Comparative Studies on Modeling Users' Multifaceted Interest Correlation for Social Recommendation

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Abstract. Recommender systems are essential for providing online users with items that might interest them. The research work of this paper is mainly classified into three aspects, one is based on the classification of research questions, one is based on the classification of research methods, and one is based on the classification of measures. The main techniques used in social recommender systems are the memory-based method and the model-based method. The aims of research papers are divided into increasing the accuracy of prediction and improving the performance of recommendations. In the classification of research methods, there are Content-based, Collaborative Filtering, and Hybrid Methods. And the output of these recommender systems can be divided into the value of the ratings and top-N items. The measurement methods mainly focus on the quality of prediction and the quality of the set. Finally, this paper also suggests feasible future research directions for the readers.

Keywords: Social recommender systems · social recommendation

1 Introduction

With the rapid development of the Internet, people are overwhelmed by the amount of information available to them every day and this makes it difficult for people to choose the products they need. For instance, a user searching for item A on the internet gets thousands of information on product related to it, which makes it difficult for the user to choose the specific product he needs. However, if there is a recommender system that knows the user's preferences and can recommend ten to twenty relevant products to him/her, then the user can easily choose the product he/she needs and have a good online shopping experience. Therefore, most people nowadays have an urgent need for an accurate and reliable social recommender system.

We select a recent paper about the research of building a multifaceted interest association model for users (reference [1]). Based on reading and analysis of several relative references about the social recommender systems. In Sect. 2, we divide the references based on the research objects, including the techniques and aims of social recommender

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systems; in Sect. 3, we divided them based on research methods, including memory-based, model-based methods and output categories; and in Sect. 4, we divide them based on experimental analysis, including quality of prediction, quality of the set and other.

The rest of the paper is organized as follows. Section 2 gives the classification of research objects of social recommender systems. Section 3 introduces the classification of research methods. Section 4 introduces the comparison of experimental analysis in related literature. Section 5 discusses the research opportunities for future work and Section 6 concludes the paper.

2 Classification of Research Objects

2.1 Criteria

Social recommender systems utilize social network information to improve traditional recommendation techniques. Due to the innate character of existing social recommendation methods, they can be divided into two main categories: memory-based methods and model-based methods. In addition, different improvements of social recommendation to the traditional recommendation systems have different aims. In this section, two independent and different criteria would be used to divide research objects into different types:

1) **Techniques Categories**. There are two types here: **Memory-based method** or **Model-based method**. The memory-based method aims to recommend items to users through their friends who are similar to them. The model-based method is to use techniques such as data mining, and deep learning and then apply them utilizing users' social relation to making an intelligent prediction.
2) **Main Goals**. There are two kinds of goals here: **Increasing the accuracy of prediction** or **Improving the performance of recommendation**. Increasing the accuracy of prediction means the recommendation systems can better predict whether target users will like or consume the recommended items. Improving the performance of recommendations involves several aspects, including improving users' trust in the recommendation systems, improving the attractiveness of recommended items to users, and improving overall performance and efficient use of information.

Table 1. Different Research Objects

Techniques Categories	Main Goals	
	Increasing the accuracy of prediction	Improving the performance of recommendation
Memory-based	I. [8, 13–15]	II. [2, 4, 17, 27]
Model-based	III. [3, 5, 6, 9–12, 18, 20–26, 28–33]	IV. [16]

2.2 Explanation of Different Types

Based on the appeal classification standard, we give the classification in Table 1. The meaning of each class is as follows:

2.2.1 Type I: Increasing the Accuracy of Prediction and Memory-Based

This type is applying the memory-based method to increase the accuracy of prediction. References ([8, 13–15]) belong to Type I. Reference [8] introduces an optimization algorithm, in order to create a weighting scheme based on the data of different ratings on different items, that automatically determine suitable weights for more accurate prediction. Reference [13] proposed a collaborative filtering method of replacing finding similar users with propagating trust over the users' trust network, and it is proved effective in accuracy. Reference [14] builds up a trust-based matrix factorization model, a dense training dataset by filling in some missing values using social information. Reference [15] takes all the significant benefits of combining the model with trust to improve the accuracy of the recommendation process.

2.2.2 Type II: Improving the Performance of Recommendation and Memory-Based

This type is applying the memory-based method to improve the performance of recommendations. References ([2, 4, 17, 27]) belong to Type II. Reference [2] considers the aspects of decision-making and advice-seeking, then proposes a model increasing the users' trust in the recommendation system. Reference [4] utilizes the users' familiarity network and similarity network to improve the attractiveness of recommended items to users. Reference [17] makes use of users' complex dynamic and general static preferences over time to improve the total performance of the social recommender system. Reference [27] proposes a personalized attention network, applying attention mechanisms to select and highlight informative words and news at both the word and news levels, to increase the attractiveness of recommended items to users.

2.2.3 Type III: Increasing the Accuracy of Prediction and Model-Based

This type applies the model-based method to increase the accuracy of prediction. References ([3, 5, 6, 9–12, 18, 20–26, 28–33]) belong to Type III. Reference [3] proposes a social exposure-based recommendation model, SoEXBMF, to integrate two social influences on user exposure, social knowledge influence, and social consumption influence, into the basic exposure-based matrix factorization model for better recommendation accuracy. Reference [5] proposes a model that combines three factors: recipient interest, item quality, and interpersonal relationship, and uses machine learning to estimate the values of interest, quality, and influence vectors to improve prediction accuracy. Reference [6] proposes the model called SocialMF forcing the user feature vectors to be close to those of their neighbours, significantly reducing the recommendation error, especially for cold-start users. Reference [9] builds up a two-step framework to elaborate on friends' check-ins, which improves the accuracy of recommendation prediction. References [10–12] come up with methods to predict the missing values of the user-item matrix. Reference [18] introduces an optimization problem that includes the terms of global social context and local social context, taking the influence of both global and local social context into account for a better recommendation. Reference [20] proposes a unified framework for Point-of-Interest recommendation, combining check-in relationships with auxiliary information such as geographical position and social relationship, for better performance in prediction. Reference [21] utilizes the geographical influence, the high variation of geographical influence across POIs, and their physical distance to increase the accuracy of recommendation prediction. Reference [22] proposes a joint-topic semantic-aware social matrix decomposition model built on social network structure and Topic-Enhanced Word Embedding representation to learn the latent features of users and votes for a more accurate voting recommendation. Reference [23, 24] proposes methods to distinguish and learn the strong and weak ties for increasing the accuracy of social recommendation. Reference [25] uses the method of machine learning to cope with the problem of limited attention. Reference [26] utilizes web embedding technology, proposing an embedding-based recommendation method. Reference [28] explores better prediction by merging sparse rating data and sparse social trust networks. Reference [29] proposes a recommendation system method based on social circles, and social trust circles are estimated from existing rating data combined with social network data. Reference [30] explores a new social relationship, membership combined with friendship which is integrated into the collaborative filtering recommender for better performance of prediction. Reference [31] incorporates the data of global and local influence nodes into a traditional recommendation model to improve recommendation accuracy. Reference [32] develops a model, SBPR (Social Bayesian Personalized Ranking), which makes use of social connections to accurately estimate users' rankings of items. Reference [33] proposes an online recommendation framework from the perspective of online users' preferences.

2.2.4 Type IV: Improving the Performance of Recommendation and Model-Based

This type is applying the model-based method to improve the performance of recommendations. References ([16]) belong to Type IV. Reference [16] develops a dynamic graph attention model: Dynamic Graph Recommendation (DGRec), to consider moment-to-moment changes in user preferences to improve the attraction of recommended items to users.

3 Classification of Research Methods

3.1 Criteria

There are many techniques used in the field of social recommender systems, and they can be divided into three methods generally. And the output categories of the systems' recommended items are also noteworthy. In this section, two independent and different criteria would be used to divide research objects into different types:

1) **Method Categories**. There are three types here: **Content-based**, **Collaborative Filtering**, or **Hybrid Method**. The contend-based method considers users' preferences for some items in their historical behavior for recommendations. The collaborative

Table 2. Different Research Objects

Methods Categories	Output Categories	
	The value of ratings	List of TOP-N items
Content-based	I. [2, 4, 11, 12, 17, 27]	II. [7, 21]
Collaborative Filtering	III. [6, 8, 10, 13, 14, 28]	IV. [18, 25, 30]
Hybrid Method	V. [15, 22, 26, 29, 31, 33]	VI. [3, 5, 9, 16, 20, 23, 24, 32]

Filtering method predicts items a user will like by their preference and users who are similar to he/she. The hybrid method combines the Content-based method and Collaborative Filtering method together.

2) **Output Categories**. There are two kinds of output here: **The value of ratings** or **List of TOP-N items**. There are three main methods used in social recommender systems, and it is equally important to understand how their output is expressed.

3.2 Explanation of Different Types

Based on the appeal classification standard, we give the classification in Table 2. The meaning of each class is as follows:

3.2.1 Type I: The Value of Ratings and Content-Based

This type is using the content-based method and the output is the value of ratings. References ([2, 4, 11, 12, 17, 27]) belong to Type I. Reference [2] constructs a model consisting of two parts: the first part is a trust-based recommender system for the semantic web which calculates the score of membership, uncertainty, and non-membership and then the degree of importance. The second part is initializing and updating the degree of trust in the recommenders. Reference [4] proposes a personalized recommendation model which can calculate the recommendation score relating to users' social relations. Then the items with high recommendation scores will be recommended. Reference [11] makes use of two matrices U and V. U is user latent feature space and V is low-dimensional item latent feature space. Then transfer the value of $U^T V$ by logistic function and mapping function designed in the paper to predict the missing value in the User-Item Matrix. Reference [12] systematically proposes a matrix factorization objective function with social regularization which can be extended to other contextual information. Then we can predict the missing value in the User-Item Matrix. Reference [17] proposes a model named Attentive Recurrent Social Recommendation. The model can be divided into two parts. The first part captures the dynamic preferences of users. The second part shows the stationary of users' fixed interest. Reference [27] proposes a personal attention network, using a query vector for word-level and news-level attention networks for a better understanding of user representations for accurate news recommendations.

3.2.2 Type II: List of TOP-N Items and Content-Based

This type is using the content-based method and the output is a list of TOP-N items. References ([7, 21]) belong to Type II. Reference [7] proposes a random walk-based method on social recommendation which utilize the knowledge from auxiliary domains to predict users' behaviours. Reference [21] proposes a model focusing on point-of-interest-specific geographical influence.

3.2.3 Type III: The Value of Ratings and Collaborative Filtering

This type is using collaborative filtering method and the output is the value of ratings. References ([6, 8, 10, 13, 14, 28]) belong to Type III. Reference [6] proposes a model called SocialMF, where MF represents matrix factorization. It let the user's eigenvector be close to its neighbours so that they can get well know of cold-start users. Reference [8] proposes an optimization algorithm that can calculate the weights of different items automatically with the rates of training users. This way helps improve the performance of the collaborative filtering method. A novel probabilistic factor analysis framework is proposed in reference [10]. The framework blends the preference of the user and the preference of his/her trusted friends. In reference [13], it proposes a trust-aware recommendation system, replacing similarity weight with trust weight in order to mitigate the hazards of data sparsity. Reference [14] proposes a method utilizing social information to address the problem of data sparsity. In addition, it uses different rules for cold start users and normal users to produce pseudo ratings. Reference [28] integrates spare rating data and sparse social trust networks given by users to improve the performance of collaborative filtering methods.

3.2.4 Type IV: List of TOP-N Items and Collaborative Filtering

This type is using collaborative filtering method and the output is a list of TOP-N items. References ([18, 25, 30]) belong to Type IV. Reference [18] formulates an optimization problem to exploit local and global social contexts for the recommendation. Reference [25] focuses on addressing the problem of limited attention in the social recommendation. The paper develops an algorithm to optimize users' latent features and the appropriate number of their influential friends corresponding attention. Reference [30] discusses an innovative social relationship, which is about membership and its combined role with friendship. And this new relationship will be merged into the collaborative filtering recommendation systems.

4 Rivew of Experimental Analysis

In this section, we will classify the metric of evaluation and system factors, as shown in Table 3. In Table 3, all experimental analysis is also classified according to the metric and factors. It can be seen from Table 3 that most of the references compare the quality of prediction, quality of the set, and quality of the list.

Table 3. Experiments with Different Metrics and Factors

System Factors	Metric		
	Quality of the prediction	Quality of the set	Others
Users' rating features	[8, 11, 14, 31, 33]	[16]	[16]
Item features	[2, 4, 20, 22, 23, 25]	[5, 9, 20–25, 32]	[17]
Social groups' features	[3, 6, 18, 26, 28–30]	[3, 28, 30]	[3, 28]
Others	[7, 10, 12, 13, 15]	[7, 27]	[27]

4.1 Metric of Evaluation

Quality of prediction includes MAE (mean absolute error), NMAE (Normalized Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), Precision and Coverage. The formulas are as follows:

$$MAE = \frac{1}{|U|} \sum_{(i,j) \in U} \left| r_{ij} - \widehat{r_{ij}} \right| \tag{1}$$

where U is the testing set, $|U|$ is the size of U, (i, j) is a pair of (user i, item j).

$$NMAE = \frac{NMAE}{|r_{max} - r_{min}|} \tag{2}$$

$$MSE = \sum_{(i,j) \in U} \frac{\left(r_{ij} - \widehat{r_{ij}}\right)^2}{|U|} \tag{3}$$

$$RMSE = \sum_{(i,j) \in U} \sqrt{\frac{\left(r_{ij} - \widehat{r_{ij}}\right)^2}{|U|}} \tag{4}$$

$$Precision = \frac{|(Recommended\ list) \cap (Test\ set)|}{|Recommended\ list|} \tag{5}$$

Coverage is the ratio of items recommended by the recommendation system to the total items.

Quality of the set includes Recall, ROC (Receiver Operating Characteristic) F1 score and AUC (Area under curve). The formulas are as follows:

$$Recall = \frac{|(Recommended\ list) \cap (Test\ set)|}{|Test\ set|} \tag{6}$$

$$F1 = \frac{2 \times precision \times recall}{precision + recall} \tag{7}$$

AUC represents the area under the ROC curve, which measures the extent to which a recommender system is able to distinguish items that users like from those they dislike.

The quality of the list includes HR (Hit Ratio), Normalized Discounted Cumulative Gain (NDCG), and Mean Reciprocal Rank (MRR).

4.2 System Factors

Users' rating features are factors that describe the characteristic of ratings that can influence the metric. Such as users' attention variances, the value of users' ratings, the number of users' ratings, and so on.

Item features are a factor that describes the characteristic of items that can influence the metric. Such as the number of recommended items, aspects considered of the items, network related to the item, and so on.

Social groups' features are factors that describe the social groups' behaviors which can influence the metric. Such as degrees of a user's social group, the contribution from the local social context, friends' consumption, the influence of social networks, fusing membership, and so on.

Other factors include trust between the user and social network, trust information, the density of the training set, and the number of negative samples to combine with a positive sample.

4.3 Experimental Comparison

In reference [8], the author compares the difference in prediction accuracy for different constant values ρ, where ρ is related to the likelihood of a training user being similar to a user outside the training database. It also conducted the experiments comparing proposed weighting scheme to the existing weighting scheme and comparing the weighted memory-based approach to the standard memory-based approach.

In reference [11], the author mainly focuses on how the impact of parameter λ which balances the information from the user-item rating matrix and the user social network to MAE.

In reference [14], the author compares the performance of the proposed model with the performance of six other methods under the criteria of MAE and RMSE with the optimal parameter settings.

In reference [31], the author conducts an experiment to compare the proposed model with other models under the metrics MAE and RMSE.

In reference [33], the author compares the proposed method with four online recommendation algorithms and two offline recommendation algorithms under the criteria MAE and RMSE. And the author evaluates the performance by changing the percentage of user rating samples.

In reference [16], the author evaluates the proposed model by dividing the model into three classes of recommenders in terms of Recall and NDCG.

In reference [2] the author calculates the values of membership, uncertainty, and non-membership of product P and then observes the number of recommendations with the change of iteration.

In reference [4] the author conducted a survey to gather the sense of target users' experience with the widget to judge the prediction precision of the proposed algorithm.

In reference [25], the author compares the proposed algorithm with several advanced methods on four real-world datasets under the metric: RMSE and MAE. And the author also quantifies the fraction of consumed items that are in the top-K ranking list sorted by the estimated rankings by Recall@K.

In reference [5], the author uses the F1 measure to evaluate the precision of the proposed learning algorithm and concerns the factor: aspects considered of the items.

In reference [9], the author evaluates the proposed models with the metrics: Precision@K, Recall@K, and concerns the factor: number of recommended items.

In reference [20], the author evaluates the proposed model in terms of Precision@K, Recall@K, and concerns the factor: number of recommended items.

In reference [21], the author uses two real data set and evaluates the model in terms of Precision@K and Recall@K and concerns the factor: number of recommended items.

In reference [22], the author compares the proposed method with other advanced baseline methods in terms of Precision@K and Recall@K and concerns the factor: number of recommended items.

In reference [23], the author compares the proposed method with some state-of-art methods in terms of Precision, Recall, MAE, and RMSE and concerns the factor: number of recommended items.

In reference [24], the author compares the proposed method with some state-of-art methods in terms of Precision, Recall, MAE, and RMSE and concerns the factor: number of recommended items.

In reference [25], the author compares the proposed method with some state-of-art methods in terms of Precision and concerns the factor: number of recommended items.

In reference [32], the author conducts experiments on four real data sets and evaluates the proposed model in terms of AUC and concerns the factor: number of recommended items.

In reference [17], the author compares the proposed model with other state-of-the-art models in terms of the metrics for top-K ranking performance: HR and NDCG.

In reference [6], the author conducts experiments on the two data sets and compares the proposed model with existing methods. It is evaluated in terms of RMSE and concerns the facto: influence of social networks.

In reference [18], the author compares the proposed framework with some state-of-art methods in terms of MAE and RMSE and is concerned with the factor: contribution from local social context.

In reference [26], the author evaluates the methods by experiments using two real datasets in terms of MAE and RMSE and is concerned with the factor: latent information from social connection.

In reference [28], the author uses four large-scale data and compares the proposed method with the state-of-the-art recommendation algorithms in terms of Precision, Recall, F1-score, and NDCG and concerns with the factors: degrees of a user's social group.

In reference [29], the author experiments with the proposed model with publicly available data in terms of MAE and RMSE and concerns with the factors: social information weight.

In reference [3], the author conducts experiments to evaluate the quality of the proposed model in terms of Precision, Recall, and NDCG and concerns with friend consumption.

In reference [30], the author explores the impact of fusing membership in terms of Precision and Recall.

In reference [7], the author raises two questions and solves them with the proposed method and compares it with other methods in terms of Precision and Recall. The author also concerns with the factor: density of the training set.

In reference [10], the author conducts experiments to compare the proposed method with other state-of-the-art collaborative filtering and trust-aware recommendation methods in terms of MAE and RMSE. The author is concerned with the factors influencing the metrics: the number of observed ratings and trust between the user and social network.

In reference [12], the author compares the proposed method with other state-of-the-art recommendation methods in terms of MAE and RMSE and is concerned with the factor: trust between the user and social network.

In reference [13], the author evaluates the proposed architecture in terms of MAE and concerns with the factor: trust information.

In reference [15], the author conducts experiments by setting a control group in terms of MAE and concerns with the factor: trust information.

In reference [27], the author conducts experiments on a real-world data set in terms of AUC, MRR, nDCG and is concerned with the factor: the number of negative samples to combine with a positive sample.

5 Discussion and Suggestion

This paper discusses the research methods and research objects of various references and finds that most of the papers focus on using the model-based method on social recommender systems, and most of them study how to increase the prediction accuracy, while the research on proposing a framework which makes use of users' multiple interest correlation and improving the performance of social recommender systems are few. Therefore, this paper puts forward the following directions, which can provide directions for future social recommender systems research:

1) Research on proposing a model which can utilize the users' interest correlation homogenously. Every user is different online. They will show their characteristics because of the different circles of friends, the different reserves of social knowledge, the real-time change of interest in items, and so on.
2) In the future of social recommender systems research, attention should be paid to the timeliness of user information. We should notice that users' attention to products changes over time. It would be useless to make recommendations based on a user's behavior a year ago or even five years ago. For some specific domains, the user's attention to products will change even more quickly.
3) According to the classification of research methods, the output of social recommender systems is the value of the ratings or top-N items. Users will trust the recommendation more if the recommended items are accompanied by some reasons for the recommendation. Therefore, how to make the output results more detailed is a direction that can be studied in the future.
4) Novel metrics other than the common ones such as Precision, Recall, RMSE, and MAE should be considered when evaluating the performance of the social recommender systems. Novel metrics can provide researchers with different perspectives to improve social recommender systems. For example, metrics can be designed to

focus on users' trust in the recommender system, proving the stability and potential of a recommender system to be promoted from the perspective of trust value.

6 Conclusion

Through the previous analysis, we find that most of the research on improving social recommender systems are focusing on increasing the accuracy of prediction, but few of them pay attention to improving the performances of models. Besides, in the future, it is a direction that develops novel metrics to evaluate the quality of social recommender systems from different perspectives even though some of these novel metrics may contradict with increasing the accuracy of prediction. Therefore, this kind of research perspective can be further studied in the future.

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