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Completed Research

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Abstract

Recommender Systems have been intensively used in Information Systems in the last decades, facilitating the choice of items individually for each user based on your historical. Clustering techniques have been frequently used in commercial and scientific domains in data mining tasks and visualization tools. However, there is a lack of secondary studies in the literature that analyze the use of clustering algorithms in Recommender Systems and their behavior in different aspects. In this work, we present a Systematic Literature Review (SLR), which discusses the different types of information systems with the use of the clustering algorithm in Recommender Systems, which typically involves three main recommendation approaches found in literature: collaborative filtering, content-based filtering, and hybrid recommendation. In the end, we did a quantitative analysis using K-means clustering for finding patterns between clustering algorithms, recommendation approaches, and some datasets used in their publications.

Keywords

Machine learning, clustering algorithms, recommender systems.

Introduction

Considering the increasing amount and variety of products, services and information, which are daily made available on the Web services, the management of data is hard to manage. For helping puzzled users from making decisions, recommender systems evolved into focus, promoting users' access to information about the items they are most probable to be attracted. Recommender Systems (RS) appear to suggest items individually for each user based on his historical or preferences. The purpose is to inform the user about the items that should be of interest in many different choices. (Meira et al. 2018). RS technologies are of extreme importance when implementing e-commerce Information Systems (IS). In the last decades, e-commerce sites have increasingly invested in systems capable of offering to their customers reasonable recommendations about what products to buy. This exercise leads to an estimation that the recommendations generate about 10-30% gain in the comporation lucre and products revenue (Sharma et al. 2015). RS can improve web services in different scenarios: such as classifying patterns of friendships and recommending new friends on social networks (Farseev et al. 2017; Du et al. 2017; Huang et al. 2015). Other services are recommending best movies according to user profile (Ahuja et al. 2019; Bhuvanya et al. 2018; Brbi et al. 2015), hotels who a browsing user will access (Bagherifard et al. 2017; Pandia et al. 2017), design methods for building software interfaces (Fuge et al. 2014) and others.

Nowadays, It is hard to imagine projects without recommender modules which be able to improve the quality of service. As a result, many researchers and developers are increasingly interested in alternative mathematical and computational models to facilitate the recommendation of products and items, either using predictive techniques (as classifiers algorithms) or descriptive techniques into approaches as collaborative filtering, content-based filtering and hybrid recommendation (Sharma and Gera 2013; Thorat et al. 2015; Nagarnaik and Thomas 2015). In concern about descriptive techniques, an alternative is data clustering algorithms. These algorithms can be used for finding groups or clusters of objects. In other words, in e-commerce scenario, cluster algorithms can find groups of similar products or customers, meaning that objects are mainly either products or customers. Each group has objects which show similar features or properties relevant to the domain under study. Data clustering can provides robust and very effective techniques (Balijepally 2011).

In this way, presenting the state-of-the-art of IS projects that use clustering algorithms for recommending objects in RS context. In this way, this work presents a Systematic Literature Review (RSL), adapting the methodologies proposed by Kitchenham (2004) and Boell and Cecez-Kecmanovic (2011), in order to investigate which approach of Recommender Systems that use data clustering algorithms. Moreover, we are interested in understanding how clustering algorithms are used in IS projects that uses RS technologies. We are mainly interested in three domains: types of clustering algorithms used, datasets used for experimental analysis, and recommendation approaches. The use of this strategy is to understand the relationship between these three domains under a quantitative analysis. For this, clustering algorithm (K-means) was used in our experiment.

This work is organized as follows: Section 2 describes basic concepts of clustering algorithms and main characteristics of recommender systems approaches. Section 3 describes the process of systematic study. Moreover, quantitative analysis of the clustering algorithms presents recommendation system projects; Section 4 describes a general discussion on the architecture of recommendation systems with clustering algorithms; Section 5 describes our conclusions about the whole systematic study process.

Basic Concepts

Data Clustering Algorithms

Data Clustering is an area that presents a set of techniques capable of grouping data that do not contain labels or previous knowledge. A dataset is composed by a set of objects. Each object is composed by a set of features. This area comprises algorithms whose objective is to find a certain number of clusters of objects in such a way that the objects belonging to each group present features more similarity if compared to the elements of other groups. There are different types of structures created by clustering algorithms, but each algorithm has a unique structure of one of these types that best assign the data (Xu and Wunsch 2005). Thus, each structure contains a different perspective about the data, where each algorithm builds a different formation of groups, such as partitional, hierarchical, fuzzy, co-clustering among others, data clustering (Mitchell 1997). Partitional clustering builds a single data partitioning where subdivide the datasets into a set of k groups, where k is the number of clusters. Hierarchical clustering basically aims to build a dendrogram. Fuzzy clustering gather algorithms that can associate objects to more than one cluster. Co-clustering allows simultaneous clustering of objects and features.

A meaningful advantage of data clustering algorithms is finding data patterns. So, in RS, a clustering algorithm can be used either for grouping users based on their profile features, or for grouping objects to be sell (movies, books, and others) to recommend similar objects to users.

Recommendation Approaches in RS

RSs mainly use artificial intelligence techniques to recommend items to users. For projecting a RS, a decision must be made by the designer regarding to the recommendation approach. Sharma and Gera (2013) indicate that recommender systems can mainly based on one of these three approaches: collaborative filtering, content-based filtering, and hybrid recommendation.

Collaborative Filtering: The main characteristic of the collaborative filtering (CF), also called collaborative recommendation, is the exploration of information about past behaviors or opinions of users of a specific community. This information predicts some items that a given system user is most likely to purchase for that product. These types of systems are currently in the broad market, in particular as a tool on websites or mobile online retail applications to customize content for the needs of a particular customer (the current user) and thus promote additional items and develop more sales. Purely collaborative approaches use a user-item matrix of ratings given as the only input. Typically, it produces the following types of output: (a) a numeric forecast indicating how much the current user may like or dislike a particular item and (b) a list of *N* recommended items, characterized as a top-*N* list. There are basically two types of categories in this approach: (i) collaborative filtering based on the closest user, also called user based collaborative filtering - CFU; and (ii) collaborative filtering based on the closest item, also called item based collaborative filtering - CFI. The main idea of CFU is to discover from other users (peer users) those who have characteristics similar to current users in the past, given a database of assessments with user id as the entry identifier. Then, for each item that the current user has not yet seen, a forecast is calculated based on the item ratings made by peer users. For example, by accessing user profiles in an online book store, the recommendation system has access to all user data, such as age, country, city, and books purchased. With this information, the system can identify users who share the same preference for books and then suggest books purchased by similar users. On the other hand, CFI is the calculation based on the similarity between items and not users. For example, imagine that book A has the following ratings: (3, 5, 4, 1), and they are similar to the ratings in book B: (3, 4, 3, 1). There is also a partial similarity to ratings of book C: (3, 3, 5, 2). The idea of CFI is to look at user X ratings for these similar books. User X rated “4" for book B and a “3" for book C. An item-based algorithm calculates a weighted average of these assessments and predicts an assessment for book A in an interval between 3 and 4.

Content-based Filtering: Also called content-based recommendation, this is a type of recommendation in which it recommends an item to a user depending on a set of the user features. Computationally, the simplest way to describe cataloged items is to maintain a list of attributes for each item. For example, for a book recommender, it can use the genre, the name of the author, the publisher, or something that describes the item, and stores this information in a relational database system, according to a category (table). When user preferences are described in terms of their interests, the recommendation task is to match the item’s features and the user’s preferences. As an example, consider a user who is looking for a new smartphone using a website. When the user finds a specific smartphone (item), the recommendation system gathers information about the smartphone. It searches a database for smartphones that have similar features, such as price, frontal and back cameras quality, and memory capacity. The system returns the results of this query to the user as recommendations.

Hybrid Recommendation: Throughout the previous sections, we presented different recommendation approaches in RS. However, in some cases, it is necessary to use hybrid strategies to a recommendation task. A hybrid recommendation approach combine different types and components of recommendation approaches, recommending items based both on users and items features. For example, in social networks like Facebook, the recommendation strategy tends to recommend user profiles based on their tastes or interests. Then, the system adopts user profiles as items and then accesses its content to search for new similar profiles. Finally, the two profile groups are returned as a recommendation.

Systematic Literature Review Methodology

In this work, we conduct a Systematic Literature Review (RSL) to map the state-of-the-art of the use of clustering algorithms in RSs. Our study intend to present relevant studies in the domain of RS that uses any approach based on data clustering. Our methodology adapted the methodology proposed by Kitchenham (2004) and Boell and Cecez-Kecmanovic (2011). Our methodology is composed by the following steps: formulation of the research questions, selection of publication databases, study selection, information extraction and synthesis of results.

Research Protocol

Aiming to find all relevant primary studies related to each recommendation approach, we defined the following research questions (RQ):

RQ1: Which type of clustering algorithms are used in RSs ?
RQ2: Which are the domains of the datasets used for experimental analysis?
RQ3: Which recommendation approaches are most used?

To answer these questions, we read the publications selected for this study and listed the used clustering algorithms, the datasets used in these studies, and the measures used in experimental evaluation. Selected publications in our review should present consistent data on the use of data clustering techniques in RS domain. Domains complementary to data clustering were included. In this way, we defined the following exclusion criteria: (i) Publications should be associated with the use of data clustering in RSs; (ii) Publications must be the full article format; (iii) Publications must be in English. Publications in other languages are excluded; (iv) Publications must be unique. If duplicated, a copy is deleted; and (v) Publications must be between 2013 and 2019. We used the following databases for our research: SCOPUS and ACM. We used the following string search: *"Collaborative filtering" OR "collaborative recommendation" OR "content-based filtering" OR "content-based recommendation" OR "Hybrid recommendation" AND clustering*. Our query was adapted for each database. We inspected only the publication title, abstract, and keywords. The query returned a total of 106 articles, being 50 from ACM, and 56 from SCOPUS. Afterward, the articles were fully read. After applying our exclusion criteria, we selected 49 primary studies, being 39 from SCOPUS, 9 from ACM, and 1 duplicated between portals.

Results

We analyzed the selected studies for answering RQ1, regarding to types of clustering algorithms. Table 1 shows the results. In the 49 analyzed studies, five different types of algorithms were used. Partitional algorithms are the most prevalent, with 1 article using K-medoids (Ding 2017) and the other 18 publications used K-means. K-means is predominant in RS due to its simplicity and effectiveness. This algorithm usually converges to a viable solution. Regarding to hierarchical algorithms, all clustering algorithms used in the papers was an agglomerative hierarchical algorithm. In the last line of the table (Adapted Algorithms), we gathered studies that proposed adapted clustering algorithms to recommendation problems, totalling 8 studies. These different algorithms were proposed in different studies: COFIBA (Li et al. 2016), probabilistic Clustering (D'Addio and Manzato 2016), CHFSA (Hdioud et al. 2016) and a nonparametric pairwise clustering algorithm for movieLens dataset (Liu et al. 2015). Yu et al. (2018) applied multiview clustering on recommendation system. Farseev et al. (2017) used a strategy based on Multi-Layer Graphs for recommendation. Tsikrika et al. (2017) used a density-based clustering for identifying the most similar users or items. Fuge et al (2014) applied spectral clustering for recommending design methods. The first, the fourth and the eight are statistical-based; the second is probabilistic-based, and the third and fifth is a modified feature extraction algorithm for clustering. The sith is graph-based and the seventh is density-based algorithm.

After, we analyzed the studies to answer RQ2, regarding to datasets domain used for experimental analysis in these 49 studies. Figure 1 shows our results. Each study uses either a dataset from a specific domain (Movies, Hotel, CTI dataset, Jobs, Yahoo, Social Network, Shopping and Design Methods) or a proprietary dataset, without a description of data (such as its domain or content description), which we categorized as "Not specified.". Analyzing the figure, we observe that movies domain is more used in the RS studies we analyzed. One reason for this result is the easy data access. The literature commonly adopts one of them, known as MovieLens. MovieLens is a dataset containing rating users to movies.

Finally, we analyzed the studies to answer RQ3, regarding to recommendation approaches. Each publication may use more than one recommendation approach. Figure 2 shows the role of each aspect. This result reveals that collaborative filtering is widely researched on recommendation systems based clustering algorithms. Another observation is that all studies use content-based filtering also contain collaborative filtering.

Types of Clustering Algorithms	Publications	Number of Publications
Partitional	(Ding et al. 2017) (Khatwan et al. 2018) (Khan et al. 2018) (Sridevi and Rao 2017) (Bagherifard et al. 2017) (Hasan et al. 2019) (Pandya et al. 2016) (Lu et al. 2016) (Cho et al. 2015) (Mawane et al. 2018) (Ma et al. 2015) (Tian et al. 2019) (Wu et al. 2014) (Forsati et al. 2015) (Darshna et al. 2018) (Brbi and Aarko 2015) (Ahuja et al. 2019) (Yang et al. 2018) (Boratto et al. 2016) (Wen et al. 2018) (Ghanzafar et al. 2014) (Nandi et al. 2013)	22
Hierarchical	(Li et al. 2017) (Mittal and Sinha 2017) (He et al. 2019) (Proios et al. 2015) (Li et al. 2014) (Guan et al. 2018) (Sharif et al, 2015) (Son et al. 2017) (Bhuvanya et al. 2018) (Khan et al. 2018)	10
Fuzzy-clustering	(D'Addio and Manzatto 2016) (Gurcan et al. 2015) (Wei-Jin et al. 2018) (Behera et al. 2018)	4
Co-clustering	(Chen et al. 2017) (Rodrigues et al. 2017) (Tran et al. 2019) (Wu et al. 2016) (Khan et al. 2018) (Du et al. 2017) (Huang et al. 2015)	7
Adapted Algorithms	(Li et al.2016) (D'Addio and Manzatto 2016) (Hdioud et al. 2016) (Liu et al. 2015) (Yu et al. 2018) (Farseev et al. 2017) (Tsikrika et al. 2017) (Fuge et al. 2014)	8

Table 1. Publications per Types of Clustering Algorithms

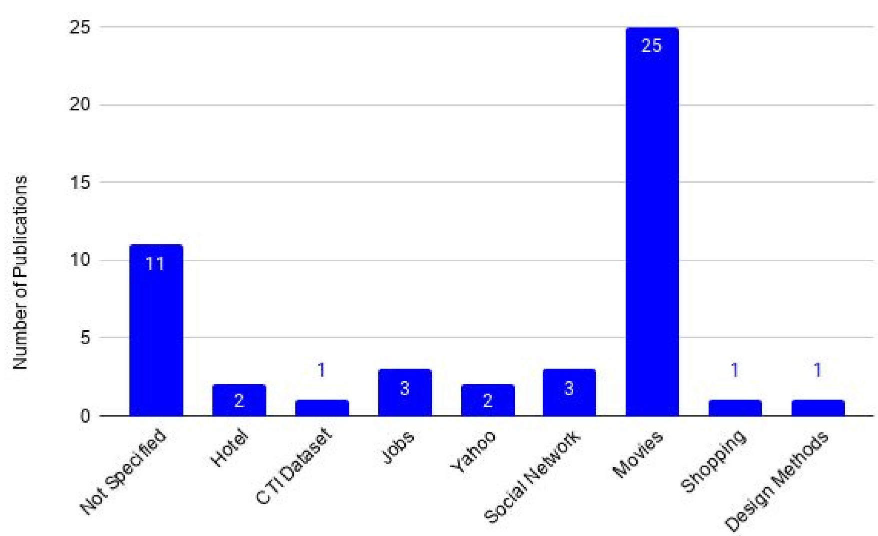

Figura 1. Number of publications per domain of dataset used for experimental analysis

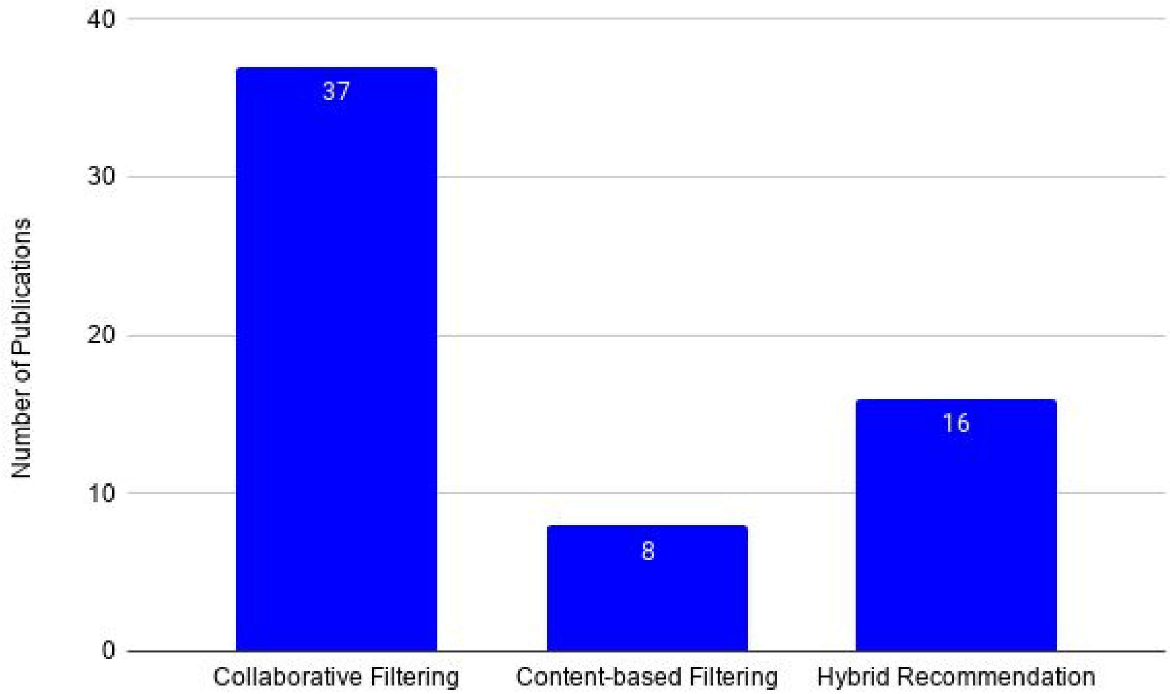

Figure 2. Number of publications per each recommendation approach

Recommendation Approach	Discussion
Collaborative Filtering	In general, clustering algorithms based on ratings features use mainly three types of clustering (partitional, hierarchical and fuzzy). Co-clustering algorithms is usually used on relationship between users and items (CFU category).
Content-based Filtering	In general, content-based RSs use the output of the clustering algorithm process. Thus, content-based algorithm generates recommendations based on specific cluster that is similar to the user that needs a recommendation.
Hybrid Recommendation	In general, it follows these steps: 1) Clustering using different algorithms (except co-clustering); 2) The system makes a content-based prediction on items that have not been rated; 3) Constructs a new rating matrix; 4) The final rating is a combination of two sets of ratings.

Table 2. General discussion regarding to each recommendation approach

Discussion

Throughout this study, we present essential characteristics in construction of RS using clustering algorithms. Each characteristic, in general, uses a peculiar behavior that helps in the creation of the recommendation. Table 2 shows a discussion about general RS characteristics or each recommendation approach. An important observation is the use of the co-clustering algorithm in collaborative filtering. This strategy is usually applied in CFU category. Furthermore, we analyzed the similarity between the answers to our research questions. For this, we used a clustering technique for understand patterns between three Research Questions. First of all, we represent the publications as objects composed by 3 features: "*recommendation approach*", "*type of clustering*" and "*dataset domain*". The values for "*recommendation approach*" are: {"Collaborative Filtering", "Content-based Filtering", "Hybrid Recommendation"}. The values for "*type of clustering*" are: {"Partitional", "Hierarchical", "Fuzzy-clustering", "Co-clustering", "Adapted Algorithms"}. The values for "*dataset domain*" are: {"Hotel", "CTI dataset", "Jobs","Yahoo","Movies",”Social Network”, “Shopping”, “Design Methods”, “Not Specified”}. Papers with more than one recommendation approach or dataset generated more than one object. K-means was applied with k = 3 for this dataset. The value of *k* is due to the three different types of recommendation approaches. The initial idea is that the clusters disperse concerning the different types of approaches. The K-means algorithm allows us to observe the quality of the clusters from the centroids. The result shows us clusters with the following centroids: centroid 1: ("Hybrid Recommendation," "Particional" and "Not Specified"); centroid 2: ("Collaborative Filtering", "Partitional Clustering" and "Movies") and centroid 3: ("Collaborative Filtering", "Fuzzy", and "Movies"). The general centroid of all objects is formed by (“Collaborative Filtering”, “Partitional Clustering”, “Movies”). This general centroid shows us that most researches in collaborative filtering use partitional clustering with a movie datasets. Our dataset for executing this clustering process is available at https://bit.ly/2yHqp0r.

Conclusion

Currently, recommendation systems are widely present in e-commerce, social networks, and among other domains. Since its introduction, research in recommendation systems has evolved. A progressive step in the history of recommendation systems is the adoption of data clustering algorithms. Thus, it allows systems to achieve more data descriptions based on user information, promoting the personalization of recommendations. In this work, we analyzed the answers to to our research questions regarding to types of clustering algorithms, recommendations approaches and datasets domains. We also applied the clustering algorithm K-Means to identify patterns in the analyzed studies. Results revealed us a frequent use of collaborative filtering, with the use of partitional algorithms, using datasets in the Movies domain.

Data clustering area has several algorithms described in literature, with various characteristics. However, it lacks alternative approaches to solutions in RS. During this study, we detected that partitional algorithms and hierarchical algorithms continue to be widely present in RS. Also, the main explored recommendation approach is collaborative filtering. We also observed in literature that choosing a clustering algorithm to be used in a recommendation system is a difficult task due to data distribution and granularity.

An interesting study that is not present in previous literature is the investigation of adaptive recommendation techniques using clustering algorithms, where the data are sensitive to distribution over time. In this scenario, a current recommendation may not be a relevant recommendation at a later time.

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