A Survey of Collaborative Filtering Algorithms for Social Recommender Systems

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***Abstract* — This paper introduces the status of social recommender system research in general and collaborative filtering in particular. For the collaborative filtering, the paper shows the basic principles and formulas of two basic approaches, the user-based collaborative filtering and the item-based collaborative filtering. For the user or item similarity calculation, the paper compares the differences between the cosine-based similarity, the revised cosine-based similarity and the Pearson-based similarity. The paper also analyzes the three main challenges of the collaborative filtering algorithm and shows the related works facing the challenges. To solve the Cold Start problem and reduce the cost of best neighborhood calculation, the paper provides several solutions. At last it discusses the future of the collaborative filtering algorithm in social recommender system.**

***Keywords* — social network analysis; recommender system; collaborative filtering; cold start; sparsity problem**

I. INTRODUCTION

From the establishment of Facebook, WeChat and etc., social network has been an essential part of our life. Web users generate a huge volume of information every day. It becomes increasingly important to find and deliver personalized and useful information to each user. Therefor social recommender systems have been adopted in the social network. Its key idea is to discover relevant information and predict user behavior with data mining and social recommender methods. [1]

Social recommender system has an interdependent relationship with social network. Social network supplies abundant raw user data, i.e. users' profile, comments, tags, friends, to social recommender systems. Social recommender systems provide personalized and precise results to the users, improve the user experience of the social network, and help the social network to attract more users.

The current research efforts are focused on the following major social network recommender systems: the collaborative filtering recommender system, content-based recommender system, knowledge-based recommender system and hybrid recommender system based on the above systems. The paper mainly talks about the collaborative filtering system and the challenges that it is facing. [2]

The collaborative algorithm is one of the most successful and widely applied social recommender algorithms. [5-8] It was first proposed by Goldberg, Nichols, Oki and Terry in 1992. [9] They built a system called *Tapestry* with collaborative method to filter the e-mails. Though the system could only cover a small amount of users and require the attributes of the users, it indeed gave a new recommender method. [10]

Collaborative filtering supposes the users with the same interests may like the similar items. Different from the content-based recommender algorithms, collaborative filtering does not need to identify the content of items but to collect the rating of users to them and gives the recommender results to users finally. It collects the rating of many users in social network and filters the disorder and unrelated information. It has been applied to electronic commerce [11] and personalized online community. [3]

Last.fm is one of the applications that already applied collaborative filtering method. It is the largest online social music platform worldwide which collects the playlists and some simple operations of users. It also collects the social behaviors i.e. comments, friends and music tags. Based on the information, Last.fm recommends music to users and adds metadata to users' homepage. [4]

The remaining sections of the paper are organized as follows. Section II gives a brief introduction about the basic collaborative filtering algorithms. Section III introduces the challenges faced in collaborative filtering recommender systems, which are cold start, high cost of best neighbor and sparsity problem. Section IV discusses the future research directions and Section V is the conclusion.

II. THE BASIC COLLABORATIVE FILTERING ALGORITHMS

Collaborative filtering calculates the similarities of different users and gets the recommendation results accordingly. It picks users/items that have high similarity with the user/item of interest as the neighbors. The characteristics of the neighbors (i.e. ratings, comments, behaviors) will then be evaluated and be used for prediction and recommendation for the user/item of interest.

Two of the main collaborative filtering types are user-based collaborative filtering and item-based collaborative filtering. [14] They all belong to the memory-based collaborative filtering. Another major algorithm is model-based collaborative filtering and we mainly talk about the former algorithm in this paper. [13]

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A. User-based collaborative filtering

User-based collaborative filtering (UBCF) takes the users with the same rating to a given item as a user set. It then predicts the user's rating to another item according to others' rating in the same user set.

The critical part of the UBCF algorithm is to find the best user set (neighbors) for the chosen user. In other words, the key is to find the neighbors with the greatest similarities with the chosen user. After getting the similarity of the user to others, we choose the similar neighbors of users according to the similarity. At last, we predict the rating of users to specific items with the rating history of neighbors and get the recommender results.

We define the average rating to all items of a user *i*

$$\bar{v}_i = \frac{1}{|I_i|}\sum_{I_j \in I_i} v_{ij} \tag{1}$$

v_{ij} is the user *i*'s rating to item *j*, Ii is the set of items rated by user *i*. According to the average rating and user similarity, we get the prediction equation

$$p_{i,j} = \bar{v}_i + \kappa\sum_{k=1}^{n} w(i,k)(v_{kj} - \bar{v}_k) \tag{2}$$

Among the equation, *w(i,k)* represents the similarity of user i and user k. K is the normalization factor and it is defined a

$$\kappa = \left(\sum w(i,k)\right)^{-1} \tag{3}$$

There are two key steps to solve this equation. At first collecting the all rating of items of the chosen user. Then calculating the similarity of the users. There are two general methods to calculate the user similarity, one is to calculate the cosine similarity and the other is to calculate the Pearson coefficient. The cosine similarity is defined as

$$w(u,v) = \frac{\sum_{i\in I} r_{u,i} r_{v,i}}{\sqrt{\sum_{i\in I} r_{u,i}^2}\sqrt{\sum_{i\in I} r_{v,i}^2}} \tag{4}$$

Among the equation, $r_{u,i}$ means the rating of user *u* to item *i.* To eliminate the limitation of just considering the similarity of the dimension but not the difference of different dimensions, we revise the cosine similarity by subtracting the mean value from every dimension, then we get a revised cosine similarity equation and it is widely applied in calculation of the similarity

$$w(u,v) = \frac{\sum_{i\in I}\left(r_{u,i} - \bar{r}_i\right)\left(r_{v,i} - \bar{r}_i\right)}{\sqrt{\sum_{i\in I}\left(r_{u,i} - \bar{r}_i\right)^2}\sqrt{\sum_{i\in I}\left(r_{v,i} - \bar{r}_i\right)^2}} \tag{5}$$

The second way of calculating the similarity is to get the Pearson coefficient that is the covariance of the rating of user *u* and *v* to corresponding items. The equation is

$$w(u,v) = \frac{\sum_{i\in I}\left(r_{u,i} - \bar{r}_u\right)\left(r_{v,i} - \bar{r}_v\right)}{\sqrt{\sum_{i\in I}\left(r_{u,i} - \bar{r}_u\right)^2}\sqrt{\sum_{i\in I}\left(r_{v,i} - \bar{r}_v\right)^2}} \tag{6}$$

For the discovery of the nearest neighbors, there are two general methods——k nearest neighbors (KNN) method and setting threshold method.

K nearest neighbors means to choose the k nearest (i.e. the highest similarity) users. As Figure 1 shows below, if we want to choose the top 3 nearest neighbors of point 1. We set k=3, then choose the top 3 nearest points as the neighbors: 2, 4 and 7.

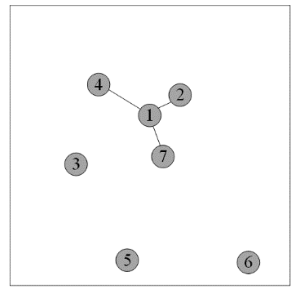

Figure 1. K Nearest Neighbors method.

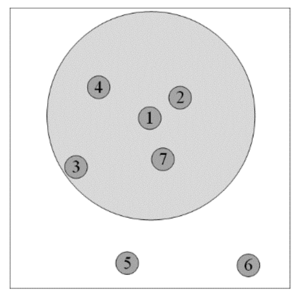

Figure 2. Setting Threshold Neighbor Chosen method.

Setting threshold is to give a threshold δ at first, if the similarity between user u and v is bigger than δ, then user v will be chosen as the neighbor, either will not be chosen. The nearest neighbors are in a circle whose center is user u and radius is the threshold. In Figure 2, we set threshold equals to k, so point 2, 4, 7, 3 will be chosen. [15]

Comparing with two methods, KNN will choose the neighbors with the highest similarity but if the value of k is too big, the accuracy will decrease. For the threshold setting method, the number of neighbors may be small in some situation but there will not exist large difference among chosen neighbors. KNN has an advantage that no matter how low the similarity is, there are always k neighbors will be chosen. Therefore, KNN is widely applied in reality.

The last step is to generate the recommender results. We need to predict the rating of user u to a specific item i. The general method is to calculate the average rating of chosen neighbors to item i

$$r_{u,i} \quad \frac{1}{k}\sum_{v\in U} r_{v,i} \tag{7}$$

$r_{u,i}$ is the predicting rating of user u to item I. N is the set of similar neighbors of user u, $r_{v,i}$ is the rating of neighbor v to item i. [16]

To improve the method, two algorithms using weighted averaging are proposed. The first algorithm is to calculate the weighted average of near neighbors. The other one is to calculate the increment of users' rating then calculates the weighted averaging of it. Two equations are shown below

$$r_{u,i} = \frac{\sum_{v\in N} sim_{u,v} \times r_{v,i}}{\sum_{v\in N} sim_{u,v}} \tag{8}$$

$$r_{u,i} = \bar{r}_u + \frac{\sum_{v\in N} sim_{u,v} \times (r_{v,i} - \bar{r}_v)}{\sum_{v\in N} sim_{u,v}} \tag{9}$$

$sim_{u,v}$ represents the similarity between user u and its bear neighbor v. From the equation we could find that the influence of neighbor to user increases in directly proportion to the similarity between them. [17]

B. Item-based Collaborative Filtering

Item-based collaborative filtering (IBCF) is to compare the similarity of different items, then to predict the rating to a similar item of a user according to its current rating of items. The item can be figured as film or movie in reality.

Like the UBCF algorithm, we need to collect the rating to different items of the same user. The three steps of predicting are the same as the UBCF.

In IBCF, we define the prediction of the user *i* to item *j* is

$$p_{i,j} = \kappa \sum_{k=1}^{m} w(k,j) \bullet v_{i,k} \tag{10}$$

κ is the normalization factor defined by (3). *w(k,j)* is the similarity of items and calculated by cosine similarity defined by (4).

The reason of discarding Pearson coefficient is that IBCF only collect the rating to items of the same user and r_u equals to r_v in this situation.

KNN is also applied in the item-based collaborative filtering. The difference is that the similar neighbors of item i is chosen among the rated items of user u.

The generation of recommender results uses the same algorithm as UBCF.

III. The Challenge Faced by Collaborative Filtering

Though the collaborative filtering algorithm has been putting forward for many years, there are problems and challenges in this algorithm. For example, cold start problem, the various weights of different items, the sparsity problem, and the high cost of finding the best neighbor.

A. Cold Start Problem

Cold start problem exists in a lot of domains. In social network analysis, cold start means there are not enough data to be analyzed or the users are sparse. For example, a new user of one online social website, he/she doesn't have any friend or rated item, the recommendation to this kind of user is not easy. There are two kinds of cold start problems in collaborative filtering system, new user or new item.

For the new user, we could replenish user's profile in different ways, the general approach is to require user provide their profile while login the social account. For the user lack of profile, we could get their information using the open data in the Internet i.e. browser history, searching history and blogs. These approaches must be applied in the precondition of not accessing users' privacy. W.F. Ding and X.L. Zheng in Zhejiang University has approved an active sampling based on PureSVD model algorithm to solve the problem of new user. The method produces an item list that maximizes model parameter change based on pure singular value decomposition (PureSVD). By querying new user with specific item list, the ratings are obtained for training the corresponding user's parameter in PureSVD model; it performs prediction for new users in return. [44]

For the new item, we could combine the collaborative filtering and content-based recommender algorithm. Content-based means to compare the similarity of the content of different items and generate the recommendation. For example, the theme of the book, the genre of the music, the procedure is shown in Figure. 3. For a specific user A, we could find its neighbor B by collaborative filtering and get the item Y which is similar to item X with content-based recommender algorithm. If user B likes item X, we recommend item Y to user A. Figure. 4 shows this recommender method.

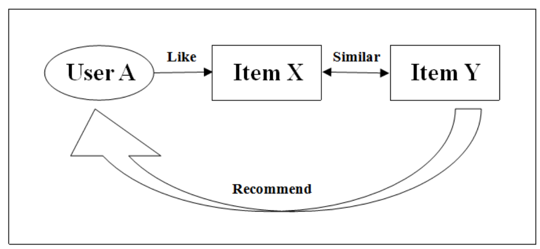

Figure 3. Content-based recommender.

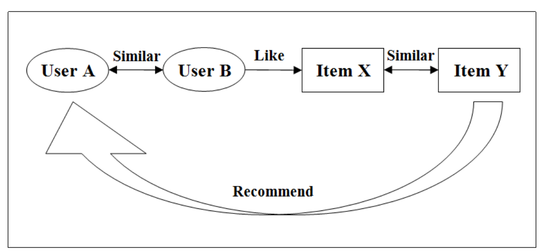

Figure 4. Collaborative filtering and content-based hybrid algorithm.

[18-19] combine the content-based algorithm and collaborative filtering algorithm, but the content-based algorithm could only be applied in item with texts. [20-21] propose a method introducing trustful friends into it, every user has a trustful user lists besides the rating of items. [22] uses different ways to evaluate the performance of the method with trustful friends. [23] collects the rating data and the user relationship data, predicting the rating of new item using both KKN and trustful friends. This method could behave much

better than traditional recommender algorithms. [24-26] introduce social tags to solve cold start problems. [29] proposes a new similarity calculation method - PIP(Proximity, Impact, Popularity). This method aims to make use of the implicit inforamtion among the users' rating information to improve the similarity between users.

[46] transforms the cold start problem into an optimization problem. It proposes few optimal algorithms that perform better former greedy optimal algorithms. [47][49] add deep learning method into the timeSVD++ collaborative filtering model. It applies neural network in item content feature selection and the prediction results in cold start dataset are better than former algorithms. [48] focuses the pure CF without item content. It proposes an *ExcUseMe* model dealing with item cold start problem. It selects users appealing to have more interactions with items to modeling new items. [50] introduces a *Merge* method that takes the ratings of trust friends as the ratings of a new user. It also introduces a way to evaluate the confidence between users. [51] combines the demographic data and Facebook like data with online purchasing to solve the cold start problem with side information. [52] takes classification methods, semantic similarity evaluation and heuristic algorithms into the novel user cold start problems and it hands on many real world datasets to verify its performance.

As a conclusion, the cold start problem is still hot topic today's collaborative filtering research. Designing Hybrid methods with information from other domains and techniques from machine learning has been mainstream.

B. The Problem of High Cost of Finding The Best Neighbor

We need to find the best neighbor of a user in UBCF and it usually need to consider all ratings of the item, the cost of calculation is very high. There are two new methods to solve this problem, sampling and clustering.

Sampling means to set a subset of users, the subset has the priority to be applied in the calculation of best neighbor. X. Zeng in University of Electronic Science and Technology of China has developed a naïve Bayes based shift learning algorithm to take sample. [43]

Clustering is a procedure of classifying similar items in different sets of groups. After applying the clustering algorithm to social network user, the best neighbor of a user can be easily found. K.H. Chen and P.P. Han in Zhejiang University have proposed a user clustering based social network recommendation algorithm. In this paper, it proposes GCCR, a hybrid method combining both graph-summarization and content-based algorithms by a two-phase user clustering approach, which can recommend subjects according to user interests. In additional, by separating the task into offline and online parts, GCCR works more efficiently online by using the pre-processed offline results. [42]

[53] uses clustering method to automatically detect user subgroups in multi-criteria collaborative filtering. It also supports incremental updates of the ratings. [54] proposes a novel entropy-based neighbor selection algorithm through measuring uncertainty of entity vectors. [55] unifies the state of art user-based and item-based nearest neighbor selection algorithms and proposes a novel user-based nearest neighbors collaborative filtering algorithm. [57] evaluates the neighbor performance predictors by measuring the predictive power. The predictors are used to score the neighbors to find the best neighbor.

As the performance of the computer improves, to improve the accuracy of the neighbor selection in collaborative filtering is more important than reducing the cost of it.

C. Sparsity Problem

Collaborative filtering recommends mainly according to the rating of users to items, the more the ratings, and the better recommendation performance it will get. In reality, users usually could not rate all items and there is a large amount of items that never be rated. In the user-item rating matrix, it will generate a high-dimension sparse matrix and the similarity calculated by this matrix is not accurate. So the data sparsity is a key factor influencing the quality of recommendation results. [12]

There are two major solutions for the sparsity problem. The first one uses filling or decreasing the dimension to decrease the sparsity of the matrix. Another solution improves the efficiency of the algorithms without changing the sparsity of the matrix. [31]

In the first method, there are filling method and dimension-decreasing method. For filling method, the first way is to set the value of unrated item to fixed default value. But this way has a low reliability. The second way is fill the blank using the similarity between items and users. It supposes that the items with same property may have the similar rating. So this way usually combined with the content-based recommender algorithms. The third way is to fill with machine learning methods. Some scholars propose methods using Bayes method [33-34] or neural network to predict the rating of unrated items. [35-36]

There are some methods to improve the accuracy of the algorithms in the condition without changing the sparsity of the matrix. Some methods have been discussed in this paper, i.e. item-based collaborative filtering, [37] singular value decomposition, [38,39] introducing trustful friends, [22] introducing clustering algorithms. [40]

[41] uses Person coefficient to evaluate the similarity of users and compose a social network with the similarity. After expanding the network with neighbors' information, the whole system could recommend with high efficiency. [45] proposes an influence-set based collaborative filtering. This method defines a new rating prediction algorithm and remiss the sparsity problem in a certain extent.

As the developing of machine learning algorithms, a method called matrix factorization is now the major method to decrease the sparsity of the matrix. [58] proposes a non negative matrix factorization based on Bayesian probabilistic model. As the improvement of the computing performance of the computer, multi-dimensional data called tensor are applied to reduce the sparsity problem since more data provide more information. The construction of tensor needs data from multiple domains and networks. So the cross-domain collaborative filtering problems are proposed in recent years.

[59] build 3 mode tensor with check-in information and uses collaborative tensor factorization to fill the missing entries. [61] takes Who, What, When and Where to compose four-dimension tensors. It designs efficient to reduce the sparsity of the tensor and works it on large-scale Flickr photo dataset. [62] adds context-aware technique to the tensor decomposition and make recommendations for point of interest (user's interested locations).

For the connection of different online accounts of the same user, we could combine more data from multiple dimensions and the optimization of sparsity reduction in high-dimensional data is still a challenge.

IV. THE FUTURE RESEARCH DIRECTIONS

The collaborative filtering method is just applied in the situation that users rate something on the social network. The precondition of this method is that the network or website must has the function of rating items. Though many other methods have been added to collaborative filtering, there are restraints for this method.

In the future studies, the collaborative filtering method may be added to other social recommender systems like content-based recommender algorithm.

Since the appearance of Twitter and Facebook, the amount of information increases in exponential trend. To identify the characteristics of the users, the natural language processing (NLP) method will be more efficient. NLP is a subject of artificial intelligence (AI) and its main task is to identify the semantic of the human language. Applying this method in the best neighbor selection of collaborative is an aspect of future study.

Some mathematical methods such as naïve Bayes, LDA, matrix factorization and tensor decomposition have applied in the collaborative filtering algorithm. These hybrid methods improve the performance of the algorithm but there are spaces to add more methods or to revise the current algorithms. For example, introduce a weight allocation system and apply it to the similarity calculation.

To improve the accuracy of the recommendation, a multi-criteria collaborative filtering was proposed. The rating of user to item is expanded from singular pair to multiple pairs that one user has multiple ratings to a specific item.

V. CONCLUSION

Collaborative filtering has been used in social recommender systems for a period of time. There are user-based collaborative filtering and item-based collaborative filtering. The key of the collaborative filtering is user/item similarity calculation.

The current research of the collaborative filtering focus on the optimization of the existing models, i.e. the improvement of the similarity calculation; the integration of various methods, i.e. the context-aware collaborative filtering; the appliance in multi-dimensional data, i.e. the cross domain collaborative filtering.

For the cold start problem in collaborative filtering, further research is needed to improve the performance of optimization model. The tag-based recommender algorithm can also be considered in future study.

For the high cost problem of finding the best neighbor, some mathematical techniques in data mining like clustering are added to the algorithm. Aiming to improve the efficiency and reduce the cost. The design of neighbor confidence evaluation algorithms is important too.

For the sparsity problem, filling blank of matrix and decreasing the dimension of matrix are proposed to solve this problem. The matrix factorization and tensor decomposition are the most popular topics in these years.

In a real world application, single recommender algorithm often cannot meet the performance requirements. Combining multiple recommender algorithms into a hybrid recommender system is gaining popularity.

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REFERENCES

[1] Ido Guy and David Carmel, "Social Recommender Systems Tutorial," IBM Research-Haifa, Israel. WWW 2011. Hyderabad India.

[2] Yu Chen, "Social Recommender Systems Methods and User Issues," Human Computer Interaction Group. EPFL. 2011.

[3] Weiliang Kong, "Research on the Key Problems of Collaborative Filtering Recommender System," Wuhan, Central China Normal University, 2013.

[4] J.L. Herlocker, J.A. Konstan, A. Borchers, "An Algoritmic Framwork for Performing Collaborative Filtering," Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieve, 1999, pp. 230-237.

[5] H. Wu, Y.G. Wang, Z. Wang, "Two-Phase Collaborative Filtering Algorithm Based on Co-Clustering," Journal of Software, 21(5), pp. 1042-1054

[6] S.J. Gong, "A Collaborative Filtering Recommendation Algorithm Based on User Clustering and Item Clustering," Journal of Software, 2010, 5(7), pp. 745-752.

[7] C.B. Huang, S.J. Gong, "Employing rough set theory to alleviate the sparsity issue in ecommender system," Proceeding of Seventh International Conference on Machine Learning and Cybernetics, 2008, pp. 1610-1614.

[8] J. Bobadilla, F.Ortega, A. Hernando, "A collaborative filtering similarity measure based on singularities Information," Processing and Mannagement, 2012, 48, pp. 204-217.

[9] D. Goldberg, D. Nichols, M.O. Brian, "Using Collaborative Filtering to Weave an Inforamtion Tapestry," Communications of the ACM, 1992, 35(12), pp.61-70.

[10] C.G. Huang, J. Yin, J. Wang, "Uncertain Neighbors' Collaborative Filtering Recommendation Algorithm," Chineses Journal of Computers, 2010, 33(8), pp.1369-1377

[11] J. Bobadilla, F.Ortega, A. Hernando, "A collaborative filtering similarity measure based on singularities," Processing & Mannagement, 2012, 42(2), pp. 204-217.

[12] H.W. Ma, G.W. Zhang, P, Li, “Survey of Collaborative Filtering Algorithms,” Journal of Chinese Computer Systems, 2009, 30(7), pp. 1282-1288.

[13] J.S. Breese, D. Heckerman, C. Kadie, “Empirical Analysis of Predictive Algorithms for Collaborative Filtering,” Proceedings of the 14th Conference on Uncentanity in Artificial Intelligence, 1998, 461(8), pp. 43-52.

[14] C. Yang, H. Li, “Personalize Context and Item Class Based Resource Recommendation,” Computer Science, 2011, 38(10A), pp. 175-177.

[15] H.K. Zhu, “Study of Statistical Forecasting in Recommender Systems,” Shanghai Jiaotong University, 2010.

[16] C. Li, “Research on the Bottleneck Problems of Collaborative Filtering in E-commerce Recommender Systems,” Heifei University of Technology, 2009.

[17] N. Zhao, “Research and Realization of Mobile Terninals Personalized Application Services Push System,” Ocean University of China, 2012.

[18] S.T. Park, W. Chu, “Pairwise preference regression for cold-start recommendation,” Proceedings og the 3rd ACM Conference on Recommender Systems,” 2009. pp. 21-28.

[19] J. Salter, N. Antonopoulos, “Cinima Screen Recommender Agent: Combining Collaborative and Content-based Filtering,” IEEE Intelligent Systems, 2006, 21(1), pp. 35-41.

[20] M. Jamali, M.Ester, “Trust Walker: A Random Walk Model for Combining Trust-based and Item-based Recommendation,” Proceedings of the 15th ACM International Conference on Knowledge Discovery and Data Mining, 2009, pp. 397-406.

[21] M.S. Shang, L.Y. Lv, W. Zeng, “Relevance Is More Significant than Correlation Information Filtering on Space Data,” Europhysics Letters, 2009, 88(6):68008.

[22] R. Sinha, K. Swearingen, “Comparing Recommendations Made by Online Systems and Friends,” DELOS Workshop: Personalization and Recommder Systems in Digital Libraries, 2001.

[23] F.K. Liu, H.J. Lee, “Use of Social Network Information to Enhance Collaborative Filtering Performance,” Expert Systems with Applications, 2010, 37(7), pp. 4772-4778.

[24] H.N. Kim, A. Alkhaldi, A.E. Saddik, “Collaborative user modeling with user-generated tags for social recommender systems,” Expert Systems with Applications, 2011, 38(7), pp. 8488-8496.

[25] Z.K. Zhang, C. Liu, Y.C. Zhang, “Solving the Cold-start Problem in Recommender Systems with Social Tags,” Europhysics Letters, 2010, 92(2):28002.

[26] T. Zhou, R.Q. Su, R.R Liu, “Accurate and Diverse Recommender via Eliminating Redundant Correlations,” New Journal of Physics, 2009, 11:123008.

[27] W.Zhang, “Relational Distance-Based Collaborative Filtering,” Proceedings of the 31st annual international ACM SIGIR conference on Research and development in information retriecal, 2008, pp. 877-878.

[28] W. Chu, S.T. Park, “Personalized Recommendation on Dynamic Content Using Predictive Bilinear Models,” Prodeedings of the 18th international conference on World wide web, 2009, pp. 691-700.

[29] H.Y. Ahn, “A new similarity measure for collaborative filtering to alleviate the new user Cold-starting Problem,” Information Science, 2008, 178(1), pp. 37-51.

[30] B. Li, Q. Yang, X.Y. Xue, “Can Movies and Books Collaborate? Cross-Domain Collaborative Filtering for Sparsity Reduction,” Proceedings of the Twenty-First International Joint Conference on Artificial Intelligence, 2009, pp. 2052-2057.

[31] J.T. Du, “A Study on Recommedation Model Based on Rough Set,” Hangzhou Dianzi University, 2009.

[32] B. Kim, Q. Li, C. Park, “A New Approach for Combining Content-based And Collaborative Filters,” Journal of Intelligent Information System, 2006, 27(1), pp. 79-91.

[33] K.Y. Jung, H.J. Hwang, U.G. Kang, “Constructing Full Matrix Through Naïve Bayesian for Collaborative Filtering,” Proceedings of the 2006 International Conference on Intelligent Computing, 2006, pp.1210-1215.

[34] D.X. Li, M.L. Xie, X.B. Zhao, “Collaborative filtering recommendation algorithm based on naïve Bayesian method,” Journal of Computer Applications, 2010, 30(6), pp. 1523-1526.

[35] F.Z. Zhang, J.F. Chang, D. Wang, “Multi-Criteria Recommendation Algorithm Based on Widrow-Hoff Neural Network,” PR & AI, 2011, 24(2), pp. 233-242.

[36] L. Zhang, J.L. Chen, X.W. Meng, “BP Neural Networks-Based Collaborative Filtering Recommendation Algorithm,” Journal of Beijing University of Posts and Telecommunications, 2009, 32(6), pp. 42-46.

[37] B. Sarwar, G. Karypis, J. Konstan, “Item-based Collaborative Filtering Recommendation Algorithms,” Proceedings of the 10th International World Wide Web Conference, 2001, pp. 285-295.

[38] B. Sarwar, G. Karypis, J. Konstan, “Analysis of Recommendation Algorithms for E-commerce,” Proceedings of ACM Conference on Electronic Commerce, 2000, pp. 158-167.

[39] M.G. Vozalis, K.G. Margaritis, “Applying SVD on Item-Based Filtering,” Proceedings of 5th International Conference on Intelligent Systems Deisign and Applications, 2005, pp. 464-469.

[40] H. Wang, L.J. Gao, T.Z. Wang, “Collaborative filtering recommendation based on user clustering in personalization service,” Computer Applications, 2007, 27(5), pp.1225-1227.

[41] Y.U. Ryu, H.K. Kim, Y.H. Cho, “Peer-oriented Content Recommendation In A Social Network,” Proceedings of the 16th Workshop on Information Technology and Systems, 2006, pp. 115-120.

[42] K.H. Chen, P.P. Han and J. Wu, “User Clustering Based Social Network Recommendation,” Chinese Jounal of Computers, vol. 36 No. 2, Feb. 2013, pp. 349–359.

[43] X. Zeng, “Research on Online Social Network User Classification and Sampling,” Chengdu, University of Electronic Science and Technology of China, 2013.

[44] W.F. Ding, X.L. Zheng and D.R. Chen, “Active Sampling Based on PureSVD Model for Collaborative Filtering,” Journal of Beijing University of Posts and Telecommunications, vol 36 No. 4, Aug. 2013, pp. 23-26.

[45] J. Chen, J, Yin, “A Collaborative Filtering Recommendation Algorithm Based on Influence Sets,” Journal of Software, 2007, 18(7), pp. 1685-1694.

[46] Anava, Oren, et al. "Budget-constrained item cold-start handling in collaborative filtering recommenders via optimal design." *Proceedings of the 24th International Conference on World Wide Web*. ACM, 2015.

[47] Wei, Jian, et al. "Collaborative Filtering and Deep Learning Based Hybrid Recommendation for Cold Start Problem." Dependable, Autonomic and Secure Computing, 14th Intl Conf on Pervasive Intelligence and Computing, 2nd Intl Conf on Big Data Intelligence and Computing and Cyber Science and Technology Congress (DASC/PiCom/DataCom/CyberSciTech), 2016 IEEE 14th Intl C. IEEE, 2016.

[48] Aharon, Michal, et al. "ExcUseMe: Asking Users to Help in Item Cold-Start Recommendations." *Proceedings of the 9th ACM Conference on Recommender Systems*. ACM, 2015.

[49] Wei, Jian, et al. "Collaborative filtering and deep learning based recommendation system for cold start items." *Expert Systems with Applications* 69 (2017): 29-39.

[50] Guo, Guibing, Jie Zhang, and Daniel Thalmann. "Merging trust in collaborative filtering to alleviate data sparsity and cold start." *Knowledge-Based Systems* 57 (2014): 57-68.

[51] Sedhain, Suvash, et al. "Social collaborative filtering for cold-start recommendations." *Proceedings of the 8th ACM Conference on Recommender systems*. ACM, 2014.

[52] Lika, Blerina, Kostas Kolomvatsos, and Stathes Hadjiefthymiades. "Facing the cold start problem in recommender systems." *Expert Systems with Applications* 41.4 (2014): 2065-2073.

[53] Nilashi, Mehrbakhsh, et al. "Clustering-and regression-based multi-criteria collaborative filtering with incremental updates." *Information Sciences* 293 (2015): 235-250.

[54] Nilashi, Mehrbakhsh, et al. "A Multi-Criteria Collaborative Filtering Recommender System Using Clustering and Regression

Techniques." *Journal of Soft Computing and Decision Support Systems* 3.5 (2016): 24-30.

[55] Kaleli, Cihan. "An entropy-based neighbor selection approach for collaborative filtering." *Knowledge-Based Systems* 56 (2014): 273-280.

[56] Verstrepen, Koen, and Bart Goethals. "Unifying nearest neighbors collaborative filtering." *Proceedings of the 8th ACM Conference on Recommender systems*. ACM, 2014.

[57] Bellogín, Alejandro, Pablo Castells, and Iván Cantador. "Neighbor selection and weighting in user-based collaborative filtering: a performance prediction approach." *ACM Transactions on the Web (TWEB)* 8.2 (2014): 12.

[58] Hernando, Antonio, Jesús Bobadilla, and Fernando Ortega. "A non negative matrix factorization for collaborative filtering recommender systems based on a Bayesian probabilistic model." *Knowledge-Based Systems*97 (2016): 188-202.

[59] Luan, Wenjing, Guanjun Liu, and Changjun Jiang. "Collaborative tensor factorization and its application in POI recommendation." *2016 IEEE 13th International Conference on Networking, Sensing, and Control (ICNSC)*. IEEE, 2016.

[60] Symeonidis, Panagiotis. "Matrix and Tensor Decomposition in Recommender Systems." *Proceedings of the 10th ACM Conference on Recommender Systems*. ACM, 2016.

[61] Bhargava, Preeti, et al. "Who, what, when, and where: Multi-dimensional collaborative recommendations using tensor factorization on sparse user-generated data." *Proceedings of the 24th International Conference on World Wide Web*. ACM, 2015.

[62] Yao, Lina, et al. "Context-aware Point-of-Interest Recommendation Using Tensor Factorization with Social Regularization." *Proceedings of the 38th International ACM SIGIR Conference on Research and Development in Information Retrieval*. ACM, 2015.