
tt0116287	Fear (1996)
tt1714203	Piranha 3DD (2012)
tt0138510	Idle Hands (1999)
tt0486583	Fred Claus (2007)
tt0103893	Buffy the Vampire Slayer (1992)
tt1540011	Blair Witch (2016)
tt0395972	North Country (2005)
tt0094963	The Dead Pool (1988)
tt0419294	Three Burials (2005)
tt1114677	Hannah Montana: The Movie (2009)
tt0048028	East of Eden (1955)
tt0388419	Christmas with the Kranks (2004)
tt0275022	Crossroads (2002)
tt0097981	A Nightmare on Elm Street 5: The Dream Child (1989)
tt3405236	Raees (2017)
tt0058182	A Hard Day's Night (1964)
tt1172994	The House of the Devil (2009)
tt1273678	The Spy Next Door (2010)
tt1477715	This Is It (2009)
tt1571249	The Skeleton Twins (2014)
tt0239948	Saving Silverman (2001)
tt0272207	Narc (2002)
tt2994190	Camp X-Ray (2014)
tt0410097	Hustle & Flow (2005)
tt1064932	Welcome to the Sticks (2008)
tt0112453	Balto (1995)
tt0425430	The Messengers (2007)
tt0094964	Dead Ringers (1988)
tt3387542	The Forest (2016)
tt1340107	In a Better World (2010)
tt2274648	Hellboy (2019)

tt0763831	A Thousand Words (2012)
tt1667310	Deadfall (2012)
tt1186370	Spread (2009)
tt0133385	Asterix and Obelix vs. Caesar (1999)
tt1658837	The Tall Man (2012)
tt0288045	The Medallion (2003)
tt1787988	Talaash (2012)
tt0091187	Heartbreak Ridge (1986)
tt2938956	The Transporter Refueled (2015)
tt0170691	Tigerland (2000)
tt0119360	In & Out (1997)
tt4158096	Free Fire (2016)
tt0316465	Radio (2003)
tt1846589	Hunter Killer (2018)
tt0800240	Deception (2008)
tt1130988	JCVD (2008)
tt5215952	The Wailing (2016)
tt3758172	Jungle (2017)
tt0765476	Meet Dave (2008)
tt0091867	A Room with a View (1985)
tt2493486	Last Knights (2015)
tt1426329	Lovelace (2013)
tt0100258	Night of the Living Dead (1990)
tt0112896	Dracula: Dead and Loving It (1995)
tt1045670	Happy-Go-Lucky (2008)
tt3086442	Goodnight Mommy (2014)
tt0257756	High Crimes (2002)
tt0072308	The Towering Inferno (1974)
tt0113326	Rumble in the Bronx (1995)
tt0085750	Jaws 3-D (1983)
tt0068555	Everything You Always Wanted to Know About Sex * But Were Afraid to Ask (1972)
tt0119256	Hard Eight (1996)
tt0118708	Beverly Hills Ninja (1997)
tt0490084	Because I Said So (2007)
tt0337697	The Prince and Me (2004)
tt0913425	Broken Embraces (2009)
tt0896798	Cleaner (2007)
tt0386064	Tae Guk Gi: The Brotherhood of War (2004)
tt1078188	Boy A (2007)
tt1562871	Ra.One (2011)
tt0760329	The Water Horse (2007)
tt0092106	The Transformers: The Movie (1986)
tt0429591	Aquamarine (2006)
tt4520364	Morgan (2016)

tt0095253	The Great Outdoors (1988)
tt0099044	Another 48 Hrs. (1990)
tt0105275	Romper Stomper (1992)
tt1262981	World's Greatest Dad (2009)
tt6306064	Adrift (2018)
tt3401882	Fist Fight (2017)
tt1620680	A Wrinkle in Time (2018)
tt1024943	Om Shanti Om (2007)
tt2990140	The Christmas Chronicles (2018)
tt1031969	The Rocker (2008)
tt0084522	Porky's (1981)
tt0283003	Spun (2002)
tt0087597	The Last Starfighter (1984)
tt0061735	Guess Who's Coming to Dinner (1967)
tt0067093	Fiddler on the Roof (1971)
tt1251757	Middle Men (2009)
tt0430912	Basic Instinct 2 (2006)
tt0097770	Lock Up (1989)
tt1596345	Pawn Sacrifice (2014)
tt2172584	Maps to the Stars (2014)
tt3892172	Leave No Trace (2018)
tt0238936	Devdas (2002)
tt1314228	Did You Hear About the Morgans? (2009)
tt0259288	Dragonfly (2002)
tt1839596	Rockstar (2011)
tt3181822	The Boy Next Door (2015)
tt1827487	Once Upon a Time in Anatolia (2011)
tt0104389	The Hand That Rocks the Cradle (1992)
tt0103759	Bad Lieutenant (1992)
tt0063415	The Party (1968)
tt0098273	Sea of Love (1989)
tt0085382	Cujo (1983)
tt3513498	The Lego Movie 2: The Second Part (2019)
tt0057193	It's a Mad Mad Mad Mad World (1963)
tt0317676	House of the Dead (2003)
tt0808357	Lust Caution (2007)
tt2091473	Promised Land (2012)
tt6543652	Cold War (2018)
tt0281364	Wasabi (2001)
tt0100404	Presumed Innocent (1990)
tt6772950	Truth or Dare (2018)
tt0838247	After.Life (2009)
tt0091635	9Â½ Weeks (1986)
tt0856288	Inside (2007)
tt0069947	The Day of the Jackal (1973)

tt2637294	Hot Tub Time Machine 2 (2015)
tt0107507	Manhattan Murder Mystery (1993)
tt1783732	John Dies at the End (2012)
tt0498381	Rings (2017)
tt0775529	The Savages (2007)
tt3077214	Suffragette (2015)
tt1316536	The Loved Ones (2009)
tt0074811	The Tenant (1976)
tt0360139	Chasing Liberty (2004)
tt0329717	Hollywood Homicide (2003)
tt0454970	Turistas (2006)
tt0100477	The Rescuers Down Under (1990)
tt1303828	Defendor (2009)
tt2039338	Flatliners (2017)
tt1073241	Nothing But the Truth (2008)
tt2178470	Yeh Jawaani Hai Deewani (2013)
tt2396589	Mudbound (2017)
tt0115697	Black Sheep (1996)
tt0040506	Key Largo (1948)
tt2119543	The House with a Clock in Its Walls (2018)
tt0162677	Summer of Sam (1999)
tt0097162	Dead Calm (1989)
tt0220506	Halloween: Resurrection (2002)
tt0420238	The Tale of Despereaux (2008)
tt0082432	Gallipoli (1981)
tt0114319	Sabrina (1995)
tt0092513	Adventures in Babysitting (1987)
tt0090022	Silverado (1985)
tt0115759	Broken Arrow (1996)
tt0799934	Be Kind Rewind (2008)
tt1778304	Paranormal Activity 3 (2011)
tt1161864	The Rite (2011)
tt3063516	Bad Grandpa (2013)
tt0443701	The X Files: I Want to Believe (2008)
tt1179056	A Nightmare on Elm Street (2010)
tt0313542	Runaway Jury (2003)
tt0138524	Intolerable Cruelty (2003)
tt1216487	The Girl Who Played with Fire (2009)
tt0468492	The Host (2006)
tt0446755	The Painted Veil (2006)
tt0083929	Fast Times at Ridgemont High (1982)
tt0111070	The Santa Clause (1994)
tt0098084	Pet Sematary (1989)
tt0107206	In the Line of Fire (1993)
tt1109624	Paddington (2014)

tt0038787	Notorious (1946)
tt0362478	The Box (2009)
tt0025316	It Happened One Night (1934)
tt6139732	Aladdin (2019)
tt1078588	My Sister's Keeper (2009)
tt0302640	The Hot Chick (2002)
tt1781769	Anna Karenina (2012)
tt1226273	Edge of Darkness (2010)
tt0981227	Nick and Norah's Infinite Playlist (2008)
tt1590193	The Commuter (2018)
tt0104694	A League of Their Own (1992)
tt0114924	While You Were Sleeping (1995)
tt0106611	Cool Runnings (1993)
tt0406375	Zathura: A Space Adventure (2005)
tt0480255	The Losers (2010)
tt1470827	Monsters (2010)
tt0365686	Revolver (2005)
tt0348333	Waiting... (2005)
tt0082398	For Your Eyes Only (1981)
tt2548396	The Cloverfield Paradox (2018)
tt5758778	Skyscraper (2018)
tt4481414	Gifted (2017)
tt1397514	Journey 2: The Mysterious Island (2012)
tt0116705	Jingle All the Way (1996)
tt1532503	Beginners (2010)
tt0086567	WarGames (1983)
tt1791528	Inherent Vice (2014)
tt1477076	Saw 3D: The Final Chapter (2010)
tt0808279	Funny Games (2007)
tt3195644	Insidious: Chapter 3 (2015)
tt1564585	Skyline (2010)
tt1675192	Take Shelter (2011)
tt1232200	That's My Boy (2012)
tt0065421	The Aristocats (1970)
tt0126886	Election (1999)
tt0406816	The Guardian (2006)
tt5164432	Love Simon (2018)
tt0056193	Lolita (1962)
tt1213644	Disaster Movie (2008)
tt1204342	The Muppets (2011)
tt0401445	A Good Year (2006)
tt0960731	Bedtime Stories (2008)
tt3381008	The Brothers Grimsby (2016)
tt0119229	Grosse Pointe Blank (1997)
tt0117318	The People vs. Larry Flynt (1996)

tt1615160	The Foreigner (2017)
tt0082010	An American Werewolf in London (1981)
tt0079574	Moonraker (1979)
tt0357277	Elektra (2005)
tt1103153	Killers (2010)
tt2980592	The Guest (2014)
tt4465564	Fifty Shades Darker (2017)
tt0808417	Persepolis (2007)
tt0109444	Clear and Present Danger (1994)
tt0155267	The Thomas Crown Affair (1999)
tt2172934	3 Days to Kill (2014)
tt0117666	Sling Blade (1996)
tt0416236	The Spiderwick Chronicles (2008)
tt1385867	Cop Out (2010)
tt0464154	Piranha 3D (2010)
tt1985966	Cloudy with a Chance of Meatballs 2 (2013)
tt1714915	Only Lovers Left Alive (2013)
tt0204946	Bring It On (2000)
tt0032551	The Grapes of Wrath (1940)
tt0499556	War (2007)
tt0093428	The Living Daylights (1987)
tt0185125	All About My Mother (1999)
tt0054047	The Magnificent Seven (1960)
tt0013442	Nosferatu (1922)
tt2140379	Self/less (2015)
tt0057546	The Sword in the Stone (1963)
tt4016934	The Handmaiden (2016)
tt1230414	It's Complicated (2009)
tt4094724	The Purge: Election Year (2016)
tt1637706	Our Idiot Brother (2011)
tt1289406	Harry Brown (2009)
tt0395699	The Pacifier (2005)
tt2679042	Hitman: Agent 47 (2015)
tt1034331	Righteous Kill (2008)
tt0363589	Elephant (2003)
tt0111495	Three Colors: Red (1994)
tt2567026	Alice Through the Looking Glass (2016)
tt0498353	Hostel: Part II (2007)
tt0090264	A View to a Kill (1985)
tt0468489	Half Nelson (2006)
tt1164999	Biutiful (2010)
tt0213847	Malena (2000)
tt0914863	Unthinkable (2010)
tt0107120	Hocus Pocus (1993)
tt0396555	Meet the Robinsons (2007)

tt0086979	Blood Simple (1984)
tt0498399	We Own the Night (2007)
tt0120780	Out of Sight (1998)
tt1440292	Submarine (2010)
tt0058385	My Fair Lady (1964)
tt1559547	Beautiful Creatures (2013)
tt1135985	Sex Drive (2008)
tt1456635	Goon (2011)
tt1853739	You're Next (2011)
tt6266538	Vice (2018)
tt0460740	Cashback (2006)
tt0118887	Cop Land (1997)
tt1263670	Crazy Heart (2009)
tt1667353	Mirror Mirror (2012)
tt1486192	The Raven (2012)
tt0844708	The Last House on the Left (2009)
tt1859650	To Rome with Love (2012)
tt1655420	My Week with Marilyn (2011)
tt0095647	Mississippi Burning (1988)
tt4682786	Collateral Beauty (2016)
tt1981128	Geostorm (2017)
tt0455760	Dead Silence (2007)
tt0105417	Sister Act (1992)
tt0270288	Confessions of a Dangerous Mind (2002)
tt0327437	Around the World in 80 Days (2004)
tt0252076	Maid in Manhattan (2002)
tt0114214	The Quick and the Dead (1995)
tt0097493	Heathers (1988)
tt1506999	Haywire (2011)
tt0090329	Witness (1985)
tt0346156	Sky Captain and the World of Tomorrow (2004)
tt0285742	Monster's Ball (2001)
tt0371606	Chicken Little (2005)
tt3072482	Hardcore Henry (2015)
tt0094862	Child's Play (1988)
tt0100758	Teenage Mutant Ninja Turtles (1990)
tt0402399	The New World (2005)
tt0108394	Three Colors: Blue (1993)
tt0154506	Following (1998)
tt0107144	Hot Shots! Part Deux (1993)
tt1293847	xXx: Return of Xander Cage (2017)
tt0882977	Snitch (2013)
tt0119137	Flubber (1997)
tt0382077	Hide and Seek (2005)
tt0101761	The Doors (1991)

tt0821640	Ghosts of Girlfriends Past (2009)
tt3322364	Concussion (2015)
tt1020072	Selma (2014)
tt1126590	Big Eyes (2014)
tt2132285	The Bling Ring (2013)
tt0472181	The Smurfs (2011)
tt0151738	Never Been Kissed (1999)
tt0105698	Universal Soldier (1992)
tt0450188	La Vie en Rose (2007)
tt3949660	Teenage Mutant Ninja Turtles: Out of the Shadows (2016)
tt0096061	Scrooged (1988)
tt2125435	Beasts of the Southern Wild (2012)
tt0274812	Secretary (2002)
tt1297919	Blitz (2011)
tt0105665	Twin Peaks: Fire Walk with Me (1992)
tt3316948	American Ultra (2015)
tt1389072	Downsizing (2017)
tt6343314	Creed II (2018)
tt4572514	Patriots Day (2016)
tt0116365	The Frighteners (1996)
tt0137363	Arlington Road (1999)
tt0098258	Say Anything... (1989)
tt1598822	New Year's Eve (2011)
tt3850214	Dope (2015)
tt0370032	Ultraviolet (2006)
tt0098554	Uncle Buck (1989)
tt0048545	Rebel Without a Cause (1955)
tt0457513	Scoop (2006)
tt1083452	Eddie the Eagle (2015)
tt1023481	Step Up 2: The Streets (2008)
tt0104797	Malcolm X (1992)
tt0088011	Romancing the Stone (1984)
tt0100502	RoboCop 2 (1990)
tt0138749	The Road to El Dorado (2000)
tt0132477	October Sky (1999)
tt0455967	John Tucker Must Die (2006)
tt0048424	The Night of the Hunter (1955)
tt0097216	Do the Right Thing (1989)
tt2823054	Mike and Dave Need Wedding Dates (2016)
tt0087884	Paris Texas (1984)
tt2592614	Resident Evil: The Final Chapter (2016)
tt0307479	Solaris (2002)
tt1294226	The Last Song (2010)
tt0356470	A Cinderella Story (2004)
tt1229822	Jane Eyre (2011)

tt1666801	The Duff (2015)
tt0100935	Wild at Heart (1990)
tt3544112	Sing Street (2016)
tt1555149	Elite Squad: The Enemy Within (2010)
tt0817177	Flipped (2010)
tt0099582	Flatliners (1990)
tt0079945	Star Trek: The Motion Picture (1979)
tt0069704	American Graffiti (1973)
tt0364045	Taking Lives (2004)
tt0086541	Videodrome (1983)
tt1029234	Martyrs (2008)
tt0166896	The Straight Story (1999)
tt0384680	The Weather Man (2005)
tt1292566	How to Be Single (2016)
tt0367110	Swades (2004)
tt0120885	Wag the Dog (1997)
tt0839980	Semi-Pro (2008)
tt0419887	The Kite Runner (2007)
tt0035423	Kate & Leopold (2001)
tt1625346	Young Adult (2011)
tt0469641	World Trade Center (2006)
tt1020558	Centurion (2010)
tt0245674	Thir13en Ghosts (2001)
tt0118928	Dante's Peak (1997)
tt1571234	Mortal Engines (2018)
tt0862856	Trick 'r Treat (2007)
tt0317648	Hidalgo (2004)
tt0371246	Spanglish (2004)
tt1219342	Legend of the Guardians: The Owls of Ga'Hoole (2010)
tt0024216	King Kong (1933)
tt0456554	Grandma's Boy (2006)
tt0049406	The Killing (1956)
tt0250797	Unfaithful (2002)
tt0101889	The Fisher King (1991)
tt0852713	The House Bunny (2008)
tt0038355	The Big Sleep (1946)
tt0154420	The Celebration (1998)
tt0290095	The Tuxedo (2002)
tt1716772	The Inbetweeners Movie (2011)
tt2370248	Short Term 12 (2013)
tt4287320	The Circle (2017)
tt0115685	The Birdcage (1996)
tt2179116	The Kings of Summer (2013)
tt0049730	The Searchers (1956)
tt1974419	The Neon Demon (2016)

tt0092563	Angel Heart (1987)
tt1051904	Goosebumps (2015)
tt0107822	The Piano (1993)
tt5649144	The Florida Project (2017)
tt5742374	You Were Never Really Here (2017)
tt3967856	Okja (2017)
tt0090305	Weird Science (1985)
tt0110074	The Hudsucker Proxy (1994)
tt1911658	Penguins of Madagascar (2014)
tt0864761	The Duchess (2008)
tt0368226	The Room (2003)
tt0185183	Battlefield Earth (2000)
tt0383028	Synecdoche New York (2008)
tt0141926	U-571 (2000)
tt0092007	Star Trek IV: The Voyage Home (1986)
tt1152398	Beastly (2011)
tt1600195	Abduction (2011)
tt2357291	Rio 2 (2014)
tt2057392	Eye in the Sky (2015)
tt2358891	The Great Beauty (2013)
tt0377818	The Dukes of Hazzard (2005)
tt0405325	Sky High (2005)
tt0065214	The Wild Bunch (1969)
tt0043456	The Day the Earth Stood Still (1951)
tt1117385	Felon (2008)
tt0017925	The General (1926)
tt0064757	On Her Majesty's Secret Service (1969)
tt0108525	Wayne's World 2 (1993)
tt0795351	Case 39 (2009)
tt0108037	The Sandlot (1993)
tt1235522	Broken City (2013)
tt0810913	Jack and Jill (2011)
tt0088939	The Color Purple (1985)
tt0815245	The Uninvited (2009)
tt1674771	Entourage (2015)
tt2436386	Project Almanac (2015)
tt0120832	Snake Eyes (1998)
tt0386032	Sicko (2007)
tt0087078	Conan the Destroyer (1984)
tt4731136	A Cure for Wellness (2016)
tt0411061	88 Minutes (2007)
tt0264616	Frailty (2001)
tt2400463	The Invitation (2015)
tt0374546	Spring Summer Fall Winter... and Spring (2003)
tt0345950	The SpongeBob SquarePants Movie (2004)

tt0265349	The Mothman Prophecies (2002)
tt0427392	The Invasion (2007)
tt2494362	Bone Tomahawk (2015)
tt0117802	Swingers (1996)
tt1126591	Burlesque (2010)
tt0465551	Notes on a Scandal (2006)
tt0113161	Get Shorty (1995)
tt1979376	Toy Story 4 (2019)
tt0114694	Tommy Boy (1995)
tt3416532	A Monster Calls (2016)
tt2017038	All Is Lost (2013)
tt0105690	Under Siege (1992)
tt0117333	Phenomenon (1996)
tt1095217	Bad Lieutenant: Port of Call New Orleans (2009)
tt1259528	Den of Thieves (2018)
tt1093908	Confessions of a Shopaholic (2009)
tt0398712	Assault on Precinct 13 (2005)
tt0109254	Beverly Hills Cop III (1994)
tt1512235	Super (2010)
tt2726560	The Longest Ride (2015)
tt0084503	Pink Floyd: The Wall (1982)
tt1781922	No Escape (2015)
tt0111280	Star Trek Generations (1994)
tt1840417	The Words (2012)
tt0311289	Holes (2003)
tt1020530	Eden Lake (2008)
tt0371257	Stay (2005)
tt0403702	Youth in Revolt (2009)
tt1528071	Horns (2013)
tt1605717	Frank (2014)
tt0378109	Into the Blue (2005)
tt0303816	Cabin Fever (2002)
tt2002718	Machete Kills (2013)
tt1985949	The Angry Birds Movie (2016)
tt0069293	Solaris (1972)
tt1433811	Disconnect (2012)
tt1220198	The Fourth Kind (2009)
tt1336608	Rock of Ages (2012)
tt0088930	Clue (1985)
tt2980648	The Hundred-Foot Journey (2014)
tt4695012	It Comes at Night (2017)
tt0787475	Hot Rod (2007)
tt0106220	Addams Family Values (1993)
tt1234719	Red Dawn (2012)
tt0164181	Stir of Echoes (1999)

tt1683526	Detachment (2011)
tt3691740	The BFG (2016)
tt0092675	Bloodsport (1988)
tt0251736	House of 1000 Corpses (2003)
tt0211933	Awake (2007)
tt1954470	Gangs of Wasseypur (2012)
tt1379182	Dogtooth (2009)
tt0446059	Fearless (2006)
tt0477071	Premonition (2007)
tt3882082	The Boy (2016)
tt0494238	Inkheart (2008)
tt2082197	Barfi! (2012)
tt1655460	Wanderlust (2012)
tt0483607	Doomsday (2008)
tt3203606	Trumbo (2015)
tt0286112	Shaolin Soccer (2001)
tt0119173	G.I. Jane (1997)
tt0164334	Along Came a Spider (2001)
tt3605418	Knock Knock (2015)
tt0088170	Star Trek III: The Search for Spock (1984)
tt0076786	Suspiria (1977)
tt0462465	Outlander (2008)
tt0119099	Fallen (1998)
tt1242432	I Spit on Your Grave (2010)
tt1711425	21 & Over (2013)
tt1568921	The Secret World of Arrietty (2010)
tt0770752	Fool's Gold (2008)
tt0233469	Collateral Damage (2002)
tt0115963	The Craft (1996)
tt0389557	Black Book (2006)
tt2334649	Fruitvale Station (2013)
tt0086066	The Outsiders (1983)
tt0344510	A Very Long Engagement (2004)
tt0253754	Star Trek: Nemesis (2002)
tt2649554	Midnight Special (2016)
tt0090863	The Color of Money (1986)
tt0113540	Kids (1995)
tt0107808	A Perfect World (1993)
tt1467304	The Human Centipede (First Sequence) (2009)
tt0368933	The Princess Diaries 2: Royal Engagement (2004)
tt0401711	Paris je t'aime (2006)
tt1280558	A Wednesday (2008)
tt1726669	Killer Joe (2011)
tt0091790	Pretty in Pink (1986)
tt2386490	How to Train Your Dragon: The Hidden World (2019)

tt3522806	Mechanic: Resurrection (2016)
tt0093010	Fatal Attraction (1987)
tt0085794	The King of Comedy (1982)
tt0120461	Volcano (1997)
tt0056218	The Manchurian Candidate (1962)
tt3748172	Gerald's Game (2017)
tt2870612	As Above So Below (2014)
tt1241317	Death Note (2017)
tt0427229	Failure to Launch (2006)
tt0082495	Halloween II (1981)
tt0183523	Mission to Mars (2000)
tt0884732	The Wedding Ringer (2015)
tt0171363	The Haunting (1999)
tt0862846	Sunshine Cleaning (2008)
tt3007512	The Water Diviner (2014)
tt1121096	Seventh Son (2014)
tt0871510	Chak de! India (2007)
tt0481141	No Reservations (2007)
tt0101393	Backdraft (1991)
tt0043265	The African Queen (1951)
tt0120738	Lost in Space (1998)
tt1374992	Upside Down (2012)
tt1582507	House at the End of the Street (2012)
tt0120791	Practical Magic (1998)
tt1341167	Four Lions (2010)
tt0150377	Double Jeopardy (1999)
tt1619029	Jackie (2016)
tt0118607	Amistad (1997)
tt0102492	My Girl (1991)
tt0804461	Death Sentence (2007)
tt0351977	Walking Tall (2004)
tt0861689	Blindness (2008)
tt4849438	Baahubali 2: The Conclusion (2017)
tt1098327	Dragonball Evolution (2009)
tt0963794	The Ruins (2008)
tt1586265	What to Expect When You're Expecting (2012)
tt0970452	Solomon Kane (2009)
tt0091326	The Karate Kid Part II (1986)
tt0478134	In the Valley of Elah (2007)
tt0995039	Ghost Town (2008)
tt1912398	God Bless America (2011)
tt0077928	Midnight Express (1978)
tt1366344	The Sitter (2011)
tt0455538	How to Lose Friends & Alienate People (2008)
tt1082868	Quarantine (2008)

tt0235198	Audition (1999)
tt7959026	The Mule (2018)
tt0067185	Harold and Maude (1971)
tt1645089	Inside Job (2010)
tt0374536	Bewitched (2005)
tt0120844	Star Trek: Insurrection (1998)
tt0811080	Speed Racer (2008)
tt0102975	Star Trek VI: The Undiscovered Country (1991)
tt1352824	Chloe (2009)
tt1726592	Before I Go to Sleep (2014)
tt0120631	Ever After: A Cinderella Story (1998)
tt0095631	Midnight Run (1988)
tt1486834	What If (2013)
tt0053472	Breathless (1960)
tt0374887	Munna Bhai M.B.B.S. (2003)
tt0089755	Out of Africa (1985)
tt0133952	The Siege (1998)
tt0377471	Be Cool (2005)
tt0451094	Lady Vengeance (2005)
tt1186367	Ninja Assassin (2009)
tt0077766	Jaws 2 (1978)
tt0059113	Doctor Zhivago (1965)
tt0443489	Dreamgirls (2006)
tt0116225	Escape from L.A. (1996)
tt0076666	Saturday Night Fever (1977)
tt0385307	Miss Congeniality 2: Armed & Fabulous (2005)
tt4686844	The Death of Stalin (2017)
tt4218572	Widows (2018)
tt0420294	The Texas Chainsaw Massacre: The Beginning (2006)
tt1365050	Beasts of No Nation (2015)
tt0061184	Who's Afraid of Virginia Woolf? (1966)
tt0368709	Elizabethtown (2005)
tt0305711	Just Married (2003)
tt0139239	Go (1999)
tt1245112	[Rec] 2 (2009)
tt0340377	The Station Agent (2003)
tt0971209	A Perfect Getaway (2009)
tt0130018	I Still Know What You Did Last Summer (1998)
tt2377322	Deliver Us from Evil (2014)
tt0085333	Christine (1983)
tt0329774	xXx: State of the Union (2005)
tt1591479	Act of Valor (2012)
tt0364517	Love Me If You Dare (2003)
tt1679335	Trolls (2016)
tt0119051	The Edge (1997)

tt0088161	Splash (1984)
tt0416315	Wolf Creek (2005)
tt1321511	Oldboy (2013)
tt0425413	Run Fat Boy Run (2007)
tt0093629	A Nightmare on Elm Street 3: Dream Warriors (1987)
tt3717252	Underworld: Blood Wars (2016)
tt0165929	Romeo Must Die (2000)
tt0866439	Made of Honor (2008)
tt1343097	The Girl Who Kicked the Hornet's Nest (2009)
tt0329575	Seabiscuit (2003)
tt0477051	Norbit (2007)
tt0083511	48 Hrs. (1982)
tt2051879	Europa Report (2013)
tt0338095	High Tension (2003)
tt0414852	District B13 (2004)
tt1149362	The White Ribbon (2009)
tt0423294	Surf's Up (2007)
tt0493430	Jackass Number Two (2006)
tt0056217	The Man Who Shot Liberty Valance (1962)
tt0120749	Mercury Rising (1998)
tt0370986	Mysterious Skin (2004)
tt1763303	The First Time (2012)
tt0114558	Strange Days (1995)
tt0147612	Happiness (1998)
tt0131325	Bowfinger (1999)
tt0113481	Johnny Mnemonic (1995)
tt1323045	Frozen (2010)
tt0219965	Bandits (2001)
tt0421054	Domino (2005)
tt3713166	Unfriended (2014)
tt0096734	The 'Burbs (1989)
tt0316356	Open Range (2003)
tt1268799	A Very Harold & Kumar 3D Christmas (2011)
tt0055031	Judgment at Nuremberg (1961)
tt0463998	Freedom Writers (2007)
tt0104652	Porco Rosso (1992)
tt0061578	The Dirty Dozen (1967)
tt0091167	Hannah and Her Sisters (1986)
tt0315983	House of Sand and Fog (2003)
tt0139809	The Thirteenth Floor (1999)
tt0356618	The Forgotten (2004)
tt0316396	Peter Pan (2003)
tt1186830	Agora (2009)
tt1191111	Enter the Void (2009)
tt0113243	Hackers (1995)

tt0036613	Arsenic and Old Lace (1944)
tt1034389	The Eagle (2011)
tt3045616	Mortdecai (2015)
tt0851578	Paprika (2006)
tt1893256	Redemption (2013)
tt0090859	Cobra (1986)
tt1320261	Gulliver's Travels (2010)
tt2013293	The Wind Rises (2013)
tt0986233	Hunger (2008)
tt2101341	Dead Man Down (2013)
tt1226753	The Debt (2010)
tt5294550	All the Money in the World (2017)
tt0486551	Beerfest (2006)
tt0120694	Halloween H20: 20 Years Later (1998)
tt0292490	Dil Chahta Hai (2001)
tt1278340	Dead Snow (2009)
tt2106361	Into the Storm (2014)
tt3606752	Cars 3 (2017)
tt0445990	Invincible (2006)
tt1991245	Chernobyl Diaries (2012)
tt0145531	Stigmata (1999)
tt1473832	Bridget Jones's Baby (2016)
tt0423977	Charlie Bartlett (2007)
tt0056923	Charade (1963)
tt0457400	Land of the Lost (2009)
tt1712261	Triple 9 (2016)
tt0061811	In the Heat of the Night (1967)
tt0078841	Being There (1979)
tt0450345	The Wicker Man (2006)
tt0103786	Beethoven (1992)
tt0795461	Scary Movie 5 (2013)
tt2937898	A Most Violent Year (2014)
tt0120177	Spawn (1997)
tt0075029	The Outlaw Josey Wales (1976)
tt1687901	The Awakening (2011)
tt0087803	1984 (1984)
tt0300051	Jersey Girl (2004)
tt2039393	The Gambler (2014)
tt0433387	Harsh Times (2005)
tt1608290	Zoolander 2 (2016)
tt1130080	The Informant! (2009)
tt1586752	Machine Gun Preacher (2011)
tt0094947	Dangerous Liaisons (1988)
tt1588334	Jeff Who Lives at Home (2011)
tt0086393	Superman III (1983)

tt0426592	Superhero Movie (2008)
tt1462041	Dream House (2011)
tt2262227	The Book of Life (2014)
tt1711525	Office Christmas Party (2016)
tt0070917	The Wicker Man (1973)
tt0091474	Manhunter (1986)
tt1242422	Cell 211 (2009)
tt0970411	City of Ember (2008)
tt4530422	Overlord (2018)
tt0120148	Sliding Doors (1998)
tt1562872	Zindagi Na Milegi Dobara (2011)
tt2402157	The November Man (2014)
tt0873886	Red State (2011)
tt0103919	Candyman (1992)
tt0104815	El Mariachi (1992)
tt0095963	Red Heat (1988)
tt1990314	Robot & Frank (2012)
tt0083131	Stripes (1981)
tt1850457	Sisters (2015)
tt0053779	La Dolce Vita (1960)
tt2870756	Magic in the Moonlight (2014)
tt2359024	Blue Ruin (2013)
tt1583420	Larry Crowne (2011)
tt2053425	Rust and Bone (2012)
tt1441952	Salmon Fishing in the Yemen (2011)
tt0219699	The Gift (2000)
tt0091419	Little Shop of Horrors (1986)
tt0237534	Brotherhood of the Wolf (2001)
tt0021884	Frankenstein (1931)
tt0317303	Daddy Day Care (2003)
tt1300851	The Boondock Saints II: All Saints Day (2009)
tt0185014	Wonder Boys (2000)
tt0069762	Badlands (1973)
tt0032904	The Philadelphia Story (1940)
tt3530002	The Night Before (2015)
tt0178868	Ringu (1998)
tt2109184	Paranormal Activity 4 (2012)
tt0285492	CubeÂ²: Hypercube (2002)
tt0111255	The Specialist (1994)
tt1961175	American Assassin (2017)
tt2531344	Blockers (2018)
tt0453556	TMNT (2007)
tt0099052	Arachnophobia (1990)
tt2910814	The Signal (2014)
tt0120324	A Simple Plan (1998)

tt0080453	The Blue Lagoon (1980)
tt0462200	Black Snake Moan (2006)
tt2401878	Anomalisa (2015)
tt0110989	RiÂ¢hie RiÂ¢h (1994)
tt1270262	The Devil's Double (2011)
tt2364841	Runner Runner (2013)
tt1258972	The Man with the Iron Fists (2012)
tt0369436	Four Christmases (2008)
tt0088993	Day of the Dead (1985)
tt0107943	The Remains of the Day (1993)
tt0101452	Bill & Ted's Bogus Journey (1991)
tt0093191	Wings of Desire (1987)
tt0112870	Dilwale Dulhania Le Jayenge (1995)
tt0098536	Turner & Hooch (1989)
tt1210042	Brooklyn's Finest (2009)
tt0271027	Kiss of the Dragon (2001)
tt0166813	Spirit: Stallion of the Cimarron (2002)
tt0421082	Control (2007)
tt3348730	Jigsaw (2017)
tt0347304	Kal Ho Naa Ho (2003)
tt1197628	Observe and Report (2009)
tt0049833	The Ten Commandments (1956)
tt0831887	The Spirit (2008)
tt2226597	The Mountain Between Us (2017)
tt4139588	Polar (2019)
tt0080749	The Fog (1980)
tt0115751	Breaking the Waves (1996)
tt0114436	Showgirls (1995)
tt1185416	When in Rome (2010)
tt0327679	Ella Enchanted (2004)
tt0450314	Punisher: War Zone (2008)
tt0300556	Timeline (2003)
tt0472160	Penelope (2006)
tt0800069	The Hills Have Eyes II (2007)
tt0256009	The Devil's Backbone (2001)
tt0380389	Goal! The Dream Begins (2005)
tt0243017	Waking Life (2001)
tt0482572	Pride and Glory (2008)
tt0097815	Major League (1989)
tt0333780	Legally Blonde 2: Red White & Blonde (2003)
tt0117887	That Thing You Do! (1996)
tt0046911	Diabolique (1955)
tt0382628	Dark Water (2005)
tt0938330	Silent Hill: Revelation (2012)
tt5638642	The Ritual (2017)

tt2545118	Blackfish (2013)
tt0360201	Wimbledon (2004)
tt0048728	To Catch a Thief (1955)
tt0388125	In Her Shoes (2005)
tt0397313	Eight Below (2006)
tt0094332	The Witches of Eastwick (1987)
tt0113957	The Net (1995)
tt0356680	The Family Stone (2005)
tt0492044	The Haunting in Connecticut (2009)
tt0327162	The Stepford Wives (2004)
tt0258153	S1m0ne (2002)
tt0120913	Titan A.E. (2000)
tt2574698	Gunday (2014)
tt0310775	Sympathy for Mr. Vengeance (2002)
tt0086006	Never Say Never Again (1983)
tt2025690	The Finest Hours (2016)
tt2083383	Trouble with the Curve (2012)
tt0780511	Everybody's Fine (2009)
tt0264395	Basic (2003)
tt1618434	Murder Mystery (2019)
tt0110005	Heavenly Creatures (1994)
tt0815241	Religulous (2008)
tt3332064	Pan (2015)
tt0120686	Stepmom (1998)
tt0111507	Three Colors: White (1994)
tt5247022	Paterson (2016)
tt5028340	Mary Poppins Returns (2018)
tt1758692	Like Crazy (2011)
tt0124298	Blast from the Past (1999)
tt2390361	Enough Said (2013)
tt0800308	Appaloosa (2008)
tt0401997	Breach (2007)
tt1742334	Sabotage (2014)
tt4430212	Drishyam (2015)
tt3850590	Krampus (2015)
tt0476964	The Brave One (2007)
tt1527788	The Man from Nowhere (2010)
tt0119978	The Rainmaker (1997)
tt0062765	Bullitt (1968)
tt0146336	Urban Legend (1998)
tt0805570	The Midnight Meat Train (2008)
tt3322420	Queen (2013)
tt0190865	Vertical Limit (2000)
tt1748179	Red Lights (2012)
tt0098206	Road House (1989)

tt0817538	Drillbit Taylor (2008)
tt0089469	Legend (1985)
tt1438254	Charlie St. Cloud (2010)
tt1243974	Aloha (2015)
tt0089686	A Nightmare on Elm Street 2: Freddy's Revenge (1985)
tt0297284	Mindhunters (2004)
tt1093357	The Darkest Hour (2011)
tt2356180	Bhaag Milkha Bhaag (2013)
tt0104231	Far and Away (1992)
tt3716530	Elle (2016)
tt4575576	Christopher Robin (2018)
tt1753383	A Dog's Purpose (2017)
tt1232776	Fish Tank (2009)
tt0085407	The Dead Zone (1983)
tt0088286	Top Secret! (1984)
tt0466342	Date Movie (2006)
tt0109446	The Client (1994)
tt0427470	The Lookout (2007)
tt1783232	Conquest 1453 (2012)
tt0416508	Becoming Jane (2007)
tt0120693	Half Baked (1998)
tt0191397	The Replacements (2000)
tt5478478	Hostiles (2017)
tt0228786	The Crimson Rivers (2000)
tt0491152	Something Borrowed (2011)
tt0390022	Friday Night Lights (2004)
tt0099365	Darkman (1990)
tt0118849	Children of Heaven (1997)
tt0301470	Jeepers Creepers 2 (2003)
tt0113409	In the Mouth of Madness (1994)
tt0489049	Fanboys (2009)
tt0036342	Shadow of a Doubt (1943)
tt0052561	Anatomy of a Murder (1959)
tt1661382	Grudge Match (2013)
tt0368794	I'm Not There (2007)
tt2058673	Point Break (2015)
tt1704573	Bernie (2011)
tt0089175	Fright Night (1985)
tt0255798	The Animal (2001)
tt0758794	We Are Marshall (2006)
tt0466909	The Omen (2006)
tt0408345	Firewall (2006)
tt0492956	The Game Plan (2007)
tt1645080	The Art of Getting By (2011)
tt0431021	The Possession (2012)

tt0047437	Sabrina (1954)
tt0082348	Excalibur (1981)
tt0081633	Time Bandits (1981)
tt0099422	Dick Tracy (1990)
tt2265398	Drinking Buddies (2013)
tt1135084	Takers (2010)
tt4540710	Miss Sloane (2016)
tt0036868	The Best Years of Our Lives (1946)
tt0109424	Chungking Express (1994)
tt1116184	Jackass 3D (2010)
tt0047528	La Strada (1954)
tt0385700	Final Fantasy VII: Advent Children (2005)
tt2105044	V/H/S (2012)
tt0988047	Traitor (2008)
tt6565702	Dark Phoenix (2019)
tt0313443	Out of Time (2003)
tt0844479	The Collector (2009)
tt0814022	Bangkok Dangerous (2008)
tt0808506	The Girl Who Leapt Through Time (2006)
tt0074860	Marathon Man (1976)
tt0076618	The Rescuers (1977)
tt0070723	Soylent Green (1973)
tt0116409	The Ghost and the Darkness (1996)
tt0199753	Red Planet (2000)
tt0480669	Timecrimes (2007)
tt0349710	Ladder 49 (2004)
tt0089670	National Lampoon's European Vacation (1985)
tt3647498	Blood Father (2016)
tt0083922	Fanny and Alexander (1982)
tt0086197	The Right Stuff (1983)
tt2234003	Calvary (2014)
tt0023969	Duck Soup (1933)
tt0067800	Straw Dogs (1971)
tt0804522	Rendition (2007)
tt0266489	Duplex (2003)
tt2005374	The Frozen Ground (2013)
tt1821480	Kahaani (2012)
tt0862467	Valhalla Rising (2009)
tt3014866	Criminal (2016)
tt1166100	Ghajini (2008)
tt0049470	The Man Who Knew Too Much (1956)
tt2387499	Keeping Up with the Joneses (2016)
tt0091949	Short Circuit (1986)
tt1075747	Jonah Hex (2010)
tt0098382	Star Trek V: The Final Frontier (1989)

tt0082418	Friday the 13th Part 2 (1981)
tt3741700	Godzilla: King of the Monsters (2019)
tt0111438	Timecop (1994)
tt0091530	The Mission (1986)
tt1273235	A Serbian Film (2010)
tt1029360	Poltergeist (2015)
tt0280609	Dog Soldiers (2002)
tt6663582	The Spy Who Dumped Me (2018)
tt1313092	Animal Kingdom (2010)
tt0083791	The Dark Crystal (1982)
tt1606392	Win Win (2011)
tt1137450	Death Wish (2018)
tt1772240	Apollo 18 (2011)
tt1592873	LOL (2012)
tt1075417	Race to Witch Mountain (2009)
tt0106701	Dennis the Menace (1993)
tt0070355	Magnum Force (1973)
tt1059786	Eagle Eye (2008)
tt0272152	K-PAX (2001)
tt1217613	Battle Los Angeles (2011)
tt2637276	Ted 2 (2015)
tt0489270	Saw III (2006)
tt1617661	Jupiter Ascending (2015)
tt0102798	Robin Hood: Prince of Thieves (1991)
tt0352248	Cinderella Man (2005)
tt2704998	Game Night (2018)
tt0116209	The English Patient (1996)
tt0299977	Hero (2002)
tt0295701	xXx (2002)
tt0200465	The Bank Job (2008)
tt0111282	Stargate (1994)
tt0838221	The Darjeeling Limited (2007)
tt1007028	Zack and Miri Make a Porno (2008)
tt1365519	Tomb Raider (2018)
tt1398426	Straight Outta Compton (2015)
tt0455590	The Last King of Scotland (2006)
tt1583421	G.I. Joe: Retaliation (2013)
tt2446042	Taken 3 (2014)
tt0461770	Enchanted (2007)
tt0029583	Snow White and the Seven Dwarfs (1937)
tt0268126	Adaptation. (2002)
tt0829150	Dracula Untold (2014)
tt0100157	Misery (1990)
tt0117381	Primal Fear (1996)
tt0099810	The Hunt for Red October (1990)

tt2709768	The Secret Life of Pets (2016)
tt0120630	Chicken Run (2000)
tt4776998	The Promise (2016)
tt1872194	The Judge (2014)
tt0090756	Blue Velvet (1986)
tt0986263	Surrogates (2009)
tt0117998	Twister (1996)
tt0307901	25th Hour (2002)
tt0134119	The Talented Mr. Ripley (1999)
tt0120917	The Emperor's New Groove (2000)
tt0067992	Willy Wonka & the Chocolate Factory (1971)
tt0418763	Jarhead (2005)
tt0122690	Ronin (1998)
tt0276751	About a Boy (2002)
tt1226229	Get Him to the Greek (2010)
tt1964418	Tomorrowland (2015)
tt1078912	Night at the Museum: Battle of the Smithsonian (2009)
tt3553976	Captain Fantastic (2016)
tt0120863	The Thin Red Line (1998)
tt2557490	A Million Ways to Die in the West (2014)
tt0756683	The Man from Earth (2007)
tt0138704	Pi (1998)
tt7784604	Hereditary (2018)
tt0112851	Desperado (1995)
tt1700841	Sausage Party (2016)
tt0266308	Battle Royale (2000)
tt0195685	Erin Brockovich (2000)
tt2023587	Mama (2013)
tt0450278	Hostel (2005)
tt0094012	Spaceballs (1987)
tt5109784	Mother! (2017)
tt0058150	Goldfinger (1964)
tt0087538	The Karate Kid (1984)
tt0146882	High Fidelity (2000)
tt0050825	Paths of Glory (1957)
tt0366548	Happy Feet (2006)
tt0183790	A Knight's Tale (2001)
tt0112697	Clueless (1995)
tt0311429	The League of Extraordinary Gentlemen (2003)
tt0084602	Rocky III (1982)
tt1033643	What Happens in Vegas (2008)
tt0109707	Ed Wood (1994)
tt0128445	Rushmore (1998)
tt0129167	The Iron Giant (1999)
tt0103772	Basic Instinct (1992)

tt0443680	The Assassination of Jesse James by the Coward Robert Ford (2007)
tt1935179	Mud (2012)
tt2333784	The Expendables 3 (2014)
tt0120746	The Mask of Zorro (1998)
tt5726616	Call Me by Your Name (2017)
tt1229340	Anchorman 2: The Legend Continues (2013)
tt4263482	The Witch (2015)
tt0478304	The Tree of Life (2011)
tt1355683	Black Mass (2015)
tt0359013	Blade: Trinity (2004)
tt0063442	Planet of the Apes (1968)
tt0389722	30 Days of Night (2007)
tt0106856	Falling Down (1993)
tt0338348	The Polar Express (2004)
tt1628841	Independence Day: Resurgence (2016)
tt2345759	The Mummy (2017)
tt1488555	The Change-Up (2011)
tt0109506	The Crow (1994)
tt0056869	The Birds (1963)
tt7349662	BlacKkKlansman (2018)
tt0082694	Mad Max 2: The Road Warrior (1981)
tt2369135	Need for Speed (2014)
tt0442933	Beowulf (2007)
tt2005151	War Dogs (2016)
tt0307453	Shark Tale (2004)
tt0346491	Alexander (2004)
tt0415306	Talladega Nights: The Ballad of Ricky Bobby (2006)
tt0375912	Layer Cake (2004)
tt0101540	Cape Fear (1991)
tt1465522	Tucker and Dale vs Evil (2010)
tt1231587	Hot Tub Time Machine (2010)
tt0465494	Hitman (2007)
tt1527186	Melancholia (2011)
tt0142688	The Ninth Gate (1999)
tt1038988	REC (2007)
tt2404463	The Heat (2013)
tt1220634	Resident Evil: Afterlife (2010)
tt1253864	Immortals (2011)
tt0120188	Three Kings (1999)
tt0074285	Carrie (1976)
tt3631112	The Girl on the Train (2016)
tt0054698	Breakfast at Tiffany's (1961)
tt0106308	Army of Darkness (1992)
tt0061852	The Jungle Book (1967)
tt0096754	The Abyss (1989)

tt0275847	Lilo & Stitch (2002)
tt0978762	Mary and Max (2009)
tt0372588	Team America: World Police (2004)
tt1528100	Exodus: Gods and Kings (2014)
tt0398165	The Longest Yard (2005)
tt0918940	The Legend of Tarzan (2016)
tt0337563	13 Going on 30 (2004)
tt0140352	The Insider (1999)
tt1001508	He's Just Not That Into You (2009)
tt0086960	Beverly Hills Cop (1984)
tt0061512	Cool Hand Luke (1967)
tt0454841	The Hills Have Eyes (2006)
tt1821694	RED 2 (2013)
tt5519340	Bright (2017)
tt0021749	City Lights (1931)
tt0465538	Michael Clayton (2007)
tt0990407	The Green Hornet (2011)
tt0448115	Shazam! (2019)
tt1139328	The Ghost Writer (2010)
tt0078346	Superman (1978)
tt5164214	Ocean's Eight (2018)
tt0172493	Girl Interrupted (1999)
tt0327084	Over the Hedge (2006)
tt1277953	Madagascar 3: Europe's Most Wanted (2012)
tt0445934	Blades of Glory (2007)
tt1129442	Transporter 3 (2008)
tt0810819	The Danish Girl (2015)
tt0106677	Dazed and Confused (1993)
tt0177971	The Perfect Storm (2000)
tt0424136	Hard Candy (2005)
tt1155076	The Karate Kid (2010)
tt0094898	Coming to America (1988)
tt1288558	Evil Dead (2013)
tt1091722	Adventureland (2009)
tt0120744	The Man in the Iron Mask (1998)
tt0832266	Definitely Maybe (2008)
tt0104714	Lethal Weapon 3 (1992)
tt0380510	The Lovely Bones (2009)
tt0106697	Demolition Man (1993)
tt0041959	The Third Man (1949)
tt0108160	Sleepless in Seattle (1993)
tt0285823	Once Upon a Time in Mexico (2003)
tt0053604	The Apartment (1960)
tt0091064	The Fly (1986)
tt6823368	Glass (2019)

tt0017136	Metropolis (1927)
tt0988595	27 Dresses (2008)
tt1411250	Riddick (2013)
tt2170439	Horrible Bosses 2 (2014)
tt1279935	Date Night (2010)
tt0120082	Scream 2 (1997)
tt0120891	Wild Wild West (1999)
tt2316411	Enemy (2013)
tt5580036	I Tonya (2017)
tt0963966	The Sorcerer's Apprentice (2010)
tt0986264	Like Stars on Earth (2007)
tt1661199	Cinderella (2015)
tt0408790	Flightplan (2005)
tt0122151	Lethal Weapon 4 (1998)
tt0119081	Event Horizon (1997)
tt0058331	Mary Poppins (1964)
tt1611224	Abraham Lincoln: Vampire Hunter (2012)
tt0330793	The Punisher (2004)
tt0834001	Underworld: Rise of the Lycans (2009)
tt0145681	The Bone Collector (1999)
tt2226417	Insidious: Chapter 2 (2013)
tt0293564	Rush Hour 3 (2007)
tt0107207	In the Name of the Father (1993)
tt0115798	The Cable Guy (1996)
tt0859163	The Mummy: Tomb of the Dragon Emperor (2008)
tt0472399	The Mechanic (2011)
tt0094625	Akira (1988)
tt0261392	Jay and Silent Bob Strike Back (2001)
tt1935859	Miss Peregrine's Home for Peculiar Children (2016)
tt2140373	Saving Mr. Banks (2013)
tt0458481	Sin City: A Dame to Kill For (2014)
tt0046912	Dial M for Murder (1954)
tt1057500	Invictus (2009)
tt0033870	The Maltese Falcon (1941)
tt0309593	Final Destination 2 (2003)
tt1502712	Fantastic Four (2015)
tt1216475	Cars 2 (2011)
tt1489889	Central Intelligence (2016)
tt0435705	Next (2007)
tt0102685	Point Break (1991)
tt1462758	Buried (2010)
tt3062096	Inferno (2016)
tt0465602	Shoot 'Em Up (2007)
tt1655441	The Age of Adaline (2015)
tt1469304	Baywatch (2017)

tt0120587	Antz (1998)
tt2080374	Steve Jobs (2015)
tt0089880	Rambo: First Blood Part II (1985)
tt2338151	PK (2014)
tt0257106	Scary Movie 2 (2001)
tt0443274	Vantage Point (2008)
tt2873282	Red Sparrow (2018)
tt0055254	101 Dalmatians (1961)
tt1054606	The Imaginarium of Doctor Parnassus (2009)
tt1496025	Underworld Awakening (2012)
tt0120484	The Waterboy (1998)
tt4555426	Darkest Hour (2017)
tt0177789	Galaxy Quest (1999)
tt0122933	Analyze This (1999)
tt0938283	The Last Airbender (2010)
tt1568338	Man on a Ledge (2012)
tt1267297	Hercules (2014)
tt0454945	She's the Man (2006)
tt0095705	The Naked Gun: From the Files of Police Squad! (1988)
tt1188729	Pandorum (2009)
tt1335975	47 Ronin (2013)
tt1568911	War Horse (2011)
tt0104691	The Last of the Mohicans (1992)
tt0780571	Mr. Brooks (2007)
tt0822832	Marley & Me (2008)
tt0892782	Monsters vs. Aliens (2009)
tt0042876	Rashomon (1950)
tt0092991	Evil Dead II (1987)
tt0277027	I Am Sam (2001)
tt0266987	Spy Game (2001)
tt0055928	Dr. No (1962)
tt0094291	Wall Street (1987)
tt0310793	Bowling for Columbine (2002)
tt0159097	The Virgin Suicides (1999)
tt0100403	Predator 2 (1990)
tt1714206	The Spectacular Now (2013)
tt0889583	BrÃ¼no (2009)
tt0128442	Rounders (1998)
tt0088944	Commando (1985)
tt1860357	Deepwater Horizon (2016)
tt0097958	National Lampoon's Christmas Vacation (1989)
tt0385002	Green Street Hooligans (2005)
tt0110322	Legends of the Fall (1994)
tt0448694	Puss in Boots (2011)
tt0762107	I Now Pronounce You Chuck & Larry (2007)

tt0072431	Young Frankenstein (1974)
tt0272338	Punch-Drunk Love (2002)
tt3532216	American Made (2017)
tt0072684	Barry Lyndon (1975)
tt0452694	The Time Traveler's Wife (2009)
tt1727388	The Way Way Back (2013)
tt1600196	The Drop (2014)
tt0387808	Idiocracy (2006)
tt0066999	Dirty Harry (1971)
tt0159365	Cold Mountain (2003)
tt0042332	Cinderella (1950)
tt0398808	Bridge to Terabithia (2007)
tt1560747	The Master (2012)
tt1121931	Crank: High Voltage (2009)
tt0074958	Network (1976)
tt0335438	Starsky & Hutch (2004)
tt0397535	Memoirs of a Geisha (2005)
tt0475394	Smokin' Aces (2006)
tt0257076	S.W.A.T. (2003)
tt0391198	The Grudge (2004)
tt0805564	Lars and the Real Girl (2007)
tt0890870	Saw IV (2007)
tt2848292	Pitch Perfect 2 (2015)
tt0102138	JFK (1991)
tt0413099	Evan Almighty (2007)
tt1809398	Unbroken (2014)
tt0410297	The Lake House (2006)
tt1980929	Begin Again (2013)
tt1334260	Never Let Me Go (2010)
tt0980970	The Chronicles of Narnia: The Voyage of the Dawn Treader (2010)
tt1034303	Defiance (2008)
tt1403981	Remember Me (2010)
tt0084516	Poltergeist (1982)
tt2191701	Grown Ups 2 (2013)
tt0047296	On the Waterfront (1954)
tt0036775	Double Indemnity (1944)
tt6857112	Us (2019)
tt0022100	M (1931)
tt0301357	Good Bye Lenin! (2003)
tt0989757	Dear John (2010)
tt0040522	Bicycle Thieves (1948)
tt0242423	Dude Where's My Car? (2000)
tt0389790	Bee Movie (2007)
tt0082198	Conan the Barbarian (1982)
tt1563738	One Day (2011)

tt0306047	Scary Movie 3 (2003)
tt3416742	What We Do in the Shadows (2014)
tt0350258	Ray (2004)
tt1399683	Winter's Bone (2010)
tt0280590	Mr. Deeds (2002)
tt0473705	State of Play (2009)
tt0307987	Bad Santa (2003)
tt1389137	We Bought a Zoo (2011)
tt0109831	Four Weddings and a Funeral (1994)
tt2101441	Spring Breakers (2012)
tt0276919	Dogville (2003)
tt3640424	Allied (2016)
tt1549920	The Last Stand (2013)
tt2975578	The Purge: Anarchy (2014)
tt0437086	Alita: Battle Angel (2019)
tt0417148	Snakes on a Plane (2006)
tt1100089	Foxcatcher (2014)
tt1213641	First Man (2018)
tt0472033	9 (2009)
tt0107362	Last Action Hero (1993)
tt6320628	Spider-Man: Far from Home (2019)
tt0099938	Kindergarten Cop (1990)
tt1939659	Carrie (2013)
tt5074352	Dangal (2016)
tt0804497	It's Kind of a Funny Story (2010)
tt0387131	The Constant Gardener (2005)
tt0118842	Chasing Amy (1997)
tt0430105	Four Brothers (2005)
tt3300542	London Has Fallen (2016)
tt1855325	Resident Evil: Retribution (2012)
tt0369441	Fun with Dick and Jane (2005)
tt0120888	The Wedding Singer (1998)
tt1255953	Incendies (2010)
tt0471042	Tower Heist (2011)
tt0340855	Monster (2003)
tt0481536	Harold & Kumar Escape from Guantanamo Bay (2008)
tt1034032	Gamer (2009)
tt0120784	Payback (1999)
tt0424345	Clerks II (2006)
tt3322940	Annabelle (2014)
tt4178092	The Gift (2015)
tt2042568	Inside Llewyn Davis (2013)
tt0292506	The Recruit (2003)
tt1764234	Killing Them Softly (2012)
tt1915581	Magic Mike (2012)

tt1189073	The Skin I Live In (2011)
tt0119345	I Know What You Did Last Summer (1997)
tt2209418	Before Midnight (2013)
tt2180411	Into the Woods (2014)
tt1351685	Jack the Giant Slayer (2013)
tt0086465	Trading Places (1983)
tt0053285	Sleeping Beauty (1959)
tt0277296	The Scorpion King (2002)
tt1174732	An Education (2009)
tt0324216	The Texas Chainsaw Massacre (2003)
tt2203939	The Other Woman (2014)
tt3393786	Jack Reacher: Never Go Back (2016)
tt0358082	Robots (2005)
tt0095159	A Fish Called Wanda (1988)
tt0103074	Thelma & Louise (1991)
tt0120768	The Negotiator (1998)
tt0361596	Fahrenheit 9/11 (2004)
tt0325703	Lara Croft Tomb Raider: The Cradle of Life (2003)
tt1314655	Devil (2010)
tt1019452	A Serious Man (2009)
tt0947810	Green Zone (2010)
tt0073629	The Rocky Horror Picture Show (1975)
tt3152624	Trainwreck (2015)
tt0079522	Manhattan (1979)
tt0085334	A Christmas Story (1983)
tt5083738	The Favourite (2018)
tt1924435	Let's Be Cops (2014)
tt0450232	16 Blocks (2006)
tt0112508	Billy Madison (1995)
tt0451079	Horton Hears a Who! (2008)
tt0277434	We Were Soldiers (2002)
tt1234548	The Men Who Stare at Goats (2009)
tt1204975	Last Vegas (2013)
tt0072271	The Texas Chain Saw Massacre (1974)
tt0414982	Final Destination 3 (2006)
tt0256380	Shallow Hal (2001)
tt0245844	The Count of Monte Cristo (2002)
tt0842926	The Kids Are All Right (2010)
tt0365737	Syriana (2005)
tt0088258	This Is Spinal Tap (1984)
tt2120120	Pixels (2015)
tt3371366	Transformers: The Last Knight (2017)
tt3774114	Snowden (2016)
tt0443649	10000 BC (2008)
tt0253556	Reign of Fire (2002)

tt0117913	A Time to Kill (1996)
tt0088323	The NeverEnding Story (1984)
tt2554274	Crimson Peak (2015)
tt4779682	The Meg (2018)
tt0816442	The Book Thief (2013)
tt2096672	Dumb and Dumber To (2014)
tt1758830	This Is 40 (2012)
tt1262416	Scream 4 (2011)
tt0116922	Lost Highway (1997)
tt0381707	White Chicks (2004)
tt0079417	Kramer vs. Kramer (1979)
tt1790886	The Campaign (2012)
tt0343135	Along Came Polly (2004)
tt2231461	Rampage (2018)
tt0089530	Mad Max Beyond Thunderdome (1985)
tt2446980	Joy (2015)
tt0325805	Matchstick Men (2003)
tt0046250	Roman Holiday (1953)
tt0119738	My Best Friend's Wedding (1997)
tt2177771	The Monuments Men (2014)
tt1448755	Killer Elite (2011)
tt4116284	The Lego Batman Movie (2017)
tt0467197	Max Payne (2008)
tt0815236	She's Out of My League (2010)
tt2381111	Brooklyn (2015)
tt0452594	The Break-Up (2006)
tt2267968	Kung Fu Panda 3 (2016)
tt0257360	About Schmidt (2002)
tt0379725	Capote (2005)
tt3316960	Still Alice (2014)
tt0032910	Pinocchio (1940)
tt3470600	Sing (2016)
tt0043274	Alice in Wonderland (1951)
tt0093822	Raising Arizona (1987)
tt0247638	The Princess Diaries (2001)
tt0274558	The Hours (2002)
tt0125664	Man on the Moon (1999)
tt0433362	Daybreakers (2009)
tt0100507	Rocky V (1990)
tt0106489	A Bronx Tale (1993)
tt0093105	Good Morning Vietnam (1987)
tt0384793	Accepted (2006)
tt0071230	Blazing Saddles (1974)
tt2024432	Identity Thief (2013)
tt1616195	J. Edgar (2011)

tt0312004	Wallace & Gromit: The Curse of the Were-Rabbit (2005)
tt0113568	Ghost in the Shell (1995)
tt0134273	8MM (1999)
tt1298649	The Watch (2012)
tt0249462	Billy Elliot (2000)
tt1615065	Savages (2012)
tt0149261	Deep Blue Sea (1999)
tt0040746	Rope (1948)
tt0164912	Stuart Little (1999)
tt0251160	John Q (2002)
tt0108358	Tombstone (1993)
tt1205537	Jack Ryan: Shadow Recruit (2014)
tt0164052	Hollow Man (2000)
tt0480687	Hall Pass (2011)
tt0918927	Doubt (2008)
tt0455824	Australia (2008)
tt1441395	Under the Skin (2013)
tt0259446	My Big Fat Greek Wedding (2002)
tt0054331	Spartacus (1960)
tt6146586	John Wick: Chapter 3 - Parabellum (2019)
tt0091203	Highlander (1986)
tt1055292	Life as We Know It (2010)
tt0097441	Glory (1989)
tt0046183	Peter Pan (1953)
tt0120102	Seven Years in Tibet (1997)
tt0427327	Hairspray (2007)
tt0091369	Labyrinth (1986)
tt0090728	Big Trouble in Little China (1986)
tt2543472	Wonder (2017)
tt0227445	The Score (2001)
tt3521126	The Disaster Artist (2017)
tt0070511	Papillon (1973)
tt0305357	Charlie's Angels: Full Throttle (2003)
tt0251075	Evolution (2001)
tt0268695	The Time Machine (2002)
tt0101507	Boyz n the Hood (1991)
tt1038919	The Bounty Hunter (2010)
tt0082340	Escape from New York (1981)
tt0393162	Coach Carter (2005)
tt0431197	The Kingdom (2007)
tt2034800	The Great Wall (2016)
tt0099077	Awakenings (1990)
tt0117008	Matilda (1996)
tt0093437	The Lost Boys (1987)
tt0905372	The Thing (2011)

tt0184894	Shanghai Noon (2000)
tt1862079	Safety Not Guaranteed (2012)
tt0087182	Dune (1984)
tt0475290	Hail Caesar! (2016)
tt1524137	Contraband (2012)
tt0106582	Cliffhanger (1993)
tt2561572	Get Hard (2015)
tt0418689	Flags of our Fathers (2006)
tt1692486	Carnage (2011)
tt0117438	Ransom (1996)
tt1634122	Johnny English Reborn (2011)
tt5700672	Train to Busan (2016)
tt0032976	Rebecca (1940)
tt0404032	The Exorcism of Emily Rose (2005)
tt0338564	Infernal Affairs (2002)
tt0216216	The 6th Day (2000)
tt0120657	The 13th Warrior (1999)
tt5104604	Isle of Dogs (2018)
tt0161081	What Lies Beneath (2000)
tt0482606	The Strangers (2008)
tt1648190	The Dark Tower (2017)
tt0355295	The Brothers Grimm (2005)
tt0117731	Star Trek: First Contact (1996)
tt0093748	Planes Trains & Automobiles (1987)
tt2305051	Wild (2014)
tt1000774	Sex and the City (2008)
tt3488710	The Walk (2015)
tt0480025	This Is England (2006)
tt0042192	All About Eve (1950)
tt0048280	Lady and the Tramp (1955)
tt0293508	The Phantom of the Opera (2004)
tt0780521	The Princess and the Frog (2009)
tt0095956	Rambo III (1988)
tt0758730	Aliens vs. Predator: Requiem (2007)
tt0790736	R.I.P.D. (2013)
tt6155172	Roma (2018)
tt6294822	The Post (2017)
tt0113749	Mallrats (1995)
tt6499752	Upgrade (2018)
tt0486946	Wild Hogs (2007)
tt1390411	In the Heart of the Sea (2015)
tt1201167	Funny People (2009)
tt0120783	The Parent Trap (1998)
tt0033563	Dumbo (1941)
tt0103855	The Bodyguard (1992)

tt0120794	The Prince of Egypt (1998)
tt0100814	Tremors (1990)
tt0822847	Priest (2011)
tt0397065	House of Wax (2005)
tt0265459	One Hour Photo (2002)
tt1355630	If I Stay (2014)
tt0112642	Casper (1995)
tt4052882	The Shallows (2016)
tt0290673	IrrÃ©versible (2002)
tt0107977	Robin Hood: Men in Tights (1993)
tt1058017	The Invention of Lying (2009)
tt0245574	Y Tu MamÃ¡ TambiÃ©n (2001)
tt1615147	Margin Call (2011)
tt2388715	Oculus (2013)
tt0817230	Valentine's Day (2010)
tt0223897	Pay It Forward (2000)
tt1086772	Blended (2014)
tt1228987	Let Me In (2010)
tt5439796	Logan Lucky (2017)
tt1132626	Saw V (2008)
tt0113627	Leaving Las Vegas (1995)
tt0870984	Antichrist (2009)
tt0162346	Ghost World (2001)
tt0314353	Tears of the Sun (2003)
tt0362120	Scary Movie 4 (2006)
tt4209788	Molly's Game (2017)
tt0146838	Any Given Sunday (1999)
tt1131734	Jennifer's Body (2009)
tt0118694	In the Mood for Love (2000)
tt0453451	Mr. Bean's Holiday (2007)
tt0057076	From Russia with Love (1963)
tt0084827	TRON (1982)
tt4302938	Kubo and the Two Strings (2016)
tt0092965	Empire of the Sun (1987)
tt0080761	Friday the 13th (1980)
tt1638002	Love Rosie (2014)
tt1067583	Water for Elephants (2011)
tt1517260	The Host (2013)
tt1904996	Parker (2013)
tt0421239	Red Eye (2005)
tt0063350	Night of the Living Dead (1968)
tt0079116	Escape from Alcatraz (1979)
tt1821549	Nebraska (2013)
tt0365907	A Walk Among the Tombstones (2014)
tt0084726	Star Trek II: The Wrath of Khan (1982)

tt1547234	Premium Rush (2012)
tt0077975	National Lampoon's Animal House (1978)
tt2884206	I Origins (2014)
tt5462602	The Big Sick (2017)
tt0435651	The Giver (2014)
tt0907657	Once (2007)
tt1924429	Trance (2013)
tt0085959	The Meaning of Life (1983)
tt2265171	The Raid 2 (2014)
tt0455407	The Crazies (2010)
tt0101410	Barton Fink (1991)
tt0462590	Step Up (2006)
tt4172430	13 Hours (2016)
tt0070608	Robin Hood (1973)
tt0096320	Twins (1988)
tt1911644	The Call (2013)
tt0040897	The Treasure of the Sierra Madre (1948)
tt1071875	Ghost Rider: Spirit of Vengeance (2011)
tt0087928	Police Academy (1984)
tt0366627	The Jacket (2005)
tt0430357	Miami Vice (2006)
tt0077402	Dawn of the Dead (1978)
tt0337741	Something's Gotta Give (2003)
tt0133751	The Faculty (1998)
tt0329101	Freddy vs. Jason (2003)
tt4438848	Neighbors 2: Sorority Rising (2016)
tt3531824	Nerve (2016)
tt7668870	Searching (2018)
tt0113492	Judge Dredd (1995)
tt0765010	Brothers (2009)
tt0118617	Anastasia (1997)
tt0424095	Flushed Away (2006)
tt0263488	Jeepers Creepers (2001)
tt0190138	The Whole Nine Yards (2000)
tt3567288	The Visit (2015)
tt0421073	Street Kings (2008)
tt2404311	The Family (2013)
tt0182789	Bicentennial Man (1999)
tt0327554	Catwoman (2004)
tt0373883	Halloween (2007)
tt1327773	Lee Daniels' The Butler (2013)
tt1486185	Red Riding Hood (2011)
tt0795368	Death at a Funeral (2007)
tt0340163	Hostage (2005)
tt3104988	Crazy Rich Asians (2018)

tt1023114	The Way Back (2010)
tt1131729	Pirate Radio (2009)
tt0353969	Memories of Murder (2003)
tt1860213	Dirty Grandpa (2016)
tt1307068	Seeking a Friend for the End of the World (2012)
tt0117218	The Nutty Professor (1996)
tt0460791	The Fall (2006)
tt0289992	The Life of David Gale (2003)
tt4786282	Lights Out (2016)
tt0445922	Across the Universe (2007)
tt4651520	Bad Moms (2016)
tt3766354	The Equalizer 2 (2018)
tt0295700	Wrong Turn (2003)
tt2402927	Carol (2015)
tt0120890	Wild Things (1998)
tt0114069	Outbreak (1995)
tt0405508	Rang De Basanti (2006)
tt0200550	Coyote Ugly (2000)
tt0203019	Men of Honor (2000)
tt0096928	Bill & Ted's Excellent Adventure (1989)
tt1956620	Sex Tape (2014)
tt1602613	Only God Forgives (2013)
tt0465580	Push (2009)
tt1921064	Pompeii (2014)
tt0405296	A Scanner Darkly (2006)
tt0348836	Gothika (2003)
tt0137494	Entrapment (1999)
tt0472062	Charlie Wilson's War (2007)
tt0404203	Little Children (2006)
tt0097351	Field of Dreams (1989)
tt0146675	End of Days (1999)
tt0929632	Precious (2009)
tt0397101	The Skeleton Key (2005)
tt0097814	Kiki's Delivery Service (1989)
tt0419706	Doom (2005)
tt0067116	The French Connection (1971)
tt4701182	Bumblebee (2018)
tt1315981	A Single Man (2009)
tt0970866	Little Fockers (2010)
tt0384806	The Amityville Horror (2005)
tt4276820	The Founder (2016)
tt0286499	Bend It Like Beckham (2002)
tt1206543	Out of the Furnace (2013)
tt0426931	August Rush (2007)
tt0092644	Beverly Hills Cop II (1987)

tt0079944	Stalker (1979)
tt0031679	Mr. Smith Goes to Washington (1939)
tt0283111	Van Wilder: Party Liaison (2002)
tt0401383	The Diving Bell and the Butterfly (2007)
tt1509767	The Three Musketeers (2011)
tt1622979	Final Destination 5 (2011)
tt0075005	The Omen (1976)
tt5052474	Sicario: Day of the Soldado (2018)
tt0240890	Serendipity (2001)
tt0780653	The Wolfman (2010)
tt0338337	Paycheck (2003)
tt0436697	The Queen (2006)
tt2763304	T2 Trainspotting (2017)
tt0367959	Hannibal Rising (2007)
tt0799949	Epic Movie (2007)
tt0433400	Just Friends (2005)
tt1528854	Daddy's Home (2015)
tt0368008	The Manchurian Candidate (2004)
tt0070666	Serpico (1973)
tt1682180	Stoker (2013)
tt3829266	The Predator (2018)
tt1073498	Meet the Spartans (2008)
tt0236493	The Mexican (2001)
tt1702439	Safe Haven (2013)
tt0287467	Talk to Her (2002)
tt0467200	The Other Boleyn Girl (2008)
tt0096256	They Live (1988)
tt0790686	Mirrors (2008)
tt0080487	Caddyshack (1980)
tt0218967	The Family Man (2000)
tt0870111	Frost/Nixon (2008)
tt0164184	The Sum of All Fears (2002)
tt0104952	My Cousin Vinny (1992)
tt0865556	The Forbidden Kingdom (2008)
tt1135503	Julie & Julia (2009)
tt0365830	Tenacious D in The Pick of Destiny (2006)
tt0317198	Bridget Jones: The Edge of Reason (2004)
tt2503944	Burnt (2015)
tt1656190	Safe (2012)
tt1924396	The Best Offer (2013)
tt0386117	Where the Wild Things Are (2009)
tt1007029	The Iron Lady (2011)
tt1053424	Repo Men (2010)
tt3410834	Allegiant (2016)
tt0059800	Thunderball (1965)

tt0120902	The X Files (1998)
tt0327850	The Rundown (2003)
tt1114740	Paul Blart: Mall Cop (2009)
tt0390521	Super Size Me (2004)
tt0256415	Sweet Home Alabama (2002)
tt0120889	What Dreams May Come (1998)
tt2404233	Gods of Egypt (2016)
tt1078940	Couples Retreat (2009)
tt1258197	Exam (2009)
tt1063669	The Wave (2008)
tt0462504	Rescue Dawn (2006)
tt0426883	Alpha Dog (2006)
tt0119303	Home Alone 3 (1997)
tt0110478	Maverick (1994)
tt0393109	Brick (2005)
tt0186151	Frequency (2000)
tt0376136	The Rum Diary (2011)
tt3874544	The Boss Baby (2017)
tt1438176	Fright Night (2011)
tt0159273	Behind Enemy Lines (2001)
tt1588170	I Saw the Devil (2010)
tt0901476	Bride Wars (2009)
tt1327194	The Lucky One (2012)
tt0088128	Sixteen Candles (1984)
tt0061418	Bonnie and Clyde (1967)
tt0091605	The Name of the Rose (1986)
tt0112461	The Basketball Diaries (1995)
tt0104070	Death Becomes Her (1992)
tt2199571	Run All Night (2015)
tt0105112	Patriot Games (1992)
tt0343737	The Good Shepherd (2006)
tt0300471	Shanghai Knights (2003)
tt5848272	Ralph Breaks the Internet (2018)
tt0113855	Mortal Kombat (1995)
tt5814060	The Nun (2018)
tt0335245	The Ladykillers (2004)
tt0404390	Running Scared (2006)
tt0168629	Dancer in the Dark (2000)
tt1478964	Attack the Block (2011)
tt1450321	Filth (2013)
tt0112740	Crimson Tide (1995)
tt2692250	Night at the Museum: Secret of the Tomb (2014)
tt1433108	Faster (2010)
tt0480242	Dan in Real Life (2007)
tt1233227	Saw VI (2009)

tt0120184	Sphere (1998)
tt2510894	Hotel Transylvania 2 (2015)
tt0051201	Witness for the Prosecution (1957)
tt2631186	Baahubali: The Beginning (2015)
tt1027718	Wall Street: Money Never Sleeps (2010)
tt6628394	Bad Times at the El Royale (2018)
tt1571222	A Dangerous Method (2011)
tt1536044	Paranormal Activity 2 (2010)
tt0096446	Willow (1988)
tt1333125	Movie 43 (2013)
tt0477302	Extremely Loud & Incredibly Close (2011)
tt0425123	Just Like Heaven (2005)
tt3717490	Power Rangers (2017)
tt0373926	The Interpreter (2005)
tt0422720	Marie Antoinette (2006)
tt0230011	Atlantis: The Lost Empire (2001)
tt1240982	Your Highness (2011)
tt1038686	Legion (2010)
tt0119164	The Full Monty (1997)
tt0115433	101 Dalmatians (1996)
tt4500922	Maze Runner: The Death Cure (2018)
tt0052311	Touch of Evil (1958)
tt0475276	United 93 (2006)
tt0093177	Hellraiser (1987)
tt0074119	All the President's Men (1976)
tt0114388	Sense and Sensibility (1995)
tt4034354	Swiss Army Man (2016)
tt0861739	Elite Squad (2007)
tt0412019	Broken Flowers (2005)
tt1502407	Halloween (2018)
tt0409182	Poseidon (2006)
tt2193215	The Counsellor (2013)
tt0102059	Hot Shots! (1991)
tt1979388	The Good Dinosaur (2015)
tt1067106	A Christmas Carol (2009)
tt0185431	Little Nicky (2000)
tt5715874	The Killing of a Sacred Deer (2017)
tt0427152	Dinner for Schmucks (2010)
tt0044081	A Streetcar Named Desire (1951)
tt0758766	Music and Lyrics (2007)
tt4062536	Green Room (2015)
tt0318462	The Motorcycle Diaries (2004)
tt0068473	Deliverance (1972)
tt1614989	Headhunters (2011)
tt0247745	Super Troopers (2001)

tt1188996	My Name Is Khan (2010)
tt2304933	The 5th Wave (2016)
tt0081573	Superman II (1980)
tt0230030	Bedazzled (2000)
tt0133240	Treasure Planet (2002)
tt0074486	Eraserhead (1977)
tt1023111	Never Back Down (2008)
tt0277371	Not Another Teen Movie (2001)
tt0816462	Conan the Barbarian (2011)
tt0064665	Midnight Cowboy (1969)
tt0113101	Four Rooms (1995)
tt2557478	Pacific Rim: Uprising (2018)
tt0452637	Lady in the Water (2006)
tt0099871	Jacob's Ladder (1990)
tt0044706	High Noon (1952)
tt1187064	Triangle (2009)
tt1482459	The Lorax (2012)
tt6412452	The Ballad of Buster Scruggs (2018)
tt0292963	Before the Devil Knows You're Dead (2007)
tt0096969	Born on the Fourth of July (1989)
tt4501244	Why Him? (2016)
tt1502404	Drive Angry (2011)
tt0433383	Good Night and Good Luck. (2005)
tt0390384	Primer (2004)
tt5308322	Happy Death Day (2017)
tt0015864	The Gold Rush (1925)
tt0490204	Reign Over Me (2007)
tt0209958	The Cell (2000)
tt0364970	Babylon A.D. (2008)
tt0118689	Bean (1997)
tt0076752	The Spy Who Loved Me (1977)
tt1142977	Frankenweenie (2012)
tt0084805	Tootsie (1982)
tt0452702	Vacancy (2007)
tt0097239	Driving Miss Daisy (1989)
tt1144884	The Final Destination (2009)
tt1592525	Lockout (2012)
tt0758746	Friday the 13th (2009)
tt0110622	Naked Gun 33 1/3: The Final Insult (1994)
tt0064276	Easy Rider (1969)
tt0120873	U.S. Marshals (1998)
tt0098439	Tango & Cash (1989)
tt0070034	Enter the Dragon (1973)
tt0104348	Glengarry Glen Ross (1992)
tt1878870	The Edge of Seventeen (2016)

tt2854926	Tag (2018)
tt0062512	You Only Live Twice (1967)
tt1195478	The Five-Year Engagement (2012)
tt0124315	The Cider House Rules (1999)
tt2381991	The Huntsman: Winter's War (2016)
tt1235166	A Prophet (2009)
tt0066206	Patton (1970)
tt0055614	West Side Story (1961)
tt3622592	Paper Towns (2015)
tt0337921	Cellular (2004)
tt0070328	Live and Let Die (1973)
tt1524930	Vacation (2015)
tt1017460	Splice (2009)
tt0441909	Volver (2006)
tt1657507	Colombiana (2011)
tt0071360	The Conversation (1974)
tt0120907	eXistenZ (1999)
tt0060827	Persona (1966)
tt0118883	Conspiracy Theory (1997)
tt0288477	Ghost Ship (2002)
tt0118615	Anaconda (1997)
tt1623288	ParaNorman (2012)
tt2671706	Fences (2016)
tt1622547	30 Minutes or Less (2011)
tt1045772	I Love You Phillip Morris (2009)
tt0171804	Boys Don't Cry (1999)
tt7040874	A Simple Favor (2018)
tt1212419	Hereafter (2010)
tt0349205	Cheaper by the Dozen (2003)
tt0085995	National Lampoon's Vacation (1983)
tt0418819	Land of the Dead (2005)
tt5776858	Phantom Thread (2017)
tt0250258	The Experiment (2001)
tt0086034	Octopussy (1983)
tt2241351	Money Monster (2016)
tt1440728	The American (2010)
tt0066995	Diamonds Are Forever (1971)
tt0071807	The Man with the Golden Gun (1974)
tt0963178	The International (2009)
tt1386932	Ip Man 2 (2010)
tt0318649	Sahara (2005)
tt0103873	Dead Alive (1992)
tt1618442	The Last Witch Hunter (2015)
tt1216492	Leap Year (2010)
tt0122718	Small Soldiers (1998)

tt0116136	DragonHeart (1996)
tt0097742	Licence to Kill (1989)
tt1045778	Year One (2009)
tt0892318	Letters to Juliet (2010)
tt1536537	What Happened to Monday (2017)
tt0298814	The Core (2003)
tt0395584	The Devil's Rejects (2005)
tt0377109	The Ring Two (2005)
tt2224026	Home (2015)
tt0127536	Elizabeth (1998)
tt0080120	The Warriors (1979)
tt1549572	Another Earth (2011)
tt1412386	The Best Exotic Marigold Hotel (2011)
tt0479997	Season of the Witch (2011)
tt0490215	Silence (2016)
tt0111161	The Shawshank Redemption (1994)
tt1375666	Inception (2010)
tt0137523	Fight Club (1999)
tt0110912	Pulp Fiction (1994)
tt0109830	Forrest Gump (1994)
tt0120737	The Lord of the Rings: The Fellowship of the Ring (2001)
tt0068646	The Godfather (1972)
tt0167261	The Lord of the Rings: The Two Towers (2002)
tt0816692	Interstellar (2014)
tt0114369	Se7en (1995)
tt0172495	Gladiator (2000)
tt1853728	Django Unchained (2012)
tt0848228	The Avengers (2012)
tt0102926	The Silence of the Lambs (1991)
tt0361748	Inglourious Basterds (2009)
tt0120815	Saving Private Ryan (1998)
tt0108052	Schindler's List (1993)
tt0407887	The Departed (2006)
tt0482571	The Prestige (2006)
tt0080684	Star Wars: Episode V - The Empire Strikes Back (1980)
tt0499549	Avatar (2009)
tt0993846	The Wolf of Wall Street (2013)
tt0209144	Memento (2000)
tt0120689	The Green Mile (1999)
tt1130884	Shutter Island (2010)
tt0071562	The Godfather: Part II (1974)
tt0169547	American Beauty (1999)
tt0325980	Pirates of the Caribbean: The Curse of the Black Pearl (2003)
tt0120338	Titanic (1997)
tt2015381	Guardians of the Galaxy (2014)

tt0120586	American History X (1998)
tt0434409	V for Vendetta (2005)
tt0099685	Goodfellas (1990)
tt0114814	The Usual Suspects (1995)
tt0266697	Kill Bill: Vol. 1 (2003)
tt0112573	Braveheart (1995)
tt0266543	Finding Nemo (2003)
tt0371746	Iron Man (2008)
tt0086190	Star Wars: Episode VI - Return of the Jedi (1983)
tt1049413	Up (2009)
tt0167404	The Sixth Sense (1999)
tt0110357	The Lion King (1994)
tt0120382	The Truman Show (1998)
tt0073486	One Flew Over the Cuckoo's Nest (1975)
tt0105236	Reservoir Dogs (1992)
tt0338013	Eternal Sunshine of the Spotless Mind (2004)
tt1431045	Deadpool (2016)
tt0082971	Raiders of the Lost Ark (1981)
tt0114709	Toy Story (1995)
tt1392170	The Hunger Games (2012)
tt0081505	The Shining (1980)
tt0107290	Jurassic Park (1993)
tt2488496	Star Wars: Episode VII - The Force Awakens (2015)
tt1392190	Mad Max: Fury Road (2015)
tt0268978	A Beautiful Mind (2001)
tt0119217	Good Will Hunting (1997)
tt0477348	No Country for Old Men (2007)
tt2267998	Gone Girl (2014)
tt1010048	Slumdog Millionaire (2008)
tt0198781	Monsters Inc. (2001)
tt0088247	The Terminator (1984)
tt0264464	Catch Me If You Can (2002)
tt0095016	Die Hard (1988)
tt0208092	Snatch (2000)
tt0903624	The Hobbit: An Unexpected Journey (2012)
tt0078748	Alien (1979)
tt0401792	Sin City (2005)
tt1454468	Gravity (2013)
tt0180093	Requiem for a Dream (2000)
tt0246578	Donnie Darko (2001)
tt1300854	Iron Man 3 (2013)
tt1201607	Harry Potter and the Deathly Hallows: Part 2 (2011)
tt0416449	300 (2006)
tt0066921	A Clockwork Orange (1971)
tt0435761	Toy Story 3 (2010)

tt0800369	Thor (2011)
tt4154756	Avengers: Infinity War (2018)
tt3659388	The Martian (2015)
tt1675434	The Intouchables (2011)
tt0458339	Captain America: The First Avenger (2011)
tt1119646	The Hangover (2009)
tt1205489	Gran Torino (2008)
tt2395427	Avengers: Age of Ultron (2015)
tt1843866	Captain America: The Winter Soldier (2014)
tt0086250	Scarface (1983)
tt0118715	The Big Lebowski (1998)
tt1228705	Iron Man 2 (2010)
tt0120915	Star Wars: Episode I - The Phantom Menace (1999)
tt0211915	AmÃ©lie (2001)
tt0947798	Black Swan (2010)
tt0770828	Man of Steel (2013)
tt0253474	The Pianist (2002)
tt0317248	City of God (2002)
tt0145487	Spider-Man (2002)
tt0121766	Star Wars: Episode III - Revenge of the Sith (2005)
tt0075314	Taxi Driver (1976)
tt0097576	Indiana Jones and the Last Crusade (1989)
tt2278388	The Grand Budapest Hotel (2014)
tt0480249	I Am Legend (2007)
tt0083658	Blade Runner (1982)
tt0060196	The Good the Bad and the Ugly (1966)
tt1663202	The Revenant (2015)
tt2084970	The Imitation Game (2014)
tt1877832	X-Men: Days of Future Past (2014)
tt2582802	Whiplash (2014)
tt1045658	Silver Linings Playbook (2012)
tt0378194	Kill Bill: Vol. 2 (2004)
tt0383574	Pirates of the Caribbean: Dead Man's Chest (2006)
tt0892769	How to Train Your Dragon (2010)
tt0093058	Full Metal Jacket (1987)
tt1270798	X-Men: First Class (2011)
tt1136608	District 9 (2009)
tt0090605	Aliens (1986)
tt0050083	12 Angry Men (1957)
tt1504320	The King's Speech (2010)
tt1074638	Skyfall (2012)
tt0117951	Trainspotting (1996)
tt3498820	Captain America: Civil War (2016)
tt0405159	Million Dollar Baby (2004)
tt0382932	Ratatouille (2007)

tt0440963	The Bourne Ultimatum (2007)
tt2024544	12 Years a Slave (2013)
tt2975590	Batman v Superman: Dawn of Justice (2016)
tt0121765	Star Wars: Episode II - Attack of the Clones (2002)
tt1951264	The Hunger Games: Catching Fire (2013)
tt0457430	Pan's Labyrinth (2006)
tt0241527	Harry Potter and the Sorcerer's Stone (2001)
tt1285016	The Social Network (2010)
tt0418279	Transformers (2007)
tt3315342	Logan (2017)
tt1170358	The Hobbit: The Desolation of Smaug (2013)
tt0126029	Shrek (2001)
tt0245429	Spirited Away (2001)
tt0449088	Pirates of the Caribbean: At World's End (2007)
tt0118799	Life Is Beautiful (1997)
tt0796366	Star Trek (2009)
tt0816711	World War Z (2013)
tt1670345	Now You See Me (2013)
tt0078788	Apocalypse Now (1979)
tt1631867	Edge of Tomorrow (2014)
tt2802144	Kingsman: The Secret Service (2014)
tt0062622	2001: A Space Odyssey (1968)
tt1981115	Thor: The Dark World (2013)
tt0107048	Groundhog Day (1993)
tt0054215	Psycho (1960)
tt0369610	Jurassic World (2015)
tt0421715	The Curious Case of Benjamin Button (2008)
tt2096673	Inside Out (2015)
tt0381061	Casino Royale (2006)
tt0114746	Twelve Monkeys (1995)
tt1446714	Prometheus (2012)
tt1637725	Ted (2012)
tt0936501	Taken (2008)
tt0120903	X-Men (2000)
tt0454876	Life of Pi (2012)
tt1386697	Suicide Squad (2016)
tt1024648	Argo (2012)
tt1392214	Prisoners (2013)
tt0948470	The Amazing Spider-Man (2012)
tt1825683	Black Panther (2018)
tt0113277	Heat (1995)
tt0758758	Into the Wild (2007)
tt0780504	Drive (2011)
tt2562232	Birdman or (The Unexpected Virtue of Ignorance) (2014)
tt1211837	Doctor Strange (2016)

tt2543164	Arrival (2016)
tt2294629	Frozen (2013)
tt0073195	Jaws (1975)
tt0478970	Ant-Man (2015)
tt0316654	Spider-Man 2 (2004)
tt1276104	Looper (2012)
tt1250777	Kick-Ass (2010)
tt0116629	Independence Day (1996)
tt0295297	Harry Potter and the Chamber of Secrets (2002)
tt0119488	L.A. Confidential (1997)
tt0120735	Lock Stock and Two Smoking Barrels (1998)
tt1219289	Limitless (2011)
tt3501632	Thor: Ragnarok (2017)
tt0304141	Harry Potter and the Prisoner of Azkaban (2004)
tt0451279	Wonder Woman (2017)
tt0330373	Harry Potter and the Goblet of Fire (2005)
tt3896198	Guardians of the Galaxy Vol. 2 (2017)
tt0829482	Superbad (2007)
tt0290334	X2: X-Men United (2003)
tt4154796	Avengers: Endgame (2019)
tt3748528	Rogue One: A Star Wars Story (2016)
tt0234215	The Matrix Reloaded (2003)
tt1232829	21 Jump Street (2012)
tt0034583	Casablanca (1942)
tt0120363	Toy Story 2 (1999)
tt0332280	The Notebook (2004)
tt0258463	The Bourne Identity (2002)
tt0240772	Ocean's Eleven (2001)
tt0162222	Cast Away (2000)
tt0075148	Rocky (1976)
tt1318514	Rise of the Planet of the Apes (2011)
tt5013056	Dunkirk (2017)
tt0365748	Shaun of the Dead (2004)
tt0181689	Minority Report (2002)
tt1798709	Her (2013)
tt2527336	Star Wars: The Last Jedi (2017)
tt1323594	Despicable Me (2010)
tt0467406	Juno (2007)
tt0343818	I Robot (2004)
tt0469494	There Will Be Blood (2007)
tt0071853	Monty Python and the Holy Grail (1975)
tt0450259	Blood Diamond (2006)
tt0413300	Spider-Man 3 (2007)
tt2911666	John Wick (2014)
tt0364569	Oldboy (2003)

tt1156398	Zombieland (2009)
tt0373889	Harry Potter and the Order of the Phoenix (2007)
tt0409459	Watchmen (2009)
tt1483013	Oblivion (2013)
tt0332452	Troy (2004)
tt0945513	Source Code (2011)
tt1298650	Pirates of the Caribbean: On Stranger Tides (2011)
tt1408101	Star Trek Into Darkness (2013)
tt1663662	Pacific Rim (2013)
tt0095953	Rain Man (1988)
tt1022603	500 Days of Summer (2009)
tt2310332	The Hobbit: The Battle of the Five Armies (2014)
tt3460252	The Hateful Eight (2015)
tt0458525	X-Men Origins: Wolverine (2009)
tt3783958	La La Land (2016)
tt2250912	Spider-Man: Homecoming (2017)
tt1570728	Crazy Stupid Love. (2011)
tt1343092	The Great Gatsby (2013)
tt1411697	The Hangover Part II (2011)
tt0206634	Children of Men (2006)
tt1229238	Mission: Impossible - Ghost Protocol (2011)
tt0926084	Harry Potter and the Deathly Hallows: Part 1 (2010)
tt0470752	Ex Machina (2014)
tt0425112	Hot Fuzz (2007)
tt1659337	The Perks of Being a Wallflower (2012)
tt0289879	The Butterfly Effect (2004)
tt0417741	Harry Potter and the Half-Blood Prince (2009)
tt0356910	Mr. & Mrs. Smith (2005)
tt0242653	The Matrix Revolutions (2003)
tt0057012	Dr. Strangelove or: How I Learned to Stop Worrying and Love the Bomb (1964)
tt0112641	Casino (1995)
tt0099487	Edward Scissorhands (1990)
tt0448157	Hancock (2008)
tt0449059	Little Miss Sunshine (2006)
tt5052448	Get Out (2017)
tt0372183	The Bourne Supremacy (2004)
tt0087469	Indiana Jones and the Temple of Doom (1984)
tt2872718	Nightcrawler (2014)
tt0099785	Home Alone (1990)
tt0454921	The Pursuit of Happyness (2006)
tt0800080	The Incredible Hulk (2008)
tt1291584	Warrior (2011)
tt2872732	Lucy (2014)
tt0268380	Ice Age (2002)

tt0119116	The Fifth Element (1997)
tt0790636	Dallas Buyers Club (2013)
tt2179136	American Sniper (2014)
tt1430132	The Wolverine (2013)
tt0047396	Rear Window (1954)
tt5463162	Deadpool 2 (2018)
tt0375679	Crash (2004)
tt1457767	The Conjuring (2013)
tt1840309	Divergent (2014)
tt1499658	Horrible Bosses (2011)
tt1535108	Elysium (2013)
tt1099212	Twilight (2008)
tt1979320	Rush (2013)
tt1515091	Sherlock Holmes: A Game of Shadows (2011)
tt0443706	Zodiac (2007)
tt0367882	Indiana Jones and the Kingdom of the Crystal Skull (2008)
tt1454029	The Help (2011)
tt0887912	The Hurt Locker (2008)
tt0101414	Beauty and the Beast (1991)
tt0367594	Charlie and the Chocolate Factory (2005)
tt2103281	Dawn of the Planet of the Apes (2014)
tt1872181	The Amazing Spider-Man 2 (2014)
tt0319061	Big Fish (2003)
tt0327056	Mystic River (2003)
tt1535109	Captain Phillips (2013)
tt0407304	War of the Worlds (2005)
tt1568346	The Girl with the Dragon Tattoo (2011)
tt1790864	The Maze Runner (2014)
tt0319262	The Day After Tomorrow (2004)
tt2948356	Zootopia (2016)
tt0298148	Shrek 2 (2004)
tt2713180	Fury (2014)
tt0441773	Kung Fu Panda (2008)
tt1856101	Blade Runner 2049 (2017)
tt1951265	The Hunger Games: Mockingjay - Part 1 (2014)
tt0830515	Quantum of Solace (2008)
tt0335266	Lost in Translation (2003)
tt2245084	Big Hero 6 (2014)
tt0382625	The Da Vinci Code (2006)
tt1723121	We're the Millers (2013)
tt0217505	Gangs of New York (2002)
tt0097165	Dead Poets Society (1989)
tt0120591	Armageddon (1998)
tt3890160	Baby Driver (2017)
tt0337978	Live Free or Die Hard (2007)

tt0325710	The Last Samurai (2003)
tt2119532	Hacksaw Ridge (2016)
tt0398286	Tangled (2010)
tt0360717	King Kong (2005)
tt0120616	The Mummy (1999)
tt3183660	Fantastic Beasts and Where to Find Them (2016)
tt0765429	American Gangster (2007)
tt1895587	Spotlight (2015)
tt0362227	The Terminal (2004)
tt1399103	Transformers: Dark of the Moon (2011)
tt1396484	It (2017)
tt0405422	The 40-Year-Old Virgin (2005)
tt1055369	Transformers: Revenge of the Fallen (2009)
tt0033467	Citizen Kane (1941)
tt4972582	Split (2016)
tt2980516	The Theory of Everything (2014)
tt0780536	In Bruges (2008)
tt0099088	Back to the Future Part III (1990)
tt1245492	This Is the End (2013)
tt1727824	Bohemian Rhapsody (2018)
tt3385516	X-Men: Apocalypse (2016)
tt0093779	The Princess Bride (1987)
tt0117060	Mission: Impossible (1996)
tt1014759	Alice in Wonderland (2010)
tt0038650	It's a Wonderful Life (1946)
tt0139654	Training Day (2001)
tt1605783	Midnight in Paris (2011)
tt0217869	Unbreakable (2000)
tt0163651	American Pie (1999)
tt0032138	The Wizard of Oz (1939)
tt0387564	Saw (2004)
tt0831387	Godzilla (2014)
tt0091763	Platoon (1986)
tt0942385	Tropic Thunder (2008)
tt1060277	Cloverfield (2008)
tt0181852	Terminator 3: Rise of the Machines (2003)
tt5027774	Three Billboards Outside Ebbing Missouri (2017)
tt1905041	Fast & Furious 6 (2013)
tt1772341	Wreck-It Ralph (2012)
tt0119567	The Lost World: Jurassic Park (1997)
tt0315327	Bruce Almighty (2003)
tt1637688	In Time (2011)
tt0289043	28 Days Later... (2002)
tt0093773	Predator (1987)
tt1690953	Despicable Me 2 (2013)

tt0105695	Unforgiven (1992)
tt0112864	Die Hard with a Vengeance (1995)
tt0458352	The Devil Wears Prada (2006)
tt0493464	Wanted (2008)
tt0446029	Scott Pilgrim vs. the World (2010)
tt1217209	Brave (2012)
tt0265086	Black Hawk Down (2001)
tt1259521	The Cabin in the Woods (2011)
tt0086879	Amadeus (1984)
tt0083866	E.T. the Extra-Terrestrial (1982)
tt0443543	The Illusionist (2006)
tt0079470	Monty Python's Life of Brian (1979)
tt0070047	The Exorcist (1973)
tt2820852	Furious 7 (2015)
tt0369339	Collateral (2004)
tt0092005	Stand by Me (1986)
tt0351283	Madagascar (2005)
tt0084787	The Thing (1982)
tt0443453	Borat: Cultural Learnings of America for Make Benefit Glorious Nation of Kazakhstan (2006)
tt0478311	Knocked Up (2007)
tt0974015	Justice League (2017)
tt0349903	Ocean's Twelve (2004)
tt0317219	Cars (2006)
tt1282140	Easy A (2010)
tt4154664	Captain Marvel (2019)
tt1596343	Fast Five (2011)
tt3397884	Sicario (2015)
tt0361862	The Machinist (2004)
tt0109686	Dumb and Dumber (1994)
tt1190080	2012 (2009)
tt1210166	Moneyball (2011)
tt1371111	Cloud Atlas (2012)
tt0099674	The Godfather: Part III (1990)
tt0103639	Aladdin (1992)
tt0405094	The Lives of Others (2006)
tt0087332	Ghostbusters (1984)
tt0408236	Sweeney Todd: The Demon Barber of Fleet Street (2007)
tt0052357	Vertigo (1958)
tt0232500	The Fast and the Furious (2001)
tt0438488	Terminator Salvation (2009)
tt1650062	Super 8 (2011)
tt2294449	22 Jump Street (2014)
tt0088847	The Breakfast Club (1985)
tt3170832	Room (2015)

tt1632708	Friends with Benefits (2011)
tt0286106	Signs (2002)
tt0964517	The Fighter (2010)
tt2582846	The Fault in Our Stars (2014)
tt1065073	Boyhood (2014)
tt0119174	The Game (1997)
tt0110475	The Mask (1994)
tt0396269	Wedding Crashers (2005)
tt0230600	The Others (2001)
tt0395169	Hotel Rwanda (2004)
tt0096895	Batman (1989)
tt2381249	Mission: Impossible - Rogue Nation (2015)
tt1355644	Passengers (2016)
tt1409024	Men in Black 3 (2012)
tt1182345	Moon (2009)
tt5580390	The Shape of Water (2017)
tt6644200	A Quiet Place (2018)
tt1596363	The Big Short (2015)
tt1068680	Yes Man (2008)
tt0357413	Anchorman: The Legend of Ron Burgundy (2004)
tt0338751	The Aviator (2004)
tt0328107	Man on Fire (2004)
tt1320253	The Expendables (2010)
tt1677720	Ready Player One (2018)
tt0317919	Mission: Impossible III (2006)
tt1587310	Maleficent (2014)
tt0363163	Downfall (2004)
tt0162661	Sleepy Hollow (1999)
tt1490017	The Lego Movie (2014)
tt0343660	50 First Dates (2004)
tt0111257	Speed (1994)
tt1231583	Due Date (2010)
tt0455944	The Equalizer (2014)
tt1907668	Flight (2012)
tt0377092	Mean Girls (2004)
tt0118971	The Devil's Advocate (1997)
tt1187043	3 Idiots (2009)
tt1306980	50/50 (2011)
tt1193138	Up in the Air (2009)
tt4425200	John Wick: Chapter 2 (2017)
tt0388795	Brokeback Mountain (2005)
tt0298130	The Ring (2002)
tt0496806	Ocean's Thirteen (2007)
tt1104001	TRON: Legacy (2010)
tt0238380	Equilibrium (2002)

tt0910936	Pineapple Express (2008)
tt1453405	Monsters University (2013)
tt0117500	The Rock (1996)
tt0213149	Pearl Harbor (2001)
tt0462538	The Simpsons Movie (2007)
tt1748122	Moonrise Kingdom (2012)
tt0822854	Shooter (2007)
tt0120755	Mission: Impossible II (2000)
tt0166924	Mulholland Drive (2001)
tt0091042	Ferris Bueller's Day Off (1986)
tt0167190	Hellboy (2004)
tt0081398	Raging Bull (1980)
tt1270797	Venom (2018)
tt0120601	Being John Malkovich (1999)
tt0477347	Night at the Museum (2006)
tt0887883	Burn After Reading (2008)
tt2788710	The Interview (2014)
tt1707386	Les MisÃ©rables (2012)
tt0047478	Seven Samurai (1954)
tt0368891	National Treasure (2004)
tt0077416	The Deer Hunter (1978)
tt0970179	Hugo (2011)
tt1403865	True Grit (2010)
tt0209163	The Mummy Returns (2001)
tt2380307	Coco (2017)
tt0389860	Click (2006)
tt2109248	Transformers: Age of Extinction (2014)
tt0433035	Real Steel (2011)
tt0119396	Jackie Brown (1997)
tt0360486	Constantine (2005)
tt1646971	How to Train Your Dragon 2 (2014)
tt0087843	Once Upon a Time in America (1984)
tt0100802	Total Recall (1990)
tt0386588	Hitch (2005)
tt0399295	Lord of War (2005)
tt0944835	Salt (2010)
tt1125849	The Wrestler (2008)
tt0453467	Deja Vu (2006)
tt1477834	Aquaman (2018)
tt0359950	The Secret Life of Walter Mitty (2013)
tt0129387	There's Something About Mary (1998)
tt0163025	Jurassic Park III (2001)
tt0212720	A.I. Artificial Intelligence (2001)
tt0110148	Interview with the Vampire: The Vampire Chronicles (1994)
tt0056592	To Kill a Mockingbird (1962)

tt0053125	North by Northwest (1959)
tt0449467	Babel (2006)
tt1397280	Taken 2 (2012)
tt1041829	The Proposal (2009)
tt0064116	Once Upon a Time in the West (1968)
tt0120663	Eyes Wide Shut (1999)
tt0489099	Jumper (2008)
tt1037705	The Book of Eli (2010)
tt1951261	The Hangover Part III (2013)
tt1245526	RED (2010)
tt0113497	Jumanji (1995)
tt0472043	Apocalypto (2006)
tt0147800	10 Things I Hate About You (1999)
tt0379786	Serenity (2005)
tt0381849	3:10 to Yuma (2007)
tt0175880	Magnolia (1999)
tt0293662	The Transporter (2002)
tt1194173	The Bourne Legacy (2012)
tt0107688	The Nightmare Before Christmas (1993)
tt0814314	Seven Pounds (2008)
tt0878804	The Blind Side (2009)
tt0071315	Chinatown (1974)
tt2004420	Neighbors (2014)
tt2194499	About Time (2013)
tt0190590	O Brother Where Art Thou? (2000)
tt0031381	Gone with the Wind (1939)
tt0104431	Home Alone 2: Lost in New York (1992)
tt3682448	Bridge of Spies (2015)
tt1253863	300: Rise of an Empire (2014)
tt0092099	Top Gun (1986)
tt1179933	10 Cloverfield Lane (2016)
tt0116367	From Dusk Till Dawn (1996)
tt1152836	Public Enemies (2009)
tt0100405	Pretty Woman (1990)
tt0117571	Scream (1996)
tt1517451	A Star Is Born (2018)
tt0119177	Gattaca (1997)
tt0119528	Liar Liar (1997)
tt0348150	Superman Returns (2006)
tt1735898	Snow White and the Huntsman (2012)
tt0118880	Con Air (1997)
tt1981677	Pitch Perfect (2012)
tt0413267	Shrek the Third (2007)
tt0094226	The Untouchables (1987)
tt0800320	Clash of the Titans (2010)

tt0103644	AlienÂ³ (1992)
tt0109040	Ace Ventura: Pet Detective (1994)
tt0473075	Prince of Persia: The Sands of Time (2010)
tt1591095	Insidious (2010)
tt0119822	As Good as It Gets (1997)
tt1951266	The Hunger Games: Mockingjay - Part 2 (2015)
tt0278504	Insomnia (2002)
tt0103776	Batman Returns (1992)
tt0808151	Angels & Demons (2009)
tt1197624	Law Abiding Citizen (2009)
tt1133985	Green Lantern (2011)
tt0203009	Moulin Rouge! (2001)
tt1790885	Zero Dark Thirty (2012)
tt1645170	The Dictator (2012)
tt5095030	Ant-Man and the Wasp (2018)
tt0120201	Starship Troopers (1997)
tt0320661	Kingdom of Heaven (2005)
tt1478338	Bridesmaids (2011)
tt1259571	The Twilight Saga: New Moon (2009)
tt0120623	A Bug's Life (1998)
tt0800039	Forgetting Sarah Marshall (2008)
tt0838283	Step Brothers (2008)
tt1091191	Lone Survivor (2013)
tt2283362	Jumanji: Welcome to the Jungle (2017)
tt0112384	Apollo 13 (1995)
tt0265666	The Royal Tenenbaums (2001)
tt0187078	Gone in 60 Seconds (2000)
tt0106977	The Fugitive (1993)
tt0332379	School of Rock (2003)
tt1028528	Death Proof (2007)
tt2106476	The Hunt (2012)
tt0056172	Lawrence of Arabia (1962)
tt1013752	Fast & Furious (2009)
tt0411477	Hellboy II: The Golden Army (2008)
tt0401729	John Carter (2012)
tt0463854	28 Weeks Later (2007)
tt3799694	The Nice Guys (2016)
tt3040964	The Jungle Book (2016)
tt1706620	Snowpiercer (2013)
tt1638355	The Man from U.N.C.L.E. (2015)
tt3731562	Kong: Skull Island (2017)
tt2771200	Beauty and the Beast (2017)
tt0096283	My Neighbor Totoro (1988)
tt0190332	Crouching Tiger Hidden Dragon (2000)
tt0286716	Hulk (2003)

tt0320691	Underworld (2003)
tt0955308	Robin Hood (2010)
tt0112471	Before Sunrise (1995)
tt1650554	Kick-Ass 2 (2013)
tt0486576	Fantastic 4: Rise of the Silver Surfer (2007)
tt0486655	Stardust (2007)
tt4912910	Mission: Impossible - Fallout (2018)
tt0290002	Meet the Fockers (2004)
tt0061722	The Graduate (1967)
tt0187393	The Patriot (2000)
tt0258000	Panic Room (2002)
tt0212985	Hannibal (2001)

APPENDIX E – FULL LIST OF MOVIES PROVIDED TO TEST THE RECOMMENDATION MODEL

IMDB ID	Movie Title	Year of Release	Genres
tt0406650	The Chumscrubber	2005	Comedy Drama
tt6826438	Parmanu: The Story of Pokhran	2018	Action Drama History
tt4537896	White Boy Rick	2018	Crime Drama
tt0318034	Russian Ark	2002	Drama Fantasy History
tt1277737	The Stoning of Soraya M.	2008	Drama
tt1337057	Rampage	2009	Action Crime Thriller
tt0095082	Eight Men Out	1988	Drama History Sport
tt0488414	Omkara	2006	Action Crime Drama
tt0437800	Akeelah and the Bee	2006	Drama Family
tt0045897	I Confess	1953	Crime Drama Thriller
tt0038733	A Matter of Life and Death	1946	Comedy Drama Fantasy
tt2725962	What We Did on Our Holiday	2014	Comedy Drama
tt0393735	The Shaggy Dog	2006	Comedy Family Fantasy
tt1753496	Resident Evil: Damnation	2012	Action Animation Horror
tt0102005	Harley Davidson and the Marlboro Man	1991	Action Crime Drama
tt4913966	The Curse of La Llorona	2019	Horror Mystery Thriller
tt1229827	Jonas Brothers: The 3D Concert Experience	2009	Documentary Music
tt1046997	Miracle at St. Anna	2008	Action Drama War
tt0078087	Piranha	1978	Comedy Horror Sci-Fi
tt0117128	Mystery Science Theater 3000: The Movie	1996	Comedy Sci-Fi
tt0325537	Head of State	2003	Comedy
tt5886440	Marrowbone	2017	Drama Horror Thriller
tt1440732	Bel Ami	2012	Drama History Romance
tt0089606	My Life as a Dog	1985	Comedy Drama
tt0401233	Appleseed	2004	Action Animation Drama
tt0081070	The Long Good Friday	1980	Crime Drama Mystery
tt0960890	Zombie Strippers!	2008	Comedy Horror Sci-Fi
tt0077663	Heaven Can Wait	1978	Comedy Fantasy Romance
tt0088206	Supergirl	1984	Action Adventure Fantasy
tt4799066	Midnight Sun	2018	Drama Romance
tt1656192	Special Forces	2011	Action Drama War
tt6108090	Secret Superstar	2017	Drama Music
tt0082377	The Final Conflict	1981	Horror
tt0113305	Higher Learning	1995	Crime Drama Romance
tt1781069	Zeitgeist: Moving Forward	2011	Documentary
tt0402057	Beowulf & Grendel	2005	Action Adventure Drama
tt0167427	Superstar	1999	Comedy Romance
tt0102782	Return to the Blue Lagoon	1991	Adventure Drama Romance
tt1027862	Swing Vote	2008	Comedy Drama
tt4181052	Special Correspondents	2016	Comedy
tt0396184	With Blood on My Hands: Pusher II	2004	Action Crime Drama
tt0195234	Saving Grace	2000	Comedy Crime
tt0048261	Kiss Me Deadly	1955	Crime Film-Noir Mystery
tt0302674	Gerry	2002	Adventure Drama Mystery
tt0050086	3:10 to Yuma	1957	Drama Thriller Western
tt5670152	Traffik	2018	Action Crime Drama

tt0086312	Silkwood	1983	Biography Drama History
tt0062138	Point Blank	1967	Crime Drama Thriller
tt1654523	Night Train to Lisbon	2013	Mystery Romance Thriller
tt1498569	Restless	2011	Drama Romance
tt0097722	Lean on Me	1989	Drama
tt0095519	License to Drive	1988	Comedy
tt0109759	Exotica	1994	Drama
tt2620590	Leatherface	2017	Crime Horror Thriller
tt0087365	Greystoke: The Legend of Tarzan Lord of the Apes	1984	Adventure Drama
tt7581902	Sonu Ke Titu Ki Sweety	2018	Comedy Romance
tt0361841	Little Black Book	2004	Comedy Drama Romance
tt0071141	Ali: Fear Eats the Soul	1974	Drama Romance
tt0032484	Foreign Correspondent	1940	Action Romance Thriller
tt1131724	NULL	2017	Thriller
tt0071249	Bring Me the Head of Alfredo Garcia	1974	Action Crime Drama
tt0087799	Night of the Comet	1984	Comedy Horror Sci-Fi
tt1434447	Rocket Singh: Salesman of the Year	2009	Comedy Drama
tt0155711	Flawless	1999	Comedy Crime Drama
tt0080569	Cruising	1980	Crime Drama Mystery
tt0075223	Silver Streak	1976	Action Comedy Crime
tt0014429	Safety Last!	1923	Action Comedy Thriller
tt0250081	Storytelling	2001	Comedy Drama Romance
tt0417056	Pledge This!	2006	Comedy
tt0422091	Dhoom	2004	Action Crime Thriller
tt0097737	Leviathan	1989	Adventure Horror Mystery
tt0299117	Roger Dodger	2002	Comedy Drama
tt0400234	Black Friday	2004	Action Crime Drama
tt1230385	The Yellow Sea	2010	Action Drama Thriller
tt1798243	Rudderless	2014	Comedy Drama Music
tt0080923	Inferno	1980	Horror
tt0100318	Pacific Heights	1990	Thriller
tt1555064	Country Strong	2010	Drama Music
tt0304711	The Order	2003	Horror Mystery Thriller
tt0373450	Where the Truth Lies	2005	Crime Drama Mystery
tt1839654	The Magic of Belle Isle	2012	Comedy Drama
tt5462326	Mom and Dad	2017	Comedy Horror Thriller
tt0458364	The Ex	2006	Comedy Romance
tt0042804	The Young and the Damned	1950	Crime Drama
tt0893402	Franklyn	2008	Drama Fantasy Sci-Fi
tt1172571	The Children	2008	Horror Mystery Thriller
tt0250468	Killing Me Softly	2002	Drama Mystery Romance
tt4701724	Early Man	2018	Adventure Animation Comedy
tt0345551	Latter Days	2003	Comedy Drama Romance
tt0055471	Splendor in the Grass	1961	Drama Romance
tt7218518	Padman	2018	Comedy Drama
tt0432637	Krrish	2006	Action Adventure Sci-Fi
tt0088194	Streets of Fire	1984	Action Crime Drama
tt0409345	Surveillance	2008	Crime Drama Mystery
tt0110222	Kabhi Haan Kabhi Naa	1994	Comedy Drama Music
tt1104733	Hamlet 2	2008	Comedy Music
tt2011159	No Good Deed	2014	Action Crime Drama
tt0346094	Distant	2002	Drama
tt0089118	F/X	1986	Action Thriller
tt0105156	Poison Ivy	1992	Drama Thriller
tt0808276	Cold Prey	2006	Horror Thriller
tt0249380	Rape Me	2000	Crime Drama Thriller
tt0108188	Sonatine	1993	Action Comedy Crime
tt0065377	Airport	1970	Action Drama Thriller
tt0104438	Honeymoon in Vegas	1992	Comedy Romance Thriller

tt0074899	Midway	1976	Action Drama History
tt3137630	David Brent: Life on the Road	2016	Comedy Music
tt0059260	Help!	1965	Adventure Comedy Musical
tt1945084	Everly	2014	Action Thriller
tt0076257	The Kentucky Fried Movie	1977	Comedy
tt0770772	I Think I Love My Wife	2007	Comedy Drama Romance
tt3702652	The Other Side of the Door	2016	Horror
tt0295289	A Guy Thing	2003	Comedy Romance
tt0116731	The Juror	1996	Drama Thriller
tt7137380	Destroyer	2018	Action Crime Drama
tt0057611	The Silence	1963	Drama
tt0366292	One Missed Call	2003	Horror Mystery
tt0060397	Fantastic Voyage	1966	Adventure Family Sci-Fi
tt0455323	Being Flynn	2012	Drama
tt5360952	The Hurricane Heist	2018	Action Adventure Crime
tt0479751	Sivaji	2007	Action Drama Thriller
tt5316540	Close	2019	Action Thriller
tt0348121	Steamboy	2004	Action Adventure Animation
tt0103994	Like Water for Chocolate	1992	Drama Romance
tt2366608	Lost River	2014	Drama Fantasy Mystery
tt1053859	The Grudge 3	2009	Horror Mystery Thriller
tt0027125	Top Hat	1935	Comedy Musical Romance
tt0055184	The Misfits	1961	Drama Romance Western
tt0065143	The Bird with the Crystal Plumage	1970	Horror Mystery Thriller
tt0099850	Internal Affairs	1990	Crime Drama Thriller
tt0079221	Gol Maal	1979	Comedy Romance
tt5666304	The Little Hours	2017	Comedy Romance
tt0108101	Shadowlands	1993	Biography Drama Romance
tt0094072	Summer School	1987	Comedy Romance
tt0087892	A Passage to India	1984	Adventure Drama History
tt0049513	Moby Dick	1956	Adventure Drama
tt0058700	The Last Man on Earth	1964	Horror Sci-Fi
tt2172935	Metallica Through the Never	2013	Music
tt0073705	Shivers	1975	Horror Sci-Fi
tt0420609	Infamous	2006	Biography Crime Drama
tt0082783	My Dinner with Andre	1981	Biography Comedy Drama
tt0102175	Jungle Fever	1991	Drama Romance
tt0369060	Infernal Affairs II	2003	Action Crime Drama
tt1610996	Absentia	2011	Drama Horror Mystery
tt0079766	Quadrophenia	1979	Drama Music
tt0082782	My Bloody Valentine	1981	Horror Mystery Thriller
tt0462338	The Hoax	2006	Comedy Drama
tt2212008	The Bag Man	2014	Crime Drama Thriller
tt2383068	The Sacrament	2013	Horror Thriller
tt0488798	Welcome	2007	Comedy Romance
tt0093185	The Hidden	1987	Action Crime Horror
tt0083169	Taps	1981	Drama
tt0780608	Smiley Face	2007	Comedy
tt0077572	Force 10 from Navarone	1978	Action Drama War
tt4291600	Lady Macbeth	2016	Drama Romance
tt1391034	And Soon the Darkness	2010	Drama Horror Mystery
tt1274295	Kaminey	2009	Action Crime Drama
tt0106452	Body Snatchers	1993	Horror Sci-Fi
tt0819714	The Edge of Love	2008	Biography Drama Romance
tt2094064	Much Ado About Nothing	2012	Comedy Drama Romance
tt0211934	Baadshah	1999	Action Comedy Crime
tt0800027	Feast of Love	2007	Drama Romance
tt1016075	Fame	2009	Comedy Drama Musical
tt1016268	Enron: The Smartest Guys in the Room	2005	Documentary

tt0808185	The Bothersome Man	2006	Comedy Drama Fantasy
tt0492486	Shrooms	2007	Comedy Horror Mystery
tt0264761	Kissing Jessica Stein	2001	Comedy Drama Romance
tt2980706	Planes: Fire & Rescue	2014	Adventure Animation Comedy
tt0410730	Taxidermia	2006	Comedy Drama Horror
tt0910905	In the Electric Mist	2009	Crime Drama Mystery
tt0072730	A Boy and His Dog	1975	Comedy Drama Sci-Fi
tt0082817	Nighthawks	1981	Action Crime Thriller
tt0073018	French Connection II	1975	Action Crime Drama
tt1291465	Raajneeti	2010	Crime Drama
tt0085255	Blue Thunder	1983	Action Crime Drama
tt3835080	NULL	2016	Horror Thriller
tt0065112	Topaz	1969	Drama Thriller
tt5785170	Toilet - Ek Prem Katha	2017	Comedy Drama
tt0204175	Boys and Girls	2000	Comedy Drama Romance
tt5322012	Wish Upon	2017	Drama Fantasy Horror
tt1103982	The Girlfriend Experience	2009	Drama
tt2034139	The Last Exorcism Part II	2013	Horror Thriller
tt0109370	Canadian Bacon	1995	Comedy
tt2386404	He Never Died	2015	Comedy Drama Fantasy
tt0102915	Showdown in Little Tokyo	1991	Action Comedy Crime
tt0105378	Shadows and Fog	1991	Comedy
tt0095897	The Presidio	1988	Action Crime Mystery
tt1018818	Assassination of a High School President	2008	Comedy Crime Mystery
tt6116856	The Night Comes for Us	2018	Action Thriller
tt0076740	Sorcerer	1977	Adventure Drama Thriller
tt1996264	For a Good Time Call...	2012	Comedy
tt0192731	Urban Legends: Final Cut	2000	Horror Mystery Thriller
tt1294213	Solitary Man	2009	Comedy Drama Romance
tt0374271	In Your Name	2003	Action Drama Romance
tt5859238	Lucky	2017	Comedy Drama
tt0067741	Shaft	1971	Action Crime Thriller
tt2784512	Zombeavers	2014	Action Adventure Comedy
tt0075222	Silent Movie	1976	Comedy
tt0104237	Damage	1992	Drama Romance
tt1524575	The Vatican Tapes	2015	Horror Thriller
tt0098309	She-Devil	1989	Comedy
tt0056262	The Music Man	1962	Comedy Musical Romance
tt0095655	Moonwalker	1988	Action Crime Fantasy
tt0117107	Mulholland Falls	1996	Crime Drama Mystery
tt0422272	Fragile	2005	Horror Mystery Thriller
tt0059243	The Great Race	1965	Action Adventure Comedy
tt1395054	Once Upon a Time in Mumbai	2010	Action Crime Drama
tt0376105	Racing Stripes	2005	Adventure Comedy Drama
tt2216240	A Hijacking	2012	Drama Thriller
tt0095593	Married to the Mob	1988	Comedy Crime Romance
tt1139592	Jeepers Creepers III	2017	Action Horror Mystery
tt1438173	Bait	2012	Action Adventure Drama
tt0492389	Furry Vengeance	2010	Comedy Family
tt0073747	The Stepford Wives	1975	Horror Mystery Sci-Fi
tt0360556	Fahrenheit 451	2018	Drama Sci-Fi Thriller
tt0094027	Stand and Deliver	1988	Biography Drama
tt0086373	Strange Brew	1983	Comedy Crime Sci-Fi
tt0095468	A Short Film About Killing	1988	Crime Drama
tt2621000	Jolly LLB	2013	Comedy Drama
tt0054033	The Little Shop of Horrors	1960	Comedy Horror
tt3175038	Ek Villain	2014	Action Crime Drama
tt0332658	Intermission	2003	Comedy Crime Drama
tt0106627	The Crush	1993	Drama Thriller

tt0997047	College Road Trip	2008	Adventure Comedy Drama
tt0056241	The Miracle Worker	1962	Biography Drama
tt0413015	Mrs Henderson Presents	2005	Comedy Drama Music
tt0144814	The Rage: Carrie 2	1999	Horror Sci-Fi Thriller
tt0055798	Birdman of Alcatraz	1962	Biography Crime Drama
tt1554091	A Better Life	2011	Drama Romance
tt1966359	Father Figures	2017	Adventure Comedy Drama
tt0071994	Phantom of the Paradise	1974	Comedy Drama Fantasy
tt0453729	Iqbal	2005	Drama Sport
tt0805526	Facing the Giants	2006	Drama Sport
tt0279111	Gods and Generals	2003	Biography Drama History
tt0083624	Basket Case	1982	Comedy Horror
tt0080474	Brubaker	1980	Crime Drama
tt0085154	All the Right Moves	1983	Drama Romance Sport
tt2247476	When the Game Stands Tall	2014	Drama Sport
tt0106664	The Dark Half	1993	Horror Mystery Thriller
tt0067549	The Panic in Needle Park	1971	Drama
tt0050539	The Incredible Shrinking Man	1957	Horror Sci-Fi
tt0879843	Katyn	2007	Drama History War
tt1499666	Castaway on the Moon	2009	Drama Romance
tt0058888	Red Beard	1965	Drama
tt2126357	Second Act	2018	Comedy Drama Romance
tt3447364	Detective Byomkesh Bakshy!	2015	Action Mystery Thriller
tt0118767	Brother	1997	Crime Drama Romance
tt0035093	Mrs. Miniver	1942	Drama Romance War
tt1316622	Wrecked	2010	Adventure Drama Mystery
tt0110081	To Live	1994	Drama War
tt1604171	Prom	2011	Comedy Drama Family
tt0048380	Mister Roberts	1955	Comedy Drama War
tt0072281	The Three Musketeers	1973	Action Adventure
tt0062376	To Sir with Love	1967	Drama
tt0039420	The Ghost and Mrs. Muir	1947	Comedy Drama Fantasy
tt0057372	The Nutty Professor	1963	Comedy Romance Sci-Fi
tt0102388	The Man in the Moon	1991	Drama Romance
tt2309224	Big Bad Wolves	2013	Drama Horror Thriller
tt4009460	Saving Christmas	2014	Comedy Family
tt1701990	Detention	2011	Comedy Horror Mystery
tt0060955	Seconds	1966	Sci-Fi Thriller
tt0484562	The Seeker: The Dark Is Rising	2007	Adventure Drama Family
tt0107286	Judgment Night	1993	Action Crime Drama
tt0089695	No Retreat No Surrender	1986	Action Comedy Crime
tt0088272	Tightrope	1984	Crime Mystery Thriller
tt1743720	The Greatest Movie Ever Sold	2011	Comedy Documentary
tt0191043	The Color of Paradise	1999	Drama Family
tt3125324	Beyond the Lights	2014	Drama Music Romance
tt3508840	The Assassin	2015	Action Drama History
tt0338325	Paparazzi	2004	Action Crime Drama
tt0080025	Time After Time	1979	Adventure Drama Sci-Fi
tt0448075	The Night Listener	2006	Crime Mystery Thriller
tt0081318	City of the Living Dead	1980	Horror
tt0110631	Nightwatch	1994	Thriller
tt1791614	Struck by Lightning	2012	Comedy Drama
tt2262315	The Good Neighbor	2016	Crime Drama Horror
tt1183374	Pet	2016	Horror Thriller
tt0052948	Journey to the Center of the Earth	1959	Adventure Family Fantasy
tt0806027	Blood: The Last Vampire	2009	Action Horror Thriller
tt0347332	Khakee	2004	Action Crime Drama
tt0094824	Caddyshack II	1988	Comedy Sport
tt7026672	Every Day	2018	Drama Fantasy Romance

tt5814592	The Party	2017	Comedy Drama
tt0040416	Hamlet	1948	Drama
tt2474976	The Hallow	2015	Horror
tt0338097	Head in the Clouds	2004	Drama Romance War
tt0290329	Visitor Q	2001	Comedy Drama Horror
tt0023649	Vampyr	1932	Fantasy Horror
tt0337578	Baghban	2003	Drama Romance
tt0111419	Thumbelina	1994	Animation Family Fantasy
tt1610452	Band Baaja Baaraat	2010	Comedy Drama Romance
tt0118564	Affliction	1997	Drama Mystery Thriller
tt0072226	The Sugarland Express	1974	Crime Drama
tt0783238	The Dead Girl	2006	Crime Drama Mystery
tt0367631	D.E.B.S.	2004	Action Comedy Romance
tt0101787	Dying Young	1991	Drama Romance
tt3704538	V/H/S Viral	2014	Horror Thriller
tt1319718	Little Big Soldier	2010	Action Adventure Comedy
tt0025913	Triumph of the Will	1935	Documentary History War
tt3748440	Blue Mountain State: The Rise of Thadland	2016	Comedy Sport
tt4382552	Hot Girls Wanted	2015	Documentary
tt1700844	The Deep Blue Sea	2011	Drama Romance
tt1954701	A Coffee in Berlin	2012	Comedy Drama
tt0850253	Battle in Seattle	2007	Action Drama
tt0292542	Son of the Bride	2001	Comedy Drama
tt0059037	The Cincinnati Kid	1965	Drama
tt4126476	After	2019	Drama Romance
tt0297162	Half Past Dead	2002	Action Crime Thriller
tt0077369	Convoy	1978	Action Drama
tt6257174	The Miseducation of Cameron Post	2018	Drama
tt0110907	Ready to Wear	1994	Comedy Drama
tt6967980	Bareilly Ki Barfi	2017	Comedy Romance
tt0082118	The Burning	1981	Horror
tt0421051	Daniel the Wizard	2004	Comedy Crime Fantasy
tt0076590	Rabid	1977	Horror Sci-Fi
tt0099776	Europa Europa	1990	Drama History War
tt0087075	The Company of Wolves	1984	Drama Fantasy Horror
tt0033717	High Sierra	1941	Action Adventure Crime
tt3095734	Monster Trucks	2016	Action Adventure Comedy
tt0240200	Water	2005	Drama Romance
tt0081529	Smokey and the Bandit II	1980	Action Comedy
tt0056264	Mutiny on the Bounty	1962	Adventure Drama History
tt4504044	The Prodigy	2019	Horror Thriller
tt2224317	Lootera	2013	Drama Romance
tt0070698	Sisters	1972	Horror Mystery Thriller
tt0100740	Tales from the Darkside: The Movie	1990	Comedy Fantasy Horror
tt0113613	The Last Supper	1995	Comedy Crime Drama
tt2679552	I.T.	2016	Crime Drama Mystery
tt0473188	Bobby Z	2007	Action Crime Thriller
tt0119718	Mr. Magoo	1997	Adventure Comedy Family
tt0346723	Chalte Chalte	2003	Drama Romance
tt0337579	Barbershop 2: Back in Business	2004	Comedy Drama
tt2281159	Contracted	2013	Drama Horror Thriller
tt4669788	On the Basis of Sex	2018	Biography Drama
tt2338454	Unicorn Store	2017	Comedy Drama Fantasy
tt0047834	Animal Farm	1954	Animation Drama
tt0094746	Biloxi Blues	1988	Comedy Drama
tt0263975	The Girl with the Red Scarf	1977	Drama Romance
tt0081383	Prom Night	1980	Horror Thriller
tt1275863	Love Aaj Kal	2009	Comedy Drama Romance
tt0409011	Lovewrecked	2005	Adventure Comedy Romance

tt0072901	The Twelve Tasks of Asterix	1976	Adventure Animation Comedy
tt0365847	The Myth	2005	Action Adventure Comedy
tt0071970	The Parallax View	1974	Drama Thriller
tt0046126	Niagara	1953	Film-Noir Thriller
tt2126235	Collide	2016	Action Crime Thriller
tt3628584	Barbershop: The Next Cut	2016	Comedy Drama
tt0082334	The Entity	1982	Drama Horror
tt1392197	Marmaduke	2010	Comedy Family
tt0100530	The Russia House	1990	Drama Romance Thriller
tt3707104	Mine	2016	Drama Fantasy Thriller
tt2331047	Rememory	2017	Drama Mystery Sci-Fi
tt0072962	F for Fake	1973	Documentary
tt0086361	Staying Alive	1983	Drama Music Romance
tt0857376	Gabriel	2007	Action Fantasy Horror
tt0192111	Head Over Heels	2001	Comedy Mystery Romance
tt1121794	Sword of the Stranger	2007	Action Adventure Animation
tt0094631	Alien Nation	1988	Action Sci-Fi
tt2639336	Greta	2018	Drama Mystery Thriller
tt0053580	The Alamo	1960	Adventure Drama History
tt0040068	Abbott and Costello Meet Frankenstein	1948	Comedy Fantasy Horror
tt0488478	NULL	2007	Crime Drama Thriller
tt0419058	Phir Hera Pheri	2006	Comedy Crime
tt1142433	Post Grad	2009	Comedy Romance
tt0082250	Death Wish II	1982	Action Crime Drama
tt0976222	Bandslam	2009	Comedy Drama Family
tt0495034	Golmaal: Fun Unlimited	2006	Action Comedy Drama
tt0071746	Lenny	1974	Biography Drama
tt2181831	Shahid	2012	Biography Crime Drama
tt0367495	Anbe Sivam	2003	Adventure Comedy Drama
tt1371155	Made in Dagenham	2010	Biography Comedy Drama
tt0059749	The Spy Who Came In from the Cold	1965	Drama Thriller
tt0096945	Blind Fury	1989	Action Comedy Crime
tt8169446	Wine Country	2019	Comedy
tt1486193	5 Days of War	2011	Action Drama War
tt0084302	The Marathon Family	1982	Comedy Drama
tt0358349	Agent Cody Banks 2: Destination London	2004	Action Adventure Comedy
tt0093075	The Gate	1987	Fantasy Horror
tt0376479	American Pastoral	2016	Crime Drama
tt0082766	Mommie Dearest	1981	Biography Drama
tt0087910	The Philadelphia Experiment	1984	Adventure Drama Romance
tt0106453	Body of Evidence	1992	Drama Thriller
tt0046521	I Vitelloni	1953	Comedy Drama
tt0089424	Kiss of the Spider Woman	1985	Drama
tt1212974	Bitch Slap	2009	Action Comedy Crime
tt2215719	Katy Perry: Part of Me	2012	Documentary Music
tt1836944	The Baytown Outlaws	2012	Action Comedy Crime
tt2172071	Student of the Year	2012	Comedy Drama Romance
tt1833844	Berberian Sound Studio	2012	Drama Horror Thriller
tt6484982	Newton	2017	Drama
tt0452643	Love and Other Disasters	2006	Comedy Drama Romance
tt2608732	TPB AFK: The Pirate Bay Away from Keyboard	2013	Documentary
tt2802136	Home Sweet Hell	2015	Comedy Crime Thriller
tt1119191	The Killing Room	2009	Mystery Thriller
tt0325258	Dickie Roberts: Former Child Star	2003	Comedy
tt0330099	The Brown Bunny	2003	Drama
tt0091578	My Beautiful Laundrette	1985	Comedy Drama Romance
tt0217756	Ready to Rumble	2000	Comedy Sport
tt0054407	Le Trou	1960	Crime Drama Thriller
tt1718199	Dragon	2011	Action Crime Drama

tt0422093	Diary of a Mad Black Woman	2005	Comedy Drama Romance
tt0480269	Interview	2007	Drama
tt2414766	Frequencies	2013	Mystery Romance Sci-Fi
tt0084412	Night Shift	1982	Comedy
tt0110882	Before the Rain	1994	Drama War
tt0981072	The Lucky Ones	2008	Comedy Drama War
tt4430136	Pyaar Ka Punchnama 2	2015	Comedy Drama Romance
tt0037638	Detour	1945	Crime Drama Film-Noir
tt0093677	Opera	1987	Horror Mystery Thriller
tt2409818	Open Windows	2014	Crime Horror Thriller
tt0399877	What the #$*! Do We (K)now!?	2004	Comedy Documentary Drama
tt0089003	Death Wish 3	1985	Action Crime Drama
tt0091680	One Crazy Summer	1986	Comedy Romance
tt0331952	The Clearing	2004	Drama Mystery Thriller
tt1151309	Bigger Stronger Faster*	2008	Documentary Sport
tt1185420	Dostana	2008	Comedy Drama Romance
tt0071487	The Phantom of Liberty	1974	Comedy
tt1883367	The Human Centipede III (Final Sequence)	2015	Comedy Horror
tt0368667	Interstella 5555: The 5tory of the 5ecret 5tar 5ystem	2003	Action Adventure Animation
tt0059170	Faster Pussycat! Kill! Kill!	1965	Action Comedy
tt0157472	Clockstoppers	2002	Action Adventure Comedy
tt0078504	The Wiz	1978	Adventure Family Fantasy
tt1287468	Cats & Dogs: The Revenge of Kitty Galore	2010	Action Comedy Family
tt0119861	Pardes	1997	Drama Musical Romance
tt0016847	Faust	1926	Drama Fantasy Horror
tt0059825	The Train	1964	Thriller War
tt3181776	Momentum	2015	Action Crime Thriller
tt0289635	Young Adam	2003	Crime Drama
tt0109035	Above the Rim	1994	Crime Drama Sport
tt0145893	Simply Irresistible	1999	Comedy Drama Fantasy
tt0098663	The Wizard	1989	Adventure Comedy Drama
tt0400426	Far Cry	2008	Action Adventure Sci-Fi
tt5882970	Tubelight	2017	Drama War
tt0117603	Set It Off	1996	Action Crime Drama
tt0053318	Suddenly Last Summer	1959	Drama Mystery Thriller
tt0118632	The Apostle	1997	Drama
tt0102426	Mediterraneo	1991	Comedy Drama War
tt2561546	The Town That Dreaded Sundown	2014	Horror Mystery Thriller
tt0099994	Leatherface: Texas Chainsaw Massacre III	1990	Horror Thriller
tt0274117	Read My Lips	2001	Crime Drama Romance
tt1341710	The Shrine	2010	Horror
tt0765447	Evening	2007	Drama Romance
tt0477078	Rocket Science	2007	Comedy Drama
tt0071455	Earthquake	1974	Action Drama Thriller
tt0081114	Maniac	1980	Drama Horror Thriller
tt0119361	In the Company of Men	1997	Comedy Drama
tt0420509	The Aura	2005	Crime Drama Thriller
tt1407061	Just Wright	2010	Comedy Romance Sport
tt1183919	Marley	2012	Biography Documentary Music
tt0099819	I Love You to Death	1990	Comedy Crime
tt1878841	The Darkness	2016	Horror Thriller
tt0780567	Imagine That	2009	Comedy Drama Family
tt1213012	Alpha and Omega	2010	Adventure Animation Comedy
tt0105217	Raising Cain	1992	Crime Drama Horror
tt0087507	Johnny Dangerously	1984	Comedy Crime
tt0249371	Ashoka the Great	2001	Action Biography Drama
tt0081698	Used Cars	1980	Comedy
tt0077578	Foul Play	1978	Comedy Mystery Thriller
tt0099204	Cadillac Man	1990	Comedy Crime

tt0020697	The Blue Angel	1930	Drama Music
tt0091278	Iron Eagle	1986	Action Thriller War
tt0099012	Alice	1990	Comedy Romance
tt2103264	Emperor	2012	Drama History War
tt0095583	Maniac Cop	1988	Action Crime Horror
tt7363076	Raid	2018	Action Crime Drama
tt0424908	Copying Beethoven	2006	Biography Drama Music
tt0063032	The Great Silence	1968	Western
tt2404738	Witching and Bitching	2013	Action Comedy Fantasy
tt1134629	The Private Lives of Pippa Lee	2009	Comedy Drama Romance
tt0107983	Romeo Is Bleeding	1993	Crime Drama Romance
tt0117826	Bordello of Blood	1996	Comedy Fantasy Horror
tt0093578	Mr. India	1987	Action Comedy Drama
tt2168910	Cocktail	2012	Comedy Drama Romance
tt0234000	Kaho Naa... Pyaar Hai	2000	Action Romance
tt1854236	Love Is All You Need	2012	Comedy Drama Romance
tt0134154	Ride with the Devil	1999	Drama Romance War
tt0772193	Primeval	2007	Action Adventure Crime
tt5664636	Goosebumps 2: Haunted Halloween	2018	Adventure Comedy Family
tt0060934	The Sand Pebbles	1966	Adventure Drama Romance
tt0077588	The Fury	1978	Horror Sci-Fi
tt0496436	White Noise 2: The Light	2007	Drama Fantasy Horror
tt0091993	SpaceCamp	1986	Adventure Family Sci-Fi
tt0810823	The Deaths of Ian Stone	2007	Horror Thriller
tt0458367	Right at Your Door	2006	Drama Sci-Fi Thriller
tt0118751	Border	1997	Action Drama History
tt0418362	Mujhse Shaadi Karogi	2004	Comedy Drama Musical
tt0050371	A Face in the Crowd	1957	Drama Music
tt0028772	A Day at the Races	1937	Comedy Musical Sport
tt1841642	Demonic	2015	Horror Thriller
tt4348012	Mayhem	2017	Action Comedy Horror
tt1311060	A.C.O.D.	2013	Comedy
tt0089730	Once Bitten	1985	Comedy Fantasy Horror
tt0097289	Erik the Viking	1989	Adventure Comedy Fantasy
tt0453671	Garam Masala	2005	Comedy Romance
tt0376127	Anniyan	2005	Action Drama Thriller
tt2852406	Omar	2013	Crime Drama Romance
tt0326769	Biker Boyz	2003	Action Drama
tt0088117	Silent Night Deadly Night	1984	Horror Thriller
tt0116260	Eye for an Eye	1996	Crime Drama Thriller
tt1640711	A Few Best Men	2011	Comedy Romance
tt0095863	Phantasm II	1988	Action Fantasy Horror
tt0054067	Black Sunday	1960	Horror
tt0961722	Cabin Fever 2: Spring Fever	2009	Horror
tt0111418	Threesome	1994	Comedy Drama Romance
tt0475937	The Abandoned	2006	Horror Mystery Thriller
tt0265808	Stealing Harvard	2002	Comedy Crime
tt4503598	Emelie	2015	Horror Thriller
tt0054189	Purple Noon	1960	Crime Drama Thriller
tt0489327	Venus	2006	Comedy Drama Romance
tt0081696	Urban Cowboy	1980	Drama Romance Western
tt0379865	Leatherheads	2008	Comedy Drama Romance
tt0068833	The Last House on the Left	1972	Horror Thriller
tt0046534	The War of the Worlds	1953	Action Sci-Fi Thriller
tt2103267	Adore	2013	Drama Romance
tt0097240	Drugstore Cowboy	1989	Crime Drama
tt0097388	Friday the 13th Part VIII: Jason Takes Manhattan	1989	Adventure Horror Thriller
tt0248845	Hedwig and the Angry Inch	2001	Comedy Drama Music
tt0115571	The Arrival	1996	Sci-Fi Thriller

tt1381404	The Company You Keep	2012	Drama Thriller
tt1372686	Coriolanus	2011	Drama Thriller War
tt0089173	Friday the 13th: A New Beginning	1985	Horror Mystery Thriller
tt1171701	The Breath	2009	Action Drama Thriller
tt0804516	P2	2007	Crime Horror Thriller
tt0479968	One Missed Call	2008	Horror Mystery
tt1127715	Sin Nombre	2009	Adventure Crime Drama
tt0192614	The Skulls	2000	Action Crime Drama
tt0964539	Pathology	2008	Crime Horror Thriller
tt0364343	The Final Cut	2004	Drama Sci-Fi Thriller
tt0408777	The Edukators	2004	Drama Romance
tt1620933	Paan Singh Tomar	2012	Action Biography Crime
tt0067065	Escape from the Planet of the Apes	1971	Action Sci-Fi
tt0490076	All the Boys Love Mandy Lane	2006	Horror
tt2294677	In a World...	2013	Comedy
tt0110729	Once Were Warriors	1994	Crime Drama
tt7431594	Race 3	2018	Action Thriller
tt0062711	Barbarella	1968	Adventure Comedy Fantasy
tt0066473	Tora! Tora! Tora!	1970	Action Drama History
tt2576852	The Tale of The Princess Kaguya	2013	Adventure Animation Drama
tt1174730	City Island	2009	Comedy Drama
tt0377091	Mean Creek	2004	Crime Drama
tt7374948	Always Be My Maybe	2019	Comedy Romance
tt0039689	Out of the Past	1947	Crime Drama Film-Noir
tt1456941	Tomorrow When the War Began	2010	Action Adventure Drama
tt2358925	Unfinished Business	2015	Comedy Drama
tt0105629	Toys	1992	Adventure Comedy Drama
tt0482088	Priceless	2006	Comedy Romance
tt0380599	Oliver Twist	2005	Crime Drama
tt2752200	Young & Beautiful	2013	Drama Romance
tt1082886	The Wackness	2008	Comedy Drama Romance
tt0095444	Killer Klowns from Outer Space	1988	Comedy Horror Sci-Fi
tt2555736	The Second Best Exotic Marigold Hotel	2015	Comedy Drama
tt0034248	Suspicion	1941	Mystery Thriller
tt1435513	Hysteria	2011	Comedy Romance
tt0094608	The Accused	1988	Crime Drama
tt0079641	Nosferatu the Vampyre	1979	Horror
tt0105643	Troll 2	1990	Comedy Fantasy Horror
tt1821700	Waar	2013	Action Crime Drama
tt0899106	Love Happens	2009	Drama Romance
tt0257516	Cursed	2005	Comedy Horror
tt0169858	Neon Genesis Evangelion: The End of Evangelion	1997	Action Animation Drama
tt0102526	New Jack City	1991	Action Crime Drama
tt2317225	The Machine	2013	Action Drama Sci-Fi
tt0270846	Superbabies: Baby Geniuses 2	2004	Comedy Family Sci-Fi
tt0800325	The Dirt	2019	Biography Comedy Drama
tt2088003	Big Game	2014	Action Adventure Crime
tt0282209	Darkness Falls	2003	Fantasy Horror Mystery
tt1971352	Compliance	2012	Biography Crime Drama
tt3247714	Survivor	2015	Action Crime Thriller
tt0079714	Phantasm	1979	Horror Sci-Fi
tt0026778	A Night at the Opera	1935	Comedy Music Musical
tt0913354	Armored	2009	Action Crime Thriller
tt0383010	The Three Stooges	2012	Comedy Family
tt0357507	Boogeyman	2005	Drama Horror Mystery
tt0235737	The Salton Sea	2002	Crime Drama Mystery
tt0258470	Bubble Boy	2001	Adventure Comedy Romance
tt3616916	The Wave	2015	Action Drama Thriller
tt0095179	Friday the 13th Part VII: The New Blood	1988	Horror Thriller

tt0110527	Miracle on 34th Street	1994	Family Fantasy
tt0099763	Henry: Portrait of a Serial Killer	1986	Biography Crime Drama
tt1987680	The Upside	2017	Comedy Drama
tt0082509	Heavy Metal	1981	Adventure Animation Fantasy
tt0047673	White Christmas	1954	Comedy Musical Romance
tt1489887	Booksmart	2019	Comedy
tt5117670	Peter Rabbit	2018	Adventure Animation Comedy
tt0094761	The Blob	1988	Horror Sci-Fi Thriller
tt0060665	A Man for All Seasons	1966	Biography Drama History
tt0268397	Jimmy Neutron: Boy Genius	2001	Action Adventure Animation
tt1481572	Happythankyoumoreplease	2010	Comedy Drama Romance
tt0360009	Spartan	2004	Action Crime Drama
tt0108211	Stalingrad	1993	Drama War
tt4669986	Loving	2016	Biography Drama Romance
tt0114614	Tank Girl	1995	Action Comedy Sci-Fi
tt0037382	To Have and Have Not	1944	Adventure Comedy Romance
tt0082533	The Howling	1981	Horror
tt0056443	Sanjuro	1962	Action Crime Drama
tt0068408	Conquest of the Planet of the Apes	1972	Action Sci-Fi
tt0082089	Body Heat	1981	Crime Drama Romance
tt0308383	The Human Stain	2003	Drama Romance Thriller
tt3860916	Cargo	2017	Drama Horror Sci-Fi
tt0085811	Krull	1983	Action Adventure Sci-Fi
tt1441912	The Way	2010	Adventure Comedy Drama
tt0113253	Halloween 6: The Curse of Michael Myers	1995	Horror Thriller
tt0102250	L.A. Story	1991	Comedy Drama Fantasy
tt0785035	Ong Bak 2	2008	Action
tt0099939	King of New York	1990	Crime Thriller
tt0479537	Seraphim Falls	2006	Action Drama Thriller
tt0091499	Maximum Overdrive	1986	Action Comedy Horror
tt0073582	Deep Red	1975	Horror Mystery Thriller
tt0842929	Paranoid Park	2007	Crime Drama Mystery
tt0083946	Fitzcarraldo	1982	Adventure Drama
tt0165832	Interstate 60: Episodes of the Road	2002	Adventure Comedy Drama
tt0060153	Batman: The Movie	1966	Adventure Comedy Crime
tt6738136	Revenge	2017	Action Horror Thriller
tt0421994	Imagine Me & You	2005	Comedy Drama Romance
tt0209077	Ken Park	2002	Drama
tt0165854	The Limey	1999	Crime Drama Mystery
tt5962210	Ingrid Goes West	2017	Comedy Drama
tt0088814	The Black Cauldron	1985	Action Adventure Animation
tt0074751	King Kong	1976	Adventure Horror
tt0120684	Gods and Monsters	1998	Biography Drama
tt0091954	Sid and Nancy	1986	Biography Drama Music
tt0043278	An American in Paris	1951	Drama Musical Romance
tt0424774	The Adventures of Sharkboy and Lavagirl 3-D	2005	Action Adventure Comedy
tt0160009	The Art of War	2000	Action Adventure Crime
tt7125860	If Beale Street Could Talk	2018	Drama Romance
tt5001718	Everything Everything	2017	Drama Romance
tt0218817	Antitrust	2001	Action Crime Drama
tt5057140	Hold the Dark	2018	Adventure Drama Horror
tt0114194	The Prophecy	1995	Action Crime Drama
tt6742252	The Guilty	2018	Crime Drama Thriller
tt0108065	Searching for Bobby Fischer	1993	Biography Drama
tt0066011	Love Story	1970	Drama Romance
tt1127896	Taking Woodstock	2009	Biography Comedy Drama
tt2326612	The Captive	2014	Crime Drama Mystery
tt1198138	Obsessed	2009	Drama Thriller
tt0054167	Peeping Tom	1960	Drama Horror Thriller

tt3172532	The Diary of a Teenage Girl	2015	Comedy Drama Romance
tt0097138	Cyborg	1989	Action Sci-Fi Thriller
tt0457572	Fido	2006	Comedy Drama Horror
tt1232783	Sorority Row	2009	Horror Mystery
tt0114168	Powder	1995	Drama Fantasy Mystery
tt0454919	Pulse	2006	Horror Sci-Fi
tt0081353	Popeye	1980	Adventure Comedy Family
tt0069768	Battle for the Planet of the Apes	1973	Action Sci-Fi
tt0449994	Jodhaa Akbar	2008	Action Drama History
tt2378281	Instructions Not Included	2013	Comedy Drama
tt0077681	The Hills Have Eyes	1977	Horror Thriller
tt0061655	The Fearless Vampire Killers	1967	Comedy Horror
tt0120797	Pushing Tin	1999	Comedy Drama Romance
tt2359810	Raanjhanaa	2013	Drama Romance
tt0385705	The Football Factory	2004	Crime Drama Sport
tt0093936	The Secret of My Success	1987	Comedy Romance
tt1226681	Pontypool	2008	Fantasy Horror Thriller
tt0216651	Vampire Hunter D: Bloodlust	2000	Action Animation Fantasy
tt0331953	Club Dread	2004	Comedy Horror Mystery
tt0077394	Damien: Omen II	1978	Horror
tt0422401	Hatchet	2006	Comedy Horror Thriller
tt0067525	The Omega Man	1971	Action Sci-Fi Thriller
tt0468565	Tsotsi	2005	Crime Drama
tt0093493	Mannequin	1987	Comedy Fantasy Romance
tt0080516	The Changeling	1980	Horror
tt0482546	Miss Potter	2006	Biography Drama
tt0469623	Things We Lost in the Fire	2007	Drama
tt0056937	Cleopatra	1963	Biography Drama History
tt1563742	Overboard	2018	Comedy Romance
tt0176269	Universal Soldier: The Return	1999	Action Sci-Fi
tt0097499	Henry V	1989	Action Biography Drama
tt0067140	Duck You Sucker	1971	Drama War Western
tt5619332	Life of the Party	2018	Comedy
tt0114852	Village of the Damned	1995	Horror Sci-Fi Thriller
tt0827503	The Magician	2006	Comedy Drama
tt1440161	A Little Bit of Heaven	2011	Comedy Drama Fantasy
tt0381966	Creep	2004	Horror Mystery Thriller
tt0101640	Raise the Red Lantern	1991	Drama History Romance
tt3750872	The Wife	2017	Drama
tt0180734	Hardball	2001	Drama Sport
tt0067128	Get Carter	1971	Crime Thriller
tt2872518	The Shack	2017	Drama Fantasy
tt1431181	Another Year	2010	Comedy Drama
tt0024184	The Invisible Man	1933	Horror Sci-Fi
tt0100419	Problem Child	1990	Comedy Family
tt0046672	20 000 Leagues Under the Sea	1954	Adventure Drama Family
tt0258068	The Quiet American	2002	Drama Mystery Romance
tt3416744	The End of the Tour	2015	Biography Drama
tt0098105	Police Academy 6: City Under Siege	1989	Comedy Crime
tt0119942	Primary Colors	1998	Comedy Drama
tt0119695	Money Talks	1997	Action Comedy Crime
tt2072233	Sleepless	2017	Action Crime Thriller
tt0096794	Always	1989	Fantasy Romance
tt3760922	My Big Fat Greek Wedding 2	2016	Comedy Romance
tt0252444	Rabbit-Proof Fence	2002	Adventure Biography Drama
tt0120751	Mighty Joe Young	1998	Action Adventure Family
tt0068762	Jeremiah Johnson	1972	Adventure Drama Western
tt0106950	Fortress	1992	Action Crime Sci-Fi
tt3792960	The Brand New Testament	2015	Comedy Fantasy

tt0388980	The Greatest Game Ever Played	2005	Biography Drama History
tt1160368	12 Rounds	2009	Action Crime Thriller
tt1592281	Take This Waltz	2011	Comedy Drama
tt2404181	Belle	2013	Biography Drama Romance
tt0120633	A Civil Action	1998	Drama
tt5649108	Thoroughbreds	2017	Comedy Crime Drama
tt0105415	Singles	1992	Comedy Drama Romance
tt4934950	Talvar	2015	Crime Drama Mystery
tt5816682	Victoria & Abdul	2017	Biography Drama History
tt0075066	The Pink Panther Strikes Again	1976	Comedy Crime
tt0040724	Red River	1948	Action Adventure Romance
tt7608028	The Open House	2018	Horror Thriller
tt0479528	Rogue	2007	Action Adventure Drama
tt1018785	The Sisterhood of the Traveling Pants 2	2008	Comedy Drama Romance
tt1598642	Z for Zachariah	2015	Drama Sci-Fi Thriller
tt0499554	Reno 911!: Miami	2007	Comedy Crime
tt0086984	Body Double	1984	Crime Drama Mystery
tt4255304	The Void	2016	Horror Mystery Sci-Fi
tt0486674	What Just Happened	2008	Comedy Drama
tt0099739	Hard to Kill	1990	Action Crime Drama
tt0082846	On Golden Pond	1981	Drama
tt2238050	White Bird in a Blizzard	2014	Drama Mystery Thriller
tt2167266	Tracks	2013	Adventure Biography Drama
tt1196948	Charlie Countryman	2013	Comedy Drama Romance
tt2328900	Mary Queen of Scots	2018	Biography Drama History
tt0068638	The Getaway	1972	Action Crime Thriller
tt0093378	La Bamba	1987	Biography Drama Music
tt0335559	Win a Date with Tad Hamilton!	2004	Comedy Romance
tt0099005	Air America	1990	Action Comedy
tt0100133	Memphis Belle	1990	Action Drama War
tt0486358	Jesus Camp	2006	Documentary
tt0117894	Thinner	1996	Fantasy Horror
tt0107254	Jason Goes to Hell: The Final Friday	1993	Fantasy Horror Thriller
tt0430634	Stick It	2006	Comedy Drama Sport
tt0083284	Victory	1981	Drama Sport War
tt1731697	The Lords of Salem	2012	Horror Thriller
tt6781982	Night School	2018	Comedy
tt0062467	Wait Until Dark	1967	Horror Thriller
tt0294357	Beyond Borders	2003	Adventure Drama Romance
tt0365957	You Got Served	2004	Drama Music
tt7282468	Burning	2018	Drama Mystery
tt0038559	Gilda	1946	Drama Film-Noir Romance
tt0082869	Outland	1981	Action Crime Sci-Fi
tt0970468	Miss Pettigrew Lives for a Day	2008	Comedy Romance
tt0426578	Sophie Scholl: The Final Days	2005	Biography Crime Drama
tt0897361	I Know Who Killed Me	2007	Crime Drama Mystery
tt1334102	The Resident	2011	Drama Horror Mystery
tt0104409	Hellraiser III: Hell on Earth	1992	Horror
tt2023690	Sightseers	2012	Adventure Comedy Crime
tt1029235	Max Manus: Man of War	2008	Action Biography Drama
tt0213890	Mohabbatein	2000	Drama Musical Romance
tt0080319	9 to 5	1980	Comedy
tt0913968	The Warlords	2007	Action Drama History
tt3276924	Heist	2015	Action Crime Thriller
tt0067927	Vanishing Point	1971	Action Crime Thriller
tt0092699	Broadcast News	1987	Comedy Drama Romance
tt0804540	Taxi 4	2007	Action Comedy Crime
tt2452254	Clouds of Sils Maria	2014	Drama
tt0098213	Roger & Me	1989	Documentary

tt1934231	Delhi Belly	2011	Action Comedy Crime
tt2784678	Top Five	2014	Comedy Romance
tt0116361	Freeway	1996	Comedy Crime Drama
tt2339741	The Woman in Black 2: Angel of Death	2014	Drama Horror Thriller
tt0091557	The Mosquito Coast	1986	Adventure Drama Thriller
tt0093560	The Monster Squad	1987	Action Comedy Fantasy
tt0053946	Inherit the Wind	1960	Biography Drama History
tt0318411	The Magdalene Sisters	2002	Drama
tt0866437	The Jane Austen Book Club	2007	Comedy Drama Romance
tt0067756	Silent Running	1972	Drama Sci-Fi
tt0040725	The Red Shoes	1948	Drama Music Romance
tt0056058	Harakiri	1962	Action Drama History
tt1821658	The Nut Job	2014	Adventure Animation Comedy
tt0042041	White Heat	1949	Action Crime Drama
tt0043338	Ace in the Hole	1951	Drama Film-Noir
tt0081534	Somewhere in Time	1980	Drama Fantasy Romance
tt0078966	The China Syndrome	1979	Drama Thriller
tt2203308	Aashiqui 2	2013	Drama Music Musical
tt2402105	Dom Hemingway	2013	Comedy Crime Drama
tt0100436	Pump Up the Volume	1990	Comedy Drama Music
tt6182908	Smallfoot	2018	Adventure Animation Comedy
tt0078754	All That Jazz	1979	Drama Music Musical
tt0101669	Dead Again	1991	Drama Mystery Romance
tt0204626	The Watcher	2000	Crime Drama Mystery
tt1929263	Heaven Is for Real	2014	Biography Drama Family
tt2452200	Son of a Gun	2014	Action Crime Drama
tt2263944	Dragon Ball Z: Battle of Gods	2013	Action Adventure Animation
tt2537176	I Spit on Your Grave 2	2013	Horror Thriller
tt0112760	Cutthroat Island	1995	Action Adventure Comedy
tt0025878	The Thin Man	1934	Comedy Crime Mystery
tt0098546	UHF	1989	Comedy Drama
tt5516328	Ghost Stories	2017	Drama Horror
tt0113419	The Indian in the Cupboard	1995	Drama Family Fantasy
tt0091877	Ruthless People	1986	Comedy Crime
tt0082031	Arthur	1981	Comedy Romance
tt3369806	Max	2015	Adventure Drama Family
tt0089560	Mask	1985	Biography Drama
tt0117979	The Truth About Cats & Dogs	1996	Comedy Romance
tt0264150	View from the Top	2003	Comedy Romance
tt0119664	Metro	1997	Action Comedy Crime
tt6000478	Roman J. Israel Esq.	2017	Crime Drama Thriller
tt0963743	Angus Thongs and Perfect Snogging	2008	Comedy Drama Romance
tt0117737	Stealing Beauty	1996	Drama Mystery Romance
tt0077713	I Spit on Your Grave	1978	Horror Thriller
tt1401143	Rare Exports: A Christmas Tale	2010	Adventure Fantasy Horror
tt0055824	Cape Fear	1962	Drama Thriller
tt7752126	Brightburn	2019	Horror Sci-Fi
tt0072251	The Taking of Pelham One Two Three	1974	Action Crime Thriller
tt0101516	Bugsy	1991	Biography Crime Drama
tt0399327	The Man	2005	Action Comedy Crime
tt6304162	Loveless	2017	Drama
tt1441953	Testament of Youth	2014	Biography Drama History
tt0053976	The Virgin Spring	1960	Drama
tt0455782	The Hunting Party	2007	Adventure Comedy Drama
tt2139881	Long Shot	2019	Comedy Romance
tt0446046	Take the Lead	2006	Drama Music
tt0166396	Waking Ned Devine	1998	Comedy
tt1288403	Universal Soldier: Regeneration	2009	Action Sci-Fi Thriller
tt5935704	Padmaavat	2018	Drama History Romance

tt0118798	Bulworth	1998	Comedy Drama Romance
tt0055018	The Innocents	1961	Horror
tt1047540	Parental Guidance	2012	Comedy Family
tt0308152	Dead End	2003	Adventure Horror Mystery
tt0118665	Baby Geniuses	1999	Comedy Crime Family
tt0465142	American Dreamz	2006	Comedy Music
tt0099703	The Grifters	1990	Crime Drama Thriller
tt0366777	Millions	2004	Comedy Crime Drama
tt1379177	The Disappearance of Alice Creed	2009	Crime Thriller
tt0077269	The Boys from Brazil	1978	Drama Thriller
tt5461944	Hotel Mumbai	2018	Drama History Thriller
tt0106333	Baazigar	1993	Crime Drama Musical
tt0978759	Frozen River	2008	Crime Drama
tt2980794	Highway	2014	Crime Drama Romance
tt0260991	Joint Security Area	2000	Action Drama Thriller
tt0814685	Frontier(s)	2007	Horror
tt0058586	A Shot in the Dark	1964	Comedy Mystery
tt1334553	The Perfect Host	2010	Comedy Crime Thriller
tt0035446	To Be or Not to Be	1942	Comedy War
tt0083943	Firefox	1982	Action Adventure Thriller
tt5774450	Summer of 84	2018	Drama Horror Mystery
tt0114367	Screamers	1995	Horror Sci-Fi Thriller
tt0378793	Speak	2004	Drama
tt0099472	DuckTales the Movie: Treasure of the Lost Lamp	1990	Adventure Animation Comedy
tt0765446	Escape from Planet Earth	2013	Adventure Animation Comedy
tt4434004	Udta Punjab	2016	Action Crime Drama
tt0105488	Strictly Ballroom	1992	Comedy Drama Music
tt0080057	Zombie	1979	Horror
tt0249478	Domestic Disturbance	2001	Crime Mystery Thriller
tt2556308	Holiday	2014	Action Thriller
tt0473367	Jaane Tu... Ya Jaane Na	2008	Comedy Drama Romance
tt0070239	Jesus Christ Superstar	1973	Drama History Musical
tt0107843	Point of No Return	1993	Action Crime Drama
tt1633356	Shark Night 3D	2011	Horror Thriller
tt0066763	Anand	1971	Drama
tt0067588	Play Misty for Me	1971	Thriller
tt5719700	Home Again	2017	Comedy Drama Romance
tt0452624	The Good German	2006	Drama Mystery Thriller
tt0044121	The Thing from Another World	1951	Horror Sci-Fi
tt1474276	Summer Wars	2009	Action Animation Comedy
tt0051207	The Wrong Man	1956	Drama Film-Noir
tt0396652	Ice Princess	2005	Comedy Drama Family
tt0454082	Black Christmas	2006	Horror
tt0180052	The Adventures of Pluto Nash	2002	Action Comedy Sci-Fi
tt0069097	Play It Again Sam	1972	Comedy Romance
tt0791304	Georgia Rule	2007	Comedy Drama
tt0023427	Scarface	1932	Action Crime Drama
tt0067866	El Topo	1970	Drama Western
tt0373981	Kontroll	2003	Comedy Crime Drama
tt3177316	Honeymoon	2014	Horror Mystery Thriller
tt0454776	Amazing Grace	2006	Biography Drama History
tt0489235	My Name Is Bruce	2007	Comedy Fantasy Horror
tt3231054	Risen	2016	Action Adventure Drama
tt0072081	The Return of the Pink Panther	1975	Comedy Crime Mystery
tt0053459	Eyes Without a Face	1960	Drama Horror
tt0081562	Stir Crazy	1980	Comedy Crime
tt0063823	Yellow Submarine	1968	Adventure Animation Comedy
tt0046816	The Caine Mutiny	1954	Drama War
tt4443658	Better Watch Out	2016	Comedy Crime Horror

tt0078908	The Brood	1979	Horror Sci-Fi
tt0072856	Death Race 2000	1975	Action Comedy Sci-Fi
tt0416212	The Secret Life of Bees	2008	Drama
tt0116000	D3: The Mighty Ducks	1996	Action Comedy Drama
tt0120004	The Relic	1997	Horror Mystery Sci-Fi
tt0042593	In a Lonely Place	1950	Drama Film-Noir Mystery
tt6802308	The 15:17 to Paris	2018	Biography Drama Thriller
tt0460792	Fast Food Nation	2006	Comedy Drama Romance
tt0086320	Sleepaway Camp	1983	Horror
tt0089908	Return to Oz	1985	Adventure Family Fantasy
tt0117420	The Quest	1996	Action Adventure Drama
tt0383694	Vera Drake	2004	Crime Drama
tt0084237	The Last Unicorn	1982	Adventure Animation Drama
tt1487118	Chalet Girl	2011	Comedy Romance Sport
tt0061107	Torn Curtain	1966	Thriller
tt0091288	Jean de Florette	1986	Drama
tt0314498	The Perfect Score	2004	Comedy Crime
tt0120654	Dirty Work	1998	Comedy
tt0200087	Sarfarosh	1999	Action Adventure Drama
tt2101383	Knight of Cups	2015	Drama Romance
tt0400525	The Ice Harvest	2005	Comedy Crime Drama
tt5460276	Kaabil	2017	Action Drama Thriller
tt0060522	How to Steal a Million	1966	Comedy Crime Romance
tt0110099	I.Q.	1994	Comedy Romance
tt0246677	Heaven	2002	Crime Drama Romance
tt8079248	Yesterday	2019	Comedy Fantasy Music
tt1183923	Welcome to the Rileys	2010	Drama
tt0155776	Jawbreaker	1999	Comedy Crime Thriller
tt0060315	Django	1966	Action Western
tt1602098	Albert Nobbs	2011	Drama Romance
tt0095243	Gorillas in the Mist	1988	Biography Drama
tt2091256	Captain Underpants: The First Epic Movie	2017	Action Animation Comedy
tt2167202	Getaway	2013	Action Crime Thriller
tt0100240	The NeverEnding Story II: The Next Chapter	1990	Adventure Drama Family
tt0061809	In Cold Blood	1967	Biography Crime Drama
tt3387648	The Taking of Deborah Logan	2014	Horror Mystery Thriller
tt1178665	A Walk in the Woods	2015	Adventure Biography Comedy
tt1640548	Rampart	2011	Crime Drama
tt0116329	Fly Away Home	1996	Adventure Drama Family
tt1285009	The Strangers: Prey at Night	2018	Horror
tt0099528	The Exorcist III	1990	Drama Horror Mystery
tt6485666	Mersal	2017	Action Thriller
tt0071577	The Great Gatsby	1974	Drama Romance
tt0809504	The Accidental Husband	2008	Comedy Romance
tt1193516	Recep Ivedik	2008	Comedy
tt0096101	Short Circuit 2	1988	Comedy Drama Family
tt0087003	Broadway Danny Rose	1984	Comedy
tt0086993	The Bounty	1984	Action Adventure Drama
tt0374563	Captivity	2007	Crime Drama Horror
tt0891592	Street Fighter: The Legend of Chun-Li	2009	Action Crime Thriller
tt0337909	Calendar Girls	2003	Comedy Drama
tt3352390	Friend Request	2016	Horror Thriller
tt0924129	Crossing Over	2009	Crime Drama
tt0780516	Flawless	2007	Crime Drama Thriller
tt0301976	The United States of Leland	2003	Drama
tt0042208	The Asphalt Jungle	1950	Crime Drama Film-Noir
tt0858479	Smart People	2008	Comedy Drama Romance
tt2372678	2 States	2014	Comedy Drama Romance
tt0061619	El Dorado	1967	Drama Romance Western

tt3721964	Gringo	2018	Action Comedy Crime
tt0083190	Thief	1981	Action Crime Drama
tt0074851	The Man Who Fell to Earth	1976	Drama Sci-Fi
tt0160399	Impostor	2001	Drama Mystery Sci-Fi
tt1603257	ATM	2012	Horror Thriller
tt4897822	Where to Invade Next	2015	Comedy Documentary
tt0093137	Hamburger Hill	1987	Action Drama Thriller
tt0486640	Postal	2007	Action Comedy Crime
tt0120901	Wrongfully Accused	1998	Action Comedy Thriller
tt2799166	The Pyramid	2014	Action Adventure Horror
tt0830558	The Girl Next Door	2007	Crime Drama Horror
tt0441048	Dhoom 2	2006	Action Crime Thriller
tt0101329	An American Tail: Fievel Goes West	1991	Adventure Animation Family
tt0065134	Two Mules for Sister Sara	1970	Adventure Romance War
tt2438644	Department Q: The Keeper of Lost Causes	2013	Crime Mystery Thriller
tt2187153	Thuppakki	2012	Action Thriller
tt0465502	Igor	2008	Animation Comedy Family
tt0445620	Paradise Now	2005	Crime Drama Thriller
tt0094715	Beaches	1988	Comedy Drama Music
tt0388182	King of California	2007	Comedy Drama
tt0109456	Color of Night	1994	Mystery Romance Thriller
tt0090021	Silver Bullet	1985	Horror
tt2582502	Fathers & Daughters	2015	Drama
tt0469263	The Astronaut Farmer	2006	Adventure Drama Sci-Fi
tt0480271	Van Wilder 2: The Rise of Taj	2006	Comedy Romance
tt1648216	Three Steps Above Heaven	2010	Action Drama Romance
tt0760311	He Was a Quiet Man	2007	Drama Romance Thriller
tt0104573	Juice	1992	Action Crime Drama
tt0484740	Love in the Time of Cholera	2007	Drama Romance
tt0439289	Running with Scissors	2006	Comedy Drama
tt0071411	Dersu Uzala	1975	Adventure Biography Drama
tt0036855	Gaslight	1944	Crime Drama Film-Noir
tt0449061	London	2005	Drama Romance
tt0073440	Nashville	1975	Comedy Drama Music
tt0086154	Psycho II	1983	Crime Horror Mystery
tt1194263	Get Low	2009	Drama Mystery
tt0057197	Jason and the Argonauts	1963	Action Adventure Family
tt2424988	Gabbar is Back	2015	Action
tt3297330	Good Kill	2014	Drama Thriller War
tt0078869	The Black Hole	1979	Action Sci-Fi
tt1826590	About Last Night	2014	Comedy Romance
tt0974554	Elegy	2008	Drama Romance
tt0070215	My Name Is Nobody	1973	Comedy Western
tt3395184	Spring	2014	Horror Romance Sci-Fi
tt0034398	The Wolf Man	1941	Horror
tt0775539	Stomp the Yard	2007	Drama Music Romance
tt3623726	Ricki and the Flash	2015	Comedy Drama Music
tt1810683	Little Boy	2015	Drama History War
tt1621039	Free Birds	2013	Adventure Animation Comedy
tt2855648	Madras Cafe	2013	Action Drama Thriller
tt0107497	Malice	1993	Crime Mystery Thriller
tt0323033	Laws of Attraction	2004	Comedy Romance
tt0114594	Swimming with Sharks	1994	Comedy Crime
tt0884224	War Inc.	2008	Action Comedy Thriller
tt1014775	Beverly Hills Chihuahua	2008	Adventure Comedy Drama
tt0085701	The Hunger	1983	Drama Horror
tt0091223	House	1985	Comedy Fantasy Horror
tt0831884	Reservation Road	2007	Crime Drama Thriller
tt0102558	Nothing But Trouble	1991	Comedy

tt0045555	The Big Heat	1953	Crime Film-Noir Thriller
tt1767382	Silent House	2011	Drama Horror Mystery
tt0067959	Walkabout	1971	Adventure Drama
tt4463894	Shaft	2019	Action Comedy Crime
tt0164212	Under Suspicion	2000	Crime Drama Thriller
tt0111333	The Swan Princess	1994	Animation Comedy Family
tt0110725	On Deadly Ground	1994	Action Adventure Thriller
tt0118589	Glitter	2001	Drama Music Romance
tt0023245	The Mummy	1932	Fantasy Horror
tt0494222	Eagle vs Shark	2007	Comedy Romance
tt0098966	3 Men and a Little Lady	1990	Comedy Drama Family
tt0295427	The Master of Disguise	2002	Adventure Comedy Family
tt0087909	Phenomena	1985	Horror Mystery
tt0058450	The Umbrellas of Cherbourg	1964	Drama Musical Romance
tt0486051	Wind Chill	2007	Drama Horror Thriller
tt0105327	School Ties	1992	Drama
tt5690360	Slender Man	2018	Horror Mystery Thriller
tt0477095	Starter for 10	2006	Comedy Drama Romance
tt0892767	Horsemen	2009	Crime Drama Mystery
tt0070544	Fantastic Planet	1973	Animation Sci-Fi
tt0351817	The Twilight Samurai	2002	Drama History Romance
tt2832470	Dead Snow 2: Red vs. Dead	2014	Action Comedy Horror
tt0118531	One Eight Seven	1997	Drama Thriller
tt0859635	Super Troopers 2	2018	Comedy Crime Mystery
tt0236348	Josie and the Pussycats	2001	Comedy Music
tt0104850	Memoirs of an Invisible Man	1992	Comedy Romance Sci-Fi
tt0199626	In the Cut	2003	Mystery Thriller
tt0491747	Away from Her	2006	Drama
tt1263750	Room in Rome	2010	Drama Romance
tt0109555	Darr	1993	Drama Romance Thriller
tt0073631	Rollerball	1975	Action Sci-Fi Sport
tt1959332	American Mary	2012	Drama Horror
tt0004972	The Birth of a Nation	1915	Drama History War
tt0365885	The Upside of Anger	2005	Comedy Drama
tt0074084	NULL	1976	Drama History
tt0051418	The Blob	1958	Horror Sci-Fi
tt1849718	Agneepath	2012	Action Drama
tt0311519	The Man Without a Past	2002	Comedy Drama Romance
tt0063688	The Thomas Crown Affair	1968	Crime Drama Romance
tt0037913	Mildred Pierce	1945	Crime Drama Film-Noir
tt0038574	Great Expectations	1946	Adventure Drama Mystery
tt0051744	House on Haunted Hill	1959	Horror Mystery
tt0326905	The Great Raid	2005	Action Drama War
tt0377752	Dear Frankie	2004	Drama Romance
tt0335563	Wonderland	2003	Crime Drama Mystery
tt0271263	Eight Crazy Nights	2002	Animation Comedy Musical
tt0363282	New York Minute	2004	Comedy Crime Family
tt0091670	The Sacrifice	1986	Drama
tt1071804	Ink	2009	Action Drama Fantasy
tt0160916	The Story of Us	1999	Comedy Drama Romance
tt0107711	Nowhere to Run	1993	Action Drama Romance
tt5523010	The Nutcracker and the Four Realms	2018	Adventure Family Fantasy
tt1095174	New in Town	2009	Comedy Romance
tt0099165	The Bonfire of the Vanities	1990	Comedy Drama Romance
tt0063850	If....	1968	Drama
tt1798603	Bad Santa 2	2016	Comedy Crime Drama
tt0069945	Dark Star	1974	Comedy Sci-Fi
tt7772580	The Perfection	2018	Drama Horror Thriller
tt1714208	The Woman	2011	Horror

tt0078902	Breaking Away	1979	Comedy Drama Romance
tt0089489	Lifeforce	1985	Action Horror Mystery
tt4900716	Kapoor & Sons	2016	Comedy Drama Romance
tt0164961	Vidocq	2001	Action Crime Fantasy
tt0768212	The Last Mimzy	2007	Drama Family Sci-Fi
tt0466460	Khosla Ka Ghosla!	2006	Comedy Crime Drama
tt0489282	Strange Wilderness	2008	Adventure Comedy
tt4572792	The Book of Henry	2017	Crime Drama Thriller
tt7008872	Boy Erased	2018	Biography Drama
tt0098141	The Punisher	1989	Action Crime Drama
tt3148502	Tamasha	2015	Comedy Drama Romance
tt1928340	After the Dark	2013	Drama Fantasy Sci-Fi
tt0055499	Through a Glass Darkly	1961	Drama
tt1151922	Miss March	2009	Comedy Romance
tt0318761	Thumbsucker	2005	Comedy Drama
tt0102614	Out for Justice	1991	Action Crime Drama
tt0097368	The Fly II	1989	Horror Sci-Fi
tt5895028	13th	2016	Crime Documentary History
tt0785006	Hotel for Dogs	2009	Comedy Family
tt0214388	100 Girls	2000	Comedy Romance
tt0104561	Jo Jeeta Wohi Sikandar	1992	Comedy Drama Romance
tt1305591	Mars Needs Moms	2011	Action Adventure Animation
tt0437857	Behind the Mask: The Rise of Leslie Vernon	2006	Comedy Horror Thriller
tt0076009	Exorcist II: The Heretic	1977	Horror
tt0055601	Viridiana	1961	Comedy Drama
tt1231586	A Good Old Fashioned Orgy	2011	Comedy Romance
tt0092796	Creepshow 2	1987	Comedy Fantasy Horror
tt0102587	Only Yesterday	1991	Animation Drama Romance
tt1012804	Redbelt	2008	Drama Sport
tt1129423	Fireproof	2008	Drama Romance
tt6857166	Book Club	2018	Comedy Drama Romance
tt0116130	Down Periscope	1996	Comedy
tt0416185	Resurrecting the Champ	2007	Drama Sport
tt5580266	The Hate U Give	2018	Crime Drama
tt0795434	Namastey London	2007	Comedy Drama Romance
tt0780607	The Signal	2007	Horror Sci-Fi Thriller
tt0926762	Loft	2008	Crime Drama Mystery
tt1046947	Last Chance Harvey	2008	Drama Romance
tt0338216	Lucky You	2007	Drama Romance Sport
tt1424310	Chinese Zodiac	2012	Action Adventure Comedy
tt1092633	The Goods: Live Hard Sell Hard	2009	Comedy
tt0091083	From Beyond	1986	Horror Sci-Fi
tt1349451	Butter	2011	Comedy Drama
tt0177858	In July	2000	Adventure Comedy Romance
tt0114608	Tales from the Crypt: Demon Knight	1995	Action Fantasy Horror
tt3678782	Badlapur	2015	Action Crime Drama
tt0134619	Disturbing Behavior	1998	Horror Mystery Sci-Fi
tt1748207	Sound of My Voice	2011	Drama Mystery Sci-Fi
tt0441774	Lonely Hearts	2006	Crime Drama Romance
tt0048473	Pather Panchali	1955	Drama
tt0038991	The Stranger	1946	Crime Drama Film-Noir
tt1634121	Intruders	2011	Fantasy Horror Thriller
tt0085970	Mr. Mom	1983	Comedy Drama
tt1134854	Survival of the Dead	2009	Comedy Drama Horror
tt0120777	The Opposite of Sex	1997	Comedy
tt0080736	The Final Countdown	1980	Action Sci-Fi
tt0103924	Captain Ron	1992	Adventure Comedy
tt0373283	Saints and Soldiers	2003	Action Drama War
tt3014284	The Lego Ninjago Movie	2017	Action Adventure Animation

tt0430770	The Women	2008	Comedy Drama
tt1316037	Birdemic: Shock and Terror	2010	Action Comedy Drama
tt0102719	Problem Child 2	1991	Comedy Family
tt0951216	Mad Money	2008	Comedy Crime Thriller
tt2368553	Assault on Wall Street	2013	Action Crime Thriller
tt0104009	Cool World	1992	Animation Comedy Fantasy
tt2258337	Eega	2012	Action Comedy Fantasy
tt0089017	Desperately Seeking Susan	1985	Comedy Drama
tt5956100	Tiger Zinda Hai	2017	Action Adventure Thriller
tt1296898	Waiting for Forever	2010	Comedy Drama Romance
tt0415965	Martian Child	2007	Comedy Drama Family
tt1702425	Casa de mi Padre	2012	Comedy Western
tt0186894	Bounce	2000	Drama Romance
tt0091480	Manon of the Spring	1986	Drama
tt0082484	Quest for Fire	1981	Adventure Drama History
tt0315297	Twisted	2004	Crime Drama Mystery
tt0036244	The Ox-Bow Incident	1942	Drama Western
tt0064072	Battle of Britain	1969	Action Drama History
tt1196204	Cemetery Junction	2010	Comedy Drama
tt4154916	Replicas	2018	Drama Sci-Fi Thriller
tt1018765	Our Brand Is Crisis	2015	Comedy Drama
tt1255919	Holmes & Watson	2018	Adventure Comedy Crime
tt0101635	Curly Sue	1991	Comedy Drama Family
tt0246464	Big Trouble	2002	Comedy Crime Thriller
tt2473602	Get on Up	2014	Biography Drama Music
tt1984153	Excision	2012	Drama Horror
tt3385524	Stan & Ollie	2018	Biography Comedy Drama
tt4635372	Masaan	2015	Drama
tt0808244	Easy Virtue	2008	Comedy Romance
tt1235796	Ondine	2009	Drama Mystery Romance
tt0111693	When a Man Loves a Woman	1994	Drama Romance
tt0245238	Lost and Delirious	2001	Drama Romance
tt0112688	Clockers	1995	Crime Drama Mystery
tt0361411	Bride & Prejudice	2004	Comedy Drama Musical
tt2077833	Rowdy Rathore	2012	Action
tt0254481	Koi... Mil Gaya	2003	Action Drama Romance
tt1302067	Yogi Bear	2010	Adventure Animation Comedy
tt0404254	My Sassy Girl	2008	Comedy Drama Romance
tt0051622	The Fly	1958	Drama Horror Sci-Fi
tt7098658	Raazi	2018	Action Drama Thriller
tt0995031	Bhool Bhulaiyaa	2007	Comedy Horror Mystery
tt0133046	Teaching Mrs. Tingle	1999	Comedy Thriller
tt0120866	Titus	1999	Drama History Thriller
tt0790623	Meet Bill	2007	Comedy Drama
tt1020885	Vampire Killers	2009	Action Comedy Fantasy
tt0057358	Winter Light	1963	Drama
tt0074174	The Bad News Bears	1976	Comedy Drama Family
tt1666185	All Eyez on Me	2017	Biography Drama Music
tt0097257	Earth Girls Are Easy	1988	Comedy Musical Romance
tt0051554	Horror of Dracula	1958	Horror
tt0073580	The Passenger	1975	Drama Thriller
tt0469903	The Express	2008	Biography Drama Sport
tt0110027	Highlander: The Final Dimension	1994	Action Fantasy Romance
tt0080716	Fame	1980	Drama Music Musical
tt0074512	Family Plot	1976	Comedy Thriller
tt5286444	Neerja	2016	Biography Drama Thriller
tt0382189	My Summer of Love	2004	Drama Romance
tt0122459	Return to Me	2000	Comedy Drama Romance
tt0078163	Revenge of the Pink Panther	1978	Comedy Crime Mystery

tt4196450	The Birth of a Nation	2016	Biography Drama History
tt0115907	City Hall	1996	Drama
tt0337103	Crimson Rivers 2: Angels of the Apocalypse	2004	Action Crime Horror
tt2639254	A Little Chaos	2014	Drama Romance
tt2309021	We Are What We Are	2013	Drama Horror Thriller
tt0119891	Phantoms	1998	Horror Sci-Fi Thriller
tt0144964	Highlander: Endgame	2000	Action Adventure Fantasy
tt0051378	Elevator to the Gallows	1958	Crime Drama Thriller
tt0075824	That Obscure Object of Desire	1977	Comedy Drama
tt0091630	Night of the Creeps	1986	Comedy Horror Sci-Fi
tt1181795	Bunraku	2010	Action Drama Fantasy
tt1659338	The Numbers Station	2013	Action Thriller
tt0101829	Europa	1991	Drama Thriller
tt0037059	Meet Me in St. Louis	1944	Comedy Drama Family
tt2393845	Kill Me Three Times	2014	Action Comedy Crime
tt0961097	A Monster in Paris	2011	Adventure Animation Comedy
tt1308728	The Happytime Murders	2018	Action Comedy Crime
tt1135092	The Limits of Control	2009	Crime Drama Mystery
tt0422774	Are We Done Yet?	2007	Comedy Family Fantasy
tt1659343	Universal Soldier: Day of Reckoning	2012	Action Horror Mystery
tt4581576	Aftermath	2017	Drama Thriller
tt0110978	Texas Chainsaw Massacre: The Next Generation	1994	Comedy Horror Thriller
tt8350360	Annabelle Comes Home	2019	Horror Mystery Thriller
tt1124039	Echelon Conspiracy	2009	Action Crime Mystery
tt0479500	Nancy Drew	2007	Comedy Crime Family
tt0084777	Tenebrae	1982	Horror Mystery Thriller
tt2316801	Beauty and the Beast	2014	Drama Fantasy Romance
tt0043924	A Place in the Sun	1951	Drama Romance
tt0100114	Marked for Death	1990	Action Adventure Crime
tt1433822	The Apparition	2012	Horror Thriller
tt0324127	Suspect Zero	2004	Crime Horror Mystery
tt0318081	A Sound of Thunder	2005	Action Adventure Horror
tt0044008	A Christmas Carol	1951	Drama Fantasy
tt0273517	Darkness	2002	Horror
tt1735485	The Tunnel	2011	Horror Mystery Thriller
tt2581244	Life After Beth	2014	Comedy Fantasy Horror
tt0312549	Veronica Guerin	2003	Biography Crime Drama
tt0283026	Swimfan	2002	Drama Thriller
tt0047573	Them!	1954	Horror Sci-Fi
tt0109676	Drop Zone	1994	Action Adventure Thriller
tt1183665	Cracks	2009	Drama Thriller
tt0054632	Last Year at Marienbad	1961	Drama Mystery
tt0082307	The Beyond	1981	Horror
tt0433416	The Namesake	2006	Drama
tt1205558	Hick	2011	Comedy Drama
tt0112819	Dead Presidents	1995	Action Crime Drama
tt0095925	Pumpkinhead	1988	Fantasy Horror
tt2235779	The Quiet Ones	2014	Horror Mystery Thriller
tt4030600	The Bye Bye Man	2017	Drama Fantasy Horror
tt0086617	The Year of Living Dangerously	1982	Drama Romance War
tt0089114	Explorers	1985	Adventure Comedy Family
tt0084865	Victor Victoria	1982	Comedy Music Musical
tt0299172	Home on the Range	2004	Adventure Animation Comedy
tt0087755	The Muppets Take Manhattan	1984	Adventure Comedy Drama
tt1926313	Pyaar Ka Punchnama	2011	Comedy Drama Romance
tt0102744	Quigley Down Under	1990	Action Adventure Drama
tt0089013	Demons	1985	Horror
tt0381940	Cargo	2009	Mystery Sci-Fi Thriller
tt0056291	Knife in the Water	1962	Drama Thriller

tt0055830	Carnival of Souls	1962	Horror Mystery
tt4257926	Miracles from Heaven	2016	Biography Drama Family
tt1032825	The Other Woman	2009	Drama
tt0097858	Meet the Feebles	1989	Comedy Music Musical
tt0070948	Zardoz	1974	Adventure Fantasy Sci-Fi
tt1535970	The Ledge	2011	Drama Romance Thriller
tt0055256	One Two Three	1961	Comedy
tt0411270	The Beat That My Heart Skipped	2005	Crime Drama Music
tt0104558	Police Story 3: Super Cop	1992	Action Comedy Crime
tt0291579	He Loves Me... He Loves Me Not	2002	Romance Thriller
tt1928330	Bad Ass	2012	Action Comedy Crime
tt0075968	The Duellists	1977	Drama War
tt0100260	Nightbreed	1990	Action Fantasy Horror
tt1234541	The Butterfly Effect 3: Revelations	2009	Crime Sci-Fi Thriller
tt0116514	Hellraiser: Bloodline	1996	Horror Sci-Fi
tt0058083	Fail-Safe	1964	Drama Thriller
tt0116421	The Glimmer Man	1996	Action Comedy Crime
tt0087957	Purple Rain	1984	Drama Music Musical
tt2625030	New World	2013	Crime Drama
tt1430615	Big Miracle	2012	Biography Drama Family
tt6472976	Five Feet Apart	2019	Drama Romance
tt0896534	Deadgirl	2008	Horror
tt2183034	Earth to Echo	2014	Adventure Family Sci-Fi
tt1630036	Courageous	2011	Drama
tt0059183	The Flight of the Phoenix	1965	Adventure Drama
tt0120772	The Object of My Affection	1998	Comedy Drama Romance
tt1068641	The Burning Plain	2008	Crime Drama Romance
tt1731701	Barely Lethal	2015	Action Adventure Comedy
tt3210686	Son of God	2014	Biography Drama History
tt3280262	Cult of Chucky	2017	Comedy Fantasy Horror
tt0101316	The Lover	1992	Biography Drama Romance
tt1233381	Three Monkeys	2008	Drama
tt0104040	The Cutting Edge	1992	Comedy Drama Romance
tt2403029	The Starving Games	2013	Comedy Sci-Fi
tt0210616	Center Stage	2000	Drama Music Romance
tt3766394	Hello My Name Is Doris	2015	Comedy Drama Romance
tt0803057	The Promotion	2008	Comedy
tt2304953	Reasonable Doubt	2014	Crime Drama Thriller
tt0047849	Bad Day at Black Rock	1955	Crime Drama Mystery
tt0100212	My Blue Heaven	1990	Comedy Crime
tt0285175	Havoc	2005	Crime Drama
tt1362058	Cockneys vs Zombies	2012	Action Comedy Horror
tt0104990	Newsies	1992	Drama Family History
tt0090927	The Delta Force	1986	Action Adventure Drama
tt1699231	Quarantine 2: Terminal	2011	Horror Mystery Sci-Fi
tt0865559	My Life in Ruins	2009	Comedy Romance
tt4667094	Fifty Shades of Black	2016	Comedy

APPENDIX F – PERSONALITY-BASED KEYWORDS REFERENCE LIST

EXTROVERT PERSONALITY-BASED KEYWORDS REFERENCE LIST

abandon	cheque	doorman	hemisphere	mates	purportedly	slumped	unfortunately
abandons	chimes	dossier	herd	mathematics	pursues	smacks	unleash
abducted	civilization	downed	hiker	maze	qualifications	smelling	unlikely
abuse	classified	drained	hiking	meaningless	qualifying	smuggles	unloading
accomplished	claustrophobia	dug	hitch	mechanisms	quality	snobby	unnerved
accusing	cleanse	dusted	hitmen	medal	quarrel	snooping	unsettling
accustomed	cleaver	dysfunctional	hive	media	quicksand	software	unwavering
activating	cloak	earnestly	holographic	medicine	quits	solicitor	unwilling
activist	clone	eater	homicide	meek	rambling	solo	unworthy
admired	closely	educated	honored	mementos	rampling	solved	upsetting
adrift	collective	elects	hopefully	menacing	rashly	sorrow	uptight
advertisements	collision	element	horribly	menial	ravaged	sources	urban
advertising	comeback	eliminate	host	merpeople	raze	spawned	urchin
afterlife	comforted	eliminates	hostile	mixing	reactivate	spectral	users
alleged	comical	eludes	household	moaning	reactor	spirit	vacuum
alternate	comically	emerged	housekeeper	mugged	realm	spurred	vandalizing
ambassador	commence	emerging	humanity	mumbles	reappearance	staged	vanished
ambiguous	commented	emphasizes	humbled	murdering	rebuffs	stages	vehemently
ambition	committee	enemies	humiliates	musical	recall	starve	ventures
amusingly	communication	enforcer	hunting	musician	recalling	statues	verdict
analyzes	communicator	engages	hurries	mutagen	recklessly	staunchly	verify
angel	communist	enlistment	hurt	mute	recognized	stem	victorious
animation	compacted	enormous	hurts	mystery	reconnaissance	sting	villager
announcing	compared	entertain	hustler	negative	regain	stockbroker	viper
anxiously	compel	entrap	hybrid	negotiator	rehabilitation	stoned	visible
apologized	composure	envy	idealistic	neighboring	relatives	strictly	volunteer
apology	compromise	equal	ignite	noticing	relies	striking	vote
appeal	concedes	escorts	illuminated	notifying	remake	stud	vulnerable
appeals	conclude	evacuation	imagining	obsolete	remedy	submersible	wager
appease	condoloences	evaluation	immigrant	odious	reminiscing	submission	wages
application	confessed	examined	immortal	online	rendition	substantial	wanderer
approves	confessions	exceeding	immunity	onward	repetition	succumbs	whisper
archer	confines	excellent	implicating	operates	replacing	sucked	winner
aristocratic	conflicted	excessively	imposter	oppose	replicas	sufficient	wits

arithmetic	connect	executes	improvise	organizations	reporters	suggest	wizard
asserting	conscious	expedition	incapable	organize	repulsed	suggestion	womanizer
asset	constructed	exploration	incarcerated	outlook	required	sung	wondered
assuring	consumers	explorer	incinerates	outrage	requiring	sunken	worthless
attentive	containment	exposure	incredible	ovation	researcher	superiority	wounding
authentic	contamination	extended	inept	overbearing	resentful	supplement	wreaking
authorization	continued	extreme	infamous	owners	resents	supportive	wrecks
auto	contradictory	facsimile	infection	ownership	resolve	surgical	zombie
babe	contrary	fail	infested	painful	resorting	surplus	tumbling
babysitter	converge	fairy	infirmary	partnership	resources	surprising	ugliest
bachelorette	convert	fantastic	inflicted	patent	responded	surrender	ugly
backstage	conveyor	faster	influential	patience	restoration	surrenders	ultimatum
barcode	convicts	fearsome	inhuman	patriot	retaliate	survival	undergoes
barren	cooking	feats	injure	pattern	retreated	swarms	unethical
bashed	cooperation	fencing	injures	pauses	retreats	swatting	unfamiliar
behaves	coworkers	field	injuring	penalty	retribution	swear	unfazed
beheads	cracks	fiercely	inmate	penthouse	revels	swore	sincerity
beings	crashed	firepower	input	perceived	reverts	symptoms	skyward
beliefs	crazily	firsthand	inspecting	permitted	revived	talented	slap
betrothed	creator	flamboyant	inspection	perverse	reviving	taunt	slash
blaming	criteria	flashing	inspects	petition	revokes	taunting	slaughter
blast	crossed	flop	instructing	petitions	revolt	teacher	slaughtering
blazing	crushing	follower	intensely	phase	rich	technicality	sleeper
bleachers	cultural	forge	intercepting	phenomenon	ringing	technician	slightest
bleak	cycling	forgetting	intern	physician	riot	tensions	prospect
blissful	dance	formal	interprets	pitched	risks	terminally	prosthetic
blizzard	dangers	forming	intervention	plain	robbed	terrifies	protagonist
blockade	darkened	frail	interviewing	plow	robberies	testified	protector
blocks	deadbeat	frames	intrusion	ploy	rooted	thanked	protestant
blog	dealership	franchises	invades	plumbing	rotating	thanking	protocol
bloodthirsty	decades	friction	inventor	pointed	royalty	tight	psychic
blunder	deceit	friendly	investigated	polish	rudely	tone	punching
boardroom	decent	frightened	investigative	politics	ruling	toothless	lust
boasts	decommissione d	frightens	invulnerable	ponders	rumored	torches	lynch
boisterous	defeats	fugitives	jobs	portraits	sacrifice	torture	manifest
bombardment	defense	futile	joining	powered	salvage	tortures	manipulates
boorish	definitive	gagged	journeys	practitioner	satan	torturing	manslaughte r
boring	delete	galvanized	jumping	praise	satisfaction	touching	marked
bounces	demanded	gangs	jurisdiction	praises	scarring	township	massacre
boundaries	demons	gathering	kidnaps	praising	scoop	tradition	mastermind
brain	depicting	geek	knack	praying	scores	traditional	handles
brains	descendants	generic	lacking	precaution	scouts	trainer	happier
breached	deserve	generous	landlady	predator	scuffle	transfer	harbors
breathes	deserved	genuinely	lecherous	premature	secrecy	transformed	harming

bribed	destitute	giggles	legislation	pretended	sedative	translator	harpoon
bridal	detailed	glory	liar	pretentious	seducing	transmitted	haughty
bride	detains	gore	librarian	priest	segment	transporter	headaches
brilliant	determination	grabbed	lifeguards	privileges	selected	trapping	heists
broadcasting	devoid	grasps	lightening	prized	sensitivity	trauma	disobeyed
brokered	devour	grateful	limit	procedure	separately	traumatic	dispatcher
brutality	dialogue	gratefully	liner	prodigy	separation	travelling	disposes
burying	dignity	grieving	lingers	produces	sequences	treachery	dispute
busted	disables	groans	loans	professionall y	servants	triggers	disrupt
busting	disapproval	grumpy	logical	programmed	servitude	triumphantl y	ditch
caddy	disconnects	guidance	lottery	programs	setup	tropical	dominating
callously	disfigured	guise	luckily	promiscuous	shedding	troubled	donor
camping	disguises	hallucinating	lucrative	propeller	shines	tug	cannibals
candidates	dismember	handled	lures	proposed	signals	tumble	cheerleader
cannons	captures	castrated	casualties	certainty	championships		

INTROVERT PERSONALITY-BASED KEYWORDS REFERENCE LIST

abomination	cheat	detour	ghosts	leading	photograph	robber	syringes
aborted	chemistry	development	gifted	leaking	photographing	rotten	tardiness
absorbing	chiding	devil	giggling	lends	pimp	rousing	taste
accompanying	chores	diagnosis	gladly	leper	pinning	royalties	taunted
accurately	chose	dialogue	glances	lethal	pissed	ruckus	technically
active	civil	difficulty	glows	levitating	planner	ruin	technicians
activist	clairvoyant	dignity	gorgeous	liberty	planting	rumor	teleportation
addicted	cleavage	diplomats	grace	lighted	plateau	sacred	televised
administration	clover	discarded	grateful	liked	pleasant	sailors	tempers
admires	clutching	discomfort	grave	limited	pleases	sanitized	tempts
admitting	coastal	discourage	gravedigger	lobbyists	pleasure	saws	tentatively
admonished	coaster	discouraged	grieves	loitering	poor	scenario	terrorize
adopting	collaborating	disgusted	gruesomely	loneliness	porch	scepter	testimonies
adventurous	colonial	dislodges	guardian	lottery	positive	schoolmates	therapy
advertising	colonized	dispatcher	guardians	lovebirds	possesses	scream	thorns
aggressively	comedian	disqualified	guerrilla	loved	possibly	screeches	thoroughbred
aghast	comedies	disruption	hacking	lovers	pounce	scrubs	thoroughly
agonizing	comedy	distributed	hacks	lullaby	practical	seal	tips
alien	comfortable	disturbance	hairless	madness	practically	secreted	toddler
alright	commendation	donates	handsomely	maiden	predict	sensitive	tombstones
ambivalent	commission	donning	hanger	mail	presided	sequences	torrid
amendment	commissioned	doses	happiness	makeover	prevails	sermons	touching
angels	commit	dual	hates	manhood	primates	serpents	towed
announcing	commitments	dubs	hauling	mannered	privy	servitude	tower
annoyed	committee	dumping	headaches	mastermind	professionally	sewing	trainer
apocalypse	commotion	easy	heaven	mature	professors	sharing	trampoline

appalled	communications	eavesdropping	heir	measured	programmed	sharks	transactions
appealing	communities	echoing	heists	mechanism	prohibited	shielding	transformation
appease	commute	economically	hellish	meekly	prolonged	shines	transmitter
applauds	commuters	effortlessly	helper	melancholy	promised	shipped	traveling
appropriate	compact	eject	helpless	memorial	promotion	shocks	travelling
approval	compassion	elected	heritage	mercury	proposal	shotguns	treatment
archival	complains	eliminating	hero	merger	prospective	shoulder	trips
arguments	comply	eluded	heroically	metropolitan	prosperous	signals	tropical
ascends	concentrating	eludes	hesitant	mice	pyramids	silently	trumpets
assassination	conclude	embarrass	highlights	mindedness	quickly	simulation	twists
assaulting	condemning	embraced	hinder	miniature	quoting	simulations	unaccounted
assembling	condescendingly	emissary	hitchhike	mirrors	racetrack	sin	unavoidable
assists	conditions	employed	hitching	misconduct	rages	sized	unclear
assuring	confident	enacting	honest	misinterprets	range	skeletons	unconvinced
astral	conflicts	enclosure	honesty	missions	rapes	skiptracer	undergone
atom	confronting	enduring	honors	mistaken	reached	skulls	undeterred
atrocities	conjures	enforcer	honour	mistreated	react	slattery	undo
authorization	conn	enigmatic	hope	mob	readers	slick	uneasily
autobot	conscience	ensure	hopeful	mobbed	realized	slide	unemployed
automatically	considering	enthusiast	hopeless	mocking	reappears	slivers	unemployment
ballet	consume	entrusts	horrible	mockingly	reasonable	smacks	unexpectedly
ballistics	consumed	epilepsy	housekeeper	monopoly	reasoning	smell	unfavorable
bankruptcy	continental	erratic	housemates	motivations	reassures	smelling	unfazed
barbeque	contraband	erupting	hunter	muddy	rebuffs	sneaking	unhappy
barrier	contribute	escaping	hypnotized	multiplying	recipe	snuff	unhelpful
beanstalk	controversial	essence	identifying	murderer	reciprocates	sober	uninvited
beatings	converge	establishing	idiot	mutilating	recite	soldier	union
beckoning	conveyor	evasive	illustrations	nasty	recites	soul	unlocks
beeping	conveys	evicted	imaginary	natives	reclusive	special	unopened
behaves	counterfeit	evolved	imagine	neglect	reconciles	specializes	unpacks
behaving	counterpart	exasperated	immigrants	neighboring	recuperating	sphinx	unsolved
belittles	coven	exceeding	immortal	nerve	reflex	splashes	unsuccessful
bends	crack	exceptionally	immortality	nightly	refugee	splattering	unsure
bicker	crazed	exorcism	immortals	nostalgia	regained	spook	unsympathetic
billionaire	crazies	expected	implies	obey	regenerate	stability	unwind
blackmailing	creators	exploring	impose	objectives	reincarnated	stacked	upscale
blackness	credit	exposing	imposter	obligations	rekindling	staged	uptown
blares	creed	extends	incapable	obsessively	relaxation	stakes	urban
blaze	crestfallen	external	incidents	occult	relays	stalker	valiantly
blazing	critically	fabric	incite	occupation	reliant	stalled	vanquish
bleachers	crooked	faced	infidelities	occurrence	remarkably	stance	venable
bloodhounds	crowds	faith	influencing	odd	reneged	starring	verbally
bluff	cue	farming	informants	oddly	reopen	starve	vicinity
bonus	cyborg	fathered	infrastructure	offensive	repel	statistics	victorious

boorish	deadbeat	fatigue	infuriated	offspring	repossessed	steadfast	villain
border	deafening	fearing	initiating	online	representation	stealth	vintage
borrows	deal	fears	initiative	opportunistic	repressive	steep	virginity
botched	dealership	feats	insanity	organizes	reprimand	stinky	visualize
bounced	debauchery	federation	insight	ornate	reprimands	stocking	vividly
boyhood	decay	felony	insisting	ostensibly	reputations	stomps	volunteered
brags	decisions	finances	inspired	outskirts	rescuers	stoners	voters
breathable	declaration	firepower	inspires	ovation	research	storage	votes
bride	declare	fishing	instructed	overcharged	resemblance	storytelling	watchtower
bumping	declares	fittest	intense	overdoses	resent	stove	weaken
burst	decorated	fixates	intersect	overflow	reservation	strain	weapon
butler	decrepit	flamethrowers	intoxicated	overhear	resistance	strangways	winged
buzzing	dedication	focusing	intrigued	overlook	resisted	strap	wired
bystander	defection	forbids	invested	overnight	responsibilities	strategic	wise
cancel	defects	foreboding	investigating	overslept	restoring	strongly	withdrawals
cannibals	defying	forever	invisibility	overtakes	restraints	struggling	wonder
capacity	delays	formally	inward	overtaking	resurrected	stud	worlds
capitalism	delighted	formed	irresponsible	overwhelms	retaliate	studying	worries
captors	delivering	formulates	issue	paid	retreated	stupid	wrestling
capturing	delusional	founder	issuing	panicking	reunification	stupidly	writer
catacombs	demeanor	fractured	jackal	paraphernalia	reuniting	suave	writhing
cautious	demonstrating	frequencies	jewel	partial	revelations	subsequent	yield
cavalry	denying	frustrated	jokes	patience	revokes	suburb	zombies
caveman	deploying	frustrating	judgment	peak	revolutionary	succumb	zooms
ceased	deploys	fusion	kill	peasant	rhetoric	suggest	
cemetries	describe	gaining	kindhearted	penalty	riddled	suggested	
cermonial	deserters	gaping	kinetic	pending	rigs	suing	
chariots	destitute	geeky	kinky	performer	risk	sultry	
charms	destructive	generous	languages	persists	ritual	swearing	
chase	deteriorates	genetics	laughter	personalities	roam	switched	

SENSING PERSONALITY-BASED KEYWORDS REFERENCE LIST

abandon	convertible	fruit	momentum	resentful	tows
abandoning	conveyor	function	monkey	reside	trace
abducting	conveys	funded	monks	resides	traditional
absent	conviction	fury	morphine	resignation	tragedy
absorbing	convicts	fuse	morse	resigned	trainees
absurd	cooking	futility	mortified	resistance	trainers
abusing	cool	gambler	motion	resistant	tranquilized
academic	cooling	gaping	motionless	resisted	transfer
academy	corny	garrison	motives	resolution	transferring
accelerate	coroner	gasp	motto	resolved	transfers
accepting	corrects	gasps	mountains	resorts	transfixed

accessory	corrosive	gaze	mow	resources	transitions
accusation	counselor	geeks	murder	respectfully	translates
accusations	counselors	geishas	muscular	responded	translator
achieve	countdown	gesture	musicians	responding	transmitted
acknowledging	courtroom	gestures	muslim	restless	transplanted
acquitted	cowardice	getting	mute	restore	transporting
act	cowardly	giants	myself	restoring	traumatized
added	cowboy	giggling	nails	resume	travelling
addicted	crab	gigs	naive	resuming	treachery
adding	crap	gladly	naked	retake	treasury
adjourns	creator	gleefully	natives	retaliates	treatment
adjust	creature	glimpses	navigator	retrieving	triumph
administer	creeper	gloom	neat	revelation	tropical
admiration	creeps	goads	needy	revenue	troubles
admire	crime	goats	neglected	reverses	trumpet
adopting	cripple	godmother	negotiating	reviews	trustworthy
adopts	crisp	goodness	neighborhoods	revive	truthful
adventure	critic	gossip	neighboring	revived	turmoil
adventures	critically	governor	nerve	ridiculous	tutor
advertising	criticizing	graduate	newest	riding	twin
advising	crocodiles	grant	nights	rife	twists
advocating	crook	graph	noble	rightful	typing
affairs	crooked	gratitude	nonsensical	ring	ultimate
affectionate	crops	greatly	notebook	riot	unaware
afire	crossing	greed	noting	rioting	uncovering
agency	cruise	groans	novels	riots	uncovers
aggressively	crusade	groomed	numerous	robot	underestimated
agitated	crystal	grooming	obey	rocking	underhanded
aiming	cured	grudgingly	objectives	roles	understandable
alarming	curse	gruesomely	oblivious	rolling	understandably
alert	curve	guidance	obscene	rookie	undetected
allegiance	custom	guiding	observation	roommates	unemployed
altered	customs	gunpowder	obssessing	root	unethical
alternative	cut	gymnasium	obtaining	rotation	unhinged
amateur	cute	hallucinating	occasion	rotting	uniformed
amused	cutters	handled	occult	roughly	unintelligible
analyzing	daily	handles	odious	routine	unique
ancient	dam	handwritten	offensive	royalty	united
angel	damaging	hangar	offerings	ruby	unknowingly
angels	damn	happy	online	ruining	unloads
angering	data	harassing	operations	ruling	unlock
announcer	dated	harbor	opponents	ruptures	unmoned
announcing	daydream	harboring	opposing	rusty	unmoved
anonymously	deadly	harbors	oppressive	ruthless	unnatural

antagonistic	debating	harmed	oracle	sabotage	unpredictable
antagonize	debilitating	harvesting	oral	sabotages	unrequited
anxiety	debts	haul	orbital	sack	unresponsive
apologies	deceased	hauled	organism	sacrificed	unsettled
apologise	deceive	hauling	organizations	sacrifices	unsupervised
appeal	deceiving	havoc	ornate	sacrificing	unsure
appeals	decent	headmistress	ostensibly	sadistic	unveils
application	deception	healing	otter	safer	unwanted
appreciates	decimated	heals	outcome	sailors	unwilling
appreciation	declaration	heartbeat	outer	sake	unworthy
aquarium	declared	heartfelt	outfit	salon	update
archery	decline	heavens	outrageous	saluting	uploads
arise	decorate	heckling	overcoming	sane	upsetting
arming	deduce	hedges	overhear	sauna	upward
arson	deeply	height	overly	savages	useful
artifact	defective	helpless	overpowering	savvy	user
ascending	defending	herbs	overwhelmed	sawing	utters
aspires	defies	hero	overwhelming	scarred	vaguely
assaulted	deflects	heroic	ownership	scenario	vampire
assembled	degrading	heroin	pacing	scepter	vegetables
assertion	delayed	heroine	packaging	schools	vendor
asset	delete	hesitation	packed	schoolwork	vengeful
assumes	deletes	hideously	paddles	scolding	venture
assuming	delicate	hijacking	painful	score	venturing
assumptions	delighted	hikers	painkillers	scored	versus
assured	delights	hiking	painted	scorpion	viewers
assuring	delinquents	hitches	panels	scout	viewing
astonished	demolished	holes	paraphernalia	scrabble	views
astronauts	demon	holy	partially	scrambled	vikings
attach	demons	homemade	participants	scratched	vineyard
attacker	departure	homicide	partisan	scratches	virgin
attendants	depository	honor	partnership	screening	vocal
attended	depresses	honors	passages	scribbled	voodoo
attracting	deputies	hooded	patent	scruffy	voted
author	deserve	hooks	patience	searched	votes
authorization	deserved	horizon	patricians	section	vulnerable
autopsy	designated	hostility	patrolling	security	wander
avalanche	dessert	hosts	pausing	sedated	wandered
avoiding	detailing	hot	penalty	seduce	wandering
award	detected	humanoid	pendant	seduced	warming
aware	detention	humiliate	penicillin	seducing	warms
awful	determination	humiliated	pension	seizing	warp
awfully	devastating	humiliates	penthouse	sells	wartime
backstage	devote	humor	performances	senate	wary

backup	devoted	humorous	perks	sensitive	wasted
baffled	devotion	hungry	permitted	separates	watchtower
bakery	diamonds	hurry	persecuted	servicemen	weakened
banging	differently	hurting	persons	session	weakly
bankrupt	digging	hurts	persuaded	setting	weakness
bankruptcy	digital	hyperactive	persuading	severing	weaknesses
banter	dignity	hypnotizing	pertaining	sewing	weary
baptist	dilemma	hysterical	petition	sex	weeping
bargaining	dim	ideas	petty	shadows	welcoming
barracks	dimension	illness	philosophy	shame	werewolf
barricaded	diminutive	imagined	phobia	shank	whimpering
bathing	dimmed	imagines	phony	sharks	whirlpool
beaked	dine	imminent	pimp	shattering	whisky
beams	dinosaur	immortals	pirate	sheltering	whisper
beasts	dipping	impaired	pirates	shimmering	whistling
beckoning	disappointed	imperial	pitches	shining	wide
beetle	disapproves	impersonates	plantation	shocks	widow
beforehand	disarmed	implicate	playoffs	shuttle	wig
befriend	disciplinary	implicating	plea	sidekick	willingly
befriended	discovery	impounded	pleasant	sidelined	wise
befriending	discreet	impress	please	sider	withdrawal
begrudgingly	discreetly	imprinted	plots	siege	wits
behalf	disease	imprinting	plow	signals	wizard
behind	disgrace	improvises	plucked	significantly	wizards
belief	disguises	inactive	plucks	signing	woes
besiege	disloyalty	inanimate	plug	silence	woken
bet	dismiss	incarceration	plumber	silenced	woo
betraying	dismissed	incites	plunging	similarly	workable
bewildered	disobedient	included	plus	sin	workaholic
bigger	dispatcher	increased	pnicillin	sing	workload
bill	dispatching	increases	pockets	situations	worshipers
billionaire	disperse	incredibly	pointed	skank	worthwhile
bindings	displaying	incredulous	poisoning	skips	wracked
bird	disqualified	independence	polish	slain	writings
bitch	dissent	indignant	politicians	slapping	wronged
biting	dissuade	indulges	ponytail	slashed	yank
bits	distorted	inexplicably	port	slaying	yanks
bitter	distract	infantry	portals	slays	zombie
blacksmith	distractions	infection	portraits	sleazy	zombies
blamed	distracts	infiltration	positions	slightest	testimony
blasphemy	distributing	inflated	possessing	slipped	thanked
blasted	disturbance	influence	post	slowly	thanking
blindfolded	divers	inifintely	pouch	slumped	theme
blindly	diving	initiative	poverty	slums	themed

blockade	division	inmate	powder	slut	theorizes
blog	domestic	inner	powerless	smarter	therapy
blood	dominant	inoperable	practices	smash	thoroughly
bloodthirsty	donor	input	praise	smelling	thwarted
bluffing	donors	insanity	pranks	smokes	tight
bluntly	doomed	insect	praying	smuggles	timid
blur	dossier	insight	prays	snarls	tips
blurred	drain	insinuates	precious	snatch	tolerance
blurts	drama	inspires	precipice	snorting	toll
boardroom	dramatically	inspiring	predalien	soaring	tombstone
boil	dumbfounded	installed	predicament	solely	topples
boot	dump	instantaneously	preoccupied	solidarity	toppling
booth	dust	instructions	preserved	solved	torches
bot	dwarf	intact	presidential	solving	torment
bothering	dwindling	integration	presiding	songs	torturing
breaches	eager	intending	pressuring	soothing	tougher
breaching	earning	intensely	prey	sophisticated	towed
breasts	earns	interjects	priceless	sorrow	remained
breathable	easier	interpret	prince	sought	reminded
bridges	echoes	intervenes	princes	soul	remorse
brothel	educated	intervening	principal	spans	removal
bruise	education	intervention	principle	spared	rendered
buddy	eerily	interviewing	priority	spark	reneges
bureau	eject	intimate	privacy	sparks	renewed
bursting	elated	intimidate	privately	specialist	renovation
burying	elders	intimidating	privy	species	reopen
bust	election	invented	procedure	specifically	reopened
busted	electricity	inventions	processor	specimen	repeating
butler	electrified	investigations	proclaimed	specter	repelled
butterfly	electrocutes	investigative	produced	spectral	replicating
buyer	elephant	investment	professes	spice	repopulate
buzzing	eligible	investors	profession	spikes	reportedly
bystander	eliminating	irritated	professional	spine	requesting
caged	elusive	isolating	profiles	spiritually	require
calendar	embarks	issued	profit	splits	required
canceled	embarrasses	issuing	profitable	spontaneously	rescuers
candles	embassy	jammed	programmer	sport	research
cannibals	emphasizing	jogging	programming	spots	researching
capital	employed	journal	proposed	spotting	resembling
captivity	empress	jousting	prosperity	stables	merchandise
capturing	emptiness	junkie	prostitutes	stacked	merge
carcass	enable	justifies	prostitution	stadium	metallic
carriers	enclosed	justify	protest	stain	methane
carved	encloses	keepers	prototype	stake	mild

casualties	encourage	key	protracted	stakes	mines
cautions	endured	kidnapper	proud	stalemate	mingle
cemeteries	enforce	killings	proved	stalling	mingles
centered	engulfs	kinetic	proven	stance	minimal
central	enhance	kings	provided	starring	minted
certainly	enlisting	kneeling	providing	starter	miracle
certainty	ensuring	knight	proving	static	misgivings
chairman	entertaining	knuckle	provokes	steady	mishaps
challenging	entertainment	labeled	prowess	stickers	misstep
channel	entertains	labyrinth	psyche	stockings	mist
chant	enthusiastically	lacking	psychiatric	storyteller	mistaken
charming	entourage	lane	psychosis	stove	mixture
charms	entries	lanes	publicity	strains	mocking
chastity	entrusts	large	puddle	stranded	mockingly
cheats	envisioned	largely	punctured	strange	modeled
cheering	equally	law	punish	strangely	models
cheesy	erasing	lawyers	puppet	strangled	modest
chemistry	erratic	leaks	puppy	strategic	flashlight
cheque	escaping	leap	purchase	streak	flatly
chicks	essentially	leather	pure	stretch	flattered
chimes	established	legacy	purge	stretching	flaws
choked	esteem	legally	pushy	strewn	flipped
chokes	estrogen	legends	quantity	strict	flown
choking	eternity	lessons	quarreled	stripping	followers
chopping	ethical	lethal	quell	stroke	forbids
chunks	euthanized	levitates	quelled	strolls	foreigners
circle	evaluation	levitating	quoting	strung	forgave
cites	eventual	liberal	racers	studied	forming
citizen	evolved	liberating	racial	stun	fort
civil	examinations	lifeline	racket	subordinate	fortress
civilization	examples	lifelong	racketeer	subordinates	fragile
classes	exasperated	lifting	rampage	sucking	fragments
classical	exceedingly	lightning	rampant	sue	frames
classmates	exceptionally	likewise	range	suffer	framing
clearly	excitement	liking	ranks	suggest	franchise
clients	exciting	limited	rapists	suite	franchises
climate	excuses	linked	rare	sum	fraternity
cloaked	exercising	loathing	rarely	summit	frenzied
clothed	exhibit	lockers	rat	summon	frightening
cloudy	existed	lodge	rate	superhero	connect
clowns	existing	lodged	rattles	superheroes	conscience
clueless	expanding	loft	raw	superiority	conservative
clutching	expatriate	lone	reaching	supporters	considerable
coaster	expenses	lonely	reactions	supporting	considerably

coastline	expensive	looming	reactivated	suppressed	consideration
coaxes	explaining	loosely	readily	surfaced	considering
codenamed	explicitly	loosen	realist	surrendering	consistently
cohorts	exploit	lords	realization	surveying	consisting
colonists	exploits	loser	reaper	survivalist	consolation
colored	expose	lost	reappears	suspicion	conspiracy
comatose	exposing	love	rebel	suspicious	consternation
combined	expressions	lowest	rebellion	swallow	construction
combustible	extended	luggage	rebellious	swamps	consumes
comedy	extending	luring	rebukes	swap	contain
commander	extension	luxurious	recital	swarm	content
commandments	extent	lynch	recklessly	sweating	continually
commands	fabric	machine	reclaim	sweeps	continued
commence	factor	machinery	recognises	swiftly	continuum
commentator	faculty	machines	recollection	swipes	contraband
commented	fairies	mafia	recommend	switched	controversial
commercial	fairly	magic	recordings	swollen	conveniently
commercials	fairy	magical	recount	swoop	term
committee	falling	magnificent	recounted	swordsmanship	terror
commonwealth	falsified	maiden	recounting	swore	terrorism
communication	familiarity	mailbox	recover	sympathetic	terrorizing
compares	fanatic	mainland	recovery	symptoms	reliant
completed	fantastic	makeover	recruiter	syndicate	religion
complications	fantasy	mangled	redemption	syndrome	religious
complies	farewell	mannequin	reduced	synthetic	relocated
compliments	farmer	manufactured	reduces	syringe	melts
comply	faulty	march	reference	takeoff	memorabilia
components	favors	marching	reflects	talents	menacingly
concealed	feared	marketing	refrain	targeting	mentioned
concedes	fearful	markets	refuel	tarnish	fitting
concentration	fearing	marksman	regaining	taste	fixes
concept	federal	masquerade	regardless	tastes	fixing
concepts	feeling	masterminds	regiment	tattoo	flamethrower
conclude	fenced	mates	register	tattoos	conflicting
conclusion	fences	mature	rehearsing	team	confronting
condom	fetching	maximize	reign	tease	confusion
conduct	filmed	maze	reinforcements	techniques	congress
confessions	filthy	meaningless	rejoin	technological	tend
confident	finalize	measure	rekindle	telegrams	relentless
confidentiality	fingerprints	media	relate	temperature	meetings
confidently	firepower	medication	relatively	temporary	firsthand
confirming	firmly	meekly	relaxes	temptation	conflicted

INTUITION PERSONALITY-BASED KEYWORDS REFERENCE LIST

abandon	clutches	ensure	innocence	patriot	see	ultimate
aboard	clutching	entertainer	insanity	peace	seizes	umbrage
aboriginal	coalition	entrap	insect	peaks	selflessness	unaffected
abused	cogs	entrusted	insinuates	peddling	seniors	unafraid
accomplices	coincide	entrusts	inspecting	pedophile	sensation	unauthorized
accomplishing	colder	envies	inspire	pellet	sensing	unavoidable
accosted	collateral	epilogue	installs	penalty	sensitive	uncovering
accumulated	collective	equals	instrumental	pendulum	sensitivity	underestimate
accuracy	collides	erotic	instruments	performed	sentencing	undergo
accuse	colonized	errant	insult	perhaps	serpents	undermine
accused	column	establishing	integrates	perks	servers	unemployment
achieved	columnist	establishment	intelligent	permanently	services	unfavorable
acquire	combo	ethical	intended	perplexing	setup	unfazed
acquires	comedian	ethics	interact	personally	sewing	unfeeling
acquitted	comlies	ethnicity	intercepting	personnel	sharks	unfortunately
adjoining	commandments	evasion	interloper	perturbed	shatter	unimpressed
administer	commentators	exaggerated	interns	phase	shedding	unique
adopted	commercials	exasperated	interpreter	phenomenon	shields	united
adrift	commit	excessive	interstate	philosophy	shines	university
adultery	commodities	executives	intervene	photographing	shocked	unkempt
affair	communist	exercise	intervenes	photography	shockingly	unleashes
affection	communities	exerts	interviewing	pillar	shout	unlocking
affectionately	compared	exhausting	intoxicated	piloting	shoveling	unmoved
affordable	comparing	existent	invaders	piping	shoving	unpleasant
agencies	compartments	existing	invading	pipping	shrine	unpredictable
agenda	compelled	expected	invest	pirate	shuffling	unsettling
aghast	compels	experts	investigated	plagues	sidewalk	untied
agile	competitions	expiration	investigations	plants	siege	unwilling
agility	composition	expires	invisibility	plateau	signature	unwillingness
alias	conceives	explore	inviting	please	significance	unworthy
allegations	concept	exploring	involuntary	pleased	significantly	upbeat
alligator	condemn	extent	irate	pledges	silently	upgraded
amateurish	condemning	external	ironically	plots	sin	upgrades
ambition	confessing	extinction	irreverent	plumber	sincere	uprising
amidst	confidentiality	faggot	irritated	poet	sinful	upsetting
amorous	confiscates	fainted	irritating	poisonous	sinister	useful
amusement	conflicting	fairies	jam	polish	sinkhole	utilizing
amusing	connecting	fairy	jamming	polite	skeleton	utter
analyzed	conscience	faithful	joking	politicians	skeletons	valedictorian
ancestors	consciousness	fateful	joyfully	poll	skeptical	vanquished
angering	consoles	fathers	juggles	popularity	sketching	vehemently
angers	consult	fearsome	jumpsuits	populated	skinned	venomous
anonymously	consumes	federal	justify	porcupines	slap	versions

antagonistic	contagious	fiction	kissely	portrait	slaughters	vessels
antagonize	contained	figurines	kneel	pouring	slayers	veterans
anticipation	containers	fillings	labyrinth	praises	slicker	victor
antics	containment	filmmaker	labyrinthine	prank	slideshow	victoriously
applied	contempt	filter	laced	precaution	slightest	videos
apprehended	contentment	filtration	lacked	predator	slightly	vigilante
arch	contestants	finale	laughingly	prefer	slipper	villager
archer	contests	finalize	launcher	prehistoric	slogan	vindictive
architecture	continental	finals	lava	presidency	smarter	vineyard
arrests	continuous	fingerprints	layer	pressured	smiling	virtual
arsenal	contracted	firefighter	lazy	pretty	smirks	virus
arson	contrary	firepower	leased	prevented	snag	visually
artifact	conventionists	firmly	leaves	prices	snags	volunteered
ascend	corporation	fittest	legends	prior	snooping	voters
aside	counsel	fixing	legitimacy	privately	soaked	vulgar
aspects	counterfeit	flack	liberally	privileges	soaring	wager
assaulting	coupled	flammable	liberates	problematic	socialist	warmth
assaults	covert	flanking	liberation	proceedings	solely	wartime
assembling	crack	fleeting	lifelike	proclaim	solutions	waterbending
assertion	craftily	flesh	lifted	prognosis	sophisticated	wax
assess	crafty	flicks	lifting	programming	sounded	weakened
assimilation	crashed	flirtatious	like	programs	spacious	webcam
assumed	craving	flirty	limits	progressive	spares	weddings
assured	creeper	focusing	limping	prohibited	sparking	wild
astonished	creepy	folk	lineup	project	speared	wildlife
athletics	crippled	followers	listing	projectile	spears	wings
atrocities	critic	fooling	live	prominent	spectators	winners
attaching	criticizes	foreboding	livid	promising	spice	womanizer
attracting	crocodiles	forefinger	longtime	pronouncing	spike	wonder
avengers	crotch	forensic	loops	propagate	spiked	workplace
average	crown	foreplay	loosens	properly	spiral	worthwhile
avoiding	crucified	formerly	lottery	prospect	splits	wrecking
avoids	crucifix	frat	lovebirds	prospects	spoils	wrecks
awareness	cruelty	fraudulent	loveless	protector	sporting	wring
awful	cryptically	friction	loyalty	protestant	spouting	writings
awfully	cultured	frustrates	luckily	protracted	sprawled	wrongdoing
backpack	curator	frustratingly	lured	protruding	spying	yanking
badgering	curiosity	funding	machinery	provocative	stabilizes	yield
bailing	customs	fusion	madness	psychology	staggers	travelers
bake	cutter	futile	magnificent	publisher	staging	treadmill
bakers	cyber	futures	mailbox	purchasing	starve	tribal
bakery	dancers	gadget	majored	pursuing	statements	trident
bandage	dangerously	gaping	makeup	pushing	statues	trimming
bang	dangers	gardening	making	pyramid	stave	trips
bangs	dawning	geeky	manipulating	qualify	steadfast	triumphant

baptist	daydreaming	generated	manipulation	quality	steady	trolley
barbed	deactivate	generic	markers	quarreled	steep	troopers
barging	deactivates	genetic	marketing	queen	stern	troubling
barracks	debating	gently	marketplace	queries	stiff	tunic
barricade	deceive	genuinely	martian	quickening	stillborn	twists
barrier	decisions	ghostly	masochistic	quotes	stinky	schizophrenia
base	declaration	ghosts	masquerading	racketeer	stitches	scolding
baseball	deepest	ghouls	massacred	radical	stoned	scored
bathed	deeply	gifted	mates	railing	stoners	scornfully
beatings	defects	gifts	meaningless	raised	strange	scorpion
beauty	defies	glance	measures	rammed	strangles	scratch
beckoning	defribrillator	gleeful	meatpacking	ransom	strap	scruffy
behave	delicate	goads	media	rapes	stretch	sculpture
behaves	delicious	goofing	medical	rapists	strewn	scurrying
being	demons	goofy	mega	rapport	striking	secreted
believing	demonstrating	gossip	megalomaniacal	rattling	stripes	sedated
bend	denied	governments	meltdown	realise	stubborness	sedative
benefits	dense	grades	melting	reanimates	studied	paired
bent	dented	graveside	memoirs	reasoning	stun	pairs
bewilderment	depicted	grenades	merciful	reckless	stunned	paralyzed
bids	deploying	grill	meteors	recklessly	stuns	paranoid
biggest	depressing	groin	meters	reclusive	stupidly	pardon
billionaire	derision	grooming	midair	recognized	stylish	parlor
billowing	derisively	guided	milestone	recommended	subduing	partially
bitter	descendants	gunning	millenium	reconnect	subordinate	participated
blackmailing	descending	gunslinger	minded	recovering	succeed	participating
blackness	describe	hacking	minted	recruiter	succumb	parties
blades	deserting	handled	miracle	reflex	sue	passages
blair	deserts	hang	miraculously	regards	suffered	paternity
blank	deserved	hanged	miserable	regent	sufficiently	incriminating
blasphemous	despondent	harboring	missing	regional	suggestions	indicate
blaze	detachment	harmony	mission	regurgitates	suggestive	indifferent
bloodied	detain	harness	mockingly	rehearsals	suited	indirectly
bluffs	detecting	harpoon	modeled	reinstates	sullen	industrialist
bluntly	deteriorates	hastily	modified	rejected	summons	ineer
boasting	determines	hazing	monitoring	relatives	sunglasses	inevitably
bomber	devious	headaches	monopoly	reliant	supporters	inflated
bombers	devoured	headmistress	monster	remarking	supporting	informal
bonuses	diagnosis	heals	mood	remembered	supportive	inhumane
borderline	differing	heaven	moody	reminiscent	suppose	initiating
bots	dilemma	heck	mop	renegade	supremacists	inmate
bounes	dining	heckling	moral	renew	surfing	empties
boyhood	dip	heel	moron	renovations	surgeon	enabling
braid	diplomatic	heir	mortally	repressive	surprising	enacts
branded	directly	helpless	motionless	reprieve	surprisingly	enchanted

breakthrough	disabling	heroics	motive	reprimand	surrendered	encouragement
bridal	disapproves	hesitance	mourns	reptilian	suspecting	endures
brightens	disbarred	hesitation	mow	repulse	suspension	engineering
brilliantly	disciplinary	hibernating	multiplying	reputed	suspicion	engulfed
broadcasting	discourage	hikers	murderous	requesting	sustain	enhancing
brotherhood	discreetly	hinted	musicians	requirements	sustaining	enlist
brutality	disgrace	hiring	muzzle	rescuers	swarming	enlisting
bubble	disgusting	hitch	myth	researching	swat	enraging
buckles	disgusts	hogs	nailed	resentfully	swears	chops
buoy	dish	holographic	nationwide	resorting	swells	christians
bursting	disheartened	homemade	natured	resorts	swiftly	chuckles
buzzes	disintegrating	homicidal	naughty	resources	switch	circular
bystander	dismantles	honesty	neglect	retreating	swooping	civil
cabins	dismissal	hooded	negotiating	retribution	syndicates	claimed
caged	disobedience	hopeless	nerdy	revelers	taker	cliffs
callback	disobeyed	horrifying	network	revenue	tangled	climate
callously	disregarding	hospitalized	newest	reviewing	taps	climaxes
campaigning	dissuaded	hostile	newspapers	revolver	tardiness	clings
capsule	distorted	huddle	novels	richer	targets	cloaked
carcass	distracts	humbled	nuisance	richest	taunting	cloning
cared	distribution	humiliated	numerical	rider	taut	translating
careful	distrustful	humiliating	oath	riding	technicality	translator
caress	diversify	humility	obligations	right	techniques	transparency
caretaker	docile	humor	obliterated	riots	technologies	transportation
cartoon	docking	hungry	obnoxious	risk	teetering	traumatic
casual	dolls	hurtles	oddly	risking	teleprompter	scenic
catalog	dominant	hush	odious	rites	teller	scent
catastrophe	dominates	hut	offended	rivals	temperamental	schematics
catastrophically	doomed	hybrid	offends	robot	tempers	scheme
catwalk	dose	hyperactive	offensive	robotics	tensions	schemes
cautions	dossier	hypnotizes	online	roles	terminator	overheating
ceased	doubled	hypnotizing	onlookers	rubbish	testify	overlapping
cemeteries	downwards	iconic	onward	ruin	theft	overriding
centurion	drama	idle	opener	rummages	themes	overseer
cerebral	drifting	ignorance	opera	rush	theorist	pads
ceremonies	droid	illegally	organism	rustling	theorize	incensed
cermonial	drugging	imagine	origin	rusty	theorizes	incinerate
challenge	drunkenly	imagining	ostracized	ruthless	thrashed	included
championship	dubbing	immense	otherwise	sabotage	thrilled	incomparable
channel	dumping	immerse	outcasts	sacrifices	timely	inconspicuously
charmed	earlier	imminent	outcome	sale	tipsy	embargo
charred	earns	immortals	outfits	sang	tombstone	embarks
chastity	earrings	impale	outfitted	sarcasm	tougher	emerald
cheaper	eavesdropping	implicate	outing	sardonic	tormentors	emperor
cheat	edit	implicating	outlets	satan	torture	empress

cheerful	educated	imposter	outnumbered	satisfy	torturer	chips
cheesy	eerily	improvements	outright	sawing	trailing	chooses
cherish	effortlessly	improvised	outward	scantily	trampoline	chop
childishly	electrocuted	impulse	overcomes	scars	transfixed	chopped
chipper	elementary	incantation	overdose	scenarios	translate	choppers

THINKING PERSONALITY-BASED KEYWORDS REFERENCE LIST

abide	costume	healthy	patience	smuggler
aboriginal	counseling	heartbeat	patriarch	snatch
abrupt	countdown	hearted	payback	sniffing
absence	country	heartedly	peach	snitch
absorb	counts	heartless	peasants	snooping
absorbed	coup	heavens	pecking	soldier
absurd	cracks	heavyweight	pedal	solved
accent	cradles	help	penalty	song
acceptance	cradling	helper	perceived	sophisticated
accidents	crafted	helpless	perfection	sorrow
accomplices	creature	heroine	perks	soul
accomplish	creeper	heroism	permits	souls
accomplishment	crest	hesitate	perplexed	source
accordinly	cripple	hesitation	persecuted	sovereign
accountant	crisis	hijackers	perseveres	spared
accounts	critic	hijacking	persists	spectral
accumulated	crocodile	hiker	persons	speculate
accurate	crocodiles	hinder	pertaining	speed
accusations	crooks	hoggle	perturbed	spending
acquainted	crossed	hollows	perverted	sperm
acquires	crowded	holy	phobic	splice
adamantly	crown	homicidal	pimp	spoil
added	crows	homicide	pirate	spoiled
additionally	cruelty	honorable	pitching	sponsored
addressing	cryptic	honour	planner	spontaneous
adjourns	crystal	hook	playdate	spots
administered	culprit	hooker	playful	spring
administering	cultured	hopefully	plead	sprinklers
administration	cured	horace	pleasantries	squats
admission	cursed	hordes	please	stabilize
adolescent	cushions	horrific	pleasure	staged
adopting	cycle	hospitals	pledging	staggering
adoption	daggers	hostility	plumber	staining
adultery	dancers	hosts	plumbing	stakes
adulthood	dangerously	humping	pocketing	stalker
adventurous	dare	hunger	poise	stalks

adversity	darkly	hungry	poisonous	stallion
advertisement	dashes	hustlers	poisons	stamina
affairs	daydreaming	hut	pokes	standard
affectionately	dazzling	hypnotizes	politically	statements
affections	deadbeat	hysteria	ponder	steep
aflame	deafening	hysterically	ponders	steer
aggression	deal	ideas	popped	steers
aggressively	debating	identifiable	populated	stepmother
aliens	debts	idiotic	posed	stepson
alike	decade	idle	positively	stereotypical
alleges	decapitate	idyllic	post	stifle
allegiance	decapitating	ignoring	postcard	stimulate
alligator	deciphering	illegally	postcards	stirring
alternative	decisions	illustrating	poster	stirs
altruism	declaration	imagery	powdered	stokely
amazement	decrease	imaginable	power	stones
ambiguous	dedication	imagining	praised	stored
ambition	deemed	immediately	praises	story
ambitions	defeated	immigrant	pranks	stowed
ambitious	defiance	impaired	praying	stranded
amidst	defuse	impatiently	preacher	strangling
amusing	delays	implications	precious	strap
anchored	delicious	imported	precocious	strategy
angel	delightful	impulsive	predecessor	strengthened
angels	democracy	inappropriate	predict	stretching
angers	demonstrated	incapacitate	prediction	strict
angle	denial	incinerates	predictions	strobe
angry	depends	incites	prefer	stroke
animate	depicted	included	prehistoric	strongly
annihilates	deportation	incomparable	premonition	stubbornly
annoying	deported	incomprehensible	present	stunning
antagonistic	deposition	incorrect	presented	stupidly
antics	deputies	incredulous	presenting	stutter
anxious	derided	indefinitely	presidents	subdues
apartheid	descendants	independence	prestigious	subduing
apathetic	describe	indifferent	pretended	subsides
apparitions	descriptions	indignation	primarily	substantial
appeal	deserter	indirect	printing	succeed
appeals	deserts	indulging	prior	successes
appearing	deserved	inevitable	priority	succession
appease	designing	inexperience	privately	succumb
applause	designs	inexplicably	privy	sufficient
appoint	despises	infatuated	prize	suing
appoints	detailing	infiltrated	proclaims	summary
apprentices	detained	infiltrating	proclamation	sunlight

archeologist	detects	infuriates	professors	superiors
arise	detention	initiative	programmer	supportive
armour	detests	injected	programming	suppressed
aroused	devastating	inmate	programs	supreme
arousing	devour	insects	prohibit	surfaces
arraignment	devours	insert	prohibited	surfing
arrangement	diamonds	insider	prolonged	surgically
artifact	diary	insinuates	prom	surrender
ascends	different	insisting	promising	surrendered
aspiring	difficulties	inspector	prone	surrendering
asserting	digestive	inspire	propelling	suspension
assertion	digital	inspired	proposed	swallowed
assignment	dignity	instance	prosecution	swap
assisted	diligently	instill	prostitutes	swarming
associate	dinner	instructor	protagonist	swayed
associates	diplomatic	instrument	protest	sways
assured	dipping	instrumental	protestant	swearing
assuring	dirty	integration	protested	sweating
asteroid	disabled	interact	provoke	swells
astounding	disappointed	intercedes	prowess	swordsman
astral	disapproves	intercepting	psyche	syndicate
athletic	disarms	intermission	psychiatric	syndicates
atrocities	disaster	internal	publish	synthetic
attacker	disbarred	interpret	pulse	tactic
attire	discussions	interpreter	pummel	tactical
audition	disease	interrogation	pumpkin	tailed
authenticity	disguises	intervene	punish	tailor
automobile	disk	interviews	punishment	tap
avalanche	dislikes	intimidating	punk	taps
average	dislodges	intolerance	purchasing	targeting
avoiding	disloyalty	intrigued	purportedly	tasked
award	dismantle	involvement	quality	tattered
awful	dismissing	inwardly	questionable	taught
backed	disobeying	ironically	quits	taxes
backfires	dispel	irresponsible	quoting	tease
backing	displeasure	irritated	rabbit	technically
backpack	disrupt	isolation	racer	teenaged
backyard	distorted	issued	racketeer	telegrams
ballad	distribution	jaded	ragged	telekinesis
ballots	disturbance	journals	raids	telekinetic
band	division	joyride	ramifications	telephoned
bandits	dizzy	junkyard	randomly	televised
bankrupt	dominates	kidnapper	ranks	temperamental
bankruptcy	domineering	kingpin	rapists	temperature
banned	doubled	kneels	rapper	temptation

barcode	douses	knighted	rather	tenant
barren	dove	labyrinth	rationalize	tender
barricaded	downwards	lacking	readings	tenure
barrier	dragon	lantern	realities	terminal
barriers	drained	latches	realization	terminator
barrister	drastically	launched	reaper	terrain
beard	dreaded	lean	rebuffed	terrifying
beautician	drifts	leather	receipt	testifies
befriended	drink	legions	receptive	textbook
begrudgingly	dunk	liaison	reciting	thanked
behaving	dye	liar	recklessly	theories
behaviour	eager	liberal	recognizing	theorizes
beheading	earlier	liberate	recoils	thermal
beheads	easier	liberation	reconnect	thinkers
bend	easygoing	lifelike	reconstruct	thirst
besiege	eavesdropping	lineup	recreate	thoroughly
bespectacled	edit	lingering	recruiter	threaten
betrays	edited	lion	recuperating	thunder
bid	editing	liquidate	redeeming	tight
bidding	educational	listing	reduced	tirade
birthday	electricity	loafing	references	titles
birthmark	elemental	loans	reflect	tombstones
biting	elementary	lobotomy	refueling	tongues
bits	elite	locals	refund	tonight
bitter	elude	locusts	regime	toppling
bitterly	embarrass	lone	register	torturer
bizarre	embarrassing	loops	regrets	towers
blackmail	embarrassments	loosened	regroup	toxic
blackmailer	embracing	losing	rehearse	traditions
blanks	emotional	lovebirds	reign	trafficker
blasphemy	emperor	lowest	reinforced	traits
blindly	emphatically	luckily	reiterates	transferring
blizzard	employed	lunch	rejoice	transfers
blocking	emporium	lures	relate	transformation
blooded	empress	lurking	relation	transplants
bloodline	emptying	madman	relayed	transporting
bloodying	emulate	magic	relentless	traumatic
blossoms	endless	magician	reliant	travelling
bluffs	endures	maiden	religion	treacherous
blurred	enduring	mails	religious	tread
boardroom	enforcement	makeover	relinquishes	treasure
boasting	enlisting	makers	relocate	treat
boisterous	ensures	malevolent	relying	tremendous
bombardment	enthused	malfunctioning	remarried	tremendously
bomber	enthusiast	managers	rendered	tricking

bookkeeping	erase	managing	renders	triggering
boorish	erotic	mandibles	renews	troop
boost	erratic	manhood	renovated	tropical
bored	escaping	maniacally	renovation	troublesome
bounce	establishes	manner	renovations	troubling
bows	establishment	mannerisms	reopen	trusty
breach	estimates	manufactured	reparations	trying
bruised	eternal	marsh	repay	tumble
brutalized	ethical	marshal	replacement	twisting
budding	etiquette	mask	replacing	uncertain
buffet	evacuated	massage	replica	uncertainty
bugs	evasive	masturbate	replicas	uncharacteristically
bull	everyday	matchmaker	reprise	uncontrollable
bullying	exaggerated	mathematics	require	undefeated
buoy	examining	mature	rescue	understanding
burglary	exceeding	maze	rescuers	undertakes
bust	excess	meaningless	reside	undetected
busts	excessive	medications	resigns	undressed
camping	exchanging	meeting	resistance	unemployed
canals	excites	melt	resourceful	unfinished
cannibals	exciting	melting	respected	unhinged
capabilities	exclaim	memoirs	respectful	unintentionally
capacity	excruciating	memorial	restless	uninterested
cape	executes	menaces	restoration	unison
captives	executions	menial	restricted	unleashes
cardboard	exerts	mention	retains	unleashing
carefree	exiled	menu	retreating	unlikely
carnage	existent	merchandise	reversing	unlimited
cartoon	exiting	merchant	revived	unloading
casualties	exotic	merit	richest	unmarried
catalyst	experiments	mesh	ridden	unmoved
catastrophe	expertly	messy	rigid	unnecessary
cavalry	explore	metallic	roaring	unpacks
celebrations	expose	metaphor	robberies	unravel
celebrities	faction	methods	robbins	unresponsive
cement	faculty	mind	rocking	unsolvable
chairman	fairies	mingle	rocky	unsure
challenge	faith	minimum	rode	untie
challenged	falling	mining	romancing	unusual
channel	famed	miracle	roommates	unwelcome
chant	farmers	miraculously	root	unwitting
chants	fastest	miscarriage	ruining	unworthy
charms	fateful	miserable	rush	upgrading
chase	fathered	miserably	rusty	upset
chats	fearful	misgivings	sadly	uptown

chemistry	fearfully	misled	safer	ushers
cheque	featured	misplaced	saints	utilizes
chiding	feedback	misstep	salute	vacuum
choked	felling	mobilize	sank	valiant
chuckle	fetches	mobsters	sarcasm	vanish
circumstances	fever	mocked	satan	vegetarian
clashes	figurine	mocking	satisfication	vegetation
clashing	filed	mode	satisfy	veiled
class	final	monks	savage	vending
claws	finals	monopoly	saviors	vermin
clearing	finance	mood	sawing	verses
clever	financially	mops	scandal	vessels
cleverly	financing	moron	scanning	vet
cliff	firmly	morosely	scary	veterinarian
closely	fixes	motives	scathing	vice
clothing	flair	motto	scavengers	victoriously
cloudy	flaming	murderer	scenario	viewers
clumsily	flashback	muscles	scent	villain
clutch	flavor	musters	scepter	virtually
clutching	fleury	mutates	schedules	visitor
coalition	flustered	mystics	schematic	vividly
codenamed	foiled	nailed	scholarship	volunteered
collective	forbids	naked	scorned	volunteering
college	foreign	natives	scorpion	voting
colossal	forensics	needy	scrambling	vowed
comedies	forgave	negotiating	scrape	vulgar
comforting	formal	networks	scratching	vulnerable
comical	format	neutralizes	sculpture	wade
commends	forming	nobel	scurry	wages
commented	fortunately	noble	second	wander
commenting	fought	notorious	secrecy	warily
commission	foundation	novelist	sedated	warms
committee	fragment	novelty	seeds	warriors
commonwealth	fragments	numb	seeker	wars
communications	frat	objective	seemed	washing
commuters	freedom	obtained	seized	watery
companions	frequency	occasional	selfishness	weaken
competing	frequents	occupation	sender	weakening
completion	friction	odious	sensing	wearily
complicity	fruitless	offends	sensitive	wedding
complies	fueled	offensive	sensitivity	whirlpool
compliment	fugitives	offerings	sensual	widow
comply	fulfilled	offshore	sequencing	wig
components	funeral	onset	seriousness	wildly
composure	funny	opened	setup	wiretap

comprising	furnace	opera	sex	witchcraft
concerning	furtively	opportunistic	sexy	witches
conclude	fury	opposing	shatter	withdraw
confidentiality	futures	orbit	shattering	withdrawal
confirmation	gamble	orbital	shifted	without
congregate	gardens	order	shoplifting	witnessing
conjures	gasp	organization	shoreline	wizard
connecting	gasping	organizations	shouted	wolf
conscience	gateways	organizing	showers	wondering
consent	genetics	outcast	shuttle	working
consequently	ghastly	outdoor	sidekick	workplace
conservative	ghostly	outlandish	siders	worlds
consideration	gigs	outmoded	signifying	worms
constructed	gingerly	outnumbered	silencing	worsens
consulate	global	overcomes	silk	worthless
consumed	gnarled	overcoming	simulation	wreak
consuming	good	overflow	sincerely	wrecks
containers	gorgeous	overheard	sinister	yacht
contempt	gossip	overjoyed	sized	yield
contest	grazes	overtake	skeleton	zaps
contestants	greatly	overtaking	skeletons	zombies
continent	groin	overthrown	skilled	smell
continued	groom	overwhelmed	skips	smelling
contractors	guaranteed	pace	slash	smiled
contribute	guards	pacifying	slaughtered	smirk
contributing	guiding	painful	slayers	partygoers
controversy	gunning	paired	sleazy	passive
convenient	habits	pairs	sliced	patches
conventionists	halt	panicking	slick	patent
converge	harbors	paranormal	slightest	paternity
convict	hardened	parental	slogan	hauling
convinced	harvested	participating	slowly	haven
convulsions	hating	participation	smack	headmistress
cook	hatred	partnership	smear	healing
coousins	coroner	corporation	corrupted	heals
corny				

FEELING PERSONALITY-BASED KEYWORDS REFERENCE LIST

abducted	concluding	familiarity	lever	quoting	symbolizing
aboard	condescending	fangs	liar	rabbits	sympathetic
absolutely	condolences	fashions	liberal	racetrack	symptoms
abuses	confident	fateful	lifelike	racked	syndicate
accepting	confidentiality	fathered	limited	racketeer	systems

accomplish	confiscate	favourite	lining	rampage	tackled
accountant	conflicts	fearfully	listed	rampling	tactical
accounting	confusing	fears	live	ranks	tailpipe
accusation	confusion	federation	loafing	rapper	taker
accusations	congratulating	fend	loaned	readings	tales
acquires	connect	ferrie	loops	realized	taunt
acrobatic	connecting	fever	looting	rearranging	taunter
actively	consensus	fiction	love	reasoning	teasing
adapted	consequence	finalize	loveless	rebelled	technician
added	consistently	finance	lurks	recall	technological
addressing	conspirators	finances	luxurious	receptive	telepathically
administered	consumes	fireballs	lynch	recklessness	teleports
administering	consumption	firefighters	magnate	recognizable	tendency
administration	containment	firepower	mail	recovering	tender
adopting	continued	firsthand	manipulate	recruiting	tentative
adoration	continuum	fisherman	manipulative	reflections	tentatively
adorationwrecking	contradictory	fittest	manufacturing	reflexes	tenure
adrift	contribute	flag	marble	reform	termites
adulthood	controversy	flagging	marine	refund	territorial
advancing	copying	flagpole	martial	refused	terrorism
adventurer	corporation	flanked	matched	regard	thick
adventures	correctly	flash	mattress	reiterates	thin
advertised	corresponding	flashy	mature	relaxing	thirst
advertisement	corridors	fledgling	matured	religious	thoroughly
affectionate	corrupted	flood	meaningful	rely	thousand
against	counsel	floods	measures	rematch	thrill
aggressively	countdown	flop	medallion	remembering	thrived
alarms	countless	flower	media	rendition	toast
allergic	coup	fluent	medicinal	reparations	toasts
alleys	coupled	flung	mediocre	repel	tone
allies	crab	folk	meltdown	repentance	tonight
alludes	cradle	follower	melted	replacing	tool
ally	crafty	fooling	memoirs	replicas	topless
altered	cream	forever	memory	represented	toppling
altogether	creative	forging	menial	reprimands	touchdown
amazement	creedy	formal	merciful	researching	tougher
ambassador	crews	frames	mercilessly	reserve	towers
anarchist	cried	franchises	merger	residing	town
anew	crimson	freelance	merry	resignation	townsfolk
angel	crossed	freely	metallic	resists	trace
angers	crucified	frequents	middle	resolves	tracing
antennas	crucifixion	freshly	mile	respectively	tradition
anticipated	cryoprison	frighten	mimicking	responsibilities	traffickers
anxious	cuff	frontier	miming	restless	trailing
apparently	cultivate	function	minimum	restore	trampled

applaud	custom	gala	minor	restricted	translator
applies	customs	gallons	mirrors	resurrects	transmit
apprentices	dame	gallops	misinterpreting	retaliation	transporting
arduous	dangles	gamer	missions	retreating	traumas
arguments	dared	gap	mistrust	revolution	traumatic
artifact	darkened	gaping	mob	revolutionary	treachery
artwork	dart	gazes	mode	rhyming	treasures
ascend	deactivate	gazing	moon	ridicules	treats
ashamed	deactivated	gears	mosquito	riding	treaty
aspiring	deactivates	gene	motions	rift	trek
assaulting	debriefing	generally	motorcycles	ringleader	trembles
assembles	decades	generals	mountainous	ringside	tremendous
assistant	decapitate	gentleman	mug	risen	triangle
assurance	decapitates	gentlemen	murders	risky	tribe
astronaut	deceived	gesturing	muscles	roaming	tribute
attained	decipher	ghosts	muscular	roars	triple
attire	decorations	giver	mutagen	rocking	tumbling
attracting	deflect	glance	mystery	rod	turns
attracts	deformed	global	mystical	rods	ultimately
audacious	defuse	goblin	myth	rolling	unattractive
author	defy	goings	namely	rotating	unborn
awakening	delayed	golden	nanny	rotten	unchanged
awestruck	deliberation	grated	necessary	rubble	undergoing
bachelor	delighted	grateful	needing	rulers	undressing
backfires	demeaning	gratefully	nefarious	rumored	unemployment
bakery	demise	grave	neglected	runt	unfamiliar
ballad	democracy	greatly	negotiator	rustling	unflattering
bandaged	demon	greed	neighbour	rusty	unhelpful
bang	demonstration	grief	net	ruthless	unimpressed
banker	demoted	grin	never	sacrificed	uninterested
banned	deport	groin	nice	sailed	uninvited
barbeque	deportation	grotesque	none	salvation	unleashing
bark	deported	grudge	nothing	sank	unlikely
barrels	depose	guarantee	noticeable	satisfy	unnatural
barrow	deranged	guardians	notorious	sauna	unpopular
basically	descends	guards	nurse	savage	unsure
befell	design	guidance	objective	savior	untrue
befriend	desperation	gunning	observes	scanning	unwind
begrudgingly	destructive	habits	obssessed	scepter	update
behaviour	detached	hacker	obssessing	schemes	upriver
behest	detains	handily	obssessive	scholarship	upwards
believable	determined	handkerchief	occupation	schooling	urban
believing	detonating	handled	oddly	scoop	useless
belly	devastating	handwritten	odious	scrolls	ushered
bewildered	devotes	happiest	offensive	secluded	vacate

biblical	diagram	happily	ominously	section	vaccine
bikes	diary	hardened	operates	securities	vacuum
bits	dictatorship	haven	opposition	sedate	valiant
blackmailing	differently	headaches	opulent	segments	vehemently
blackout	dilemma	headmistress	orchestrated	segregated	vengeful
blaming	diplomatic	heartedly	order	segregation	venture
blasted	dipping	heartfelt	orderlies	selection	verify
blaster	disasters	heaven	organizing	selects	verruca
blasting	discarded	heavyweight	ornate	sensed	victoriously
blazing	disclose	helpless	ostracized	sentences	vigilante
bloom	discreet	helplessness	otter	sentinel	viral
bloopers	discretion	herd	outback	separately	visualize
bombings	disease	heritage	outcasts	servicemen	vivid
booze	diseases	heroics	outdated	sexy	voted
bosses	disloyalty	hesistation	outer	shades	voters
bossy	dismembering	highway	outlandish	shallow	votes
bounced	disorders	hijacking	outlets	shambles	voting
boxer	dispersing	hiker	outraged	shared	wages
boyish	disposes	hikes	outrageous	shatter	wander
branches	disqualified	hippy	outrages	shielding	wardrobe
brave	disrupts	historian	overall	shine	warp
breach	distancing	historical	overcomes	shredded	warriors
breached	distant	holiday	overheard	sickness	wartime
breaching	distorted	holy	overpower	signaled	washing
brink	distress	homing	overpowering	signature	waters
brooding	distribution	honesty	overtaken	similarly	weakest
bubble	disturb	honorable	overtaking	simulation	weapon
buddy	disturbances	honoring	overturns	simultaneously	weaver
budget	diver	hopping	paradise	sinful	web
bulb	diverse	hospitals	paralyzed	sites	weld
bundled	donated	host	paralyzes	situations	wells
bunks	donkey	hostility	paranormal	skater	western
burial	donning	hosts	parish	skating	whaling
bursting	doomsday	humiliated	partially	skiptracer	whip
butler	dope	hunger	participating	slashed	widower
butterfly	downfall	hunter	participation	slay	wields
butters	drains	hush	particularly	slimy	willingly
bystander	dramatically	hypnotizes	partied	smiled	wills
caged	dranged	hypodermic	parties	smuggler	winged
caitlin	drift	idle	patch	snipers	wireless
cake	drowned	ignition	patent	software	withdrawals
camaraderie	drummers	ignorance	paternal	soil	wolf
campaigning	dungeons	imaginative	patience	somebody	wonder
campfire	echoes	imagining	peak	song	wondering
canine	economic	immature	penetrate	sophisticated	worthwhile

cannibalistic	economically	impassable	perishables	sorrow	worthy
capote	ecstasy	imperial	permanent	souls	wrecking
capsizes	educate	implication	persecuted	soundly	writhing
careful	eerily	impose	perseverance	spark	writings
caretaker	either	impressed	persons	spearheaded	wrongdoing
carload	elected	improving	pertaining	specks	wry
cartons	electricity	inaccurate	philosophy	spirit	youthful
catchphrase	electrocuted	inappropriately	phobia	sponsored	zombie
category	elects	incapable	photographer	sponsoring	swapping
cater	elephants	incensed	photographing	sporting	swarms
catwalk	elude	inclination	picnic	sprays	sway
catwoman	eludes	incompetence	pipes	squeaky	swayed
cavern	elusive	inconclusive	pirate	stability	sweepers
cavity	emanating	incredulous	plain	stacks	swoop
cease	embarrass	indicated	planting	stages	swore
cemetery	embassy	inevitable	pleasant	staging	proudly
centre	embeds	inferno	pleasantly	stakes	psychologically
certainly	emerging	infiltrated	pledges	stalker	psychology
channel	emotional	infinitely	plumber	stalls	psychos
chatter	empties	ingredient	pokes	standards	puddle
cheats	enabled	inhabiting	policies	stark	purposefully
cheese	encouraged	initials	polish	stately	quick
cheque	end	initiative	poorly	statistics	landfill
cherished	energetic	inmate	populated	steady	latches
chieftain	enforcer	inscription	portrays	steak	lawsuit
chimes	engineer	insects	postpone	steep	leased
chipper	enigmatic	insist	pouch	steers	ledger
choosing	enthusiast	insistence	powerless	stirring	lemons
chores	entrap	insistent	prayer	stirs	lengths
chunks	entrusts	inspiring	praying	stoop	fabricated
cites	era	instigating	predict	storeroom	factor
citizen	essay	insubordination	preferred	strangling	faggot
civil	establishing	insurrection	prehistoric	strayed	failures
civilized	ethnicity	intact	preliminary	stressed	fairy
clans	evaluation	intellectually	premier	stretch	falsely
clashes	evening	intensifies	preserve	striking	familiar
cleaner	everlasting	interfered	pressuring	strobe	communication
cleaver	evidently	interferes	prevention	studying	communications
clinging	exams	interviewed	prey	stupid	companies
clone	executes	intimidating	primarily	subpoena	comparing
closely	exiled	introduction	primitive	substance	compensate
clouded	existing	invents	princess	subtle	competing
coaches	expect	investigation	principle	suburb	composition
coachman	expected	investments	private	suck	suspension
coalition	experienced	irritable	problematic	suing	swap

coaster	expire	jaguar	proces	sullen	prostitutes
coffins	explore	jokes	producing	sunglasses	protagonist
coil	explores	journal	prologue	supplement	knuckle
collective	expose	judgment	pronounces	supporting	labyrinth
colonel	extension	jumped	propaganda	surprisingly	external
combo	extent	knighted	prosthetic	surreal	fabric
comedy	commandeers				

JUDGING PERSONALITY-BASED KEYWORDS REFERENCE LIST

abduct	conspicuous	foes	mayday	reciting	swagger
abducting	constrictor	folk	mayhem	reckless	swamps
abide	constructed	fondness	maze	recklessness	swap
aboriginal	consult	fool	meadows	reclaim	sways
aborigine	contagious	forcefully	mechanic	recognizing	swearing
abrasive	contained	forensics	mechanism	recollections	sweeps
absence	containment	forge	media	recommend	swimsuit
accessory	contemplating	forged	medicines	recommended	swinging
accidents	contest	forgotten	meek	reconnect	swore
accomplices	continental	formal	mega	recorder	symbol
accosts	contraband	forming	megalomaniacal	recruiter	sympathetic
accounting	contradictory	fortunate	melancholy	recruitment	symphony
accurately	contributing	fortunes	melting	refuel	symptoms
accusations	contribution	fragments	memoir	regards	syndicate
acknowledged	conveniently	franchises	memoirs	register	syndicates
acknowledges	conviction	fraternity	memories	rehearsals	tackled
acquires	convulsions	freak	men	reintroduces	tails
acquitted	cooker	freeway	menaces	rejects	takeout
adamantly	coolant	frequency	mentally	relate	tap
added	corruption	frequently	menu	relics	taped
addressed	costumes	freshly	mercilessly	religion	taping
addressing	country	frighten	mere	religious	taser
adjoining	coverage	frogs	merge	reloads	task
adjourns	covert	fronts	merger	remanded	tasting
administer	cracking	fumes	messenger	remedy	taunt
admirably	cracks	functioning	metal	remembered	teachings
admired	crafted	fusion	meticulous	rendered	telekinetic
admires	creativity	gala	midnight	renewing	teleport
admiring	creed	galaxy	mile	renews	teller
adolescent	creedy	gallery	militants	replace	temptation
adopting	cripple	gallops	miners	replacement	tentacles
adrift	crisis	gambler	miracle	repossessed	tenth
adulthood	criticism	gap	misadventures	reprimand	terminal
advancing	crooked	garbled	miserably	reprimanded	terrorized
advertisements	crosshairs	gather	misplaced	reptiles	testified
advertising	crouched	gathering	mission	republic	texting

advised	crouches	gazebo	mist	rescuers	theatre
affections	crown	gazes	mistreatment	resemblance	theirs
affects	crucified	geek	moan	resembles	theories
agenda	crucifix	generals	mob	reservation	thermoptic
aggressively	cryptic	generate	mockingly	reset	thin
agitated	culminated	generation	modeled	residential	thorns
aimlessly	culminates	generous	models	residing	thorough
aired	cult	genesis	mold	resignation	thoughtful
aisles	curls	genetic	mole	resist	thoughtfully
alleges	currency	gesturing	molesting	resistant	threatened
allegiance	curve	ghouls	monopoly	resisting	thriller
allied	cushions	giggles	monster	resists	thriving
alligator	custom	giver	moorings	resolved	ties
alluding	customs	glance	mop	resourceful	timing
almost	daggers	gleefully	morale	responsibility	tipsy
alternative	dame	gloating	morgue	restrain	tirade
amazed	dancers	gloats	mosquito	restraint	tiredly
ambitious	dare	good	motivate	retiring	token
amendment	darkens	goof	motivation	reunification	toll
amorous	dazzling	goofy	motives	reverse	tombstones
analyst	deactivates	gorgeous	motorbike	reversing	tonight
ancestor	deafening	gory	motorboat	revert	torturer
anew	debating	gossip	motorcycles	revolution	tossed
angered	debts	grace	mount	revolutionary	total
animals	decade	grandeur	mourns	riddle	totaling
annoy	decay	grant	mouthpiece	ridicule	tourists
annoys	deceitful	grate	mugs	rightful	tours
anomaly	decent	graveyard	muscular	riots	towers
anthem	deception	grazes	mushrooms	risking	traits
anxieties	decisions	greed	muslim	ritualistically	trampled
anytime	decks	grenades	mutagen	rivalry	transfers
anyways	decorations	grimy	mutate	rivals	translating
apartheid	deeming	grinds	mutates	robotic	transmit
appalled	defendants	grisly	mutilating	rodent	transplanted
application	defended	grooming	muzzle	rods	trapping
applications	defies	grotesque	mysteriously	roller	travelers
apply	defunct	growing	nailing	rolling	trawlers
apprehensively	defy	gruesomely	naivete	rookie	treads
apt	delays	guardians	nap	rotation	treasury
archeologist	delicate	guards	nasty	rounded	treatments
architect	delusion	guardsmen	nationals	routes	triangle
arguments	democracy	guidance	navigation	row	tribe
ark	demon	gunner	navigator	royalty	tribesmen
armed	demons	gunshots	negative	rubber	triggered
artifact	demonstrating	hail	neighborhoods	ruined	triggering

asked	demoralized	hairless	neighboring	ruining	troupe
assassinating	depart	hallucinating	neighbours	ruled	trudges
assaulting	dependence	hallway	nerve	rulers	trumpets
assertion	depends	handedly	never	rumble	tune
assignment	deportation	handwritten	nickname	rumored	turmoil
assignments	deposition	hanged	nightmares	rung	turtles
assists	depressing	hangover	nobel	rush	tussle
assortment	deputy	harboring	nobody	rusty	tutelage
assuming	deranged	hare	nodes	ruthless	twice
athletic	derelict	harmony	nonsense	sacred	ultimate
attaching	descend	hastily	nostalgia	sacrifice	umbrella
attacker	descendants	hating	nothing	sadness	unaffected
august	descending	hauling	noticeable	safest	unauthorized
authorization	deserters	head	noticing	sailors	unbelievable
auto	deserved	headlights	notified	salute	unborn
autobiography	designs	headmistress	novelty	sanitarium	uncertainty
autographs	desires	heartedly	nun	satan	uncharacteristically
avoiding	despondent	heights	nuptials	satellite	under
awaiting	destitute	hello	nursing	satisfy	undergarments
awakening	destructive	helmets	obliges	sauna	undermining
awful	detain	helper	occupies	scam	undertake
backroom	devil	helpless	oddly	scenario	undo
ballroom	devour	herd	odious	scenarios	unemployed
bandaged	diagnoses	hesitation	offensive	scepter	unethical
bandit	diagram	hiccup	onfiscated	schemes	unexpectedly
banging	dialogue	hid	online	scientific	uniforms
bangs	diamonds	highlights	onlookers	scoops	unimpressed
bankrupt	diaper	highway	operas	scooter	uninvited
baptist	dictatorship	hijacking	operational	scorpion	unites
barbed	die	hilltop	operations	scotch	unlike
baron	diplomat	histories	operator	scout	unlikely
baroness	disabling	hitchhiker	opium	scouts	unloading
barren	disagrees	holocaust	opposing	scrap	unmasks
barricaded	disappointing	holy	opposition	scratched	unravel
barricades	disarmed	homicide	order	screening	unscathed
barrier	disarms	honoring	organizations	screens	unsettled
barron	disastrous	hoods	origin	screwing	unsure
basics	discloses	hop	ornaments	scrolls	untie
bat	disclosing	hopeful	ornate	seal	unusual
batch	disconnected	horned	ostrich	seasoned	unwanted
bats	discovery	hose	ouija	secondary	upgrade
battalion	discredit	hospitals	outfit	sector	upgraded
bedchamber	discussed	hostess	outing	secured	uploaded
beds	disemboweled	hostility	outlaw	securing	upsetting
beetle	disengage	hotline	outmoded	security	upwards

befriended	disintegrate	humiliated	outnumbered	seductively	urged
begrudgingly	dismayed	humiliation	outright	seeker	utters
behaving	dismember	humorous	overhearing	senate	vacant
behavioral	dismissing	hunger	overlook	senator	vaccine
beheaded	dismissive	hunts	overly	sensitive	vacuum
behind	disobeying	hurriedly	overtaking	sentiment	valet
being	dispatcher	hypnotizes	pacing	sentimental	valley
belief	dispathcer	hypochondriac	pagan	separately	vampire
beliefs	disposed	hysterically	pain	sequences	vanish
believer	disputes	iconic	painful	sergeants	vegetables
beloved	disrespect	ideas	pains	serpent	vein
berate	disrespectful	ignite	pairs	setting	venable
besiege	disrupt	illustrate	paralyzed	seventh	vending
besting	dissipates	imagery	parlor	sever	vendor
betrays	distributes	immature	parted	shaken	ventures
betting	distribution	immigrant	participated	shards	verbal
beverages	disturbances	immigration	participating	shaves	verbally
bible	disturbed	immunity	participation	shaving	versa
bids	ditch	impatience	partnership	shelters	verse
bill	diverted	impatiently	party	shielding	vessels
birthplace	divides	imported	passageway	shipping	veterinarian
biting	doen	imposter	passersby	shortcut	vice
blackmailing	dogs	impressing	pastor	shove	victoriously
bleachers	dolls	improving	paternity	showcases	vigilantes
bleeds	dominates	impulsively	patriarch	shrine	viking
blessed	domineering	inaccurate	pauses	shuffles	vintage
blindfolded	domino	incapacitate	payback	shunned	viper
blindly	donate	incites	peace	sideways	vodka
blinds	donated	inconclusive	pecking	significance	void
blizzard	donation	incorrect	peculiars	signifying	volunteers
block	donkeys	increased	peer	simpleton	vote
blocks	donors	indicating	pellet	sin	voters
blog	doodling	indignation	pendant	singer	voting
blooded	doomed	indulges	pension	sinister	vowing
bloody	doses	indulging	perh	sites	voyage
bluffs	doubled	industries	perpetuating	situations	vulgar
blunders	downloads	inevitably	persuaded	sized	wades
bluntly	dowry	influence	pet	skeleton	waiters
boisterous	dragons	infrared	petitions	skeletons	wallows
bombings	drama	ingredients	phases	sketch	wander
bookkeeping	dramatic	initiative	philosophical	skiing	warily
boosters	dramatically	inmate	photographing	skinny	warp
booth	drastically	inscribed	photography	skiptracer	wasp
borrow	dread	insect	physical	skirmish	watchman
bouncing	dreaded	insinuates	physics	skulls	watering

boundaries	drifting	insistence	pile	slain	watery
breakers	drilling	inspecting	pill	slam	wearer
breakthrough	drive	inspire	pining	slaughtering	weathers
breeze	drove	inspires	pipeline	slavers	weeping
brick	drum	inspiring	pirate	sleeper	weighs
bride	dubious	instantly	planner	sleeve	welcoming
brigade	dueling	institution	playdate	slender	wells
bright	duffel	instruct	pleased	slick	western
brilliant	dumbwaiter	instruction	pledge	slideshow	wets
broadway	dumpster	instructor	pledges	slight	wheelchairs
brokers	dusty	insurgents	plots	slime	whip
brotherhood	duties	intelligent	plumbing	slippers	whips
brush	dwindling	intensely	poem	slows	whispered
budge	eagerly	interact	pointedly	slumber	wildly
buffer	earning	intercept	pokes	smack	wilingly
bug	earthquake	interfering	policy	smallest	windmill
bulletproof	eastern	interviews	poll	smiling	wine
bumper	eavesdropping	intimidating	ponder	smoldering	wings
bunkers	echoes	intrigued	ponders	smuggle	winning
burglar	economies	introduction	pony	smuggles	wipes
burying	educated	introductions	poorly	snags	wiping
bust	eject	intruders	popularity	socialize	wired
butler	elects	inventing	porcelain	socializing	wiring
buzzing	elementary	inventions	posed	society	wisdom
bypass	elements	investigation	positive	softer	wise
cab	elephant	investment	possesses	softly	witchcraft
cable	eliminates	ironically	possessing	solar	witches
calming	elsewhere	irrational	posters	solitude	withdrawals
camouflage	embark	irritation	potentially	solved	witnessing
camping	embarrass	isolation	pouch	somewhere	witted
canal	embarrassment	jackpot	powerless	soot	wizard
candidates	embarrassments	jaws	practical	sophisticated	woo
cannibal	emerging	jazz	prayer	sorrow	workaholic
cannibalistic	emits	jewelry	praying	sorted	worldly
capable	emphatically	jewels	preacher	soul	worried
capsule	empress	journalist	precious	sounded	worthwhile
cards	enchanted	junction	precipice	sour	wreak
cared	enclosure	junkie	predator	sovereigns	wrestle
careless	end	jurisdiction	predicament	spacious	writer
carve	endures	justifies	predictable	spared	writhing
casually	engineering	justify	prefers	spark	writings
cater	enhance	kangaroo	premier	sparse	wrongly
caustic	enhanced	keeper	premonition	spasming	yank
cavalry	enraged	kidnapper	preparations	speakers	zombified
celebratory	enraging	kidnapping	present	spears	zoom

centered	entertaining	killing	preserving	specific	surprisingly
centuries	enthusiast	kinky	pressuring	spectators	surroundings
ceremonial	envious	knight	prey	sphinx	surveying
cermonial	equally	knights	prices	spice	suspecting
certificate	erase	label	priest	spiders	suspicion
chairman	erupting	labyrinth	printing	spilled	suspiciously
champion	escalate	lagacy	prior	spinal	reanimation
championship	essentially	landlady	priority	splice	reborn
chancellor	establishes	landmarks	privately	spoiled	recapture
channel	estimated	largely	privy	spooks	receptive
chapel	etiquette	last	prize	spots	recited
chapters	evasion	laughingly	probes	spotting	mask
charmed	eventual	laundress	processing	spurns	masochistic
charred	evolution	lawman	proclaiming	spurring	massacred
chase	exacting	laws	proculus	stable	mattress
chats	exaggerated	lax	producer	stadium	mature
cheat	exams	lean	profanity	stake	maximize
checklist	excessively	lecture	professors	stalemate	floats
chemotherapy	excites	leech	prognosis	stalker	fluent
chides	exciting	legendary	programmed	stamped	flushing
chieftain	exclaim	lend	projector	stance	flute
children	execute	lends	promising	standards	flyer
chimes	executions	lesser	propelling	startling	foe
chimpanzee	executives	levitating	proper	stave	conn
chooses	exercises	liar	propose	stealing	conscience
choppers	existent	liberate	proposed	steer	consequences
chops	existing	lifeguards	propped	stem	conservative
cinema	experience	lifeline	propulsion	stinger	considering
circulates	experimenting	lifting	prosthetic	stitches	consoles
cites	expire	liking	protest	stocking	suppose
citizen	exploded	limits	protestant	storms	sure
civil	explorers	limo	protocol	stormy	surely
classes	expose	lining	protracted	straddling	surfaces
claustrophobic	expressing	link	protruding	straightforward	surfing
cleaner	extension	lion	provocative	strains	surgeon
cleaver	extraordinary	live	provoke	strange	surprise
click	extremely	livestock	publisher	strangled	surprising
cloning	fabric	loan	publishes	streak	rat
cloud	fabricated	locating	publishing	stretching	ration
clumsily	fabulous	locket	pulse	strewn	rations
clumsy	failsafe	loft	punch	striking	rattle
clutching	failures	lookalike	punishment	strip	ravine
cluttered	fairy	loops	purple	stronghold	realm
coaster	fairytale	looted	purposely	structures	realtor
coastline	faith	looters	purposes	stud	reanimated

cogs	falcon	lost	pushy	studying	manipulates
cohorts	fantasy	louder	quaint	stuffing	manpower
coil	favour	lovebirds	qualifying	stuffy	mans
cold	feared	lovemaking	quality	stumble	manual
coldly	fearing	lucrative	quantities	stumbles	marksmanship
collapse	fearsome	lunar	quells	stump	marriages
colonial	feather	luncheon	quick	subjects	marrow
combo	feats	lurking	quicker	submersible	marvels
commence	federation	lynch	quitting	submit	flagging
commends	feeding	mace	quizzes	subpoena	flails
commentator	feigned	machete	quoting	substance	flamethrower
commissions	feigning	machines	rabbits	subtly	flanking
commitment	feigns	mafia	racked	succubus	flash
committee	fences	magician	racket	succumbing	fledgling
commonwealth	fetches	magicians	radar	sufficient	flew
communion	fever	mainland	radio	sufficiently	flips
communist	fierce	maintains	raft	suggestion	concept
companions	figure	majority	rags	suicides	condescending
compelled	finance	males	rains	suing	confessed
compels	finances	mangled	rammed	sullen	confidence
compete	firearm	manhood	rampling	summons	confronting
comply	fireplace	mania	range	sunbathing	confusing
comprised	firms	maniac	rapid	sung	conglomerate
comprising	fishes	manifestation	rapists	superiority	congressman
conceived	fixed	manipulated	rare	supportive	

PERCEIVING PERSONALITY-BASED KEYWORDS REFERENCE LIST

abducted	collect	examined	indulging	overpowered	ruptures	thriving
abomination	collective	exams	inept	overrides	rushed	thuggish
abrupt	comfortable	excavate	inevitably	overseas	ruthless	tiled
absorbing	coming	exceedingly	inexplicably	overslept	ruthlessly	tinkering
absorbs	commandments	exhausted	infection	overtakes	sacrificed	tone
academic	commences	exhibit	infested	overwhelmed	saddened	tongues
academy	commending	existed	inflatable	overwhelming	sadistic	too
accepting	commissioned	existing	influence	pagan	sadly	topless
accessed	committee	exit	infuriated	pageant	saints	tormented
accommodate	commodity	expand	ingredients	painful	salesman	torments
accommodations	commonwealth	expatriate	inhuman	painfully	salute	torpedoes
accomplices	commune	expected	initials	panel	saluting	torrent
accomplishment	communication	expecting	initiate	panels	sanitation	torture
accomplishments	communications	expensive	initiated	paralyzed	sarcasm	torturing
accountant	communicator	experiencing	initiating	paranoid	satan	touchdown
accuracy	communion	experiment	initiation	parapsychologists	satire	touched

accusations	compartments	experiments	initiative	parasource	satisfaction	tougher
accustomed	compass	expired	inland	pardon	sausage	towns
achieve	compassionate	explicitly	inmate	pardoned	savage	townsfolk
achieved	compelled	exploding	insects	parental	saw	toxic
actively	competes	exploit	inserting	parks	saws	tradition
adamant	complain	explore	insisted	parole	scalp	traditions
added	complicity	explores	insisting	parrot	scanning	tragedy
adding	complies	exploring	inspire	participation	scathing	tranquilizer
additional	compulsive	expose	installation	parties	scepter	transaction
addressed	computers	expressing	instantaneously	partly	scheduled	transfers
addressing	conclude	extends	instincts	partnership	schematics	transmitted
admiration	conclusions	extent	instructions	patience	scholarship	transplant
admission	conducts	exterior	insurgency	patiently	schoolgirls	trappers
admit	confessed	extracts	insurgents	pausing	scoop	trash
adolescent	confidentiality	facade	intending	paw	scooped	traumas
adopt	confiscate	facehuggers	intensifies	pawns	scope	traumatic
adopting	conflicting	facsimile	intentional	paying	scorpion	treat
adoration	conjure	faggot	interact	payment	scouts	treblemakers
adulthood	conn	failures	interactive	payoff	scratching	triangle
advancing	connect	faith	intermission	peak	screenplay	triggers
advertisements	consent	faithful	internal	pedophile	screwing	triple
advisers	conservative	falcon	internet	penalty	scrotum	trophy
advising	consideration	falling	interrupting	pendant	scuttles	truce
affectionate	considering	falls	intervention	penetrate	seal	trustee
affections	conspirators	famed	intimidated	pension	seals	trusting
affluent	conspire	familiar	intolerance	performer	secluded	trusty
against	conspired	fantasy	intoxicated	personalities	seclusion	tubes
agitated	conspiring	farmer	invaded	persons	secrecy	tutor
aiming	constructed	farmers	inventions	perspective	securities	twelve
alarming	consults	fashion	inventor	persuaded	sedative	twinkle
alike	consumes	fastest	invents	perverse	seduced	typing
alleged	consuming	fathers	investigation	pest	seductively	unanimous
allergic	contaminated	faults	investigations	petrified	seeker	unannounced
alliance	contemplates	favor	investments	phenomenon	seeming	unbearably
alligator	contender	favors	invisibility	philosophy	seizing	unclear
allusion	content	favour	irony	phobia	seizure	unconvinced
almost	continent	fearful	irrational	photographing	selects	uncovering
alright	contractor	fearing	irresistable	picket	selfish	undefeated
alterations	contractors	fearless	irritable	pickles	sensitivity	undergo
alters	contribution	federation	irritated	pill	sensor	undergoing
always	conventional	ferociously	irritates	pillar	sensors	understandably
amateur	convert	festival	irritation	piloted	sequences	understood
amateurs	convertible	fever	isolating	pink	sequencing	undertakes
ambassador	convey	fifth	jaded	pirate	serene	undoes
ambiguous	conviction	figurines	jellyfish	pitch	series	uneasy

amendment	convictions	figuring	jewels	placing	seventh	unescorted
analogy	cooker	fillings	joint	plagued	sexist	unethical
analyzed	cooking	filthy	jokes	plagues	shades	unexpectedly
analyzes	corny	finacee	joking	plain	shaken	unfair
ancestors	corporate	finale	journal	planetary	shallow	unfinished
anchor	corporations	finals	jovially	planned	shamed	unflattering
anchors	corps	finance	judges	planners	sharks	unfolded
angel	correspondence	financing	judgment	platter	shatter	unfortunately
animated	corrosive	fingering	justified	pleading	shattering	uniformed
announcement	cosmic	fingerprints	kicking	pleasure	shedding	unimpressed
announcing	costly	firefight	kiss	pledge	shine	unintentionally
annoyance	counselors	firemen	kissed	plugging	shores	unlikely
annoys	county	firework	knife	plumber	shortage	unlocking
answering	coupled	firmly	knights	plunging	shortcut	unlocks
antagonistic	courts	fissure	knuckle	poetry	shovel	unmoved
antiquated	coverage	fist	labeled	pointedly	showers	unofficial
anxious	coveted	flamboyant	laboratory	poise	shreds	unpacks
apocalypse	cowardly	flamethrower	labyrinthine	poised	shrine	unruly
apology	cowering	flare	lamb	poker	sider	unseen
appearances	cowers	flash	lamenting	policies	silenced	unsettled
appointed	coworkers	flask	lane	polish	silencing	unsettling
appropriate	cracking	flattered	lasted	ponder	simulated	unsolvable
approval	craps	fleeting	launcher	ponytail	sin	unspeakable
arduous	creation	fling	launching	popping	sinful	unspecified
arouses	creative	flirty	laundry	populace	sinister	unsupervised
artifact	creator	flop	lava	porcelain	sins	unsure
assassinated	creature	floppy	laws	portable	siren	unwisely
asset	credentials	flown	lean	portraying	situated	upgrading
assigns	credits	flung	leave	portrays	situations	upsetting
assistant	creed	fly	ledger	posed	skipped	uptown
assisted	creeper	flyer	ledgers	possess	skips	upwards
associates	creepers	flyers	legions	possesses	skirmish	urge
assured	creeps	focused	legitimate	postpone	slang	urgent
astral	creepy	folder	lends	powerless	slap	urging
atone	crest	folk	levitate	practical	slaughtering	ushers
attended	cripple	foods	levitates	practically	slaughters	utilizing
attentive	crippled	fooling	liberal	prank	slay	vacate
attracting	crisp	fools	liberate	prayer	slaying	vaccine
auctioned	critically	forgiveness	liberates	praying	sled	vacuum
audiences	crocodiles	forgo	liberation	precious	sliced	valiantly
auditorium	crooked	formerly	lieu	predictable	slick	valuable
aunts	crossed	formidable	lifeless	preferring	slime	values
authorizes	crossroads	forming	lifter	prejudice	slimy	vampirism
autographs	crouches	forthcoming	like	preliminary	slit	vandalism
automated	crowned	fortune	limb	prematurely	slow	vanish

autopsy	crucifix	fortunes	limitations	premonition	slowly	vanity
awakening	crumpled	forward	limousine	presentations	slumber	varied
awful	cryogenically	foundation	limp	preserve	slumps	vending
backdoor	cryptic	fractured	liner	preserving	smallest	versa
backing	cue	fragments	lingering	pretended	smartest	verses
backstage	curiosity	frame	lining	prey	smelling	vest
bakery	currency	franchise	linking	primitive	smirks	veterinarian
balks	cursed	frantic	links	privately	smoked	vice
ballad	customs	frat	literal	prize	smokescreen	videotape
ballet	cute	fraternity	litigation	procedure	snarls	vindictive
bandaged	cycles	fraternizing	livid	procession	sneezing	vines
bangs	dame	freedom	loan	proclaim	sniffs	vineyard
bankrupt	dangers	freely	locations	professes	snipers	violated
barbaric	darker	frequents	locomotive	profile	snooping	virtual
barbeque	darts	friction	longs	programmer	soaked	virus
barcode	dashes	frog	looming	programs	sobbing	visibility
bark	data	fulfilled	loosens	prohibited	sobs	visitation
barracks	dating	fulfilling	looters	promoter	socialist	voluntarily
barricade	dawning	funding	looting	prompted	solved	volunteer
barricaded	dazed	furthermore	losers	propaganda	solving	voodoo
barricading	dazzled	furtively	lottery	prophetic	somebody	voted
barrier	dazzling	future	lounging	prospect	song	voters
bashing	deadbeat	gamer	loveless	prosperity	soot	votes
basically	deal	gaping	lovingly	prostitutes	soothing	wail
bat	debts	gardening	lower	prostitution	sordid	wander
bathing	decapitate	garlic	lucrative	protector	sorrow	warheads
battalion	decay	gasp	mace	protein	soundly	warily
battlefield	deceive	gatehouse	magazines	protesters	soundproof	warms
beasts	deceiving	gazes	magic	proud	sources	warmth
beatings	decent	geek	magnet	proved	sparse	warnings
beautifully	decisive	gender	magnifying	provoke	speaker	warp
beckoning	deducing	generous	mails	psychiatric	specifically	wary
beds	deemed	germs	mainly	psychology	specimens	wasp
bedside	deepest	gesturing	maintaining	publishers	spectral	wastes
befriending	defect	ghost	maintains	pumping	speculation	wavering
behaved	deficiencies	giddily	majesty	pumpkin	spew	weakening
behaviour	dejected	giggling	maker	pupils	sphinx	weapons
belly	delete	gigs	males	puppets	spice	weary
beloved	deleted	glad	manging	purportedly	spike	website
bespectacled	deleting	gladiator	manhood	pyramids	spiked	wells
betray	delight	glancing	mannerisms	quake	spikes	wheelchairs
betrays	delights	glares	margin	qualifications	spilled	wheeling
bets	demise	global	marked	qualified	spin	whereas
betting	democracy	globe	marker	qualify	spinning	whereupon
beverages	demons	glue	marksman	quality	spiritual	whiny

bicker	demonstrating	goad	marrow	quantities	splits	whiskers
bid	demonstration	goads	marry	quartered	spontaneously	whisper
billionaire	denying	goings	marrying	quarters	spoofing	whispered
bits	deployment	goodnight	marsh	queer	spook	whistles
blackout	deportation	goofy	mask	quell	spots	whoever
blacks	depose	gorgeous	masking	quelled	spotting	wholly
blacksmiths	depression	gospel	masquerade	quest	spouses	whomever
bladed	deranged	gossip	mast	quit	sprain	widow
blasphemous	descendants	grace	masturbate	quoting	sprawled	windmill
blasted	descending	gradually	masturbating	rabbit	spraying	wipes
bleed	descends	graduates	matched	racer	spree	wise
bleeds	descriptions	grand	math	racket	sprinkler	wished
blind	deserter	grant	mattress	racketeer	squashed	withdraw
blinds	deserting	graph	mature	radio	stables	without
blinking	deserts	graphic	mayhem	raided	staffed	wizard
block	deserved	grasshoppers	measures	raider	staggers	wondered
blog	designer	grateful	mechanism	raincoat	stalker	wonderful
bloodline	desired	grease	melt	rallies	stallion	woo
bluff	desperation	greed	meltdown	rampages	stance	wordless
blunder	despondent	grid	melted	rams	starve	wore
bluntly	detached	grieving	memoirs	rare	static	worked
blurry	devastated	grill	memorable	rattle	statues	workplace
boardroom	devil	grooming	menaced	readings	steady	worms
boasts	devour	groove	menacingly	realise	stealing	worsens
bogged	devours	groundwork	merchandise	realized	steep	worthwhile
boiler	diary	growth	mercury	really	steer	wounded
bomber	dictatorship	guardians	mercy	reanimates	steers	wrath
bombers	diet	guards	merger	reappears	stem	wreaking
boosting	digestive	guardsmen	merit	reasoning	sticky	wrench
booze	dignity	guessing	messes	reassignment	stimulate	wrestling
border	dinner	guidance	messing	rebuffed	stipulates	writers
bosses	disables	gunman	metaphor	rebuked	stirs	yield
brags	disappearances	hackers	meter	recall	stocked	youthful
branches	disappeared	hacking	mice	receipt	stomps	zombies
branding	disappointing	hallucinates	microscopic	recited	stoned	thankfully
brazenly	disbarred	hallways	middle	reciting	story	theatre
breached	disbelief	halted	militants	reckless	stout	theorizes
breakdown	disc	hamster	mind	recklessly	stove	theory
breakthrough	discarded	handily	mindlessly	recognises	strained	thick
breakup	discomfort	handled	minefield	recognizing	strange	thinkers
breaths	discreetly	handsome	mingle	recommend	strategies	thorn
breeding	disfiguring	handsomely	mini	reconciles	stretch	thorns
bribes	disgruntled	hangover	minivan	reconditioning	stretcher	thorough
bridesmaid	disgusting	happier	minus	reconstruct	stricken	thoroughly
brigade	dish	harbors	miraculous	recounted	strict	threaten

brighter	disheartened	harming	mirroring	recovering	strobe	threatened
brightest	disinterested	hasty	miscarriage	redeem	strokes	rowdy
brightly	dislike	hateful	miserable	redoing	stroll	rowing
bringing	disloyalty	hating	misgivings	reduces	strolls	rows
broadsided	dismissing	haunted	misplaced	reference	strongest	royalty
brooding	disoriented	haunting	mission	referenced	stronghold	rubber
brotherhood	dispatches	haunts	missions	refrain	strongly	rubbish
brothers	dispensing	heading	mistaking	refund	studied	ruby
bruises	displaying	headmistress	mistook	refused	studying	rugged
brushed	displeasure	heals	mixing	refusing	stumbling	ruling
brutality	disrespectful	hearing	mobile	regaining	stunning	rumors
bubble	disrupting	heartbeat	models	regardless	stuns	runaway
bugged	dissent	heartbroken	modified	regimen	stunt	runner
bump	dissipates	heartedly	mole	region	stupid	outfit
bundle	distortion	hearth	molesting	regulations	stutter	outing
burial	distributed	heartless	monastery	rehearsals	stuttering	outlaw
burps	divers	hearty	monks	rehearsing	subdued	outlaws
burying	diverse	heavyweight	monster	relate	subdues	outmoded
busted	docile	heir	mops	relating	submachine	outraged
busting	docking	hellish	moral	relax	submerged	outrageous
butler	dominated	help	mortal	relegated	submersible	outsider
buyers	doomed	heralds	mortals	reliant	subordinate	ovation
buzz	doses	herd	motel	religious	suburb	overflow
cabins	dossier	heritage	mothers	reluctantly	sufficient	overgrown
cackles	dousing	hesitantly	motivated	remarried	suitor	overjoyed
cadet	dove	hesitate	motivation	reminder	sulking	incorrectly
cages	downhill	hesitation	motives	reminiscent	sultry	increased
cakes	drained	hijackers	motorbikes	renamed	summon	incredibly
calendar	drama	hiker	motto	rendering	summoning	incredulous
cameraman	drank	hikes	mountainous	renovation	sunbathing	independence
campaigning	drastically	hilltop	mountains	rental	sunlight	indeterminate
camping	dream	hinted	movable	repeat	sunrise	indicates
canceled	dreaming	hinting	movies	repelled	supercomputer	indicating
candidates	drenched	hitch	mug	replace	superhero	indifferent
cannibals	drift	hitching	mugger	replicants	superimposed	indifferently
cans	drill	hive	murderers	replicate	superiority	indirectly
capable	drip	holidays	mutated	replicating	supporting	induction
capacity	drowned	homestead	mysteriously	reportedly	supportive	essential
cape	drugged	homework	nationwide	reporting	suppose	essentially
capsule	dubbing	homeworld	natured	reputations	surely	eternal
captions	dull	honesty	naught	require	surfaces	eternity
captors	dwarf	honey	naughty	rescuers	surgical	ethical
cared	dwelling	honorable	navigator	researchers	surprising	etiquette
cares	earnestly	honored	negatives	resembling	surprisingly	evicted
carols	easter	honoring	neglect	resentful	surrenders	eviction

carving	eatery	honors	negligence	reserve	surreptitiously	evident
cashiers	economic	hooded	negotiating	resets	survey	evidently
catwalk	economically	hordes	negotiator	residing	surveying	exam
cavill	edit	horizon	neighbor	resignation	survival	examine
celebrities	edited	horrible	neighboring	resisted	survivalist	cloudy
censored	editing	horrified	nerve	resolute	suspecting	clumsily
centered	educated	hose	newcomer	resolved	suspension	clutches
ceremonial	eject	hostility	newest	resolves	sustain	clutching
certainly	ejects	howling	news	respectively	swap	coachman
certainty	elections	humbly	newsman	restless	swat	cocktails
chairman	elects	humiliates	nobel	restoring	sweater	cocky
champion	elegant	humping	nobody	retain	swerve	coil
chances	eletricity	hurrying	nonsense	retaliate	swoops	coils
channel	elsewhere	hurts	noticeable	retrieved	symbolic	coincidentally
chaos	emanating	hypnosis	noticed	revenue	sympathetic	coincides
chapel	embark	iconic	notified	reverses	symphony	collage
chart	embarks	ideas	notion	reverts	synergy	terribly
charter	embassy	ignorance	novelty	revived	synthetic	terrify
chastity	emotion	ignoring	obeys	revives	tactic	terrorism
chats	emphasis	illegally	objective	revokes	tactical	testifying
chatter	emphatically	illustration	obligations	revolutionary	tags	thanked
cheap	employs	imagery	obsessive	revolving	talent	thankful
cheaply	empress	imagine	obtained	rewards	talisman	romancing
chemicals	enable	imagined	occasion	rework	tangled	rookie
cherished	enables	imagining	occupying	rhymes	tap	root
chewing	enacts	immediate	odd	rich	tapping	roses
chimpanzees	enchanted	immerse	odious	richer	tasks	rotates
choices	enclosure	immortals	offended	rickety	tauntingly	rotten
choking	endangering	impatience	offensive	rider	taut	orphaned
chop	endure	impatiently	online	riding	tax	ostrich
chromium	endured	impending	onlookers	rift	technical	outage
chronic	enduring	implicate	onslaught	rightful	technicality	outburst
chute	enhance	implicating	operations	rights	technically	outcast
circular	enrols	implicitly	operators	rioting	techniques	outdoor
circumstances	entertain	implies	opponents	risking	technologies	inaccurate
cites	entertains	imposed	oppose	risks	teenage	inactive
civil	enthusiast	imposing	optimism	risky	telekinetic	incapacitated
clan	entrap	impounded	orbital	road	temper	incapacitates
clarify	envious	imprisonment	orchestra	roam	tenement	incensed
class	envisioned	improving	organises	roar	tensions	inconclusive
claustrophobic	episodes	impulsively	organizer	roller	tentative	erupting
cleaner	eradicate	clogged	eraser	clever	cliffs	essay
clear	erased	cloning	erupt			