A hybrid collaborative filtering model with context and folksonomy for social recommendation

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ABSTRACT. *To address data sparsity problem and lack of context in neighbourhood-based collaborative filtering (CF), this paper proposes a hybrid CF model combining context and tag information. Firstly, all users were divided into different groups by their profile and contextual information using clustering, aiming to reduce the sparsity and dimension of ratings data. Then, a folksonomy network model (FNM) was developed based on tag information to analyze the relevance between different items. Then, the FNM was incorporated into the similarity measuring process of neighbourhood-based CF for the improvement of recommendation accuracy. Through the experiments on three real-world datasets, it is clear that our method outperforms other methods in recommendation quality, which means our model is more applicable in situations where context and folksonomy are critical to the success of the application, just like in social commerce and virtual community websites.*

RÉSUMÉ. *Pour résoudre le problème de rareté des données et de manque de contexte dans le filtrage collaboratif par quartier (CF), cet article propose un modèle hybride CF combinant contexte et informations de balise. Tout d'abord, tous les utilisateurs ont été divisés en différents groupes en fonction de leur profil et de leurs informations contextuelles à l'aide de la mise en cluster, dans le but de réduirela rareté et la dimension des données nominales. Ensuite, un modèle de réseau de folksonomie (FNM) a été développé sur la base des informations de balise pour analyser la pertinence entre différents éléments. Ensuite, le FNM a été intégré au processus de mesure de la similarité des FC basées sur le quartier afin d'améliorer la précision des recommandations.Grâce aux expériences sur trois ensembles de données du monde réel, il est clair que notre méthode surpasse celle des autres méthodes en termes de qualité des recommandations, ce qui signifie que notre modèle est plus applicable dans les situations où le contexte et la folksonomie sont essentiels au succès de l'application, tout comme dans le commerce social et des sites Web de communautés virtuelles.*

KEYWORDS: *collaborative filtering, hybrid recommendation, context, folksonomy, social tag*.

MOTS-CLÉS: filtrage collaboratif, recommandation hybride, contexte, folksonomie, balise sociale.

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1. Introduction

The past few decades have witnessed the growth of electronic commerce (e-commerce) into an essential way of doing business. With the advancement of the Internet and mobile communication technologies, e-commerce has given birth to an array of new products, services and related business modes. It has also stimulated an exponential increase in the number of consumers and products, as well as the amount of relevant information. In this case, users are submerged in a sea of options with varied quality. Dubbed as “information overload”, this phenomenon adds to the difficulty in making recommendations based on user interests. To overcome the problem, personalized recommendation has become a hot spot in the research community (Lv *et al.*, 2012). As the most successful application of personalized recommendation, recommender systems collect the information from users about their favoured items, and then recommend to them the items that may fit their needs. So far, recommender systems have been applied in the recommendation of various products/services, ranging from common products like books, movies and songs to high-risk products/services like stocks and funds.

Recommender systems usually centre on the well-known collaborative filtering (CF) algorithms (Sarwar *et al.*, 2001). There are two primary CF approaches: neighbourhood-based models (NBMs) and latent factor models (LFMs) (Shi *et al.*, 2014). The NBMs recommend products to the target user based on the relationship between his/her active neighbours. The models require no information about the items other than their user ratings (Bobadilla *et al.*, 2013). By contrast, the LFMs map both items and users into a latent factor space, and weigh each entity with a feature vector inferred from the existing ratings. The predicted ratings are the inner product of the corresponding vector pairs. It is clear that the NBM-based CF has an edge in situations where it is hard to analyse the different aspects of the data, such as songs, videos and other digital products/services. Therefore, NBM-based CF has been extensively adopted in recommender systems and Internet businesses (e.g. Amazon).

Despite the advantages, NBM-based CF suffers from some drawbacks, including data sparsity and the lack of context (Yang *et al.*, 2014). The data sparsity is commonly seen in many situations. For example, the user-item rating matrix tends to be extremely sparse, making it difficult to identify similar users and items by NBM-based CF. The problem is also called the cold-start problem (Lika *et al.*, 2014), when a new user or item has just entered the system. New items cannot be recommended before getting rated, while new users receive few or no recommendation because they have not rated or purchased any product/service. Multiple dimensionality reduction measures have been proposed to eliminate data sparsity, namely singular value decomposition and principal component analysis. At the removal of certain users or items, however, such measures often lose useful information or recommendation or lose control of recommendation quality.

The lack of context also severely affects the quality of NBM-based CF recommendation. Due to the time-variant and context-dependent nature of consumer interests and demands in e-commerce (Adomavicius and Tuzhilin, 2010), the accurate prediction of consumer preference undoubtedly depends on the relevance of the contextual information. It is important to introduce the context of user decision into the recommendation process. Before pushing personalized content, it is important to determine when and what content should be recommended to a consumer. For example, a user might prefer to read stock market report on weekday evenings, but go shopping or watch movies/TV shows on weekends. Based on historical ratings data, the recommendation process of traditional CF methods largely ignores the contextual information of different users.

In light of the above problems, this paper proposes a hybrid NBM-based CF model that introduces context and tag information into traditional similarity measuring and rating prediction. The remainder of this paper is organized as follows: Section 2 reviews the key aspects of basic CF approaches; Section 3 introduces and explains the context-based clustering models, folksonomy network model (FNM) and the hybrid model; Section 4 provides and discusses the experimental results; Section 5 wraps up the research with some valuable conclusions and future research directions.

2. Related work

2.1. Collaborative filtering

CF generates recommendations based on the data about user ratings of items. First, the CF searches for users giving the same or similar ratings on certain items. After finding these users with common tastes, the CF will recommend the items highly rated among these users. In general, the similarity between two users is positively correlated with the number of similar rated items. The workflow of the CF can be expressed as follows.

Assume that $U=\{u_i|i=1,2,\ldots,m\}$ is a set of m users and $I=\{I_j|j=1,2,\ldots,n\}$ is a set of n distinct items. Let the user ratings set $R=\{(u_i, I_j)|u_i \in U, I_j \in I\}$ be a $m\times n$ matrix, as shown in equation (1).

$$R=\left(r_{u_i,I_j}\right)_{m\times n}, r_{u_i,I_j}=\begin{cases} S \text{ if } u_i \text{ rated } I_j \\ \varnothing \text{ if } u_i \text{ not rated } I_j \end{cases} \quad (1)$$

where $r_{u,I}$ is the rating of item I by user u, an indicator of user preference for different items. Usually, $r_{u,I}$ is equal to a real number denoted by S. When $r=\varnothing$, it means that user u_i does not rate item I_j.

After the data preparation, a similarity function is needed to measure the similarity between two users. Two of the most well-known similarity measures are cosine similarity and Pearson correlation coefficient, as defined in equations (2) and (3), respectively.

$$Sim_{\cos} = \frac{\sum_{I(u_i,u_j)} r_{u_i,I} \cdot r_{u_j,I}}{\sqrt{\sum_{I(u_i,u_j)} r_{u_i,I}^{\ 2}} \cdot \sqrt{\sum_{I(u_i,u_j)} r_{u_j,I}^{\ 2}}} \tag{2}$$

$$Sim_{Person} = \frac{\sum_{I(u_i,u_j)} (r_{u_i,I} - r_{u_i}^*)(r_{u_j,I} - r_{u_j}^*)}{\sqrt{\sum_{I(u_i,u_j)} (r_{u_i,I} - r_{u_i}^*)^2} \sqrt{\sum_{I(u_i,u_j)} (r_{u_j,I} - r_{u_j}^*)^2}} \tag{3}$$

where $r_{u,I}$ is the rating of item I by user u; r_u^* is the mean rating of user u; $I(u_i,u_j)$ are the items co-rated by users u_i and u_j.

Once the similarity has been calculated, the rating of item I_j by user u_i can be predicted by traditional CF methods, as shown in equation (4).

$$PR(u_i, I) = r_{u_i}^* + b_u + b_i \tag{4}$$

2.2. Literature review

The user-item rating matrix is the sole basis for traditional CF approaches to predict the rating of items by target users. In spite of the immense popularity, the CF still faces some potential problems.

(1) The rapid growth of users and commodities, coupled with the insufficiency of user rating information in e-commerce, has resulted in an extreme sparsity of user rating data.

(2) Most CF methods fail to take account of context, which is recognized as an important factor of recommendation in e-commerce (Abbas *et al.*, 2015).

To solve the problem of data sparsity, some researchers developed various quality prediction strategies based on local and global similarities (Anand and Bharadwaj, 2011). Some created data mining algorithms to filter unseen items or employed pure rating data in prediction, namely dimensionality reduction (Wang and Li, 2015), pattern mining and latent semantic models (Najafanadi and Mahrin, 2016). Some others attempted to improve the overall recommendation performance and ameliorate the data sparsity, with the aid of trust-based methods (Ozsoy and Polat, 2013), social tagging (Belem *et al.*, 2014) or social information (Wang *et al.*, 2016).

The extreme case of data sparsity, the initial ratings are insufficient to support reliable recommendations. Such a problem is known as a cold start. The previous studies have employed different approaches to overcome information overload for a better rating prediction, such as clustering (Pereira and Hruschka, 2015), latent features (Wang *et al.*, 2016), matrix factorization (Liu *et al.*, 2013), and the combination of explicit ratings and prediction errors (Kim *et al.*, 2011). In light of user-preferred items in the past and the features of such items, Sharma *et al.* (2015) utilized the factorized bilinear similarity model to recommend the new items ranked in the top-N places. Chen *et al.* (2013) introduced trust and distrust information to CF-based recommendation method for new users. Besides, Deng (2016) integrated side information with neighborhood based CF for the advance of the recommendation quality, which can expose users' preferences about items.

The above studies have made several improvements on traditional CF algorithms, and partially reduced the effect of data sparsity on prediction accuracy. However, in most of the improved CF approaches, the similarity is measured with all items sharing the same weight to rating data, and the attributes of items unhelpful to similarity generation.

The context is essential to personalized recommendation. Champiri *et al.* (2015) suggested that recommender systems should be able to satisfy user demand in different contexts. Whereas the traditional CF fails to consider the context, Adomavicius and Tuzhilin presented a method for rating prediction in a multidimensional space including contextual information. The dataset was divided into dimensions for different contexts, and the recommendation was made specifically for the selected type of context. To solve the cold start problem, Wu and Shih (2015) introduced a new framework for context-aware recommender system based on rich resources for user generated content. The framework collects ratings and extracts related contextual information from the social media. Hariri *et al.* (2012) gathered context information and employed latent Drichlet allocation model to mine popular tags a for music recommendation. Other studies used places of interest (POI) (2013) or multi-dimensional ontology model (Rodriguez *et al.*, 2013) to represent mobile user contexts for mobile services recommendation. These studies divide users into different groups by their profile or item type, and then make recommendations by the traditional CF. Despite considering the context factor, the previous research has overlooked the user environment that may affect the recommendation process.

To sum up, none of the previous studies has taken account of both user rating behaviour and the context of similarity measuring. The neglection dampens the prediction accuracy and the recommendation quality. As a result, the two factors must be considered simultaneously to ensure the prediction accuracy and enhance the quality of collaborative recommendation.

3. Proposed model

In this paper, a new hybrid approach, called context-folksonomy-based collaborative filtering (CTBCF) is proposed to provide an enhanced recommendation incorporating context and tag information with NMB-based CF. The proposed model is implemented in two phases: user clustering phase and tag relevance measuring phase, as shown in Figure 1.

In the first phase, the CTBCF collects user-item rating data and context, and clusters users into different groups by contextual information, so as to reduce the sparsity of rating matrix. Once the clusters are obtained, the cluster data along with their centres are stored for future recommendations.

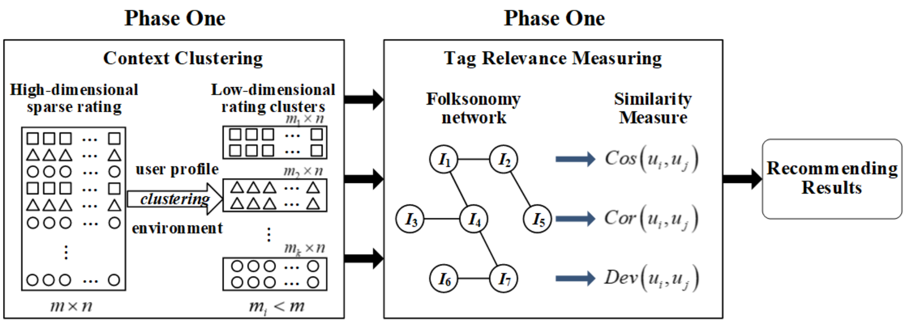

Figure 1. The framework of our proposed model

In the second phase, the CTBCF constructs a folksonomy network to analyse item relevance based on tag information, and then incorporates folksonomy network into traditional similarity calculation, so as to enhance the prediction. Finally, the recommendations are made by computing the weighted average of item ratings.

3.1. Context clustering model

To reduce the sparsity of rating data, all users were clustered into several groups by contextual information. Hence, the rating matrix was split into several low-dimension matrices for further analysis, thus lowering its sparsity.

According to Abbas *et al.*, the user context is a major influencing factor of user acceptance of recommender system. The previous research on e-commerce has suggested that user profile (e.g. age and occupation) has a significant impact on the selection of stores and products, the choice of purchase channels, and the perception of item attributes. Besides, Rodriguez *et al.* (2013) found that two factors, perceived waiting time and crowding, have strong mediating effect on the formation of attitude and use intention to some self-service technologies. From the above studies, it is concluded that the context can be constructed on user profile and environment information. The former describes personal features that may affect user preference. For instance, people of the same age and work tend to have similar interests. The latter represents the conditions for commerce activities in different places and times. Therefore, context information in this study contains both user profile and environment information.

User profile, denoted as C_u, consists of age, gender, occupation and location. It can be expressed as equation (5).

$$\begin{cases} C_u = \langle Age, Gender, Occupation, Location \rangle \\ Age \in \left(A = \{ A_i \mid i = 1,2,\ldots,7 \} \right) \\ Gender \in \left(G = \{0,1\} \right) \\ Occupation \in \left(O = \{ O_i \mid i = 1,2,\ldots,20 \} \right) \\ Location \in \left(L = \{ L_i \mid i = 1,2,\ldots,240 \} \right) \end{cases} \tag{5}$$

where the set *Age* is composed of 7 brackets: under 18, 18~24, 25~34, 35~44, 45~49, 50~55 and older than 56; the set *Gender* covers two elements: male (1) and female (0); the set *Occupation* consists of over 20 different occupations, such as teacher, doctor, engineer, student and so on; the set *Location* includes 240 different zip codes.

Environment information, denoted as C_s, encompasses three subsets: weather, time and holiday. It can be expressed as equation (6).

$$\begin{cases} C_s = \langle Weather,\ Time\ ,\ Holiday \rangle \\ Weather \in \left(W = \{ W_i \mid i = 1,2,\ldots,n \} \right) \\ Time \in \left(T = \{ T_i \mid i = 1,2,3 \} \right) \\ Holiday \in \left(H = \{0,1\} \right) \end{cases} \tag{6}$$

where the set *Weather*, denoted as W, has n kinds of unique weathers; the set *Time* is split into morning, afternoon and evening; the set *Holiday* equals either 0 (non-holiday) or 1 (holiday).

User clustering was performed after the description of context. All users were divided into several groups based on similarity. The users in the same group bear high resemblance and those in different groups have marked differences. In other words, users in the same group have similar contexts, while users in different groups have different contexts.

It is assumed that $U=\{u_i|i=1,2,\ldots,m\}$ is a set of m users, and context is denoted by set $C=<C_u, C_s>$. For any user u_i, the context of u_i can be defined in equation (7).

$$C_i = \langle C_{ui}, C_{si} \rangle = (A_i, G_i, O_i, L_i, W_i, T_i, H_i) \tag{7}$$

where C_i is a hybrid variable composed of binary variables (*Holiday* and *Gender*) and nominal variable (*Age*, *Occupation*, *Location*, *Weather* and *Time*). The data C_i cannot be processed with general clustering algorithms.

Therefore, the dissimilarity matrix was employed to depict the differences of C_i. Dissimilarity d (C_i, C_j) of context is defined in equation (8).

$$d(C_i, C_j) = \sum_{v=1}^{l} \delta_{ij}^{v} \cdot \eta_{ij}^{v} \Big/ \sum_{v=1}^{l} \delta_{ij}^{v} \tag{8}$$

where C_i consists of v(v=1,2,…,l) hybrid variables; δ_{ij}^{v} and η_{ij}^{v} are indicator functions. If the v-th variable of C_i or C_j is missing, $\delta_{ij}^{v}=0$; otherwise, $\delta_{ij}^{v}=1$. When the v-th variables of C_i and C_j are the same, $\eta_{ij}^{v}=1$; otherwise, $\eta_{ij}^{v}=0$.

Once the dissimilarity matrix of context was obtained, the KSP algorithm (Deng and Jin, 2015) was utilized to cluster the context data.

3.2. Folksonomy network model

With the advent of tagging technology, users are enabled to share opinions on various types of Internet resources using arbitrary tags according to their tastes. These tags can represent item relevance and user preference, and can be utilized to enhance recommendation quality (Naseri *et al.*, 2013). Therefore, an FNM was constructed based on tag information to analyse item relevance, and then integrated into the NBM-based CF model to improve the accuracy of rating prediction.

In the FNM, the item relevance is classified into three categories of tag links: strong link, medium link and weak link.

(1) Strong link: if two items are assigned the same/similar tags by the same user, the corresponding tag link is a strong link.

(2) Medium link: if two items are assigned the same/similar tags by different users, the corresponding tag link is a medium link.

(3) Weak link: if two items are assigned dissimilar tags by the same user, the corresponding tag link is a weak link.

For better illustration of the three types of tag links, a 2-user-5-item example is depicted in Figure 2.

In Figure 2, the tag link between each pair of items tagged by user Leo are weak links, such as T_1 (Action) & T_5 (Drama), T_9 (China) & T_5 (Britain) and so on. The items “The Matrix Revolutions” and “Inception” are tagged by user Bell and user Jack with tags T_1 (Action) and T_7 (Sci-Fi). Thus, there is a medium link between the two items. The items "Kung Fu Panda 2" and "The Matrix Revolutions" are both tagged with T_1 (Action) by user Bell, indicating a strong link between them.

After defining tag link, the author selected a weight measurement to depict the importance of each tag link. In this research, the weight of a tag link is considered from two aspects: tag similarity and tag link category.

For tag similarity, each pair of tags can be simply regarded as word sets due to the random format of tags in folksonomy. Tag similarity (*TS*) between tagged item I_i and I_j can be calculated by the Jaccard index, as shown in equation (9).

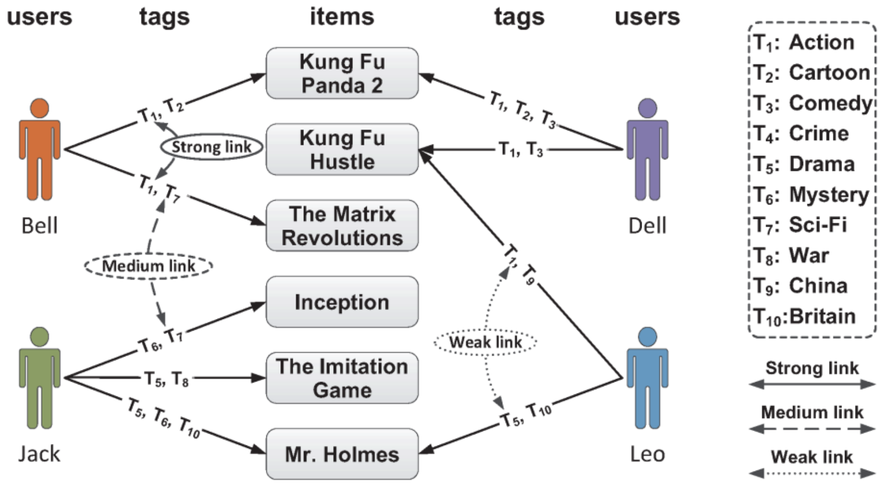

Figure 2. An example of tag links

$$TS\left(I_i, I_j\right) = Sim_{JS}\left(I_m, I_n\right) = \frac{\left|T_m \cap T_n\right|}{\left|T_m \cup T_n\right|} \tag{9}$$

where T_m and T_n are the tags of item I_i and I_j, respectively.

Then, the occurrence probability of the three tag link categories was taken as an adjusting coefficient, and introduced to the weight calculation. Let us denote the occurrence probability of strong link, medium link and weak link by P_s, P_m and P_w, respectively. So, the tag relevance (*TR*) between tagged items *i* and *j* can be obtained in equation (10).

$$\begin{gathered} TR\left(I_i, I_j\right) = P_s^{-1} \cdot \sum TS_s\left(I_i, I_j\right) + P_m^{-1} \cdot \sum TS_m\left(I_i, I_j\right) + P_w^{-1} \cdot \varepsilon \\ P_s = N_s / N,\ P_m = N_m / N,\ P_w = N_w / N \end{gathered} \tag{10}$$

where TS_s is the tag similarity of tag pair with strong link; TS_m is the tag similarity of tag pair with medium link. Due to the lack of tag pair with weak link, a constant ε with the minimal tag similarity was applied to restrict the importance of weak links; N_s, N_m and N_w respectively denote the number of the strong, medium and weak links in folksonomy data, and $N = N_s+N_m+N_w$.

Then, the FNM was defined based on tag link. The folksonomy network is an undirected weighted graph. In the network, each node denotes a specified item, and the weight of each edge denotes the tag link between the two corresponding items. For instance, a simple FNM was constructed based on the folksonomy data between user Dell and user Leo (Figures 2 and 3). Apparently, the FNM can also be depicted as an adjacency matrix denoted by *TR* (Table 1).

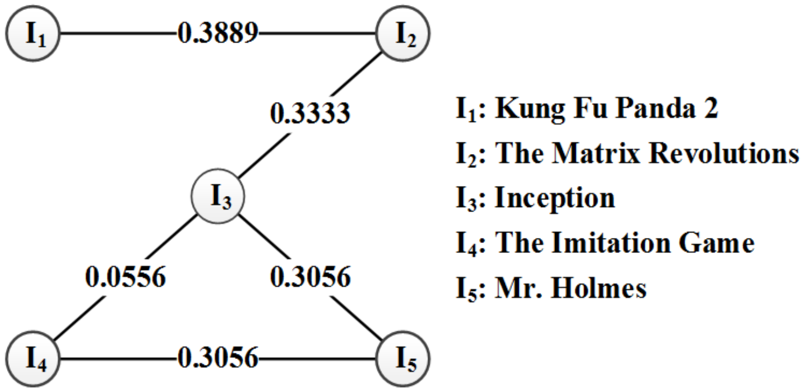

Figure 3. An example of FNM

Table 1. Tag Relevance of example FNM.

	I_1	I_2	I_3	I_4	I_5
I_1	---	0.3889	---	---	---
I_2	0.3889	---	0.3333	---	---
I_3	---	0.3333	---	0.0556	0.3056
I_4	---	---	0.0556	---	0.3056
I_5	---	---	0.3056	0.3056	---

3.3. Model integration

After the construction of the FNM, the folksonomy information F was integrated into the rating prediction process, as shown in equation (11).

$$PR(u_i, I) = r_{u_i}^* + b_u + b_i + \frac{\sum_{j \in R(u)} \omega_{ij}\left(r_{u_j} - b_{u_j}\right)}{\left|R(u)\right|^{\alpha}} + \frac{\sum_{k \in N(u)} c_{ik}\left(r_{u_j} - b_{u_j}\right)}{\left|N(u)\right|^{\alpha}} + F \tag{11}$$

where r_{ui}^* is the overall average rating; b_u and b_i are the observed deviations of user u and item i, respectively; ω_{ij} and c_{ik} are the relevance weight of items and the implicit user preference bias, respectively; $R(u)$ is the set of items rated by u; $N(u)$ is the set of items with implicit rating by u; α is a constant (0.5) to control the degree of normalization.

The item-oriented rating interactions in the above equation can be calculated by equation (12), and the rating prediction equation (11) can be reduced to equation (13).

$$E = \frac{\sum_{j \in R(u)} \omega_{ij}\left(r_{u_j} - b_{u_j}\right)}{\left|R(u)\right|^{\alpha}} + \frac{\sum_{k \in N(u)} c_{ik}\left(r_{u_j} - b_{u_j}\right)}{\left|N(u)\right|^{\alpha}} \tag{12}$$

$$PR(u_i, I) = r_{u_i}^* + b_u + b_i + E + F \tag{13}$$

Because the rating data and the folksonomy data are parallel data sources, there must be a coefficient to balance the importance of E and F. In this paper, a coefficient β is introduced in equation (14). The coefficient β strikes a balance between the information from user rating and the FNM. If β = 0, the rating prediction only relies on user rating; if not, the rating prediction relies on both user rating and the FNM.

$$PR(u_i, I) = r_{u_i}^* + b_u + b_i + \beta E + (1 - \beta) F \tag{14}$$

Furthermore, the tag link should be normalized before integration to avoid magnitude difference. The normalization process is defined in equation (15), which ensures that TR falls in the interval of [0, 1].

$$TR = \frac{TR(I_i, I_j) - TR_{\min}(I_i, I_j)}{TR_{\max}(I_i, I_j) - TR_{\min}(I_i, I_j)} \tag{15}$$

In consideration of the FNM, three factors were utilized in the *F* calculation process for prediction:

(1) The item set tagged by user *u*, $T_p(u)$, which indicates the active user's tagging preference;

(2) The item set sharing a tag link with item *i*, $T_n(i)$, which contains the items connected to the tagged item;

(3) The tag relevance $TR(I_i,I_j)$ between item *i* and item *j*.

Therefore, the folksonomy information *F* can be computed in following equation.

$$F = \frac{\sum_{j \in T_n(I)} TR\left(I_i, I_j\right)\left(r_{u_j} - b_{u_j}\right)}{\left|T_n\left(I\right)\right|^{\alpha}} + \frac{\sum_{k \in T_p(u)} c_{ik}\left(r_{u_j} - b_{u_j}\right)}{\left|T_p\left(u\right)\right|^{\alpha}} \tag{16}$$

Thus,the rating prediction equation (14) can be transformed into equation (17).

$$\begin{aligned} PR\left(u_i, I\right) &= r_{u_i}^{*} + b_u + b_i + \beta E + \left(1-\beta\right) F \\ E &= \frac{\sum_{j \in R(u)} \omega_{ij}\left(r_{u_j} - b_{u_j}\right)}{\left|R\left(u\right)\right|^{\alpha}} + \frac{\sum_{k \in N(u)} c_{ik}\left(r_{u_j} - b_{u_j}\right)}{\left|N\left(u\right)\right|^{\alpha}} \\ F &= \frac{\sum_{j \in T_n(I)} TR\left(I_i, I_j\right)\left(r_{u_j} - b_{u_j}\right)}{\left|T_n\left(I\right)\right|^{\alpha}} + \frac{\sum_{k \in T_p(u)} c_{ik}\left(r_{u_j} - b_{u_j}\right)}{\left|T_p\left(u\right)\right|^{\alpha}} \end{aligned} \tag{17}$$

4. Experimental results

In this section, numerical experiments are designed to verify the effectiveness of our model. The experiments were carried out on three real-world datasets, and the CTBCF was contrasted with the other three CF-based model.

4.1. Experiment design

Without loss of generality, all the experiments were performed on three real world datasets provided by GroupLens Research Group at University of Minnesota. These datasets are open to the public for research purposes. The features of these datasets are depicted in Table 2. Specifically, the author downloaded the MovieLens datasets, in which the ratings on movies are in the scale of 1 to 5, and the tags are labelled arbitrarily by users.

For each dataset, we employed 80% and 90% of data as the training datasets and 20% and 20% of data as the test set. That is, 80% and 90% of the users served as the reference for similarity calculation, and 20% and 10% of data were target users of actual recommendation. Similarly, 80% and 90% of the movies were used for similarity calculation, while 20% and 10% were actually recommended to users. Of course, meaningless tags like numbers and symbols were removed before the experiments.

The root means square error (RMSE) (Said and Belogin, 2014) was selected to evaluate the performance of our approach. The RMSE is a commonly used metric of statistical accuracy. Its value is negatively correlated with the prediction accuracy. This metric is defined in equation (18).

Table 2. Characteristics of three Movielens datasets

Dataset	User	Movie	Rating	Sparsity
MovieLens-100K	943	1682	100K	6.30%
MovieLens-10M	71567	10681	10M	1.31%
MovieLens-20M	138,493	27,278	20M	0.53%

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(R_i^* - R_i\right)^2} \tag{18}$$

where R_i^* is the predicted rating; R_i is the corresponding existing rating; N is the number of user ratings in the rating matrix.

4.2. Experimental results

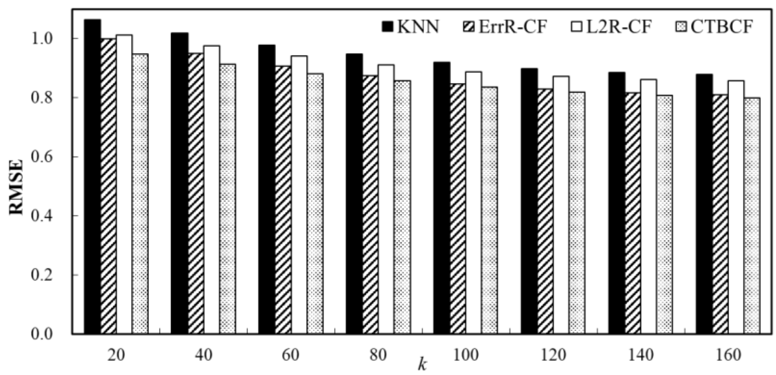

Figure 4. Comparison of four algorithms on MovieLens-100K @ 80%

The contrast CF algorithms include an item-based CF algorithm (KNN), an item-based CF approach based on item rating prediction (ErrR-CF), and a tag-based CF method (L2R-CF). Both the KNN and ErrR-CF predict rating based on cosine similarity, and L2R-CF relies on rating deviation. The comparison was performed with parameters α and β both set at 0.5.

The experimental results of the four algorithms on three real-world datasets @ 80% are shown in Figures 4-6 respectively.

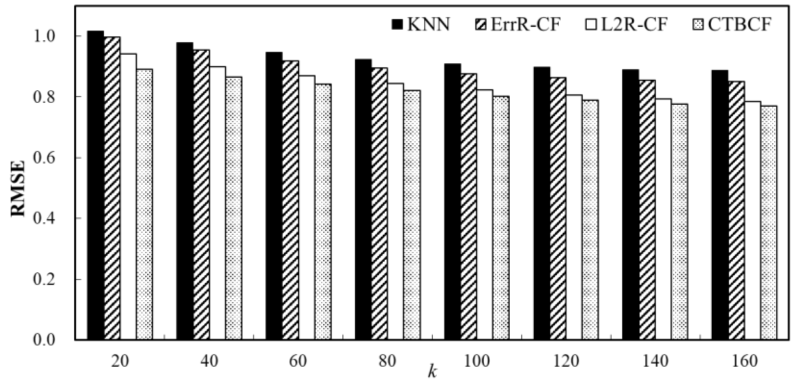

Figure 5. Comparison of four algorithms on MovieLens-10M @ 80%

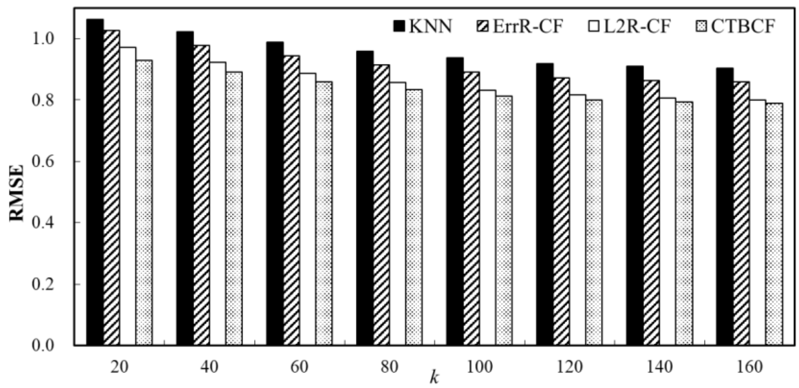

Figure 6. Comparison of four algorithms on MovieLens-20M @ 80%

Figure 4 depicts the RMSEs of the four algorithms on MovieLens-100K. As shown in the figure, the minimum RMSE of the CTBCF is 0.7981, about 90.19%, 98.60% and 93.87% of that of KNN (0.8849), ErrR-CF (0.8094) and L2R-CF (0.8502), respectively. It is clear that the ErrR-CF and the CTBCF outperform the KNN and the L2R-CF, owing to the absence of tag data on contextual data in MovieLens-100K. When context data are available, the CTBCF has better performance than the ErrR-CF. Thus, the proposed approach boasts the minimum RMSE on MovieLens-100K with the setting at 80%.

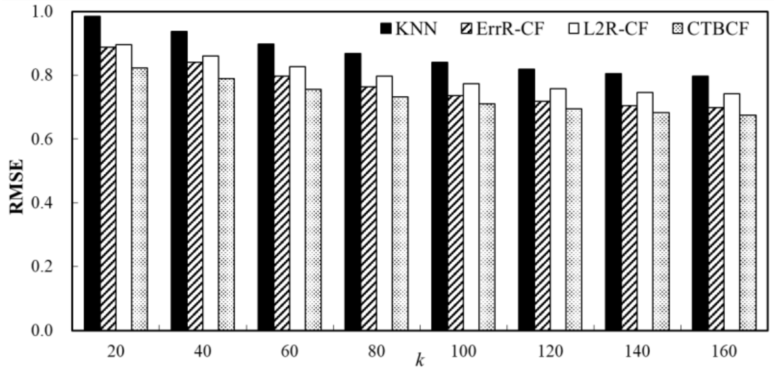

Figure 7. Comparison of four algorithms on MovieLens-100K @ 90%

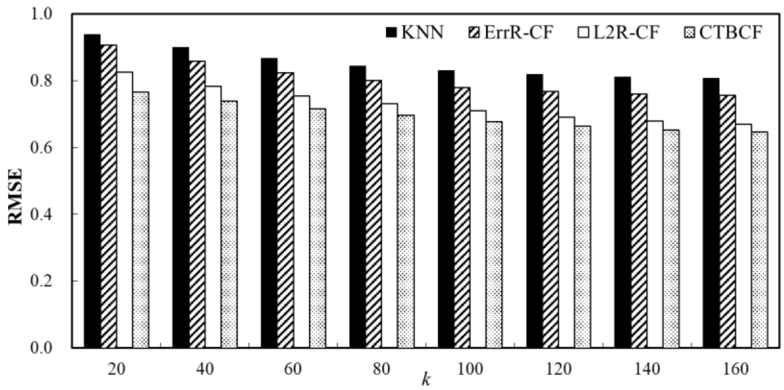

Figure 8. Comparison of four algorithms on MovieLens-10M @ 90%

Figure.5 presents the RMSEs of the four algorithms on MovieLens-10M, and the minimum RMSEs of the four algorithms are 0.8847, 0.8499, 0.7705 and 0.7662, respectively. Unlike Figure.4, the L2R-CF has a lower RMSE than the KNN and the ErrR-CF, thanks to the tag information in MovieLens-10M. In terms of the minimum RMSE, the CTBCF is 0.1185, 0.0837 and 0.0043 lower than the KNN, the ErrR-CF and the L2R-CF, respectively. Hence, our model still possesses the minimum RMSE on MovieLens-10M at the setting of 80%.

Figure.6 displays the RMSEs of the four algorithms on MovieLens-20M. The minimum RMSE of the CTBCF is 0.7892, which is 0.1139, 0.0655 and 0.0053 smaller than the KNN (0.9031), the ErrR-CF (0.8547) and the L2R-CF (0.7945), respectively. Similar to the results in Figure.5, the CTBCF outperforms other three CF methods in the minimum RMSE on MovieLens-20M @ 80%.

The results on all datasets @ 90% are presented in Figures 7-9, respectively.

Figure.7 shows the RMSE results on MovieLens-100K @ 90%. The minimum RMSE values are 0.7976 (KNN), 0.6993 (ErrR-CF), 0.7422 (L2R-CF) and 0.6740 (CTBCF). Similar to the results on the same dataset with the setting of 80%, ErrR-CF and CTBCF outperform KNN and L2R-CF without any tag information, and CTBCF has better performance than ErrR-CF when the context data are available.

Figures 8 and 9 indicate the RMSEs of all algorithms on MovieLens-10M and MovieLens-20M at the setting of 90%, respectively. Due to both context and tag information in these two datasets, L2R-CF and CTBCF have lower RMSEs than KNN and ErrR-CF, and CTBCF is 0.0154 and 0.0189 lower than L2R-CF on MovieLens-10M and MovieLens-20M, respectively. Therefore, our model possesses the minimum RMSE on MovieLens-10M and MovieLens-20M.

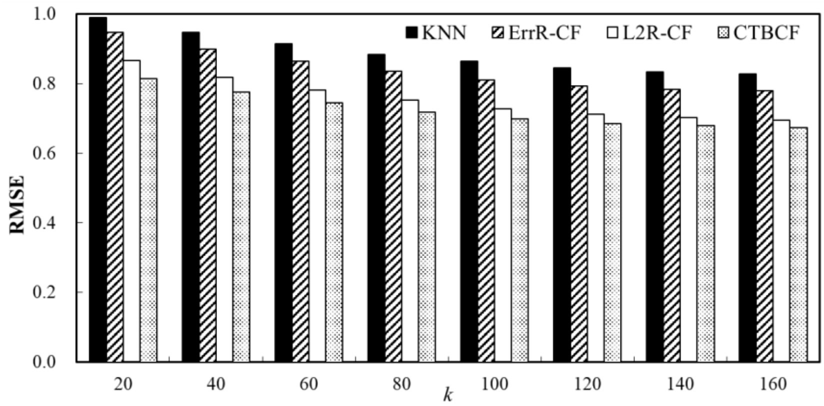

Figure 9. Comparison of four algorithms on MovieLens-20M @ 90%

According to Figures 4-9, it is apparent that our proposed approach has the lowest minimum RMSE among all four algorithms on the three datasets with different settings, even in the case of lacking tag information.

5. Conclusion

This paper presents an improved CF method to enhance the prediction quality of collaborative recommendation. The CTBCF clusters user into different groups based on contextual information, seeking to reduce the data sparsity of user-item rating matrix and eliminate the effect of rating sparsity on prediction quality. For the convenience of rating prediction, an FNM was built on tag information to obtain folksonomy relevance between item pairs, and was then integrated with NBM-based CF to improve recommendation accuracy.

The experimental results show that the CTBCF succeeds in elevating the quality of rating prediction. Compared with other three algorithms, CTBCF has the minimum value of RMSE. This means that the proposed approach outperforms the other three typical CF approaches in terms of prediction quality. Thus, the CTBCF is more applicable in situations where context and folksonomy are critical to the success of the application, just like in social commerce and virtual community websites.

Our future research will focus on handling big data in social commerce. So, parallel algorithms will be developed to expand and accelerate the computation.

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