IMPROVED COLLABORATIVE FILTERING USING CLUSTERING AND ASSOCIATION RULE MINING ON IMPLICIT DATA

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Special Dedicated to my beloved father

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In the name of Allah The Most Gracious The Most Merciful, first and foremost, all praises to Allah who has created us and gave us intelligence and guidance. And peace be upon our prophet the teacher of all mankind and peace be upon his family.

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ABSTRACT

The recommender systems are recently becoming more significant due to their ability in making decisions on appropriate choices. Collaborative Filtering (CF) is the most successful and most applied technique in the design of a recommender system where items to an active user will be recommended based on the past rating records from like-minded users. Unfortunately, CF may lead to poor recommendation when user ratings on items are very sparse (insufficient number of ratings) in comparison with the huge number of users and items in user-item matrix. In the case of a lack of user rating on items, implicit feedback is used to profile a user's item preferences. Implicit feedback can indicate users' preferences by providing more evidences and information through observations made on users' behaviors. Data mining technique, which is the focus of this research, can predict a user's future behavior without item evaluation and can too, analyze his preferences. In order to investigate the states of research in CF and implicit feedback, a systematic literature review has been conducted on the published studies related to topic areas in CF and implicit feedback. To investigate users' activities that influence the recommender system developed based on the CF technique, a critical observation on the public recommendation datasets has been carried out. To overcome data sparsity problem, this research applies users' implicit interaction records with items to efficiently process massive data by employing association rules mining (Apriori algorithm). It uses item repetition within a transaction as an input for association rules mining, in which can achieve high recommendation accuracy. To do this, a modified preprocessing has been employed to discover similar interest patterns among users. In addition, the clustering technique (Hierarchical clustering) has been used to reduce the size of data and dimensionality of the item space as the performance of association rules mining. Then, similarities between items based on their features have been computed to make recommendations. Experiments have been conducted and the results have been compared with basic CF and other extended version of CF techniques including K-Means Clustering, Hybrid Representation, and Probabilistic Learning by using public dataset, namely, Million Song dataset. The experimental results demonstrate that the proposed technique exhibits improvements of an average of 20% in terms of Precision, Recall and F-measure metrics when compared to the basic CF technique. Our technique achieves even better performance (an average of 15% improvement in terms of Precision and Recall metrics) when compared to the other extended version of CF techniques, even when the data is very sparse.

ABSTRAK

Recommender systems semakin penting kerana keupayaannya dalam membuat keputusan pemilihan yang tepat. *Collaborative Filtering (CF)* adalah teknik yang paling berjaya dan berkesan dalam rekabentuk sebuah *recommender systems* di mana perkara-perkara yang berkaitan dengan pengguna aktif adalah disyorkan berdasarkan kepada rekod penilaian item di kalangan pengguna yang mempunyai kecenderungan yang sama. Malangnya, *CF* berkemungkinan membawa kepada pengesyoran yang tidak berkesan apabila penilaian item adalah sedikit (kekurangan bilangan penilaian item) berbanding dengan bilangan pengguna yang ramai dan item yang banyak dalam matriks pengguna-item. Dalam kes di mana kurangnya penilaian ke atas item, maklumbalas yang tersirat digunakan untuk memprofil pilihan barangan pengguna. Maklumbalas yang tersirat boleh memberikan gambaran tentang pilihan pengguna dengan memberikan bukti dan maklumat melalui pemerhatian yang dibuat ke atas tingkahlaku pengguna. Teknik *data mining* yang merupakan fokus kajian ini boleh mengandai tingkahlaku pengguna pada masa akan datang tanpa penilaian item dan mampu juga menganalisa pilihan pengguna. Untuk menyiasat tahap kajian ke atas *CF* dan maklumbalas implisit, sorotan literatur yang sistematik telah dibuat ke atas kajian-kajian yang telah dijalankan dalam bidang berkaitan *CF* dan maklumbalas implisit. Untuk mengenalpasti tinglahlaku pengguna yang mempengaruhi *recommender system*, dan berdasarkan pada teknik *CF*, pemerhatian kritikal telah dijalankan ke atas set data *recommendation* awam. Untuk mengatasi masalah data *sparsity*, kajian ini telah menggunakan rekod interaksi nyata pengguna beserta dengan item untuk memproses secara efektif data yang besar dengan menggunakan *association mining rules* (*Apriori algorithm*). Ianya menggunakan pengulangan item dalam satu-satu transaksi sebagai input, di mana ini akan dapat memberikan *recommendation* yang tepat. Untuk itu, satu modifikasi prapemprosesan telah dbuat untuk mencari pola minat yang sama dikalangan pengguna. Sebagai tambahan, teknik *clustering* (*Hierarchical clustering*) telah digunakan untuk mengurangkan saiz data dan dimensi ruang item sebagai hasil *rule mining*. Kemudian, persamaan antara item berasaskan ciri masing-masing dikomputerkan bagi membuat cadangan. Ujian-ujian telah dijalankan dan keputusan ujian telah dibandingkan dengan teknik *CF* yang asas dan juga yang dikembangkan seperti *K-Means Clustering*, *Hybrid Representation*, dan *Probabilistic Learning* dengan menggunakan set data awam yang dinamakan set data *Million Song*. Keputusan-keputusan ujian telah menunjukkan bahawa teknik yang dicadangkan telah menunjukkan penambahbaikan pada purata 20% dari segi metriks *Precision, Recall* dan *F-measure* apabila dibandingkan dengan teknik *CF* yang asas. Teknik yang kami gunakan telah menunjukkan prestasi yang lebih baik (purata 15% penambahbaikan dari segi metriks *Precision* dan *Recall*) apabila dibandingkan dengan teknik-teknik *CF* yang telah dikembangkan, walaupun pada ketika data adalah *sparse*.

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LIST OF ABBREVIATIONS

CBF	-	Content-Based Filtering
CF	-	Collaborative Filtering
CVS	-	Cosine Vector Similarity
GUI	-	Graphical User Interface
KNN	-	k-Nearest Neighbor
PCC	-	Pearson Correlation Coefficient
PSO	-	Particle Swarm Optimization
SLR	-	Systematic Literature Review
SVD	-	Singular Value Decomposition
WEKA	-	Waikato Environment for Knowledge Analysis

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CHAPTER 1

INTRODUCTION

1.1 Research Background

The World Wide Web is changing radically on an unprecedented amount of information. The enormous amount of information in the world is growing with the increasing popularity of web. The web is a wide environment and dynamic that different users can publish their documents in it. On the other hand, the web is an important source of information available to the public (Xie *et al*., 2014; Huang *et al.*, 2015).

De Campos *et al.* (2010) stated that much information is available online with the fast development of the Internet. Rapid growth of information (such as online news, books, articles, music, movies, etc.) on the web has caused users to face difficulty in accessing the right information. Nowadays, music information retrieval technology and music recommendation technique have gained greater attention among the commercially renowned music recommender system operators such as like Last.fm[1], Pandora.com[2], etc (Park *et al*., 2012). Park *et al*. (2012) stated few researches have been done in the music recommendation field. The e-commerce and entertainment websites (such as Amazon, CDNow, Yahoo, etc.) offer same

[1] http://www.last.fm.
[2] http://www.pandora.com.

appearance to every user considered of the browsing history. These websites provides suggestions to their potential users without navigation guides tailored to user's preferences and needs. As a result, users are overloaded with information produced by the search engine and they spend more time and more search effort to locate the right information at the right time. For solving this problem, recommender systems have been the considerable subject for researchers to help internet users in easily finding needed information (De Campos *et al.*, 2010 and Xie *et al.*, 2014). In other words, Due to the increased overloading problem of information, the recommender systems are becoming more significant in the age of rapid development of the Internet technology. Recommender systems have become an essential mechanism which provides users with useful selected information; in which this could be effective in making a decision for example in purchasing a product, selecting a movie to watch or doing any other online activity that requires making a choice or a decision (Xie *et al*., 2014; Huang *et al*., 2015).

According to Kaleli (2014) recommender systems analyze the behavior of internet user to offer the best items (data, information, goods, etc.) which is considered of interest to user. On the other hand, recommender systems are the intelligent tools to deal with the problem of overloaded information in the search results and help the internet user to access to right information across wide range of information on the web. According to Bae and Kim (2010), recommender systems can apply data mining techniques at predicting the user's future behavior and users' preferences to increase the chance of repurchasing. In general, data mining techniques explore and analyze the large quantities of data (such as users, items) to discover meaningful patterns and rules. Applying these techniques to recommender systems can lead decision making and to predict the effect of decisions (Nakatsuji et al., 2016, Kaleli, 2014, Hung, 2005). In general, data mining techniques are defined as extracting or mining knowledge from data. These techniques are used for the exploration and analysis of large quantities of data in order to discover meaningful patterns and rules to improve the recommendation quality and the scalability problems (Nakatsuji *et al.*, 2016, Kaleli, 2014).

Recommendation system predicts the particular requirements of user base on its analysis of the previous buying behavior of user and its understanding of the user in order to recommend products that contain user needed requirements. The entertainment and shopping websites where the wealth of information is growing so quickly adapt themselves to each user with using recommendation system. In a sense, personalization of search engine results based on user intent is the goal of a recommendation system in order to deliver a high variety of user needs (Zhou *et al.*, 2015, Cao and Li, 2007; Hung, 2005).

The recommender systems endeavor on discovering the users' preferences, learn about these preferences and eventually based on this, anticipate the users' needs. A recommender system works within a given domain which actually concerns the interest of the users (De Campos *et al.,* 2010). So, based on how recommender systems are made, there are three main categories of recommendation techniques, including: Content-based Filtering (CBF), Collaborative Filtering (CF), and Knowledge based as shown in Figure 1.1(Pin-Yu *et al.,* 2010; Bellogín *et al.*, 2013). Some systems use hybrid recommender systems which make use of more than one recommendation technique in order to enhance the performance of available recommendation techniques for example, Wu *et al.*, (2014) combined CBF and CF to build a hybrid recommender system. Fernández *et al.* (2011) proposed a combination of a CBF with a knowledge-based technique to produce the recommendations. Figure 1.1 shows recommendation techniques that have been proposed to implement recommender systems (Montenegro *et al.*, 2012; Pin-Yu *et al.,* 2010; Bellogín *et al.*, 2013):

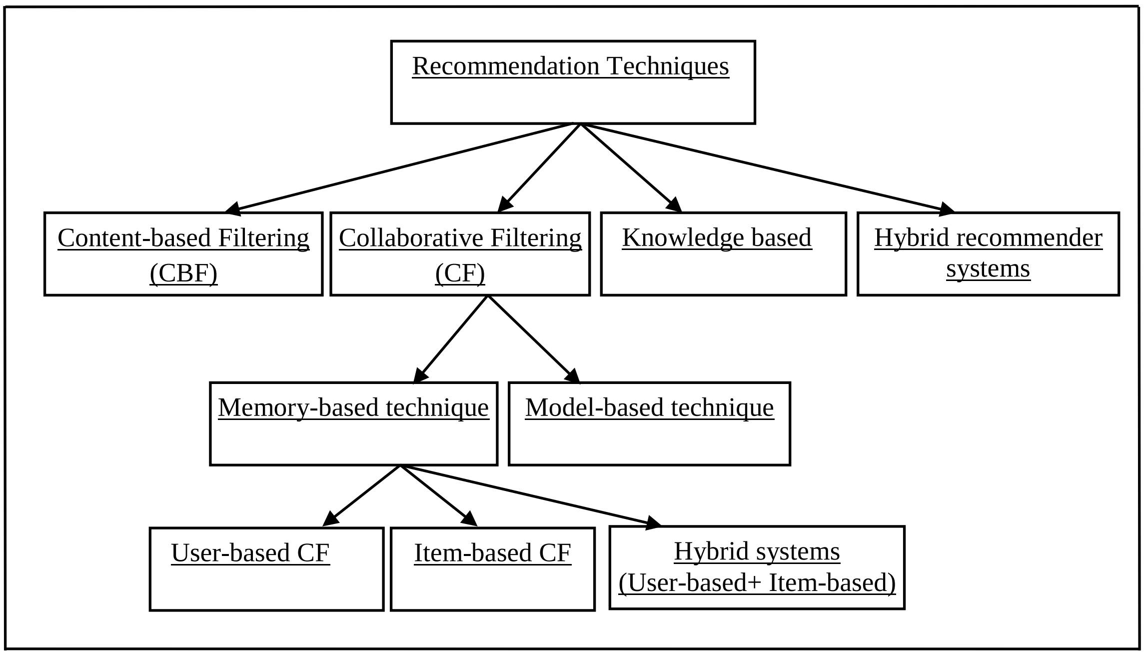

Figure 1.1 Recommendation techniques (Pin-Yu *et al.,* 2010; Bellogín *et al.*, 2013)

The CBF recommends items that are similar to the ones that users preferred in the past. Recommendations are made by automatically matching a customer's interests with items' contents (Pin-Yu *et al.,* 2010; Wu *et al.,* 2014). CBF does not take advantage of shared features or attributes among users' preferences in offering important recommendations to other comparable users. This is because it recommends items that are similar to those which users already know (Bellogín *et al.*, 2013; Horsburgh *et al.,* 2015). On the contrary, CF recommends items based on compatible users' ratings on items rather than the contents or attribute of items. Thus, an analysis of users' ratings on items provide recommendations for users according to what user with similar preferences and tastes have liked in the past (Pin-Yu *et al.*, 2010). According to Choi and Suh (2013), CF-based recommender systems automate the word-of-mouth recommendation process, in which people share their opinions on same items. CF is then seemed as being contrastive to the knowledge-based technique. This is because knowledge-based technique suggests products based on deduction about users' needs and preferences. This technique does not depend on users' profile and rating. Nor does it based on the word-of-mouth, like the CF technique. Knowledge-based filtering usually generates a recommendation based on the matched users' needs and preferences as well as the available items (Bellogín *et al.*, 2013; Boratto *et al.*, 2015).

The CF is one of the most successful recommender techniques among techniques used in recommender systems to overcome the information overload because it provides the best results and accurate recommendations even though it has simplistic algorithm (Nakatsuji *et al*., 2016, Kaleli, 2014; Kim *et al*., 2011). CF is easy to implement and is effective. CF technology has the means to recommend unanticipated items by identifying similar users who rated the items without any content attribute compared to other recommender techniques (e.g., content based technique (Liu *et al*., 2014)). Moreover, CF does not need any domain knowledge about the items and users unlike knowledge-based techniques (Ghazanfar and Prügel-Bennett, 2014). Because of its simplicity in both theory and implementation, CF can be applied to virtually any kind of items viz. movies, books, papers, jokes, news, locations of holidays, songs, web sites, stocks etc. In other words, CF techniques are more often implemented than knowledge-based and content filtering in recommendation systems, since they often result in better predictive performance and recommendations accuracy. The main reason is that, CF techniques are independent of data used by knowledge-based techniques and content filtering, which are invasive and time consuming to collect (Nakatsuji *et al.,* 2016; Ranjbar et al., 2015). CF technique generates recommendations via the ratings of a set of similar users or items known as neighbors (Ranjbar *et al*., 2015; Berkovsky *et al*., 2012).

User information stored in users profile in the recommender systems are collected by the feedback techniques. Recommender systems use users profile in order to reflect user interests and make recommendation. The feedback techniques to obtain information about user preferences are grouped into two types: Explicit and Implicit feedback (Núñez-Valdéz *et al.,* 2012). In the explicit feedback, users evaluate the products by assigning a score to them. In this feedback, users unequivocally express their interests in products (Jawaheer, 2010). The most common explicit feedback system for evaluating the products by users on the web are consists of explicit rating “5 stars” (ratings of user are stated in a 1~5 scale) and explicit rating “Like”.

For instance, social networks such as YouTube and Facebook provide user with using the like rating system to rate the contents. On the other hand, Movilens

Film affinity and Amazon online store provide users with using the star ratings system to identify which products are of user interest. Another explicit feedback system is Google+1 that Google added to its search engine and allows users to evaluate explicitly the websites which is more interesting for them. Serious limitation in explicit feedback is the reluctance of users to spend time providing the ratings on items (Yang *et al,* 2012).

The implicit feedback provides the evaluation of products without intervention of users. This evaluation is performed by capturing of information obtained from the activities done by the users in the application without the user being aware (Jawaheer, 2010). According to Kardan and Ebrahimi (2013) the implicit feedback can be obtained by observing user behavior and their actions in order to infer the user interests. For example, when the user reads an article online, regarding to the time that user spend to read the article, the system could automatically infer whether the article is on interest of user or an internet radio is able to track which songs a user has listened to. Implicit feedback is used to filter and recommend a variety of items (such as articles, books, movies, television programs, web documents, etc) by understanding user preferences and interests based on user behavior and actions made by the user in the system. Types of implicit feedback include search patterns, mouse movement, browsing history, purchase history, etc. For example, when a user purchases many books with the same author, the system could understand that user likes that author (Kaleli, 2014; Zhao and Ordóñez de Pablos, 2011; Hu *et al.,* 2008).

1.2 Background of Problem

While the number of products on the web is increase, ability of internet users in getting appropriate product recommendations is decreased so finding the right information that best meet requirements and preferences of user become difficult due to information overload and diversity of data for example users may access the incorrect or irrelevant information.

The CF technique infers commonalities between the active user and his neighbors (users who have similar preferences with active user) on the basis of their ratings and then makes recommendations based on inter-user comparisons (Zhou *et al.*, 2015; Pinho Lucas *et al.*, 2012). In this technique, make recommendations are based on evaluation of the profile of the active user and his/her neighbors. CF uses the rating system that allows users to explicitly input preference ratings about products in order to detect which products are of user interest and identifying similar users (neighbors). Rating on products based CF technique can be showed as the flow of predicting how a user rates a given product from other user ratings. The following four steps describe the trend of CF technique (Bauer and Nanopoulos, 2014; Xie *et al.*, 2014):

i. Collect user’s ratings of available items (e.g. movies, CDs or books) in user profile (user rating database) in order to show the preferences of user in the corresponding domain.
ii. Identify a set of users (known as neighbors) that are similar to the active user. CF evaluates the likings similarity between users based on their ratings on common items in the user profile. For example, either they have given similar rating on available items or they have used similar items.
iii. Predict the rating on products that active user would give by observing the ratings of neighbors of active user. Notice that, when trying to predict the rating on a specific item, there will be many vacant ratings of the product in neighborhood of active user. In the other words, a significant number of neighbors have not rated the product therefore mechanisms should be developed that enable to predict ratings on products based on minimum number of ratings.
iv. Find products that the active user is interests in to be recommended based on interests of like-minded users.

Drawbacks inherited by CF in recommender systems are reflected in incorrect recommendation. False positive or false negative is error in a recommendation that may be happened. In false positive, products are recommended that the customer does not like them. False negative consists of products that were not recommended, in spite of the customer would have liked them (Xie *et al.,* 2014; Pinho Lucas *et al.,* 2012). In order to reduce these errors in a recommendation, techniques applied in recommender systems should be improved to alleviate drawbacks in recommender systems. However, CF suffers from four basis drawbacks to be described as follow:

- Data Sparsity problem refers to the lack of number of ratings on products for generating accurate predictions and identifying similar users (neighbors). CF is not able to find nearest-neighbors for users and produce the correct recommendations when the number of ratings obtained is very less compared to the number of ratings that are needed for prediction (Kardan and Ebrahimi (2013; Shi *et al*., 2014). The most eminent shortcoming of the CF technique is the sparsity problem since, it makes recommendation results unreliable.
- Cold_start problem occurs when an item is newly added in the system or new user has just started to use the system. CF is unable to make good recommendation for the new user because the system has insufficient information on the user (insufficient previous ratings or purchases) to generate recommendation for them. Similarity, in the case of new items, it is unlikely that CF recommend these new items to users because no purchased or ratings expressed by users on these items (Lam *et al.,* 2008; Pinho Lucas *et al.,* 2012).
- Scalability problem refers to declining performance of the recommender systems because of large numbers of items or users. Computational time for searching the nearest neighbors for active user or generating recommendations increases significantly due to an increased number of items and users (Pinho Lucas *et al.,* 2012; Acilar and Arslan, 2009).
- Gray sheep problem leading to poor recommendation for the users whose opinions are not similar with the ones of any group of users. In fact, a user may be taken in the situation of gray sheep, when spend long time in the condition of cold-start problem, because such user has not shown interest on products of system (Pinho Lucas *et al.,* 2012).

1.3 Problem Statement

The success of CF technique strongly depends on the interaction of users with the system; it requires ratings on the available items so that correct recommendations can be made. However, it is impossible for a system to have a complete database with the evaluations on available items due to huge amount of items. The number of ratings obtained is relatively small compared to number of ratings needed for prediction of the vacant ratings; therefore, sparsity problem occurs. Sparsity problem refers to the lack of user ratings needed for prediction of users' preferences in comparison with the large number of users and items in a user/item matrix. Recommender systems are not able to find interests of user correctly and hence, computing prediction becomes incorrect when a user rates few products. This is a significant challenge because it is difficult and costly to obtain sufficient information of evaluation from users about products of system while the number of products increases.

In short, the problem that is addressed in this research is data sparsity (insufficient number of ratings) in which it causes the CF not able to make correct recommendations.

1.4 Research Questions

The following research questions are defined for this research:

1) How does the CF technique work when sparsity is an issue (The number of ratings on items is insufficient for prediction and recommendation)?
   - What implicit data and data mining techniques can be used to extract knowledge about users' preferences?
   - Which available recommendation datasets about users' preferences for a set of items are more effectively employed as a benchmark of implicit data?

2) How can we utilize implicit feedback and data mining techniques to overcome the sparsity problem in the CF technique?
   - How does the analysis of implicit data be effectively integrated into CF recommender system?
   - Can implicit feedback and data mining techniques help to improve the performance of CF technique in sparse data? (be addressed by considering experimental methodology)
   - Do data mining techniques in CF effectively exploit the implicit data and analyze users' preferences in improving accuracy of recommendations?

1.5 Research Objectives

The research seeks to address the following objectives:

1) To investigate the state of research in CF technique and implicit feedback.
2) To investigate user activities that can influence recommender system developed based on CF technique.
3) To improve the CF technique by considering implicit feedback and data mining techniques in which dealing with sparsity problem.
4) To evaluate the improved CF technique by conducting experiments on public dataset.

1.6 Research Scope

Firstly, in order to investigate the CF technique and implicit feedback, we will conduct a systematic review on the relevant published related articles. This study needs a more in-depth knowledge on how to improve the CF by identifying the user preferences from their implicit behavior; and the sparsity problem which puts a limit to this technique, has to be given consideration.

To achieve the second objective which is to investigate users' activities that influence the recommender system developed based on the CF technique, the analysis and description of the public recommendation datasets (such as Jester, MovieLens, Million Song datasets, etc) will be done. Then, we will conduct a critical observation on research articles to explore and present the users' activities which are explored from the public datasets. The critical observation conducted will help in discussing several issues related to datasets: (1) the ways to enhance users' feedback and present an overview of state-of-the-art techniques in a recommender systems, (2) to investigate the historical record of users' activities that can influence the recommender system developed based on CF technique, (3) to identify implicit feedback datasets and which attributes in public datasets (social tagging, social relations, categorical data) hold more significant information to provide accurate recommendations.

In achieving the third objective which is to propose the improved CF technique, the implicit feedback and data mining techniques (for example: association rules, clustering, classification) will be given ample consideration. Implicit feedback shows how and how often a user operates in the system. This will provide us with sufficient information about the user's interests, which will eventually help in decreasing the dependency of the CF technique on the user's rating and hence, improve the prediction quality and recommendation accuracy. In our proposed technique, in order to overcome sparsity problem in CF, we plan to acquire the users' interests by analyzing implicit interaction of a user with items. For data mining techniques, we will consider data mining techniques to be sensitive to sparsity problem so that accurate recommendations can be made. The data mining techniques have been effective in improving the accuracy of recommendations by analyzing users' preferences and exploring and mining knowledge from web data. Moreover, data mining techniques are induced off- line, before the user logs onto the system, and therefore, the time spent on modeling user interests has no effect on the users' response time.

Finally, an experimental evaluation on the public dataset as benchmark data will be conducted in order to evaluate the proposed technique. This experiment will be conducted to evaluate the accuracy of the generated recommendation by improving the CF technique. The improvement is made by comparing the proposed technique with the basic CF, based on the defined evaluation metrics under sparse data conditions.

1.7 Research Contributions and Significance

The major contributions of this study can be summarized as in the following paragraphs:

1) Systematic Literature Review (SLR) report on state of research and practice of CF technique and implicit feedback

Based on the extensive review done on the research articles and studies conducted on the trend of CF and implicit feedback, this research has provided SLR in the area of study. SLR is a method of Evidence-based Software Engineering (EBSE) which applies an evidence-based approach for software engineering research and practice. This study provides some valuable insights on identifying the elements in CF that can be improved and also identifying the potential users' activities that can be integrated with CF in order to overcome the sparsity problem. SLR report provides insights to practitioners and researchers to determine a useful starting point for further research in the area of CF and implicit feedback. One of the first research studies to investigate the CF technique and implicit feedback with conducting SLR.

2) Implicit feedback based on users' activities

CF technique is realistic because it takes implicit feedback into consideration to improve the user recommendations in the case of absence of a sufficient amount of available ratings on items. User activities enrich the user profiles by exploiting the existing information sources beyond the user/item matrix (such as interests of users on properties of items: a user watches a movie of a specific genre), hence providing a huge opportunity to improve the recommendation accuracy. Conducting a critical observation on research papers will be done in order to present the users' activities explored from public datasets. The report of the critical observation supports and motivates practitioners and researchers by providing the state-of-the-art knowledge on public datasets and providing guidelines on how to implement and validate recommender systems under different domains to support users in various decision activities. One of first research studies to describe and analyze public recommendation datasets systematically.

3) Improved CF based on data mining techniques and implicit feedback

CF is the most popular and successful technique used in recommender systems and is also the center of this research. Extensive work on CF has been done in the past decade, and many recommendation techniques have been developed. However, there are still major research issues that remain unsolved or overlooked. This research applies implicit feedback and data mining techniques to improve the current CF for achieving further improvement in recommendation accuracy. A new recommendation technique will be proposed to address sparsity problem by using data mining techniques and implicit data in forming recommendations.

Experimental results from evaluating the improved CF will be conducted to show the improvements of improved CF technique against basic CF and show how accurate the recommendation can be made.

1.8 Organization of Thesis

A brief introduction to recommender systems and CF technique were given in the Chapter 1. The remainder of this thesis is organized as follows:

Chapter 2: presents the literature reviews where it discusses previous research studies and the gap that exists in the studied area.

Chapter 3: outlines the research methodology of this thesis. The research methodology and instruments applied in this research is described in this Chapter 3.

Chapter 4: presents a report on the investigation of the state of research and practice of CF technique and implicit feedback by examining the published articles.

Chapter 5: describes a number of publicly recommendation datasets and presents an overview of state-of-the-art techniques in recommender systems and the historical record of users' activities.

Chapter 6: proposes a new technique for recommendations based on user profiles created from implicit user feedback and employing the data mining techniques as solution to the sparsity problem.

Chapter 7: provides a description of experimental methodology used in this thesis. The experiments for evaluating the proposed method in addressing the research problem will be given in this Chapter.

Chapter 8: summarizes the research results and achievements of this thesis and draws the direction for future works.

REFERENCES

Abdullah, N., Xu, Y. and Geva, S. (2010). Infrequent Purchased Product Recommendation Making based on User Behaviour and Opinions in E-commerce Sites. IEEE International Conference on Data Mining Workshops (pp. 1084-1091).

Acilar, A. M., and Arslan, A. (2009). A collaborative filtering method based on artificial immune network. Expert Systems with Applications. 36(4): 8324-8332.

Adomavicius, G., and Zhang, J. (2012). Impact of data characteristics on recommender systems performance. ACM Transactions on Management Information Systems (TMIS), 3(1), 3.

Adomavicius, G., and Tuzhilin, A. (2005). Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. IEEE Transactions on Knowledge and Data Engineering, 17(6), 734–749.

Albadvi, A., and Shahbazi, M. (2009). hybrid recommendation technique based on product category attributes. Expert Systems with Applications, 36 (9), 11480–11488.

Ahn, H. J., Kang, H., and Lee, J. (2010). Selecting a small number of products for effective user profiling in collaborative filtering. Expert Systems with Applications, 37(4), 3055-3062.

Amatriain, X., Jaimes, A., Oliver, N., and Pujol, J. M. (2011). Data mining methods for recommender systems. In Recommender Systems Handbook(pp. 39-71). Springer US.

Anand, D., and Mampilli, B. S. (2014). Folksonomy-based fuzzy user profiling for improved recommendations. Expert Systems with Applications, 41(5), 2424-2436.

Anand, D., and Bharadwaj, K. (2011). Utilizing various sparsity measures for enhancing accuracy of collaborative recommender systems based on local and global similarities. Expert systems with applications, 38(5), 5101-5109.

Bae, J. K., and Kim, J. (2010). Integration of heterogeneous models to predict consumer behavior. Expert Systems with Applications, 37(3), 1821–1826.

Barragáns-Martínez, A. B., Costa-Montenegro, E., Burguillo, J. C., Rey-López, M., Mikic-Fonte, A., and Peleteiro, A. (2010). "A hybrid content-based and item-based collaborative filtering approach to recommend TV programs enhanced with singular value decomposition." Information Sciences 180(22): 4290-4311.

Basu Roy, S., Amer-Yahia, S., Chawla, A., Das, G., and Yu, C. (2010). Space efficiency in group recommendation. Very Large Data Base Journal, 19(6), 877–900.

Bakshi, S., Jagadev, A. K., Dehuri, S., & Wang, G. N. (2014). Enhancing scalability and accuracy of recommendation systems using unsupervised learning and particle swarm optimization. Applied Soft Computing, 15, 21-29.

Bauer, J., and Nanopoulos, A. (2014). Recommender systems based on quantitative implicit customer feedback. Decision Support Systems, 68, 77-88.

Baudisch, P., and Brueckner, L. (2002). Lowering the entry barrier to personalized TV program recommendation. In International Conference on Adaptive Hypermedia and Adaptive Web Systems (pp. 58-68). Springer Berlin Heidelberg.

Bedi, P., and Sharma, R. (2012). Trust based recommender system using ant colony for trust computation. Expert Systems with Applications, 39(1), 1183-1190.

Berkovsky, S., Kuflik, T., & Ricci, F. (2012). The impact of data obfuscation on the accuracy of collaborative filtering. Expert Systems with Applications,39(5), 5033-5042.

Bertin-Mahieux, T., Ellis, D.PW., Whitman, B. and Lamere, P. (2011). The million song dataset. Paper presented at the ISMIR 2011: Proceedings of the 12th International Society for Music Information Retrieval Conference, October-2011, Miami, Florida.

Bellogín, A., Castells, P., and Cantador, I. (2014). Neighbor selection and weighting in user-based collaborative filtering: a performance prediction approach. ACM Transactions on the Web (TWEB), 8(2), 12.

Bellogín, A., Wang, J., and Castells, P. (2013). "Bridging memory-based collaborative filtering and text retrieval." Information retrieval, 16(6), 697-724.

Beecham, S., Badoo, N., Hall, T., Robinson, H., Sharp, H. (2007). Motivation in software engineering: a systematic review. Information and Software Technology Journal 50 (9–10), 860–878.

Bennett, J and Lanning, S. (2007). The Netflix prize. In Proceedings of the KDD-Cup and Workshop at the 13th SIGKDD International Conference on Knowledge Discovery and Data Mining.

Bilge, A., and Polat, H. (2013). A comparison of clustering-based privacy-preserving collaborative filtering schemes. Applied Soft Computing, 13(5), 2478-2489.

Bobadilla, J., Ortega, F., Hernando, A., & Glez-de-Rivera, G. (2013). A similarity metric designed to speed up, using hardware, the recommender systems k-nearest neighbors algorithm. Knowledge-Based Systems, 51, 27-34.

Bobadilla, J., Hernando, A., Ortega, F., and Gutiérrez, A. (2012). Collaborative filtering based on significances. Information Sciences, 185(1), 1-17.

Bobadilla, J., Ortega, F., Hernando, A., and Bernal, J. (2012). Generalization of recommender systems: Collaborative filtering extended to groups of users and restricted to groups of items. Expert systems with Applications, 39(1), 172-186.

Bobadilla, J., Ortega, F., Hernando, A., and Alcalá, J. (2011). Improving collaborative filtering recommender system results and performance using genetic algorithms. Knowledge-based systems, 24(8), 1310-1316.

Bobadilla, J., Serradilla, F., and Bernal, J. (2010). A new collaborative filtering metric that improves the behavior of recommender systems. Knowledge-Based Systems, 23(6), 520-528.

Boratto, L., Carta, S., and Fenu, G. (2015). Discovery and representation of the preferences of automatically detected groups: Exploiting the link between group modeling and clustering. Future Generation Computer Systems.

Braida, F., Mello, C. E., Pasinato, M. B., and Zimbrão, G. (2015). Transforming collaborative filtering into supervised learning. Expert Systems with Applications, 42(10), 4733-4742.

Briguez, C. E., Budan, M. C., Deagustini, C. A., Maguitman, A. G., Capobianco, M., and Simari, G. R. (2014). Argument-based mixed recommenders and their application to movie suggestion. Expert Systems with Applications, 41(14), 6467-6482.

Birtolo, C., and Ronca, D. (2013). Advances in clustering collaborative filtering by means of fuzzy C-means and trust. Expert Systems with Applications,40(17), 6997-7009.

Blanco-Fernández, Y., López-Nores, M., Gil-Solla, A., Ramos-Cabrer, M., Pazos-Arias, J.J. (2011). Exploring synergies beween content-based filtering and spreading activation techniques in knowledge-based recommender systems, Information Sciences 181- 4823–4846.

Burke, R. (2002). "Hybrid recommender systems: Survey and experiments," User Modeling and User-Adapted Interaction, vol. 12, pp. 331-370.

Bu, M., Luo, Sh., and He, J. (2009). A fast collaborative filtering algorithm for implicit binary data. CAID and CD. IEEE 10th International Conference on Computer-Aided Industrial Design and Conceptual Design.

Brereton, P., Kitchenham, B., Budgen, D., Turner, M., and Khalil, M. (2007). "Lessons from applying the systematic literature review process within the software engineering domain." Journal of Systems and Software 80(4): 571-583.

Brozovsky, L., and Petricek, V. (2007). Recommender system for online dating service. arXiv preprint.

Cacheda, F., Carneiro, V., Fernández, D., and Formoso, V. (2011). Comparison of collaborative filtering algorithms: Limitations of current techniques and proposals for scalable, high-performance recommender systems. ACM Transactions on the Web (TWEB), 5(1), 2.

Cai, Y., Lau, R. Y., Liao, S. S., Li, C., Leung, H. F., and Ma, L. C. (2014). Object typicality for effective Web of Things recommendations. Decision Support Systems, 63, 52-63.

Cai, Y., Leung, H. F., Li, Q., Min, H., Tang, J., and Li, J. (2014). Typicality-based collaborative filtering recommendation. Knowledge and Data Engineering, IEEE Transactions on, 26(3), 766-779.

Cao, Y., and Li, Y. (2007). "An intelligent fuzzy-based recommendation system for consumer electronic products." Expert Systems with Applications 33(1): 230-240.

Casino, F., Domingo-Ferrer, J., Patsakis, C., Puig, D., and Solanas, A. (2015). A k-anonymous approach to privacy preserving collaborative filtering. Journal of Computer and System Sciences, 81(6), 1000-1011.

Colace, F., De Santo, M., Greco, L., Moscato, V., and Picariello, A. (2015). A collaborative user-centered framework for recommending items in Online Social Networks. Computers in Human Behavior, 51, 694-704.

Chen, M. H., Teng, C. H., and Chang, P. C. (2015). Applying artificial immune systems to collaborative filtering for movie recommendation. Advanced Engineering Informatics, 29(4), 830-839.

Chen, Y. C., Lin, Y. S., Shen, Y. C., and Lin, S. D. (2013). A modified random walk framework for handling negative ratings and generating explanations.ACM Transactions on Intelligent Systems and Technology (TIST), 4(1), 12.

Chen, L., Zeng, W., and Yuan, Q. (2013). A unified framework for recommending items, groups and friends in social media environment via mutual resource fusion. Expert Systems with Applications, 40(8), 2889-2903.

Cheng, L. C., and Wang, H. A. (2014). A fuzzy recommender system based on the integration of subjective preferences and objective information. Applied Soft Computing, 18, 290-301.

Cho, Y. H., and Kim, J. K. (2004). Application of web usage mining and product taxonomy to collaborative recommendations in e-commerce. Expert System with Applications, 26 (2), 233–246.

Choi, K., Yoo, D., Kim, G., and Suh, Y. (2012). A hybrid online-product recommendation system: Combining implicit rating-based collaborative filtering and sequential pattern analysis. Electronic Commerce Research and Applications, 11(4), 309-317.

Choi, K. and Suh, Y. (2013). "A new similarity function for selecting neighbors for each target item in collaborative filtering." Knowledge-Based Systems 37(0): 146-153.

Dakhel, G. M., and Mahdavi, M. (2011). A new collaborative filtering algorithm using K-means clustering and neighbors' voting. Hybrid Intelligent Systems (HIS), 2011 11th.International Conference.

Da Costa, A. F., and Manzato, M. G. (2016). Exploiting multimodal interactions in recommender systems with ensemble algorithms. Information Systems,56, 120-132.

De Campos, L. M., Fernández-Luna, J. M., Huete, J. F., and Rueda-Morales, M. A., (2010). "Combining content-based and collaborative recommendations: A hybrid approach based on Bayesian networks." International Journal of Approximate Reasoning 51(7): 785-799.

Deshpande, M., and Karypis, G. (2004). Item-based top-N recommendation algorithms. ACM Transactions on Information Systems., 22(1), 143-177.

Devi, M. K., and Venkatesh, P. (2013). Smoothing approach to alleviate the meager rating problem in collaborative recommender systems. Future Generation Computer Systems, *29*(1), 262-270.

Eckhardt, A. (2012). Similarity of users'(content-based) preference models for Collaborative filtering in few ratings scenario. Expert Systems with Applications, 39(14), 11511-11516.

Elahi, M., Ricci, F., and Rubens, N. (2013). Active learning strategies for rating elicitation in collaborative filtering: A system-wide perspective. ACM Transactions on Intelligent Systems and Technology (TIST), 5(1), 13.

Feng, H., Tian, J., Wang, H. J., & Li, M. (2015). Personalized recommendations based on time-weighted overlapping community detection. Information & Management, 52(7), 789-800.

Formoso, V., Fernández, D., Cacheda, F., and Carneiro, V. (2013). Using profile expansion techniques to alleviate the new user problem. Information Processing & Management, 49(3), 659-672.

García-Borgoñon, L., Barcelona, M. A., García-García, J. A., Alba, M., & Escalona, M. J. (2014). Software process modeling languages: A systematic literature review. Information and Software Technology, 56(2), 103-116.

Gan, M., and Jiang, R. (2013). Improving accuracy and diversity of personalized recommendation through power law adjustments of user similarities. Decision Support Systems, 55(3), 811-821.

Gantner, Z., Rendle, S., Freudenthaler, C., and Schmidt-Thieme, L. (2011). "MyMediaLite: A Free Recommender System Library." Proceedings of the fifth ACM conference on Recommender systems. (978-1-4503-0683-6): 305-308.

Geng, B., Li, L., Jiao, L., Gong, M., Cai, Q., and Wu, Y. (2015). NNIA-RS: A multi-objective optimization based recommender system. Physica A: Statistical Mechanics and its Applications, 424, 383-397.

Gogna, A., and Majumdar, A. (2015). A Comprehensive Recommender System Model: Improving Accuracy for Both Warm and Cold Start Users. Access, IEEE, 3, 2803-2813.

Ghazarian, S., and Nematbakhsh, M. A. (2015). Enhancing memory-based collaborative filtering for group recommender systems. Expert Systems with Applications, 42(7), 3801-3812.

Ghazanfar, M. A., and Prügel-Bennett, A. (2014). Leveraging clustering approaches to solve the gray-sheep users problem in recommender systems. Expert Systems with Applications, 41(7), 3261-3275.

Ghazanfar, M. A., Prügel-Bennett, A., and Szedmak, S. (2012). Kernel-mapping recommender system algorithms. Information Sciences, 208, 81-104.

Gharibshah, J., & Jalili, M. (2014). Connectedness of users–items networks and recommender systems. Applied Mathematics and Computation, 243, 578-584.

Gotardo, R. A., Teixeira, C. A. C., and Zorzo, S. D. (2008). An approach to recommender system applying usage mining to predict users interests. IWSSIP. 15th International Conference on Signals and Image Processing.

Gogna, A., and Majumdar, A. (2015). Matrix completion incorporating auxiliary information for recommender system design. Expert Systems with Applications, 42(14), 5789-5799.

Hawalah, A., and Fasli, M. (2014). Utilizing contextual ontological user profiles for personalized recommendations. Expert Systems with Applications,41(10), 4777-4797.

Hanani, U., Shapira, B., Shoval, P. (2001). Information filtering: overview of issues, research and systems, User Modeling and User-Adapted Interaction 11- 203–259.

Hang, Y., Guiran, C., and Xingwei,W. (2009). A Cold-Start Recommendation Algorithm Based on New User's Implicit Information and Multi-attribute Rating Matrix. HIS '09. Ninth International Conference on Hybrid Intelligent Systems.

Hahsler, M. (2011). "recommenderlab: A Framework for Developing and Testing Recommendation Algorithms." NSF Industry/University Cooperative Research Center for Net-Centric Software & Systems.

Hernando, A., Moya, R., Ortega, F., and Bobadilla, J. (2014). Hierarchical graph maps for visualization of collaborative recommender systems. Journal of Information Science, 40(1), 97-106.

Hernando, A., Bobadilla, J., Ortega, F., and Tejedor, J. (2013). Incorporating reliability measurements into the predictions of a recommender system.Information Sciences, 218, 1-16.

Hoseini, E., Hashemi, S., and Hamzeh, A. (2012). SPCF: a stepwise partitioning for collaborative filtering to alleviate sparsity problems. Journal of Information Science. doi:10.1177/0165551512451667.

Hostler, R. E., Yoon, V. Y., & Guimaraes, T. (2012). Recommendation agent impact on consumer online shopping: The Movie Magic case study. Expert Systems with Applications, 39(3), 2989-2999.

Horsburgh, B., Craw, S., and Massie, S. (2015). Learning pseudo-tags to augment sparse tagging in hybrid music recommender systems. Artificial Intelligence, 219, 25-39.

Hsu, M. (2008). "A personalized English learning recommender system for ESL students," Expert Systems with Applications, vol. 34, pp. 683-688.

Hsiao, K. J., Kulesza, A., and Hero, A. O. (2014). Social collaborative retrieval. IEEE Journal of Selected Topics in Signal Processing, 8(4), 680-689.

Hu, L., Song, G., Xie, Z., and Zhao, K. (2014). Personalized recommendation algorithm based on preference features. Tsinghua Science and Technology,19(3), 293-299.

Hu, Y., Koren, Y., Volinsky, C. (2008). Collaborative filtering for implicit feedback datasets. Presented at the proceedings of the 2008 eighth IEEE international conference on data mining. vol., no., pp.263,272.

Huang, S., Ma, J., Cheng, P., and Wang, S. (2015). A hybrid multigroup coclustering recommendation framework based on information fusion. ACM Transactions on Intelligent Systems and Technology (TIST), 6(2), 27.

Huang, C. L., Yeh, P. H., Lin, C. W., and Wu, D. C. (2014). Utilizing user tag-based interests in recommender systems for social resource sharing websites. Knowledge-Based Systems, 56, 86-96.

Huang, Z., Chen, H., Zeng, D. (2004). Applying associative retrieval techniques to alleviate the sparsity problem in collaborative filtering, ACM Transactions on Information Systems 22 -116-142.

Hung, L.-p. (2005). "A personalized recommendation system based on product taxonomy for one-to-one marketing online." Expert Systems with Applications 29(2): 383-392.

Hwang, W. S., Lee, H. J., Kim, S. W., Won, Y., and Lee, M. S. (2016). Efficient recommendation methods using category experts for a large dataset. Information Fusion, 28, 75-82.

Ignatov, D. I., Nikolenko, S. I., Abaev, T., and Poelmans, J. (2016). Online recommender system for radio station hosting based on information fusion and adaptive tag-aware profiling. Expert Systems with Applications, 55, 546-558.

Javari, A., and Jalili, M. (2015). Accurate and novel recommendations: an algorithm based on popularity forecasting. ACM Transactions on Intelligent Systems and Technology (TIST), 5(4), 56.

Jawaheer, G. (2010). Comparison of implicit and explicit feedback from an online music recommendation service. Presented at the proceedings of the 1st international workshop on information heterogeneity and fusion in recommender systems, Barcelona, Spain.

Junior, E. B., Manzato, G., and Goularte, R. (2013). Hybrid recommenders: incorporating metadata awareness into latent factor models. In Proceedings of the 19th Brazilian symposium on multimedia and the web (pp. 317-324). ACM.

Kardan, A., and Ebrahimi, M. (2013). "A novel approach to hybrid recommendation systems based on association rules mining for content recommendation in asynchronous discussion groups." Information Sciences 219(0): 93-110.

Kaššák, O., Kompan, M., and Bieliková, M. (2015). Personalized hybrid recommendation for group of users: Top-N multimedia recommender. Information Processing & Management, 52(3), 459-477.

Kagita, V. R., Pujari, A. K., and Padmanabhan, V. (2015). Virtual user approach for group recommender systems using precedence relations. Information Sciences, 294, 15-30.

Kaleli, C. (2014). An entropy-based neighbor selection approach for collaborative filtering. Knowledge-Based Systems, 56, 273-280.

Kim, H. N., and El Saddik, A. (2015). A stochastic approach to group recommendations in social media systems. Information Systems, 50, 76-93.

Kim, H. N, and Kim, H. J. (2014). A framework for tag-aware recommender systems. Expert Systems with Applications, 41(8), 4000-4009.

Kim, H. N., Ha, I., Lee, K. S., Jo, G. S., and El-Saddik, A. (2011). Collaborative user modeling for enhanced content filtering in recommender systems. Decision Support Systems, 51(4), 772-781.

Kim, H. N., El-Saddik, A., and Jo, G. S. (2011). Collaborative error-reflected models for cold-start recommender systems. Decision Support Systems,51(3), 519-531.

Kim, H. K., Kim, J. K., and Ryu, Y. U. (2009). Personalized recommendation over a customer network for ubiquitous shopping. IEEE Transactions on Services Computing, 2, 140–151.

Kim, H. N., Ji, A. T., Ha, I., and Jo, G. S. (2010). Collaborative filtering based on collaborative tagging for enhancing the quality of recommendation. Electronic Commerce Research and Applications, 9(1), 73–83.

Kitchenham, B., and Charters,S. (2007). Guidelines for performing Systematic Literature Re-views in Software Engineering. Technical Report EBSE 2007-001, Keele University and Durham University Joint Report.

Kitchenham, B., Brereton, P., Budgen, D., Turner, M., Bailey, J., and Linkman, S. (2009). "Systematic literature reviews in software engineering – A systematic literature review." Information and Software Technology 51(1): 7-15.

Kitchenham, B., and Brereton, P. (2013). "A systematic review of systematic review process research in software engineering." Information and Software Technology 55.12: 2049-2075.

Kim, S., and Yum, B. (2011). Recommender system based on click stream data using association rule mining. Expert Systems with Applications, 38(10), 13320-13327.

Kolomvatsos, K., Anagnostopoulos, C., and Hadjiefthymiades, S. (2014). An efficient recommendation system based on the optimal stopping theory.Expert Systems with Applications, 41(15), 6796-6806.

Koren, Y. (2010). Factor in the neighbors: Scalable and accurate collaborative filtering. ACM Transactions on Knowledge Discovery from Data (TKDD), 4(1), 1.

Krestel, R., & Fankhauser, P. (2012). Personalized topic-based tag recommendation. Neurocomputing, 76(1), 61-70.

Lam, X.N., Vu, T., Le, T.D., Duong, A.D. (2008). Addressing cold-start problem in recommendation systems, in: Proceedings of the 2nd International Conference on Ubiquitous Information Management and Communication, pp. 208–211.

Langseth, H., and Nielsen, T. D. (2012). A latent model for collaborative filtering. International Journal of Approximate Reasoning, 53(4), 447-466.

Langseth, H., and Nielsen, T. D. (2015). Scalable learning of probabilistic latent models for collaborative filtering. Decision Support Systems, 74, 1-11.

Lee, J., Sun, M., and Lebanon, G. (2012). Prea: Personalized recommendation algorithms toolkit. Journal of Machine Learning Research, 2699-2703.

Lee, J. W., Kim, H. J., and Lee, S. G. (2010). Conceptual collaborative filtering recommendation: A probabilistic learning approach. Neurocomputing, 73(13), 2793-2796.

Lee, T. Q., Park, Y., and Park, Y. T. (2008). A time-based approach to effective recommender systems using implicit feedback. Expert Systems with Applications,34(4): 3055-3062.

Lee, T. Q., Park, Y., and Park, Y.T. (2009). "An empirical study on effectiveness of temporal information as implicit ratings." Expert Systems with Applications 36(2, Part 1): 1315-1321.

Li, X., and Chen, H. (2013). Recommendation as link prediction in bipartite graphs: A graph kernel-based machine learning approach. Decision Support Systems, 54(2), 880-890.

Lin, W., Alvarez, S. A., and Ruiz, C. (2002). Efficient adaptive-support association rule mining for recommender systems. Data Mining Knowl. Disc. 6, 1, 83–105.

Liang, H., Xu, Y., Li, Y., and Nayak, R. (2008). Collaborative Filtering Recommender Systems Using Tag Information. WI-IAT '08. IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology.

Lika, B., Kolomvatsos, K., and Hadjiefthymiades, S. (2014). Facing the cold start problem in recommender systems. Expert Systems with Applications,41(4), 2065-2073.

Liu, J., Sui, C., Deng, D., Wang, J., Feng, B., Liu, W., and Wu, C. (2016). Representing conditional preference by boosted regression trees for recommendation. Information Sciences, 327, 1-20.

Liu, W., Wu, C., Feng, B., and Liu, J. (2015). Conditional preference in recommender systems. Expert Systems with Applications, 42(2), 774-788.

Liu, H., Hu, Z., Mian, A., Tian, H., & Zhu, X. (2014). A new user similarity model to improve the accuracy of collaborative filtering. Knowledge-Based Systems, 56, 156-166.

Liu, J., Wu, C., Xiong, Y., and Liu, W. (2014). List-wise probabilistic matrix factorization for recommendation. Information Sciences, 278, 434-447.

Liu, J., Wu, C., and Liu, W. (2013). Bayesian probabilistic matrix factorization with social relations and item contents for recommendation. Decision Support Systems, 55(3), 838-850.

Liu, Z., Qu, W., Li, H., and Xie, C. (2010). A hybrid collaborative filtering recommendation mechanism for P2P networks. Future generation computer systems, 26(8), 1409-1417.

Luo, X., Zhou, M., Xia, Y., and Zhu, Q. (2014). An efficient non-negative matrix-factorization-based approach to collaborative filtering for recommender systems. Industrial Informatics, IEEE Transactions on, 10(2), 1273-1284.

Luo, X., Xia, Y., & Zhu, Q. (2012). Incremental collaborative filtering recommender based on regularized matrix factorization. Knowledge-Based Systems, 27, 271-280.

Lv, G., Hu, C., and Chen, S. (2015). Research on recommender system based on ontology and genetic algorithm. Neurocomputing, 187, 92-97.

Ma, H., Zhou, T. C., Lyu, M. R., and King, I. (2011). Improving recommender systems by incorporating social contextual information. ACM Transactions on Information Systems (TOIS), 29(2), 9.

Martinez, L., Rodriguez,R., and Espinilla, M.(2009). REJA: A Georeferenced Hybrid Recommender System for Restaurants. IEEE/WIC/ACM International Conference on Web Intelligence and Intelligent Agent Technology.

Mehta, S., and Banati, H. (2014). Context aware filtering using social behavior of frogs. Swarm and Evolutionary Computation, 17, 25-36.

Moreno, M. N., Segrera, S., López, V. F., Muñoz, M. D., and Sánchez, Á. L. (2016). Web mining based framework for solving usual problems in recommender systems. A case study for movies′ recommendation.Neurocomputing, 176, 72-80.

Moradi, P., Ahmadian, S., & Akhlaghian, F. (2015). An effective trust-based recommendation method using a novel graph clustering algorithm. Physica A: Statistical Mechanics and its Applications, 436, 462-481.

Movahedian, H., and Khayyambashi, M. R. (2014). Folksonomy-based user interest and disinterest profiling for improved recommendations: An ontological approach. Journal of Information Science, 0165551514539870.

Melville,P., Mooney, R., and Nagarajan, R.(2002). Content-Boosted Collaborative Filtering for Improved Recommendations. In Proceedings of the Eighteenth National Conference on Artificial Intelligence (AAAI-02), 187-192, Edmonton, Alberta.

Miller, B. N., Konstan, J. A., and Riedl, J. (2004). PocketLens: Toward a personal recommender system. ACM Transactions on Information Systems, 22(3), 437-476.

Mirza, B. J., Keller, B. J., & Ramakrishnan, N. (2003). Studying Recommendation Algorithms by Graph Analysis. Journal of Intelligent Information Systems, 20(2),131-160.

Montenegro, C., Martínez, A., and Rey-López, M. (2012). "Which App? A recommender system of applications in markets: Implementation of the service for monitoring users' interaction." Expert Systems with Applications 39(10): 9367-9375.

Nakatsuji, M., and Fujiwara, Y. (2014). Linked taxonomies to capture users' subjective assessments of items to facilitate accurate collaborative filtering.Artificial Intelligence, 207, 52-68.

Nakatsuji, M., Toda, H., Sawada, H., Zheng, J. G., and Hendler, J. A. (2016). Semantic sensitive tensor factorization. Artificial Intelligence, 230, 224-245.

Najafabadi, M. K., and Mahrin, M. N. R. (2016). A systematic literature review on the state of research and practice of collaborative filtering technique and implicit feedback. Artificial Intelligence Review, 45(2), 167-201.

Nikolakopoulos, A. N., Kouneli, M. A., and Garofalakis, J. D. (2015). Hierarchical itemspace rank: Exploiting hierarchy to alleviate sparsity in ranking-based recommendation. Neurocomputing, 163, 126-136.

Núñez-Valdéz, E. R., Cueva Lovelle, J. M., Sanjuán Martínez, O., García-Díaz, V., Ordoñez de Pablos, P., and Montenegro Marín, C. E. (2012). "Implicit feedback techniques on recommender systems applied to electronic books." Computers in Human Behavior 28(4): 1186-1193.

Pan, W., Zhong, H., Xu, C., and Ming, Z. (2015). Adaptive bayesian personalized ranking for heterogeneous implicit feedbacks. Knowledge-Based Systems, 73, 173-180.

Pan, W., Liu, Z., Ming, Z., Zhong, H., Wang, X., and Xu, C. (2015). Compressed knowledge transfer via factorization machine for heterogeneous collaborative recommendation. Knowledge-Based Systems, 85, 234-244.

Pan, W., and Yang, Q. (2013). Transfer learning in heterogeneous collaborative filtering domains. Artificial intelligence, 197, 39-55.

Park, D. H., Kim, H. K., Choi, I. Y., & Kim, J. K. (2012). A literature review and classification of recommender systems research. Expert Systems with Applications, 39(11), 10059-10072.

Patra, B. K., Launonen, R., Ollikainen, V., and Nandi, S. (2015). A new similarity measure using Bhattacharyya coefficient for collaborative filtering in sparse data. Knowledge-Based Systems, 82, 163-177.

Peng, F., Lu, J., Wang, Y., Yi-Da Xu, R., Ma, C., and Yang, J. (2016). N-dimensional Markov random field prior for cold-start recommendation.Neurocomputing, 191, 187-199.

Pin-Yu, P., Chi-Hsuan, W., Gwo-Jiun, H., and Sheng-Tzong, C. (2010). The development of an Ontology-Based Adaptive Personalized Recommender System. International Conference on Electronics and Information Engineering (ICEIE), Vol. 1, pp. V1-76.

Pinho Lucas, J., Segrera, S., and Moreno, M. N. (2012). "Making use of associative classifiers in order to alleviate typical drawbacks in recommender systems." Expert Systems with Applications 39(1): 1273-1283.

Pirasteh, P., Hwang, D., and Jung, J. J. (2015). Exploiting matrix factorization to asymmetric user similarities in recommendation systems. Knowledge-Based Systems, 83, 51-57.

Polatidis, N., and Georgiadis, C. K. (2016). A multi-level collaborative filtering method that improves recommendations. Expert Systems with Applications,48, 100-110.

Qifeng, Y., Sihang, Z., and Bin, F. (2007). Research on Personalized Recommendation System of Scientific and Technological Periodical Based on Automatic Summarization. Information Technologies and Applications in Education. ISITAE '07, (pp. 34-39).

Qinjiao, M., Boqin, F., and Shanliang, P. (2012). A study of Top-N recommendation on user behavior data. IEEE International Conference on Computer Science and Automation Engineering, Vol. 2, pp. 582-586.

Rafeh, R., and Bahrehmand, A. (2012). An adaptive approach to dealing with unstable behaviour of users in collaborative filtering systems. Journal of Information Science, 38(3), 205-221.

Ramezani, M., Moradi, P., and Akhlaghian, F. (2014). A pattern mining approach to enhance the accuracy of collaborative filtering in sparse data domains. Physica A: Statistical Mechanics and its Applications, 408, 72-84.

Ranjbar, M., Moradi, P., Azami, M., and Jalili, M. (2015). An imputation-based matrix factorization method for improving accuracy of collaborative filtering systems. Engineering Applications of Artificial Intelligence, 46, 58-66.

Rana, C., and Jain, S. K. (2014). An evolutionary clustering algorithm based on temporal features for dynamic recommender systems. Swarm and Evolutionary Computation, 14, 21-30.

Rafter, R., Bradley, K., and Smyth, B. (2000). Automated collaborative filtering applications for online recruitment services. (pp. 363-368). Trento, Italy: Springer.

Ren, Y., Li, G., Zhang, J., and Zhou, W. (2013). Lazy collaborative filtering for data sets with missing values. Cybernetics, IEEE Transactions on, 43(6), 1822-1834.

Ricci, F., Rokach, L., and Shapira, B. (2011). Introduction to recommender systems handbook (pp. 1-35). Springer US.

Salah, A., Rogovschi, N., and Nadif, M. (2016). A dynamic collaborative filtering system via a weighted clustering approach. Neurocomputing, 175, 206-215.

Schafer, J.B., Konstan, J.A., and Riedl, J. (2001). E-commerc recommendation application. Journal of data mining and knowledge discovery, 5(1-2), 115-153.

Seminario, C. E., and Wilson, D. C. (2012). "Case Study Evaluation of Mahout as a Recommender Platform." workshop on recommendation utility evaluation: held in conjunction with ACM, pp. 45-50.

Shambour, Q., and Lu, J. (2012). A trust-semantic fusion-based recommendation approach for e-business applications. Decision Support Systems, 54(1), 768-780.

Shambour, Q., and Lu, J. (2015). An effective recommender system by unifying user and item trust information for B2B applications. Journal of Computer and System Sciences, 81(7), 1110-1126.

Shang, M. S., Zhang, Z. K., Zhou, T., and Zhang, Y. C. (2010). Collaborative filtering with diffusion-based similarity on tripartite graphs. Physica A: Statistical Mechanics and its Applications, 389(6), 1259-1264.

Shinde, S. K., and Kulkarni, U. (2012). Hybrid personalized recommender system using centering-bunching based clustering algorithm. Expert Systems with Applications, 39(1), 1381-1387.

Shi, Y., Larson, M., and Hanjalic, A. (2014). Collaborative filtering beyond the user-item matrix: A survey of the state of the art and future challenges. ACM Computing Surveys (CSUR), 47(1), 3.

Son, L. H. (2016). Dealing with the new user cold-start problem in recommender systems: A comparative review. Information Systems, 58, 87-104.

SongJie, G., HongWu, Y., and Hengsong, T. (2009). Combining Memory-Based and Model-Based Collaborative Filtering in Recommender System. Circuits, Communications and Systems, 2009. PACCS '09.

Sopchoke, S., and Kijsirikul, B. (2011). A step towards high quality one-class collaborative filtering using online social relationships. In Advanced Computer Science and Information System, IEEE, (pp. 243-248).

Sun, Z., Han, L., Huang, W., Wang, X., Zeng, X., Wang, M., and Yan, H. (2015). Recommender systems based on social networks. Journal of Systems and Software, 99, 109-119

Sun, X., Kong, F., and Chen, H. (2005). Using quantitative association rules in collaborative filtering. Lecture notes in computer science (Vol. 3739, pp. 822–827). Springer.

Su, X., and Khoshgoftaar, T. M. (2009). A Survey of Collaborative Filtering Techniques. Advances in Artificial Intelligence. doi: 10.1155/2009/421425.

Tan, S., Bu, J., Qin, X., Chen, C., & Cai, D. (2014). Cross domain recommendation based on multi-type media fusion. Neurocomputing, 127, 124-134.

Takács, G., Pilászy, I., Németh, B., and Domonkos, T. (2008). Investigation of Various Matrix Factorization Methods for Large Recommender Systems. Data Mining Workshops, ICDMW '08. IEEE International Conference on Data Mining, pp. 553-562.

Tsai, C. F., and Hung, C. (2012). Cluster ensembles in collaborative filtering recommendation. Applied Soft Computing, 12(4), 1417-1425.

Toledo, R. Y., Mota, Y. C., & Martínez, L. (2015). Correcting noisy ratings in collaborative recommender systems. Knowledge-Based Systems, 76, 96-108.

Tyagi, S., and Bharadwaj, K. (2013). Enhancing collaborative filtering recommendations by utilizing multi-objective particle swarm optimization embedded association rule mining. Swarm and Evolutionary Computation,13, 1-12.

Umyarov, A., and Tuzhilin, A. (2011). Using external aggregate ratings for improving individual recommendations. ACM Transactions on the Web (TWEB), 5(1), 3.

Wang, Z., Yu, X., Feng, N., & Wang, Z. (2014). An improved collaborative movie recommendation system using computational intelligence. Journal of Visual Languages & Computing, 25(6), 667-675.

Wang, S., Sun, J., Gao, B. J., & Ma, J. (2014). VSRank: A novel framework for ranking-based collaborative filtering. ACM Transactions on Intelligent Systems and Technology (TIST), 5(3), 51.

Wang, J., and Ke, L. (2014). Feature subspace transfer for collaborative filtering. Neurocomputing, 136, 1-6.

Wen, Y., Liu, Y., Zhang, Z. J., Xiong, F., and Cao, W. (2014). Compare two community-based personalized information recommendation algorithms.Physica A: Statistical Mechanics and its Applications, 398, 199-209.

Wohlin, C., Ohlsson, M., Runeson, P., Regnell, B., H¨ost, M., and Wessl´en, A. (2012). Experimentation in Software Engineering (Vol. 10.1007/978-3-642-29044-2). Springer Heidelberg New York Dordrecht London.

Wu, H., Yue, K., Pei, Y., Li, B., Zhao, Y., and Dong, F. (2016). Collaborative Topic Regression with Social Trust Ensemble for Recommendation in Social Media Systems. Knowledge-Based Systems.

Wu, M. L., Chang, C. H., & Liu, R. Z. (2014). Integrating content-based filtering with collaborative filtering using co-clustering with augmented matrices. Expert Systems with Applications, 41(6), 2754-2761.

Xie, F., Chen, Z., Shang, J., and Fox, G. C. (2014). Grey forecast model for accurate recommendation in presence of data sparsity and correlation. Knowledge-Based Systems, 69, 179-190.

Xie, F., Chen, Z., Shang, J., Feng, X., and Li, J. (2015). A link prediction approach for item recommendation with complex number. Knowledge-Based Systems, 81, 148-158.

Xu, Y., and Yin, J. (2015). Collaborative recommendation with user generated content. Engineering Applications of Artificial Intelligence, 45, 281-294.

Ya, L. (2012). "The Comparison of Personalization Recommendation for E-Commerce." Physics Procedia 25(0): 475-478.

Yan, S., Zheng, X., Chen, D., & Wang, Y. (2013). Exploiting two-faceted web of trust for enhanced-quality recommendations. Expert Systems with Applications, 40(17), 7080-7095.

Yakut, I., and Polat, H. (2012). Estimating NBC-based recommendations on arbitrarily partitioned data with privacy. Knowledge-Based Systems, 36, 353-362.

Yang, B., Lee, S., Park, S., and Lee, S.-g. (2012). Exploiting various implicit feedback for collaborative filtering. In Proceedings of the 21st ACM international conference companion on World Wide Web (WWW'12 companion) (pp. 639–640).

Yera, R., Castro, J., and Martínez, L. (2016). A fuzzy model for managing natural noise in recommender systems. Applied Soft Computing, 40, 187-198.

YiBo, R., and SongJie, G. (2009). A Collaborative Filtering Recommendation Algorithm Based on SVD Smoothing. Intelligent Information Technology

Application, 2009. IITA 2009. Third International Symposium on Intelligent Information Technology Application.

Yongli, C., Shubin, S., Liang, H., and Guorong. L. (2012). A Collaborative Filtering Algorithm Based on User Activity Level. Fifth International Conference on Business Intelligence and Financial Engineering (BIFE), pp. 80-83.

Zaier, Z., Godin, R., and Faucher, L. (2008). Evaluating Recommender Systems. AXMEDIS '08. International Conference on Automated solutions for Cross Media Content and Multi-channel Distribution, pp. 211-217.

Zanardi, V., Capra, L. (2008). Social ranking: uncovering relevant content using tag-based recommender systems. ACM conference on Recommender systems, (pp. 51-58).

Zahra, S., Ghazanfar, M. A., Khalid, A., Azam, M. A., Naeem, U., and Prugel-Bennett, A. (2015). Novel centroid selection approaches for KMeans-clustering based recommender systems. Information Sciences, 320, 156-189.

Zeng, W., Zhu, Y. X., Lü, L., and Zhou, T. (2011). Negative ratings play a positive role in information filtering. Physica A: Statistical Mechanics and its Applications, 390(23), 4486-4493.

Zhao, W., Guan, Z., and Liu, Z. (2015). Ranking on heterogeneous manifolds for tag recommendation in social tagging services. Neurocomputing, 148, 521-534.

Zhao, J., and Ordóñez de Pablos, P. (2011). Regional knowledge management: the perspective of management theory. Behaviour and Information Technology, 30(1), 39–49.

Zhang, J., Peng, Q., Sun, S., and Liu, C. (2014). Collaborative filtering recommendation algorithm based on user preference derived from item domain features. Physica A: Statistical Mechanics and its Applications, 396, 66-76.

Zhang, H., and Babar, M. (2013). "Systematic reviews in software engineering: An empirical investigation." Information and Software Technology 55(7): 1341-1354.

Zhang, Z., Lin, H., Liu, K., Wu, D., Zhang, G., and Lu, J. (2013). A hybrid fuzzy-based personalized recommender system for telecom products/services. Information Sciences, 235, 117-129.

Zhang, Z., Zhao, K., and Zha, H. (2012). Inducible regularization for low-rank matrix factorizations for collaborative filtering. Neurocomputing, 97, 52-62.

Zhang, Z. K., Zhou, T., and Zhang, Y. C. (2010). Personalized recommendation via integrated diffusion on user–item–tag tripartite graphs. Physica A: Statistical Mechanics and its Applications, 389(1), 179-186.

Zheng, N., and Li, Q. (2011). A recommender system based on tag and time information for social tagging systems. Expert Systems with Applications,38(4), 4575-4587.

Zhou, X., He, J., Huang, G., and Zhang, Y. (2015). SVD-based incremental approaches for recommender systems. Journal of Computer and System Sciences, 81(4), 717-733.

Zhu, T., Ren, Y., Zhou, W., Rong, J., & Xiong, P. (2014). An effective privacy preserving algorithm for neighborhood-based collaborative filtering. Future Generation Computer Systems, 36, 142-155.