공학박사학위논문

Emotion Based Item Recommendation Techniques in Social Cataloging Services

소셜 카탈로깅 서비스에서의 감정 기반 아이템 추천 기법

2017 년 8 월

서울대학교 대학원

전기 · 컴퓨터공학부

임 혜 원

Emotion Based Item Recommendation Techniques in Social Cataloging Services

소셜 카탈로깅 서비스에서의 감정 기반 아이템 추천 기법

지도교수 김 형 주

이 논문을 공학박사학위논문으로 제출함

2017 년 5 월

서울대학교 대학원

전기 · 컴퓨터공학부

임혜원

임혜원의 박사학위논문을 인준함

2017 년 6 월

위 원 장 ______________________ (인)

부위원장 ______________________ (인)

위 원 ______________________ (인)

위 원 ______________________ (인)

위 원 ______________________ (인)

Abstract

Emotion Based Item Recommendation Techniques in Social Cataloging Services

Hyewon Lim
Department of Computer Science Engineering
Collage of Engineering
Seoul National University

Social cataloging services allow users to catalog items, express subjective opinions, and communicate with other users. Users in social cataloging services can refer to other's activities and opinions and obtain complementary information about items through the relationships with others. However, unlike a general social networking service where user behaviors are based on the connections between users, users in social cataloging services can participate and contribute to services and can obtain the information about items without links. In contrast to a general social networking service in which actions are performed based on connections between users, You can participate and contribute. In this doctoral dissertation, we classify users into two groups as connected users and isolated users and analyze users' behaviors. Considering the characteristics of users who mainly focus on contents rather than relationships, we propose a tag emotion-based item recommendation scheme. Tags are the additional information about the item, and at the same time, it is a subjective estimation of users for items, which contains the user's feelings and opinions on the item. Therefore, if we consider the emotions contained in tags, it is possible to obtain the recommendation result reflecting the user's preferences or interest. In order to reflect the emotions of each tag, the ternary relationships between users, items, and tags are modeled by the three-order tensor, and new items are recommended based on the latent semantic information derived by a high-order singular value decomposition technique. However, the data sparsity problem occurs because the number of items in which a user is tagged is smaller than the amount of all items. In addition, since the recommendation is based on the latent semantic information among users, items, and tags, the previous tagging histories of users and items are not considered. Therefore, in this dissertation, we use item-based collaborative filtering technique to generate additional data to build an extended data set. We also propose an improved recommendation method considering the user and item profiles. The proposed method is evaluated based on the actual data of social cataloging service. As a result, we show that the proposed method improves the recommendation performances compared to the collaborative filtering and other tensor-based recommendation methods.

Keywords: Social Cataloging Service, Connected Users, Isolated Users, Recommendation, Tag, Emotion, Tensor, High-Order Singular Value Decomposition, Probabilistic Ranking

Student Number: 2008-20959

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Research Motivation

Over the past several years, online social networks have grown at an unprecedented rate, and have served as a catalyst in the explosion of online media content. Unlike the past when only a small number of people were capable of creating media for the public to consume, we are already in an era of a user-generated content deluge. As anyone becomes able to produce and consume information, the boundary of a dichotomy between “mass communication” that the information flows unilaterally to a large number of audiences and “interpersonal communication” that the interactions between individuals becomes increasingly obscure [1]. Twitter, Facebook, and YouTube are the leading online social services; they have millions of users and generate much information. These services have played an important role in allowing creative users to share their content and find an audience. By supporting user activities, they work towards “aims to enhance interconnectivity, self-expression, and information sharing” [2]. Since the participation and contribution of the users shows their interest and tendency, in the business areas, these services become a tool of analyzing and grasping users and providing appropriate marketing and advertisement to them. This allows users to choose the information that is right for them even if they do not search for information.

Social cataloging services are one of online social networks; they give more weight to catalog and estimate contents, rather than communicating with others. It allows users to consume items and share their opinions, which influences in not only oneself, but other users to choose new items. Unlike the similar online social media dealing with contents such as YouTube and Flickr, social cataloging services usually provide users with only meta-data and a fraction of the actual content, and users in these services are influenced by their personal preferences. Then, how do the users between social cataloging services and other social media are differ? Understanding of the characteristics of the users in social cataloging services can be helpful for developing services that suitable for those users.

With the overload of contents, the user suffers from difficulty in selecting items. Therefore, it is a significant task to recommend appropriated items to users based on the personal preferences. Recommender systems reduce the problem of the choice by recommending the items considering the behavior of the people and the characteristics of the items. Users’ subjective feedback for items can play an important role in item recommendation. Since user's feedback of an item is generated after consuming items, the feelings of the user obtained during consuming are directly reflected in the user's feedback. Especially, tags are valuable features for recommendation; it can be used as an additional information of items for reducing the lack of item descriptions, and as short comments and ratings for exposing personal opinions.

In this dissertation, we analysis user behaviors in social cataloging services to find the characteristics of users and proposed an item recommendation method using the emotions included in the tags and the probabilistic ranking.

1.2 Research Contributions

In this section, research contributions of this doctoral dissertation on an analysis of users in social cataloging services and a tag emotion-based item recommendation method are described. Overview of the proposed scheme is shown in Figure 1.1.

The user behaviors in social cataloging services such as rating, tagging, and writing a review of an item become a user profile representing that user. Among the various elements constituting this profile, the user's rating and tag data are the basis for recommending the appropriate item to the user. In our approach, the ternary relationships among users, item, and tags are modeled using the multi-dimensional matrix, which is called as

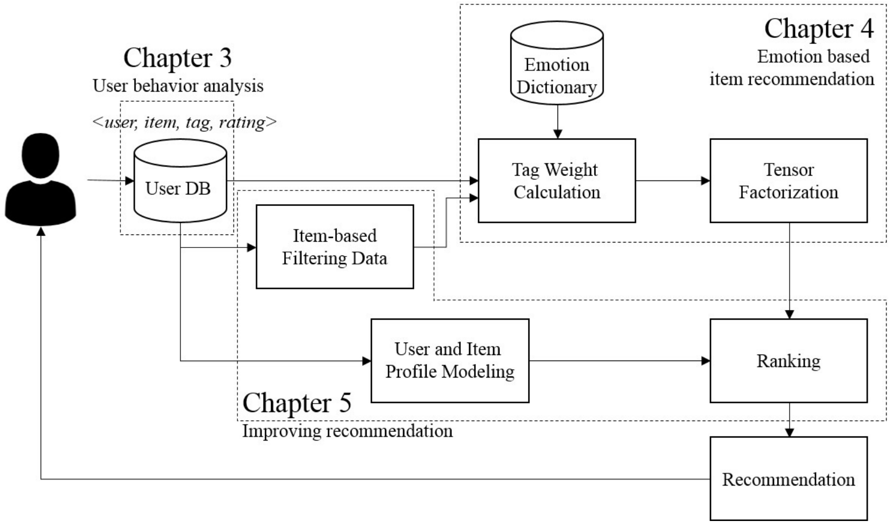


Figure 1.1 The overview of the proposed recommendation scheme.

tensor. In this case, the data sparsity problem is occurred because the number of items tagged by users is smaller than the entire number of items. To reduce the lack of data, from the initial dataset, the additional data is generated based on item-based collaborative filtering technique and is combined with the original dataset. Using the combined data, emotion in each tag is extracted utilizing the user rating and the emotion dictionary, the value of the extracted emotion is used as the weight of the initial tensor. Through the process of tensor factorization and tensor reconstruction, the recommending candidates are generated. Before the recommendation, the result of the reconstructed tensor is ranked based on the user and item profile derived by the previous tagging histories. According to the ranking score, new items are recommended to users.

The contributions of this dissertation can be summarized as follows:

- We analyze user behaviors in social cataloging services. We define isolated users and study the difference of the behavior tendency between isolated users and connected users. Much of previous research for online social networks is only focused on connected users, but isolated users account for a large part of the network. In social cataloging services, isolated users can participate in the services regardless of the relationships with others.

- We propose an emotion-based tag weighting scheme to improve the performances of item recommendation. The user ratings are assumed as the primary emotion of tags and each tag's own emotion is combined with the rating-based emotion. Previous research on recommendation using tensor modeling usually have used the likeliness that a user annotates an item by a tag. Using emotions can improve the recommendation quality as reflecting the personal preference of items.

- We improve the tag emotion-based recommendation performances by generating the additional data based on the initial dataset and ranking the recommendation result considering the previous tagging activities of users and items.

1.3 Dissertation Outline

The rest of this dissertation is organized as follows: Chapter 2 introduces background and related work of online social network, recommendation, and emotion analysis. Chapter 3 describes the analysis of user behaviors in social cataloging services. Chapter 4 explains tag emotion based item recommendation method using tensor modeling. Chapter 5 shows data addition using item-based collaborative filtering and ranking reconstructed tensor using tag-based BM25 algorithm. Chapter 6 discusses conclusions and future work.

Chapter 2

Backgrounds and Related Work

In this chapter, backgrounds and related work will be introduced in Section 2.1, 2.2, and 2.3. Brief introductions of online social networks and social cataloging services are presented in Section 2.1. In Section 2.2, the terminologies are described. In Section 2.3, the related work of social network analysis, item recommendation and emotion analysis is introduced in detail.

2.1 Online Social Networks and Social Cataloging Services

In recent years, the popularity web-based social communities such as Twitter, Facebook, and YouTube have grown, mainly because the proliferation of electronic devices are increased. Online social networks have served as a catalyst in the explosion of user created contents. They allow users in making relationships with others, creating and sharing own contents, and expressing personal opinions and ideas.

According to Wasserman's definition, a social network is the set of actors and the ties among them [3]. It is usually represented as a directed or undirected graph. The nodes means users, and the edges shows relationship between users. The relationships can be classified into four types of social graphs: friendship graph, interaction graph, latent graph, and following graph [4].

Online social networks can be classified roughly into two groups. One is more paying attention to interact with users such as Twitter and Facebook. They focus on the relationships between the users and these relationships lead to item sharing. The other group is more concentrating on contents such as YouTube and Flickr. Each service in this group usually has a target content like video clips and photos, and these shared contents lead to making relationships.

Online social networks are studied widely in not only computer area but also the social and behavioral science, economics, marketing, so on. Before the advent of social media, the researchers are used a small sample for an experiment, but nowadays online social networks offers a large dataset. Using this large data, researchers analyze the social network based on the social theories and algorithms; it provides an opportunity to prove the hypotheses of the previous research. The applications are built on the results of social network analysis. The analysis depends on the view of the network from the macro level dealing with the entire graph to the micro level dealing with the individual users.

Social cataloging services such as Movielens and LibraryThing are one of online social networks having a target content. Services allow users to catalog items which can have consumed or desired, represent personal opinions as writing reviews, rating, and tagging, make relationship and communicate with others. The aim of such services is extended from the easy retrieval of the information as a primary function to expressing users' opinions and sharing their ideas with others [5]. Social cataloging service usually provides the metadata of items for the convenience of users. However, with the rapidly increasing new items, users still have to spend much time looking for items according to their interests, which increases the fatigue of information selection. Therefore, providing better recommendation is an important issue.

2.2 Terminologies

We define the concepts and the entities used in this research. In order to describe users in social cataloging services who rate and tag items, let $U = \{u_1, u_2, u_3, ..., u_{|U|}\}$ be the set of the users, $I = \{i_1, i_2, i_3, ..., i_{|I|}\}$ be the set of items, $R = \{r_1, r_2, r_3, ..., r_{|R|}\}$ be the set of the ratings, and $T = \{t_1, t_2, t_3, ..., t_{|T|}\}$ be the set of the tags, where $|U|$,$|I|$,$|R|$,and $|T|$ are the number of users, items, ratings, and tags respectively. We denote the relationship that users assign ratings and tags to items as Y and define it as:

$$Y =< U, I, Y_{rating}, Y_{tag} > \quad (1)$$

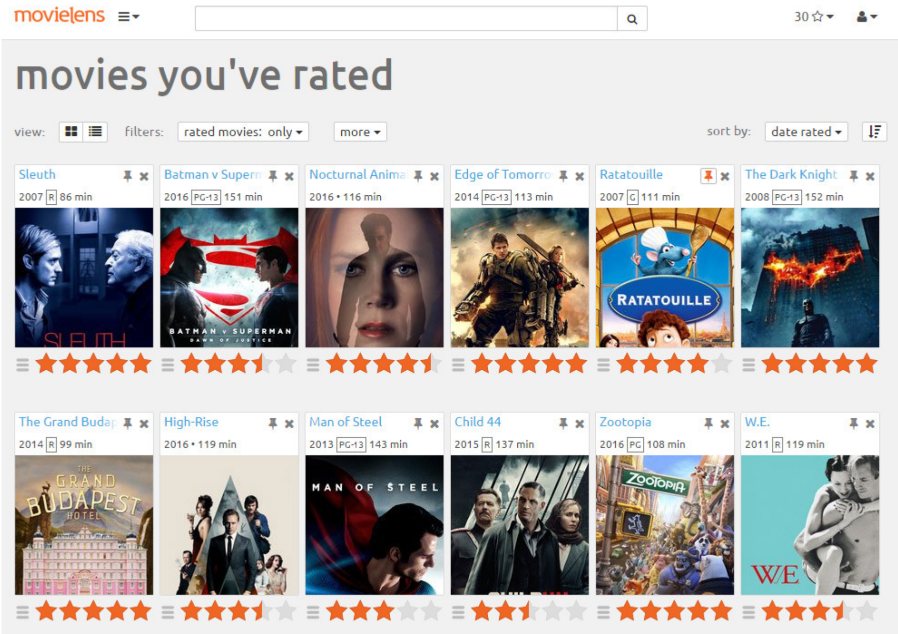


Figure 2.1 The screenshot of Movielens.

where the annotation Y_{rating} and Y_{tag} are represented as a set of triples, such as:

$$Y_{rating} \subseteq \{< u, i, r >: u \in U, i \in I, r \in R\} \tag{2}$$

and

$$Y_{tag} \subseteq \{< u, i, t >: u \in U, i \in I, t \in T\} \tag{3}$$

If rating does not exist, we describe rating as $r = \emptyset$. If tag does not exist, t = $\emptyset$; however, in this paper, we only consider the users who tagged items.

The ternary relationships among users, items, and tags are represented using a tensor which is a higher order generalization of a vector (first order tensor) and a matrix (second order tensor) [6]. Higher order tensors are also

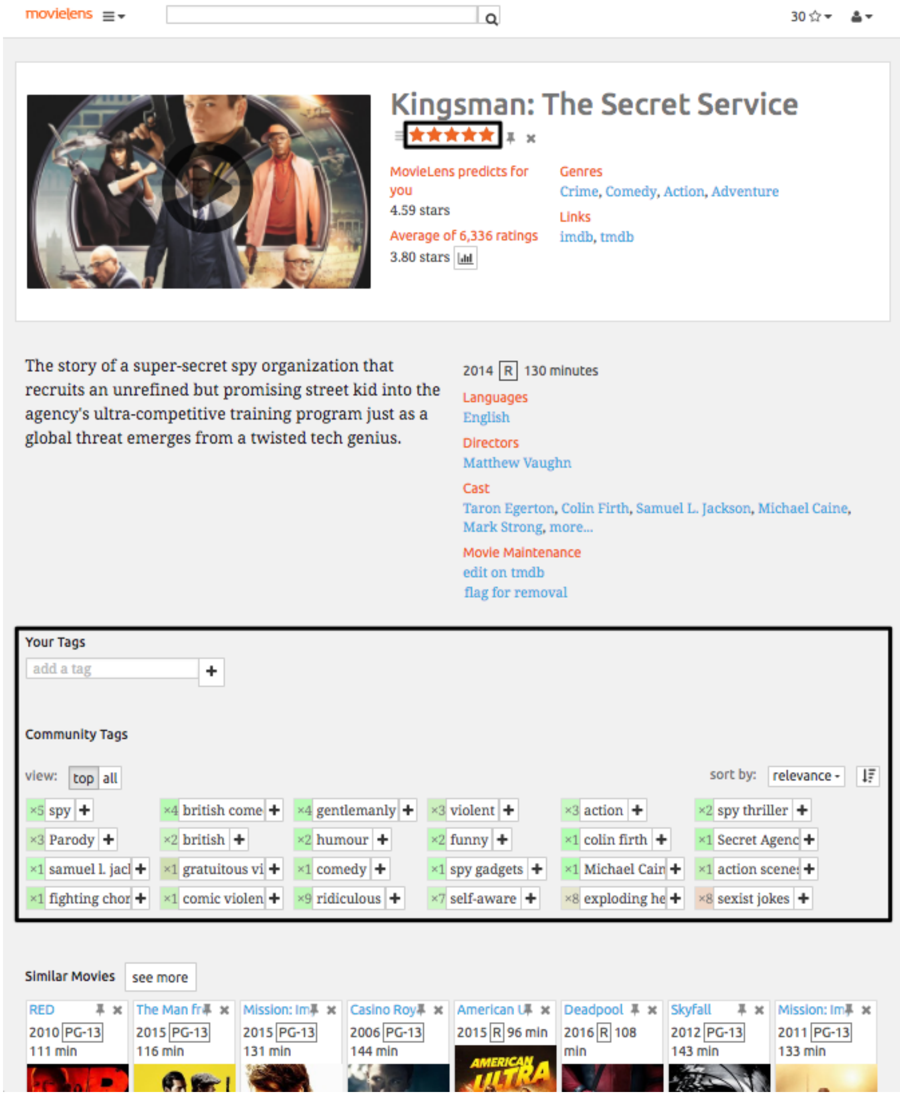


Figure 2.2 The screenshot of the rating and the tags of a movie in Movielens.

called multidimensional matrices. In this research, tensors are denoted by calligraphic upper-case letters ($\mathcal{A}$, $\mathcal{B}$, ...), matrices by uppercase letters (A, B, ...).

The ratings and tags represent the user's subjective impressions and opinions about the items. There are several terms to represent the subjectivity: feeling, emotion, mood, and sentiment. The meaning or those words are slightly different. *Feelings* are conscious phenomena; *emotions* are expression of feelings; and *sentiments* are emotions that develop and endure over time [7]. *Moods* is remnants of emotions [8]. In this dissertation, these terms are used interchangeably to refer to the user's reaction after item consumption.

2.3 Related Work

In this section, relation work of social network analysis, item recommendation and emotion analysis is presented. In Section 2.3.1, previous studies of social network analysis are described. In Section 2.3.2, previous research on item recommendation is presented. Finally, studies of emotion analysis and recommendation using emotions are described in Section 2.3.3.

2.3.1 Social Network Analysis

As online social networking services become more popular, researchers have tried to analyze the services to understand their key characteristics. At an early stage of research, much effort was attempted to analyze the characteristics of online social networks [9, 10, 11]. Researchers crawled popular online social networks and analyzed common structural properties. In online social networks, user behavior is an especially important feature in understanding phenomena present in social networks, such as social influence and user similarity. Crandall et al. [12] studied the role of user interactions between similarity and social influence. Users showed a sharp increase in similarity immediately before their first interaction; after the interaction, the similarity increased slowly. Papagelis et al. [2] investigated the effect of individual behavior types on social influence. Several studies have tried to categorize social media; the results differed based on various perspectives. Kaplan et al. [13] sorted social media services into six categories by social presence and self-presentation. Online social networks are classified by the level of self-disclosure. The study claimed that content-based social communities like YouTube are lower self-presentation than social networking services. In [14], social media services are categorized into four groups by formality and interaction. The study argued that social content sharing such as social bookmarking and social cataloging has higher interaction and lower formality than general social networking. d Much research has been done on social content sharing services, and they analyzed the services and the behaviors of users. In [15, 16, 17], researchers have studied the characteristics of online video sharing. Particularly, [15] have tried to investigate the characteristics of social content sharing services to distinguish from general online social networking services. The study showed the differences between the YouTube social network and traditional online social networks using three features: assortative linking, reciprocity, and user homophily. The study also showed the dichotomy of social and content activities and examined said activities' popularity in YouTube. Meo et al. [18] investigated the tagging and friending behaviors of users in social sharing services and the influence of design of social sharing services in user behaviors using Flickr, Delicious, and StumbleUpon. Cha et al. [19] studied the information propagation in Flickr. This research shows that the links between users are the key of information propagation, and information spreading is limited to individuals who are very close to the uploader. Au Yeung et al. [20] estimated influences based on the activities of users and proposed a probabilistic model for user adoption behavior to capture implicit influences in social content sharing services. The analysis of social cataloging services was also performed. Based on the aNobii network, Aiello et al. [21] investigated structural and evolutionary features and mined geographical information, and Tang et al. [22] studied the reading diversity of users using five similarity measures. Jamali et al. [23, 24] have investigated the characteristics of social rating networks and modeled the effect of various influences. Jiang et al. [25] identified the characteristics of users in Douban based on four information seeking modes. Fuglestad et al. [26] studied the motivations of users' participation in the social movie cataloging service.

User's participation is a key of online communities. Research on the motivation of participation in online communities has found that the reason why users participate in and contribute to the communities is to gratify their needs [27, 26]. These studies suggested that the sense of belonging and social behavior are key motivations.

However, much research has claimed that active users are actually only part of the online community and that a significant portion of users are inactive. They defined lurking as the passive contribution (i.e., rarely posting and making relationships) to social communities. Lurking is a common behavior in online communities [28, 29]. Lurkers are described as a free-rider who just obtains resources and contributes nothing [30] or as a user who passively interacts with others [31].

Several studies have focused on the reason for lurking. Katz [32] stated that 98% of visitors on large forums do not express their opinions or participate in discussion. The reason why users lurk is that they are uncomfortable with the hostility and posting in public area, and they can access various sites while they skip personal insults and abuse. Nonnecke et al. [33] conducted interviews and showed various reasons for lurking such as discomfort with public posting, need to remain an anonymous user, and unsatisfiable information with their needs. A study on the relationship between intimacy and the type of users [34] found that if the users' social-emotional need is not gratified, then they choose to lurk.

Research on lurkers in online social networks has also been conducted. In a study of lurkers on Facebook [35], the researchers defined lurking as a passive activity and ostracism as a lack of feedback from other users. The study found that measures such as belonging, self-esteem, and meaningful existence are low if the user has no feedback or refrain from sharing content. Gong et al. [36] identified that lurkers on Twitter have less social connection than active users, but prefer a relationship with active users. The study also showed the possibility of lurker profiling using their tweets. Mustafaraj et al. [37] found the difference of tweeting behavior between the silent majority and vocal minority based on the tweets during a special election for the US Senate. They showed that the opinions of a vocal minority have a significant influence. However, previous research has mainly focused on lurkers in traditional social networking services; studies on lurkers in social cataloging services are insufficient.

2.3.2 Item Recommendation

The recommender system functions as a filter of information overload. The traces of users in the system are useful for recommendation because they are presumed as personal preferences and interests [38, 39, 40]. Two main recommendation approaches are collaborative filtering and content-based filtering. Collaborative filtering models the process of asking a friend for a recommendation [41]. This approach predicts and recommends new items considering users who have similar preferences with the target user. It is domain-independent technique; it does not rely on the information of items, but user's ratings. In contrast, content-based filtering is domain-dependent method. It analyze the features of items and recommend new items similar to user profiles extracted from the previous item selection of users. Both types of recommendation techniques have various problems such as *cold-start problem* which is for new users, *grey-sheep problem* which is caused by disagreement of preferences among users, *data sparsity* due to a lack of ratings, and *scalability* for computation. Hybrid recommendation technique combines collaborative filtering and content-base filtering to avoid those limitations.

Since the purpose of the recommender systems is to improve the satisfaction by providing the information depending on user's need, it is necessary to pay attention to the subjective feedback of the user in addition to the item information.

Users in social cataloging services use tags for the purpose of facilitating retrieval of items and for sharing their opinions and communicating with other users [42]. Xu et al. [43] classifies tags into five categories: content-based tags which describe the content or categories of an object, context-based tags which represent time or location that object was created, attribute tags which show the properties of an object, subjective tags which explain user's opinion or emotion, and organizational tags for personal usage. The former three are informative tags that describe the item itself, and the latter two are tags that contain the user's individual opinion; both can be used together (e.g., good performance).

Much of the research on tagging has focused on why users are tagging, how tagging differs depending on the system, and whether the community affects user's tagging behaviors [42, 18, 44, 45]. They have reported that most of the social media services understand the importance of tagging. The tagging is being payed attention in many studies of recommendation system because it is not the fixed keyword but the user's own subject. Huang et al. [46] suggested the FRD model combining the frequency, recency and duration of the tags to find the user's personalized preferences. They found the similar users and items to the target user by appying collaborative filtering and content-based filtering, and compute the recommendation score using the target user's FRD information. Guy et al. [47] integrated tags used in social networks of business systems and proposed an item recommendation method which combines user and tag information. The authors generate the user profile for recommendation based on the various user-tag relations such as used tags, incoming tags, and indirect tags. Zhang et al. [48] suggested a diffusion-based hybrid recommendation algorithm considering the two roles of the tags that organizes items and connects between user and item. They shows that the latter role of tags is more helpful to recommend items, and the hybrid approach shows the best result. Kim et al. [49] modeled users based on their tags. They classified items into two sets, positive and negative, and calculate the tag weights of the items in both sets. After that, they found the relevant topics based on the tags for the recommendation. Research of Gedikli et al. [50, 51] have conducted to predict the rating of the item by making rating on the tag itself in order to improve the quality of the tag-based item recommendation. Kim et al. [52] proposed an item recommendation method based on implicit trust relationships derived from user's tagging information.

In recommendation systems using tags, the relationships between users, items, and tags are represented by a tripartite graph (Figure 2.3). It can capture the three pairs of relationship, i.e., user-item, user-tag, and item-tag, but loses co-existence information about users, items, and tags [53].

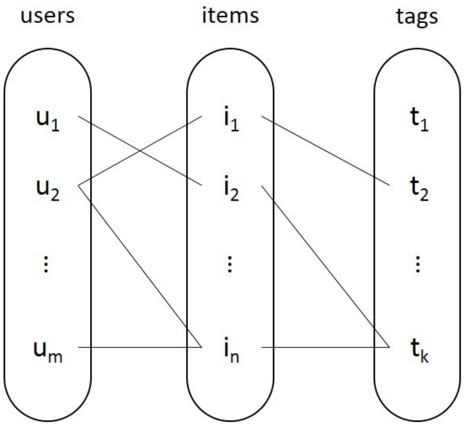


Figure 2.3 The tripartite relationships among users, items, and tags.

Expressing the ternary relationship with a multidimensional matrix instead of a tripartite graph can improve the quality of the recommendation because the ternary associations can be considered. Researchers have used a three-order tensor to represent the ternary relationship and apply the tensor factorization method to capture the latent semantic associations among them. HOSVD [54], which is one of the tensor factorization methods, has been applied in various recommendation studies.

The studies of Symeonidis et al. [55, 56] have proposed a tensor-based recommendation approach. They used a three-order tensor for user, item, and tag relationships and applied the HOSVD technique. A Kernel-SVD combination algorithm was adopted to improve the accuracy of the recommendation. Peng et al. [53] introduced the concept of hidden tag and hidden item to efficiently grasp the similarity between users and suggested a recommendation technique using Tucker decomposition. Xu et al. [57] adopted

CubeSVD [6], which has been investigated to improve personalized web search using HOSVD technique. They split an original tensor into several sub-tensors in order to reduce the sparsity of the tensor. Ifada et al. [58] studied the scalability in the tensor reconstruction process and the ranking of the recommended items. They argue that the recommendation based on the result of the tensor reconstruction process ignores the user's previous activities. Therefore, the authors ranked the result of tensor modeling utilizing Näive Bayes approach. To reduce the computational size, [59] clustered tags by topic using K-means clustering algorithm and tripartite clustering approach.

In our study, we used the tensor model and applied HOSVD as the tensor factorization method. Most of the recommendation method using the tensor model have used a binary value as an elements of the tensor. However, we used the emotion value as an initial value of the tensor for considering user's preference and impression of items.

2.3.3 Emotion Analysis and Recommendation using emotions

To improve recommender systems, much research have focused on emotional information [60, 61]. The relationship between the emotions and user's consumption have been studied in various fields, and many recommendation studies have focused on how the emotions before and after consumption affect the choice of the next item [62, 63, 64, 65, 66]. Tkalčič et al. [65] classified emotion into three stages when the user uses the recommendation system and introduced emotion detection methods and emotion usage at each stage. According to this study, user's emotion before consuming items affects user's item selection. On the consumption stage, one emotion or various emotions appear over time depending on the type of content. Finally, emotion after consumption affects the user's next behavior, which is an indicator of whether the user is satisfied with the item. Zheng et al. [67] studied the role of emotion in recommendation algorithms. They studied the recommendation considering emotion feature in context-aware splitting algorithm and differential context modeling algorithm. The evaluation showed that emotion features improve the recommendation performance. Winoto et al. [66] showed that the rating can be biased according to the user's pre-mood, and they proposed a recommendation method considering the rating bias.

SenticRank [68] is the framework which maps the tag-based user profile to the sentiment space and ranks the resources suitable for the user's query. The research was conducted for personal search, but it can be applied to the recommendation system. Qingbiao et al. [69] proposed a sentiment enhanced tag-based recommendation method which utilizes the positive and negative polarities of tag synsets for calculating similarities between resources. Dong et al. [70] applied the sentiment to product recommendation. They proposed an approach to combine the product similarity and the product sentiment; the product sentiment is obtained by extracting features from the user's review and calculate the sentiment of each feature. Garcia et al. [71] and Sun et al. [72] have applied the sentiment analysis on the user feedback. Both research reported that the sentiment analysis is effective to obtain the better recommendation. Kim et al. [73] proposed a recommendation method for tackling cold start and data sparsity issues in music recommendation systems. The authors developed UniTag, a tagging ontology, to assign meaning and scores to user tags. The UniTag ontology consists of UniMusic ontology for solving the semantic ambiguity of the tags and UniEmotion ontology for weighting the tags. The users' profiles are generated by combining the emotion weight of the tags given through the ontology and the number of plays of items. A collaborative filtering technique is applied to the user profiles to recommend music to users. This study is similar to our research in terms of using the emotions of tags, but the target content and the strategy to measure preference values is different. Our targeted content, such as movies or books, has a limited number of items to be repeated, and the users leave the feedback in the social cataloging service after consuming items outside the service. Therefore, it is difficult to use the amount of item consumption as the value of the preference in our research. We used the user's ratings as the preference value of the items. The preference based on the number of plays of music can relatively change with time, but the preference using the ratings has always the same value, and thus can be more consistently reflected.

To extract emotion, various emotion lexical resources were introduced such as SenticNet [74], Emolex [75], ANEW (Affective Norms for English Words) [76], and SentiWordNet [77]. Among them, SenticNet is an emotional vocabulary dictionary for concept-level sentiment analysis. Emotion is represented by affective dimensions consisting of pleasantness, attention, sensitivity, and aptitude and by polarity based on the dimensions. In this paper, we use SenticNet 4.0 which includes 50,000 concepts to extract the emotions contained in the tags.

Chapter 3

User Behavior in Social Cataloging Services

3.1 Motivation

Online social networking services can be classified by their differing aims, system components, and the behavioral patterns of users. Social content sharing services, which are a kind of online social networks, give more weight to content sharing than to build social relationships. They usually deal with target content such as videos for YouTube, books for LibraryThing, and images for Flickr. The main purpose of users in these services is to share items and to find other items that match interests, rather than to make a relationship or communicate with others. Such users can usually access items within the service and are more likely to choose items impulsively, and they tend to interact with others explicitly such as writing comments or sending messages.

Despite the difference in target contents, social content sharing services look very similar to each other. However, certain of those services can be distinguished by a way to provide content, and this difference can affect user's content selection and communication. Social cataloging service is one of the social content sharing services; they allow users to catalog and share items with others [78]. Such services usually provide users with only meta-data and perhaps a fraction of the actual content such as sample teaser or chapter. Users in the services tend to select items carefully based on personal preference because they cannot consume the whole of the content instantly. Also, they tend to express their opinions through review or ratings rather than casually conversing with others. Specifically, they tend to be more focused on the self-expression and maintain relationships by implicit interactions such as reading news feeds about other users without any interactions.

Surveillance is the process of monitoring other individual's actions or activities to obtain information, and social networking services are used as a tools to surveil other users to obtain information and opinions from them. Unlike the past, which shows the vertical relationship of the power, surveillance is changed into a horizontal relationship that anyone becomes an observer and can be observed, and it is possible to monitor not only other users (social surveillance) but also user's own expression or presentation (self-surveillance) [79]. The same applies to social cataloging services. Through the social surveillance, users adjust their reviews by reflecting the opinions of others. In the research of [80], the authors document a “self-presentational strategy”, which is influenced by negative ratings, and a “multiple audience effect” that consumers observe the various opinions and give the balanced ratings. The social connection function provided by the social cataloging service enables users to interact with others, and refer to other’s activities and opinions and obtain complementary information about items. However, since the link between the users is one of the various options for the user to acquire the information about items; therefore, even if the user does not have any relationships with others, they are not affected by cataloging items and sharing their experiences. That is why the majority in social cataloging services tend not to build the relationships with others. Social cataloging service is different from the conventional social networking services such as Twitter of Facebook that requires links between users. In social cataloging services, the users’ who do not have any links are not a lurker who causes the problem of free riding, but users who contribute to the service for self-satisfaction.

In this chapter, user behaviors in social cataloging services are analyzed with regard to assortative linking, reciprocity, and homophily. For the comparison by the type of services, a YouTube study [15] is utilized as a representative social content services. Also, we investigate the characteristics of the isolated users who are not connected with others but account for a substantial part of service users, and study the differences in users’ behaviors depending on whether there is a connection between users of the social cataloging service are studied.

3.2 Datasets

Social cataloging services denote the services that help or have helped users to catalog items of interest. The services provide basic features for users to create their own item lists, rate the item, and write reviews. Naturally, the users also make relationships, comment on other user's pages, and join communities much like when using online social network services, though the ways of user interactions depend on the services. In this study, we used three services as our datasets: LibraryThing, Userstory Book, and Flixster; Table 3.1 shows the summary of our datasets.

Table 3.1 The summary of the datasets.

	LibraryThing	Userstory Book	Flixster
Users	346,126	12,933	147,612
Relationships	386,056	13,591	7,058,819
Items	7,120,817	100,168	48,794
Comments	97,404	2,181	-

3.2.1 LibraryThing

LibraryThing is one of the most famous social book cataloging services launched in 2005. Presently LibraryThing has almost 2 million users and information on over 100 million books. User relationship is unilateral, and users do not need to obtain consent to be connected. In addition to the functions described above, it is possible to tag a book in a list of their own.

In a social cataloging service, user behavior related to books is relatively more active than user relationships. Therefore, it is difficult to crawl data using some users as a seed like in social network services. In this study, we choose users who have one of the more popular books in LibraryThing as a seed. The books are *A Game of Thrones*, *Mockingjay*, *Great Expectation*, and Alchemist, to name a few. We collected the data in October 2014 using breadth first search. The dataset contains 346,126 users, 386,056 unilateral relationships, 7,120,817 book entries, and 97,404 comments.

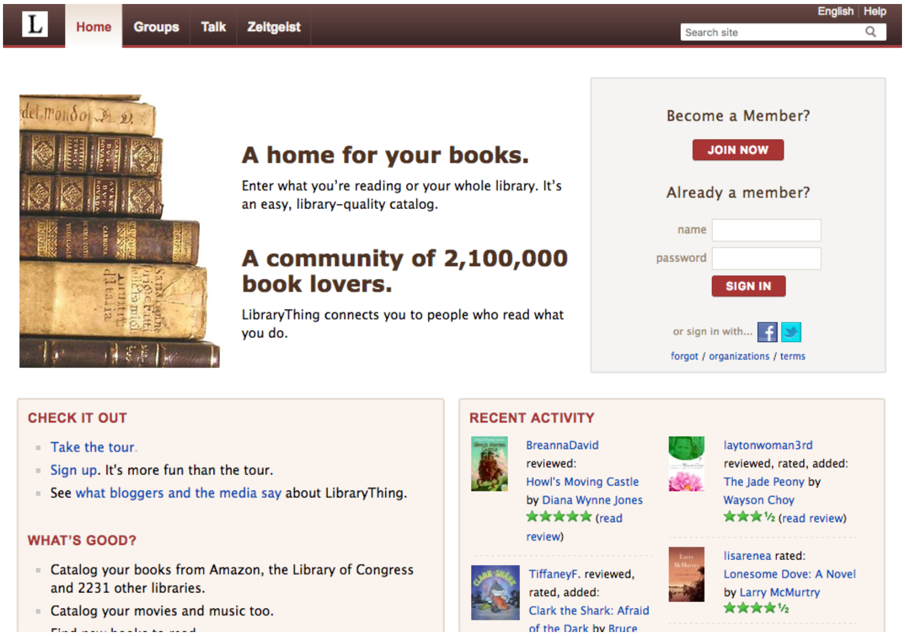


Figure 3.1 The screenshot of LibraryThing.

3.2.2 Userstory Book

Userstory Book is a social book cataloging service in South Korea launched in 2009. Presently Userstory Book has over 20,000 users and over 200,000

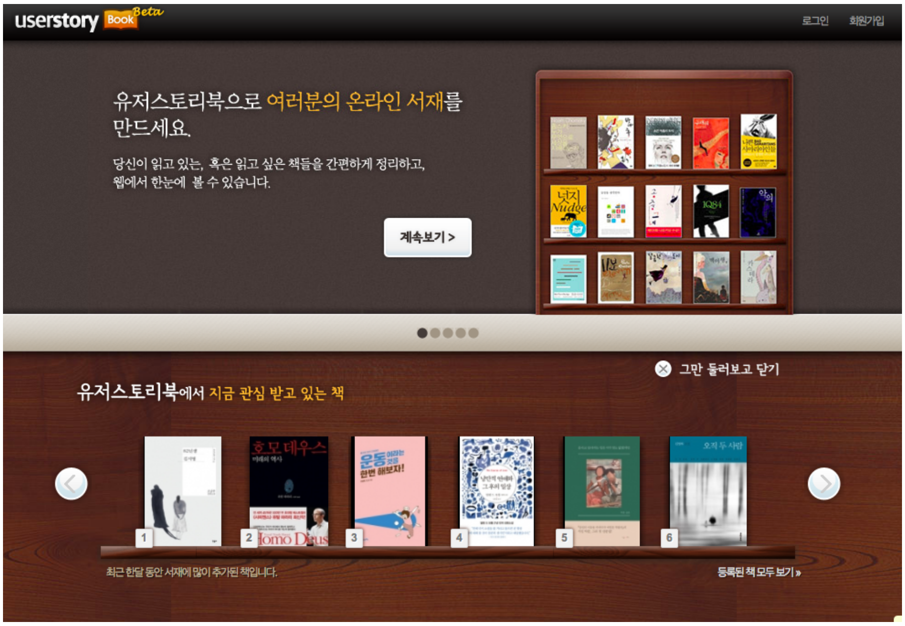


Figure 3.2 The screenshot of Userstory Book.

book entries. The relationship is unilateral like that of LibraryThing. Users cannot tag books on their own lists, but they can set the status of the books into three groups: *plans to read*, *currently reading*, and *already read*. We collected the entire data until May 8th, 2012. The dataset contains 12,933 users, 13,591 unilateral relationships, 100,168 books, and 2,181 comments. The size of the dataset is remarkably small in comparison to the Library-Thing dataset. However, the characteristics and implications of the entire network of the social cataloging service are important to understand. We will also show that Userstory Book is suitable for analyzing because the service has a similar structural tendency as the LibraryThing dataset despite the smaller size.

3.2.3 Flixster

Flixster is a social movie cataloging service that allows users to rate movies and to create social relationships. We use the dataset generated by Mohsen Jamali [23] [1]. The dataset contains 147,612 users who have rated 48,794 distinct movies (66,731 movie data points and 8,196,077 rating data), and 7,058,819 friend relationships. The relationships are crawled as a directed network, although the friendships in Flixster are actually an undirected network.

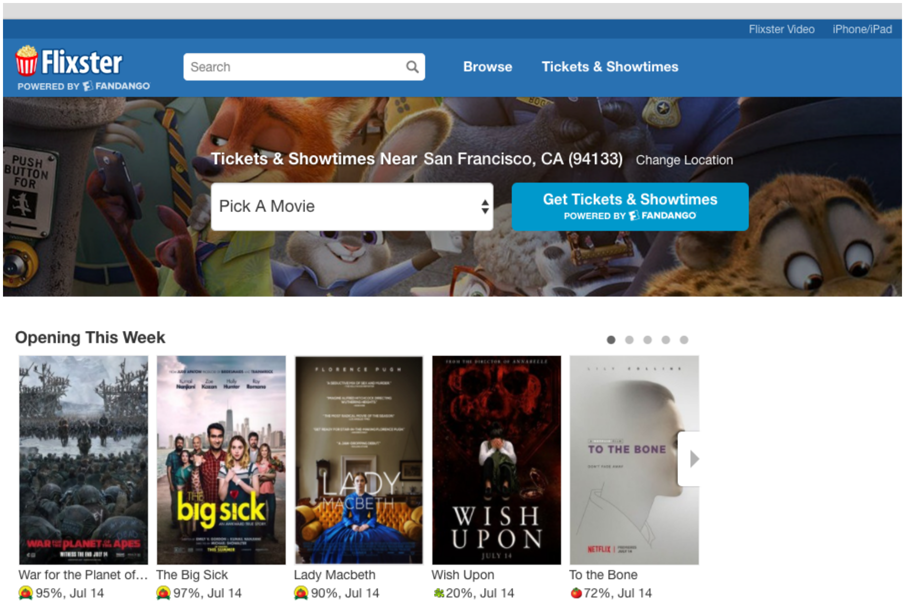


Figure 3.3 The screenshot of Flixster.

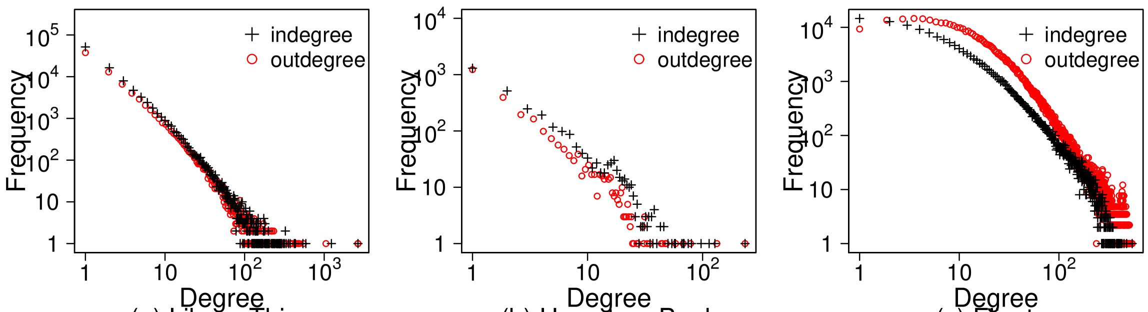
[1] http://www.cs.ubc.ca/ jamalim/datasets

3.2.4 Preliminary Analysis

In this section, we examine the basic characteristics of our datasets. We present the degree distribution of users, the distribution of items, the relation between item and user's popularity, and user interactions.

Figure 3.4 represents the in-and out-degree distribution of the datasets. In each dataset, there are extremely active users who have many friends, but users usually make few relationships with other users. In fact, 45% and 46% of the users on LibraryThing and Userstory Book have just one outgoing link. The number of users who have no out-degree is 76% and 79% respectively, and, of these, 91% of users on both datasets do not have any in-degrees either. In the case of Flixster, users who have less than 10 outgoing links are 26%, and it seems smaller than the results of the former datasets. However, it is difficult to compare the tendency of out-degree as two social book cataloging service datasets because [23] explained that they ignored many users in their dataset who have not rated any movies. There are also a few users who have many links. The user with a large number of friends has 3,800, 490, and 1,045 outgoing links on LibraryThing, Userstory Book, and Flixster, respectively.

In comparison with YouTube as a representative social content sharing service, we used the YouTube dataset provided by [16]. We used the dataset of user information from 2008, which contains information on the number of friends of more than 2 million users. The users in YouTube have 18 friends on average, whereas the users in social book cataloging services



(a) LibraryThing (b) Userstory Book (c) Flixster

Figure 3.4 The degree distribution.

have one friend on average.

Next, we consider the distribution of the number of items for each user (Figure 3.5). According to our estimation, on average, each user has 210 books at LibraryThing (median = 48), 31 books at Userstory Book (median = 3), including books planned to be read, and 55 movies at Flixster (median = 4). There are also extremely active users who have many items on their list, and their items cover the various genres of books or movies. Since our crawled data were not follow the normal distribution, Spearman correlation is used for the tests, which is a nonparametric measure of correlation. The results of Spearman's correlation analysis between the number of items a user has and the number of genres the items cover are respectively 0.87 and 0.95 for Userstory Book and Flixster. It means that there is a strong positive correlation between the activeness of users and their range of interests; namely, the extremely active users are better than the rest in expressing their interest in all genres. The result of LibraryThing dataset was excluded because they do not provide any genre information. How we obtained and classified the genre of items is described in Section 3.3.3.

We also examine the relation between the number of items and user popularity. Figure 3.6 shows that the most active users with many items are not more popular than ordinary users. The Spearman's correlation also supports the finding; the coefficients are 0.22, 0.36, and 0.07 for LibraryThing, Userstory Book, and Flixster respectively. Active behaviors such as reading many books (or watching many movies) and expressing one's interest does not affect making relationships and vice versa. This indicates that users present their impressions for their own needs and self-satisfaction and not for giving information to others.

In social cataloging services, user interactions usually occur if a user leaves messages on other users' pages; hence, we created an interaction graph based on comments on the personal pages and analyzed the user interactions. For this analysis, we only use the LibraryThing and the Userstory Book datasets because the Flixster dataset does not have information on user interactions. If there is an edge from user u to user v, it means u leaves a message on v's page. We ignore the replies of the messages and the messages written to oneself. The interaction graph of LibraryThing consists of 41,597 users and 97,404 interaction edges; 11,272 users have one or more reciprocal edges. In the case of Userstory Book, the interaction graph consists of 872 users and 1,287 interaction edges. 364 users have one or more reciprocal edges, which indicates that 12% and 6.7% of the total users have interactions with other users. Out of the nodes in the interaction graphs, about 31% of the users from both interaction graphs interact with their friends. These results mean that most users are indifferent to social behavior, and like other social content sharing services, users usually use the service for creating item lists and leaving impressions and not for communicating with other users.

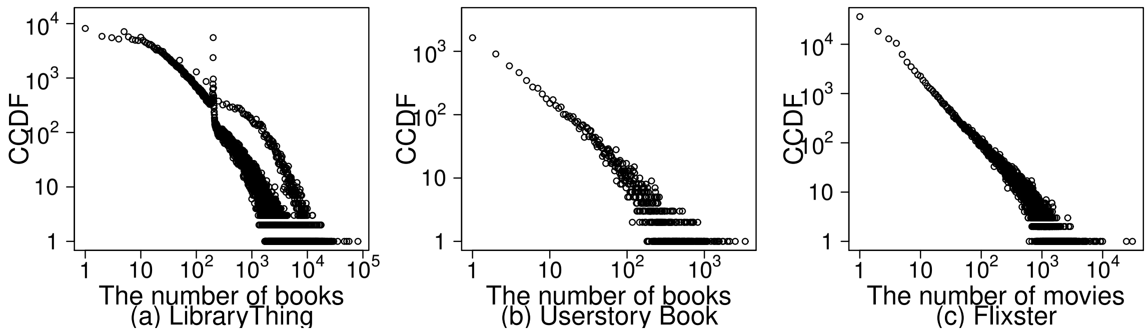


Figure 3.5 Cumulative distribution of items by how many a user has.

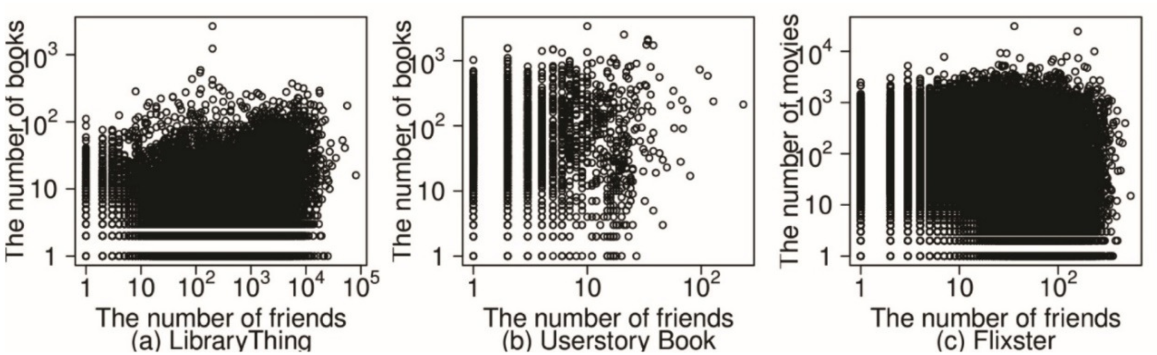


Figure 3.6 The relation between the user popularity and the number of items.

3.3 Characteristics of Users in Social Cataloging Services

Wattenhofer et al. [15] found the differences between a YouTube network and a traditional online social network in terms of assortativity, reciprocity, and homophily. We used the same methodology to investigate the characteristics of users in social cataloging services and compare the results with [15] in order to determine whether distinctions exist between general social content sharing services and social cataloging services.

3.3.1 Assortativity

Assortativity is the tendency of nodes to connect with other nodes with similar degrees of a certain unit. We examine assortative links based on user popularity. Figure 3.7(a)-(c) are the results of the LibraryThing, Userstory Book, and Flixster dataset, respectively. In the case of Flixster, we only obtain the result of the assortativity between the users with reciprocal relationships because the original Flixster service provides reciprocal relationships. The x-axis represents the in-degree of users, and the y-axis represents the average in-degree of friends. The plots show that users form social relationships with others who have a certain amount of in-degrees regardless of the number of in-degrees of themselves. This tendency has nothing to do with the type of links. We also calculated the assortativity coefficient for each dataset, and found all users (-0.028) and reciprocal users (0.241) for LibraryThing, all users (-0.087) and reciprocal users (0.006) for Userstory Book, and reciprocal users (0.02) for Flixster. In [9], the assortativity coefficients for YouTube is -0.033, and it seems similar to our datasets as a result of non-assortative. However, the assortativity measurement for the subscription network in YouTube [15] shows that most users in a subscription graph subscribe to users who are much more popular than themselves, and significant differences depend on the type of links; reciprocal users are more assortative than the entire userbase.

3.3.2 Reciprocity

In our datasets, with the exception of Flixster which provides undirectional relationships, 69% of the links in the LibraryThing dataset and 55% of the Userstory Book dataset are bidirectional. That is, the number of users who join in interacting with each other is less as described in Section 4, but the level of reciprocity is relatively high. This implies that the relationships are usually superficial and tend to be passive engagements [81]. Most of the users keep up with friends by reading news, reviews, and ratings, without actual communications. The users do not try to develop deeper connections.

In comparison with the reciprocities of other social content sharing services, our results are larger than YouTube (25.42%) [15] and similar to Flickr (68%) [19]. Mislove et al. [82] argues that many of reciprocal links are built by courtesy because Flickr informs users of new incoming links by email. In the case of CiteULike, one of the social cataloging services, they have only 93 reciprocal links out of 11,295 unilateral links [83], and this proportion is less than the results of our datasets. It appears that the target content of CiteULike is scholarly papers, and users have the more

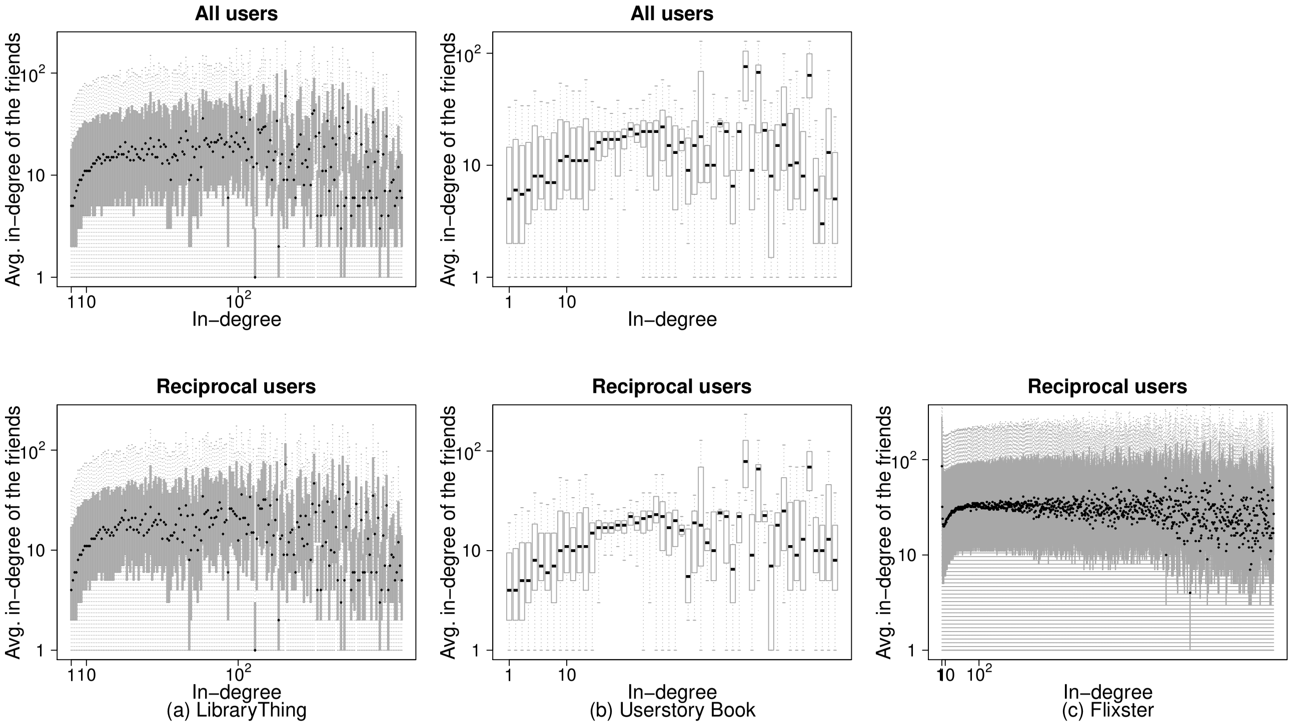


Figure 3.7 The similarities between users and friends' popularities using (a) the entire users and the reciprocal users in the LibraryThing dataset, (b) the entire users and the reciprocal users in the Userstory Book dataset, and (c) the reciprocal users in the Flixster dataset.

specific interests than users in other social cataloging services.

3.3.3 Homophily

We use genres of items for measuring homophily among users. The items in a user's list cover a wide range of genres. Thus, we assume that the most dominant genres in the user list represent the user's primary interest. Prior to the analysis, we perform the genre classification as preprocessing. The metadata of the books offered to users by Userstory Book are obtained from online bookstore. The genre information out of the metadata is based on the fine grained categories, and they are too specific; thus, we reclassified the genres in our dataset into 29 genres using the coarse grained categories in the online bookstore. Unlike the Userstory Book dataset, the LibraryThing and Flixster datasets do not have any information on genres. Accordingly, we utilized the genre information in other datasets for classifying genres. For the Flixster dataset, we classified 28 genres based on the genre information in a movie dataset from the Internet Movie Database (IMDb) [2]. We matched up the movie titles in the IMDb dataset with the titles in the Flixster dataset and applied the genre of the matched titles in our dataset. As a result, we obtained 50,868 movies with genre information out of 66,731 movies. In contrast, for LibraryThing, we could not find other datasets that have genre information of books. Thus, we have excluded the LibraryThing dataset in the homophily experiment.

For the book dataset, we measure the level of homophily in three graphs:

[2] IMDb plain text data files are available at http://www.imdb.com/interfaces

unilateral friendship, reciprocal relationship, and interaction. 47.94% of users in the unilateral friendship graph and 30.09% of users in the reciprocal friendship graph are interested in the same genre as their friends. Only 6.57% of users in the interaction graph have genres in common with other users who interacted with them. In the case of the movie dataset, only 2.75% of users in friend relationships have common interest with their friends. Also, the interest of the users with a few friends and items often matched up with the interest of their friends in the Userstory Book, but it is rare in the movie dataset. These results show the significant difference between two datasets. The average number of friends for each user in the Flixster dataset is greater than that in the book dataset, and the friendships in movie dataset are built as an undirected link. It means that many of links in Flixster can be made by courtesy, and these links make the network less homophilous. The results of the YouTube network are on average 26.58% and 27.46% for the subscription network and the comment graph, respectively [15]. To examine homophily, they used the video categories that users upload their content.

3.4 Isolated Users in Social Cataloging Service

In Section 3.2.4, we showed users who do not have any friends form a majority of the social cataloging services. These isolated users can be the users who do not participate in the services and only read other's update, or they can be the users who contribute to the services and merely disconnected with others. The former users are usually called *lurkers*, and we refer to the latter users as *unsociable users*. In this section, we study what the characteristics of the isolated users in social cataloging services are. If they are the lurkers, they have less communication with others, a small number of items in their list, and few expressions such as reviews and ratings. If the isolated users are the unsociable users, they also have less communication with others, but other behaviors are as active as the connected users. We call the users who have one or more friends as *connected users*. The percentage of the isolated users in our dataset is described in Table 3.2. Many of the users do not have any connections with others.

Table 3.2 The ratio of the isolated users in our dataset.

	LibraryThing	Userstory Book
Total Users	346,126	12,933
Isolate Users	241,806	9,348
Percentage	69.8%	72.2%

We begin by examining how many users who do not have friends communicate with other users. For this analysis, we exclude the movie dataset because the dataset does not have communication information. As a result, only 1% and 0.6% of users at LibraryThing and Userstory Book, respectively, interact with other users. Of these, the ratios of users who communicate with only one user are 83.8% and 81.3%, respectively. These results show the low interaction rate of the isolated users.

Next, we analyze whether there is a difference of the reading tendency between the connected users and the isolated users. Figure 3.8 is the result of the connected users and Figure 3.9 describes the result of the isolated users. In both graphs, the x-axis represents the number of items for the user, and the y-axis represents the percentage of the users who have items. The included graph in Figure 3.9 represent the percentage of the isolated users who have one to one hundred items. In all of our datasets, most of the isolated users have items: LibraryThing (98.9%), Userstory Book (65.8%), and Flixster (100%). LibraryThing and Flixster datasets show very low proportions of isolated users who do not have any item because datasets could be biased due to crawling, which is based on the item list; especially, the Flixster dataset seems to be limited to the users who have rated movies.

Among the isolated users, a majority has one to ten books and movies, and it is same as the result of the connected users. In comparison to the connected users, the isolated users have less items than the connected users on average in the case of LibraryThing and Userstory Book. However, the isolated users have more items than the connected users on average in the case of Flixster despite that the number of isolated users is very small.

However, the number of items each user has does not show the activeness of the user. The users cannot be active at present because they could have catalogued the items a long time ago. Thus, we count the number of

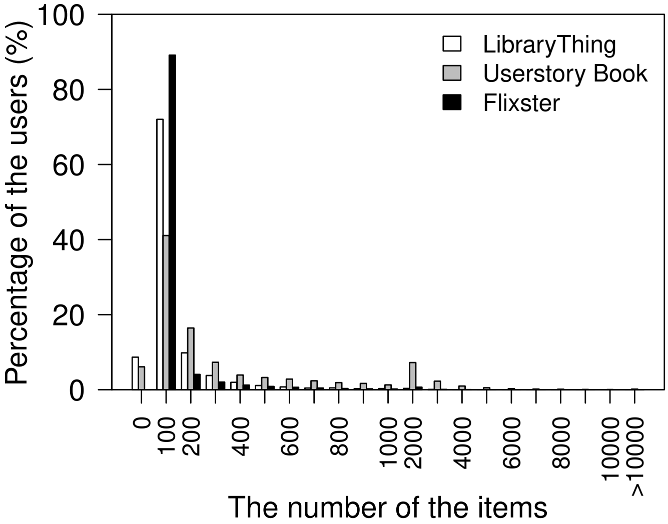


Figure 3.8 The proportion of items for the connected user.

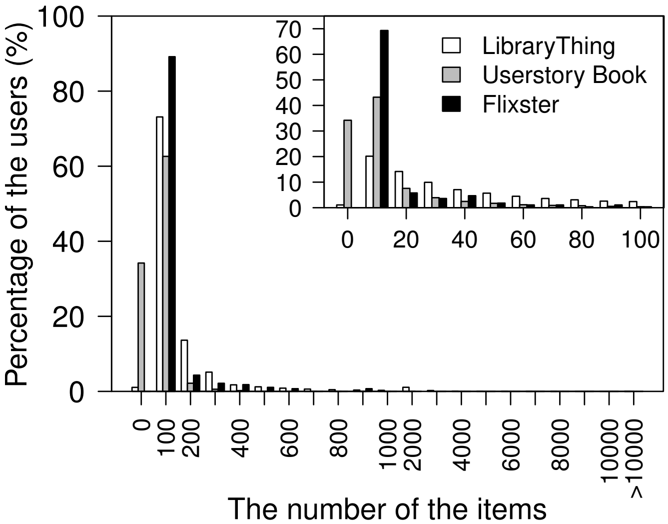


Figure 3.9 The proportion of items for the isolated user.

users who update the item list k months ago. The results are illustrated in Figure 3.10. The x-axis represents the change of the time interval and the y-axis represents the number of users who have registered new items in his or her list on a log scale. The solid line shows the results of the isolated users and the dotted line shows the results of the users who have friends. Although the two groups have a difference in the number of users who save items in the list during the time interval, the pair of user groups in all three datasets indicates a similar tendency generally. There is also no significant change in the number of users over time. The Flixster dataset shows a large difference between the two user groups, it seems that because of data bias described in Section 4. We also calculate the number of users who update only one item in the last 12 months. These users indicate that they do not use the service after the first try. As a result, isolated users and connected users at LibraryThing (7% and 6.7%), Userstory Book (28% and 12%), and Flixster (33% and 29%) updated the item list one time during the time interval. These results imply that the similar amount of the isolated users and the connected users are not interested in the services.

Next, we measure the time differences in updating the item list between isolated users and connected users. Users can save several items on the same day since users can update their list at any time and are able to consume many items per day. However, considering the nature of content with a long duration, we assume that users update the list several time a day when they register the items all at once that they had consumed in the past; thus, we ignore them in our experiment. Figure 3.11 depicts our

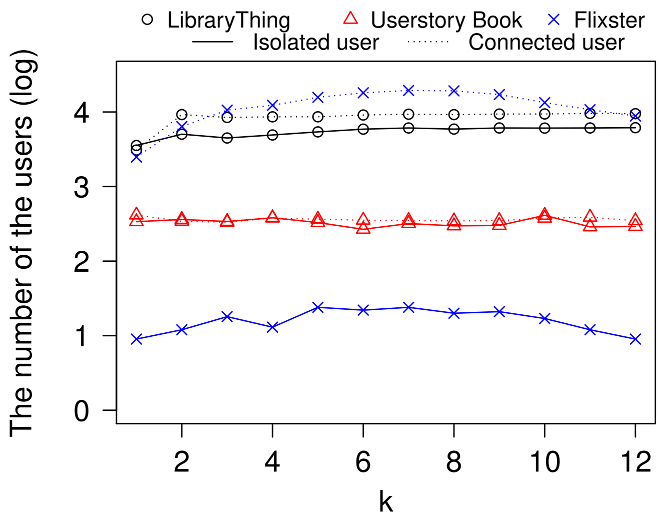
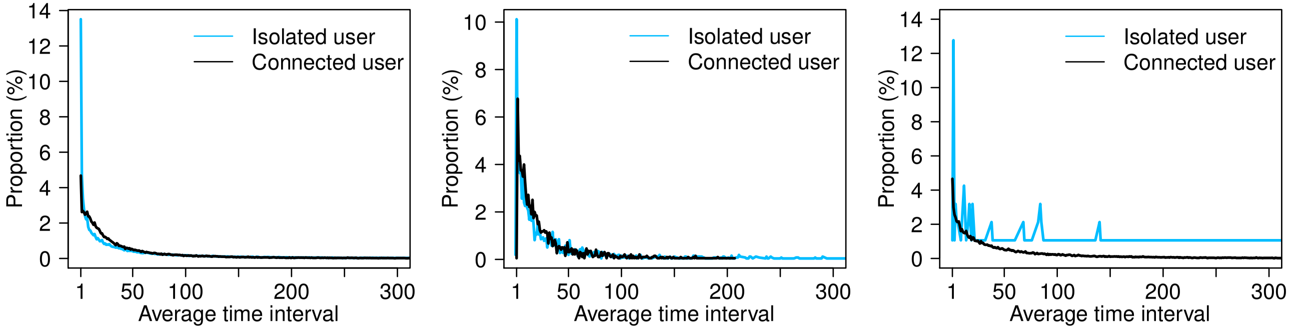


Figure 3.10 The number of users who have registered items on his or her item list in the past k months.

results. The x-axis describes the average time interval. The unit is in days, and the value is limited to 300 days. The y-axis describes the proportion of users who update the list with the time difference. In all three datasets, both isolated users and connected users show a similar tendency. The proportions of isolated and connected users who update the item list within a week on average are 31.26% and 20.24% at LibraryThing, 31.71% and 30.28% at Userstory Book, and% and 19.08% at Flixster. The users with similar portions actively add items on to the list, and the large number of users have a long time interval to update the list. This result shows that isolated users are as engaged in actions that gratify their needs as connected users.

As we have mentioned above, the users consume the items and catalog



(a) LibraryThing (b) Userstory Book (c) Flixster

Figure 3.11 The average time interval in updating the list between isolated users and connected users.

them on their lists constantly regardless of the existence of social relationships. However, there are various features that the users participate not only updating the reading list, but also the information contributions and social interactions. Thus, the statistical tests are conducted to analyze the relationships between those features in the services and whether there is any different tendencies between the connected users and isolated users. We use six features for the tests: user relationships, book reading, ratings, tags, joining date, user interactions as comments. In the case of Userstory Book, the information of joining date is not provide. Thus, the users' IDs are used as the joining date because the system assigns IDs in order of joining. The larger the ID value, the more recent users. Also, Userstory Book do not provide the tagging operation, the test for tagging is excluded.

Table 3.3 and 3.4 are the results for the connected users and isolated users respectively. Unsurprisingly, books read has correlations with rating and tagging. However, the user relationships of the connected users has a low correlation with other features. Users who have more friends do not tend to communicate with others and to read more books. It seems that some users rely on their own standards or a book recommendation on the service. The joining date has no correlation with other features. Since the users utilize the service for self-satisfaction, the time of joining is not an important factor. Tagging and rating have a correlation, but some users use either tags or ratings to express their impressions about items. There is a weak correlation between social features and user feedback for the connected users, but the isolated users has no correlation between them.

This is because of the difference of the number of users who interact with others. The result of the connected users implies that some users seem to be taking advantage of social features in their reading. Overall, there are generally the low correlations between features; it suggests that users selectively use the features in order to achieve their limited aims.

In summary, there are not much difference between the isolated users and the connected users in each service. The isolated users have many items, and a few users have huge amounts of items as the connected users. In terms of the frequency or the period of updating item list, the isolated users are similar to the connected users. These characteristics suggest that the isolated users in social cataloging services are more like the unsociable users than the lurkers; those users are disconnected with other users, but they also contribute to the services actively.

3.5 Summary

Social cataloging services allow the users to make their own item lists and share their impressions of items with others. In this paper, we have analyzed the user behaviors in social cataloging services using datasets collected from three services: LibraryThing, Userstory Book, and Flixster. The dataset of Userstory Book is quite smaller than other datasets, but it means we were able to work on a comprehensive dataset of a social cataloging service. This is also good for determining the general characteristics of social cataloging services.

In order to understand the distinguishing characteristics of the users

Table 3.3 The statistical analysis between features for the connected users.

	Relationship		Reading		Rating		Tagging		Joining		Comment	
	LT	UB	LT	UB	LT	UB	LT	UB	LT	UB	LT	UB
Relationship	1	1	0.226	0.202	0.323	0.238	0.265	-	0.119	0.008	0.370	0.246
Reading			1	1	0.441	0.821	0.667	-	-0.150	-0.131	0.231	0.161
Rating					1	1	0.457	-	-0.049	-0.235	0.260	0.121
Tagging							1	-	-0.179	-	0.258	-
Joining									1	1	-0.155	0.245
Comment											1	1

Table 3.4 The statistical analysis between features for the isolated users.

	Relationship		Reading		Rating		Tagging		Joining		Comment	
	LT	UB	LT	UB	LT	UB	LT	UB	LT	UB	LT	UB
Reading	-	-	1	1	0.266	0.754	0.378	-	-0.025	-0.013	0.076	0.054
Rating					1	1	0.314	-	-0.016	-0.125	0.076	0.029
Tagging							1	-	-0.065	-	0.079	-
Joining									1	1	-0.044	0.049
Comment											1	1

in social cataloging services, we analyzed and compared the datasets to the YouTube network, which is a representative general social content sharing service, in terms of assortativity, reciprocity, and homophily. According to the results, our datasets have low assortativity as YouTube dataset, but the tendency of following is different. Most of the users in YouTube subscribes the users who are more popular than themselves, while the users in our datasets follows the users who have a certain amount of popularity. The reciprocity rates of our dataset are higher than YouTube studies, but their interaction rates are low. It means the friendships between users tend to be superficial and passive. In the case of homophily, our results have the differences between the book datasets and the movie dataset. The users in Flixster have more friends than the users in Userstory Book, but they have a lower homophily ratio. It means that many of the connections between the users can be made by courtesy regardless of their own interests.

We also study the isolated users in social cataloging services. From our results, we found that the isolated users who are inactive in social behaviors show similar patterns to connected users. Although isolated users have few interactions with others and rarely make friends, they are as engaged as connected users in actions that satisfy their needs such as rating, review, and tagging. This shows that disregarding isolated users and mainly focusing the connected users lead to a misunderstanding in social cataloging services as with other online communities. To providing the web services to users in social cataloging services, understanding the user behaviors in those services is needed.

Chapter 4

Tag Emotion Based Item Recommendation

In Chapter 3, we classified users of the social cataloging service into two groups, i.e., connected users and isolated users, and analyzed the characteristics of them. As a result, even though many connected users have reciprocal links, communications between them and sharing each other's interests are less. On the other hand, isolated users have as much activeness as connected users, even though they are not related to other users. That is, users pay more attention to expressing their experience of items than social features. However, the lack of explicit connections between users does not imply complete isolation from social cataloging services. There is also an implicit connection centered on individual feedback as well as an explicit connection that the relationships and the communications among the users. Such implicit connections may convey the user's subjective experiences on items, which may affect the user's future item selection.

Supporting the user to choose the appropriate items for his/her preference is the issue of the social cataloging services. Because the overload of information and data hinders the user's efficient choice. In this section, we suggests a recommendation method for users of the social cataloging service. Since both connected and isolated users prioritize the activities for items, we suggest a recommendation technique using a three-order tensor modeling a weighting scheme that derives the user's emotions reflected in the tag, which is the user's subjective feedback.

4.1 Motivation

Numerous contents appear every day. Thousands of movies are made, and more than one million books are published worldwide in a year. While consuming various contents, people can link the content their own experiences and feelings, and they can interact with others about their interests through various social media. The social cataloging services, such as Goodreads[1], LibraryThing[2], and Movielens[3], allow users to catalog items and share their opinions on them with others through ratings, tags, and reviews. These services usually deal with time consuming content such as books and movies. They provide only meta-data or a fraction of the actual item such as sample teasers or chapters rather than providing the item itself. Thus, users are more likely to choose items that they want to con-

[1]http://www.goodreads.com
[2]http://www.librarything.com
[3]http://movielens.org

sume carefully based on their personal taste by referring to the estimation of other users.

The inundation of content causes users in social cataloging services to have difficulty in selecting items among plenty of information. Recommendation systems have been proposed to solve the problem, and various recommendation techniques have been studied [69, 84]. Collaborative filtering is the most widely used recommendation method based on user's past behavior. Since the purpose of the recommendation system is to provide the appropriate information to users and improve their gratification, it is necessary to pay attention to the subjective feedback of the user in addition to the information about the item. Conventional recommendation systems have utilized rating data as user's explicit feedback on items. Unlike rating, tagging data does not explicitly indicate the user's preference for the item, but it contains additional information about the user's experience since the user directly inputs the tag. Especially, a tag that reflects an individual's subjective opinion contains positive or negative valence or certain feeling; it become a cue for understanding how a user considers an item. Therefore, the utilization of tagging data for recommendation can support the user experience and complement the existing rating information, thereby providing the possibility of improving the recommendation performance. In this paper, a tag that reflects user's emotion will be called an *emotion tag*.

The user's emotions play an important role in selecting and consuming items. According to the research of [65], the emotions obtained from the action immediately before consuming the item affect the user's selection of a new item, and during consumption, the emotion changes with the passage of time. After the consumption, the emotion affects the user's next action; it can be very useful to measure the user's satisfaction with the item. In the social cataloging system, a consideration of the emotion factors can increase the accuracy of the recommendation system, since rating and tagging items can be viewed as a behavior reflecting this post-consumption feeling.

A user's rating means an overall estimation, i.e., an item is positive or negative, and the tags are a detailed and additional reason of the rating. Therefore, emotion tags can be interpreted differently depending on which valence is used. If the same tag is assigned to the different items, it can be understood as positive, negative, or sarcastic meaning depending on whether the user uses the tag to the item with the high rating or with the low rating. For example, "funny" means "peculiar" as well as "humorous". Therefore, it is necessary to consider the intention of the user in the tag for a better understanding of the user's preference.

In this chapter, we propose a tag-based item recommendation approach considering the emotions contained in tags. To calculate the tag weight, we first normalize the rating data and assign the value to each tag to consider the user's overall assessment of the item. Then, we obtain the emotion value of the emotion tags based on SenticNet [74], which is the emotion lexical resource, and arrange the tag weight using the emotion value. In this process, the weight of the same tag can be changed according to the positive or negative valence of the item.

In general, the ternary relationships of users, items, and tags are described by the tripartite graph; however, it cannot reflect the ternary association, but only three pairs of relationship, i.e., user-item, user-tag, and item-tag. Therefore, we model the relationship of users, items, and tags as a three-order tensor, which is a multi-dimensional matrix, and use a High-Order Singular Vector Decomposition (HOSVD) [54] as a tensor factorization approach to recommend the appropriate items for each user. The previous research has mainly used the existence of tags as the initial element of a tensor, but we utilized the tag weight based on the emotion as the initial value to provide enriched information of the ternary relationship. We evaluate the performance of the proposed method using Movielens data, which is a social movie cataloging service, and showed that considering the emotions of tags improve the recommendation quality.

4.2 Weighting of Tags

4.2.1 Rating Based Tag Weight

User's decisions always reflect emotion [60]. When a rating and tags are assigned to an item, tags play a role in supporting rating except when used for personal classification and retrieval as an organizational tag. We assume that the rating is the result of condensing the user's feelings about the item so that the tag has a positive or negative valence based on the rating. The rating-based tag weight based on the rating is calculated as follows:

$$weight_{base}(t_{u,i}) = \begin{cases} r_{u,i}(t) & if\ r_{u,i} \neq \emptyset \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

where $r_{u,i}$ is the rating which a user u assigned to an item i, and $r_{u,i}(t)$ is the normalized rating value for a tag t used by the user u in the item i. If the original rating is used as the tag weight, a bias may occur because the range of the rating given to the item varies depending on the user. For instance, Some users may only give a score close to five for items, and others may score a score between one to three (Figure 4.1). Thus, we vectorize each user's ratings and normalize them into a unit vector. $r_{u,i}(t)$ is described as follows:

$$r_{u,i}(t) = \frac{r_{u,i}}{\sqrt{\sum_{i=1}^{|I|} r_{u,i}^2}} \quad (5)$$

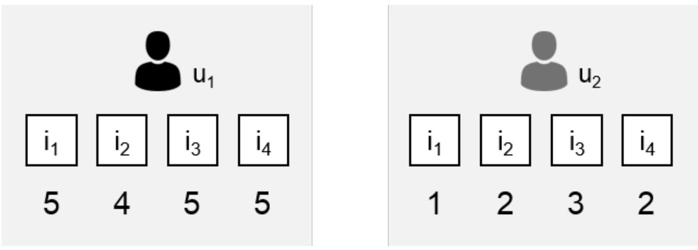


Figure 4.1 An example of the different range of the user ratings.

4.2.2 Emotion Based Tag Weight

Emotion tags contain the more detailed intensity of polarity than the rating; the local weight of each tag use the emotion value of each tag. To obtain the value, the following steps are executed for each tag t:

(1) A special character removal. Remove the special characters contained in the tag. (e.g., awesome!)

(2) A proper noun removal. Proper nouns can be used as tags, and they may contain the emotion words (e.g., Jennifer Love Hewitt, Barnes & Noble). In this case, the words do not affect the emotion of the tag; thus, those tags are removed.

(3) Calculating local weight of tag. We use the emotion dictionary to calculate $weight_{emotion}(t_{u,i})$.

   i. If the tag exists in the emotion dictionary, the emotion value of the tag is used as the tag weight.

$$weight_{emotion}(t_{u,i}) = EmotionScore(t_{u,i}) \tag{6}$$

   where $EmotionScore(t)$ gives the emotion value of tag $t_{u,i}$ in the range from -1 to 1 if the tag is included in the emotion dictionary, otherwise the value is 0.

   ii. If the tag does not exist in the emotion dictionary and is composed of more than two words, the weight is calculated in units of words.

a. Tokenizing. If the tag is composed of two or more words (e.g., great performance, this book is good), tokenize it in units of words.

b. Lemmatizing and stemming. Each word appears in the form of a root word.

c. Calculating local weight of tag. The weight of the tag is calculated based on the emotion value of each word which comprise the tag:

$$weight_{emotion}(t_{u,i}) = \frac{1}{|term_{emotion}|} \sum_{j=1}^{|term|} EmotionScore(term_j) \quad (7)$$

where a $term$ is the word which is consist of a tag t, $|term|$ is the number of words in the tag, $|term_{emotion}|$ is the number of the emotion words.

If no emotion value is finally obtained through step 3, the local weight of tag becomes 0.

4.2.3 Overall Tag Weight

The total weight of each tag $weight(t_{u,i})$ is calculated by combining the rating-based weight and the emotion tag-based weight as follows:

$$weight(t_{u,i}) = (1 - \alpha) \times weight_{base}(t_{u,i}) + \alpha \times (weight_{emotion}(t_{u,i}) \times 0.5) \quad (8)$$

where α is the parameter to control the influence of the emotion of the tag. The range of $weight(t_{u,i})$ adjusted from (-1, 1) to (-0.5, 0.5) so that the

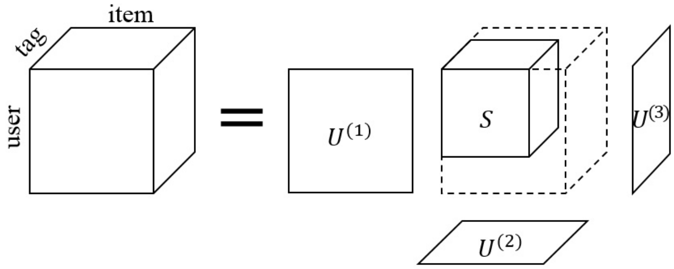


Figure 4.2 The illustration of HOSVD.

width of the range became similar to $weight_{base}(t_{u,i})$ while maintaining the polarity. The appropriate value of α is selected empirically. If the tag has no emotion value, only the rating-based weight is used to calculate the total weight (α = 0).

If the user tagged an item with several tags, the average weight of the tags is used as the weight of each tag of the item.

$$weight(t_{u,i}) = \frac{1}{|t_{u,i}|} \sum_{k=1}^{|t_{u,i}|} weight(t_{u,i}^{k}) \tag{9}$$

where $t_{u,i}^{k}$ is the k^{th} tag that user u assigned to item i.

4.3 Tensor Factorization

Tensor factorization is the recommendation technique which deals with the multidimensional data. In this paper, we applied HOSVD [54] to exploit the latent relationships among objects. HOSVD is one of the tensor factorization methods that applied SVD to a tensor which is a n-dimensional matrix. We model the ternary relationship among users, items, and tags with three-order tensor and apply HOSVD obtain the reconstructed tensor. The list of the recommended items is generated according to the latent associations in the reconstructed tensor. Figure 4.2 illustrates HOSVD, and Figure 4.3 depicts the process of HOSVD. We briefly introduce the technique.

4.3.1 High Order Singular Value Decomposition

An initial three-order tensor $\mathcal{A} \in \mathcal{R}^{|U|\times|I|\times|T|}$ is constructed, where $|U|, |I|, and|T|$ are the number of users, items, and tags, respectively. Then, tensor $\mathcal{A}$ is unfolded for all n modes. Through the unfolding process, the tensor is transformed to 2D matrices. Three new matrices A_1, A_2, and A_3 are created as follows:

$$\begin{aligned} A_1 &\in \mathcal{R}^{I_u \times I_i I_t} \\ A_2 &\in \mathcal{R}^{I_i \times I_t I_u} \\ A_3 &\in \mathcal{R}^{I_u I_i \times I_t} \end{aligned} \tag{10}$$

where I_u, I_i and I_t are the tensor dimensions. Next, SVD is applied to each of the three unfolded matrices.

$$\begin{aligned} A_1 &= U^{(1)} \cdot S_1 \cdot V_1^T \\ A_2 &= U^{(2)} \cdot S_2 \cdot V_2^T \\ A_3 &= U^{(3)} \cdot S_3 \cdot V_3^T \end{aligned} \tag{11}$$

Using the initial tensor $\mathcal{A}$ and the left singular vectors of the unfolded

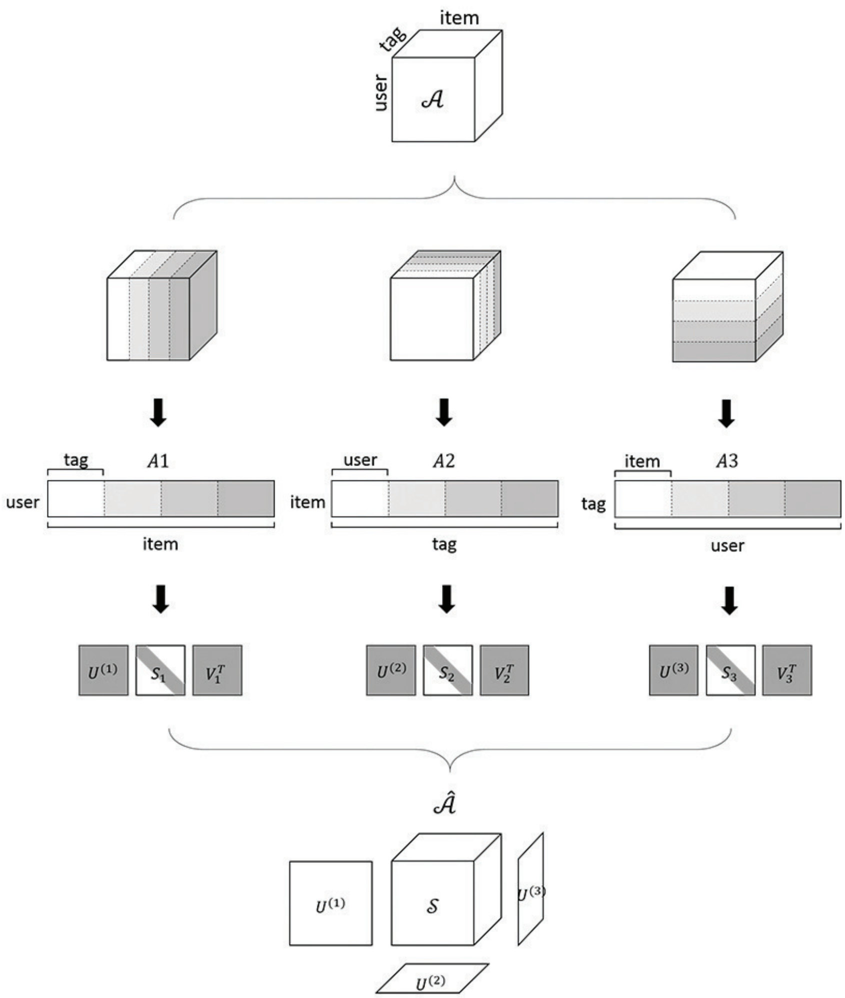


Figure 4.3 The process of HOSVD.

matrices, a core tensor $\mathcal{S}$ is constructed, which contains the ternary association between user, item, and tag. To filter out the small singular values, the parameter c_i, which is the number of dimensions to truncate for i-mode, is selected.

$$\mathcal{S} = \mathcal{A} \times_1 U_{c_1}^{(1)^T} \times_2 U_{c_2}^{(2)^T} \times_3 U_{c_3}^{(3)^T} \tag{12}$$

Finally, a reconstructed tensor $\hat{\mathcal{A}}$ is computed, which is an approximation tensor of $\mathcal{A}$, with a core tensor $\mathcal{S}$. The reconstructed tensor has new entries as well as original entries.

$$\hat{\mathcal{A}} = \mathcal{S} \times_1 U_{c_1}^{(1)} \times_2 U_{c_2}^{(2)} \times_3 U_{c_3}^{(3)} \tag{13}$$

The algorithm for the item recommendation by considering the emotions in the users' tags and the tensor factorization technique is described in Algorithm 1.

4.4 A Running Example

To facilitate the understanding of our approach, let us consider the following example. Suppose users assign ratings and tags to movies as shown in Table 4.1. In this running example, we assume that t_1 ="brave", t_2 = "disgusting", t_3 = "humanity", and t_4 = "funny", and each emotion value on the emotion dictionary is $t_1 = 0.306$, $t_2 = -0.41$, $t_3 = 0.105$, and $t_4 = 0.619$.

The usage data is modeled as a three-order tensor $\mathcal{A} \in \mathcal{R}^{3\times5\times4}$ and each activity has a weight. The weight is calculated by user's rating and the emotion value of each tag. Firstly, the rating-based weights for user u's tags $weight_{base}(t_{u,i})$ are calculated by the Equation (5). In the case of u_1, the

Algorithm 1: Emotion based item recommendation algorithm.

Input : a set of user profiles $P \in Y$
Output: a set of recommended item list for each user
for *each tag* **do**
  for *each term* $\in$ *tag* **do**
    if *term* $\neq$ *proper noun* **then**
      $score+ = EmotionScore(term)$
    end
  end
  $weight_{emotion}(tag) = score/|term|$
end
$L \leftarrow \emptyset$
for *each user* **do**
  $weight_{base}(tag) = r_{u,i}(tag)$
  if *item has multiple tags* **then**
    $weight_{emotion}(tag_{item}) =$ *average value of those tags*
  end
  $weight = (1 - \alpha) \times weight_{base}(tag) + \alpha \times weight_{emotion}(tag)$
  $L \leftarrow < u, i, t, weight >$
end
$C \leftarrow \emptyset$
Construct tensor $\mathcal{A}$ with L
Apply decomposition technique to tensor $\mathcal{A}$
Reconstruct tensor and obtain $\hat{\mathcal{A}}$
for *each user* **do**
  $C \leftarrow$ top k items based on the weight in $\hat{\mathcal{A}}$
end
return C

Table 4.1 A usage data of the running example.

User	Movie	Tag	Rating
1	2	1	2
1	2	2	2
1	3	1	2
1	4	3	3
2	1	3	3
2	2	2	2
2	4	3	5
3	1	3	4
3	5	1	4
3	5	4	4

weights of tags are 0.436 for tag t_1 and t_2, and 0.654 for tag t_3. Secondly, the emotion tag based weight $weight_{emotion}(t_{u,i})$ is computed by the Equation (6) or (7) if the emotion dictionary includes the tag or the terms comprising the tag. Finally, the overall tag weights are calculated by combining both weights based on Equation (8) and (9). For instance, if α is set to 0.2, the tag weight for $< u_1, m_2, t_1 >$ is calculated as $(0.8 \times 0.436) + 0.2 \times (0.306 \times 0.5) = 0.378$. Since u_1 tags m_2 with two tags, the final tag weight is 0.342, which is the average weight of t_1 (0.378) and t_2 (0.307). The final weight $weight(t_{u,i})$ is reported in Table 4.2.

After the tensor factorization process, we have the reconstructed tensor $\hat{\mathcal{A}}$ and new entries are generated as described in Table 4.3. These entries become the candidate for the recommendation.

Table 4.2 An initial tensor $\mathcal{A}$. The parameter α for calculating the overall weight is set to 0.07.

User	Movie	Tag	$weight(t_{u,i})$ for $\mathcal{A}$
1	2	1	0.342
1	2	2	0.342
1	3	1	0.378
1	4	3	0.533
2	1	3	0.398
2	2	2	0.218
2	4	3	0.658
3	1	3	0.471
3	5	1	0.506
3	5	4	0.506

Table 4.3 A reconstructed tensor $\hat{\mathcal{A}}$ from the usage data. New entries are generated as highlighted.

User	Movie	Tag	$weight(t_{u,i})$ for $\hat{\mathcal{A}}$
1	**1**	**3**	**0.11**
1	2	1	0.24
1	2	2	0.22
1	3	1	0.14
1	4	3	0.62
2	1	3	0.28
2	2	2	0.19
2	**3**	**1**	**0.12**
2	**3**	**2**	**0.11**
2	4	3	0.57
3	1	3	0.51
3	5	1	0.51
3	5	4	0.43

4.5 Experimental Evaluation

4.5.1 Dataset

We use the dataset of Movielens[4] to evaluate the performance of the proposed approach. Movielens is a social movie cataloging service, which allows users to rate and tag movies. The dataset has 71,567 users, 10,681 movies, 10,000,054 rating history, and 95,580 tagging histories. There are 15,230 distinct tags, and 4,009 users use tags at least once. On average, each user rates 143 movies and has 10 distinct tags. Among the users who have tagging history, 40% of the users use only one tag. Table 4.4 summarizes our dataset.

Table 4.4 The summary of Movielens dataset.

Original dataset	
the number of users	71,567
the number of movies	10,681
the number of rating histories	10,000,054
the number of tagging histories	95,580
the number of distinct tags	15,230
the number of distinct tagging users	4,009
Reduced dataset	
the number of users	210
the number of movies	544
the number of tags	365

Figure 4.4 illustrates the characteristics of our dataset. Figure 4.4(a)-(d) show the distribution of the number of distinct tags user has, the number of movies user rated, the number of rating histories user has, and the number

[4]https://grouplens.org/datasets/movielens/

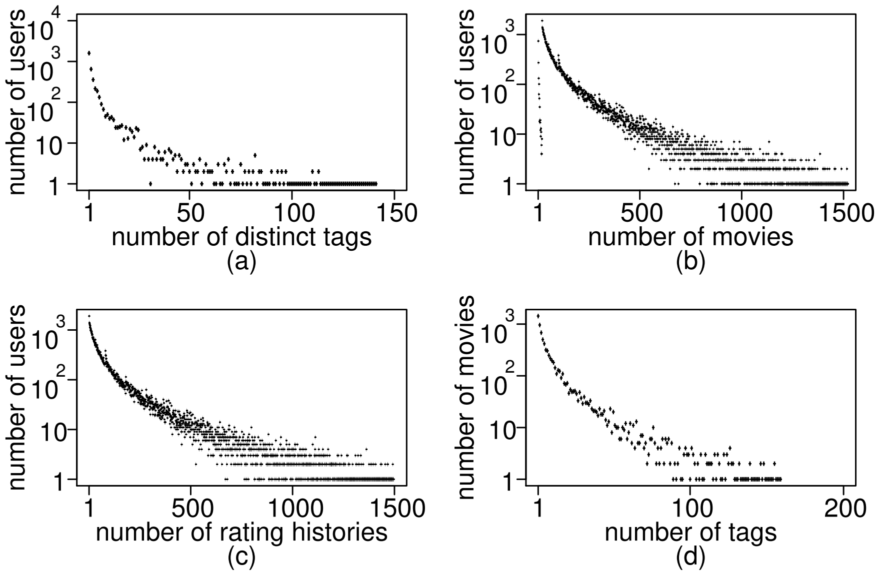


Figure 4.4 The distribution of the dataset: (a) the distribution of the number of users over the number of used distinct tags, (b) the distribution of the movies user rated, (c) the distribution of the number of rating histories user has, and (d) the distribution of the number of tags per movie.

of tags per movie, respectively. There are very few active users who rate many movies, especially those who use tags. The users have 10 distinct tags and 140 movies on average. 75% of the users have less than equal to 5 tags, and most of the users have more than 10 movies. The movies has 9 tags on average, with a maximum of 139. 95% of the users assign less than equal to 2 tags on a movie.

We limited the data for the experiment to users and movies with tagging history regardless of whether the rating exists or not. In order to obtain the dense data, we applied *p*-core [85] at level *k* to the dataset, which means that each user, item, and tag occurred at least *k* times; This process removes unfamiliar items and less frequently used tags. We applied k = 5, and finally 210 users, 544 movies, and 365 tags are used.

For implementing our approach, we used a list of actors, directors, writers, and producers provided by IMDB[5] for eliminating proper nouns and Natural Language Toolkit (NLTK) [86] for tag processing. As the emotion dictionary, SenticNet 4.0 [74] was utilized. For the data reduction process of HOSVD, we preserve 80% of the information in the original diagonal matrix S_i $(1 \leq i \leq 3)$.

4.5.2 Experimental Results

The dataset is divided into five subsets for 5-fold cross validation. For each fold, we selected 80% of each user's history as the training set and the remaining 20% as the test set. The ratio between the emotion tag and the un-emotional tag, which is called the *ordinary tag*, in each training set is reported in Table 4.5. In all training sets, the emotion tag accounted for more than 50%; namely, it seems meaningful to reflect the emotion tags that each user expressed the feelings of each movie with various intensities to the recommendation.

We conducted the experimental evaluation to find an appropriate value of the parameter α. Figure 4.5 shows the average f1-score according to the change of α value between 0.1 and 1.0 when n movies (n = 1, 2, 3, 4, 5, 10, 15, 20, 25, 30) are recommended. When α is 0.2, we had the best result on the dataset. The parameter for controlling the emotion tag-based weight is

[5] http://www.imdb.com

Table 4.5 The ratios between the emotion tag and the ordinary tag in each training set.

Set	Emotion Tag	Ordinary Tag
1	52.25%	47.75%
2	50.14%	49.86%
3	50.84%	49.16%
4	51.16%	48.84%
5	50.57%	49.43%

assigned the small value so that the rating-based weight of the tag does not change significantly when both weights are combined. The significant change in the rating-based weight means a change in the rating given by the user, and also a change in user's the overall impression of the item. The control parameter α is set to 0.2 for the rest of our experiments.

Next, we conducted the experiment for the performance analysis. To compare the performance, we consider the following methods:

- Baseline. The previous research [56] set the weight based on the existence of the tag. If user u tagged item i with tag t, the weight is 1.

$$weight(t_{u,i}) = \begin{cases} 1 & if < u, m, t > \in Y \\ 0 & \text{otherwise} \end{cases} \quad (14)$$

- Rating-based only (Rate). Regardless of the type of the tags, user's rating based weight $weight_{base}(t_{u,i})$ is used as the tag weight.

$$weight(t_{u,i}) = weight_{base}(t_{u,i}) \quad (15)$$

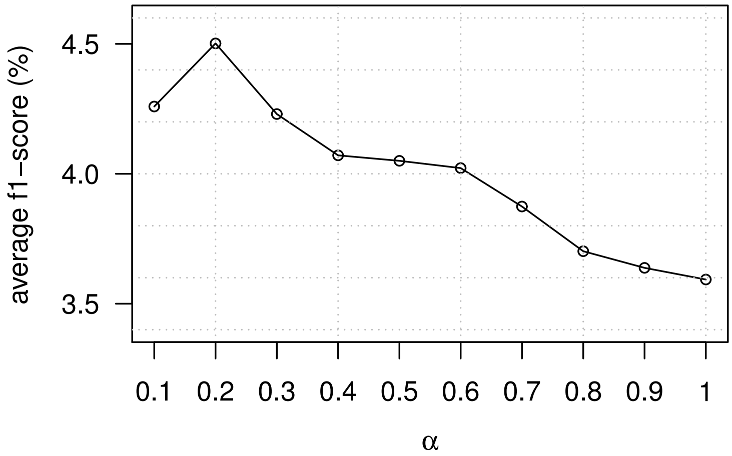


Figure 4.5 The average f1-score according to the change of α when n movies are recommended.

- Emotion Tag-based only (ET). The tag weight is calculated based only on the emotion tags, excluding the user's rating. In this case, if the weight of a tag which is not included in the emotion dictionary is assigned 0, the ternary relationship is regarded as non-existence; 0 means that the user did not attach the tag to the movie. In order to solve this problem, the range of $weight_{emotion}(t_{u,i})$ was adjusted from (-1, 1) to (0, 2).

  The emotion value of each tag cannot be regarded as a general preference for the movie. Therefore, if a movie is tagged with multiple tags, the average of the tag weights is given to each tag as the weight. The

$weight(t_{u,i})$ is calculated as follows:

$$weight(t_{u,i}) = \frac{1}{|t_{u,m}|} \sum_{j=1}^{|t_{u,m}|} (weight_{emotion}(t_j) + 1) \qquad (16)$$

where $|t_{u,m}|$ is the number of tags attached at a movie m by a user u.

The proposed approach was compared with the methods in top-n movie recommendations. As the measures for evaluating the results, the precision, recall, and f1-score were used.

$$Precision = \frac{\textit{the number of correct positive predictions}}{\textit{the number of positive predictions}} \qquad (17)$$

$$Recall = \frac{\textit{the number of correct positive predictions}}{\textit{the number of positive examples}} \qquad (18)$$

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \qquad (19)$$

The results are shown in Figures 4.6, 4.7, and 4.8: the precision, recall, and f1-score of four approaches respectively. The x-axis of each graph represents the number of recommended movies, and the y-axis represents the values of precision, recall, and f1-score, respectively. The results indicate that the recommendation method considering user's emotions shows better performance. Among them, we find that the approach considering the detailed emotions with overall valence (Rate+ET) is generally better than the other methods. In comparison with the rating-based method, the approach using both the rating-based and the emotion tag-based weight shows the better results as n is increased. It implies that reflecting the users' subjective emotion for the items enables a better understanding of the users' preferences. In the case of the method utilizing only the emotion tag, the performance is degraded as compared with the other methods. This is because not all the user's tags are in the emotion tag category, and tags express what the user felt with only a few keywords; thus, even if the average of the emotional values of all the tags attached to a movie are utilized as the tag weight, it may not represent the user's overall satisfaction and preference. All the differences in the results are statistically significant with $p < 0.05$.

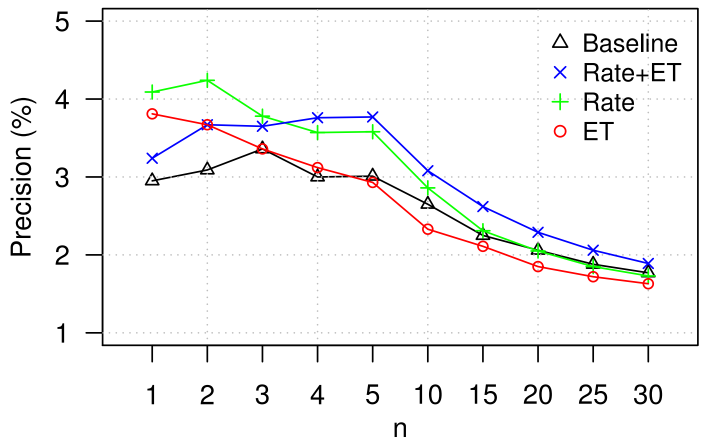


Figure 4.6 The comparisons of precision as the number of recommended item increases.

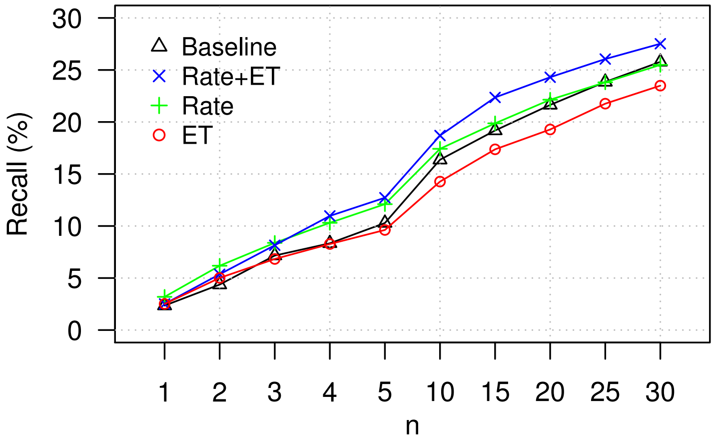


Figure 4.7 The comparisons of recall as the number of recommended item increases.

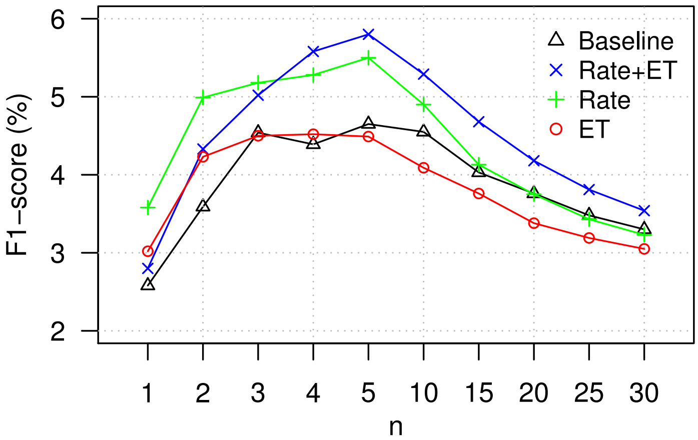


Figure 4.8 The comparisons of f1-score as the number of recommended item increases.

We also investigated how the multiple tags on the same item are handled during the calculation of the tag weight. In the proposed approach, if there is more than one tag on the item, the average value of the tags is used as the weight of each tag (Equation (9)). However, if an item has multiple tags, there are two ways to compute the weight of the tags. One is to use the weight of each tag as it is, and the other is to give the average weight of the tags attached to the item as explained in the proposed method.

Figure 4.9 indicates the average f1-score according to the change of α value when n movies are recommended by calculating tag weights in the two ways. The solid line is for the case of using the average value, and the dotted line is for the case of using each weight of the tags. When the average value is given as the weight of the tags on the same movie, the performance is better than using each weight of the tag. Figure 4.10 describes the difference in the results depending on how multiple tags in the movie are handled when the tag weights are computed based only on the emotion tag based method. What the solid and dotted lines mean is the same as in Figure 4.9. In this case, using the average value as the weight of tags shows better performance because using respective weights can reflect the various emotions that user expresses about the movie but cannot adopt the general preference deriving from the tags.

When a user tags a movie, positive and negative tags can be used together to describe a detailed emotion for the movie; it can also affects the way to handling of multiple tags. It indicates that using the average value as the weight of multiple tags can help to reflect the user's overall prefer-

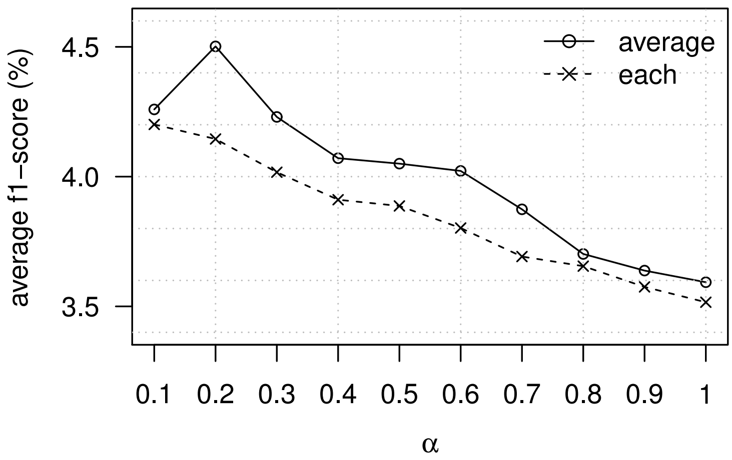


Figure 4.9 When a movie has the multiple tags, the difference of f1-score between using an average value of the tags and using each value of the tags as the weight of each tag.

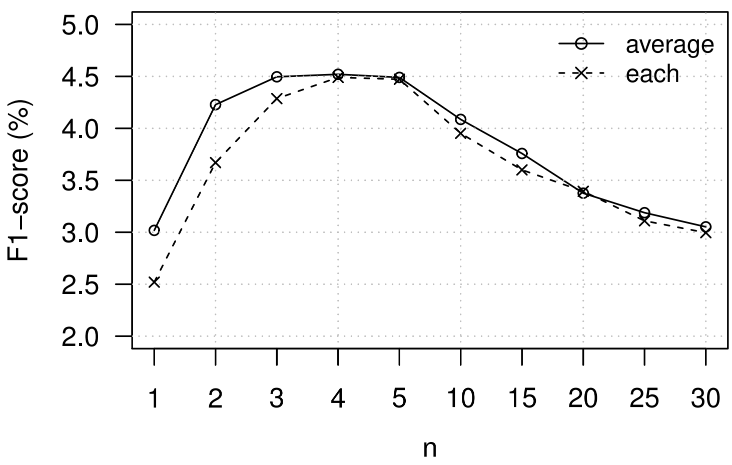


Figure 4.10 When a movie has the multiple tags and tag weights are computed based on the emotion tag based method, the difference of f1-score between using an average value of the tags and using each value of the tags as the weight of each tag.

ence for the movie.

4.6 Summary

Users in social cataloging services catalog items and share their experiences with others. Overloading of various contents causes users to have difficulty in selecting items. The recommendation system reduces the problem of the selection by recommending the item considering the behavior of the user and the characteristics of the contents.

In this study, we propose a tag-based recommendation method considering the emotions reflected in the user's tags. The user's estimation of the item is made after consuming the item; thus, the user's emotions are reflected directly, and they can play an important role in the recommendation system. The rating has an overall positive or negative valence for the item, and the tag is the detailed reason for the estimation. Therefore, when user rated and tagged an item, we utilize the rating of the item as the basic feeling of the tag and adjust the tag weight with the unique emotion value of the tag based on SenticNet, which is the emotion dictionary.

To solve the problem that ternary relationships of users, items, and tags are mapped to the three two-dimensional relations and cannot reflect the association of three entities, we express the ternary relationships as a three-order tensor and apply HOSVD, which is one of the tensor factorization methods, to the tensor. The proposed recommendation method is compared with the cases where the weight of the tag is calculated only by rating, only with the emotion value of the tag, and by the tag's existence.

The result indicates that our approach improves the recommendation performance.

Chapter 5

Improving Item Recommendation using Probabilistic Ranking

5.1 Motivation

In Chapter 4, we proposed a recommendation method considering the emotions contained in the tag based on the tensor modeling. Users in social communities use tags for a small number of items; thus, the tensor is highly sparse. To recommend an item to a user, the tensor is factorized and reconstructed. The obtained value is assumed as the users' preference for the item based on the tags, and the items are selected according to the value [56, 53, 87]. However, this approach has the problem that the user's past behaviors do not considered [58].

In this chapter, we propose a recommendation method to deal with the problems and improve the performance of recommendation based on our previous research. To reduce the sparsity of the tensor, we predict new entries applying collaborative filtering and add items to the dataset. In order to improve the quality of the recommendation, we use BM25 weighting scheme [88], a well - known document ranking method, to create a tag-based user and item profile and rank the candidates. The proposed algorithm is evaluated using the Movielens dataset.

5.2 Generating the additional data

The recommendation methods based on the user's previous activities have a common problem of sparsity [39]. This is because the number of items that the users actually rates and tags is less than the number of entire items. In this study, we make an additional data to reduce the sparsity of the dataset using item-based collaborative filtering [89]. The item-based filtering measures the similarity between items by comparing the ratings of the users and predicts the rating of the target item by computing a weighted average of the ratings of the similar items.

First, for the items tagged with tag t, the items are divided into two groups: the items tagged by the target user u and the items annotated by other users. The similarity between two groups is computed and find the most similar k items with the group of items tagged by u. There are several similarity measures: Pearson correlation, cosine similarity, and adjusted cosine similarity. In this research, adjusted cosine similarity measure is used to consider the difference in each user's rating scale.

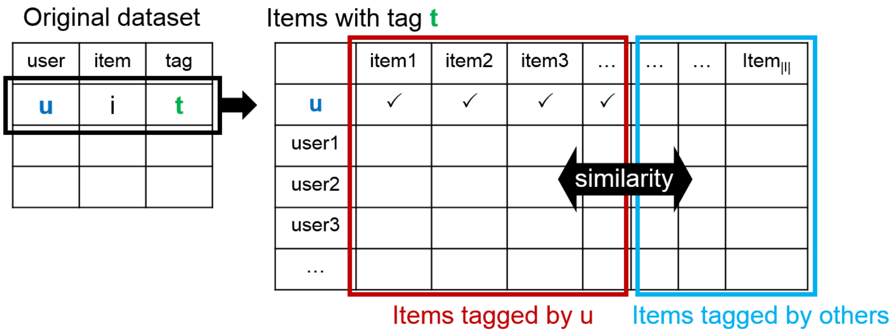


Figure 5.1 Finding the similar items for each user-tag pair.

$$sim(i_a, i_b) = \frac{\sum_{u \in U}(r_{u,i_a} - \overline{r}_u) \cdot (r_{u,i_b} - \overline{r}_u)}{\sqrt{\sum_{u \in U}(r_{u,i_a} - \overline{r}_u)^2} \cdot \sqrt{\sum_{u \in U}(r_{u,i_b} - \overline{r}_u)^2}} \tag{20}$$

where r_{u,i_a} and $r_{u,ib}$ are the ratings of the item i_a and i_b given by u. $\overline{r}_u$ is the average rating of u.

In order to calculate the tag weights as described in Section 4.2, not only the tags, but also the rating of each item is required. Thus, we predict the ratings for k items which are most similar to the target item. The weighted average of the ratings of k similar items for the predicted rating of target item is computed as follows:

$$r_{u,i} = \frac{\sum_{j \in I} sim(i,j) \cdot r_{u,j}}{\sum_{i \in I} sim(i,j)} \tag{21}$$

The additional data obtained by the item-based filtering is combined with the existing user data to reduce the sparsity of the tensor.

5.3 BM25 based candidate ranking

In general, the candidates for the recommendation as the result of the tensor factorization and reconstruction are sorted by the final value in the tensor, and top k items are recommended to the user. Ifada et al. [58] argued that this approach does not consider the user's past tagging behavior. The basic idea under the latent factor model is that a user's selection for an item is controlled by a few factors [90]. The user's preferences are explained by characterizing the user profiles and the patterns of items the user have consumed in the past, for example, genres, actors, or gender. In this paper, we use Okapi BM25 [88], which is a well-known ranking model for document retrieval, to make the tag-based user and item profile and rank the result of the reconstructed tensor $\hat{A}$ based on the similarity of the profiles. The BM25 is usually used in a search engine to calculate the relevance between a query and a document, and rank the results. It utilizes TF-IDF and consider the length of the document. The basic weighting scheme of BM25 to calculate the score between a query Q and a document D is as follows:

$$score(Q,D) = \sum_{term \in Q} log \frac{N}{df_{term}} \cdot \frac{tf_{term,d} \cdot (k_1 + 1)}{tf_{term,d} + k_1 \cdot (1 - b + b \cdot \frac{L_d}{L_{avg}})} \tag{22}$$

where L_d is the length of d and L_{avg} is the average length of all documents.

The larger the value of k, the higher the weight of the term frequency, and the closer b is to 1, the more weight is placed on the length of the document. The standard values of k_1 and b are 2 and 0.75, respectively.

In the studies of [91] and [92], the researchers applied BM25 to the folksonomy in order to improve the performance of the personalized search. We adopted the method to our research to create user and item profiles. When user u_l annotates item i_m with tag t_p, the user profile based on the user's previous tagging activities is calculated as follows:

$$score(u_l, t_p) = iuf(t_p) \cdot \frac{tf(u_l, t_p) \cdot (k_1 + 1)}{tf(u_l, t_p) + k_1 \cdot \left(1 - b + b \cdot \frac{N_{u_l,t}}{avg(N_{u,t})}\right)} \tag{23}$$

where $tf(u_l, t_p)$ is the tag frequency and $iuf(t_p)$ is the user-based inverse tag frequency. $N_{u_l,t}$ and $avg(N_{u_l,t})$ are the total number of the tagging activities of u_l and the average number of the entire users' tagging activities, respectively. The user-based tag frequency and the inverse tag frequency are computed as follows:

$$tf(u_l, t_p) = \frac{N_{u_l,t_p}}{N_{u_l,t}} \tag{24}$$

$$iuf(t_p) = log\frac{|U|}{N_{u,t_p}} \tag{25}$$

The item profile based on the tags attached to the item is calculated as follows:

$$score(i_m, t_p) = iif(t_p) \cdot \frac{tf(i_m, t_p) \cdot (k_1 + 1)}{tf(i_m, t_p) + k_1 \cdot \left(1 - b + b \cdot \frac{N_{i_m,t}}{avg(N_{i,t})}\right)} \tag{26}$$

where $tf(i_m, t_p)$ and $iif(t_p)$ are the item-based tag frequency and the inverse tag frequency, respectively. $N_{i_m,t}$ is the number of tags annotated to i_m and $avg(N_{i,t})$ is the average number of the tags assigned to all items. The item-based tag frequency and the inverse tag frequency are computed as follows:

$$tf(i_m, t_p) = \frac{N_{i_m,t_p}}{N_{i_m,t}} \tag{27}$$

$$iuf(t_p) = log\frac{|I|}{N_{i,t_p}} \tag{28}$$

The user and item profile are generated not by the reconstructed tensor, but the initial tensor. For ranking the result of the reconstructed tensor obtained by applying HOSVD to the initial tensor, the similarity between the user profile and the item profile is computed. We adopted the BM25-based cosine similarity proposed by [92].

$$sim(u_l, i_c) = \frac{\sum_{t \in T}(score(u_l, t_p) \cdot score(i_c, t_p))}{\sqrt{\sum_{t \in T}(score(u_l, t_p))^2} \cdot \sqrt{\sum_{t \in T}(score(i_c, t_p))^2}} \tag{29}$$

where i_c is the candidate item in the reconstructed tensor.

5.4 Experimental Evaluation

5.4.1 Data addition

We conducted the experimental evaluation using Movielens dataset to find the appropriate number of the similar movies for generating the additional data. The top n movies (n = 1, 2, 3, 4, 5) are recommended while increasing the number of similar movies, k, for each user-tag pair.

The results are shown in Figures 5.2, 5.3, and 5.4: the precision, recall, and f1-score based on the change in k, respectively. The x-axis of each graph represents the number of recommended movies, and the y-axis represents the values of precision, recall, and f1-score, respectively. The results indicate that the smaller the value, the higher the performance. If we find the movies similar to the group of the movies annotated tag t by user u, the smaller the k value, the movies that are more similar to the group are selected. As the value of k increases, the additional data becomes diverse and may not be relevant with the original data. Exceptionally, when the user added the movie which is most similar to the group of the movies for u and t, the performance is better than the original dataset based recommendation regardless of the number of the recommended movies. Thus, we set k to 1 for the next experiment.

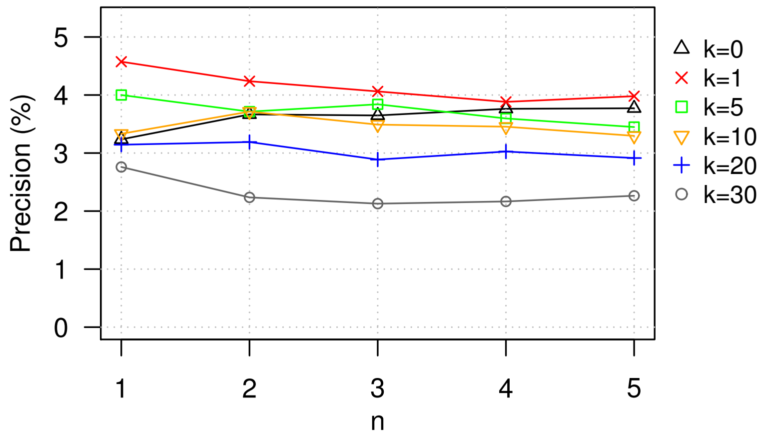


Figure 5.2 The comparisons of precision as the number of additional data increases.

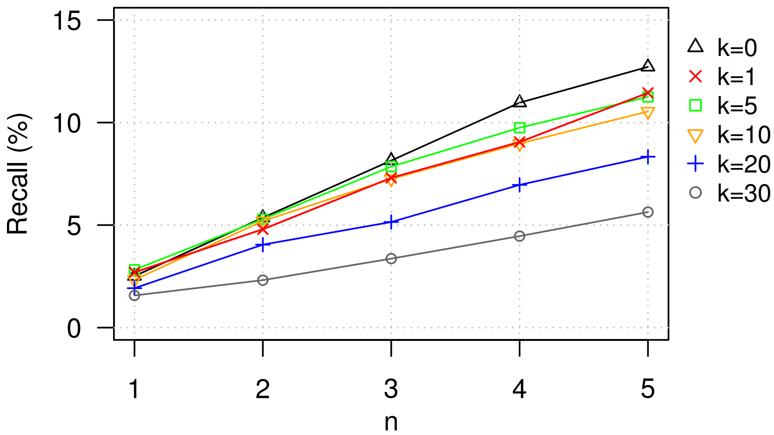


Figure 5.3 The comparisons of recall as the number of additional data increases.

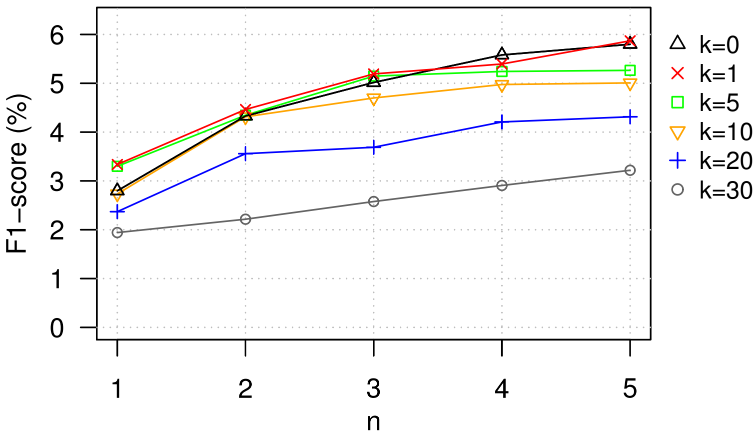


Figure 5.4 The comparisons of f1-score as the number of additional data increases.

5.4.2 Recommendation Performances

The task of the recommendation is to predict top n movies for the users. The performance of the method is measured by the precision, recall, and f1-score (Equation (17) - (19)).

Our research studied the performance of the proposed approach against the item-based collaborative filtering (CF) [89], the similarity fusion (SF) [93], which combines user-based collaborative filtering and item-based collaborative filtering by extending user-item matrix with user tags, SenticRank [68], which includes sentiment in tag-based user profile, the standard tensor-based recommendation (TF) [56] that the likeliness among users, items, and tags is used as the weight, and the tensor-based recommendation with the probabilistic ranking using Näive Bayes (Naive) [58].

Firstly, we measure the recommendation quality of our approach step by step: the tensor-based method using tag emotion based weight ("previous") [94], the data addition by item-based filtering ("data+"), and the candidate ranking using BM25 ("data+BM25"). The latter two methods are based on the tensor-based method considering tag emotion. The results are illustrated in Figure 5.5, 5.6, and 5.7: the precision, recall, and f1-score of the six approaches respectively. The x-axis of each graph represents the number of recommended movies, and the y-axis represents the values of precision, recall, and f1-score, respectively. The results describe that the expanding data is slightly increased the performance of the previous approach in Chapter 4. However, the re-ranking candidate approach outperforms the others. It infers that considering the user's previous activities is key to improve the recommendation performance.

Secondly, we examine the hypothesis that considering the ternary relationships among users, items, and tags are showed the better performance than considering the three pairs of relationship, i.e., user-item, item-tag, and user-tag. The proposed approach is compared with SF, and the results are depicted in Figure 5.8, 5.9, and 5.10. The proposed approach which is the emotion tag-based item recommendation with the data expansion and the candidate re-ranking shows the better performance than SF. It indicates that considering the ternary relationships concurrently can increase the recommendation quality. Also, the comparison with CF considering only user-item pairs is conducted, and the result confirms that the user's tags play an important role in improving the recommendation performance.

Thirdly, the proposed approach is examined against the previous research which is based on the tensor factorization: TF and Naive. Figure 5.11, 5.12, and 5.13 shows the results of the evaluations. As a result of comparing the method applying the probabilistic ranking algorithm to the result of HOSVD, BM25 shows better results than Bayes. This result reports that ranking considering the previous information of users and items after tensor reconstruction improves the recommendation performance.

Finally, we compared the proposed approach with SenticRank. In [68], the authors suggest two sentiment-based ranking methods for the personalized search in folksonomy: content-based sentiment rank and collaborative sentiment rank. We modified the content-based sentiment rank for our experiment; the calculation of the relevance score between query and resources is excluded.

$$\theta(u_i, r_a) = e^{Sim(\vec{u_i},\vec{r_a})+Sim(\vec{u_i^*},\vec{r_a^*})} \tag{30}$$

where Sim is the cosine similarity between two vectors, $\vec{u_i}$ is tag-based user profile, $\vec{r_a}$ is tag-based resource profile, $\vec{u_i^*}$ is sentiment-based user profile, and $\vec{r_a^*}$ is sentiment-based resource profile. To obtain sentiment-based profiles, the polarity of each tag is used.

The results are shown in Figure 5.14, 5.15, and 5.16. The f1-score shows that the performances of the two methods are similar in the small n, but the performance of the proposed method is improved. Compared with the approach proposed in Chapter 4 ("previous"), SenticRank performs better; it indicates that the re-ranking based on user and item profiles has an effect on improving the recommendation performance.

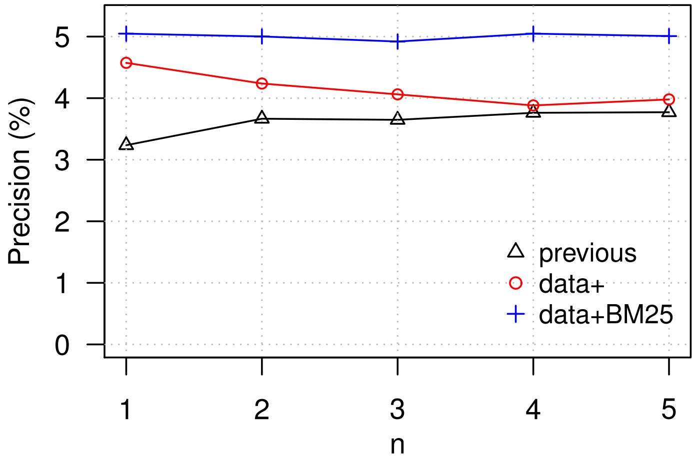


Figure 5.5 The comparisons of precision for the proposed approaches.

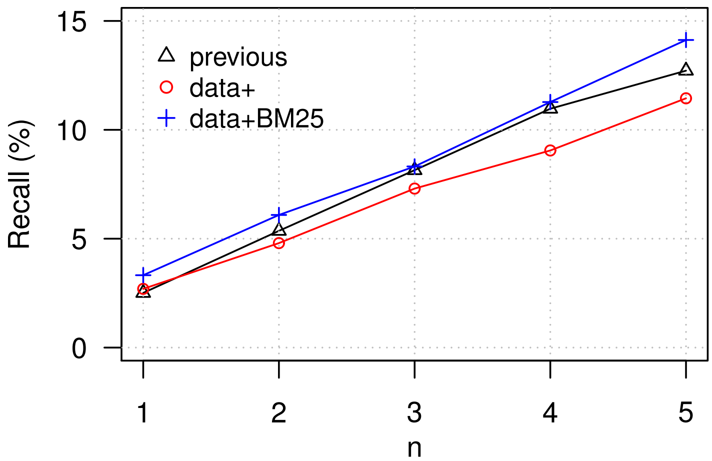


Figure 5.6 The comparisons of recall for the proposed approaches.

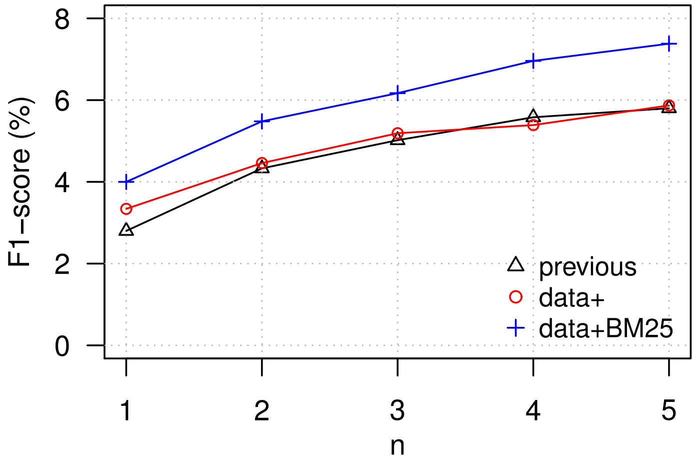


Figure 5.7 The comparisons of f1-score for the proposed approaches.

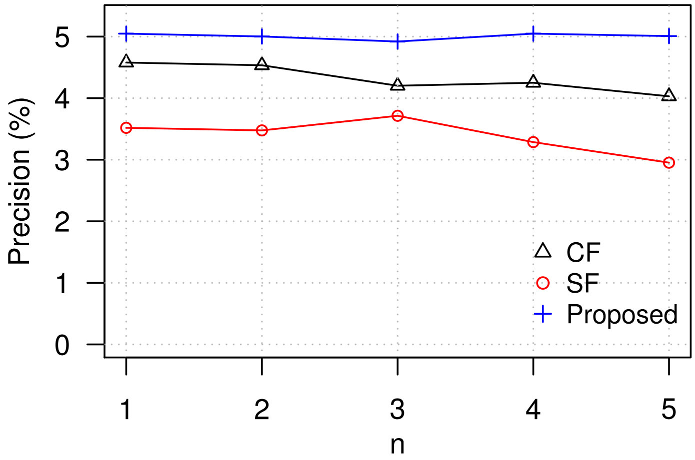


Figure 5.8 The comparisons of precision among the proposed approach, SF, and CF.

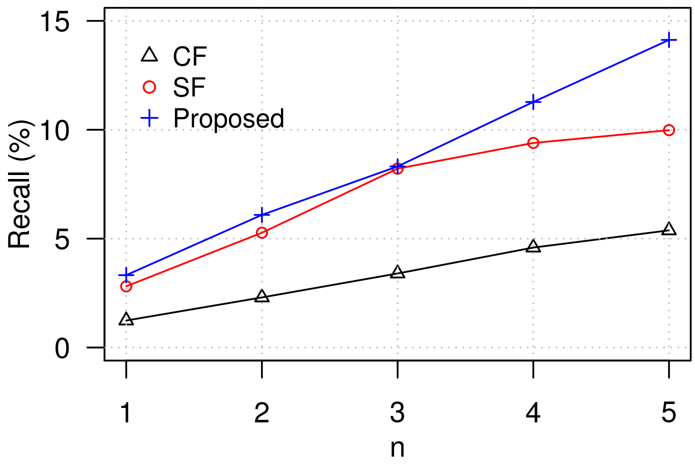


Figure 5.9 The comparisons of recall among the proposed approach, SF, and CF.

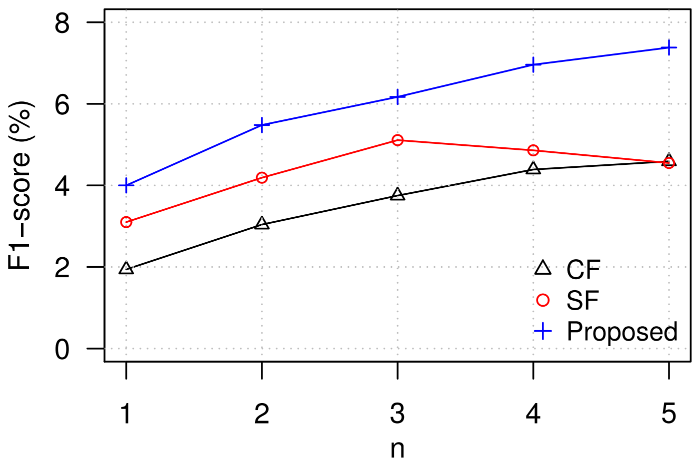


Figure 5.10 The comparisons of f1-score among the proposed approach, SF, and CF.

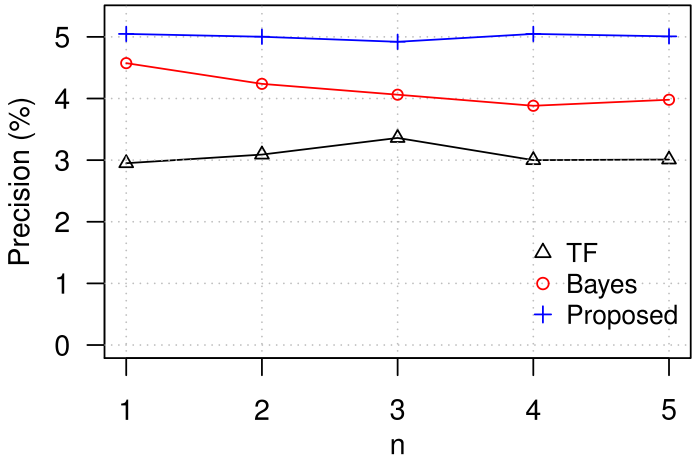


Figure 5.11 The comparisons of precision among the proposed approach, TF, and Bayes.

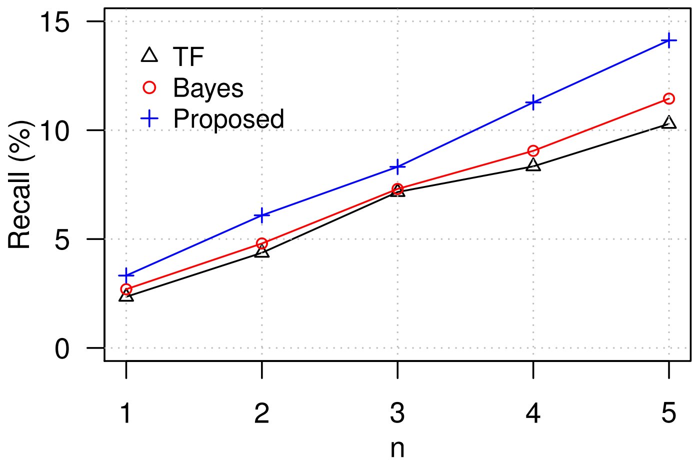


Figure 5.12 The comparisons of recall among the proposed approach, TF, and Bayes.

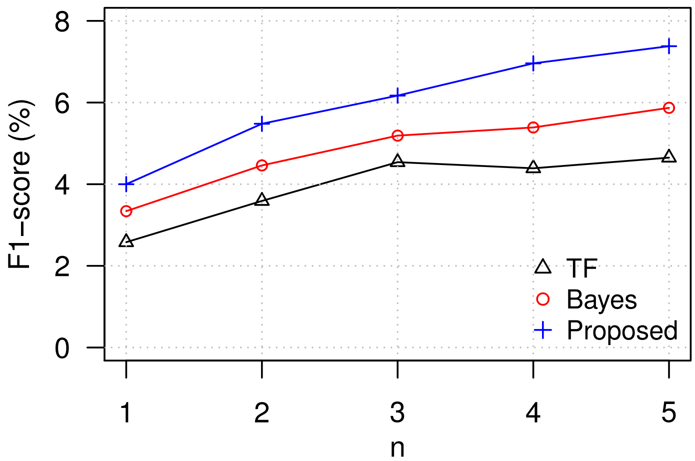


Figure 5.13 The comparisons of f1-score among the proposed approach, TF, and Bayes.

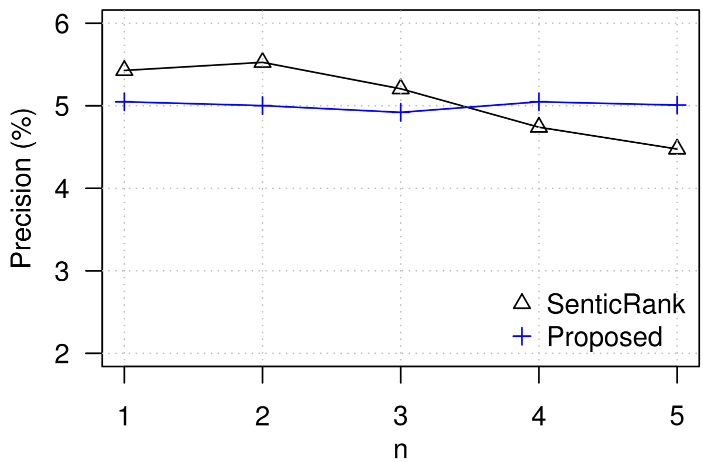


Figure 5.14 The comparisons of precision between the proposed approach and SenticRank.

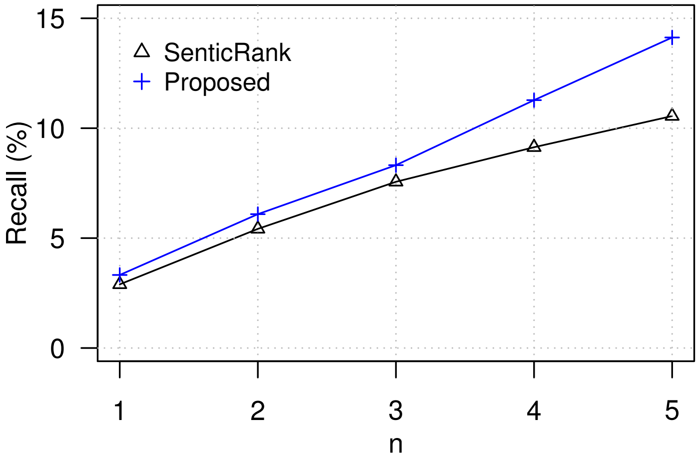


Figure 5.15 The comparisons of recall between the proposed approach and SenticRank.

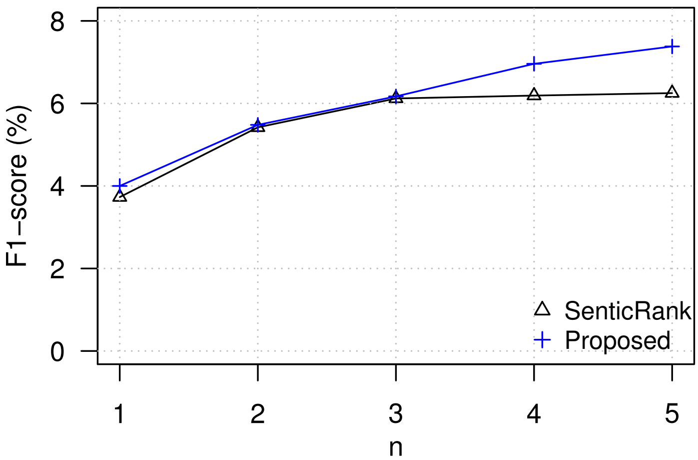


Figure 5.16 The comparisons of f1-score between the proposed approach and SenticRank.

5.5 Case Study

To verify the effect of proposed approaches in this chapter, we compare the results of the tag emotion-based recommendation. A user u in our dataset has rated several movies as follows:

Table 5.1 A list of movies user u has.

12 Monkeys
Se7en
Die Hard: With a Vengeance
Dumb & Dumber
Speed
Demolition Man
The Silence of the Lambs
Independence Day
Willy Wonka & the Chocolate Factory
Star Wars: Episode VI
The Terminator
Gattaca
Good Will Hunting
Rain Man
Sin City
Lucky Number Slevin
The Illusionist
The Fountain
Hancock

For the movies, u uses the tags such as action, classic, time travel, twist ending, fantasy, serial killer, magic, aliens, ghosts, the names of actors, and so on. The ratings of the movies are from 4.0 to 5.0. By examining the genres of the movies on the list, we can infer that the favorite movies of the user are the movies in the genre of thrill, action, crime, and drama genres. Based on the list, the three recommendation methods are applied: the primary tag emotion-based recommendation, which is described in Chapter 4, the recommendation with the data expansion, and the recommendation with the additional data and the candidate re-ranking.

Table 5.2 represents the top 15 recommended movies for u, and the results are significantly different by the recommendation methods. The movies in the various genres as well as the thriller movies are recommended by the tag emotion-based approach. For example, The Wizard of Oz or The Sound of Music are likely to have affected the tag on Willy Wonka & the Chocolate Factory. When the data is added to the original data, the recommendation results are similar with the first one, but the movies that did not appear in the previous results are found. By the third recommendation approach, u can obtain the movies that is the most similar with his/her interests since the candidate re-ranking method rearranges the results of the second approach based on the user and item profiles.

Table 5.2 The Top 15 movies recommended for user u by the three recommendation approaches.

Tag emotion-based recommendation	Data expansion	Data expansion + re-ranking
The Sixth Sense	Star Wars: Episode III	Die Hard
Catch Me If You Can	Children of Men	Armageddon
The Wizard of Oz	Terminator 2	The Sixth Sense
Desperado	Jurassic Park	True Lies
The Game	Ocean's Eleven	The Game
1984	True Lies	Terminator 2
Fight Club	American Beauty	The Matrix
Rocky	Catch Me If You Can	Desperado
Dances with Wolves	The Sixth Sense	Lethal Weapon 2
Jaws	The Green Mile	Unbreakable
The Others	The Others	Ocean's Eleven
Pulp Fiction	The Game	Back to the Future Part III
The Sound of Music	The Sound of Music	Back to the Futhre Part II
Star Wars: Episode I	The Prestige	Star Wars: Episode III
Lethal Weapon 2	Rocky	Catch Me If You Can

5.6 Summary

For recommending items to users in social cataloging services, we introduced a tensor-based tag emotion aware recommendation in Chapter 4. When the ternary relationships among users, items, and tags are modeled as a tensor, a data sparsity problem is occurred since users annotated a small number of items with tags. Also, a recommendation through the process of the tensor factorization and reconstruction disregard the previous activities of users.

In this chapter, to mitigate the problems, we proposed the improved item recommendation method. The additional data are generated using item-based collaborative filtering and combined with the original dataset. The combined data are represented as a three-order tensor and HOSVD is utilized for the recommendation. The candidates to recommend generated from the reconstructed tensor are ranked based on the tag-based user and item profile. BM25 algorithm, which is a well-known ranking scheme for a document retrieval, is used to create these profiles based on the previous tagging activities.

The experimental evaluation performed to compare the proposed method against other recommendation algorithms: collaborative filtering, the standard tensor-based recommendation, and tensor-based recommendation with Näive Bayes-based ranking. The results indicate the proposed approach outperform the other recommendation method.

Chapter 6

Conclusions

In this doctoral dissertation, we analyze the characteristics of users in social cataloging services and propose an item recommendation method. The proposed method recommends appropriate items to users using emotions reflected in the tags.

Social cataloging services allow users not only to catalog items and express personal opinions, but also to make relationships and communicate with others. The relationships of users are surmised that they are established when users join the systems and are maintained without much change. Although connected users have social links and a majority of the links are reciprocal, they are not interested in interacting with their friends. The similar preferences between users and their friends for items are not cause the interactions between them either. These indicate that the relationships between users seems to be generated by curiosity or courtesy.

The analysis result of the isolated users reported that they are as active as the connected users about cataloging items and showing their opinions. Therefore, for recommending items to users, we should mainly consider not the relationships or explicit interactions of users, but their feedback about items.

In this dissertation, we propose a tag-based item recommendation regarding emotions in tags. The ternary relationships among users, items, and tags are modeled as a tensor. To mitigate the data sparsity, the additional data are generated by item-based collaborative filtering and is combined to the initial dataset. To derive emotions from tags, ratings of users are used as the base emotion weight, and if a tag is subjective, the emotion score of the tag is combined with the base weight. The emotion score is obtained by SenticNet, which is one of the emotion dictionaries. After computing the emotion weight of the tags, a tensor is factorized and reconstructed by HOSVD method, and new entries as the candidates for recommending are obtained. They are ranked considering the previous tagging histories of users and items by BM25 ranking scheme. Our approach outperforms collaborative filtering, the standard tensor-based recommendation, and the tensor-based recommendation with a ranking scheme based on Näive Bayes.

Some issues about tag processing for extracting emotions and tensor processing are remain as future work. First, several features for deriving emotions in tags can be considered such as sarcasm, pragmatics, or world knowledge about terms. These features can increase the accuracy of emotion analysis. Second, if the emotion dictionary is extended using synonyms and antonyms, the coverage of the emotion dictionary is increased, and it can affect the recommendation quality. Third, since users tend to use few tags to the items, the tag expansion can improve the quality of the recommendation. Finally, parallel approaches or clustering approaches can be adapted to tensor factorization and reconstruction for decreasing the computation time.

Bibliography

[1] Shaomei Wu et al. "Who says what to whom on twitter". In: *Proceedings of the 20th international conference on World wide web*. ACM. 2011, pp. 705–714.

[2] Manos Papagelis, Vanessa Murdock, and Roelof van Zwol. "Individual behavior and social influence in online social systems". In: *Proceedings of the 22nd ACM conference on Hypertext and hypermedia*. ACM. 2011, pp. 241–250.

[3] Stanley Wasserman and Katherine Faust. *Social network analysis: Methods and applications*. Vol. 8. Cambridge university press, 1994.

[4] Long Jin et al. "Understanding user behavior in online social networks: A survey". In: *IEEE Communications Magazine* 51.9 (2013), pp. 144–150.

[5] Louise F Spiteri. "The impact of social cataloging sites on the construction of bibliographic records in the public library catalog". In: *Cataloging & classification quarterly* 47.1 (2009), pp. 52–73.

[6] Jian-Tao Sun et al. "Cubesvd: a novel approach to personalized web search". In: *Proceedings of the 14th international conference on World Wide Web*. ACM. 2005, pp. 382–390.

[7] Myriam D Munezero et al. "Are they different? affect, feeling, emotion, sentiment, and opinion detection in text". In: *IEEE transactions on affective computing* 5.2 (2014), pp. 101–111.

[8] Ignacio Fernández-Tobıas, Iván Cantador, and Laura Plaza. "An emotion dimensional model based on social tags: Crossing folksonomies and enhancing recommendations". In: *International Conference on Electronic Commerce and Web Technologies*. Springer. 2013, pp. 88–100.

[9] Alan Mislove et al. "Measurement and analysis of online social networks". In: *Proceedings of the 7th ACM SIGCOMM conference on Internet measurement*. ACM. 2007, pp. 29–42.

[10] Haewoon Kwak et al. "What is Twitter, a social network or a news media?" In: *Proceedings of the 19th international conference on World wide web*. ACM. 2010, pp. 591–600.

[11] Christo Wilson et al. "User interactions in social networks and their implications". In: *Proceedings of the 4th ACM European conference on Computer systems*. Acm. 2009, pp. 205–218.

[12] David Crandall et al. "Feedback effects between similarity and social influence in online communities". In: *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*. ACM. 2008, pp. 160–168.

[13] Andreas M Kaplan and Michael Haenlein. “Users of the world, unite! The challenges and opportunities of Social Media”. In: *Business horizons* 53.1 (2010), pp. 59–68.

[14] Niall Cook. *Enterprise 2.0: how social software will change the future of work*. Gower Publishing, Ltd., 2008.

[15] Mirjam Wattenhofer, Roger Wattenhofer, and Zack Zhu. “The YouTube Social Network”. In: *Sixth International AAAI Conference on Weblogs and Social Media*. 2012, pp. 354–361.

[16] Xu Cheng, Cameron Dale, and Jiangchaun Liu. *Dataset for ”statistics and social network of youtube videos”*. 2008. URL: `http://netsg.cs.sfu.ca/youtubedata` (visited on 03/16/2017).

[17] Martin J Halvey and Mark T Keane. “Analysis of online video search and sharing”. In: *Proceedings of the eighteenth conference on Hypertext and hypermedia*. ACM. 2007, pp. 217–226.

[18] Pasquale de Meo et al. “Analyzing user behavior across social sharing environments”. In: *ACM Transactions on Intelligent Systems and Technology (TIST)* 5.1 (2013), p. 14.

[19] Meeyoung Cha, Alan Mislove, and Krishna P Gummadi. “A measurement-driven analysis of information propagation in the flickr social network”. In: *Proceedings of the 18th international conference on World wide web*. ACM. 2009, pp. 721–730.

[20] Ching-man Au Yeung and Tomoharu Iwata. “Capturing implicit user influence in online social sharing”. In: *Proceedings of the 21st ACM conference on Hypertext and hypermedia*. ACM. 2010, pp. 245–254.

[21] Luca Maria Aiello et al. “Link creation and profile alignment in the aNobii social network”. In: *Social Computing (SocialCom), 2010 IEEE Second International Conference on*. IEEE. 2010, pp. 249–256.

[22] Muh-Chyun Tang, Yi-Ling Ke, and Yi-Jin Sie. “The Estimation of aNobii Users’ Reading Diversity Using Book Co-ownership Data: A Social Analytical Approach”. In: *International Conference on Social Informatics*. Springer. 2013, pp. 274–283.

[23] Mohsen Jamali and Martin Ester. “Modeling and comparing the influence of neighbors on the behavior of users in social and similarity networks”. In: *Data Mining Workshops (ICDMW), 2010 IEEE International Conference on*. IEEE. 2010, pp. 336–343.

[24] Mohsen Jamali, Gholamreza Haffari, and Martin Ester. “Modeling the temporal dynamics of social rating networks using bidirectional effects of social relations and rating patterns”. In: *Proceedings of the 20th international conference on World wide web*. ACM. 2011, pp. 527–536.

[25] Tingting Jiang. “An exploratory study on social library system users’ information seeking modes”. In: *Journal of Documentation* 69.1 (2013), pp. 6–26.

[26] Paul Fugelstad et al. “What makes users rate (share, tag, edit...)?: predicting patterns of participation in online communities”. In: *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work*. ACM. 2012, pp. 969–978.

[27] Cliff Lampe et al. “Motivations to participate in online communities”. In: *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM. 2010, pp. 1927–1936.

[28] Blair Nonnecke and Jenny Preece. “Lurker demographics: Counting the silent”. In: *Proceedings of the SIGCHI conference on Human Factors in Computing Systems*. ACM. 2000, pp. 73–80.

[29] Michael S Bernstein et al. “Quantifying the invisible audience in social networks”. In: *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM. 2013, pp. 21–30.

[30] Peter Kollock and Marc Smith. “Managing the Virtual Commons: Cooperation and Conflict in Computer Communities”. In: *Computer-mediated communication: Linguistic, social, and cross-cultural perspectives* (1996), pp. 109–128.

[31] Vladimir Soroka and Sheizaf Rafaeli. “Invisible participants: how cultural capital relates to lurking behavior”. In: *Proceedings of the 15th international conference on World Wide Web*. ACM. 2006, pp. 163–172.

[32] Jon Kats. *Luring the Lurkers*. 1998. URL: `https://news.slashdot.org/story/98/12/28/1745252/luring-the-lurkers` (visited on 03/16/2017).

[33] Blair Nonnecke and Jenny Preece. “Why lurkers lurk”. In: *AMCIS 2001 Proceedings* (2001), p. 294.

[34] Pei-Luen Patrick Rau, Qin Gao, and Yinan Ding. "Relationship between the level of intimacy and lurking in online social network services". In: *Computers in Human Behavior* 24.6 (2008), pp. 2757–2770.

[35] Stephanie J Tobin et al. "Threats to belonging on Facebook: Lurking and ostracism". In: *Social Influence* 10.1 (2015), pp. 31–42.

[36] Wei Gong, Ee-Peng Lim, and Feida Zhu. "Characterizing Silent Users in Social Media Communities." In: *ICWSM*. 2015, pp. 140–149.

[37] Eni Mustafaraj et al. "Vocal minority versus silent majority: Discovering the opionions of the long tail". In: *Privacy, Security, Risk and Trust (PASSAT) and 2011 IEEE Third Inernational Conference on Social Computing (SocialCom), 2011 IEEE Third International Conference on*. IEEE. 2011, pp. 103–110.

[38] Jürgen Buder and Christina Schwind. "Learning with personalized recommender systems: A psychological view". In: *Computers in Human Behavior* 28.1 (2012), pp. 207–216.

[39] FO Isinkaye, YO Folajimi, and BA Ojokoh. "Recommendation systems: Principles, methods and evaluation". In: *Egyptian Informatics Journal* 16.3 (2015), pp. 261–273.

[40] Jesús Bobadilla et al. "Recommender systems survey". In: *Knowledge-based systems* 46 (2013), pp. 109–132.

[41] Ana Belén Barragáns-Martınez et al. "A hybrid content-based and item-based collaborative filtering approach to recommend TV programs enhanced with singular value decomposition". In: *Information Sciences* 180.22 (2010), pp. 4290–4311.

[42] Morgan Ames and Mor Naaman. "Why we tag: motivations for annotation in mobile and online media". In: *Proceedings of the SIGCHI conference on Human factors in computing systems*. ACM. 2007, pp. 971–980.

[43] Zhichen Xu et al. "Towards the semantic web: Collaborative tag suggestions". In: *Collaborative web tagging workshop at WWW2006, Edinburgh, Scotland*. 2006.

[44] Oded Nov and Chen Ye. "Why do people tag?: motivations for photo tagging". In: *Communications of the ACM* 53.7 (2010), pp. 128–131.

[45] Shilad Sen et al. "Tagging, communities, vocabulary, evolution". In: *Proceedings of the 2006 20th anniversary conference on Computer supported cooperative work*. ACM. 2006, pp. 181–190.

[46] Cheng-Lung Huang et al. "Utilizing user tag-based interests in recommender systems for social resource sharing websites". In: *Knowledge-Based Systems* 56 (2014), pp. 86–96.

[47] Ido Guy et al. "Social media recommendation based on people and tags". In: *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*. ACM. 2010, pp. 194–201.

[48] Zi-Ke Zhang and Chuang Liu. "Hybrid recommendation algorithm based on two roles of social tags". In: *International Journal of Bifurcation and Chaos* 22.07 (2012), p. 1250166.

[49] Heung-Nam Kim et al. “Collaborative user modeling with user-generated tags for social recommender systems”. In: *Expert Systems with Applications* 38.7 (2011), pp. 8488–8496.

[50] Fatih Gedikli and Dietmar Jannach. “Rating items by rating tags”. In: *Proceedings of the 2010 Workshop on Recommender Systems and the Social Web at ACM RecSys*. 2010, pp. 25–32.

[51] Fatih Gedikli and Dietmar Jannach. “Improving recommendation accuracy based on item-specific tag preferences”. In: *ACM Transactions on Intelligent Systems and Technology (TIST)* 4.1 (2013), p. 11.

[52] Hyunwoo Kim and Hyoung-Joo Kim. “Improving recommendation based on implicit trust relationships from tags”. In: *Proceedings of the 2nd international conference on computers, networks, systems, and industrial applications*. 2012, pp. 25–30.

[53] Jing Peng et al. “Collaborative filtering in social tagging systems based on joint item-tag recommendations”. In: *Proceedings of the 19th ACM international conference on Information and knowledge management*. ACM. 2010, pp. 809–818.

[54] Lieven De Lathauwer, Bart De Moor, and Joos Vandewalle. “A multilinear singular value decomposition”. In: *SIAM journal on Matrix Analysis and Applications* 21.4 (2000), pp. 1253–1278.

[55] Panagiotis Symeonidis, Alexandros Nanopoulos, and Yannis Manolopoulos. “Tag recommendations based on tensor dimensionality reduction”. In: *Proceedings of the 2008 ACM conference on Recommender systems*. ACM. 2008, pp. 43–50.

[56] Panagiotis Symeonidis, Alexandros Nanopoulos, and Yannis Manolopoulos. “A unified framework for providing recommendations in social tagging systems based on ternary semantic analysis”. In: *IEEE Transactions on Knowledge and Data Engineering* 22.2 (2010), pp. 179–192.

[57] Yanfei Xu, Liang Zhang, and Wei Liu. “Cubic analysis of social bookmarking for personalized recommendation”. In: *Asia-Pacific Web Conference*. Springer. 2006, pp. 733–738.

[58] Noor Ifada and Richi Nayak. “Tensor-based Item Recommendation using Probabilistic Ranking in Social Tagging Systems”. In: *Proceedings of the 23rd International Conference on World Wide Web*. ACM. 2014, pp. 805–810.

[59] Dimitrios Rafailidis and Petros Daras. “The TFC model: Tensor factorization and tag clustering for item recommendation in social tagging systems”. In: *IEEE Transactions on Systems, Man, and Cybernetics: Systems* 43.3 (2013), pp. 673–688.

[60] Gustavo González et al. “Embedding emotional context in recommender systems”. In: *Data Engineering Workshop, 2007 IEEE 23rd International Conference on*. IEEE. 2007, pp. 845–852.

[61] Rahul Katarya and Om Prakash Verma. “Recent developments in affective recommender systems”. In: *Physica A: Statistical Mechanics and its Applications* 461 (2016), pp. 182–190.

[62] Hsia-Ching Chang. “Emotion barometer of reading: user interface design of a social cataloging website”. In: *CHI’09 Extended Abstracts*

on Human Factors in Computing Systems. ACM. 2009, pp. 3371–3376.

[63] Meryl Paula Gardner. “Mood states and consumer behavior: A critical review”. In: *Journal of Consumer research* 12.3 (1985), pp. 281–300.

[64] Mary Beth Oliver. “Tender affective states as predictors of entertainment preference”. In: *Journal of Communication* 58.1 (2008), pp. 40–61.

[65] Marko Tkalčič, Andrej Kosir, and Jurij Tasic. “Affective recommender systems: the role of emotions in recommender systems”. In: *Proc. The RecSys 2011 Workshop on Human Decision Making in Recommender Systems*. Citeseer. 2011, pp. 9–13.

[66] Pinata Winoto and Tiffany Y Tang. “The role of user mood in movie recommendations”. In: *Expert Systems with Applications* 37.8 (2010), pp. 6086–6092.

[67] Yong Zheng, Bamshad Mobasher, and Robin D Burke. “The Role of Emotions in Context-aware Recommendation.” In: *Decisions@ RecSys* 2013 (2013), pp. 21–28.

[68] Haoran Xie et al. “Incorporating sentiment into tag-based user profiles and resource profiles for personalized search in folksonomy”. In: *Information Processing & Management* 52.1 (2016), pp. 61–72.

[69] Zhou Qingbiao, Fang Jie, and Gaundong Xu. “Incorporating sentiment analysis for improved tag-based recommendation”. In: *Proceed-*

ings of the 2011 IEEE Ninth International Conference on Dependable, Autonomic and Secure Computing. IEEE. 2011, pp. 1222–1227.

[70] Ruihai Dong et al. "Combining similarity and sentiment in opinion mining for product recommendation". In: *Journal of Intelligent Information Systems* 46.2 (2016), pp. 285–312.

[71] Miguel Á Garcıa-Cumbreras, Arturo Montejo-Ráez, and Manuel C Dıaz-Galiano. "Pessimists and optimists: Improving collaborative filtering through sentiment analysis". In: *Expert Systems with Applications* 40.17 (2013), pp. 6758–6765.

[72] Jianshan Sun et al. "Mining affective text to improve social media item recommendation". In: *Information Processing & Management* 51.4 (2015), pp. 444–457.

[73] Hyon Hee Kim, Donggeon Kim, and Jinnam Jo. "A unified music recommender system using listening habits and semantics of tags". In: *International Journal of Intelligent Information and Database Systems 4* 8.1 (2014), pp. 14–30.

[74] Erik Cambria et al. "SenticNet: A Publicly Available Semantic Resource for Opinion Mining." In: *AAAI fall symposium: commonsense knowledge*. Vol. 10. 0. 2010.

[75] Saif M Mohammad and Peter D Turney. "Emotions evoked by common words and phrases: Using Mechanical Turk to create an emotion lexicon". In: *Proceedings of the NAACL HLT 2010 workshop on computational approaches to analysis and generation of emotion in text*. Association for Computational Linguistics. 2010, pp. 26–34.

[76] Margaret M Bradley and Peter J Lang. *Affective norms for English words (ANEW): Instruction manual and affective ratings*. Tech. rep. Technical report C-1, the center for research in psychophysiology, University of Florida, 1999.

[77] Stefano Baccianella, Andrea Esuli, and Fabrizio Sebastiani. "SentiWordNet 3.0: An Enhanced Lexical Resource for Sentiment Analysis and Opinion Mining." In: *LREC*. Vol. 10. 2010, pp. 2200–2204.

[78] Louise F Spiteri. "Social cataloguing sites: features and implications for cataloguing practique and the public library catalogue". In: *Nuevas perspectivas para la difusión y organización del conocimiento: actas del congreso*. Servicio de Publicaciones. 2009, pp. 769–785.

[79] Min-Sook Park, Jong-Kuk Shin, and Yong Ju. "A Taxonomy of Social Networking Site Users: Social Surveillance and Self-surveillance Perspective". In: *Psychology & Marketing* 32.6 (2015), pp. 601–610.

[80] Ann E Schlosser. "Posting versus lurking: Communicating in a multiple audience context". In: *Journal of Consumer Research* 32.2 (2005), pp. 260–265.

[81] Cameron Marlow et al. *Maintained relationships on Facebook*. 2009. URL: `http://overstated.net/2009/03/09/maintained-relationships-on-facebook` (visited on 01/20/2014).

[82] Alan Mislove et al. "Growth of the flickr social network". In: *Proceedings of the first workshop on Online social networks*. ACM. 2008, pp. 25–30.

[83] Danielle H Lee and Peter Brusilovsky. “Social networks and interest similarity: the case of CiteULike”. In: *Proceedings of the 21st ACM conference on Hypertext and hypermedia*. ACM. 2010, pp. 151–156.

[84] Pavlos Kefalas, Panagiotis Symeonidis, and Yannis Manolopoulos. “A graph-based taxonomy of recommendation algorithms and systems in LBSNs”. In: *IEEE Transactions on Knowledge and Data Engineering* 28.3 (2016), pp. 604–622.

[85] Vladimir Batagelj and Matjaž Zaveršnik. “Generalized cores”. In: *arXiv preprint cs/0202039* (2002).

[86] Steven Bird. “NLTK: the natural language toolkit”. In: *Proceedings of the COLING/ACL on Interactive presentation sessions*. Association for Computational Linguistics. 2006, pp. 69–72.

[87] Alexandros Nanopoulos. “Item recommendation in collaborative tagging systems”. In: *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans* 41.4 (2011), pp. 760–771.

[88] K Sparck Jones, Steve Walker, and Stephen E. Robertson. “A probabilistic model of information retrieval: development and comparative experiments: Part 2”. In: *Information processing & management* 36.6 (2000), pp. 809–840.

[89] Badrul Sarwar et al. “Item-based collaborative filtering recommendation algorithms”. In: *Proceedings of the 10th international conference on World Wide Web*. ACM. 2001, pp. 285–295.

[90] Yehuda Koren, Robert Bell, and Chris Volinsky. “Matrix factorization techniques for recommender systems”. In: *Computer* 42.8 (2009).

[91] David Vallet, Iván Cantador, and Joemon M Jose. "Personalizing web search with folksonomy-based user and document profiles". In: *European Conference on Information Retrieval*. Springer. 2010, pp. 420–431.

[92] Shengliang Xu et al. "Exploring folksonomy for personalized search". In: *Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retrieval*. ACM. 2008, pp. 155–162.

[93] Karen HL Tso-Sutter, Leandro Balby Marinho, and Lars Schmidt-Thieme. "Tag-aware recommender systems by fusion of collaborative filtering algorithms". In: *Proceedings of the 2008 ACM symposium on Applied computing*. ACM. 2008, pp. 1995–1999.

[94] Hyewon Lim and Hyoung-Joo Kim. "Item Recommendation using Tag Emotion in Social Cataloging Services". In: *Manuscript submitted for publication.* (2017).

초록

소셜 카탈로깅 서비스는 사용자가 아이템들의 목록을 만들고, 자신의 주관적인 의견을 표현하고, 다른 사용자들과 소통하게 한다. 사용자들은 다른 사용자와의 연결을 통해 그들의 행동이나 의견을 참조하고 콘텐츠에 대한 정보를 얻을 수 있는데, 사용자 간의 연결을 기반으로 행동이 이루어지는 일반적인 소셜 네트워킹 서비스와 달리 사용자들은 다른 사용자들과의 연결 없이도 서비스에 참여하고 기여할 수 있다. 본 논문에서는 소셜 카탈로깅 서비스의 사용자들을 다른 사용자들과 관계를 맺고 있는 그룹과 그렇지 않고 독립적으로 존재하는 그룹으로 나누어 사용자들의 특성을 분석한다. 또한, 관계보다는 콘텐츠에 대한 피드백에 집중하는 사용자들의 특성을 고려하여, 태그 기반의 아이템 추천 기법을 제안한다. 태그는 아이템에 대한 추가적인 정보임과 동시에 사용자의 주관적인 평가로, 해당 아이템에 대한 사용자의 감정이나 생각을 담고 있다. 따라서, 태그에 담긴 감정을 고려한다면 사용자의 선호도나 관심사가 반영된 추천 결과를 얻을 수 있다. 각 태그가 갖는 감정을 반영하기 위해 사용자와 아이템, 태그의 관계는 3차원 텐서로 모델링 되고, 그 안에 잠재된 시맨틱 정보를 기반으로 아이템을 추천한다. 이 방법의 경우, 전체 아이템의 양에 비해 사용자가 태그를 다는 아이템의 수가 적기 때문에 데이터 부족 현상이 발생한다. 또한, 텐서에 고차원 특이 값 분해를 적용해 얻은 사용자와 아이템, 태그 사이의 잠재된 정보만을 이용하여 추천하기 때문에 사용자와 아이템의 과거 태깅 이력은 고려되지 않는다는 문제가 있다. 본 논문에서는 이러한 문제를 줄이기 위해 아이템 기반 협력 필터링 기법을 이용해 추가적인 데이터를 생성하여 확장된 데이터 셋을 만든다. 그리고 사용자와 아이템의 프로필을 고려한 향상된 추천 기법을 제안한다. 제안된 방법론은 소셜 카탈로깅 서비스의 실제 데이터를 기반으로 검증하였다. 그

결과 제안된 방법론이 협력 필터링 기법이나 기존의 텐서 기반 추천 기법들에 비해 추천 성능이 향상되었음을 보였다.

주요어: 소셜 카탈로깅 서비스, 연결된 사용자, 고립된 사용자, 추천, 태그, 감정, 텐서, 고차원 특이값 분해, 확률적 랭킹

학번: 2008-20959