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Cognitive Knowledge-aware Social Recommendation via Group-enhanced Ranking Model

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Abstract
Cognitive inspired recommendation systems have attracted increasing attention in recent years, aiming at fitting user ratings on certain items. However, the performance of recommendation approaches has been limited due to the sparsity and ambiguity of cognitive knowledge user-item ratings. Top-k recommendation has therefore been addressed and has become one of the most popular research areas. The goal of top-k recommendation is to capture the relative preferences of users and fit the optimal ranking list of items. Meanwhile, the development of social networks provides a new way to model user preferences to improve the accuracy and interpretation ability of cognition-aware recommendation models. To integrate user social information into top-k recommendation, we propose a group-enhanced ranking method based on matrix factorization. In our method, we first compute trust values between users based on user trust relationships. Then, we incorporate a trust matrix into the loss function with a social-based penalty term that reduces the distances between preference vectors of trusted users. Experimental results on two real datasets from Epinions and BaiduMovies show that the proposed method outperforms several state-of-the-art methods in terms of the normalized discounted cumulative gain (NDCG) value. Our model effectively improves the accuracy of social recommendations. We propose a novel cognitive knowledge-aware group-enhanced social recommendation method for item recommendation. The model modifies the loss function by considering the user trust relationship and group-enhanced ranking and significantly improves the performance of social recommendations.

Keywords Recommendation System · Social Networks · Learning to Rank · Domain Knowledge

Introduction

Cognitive science, as an iconic scientific research category, has been studied for decades. It has attracted the attention of scientists worldwide as a cutting-edge interdisciplinary research field. Related research has focused on different cognitive processes and human behaviors involving perception, learning, reasoning and interactions of humans. In recent years, the online behaviors of users have become a hot research topic in the cognitive computation field, which encodes a great deal of valuable user information. Research on online user modeling has promoted the development of state-of-the-art approaches for better modeling various cognitive processes.

With the rapid development of the Internet, user-oriented web applications have become increasingly popular in daily life. User interests and preferences are thus captured and reflected in these applications. Modeling user preferences has become indispensable to accurately interpret user information needs for recommending items of interest, which also facilitates the comprehension of cognitive processes. Personalized recommendation techniques seek to address the problem of interpreting user preferences, which have attracted much attention in the area of information retrieval and recommendation [1].

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The applications of personalized recommendations can be divided into two scenarios: rating prediction and ranking prediction. Rating prediction aims to predict ratings of unknown items according to user history ratings. The rating values indicate the preferences of users for certain items. Recommendation systems based on rating prediction are called rating-oriented recommendation systems, such as Douban and Group Lens. Ranking prediction aims to predict ordered ranking lists of items for certain users. Ranking prediction considers the relative preferences of different items, with the top-ranked items considered more preferable to users. Recommendation systems based on ranking prediction are called ranking-oriented recommendation systems. Compared to rating-oriented recommendations, ranking-oriented recommendations have proven to be more effective and robust in different applications. Most e-commerce websites fall into this scenario. In this study, we also focus on ranking-oriented recommendations to improve the accuracy of the top-k ranked items.

Many existing studies have addressed personalized recommendations using various algorithms. Recommendation algorithms, as the core technologies of personalized recommendations, can be mainly divided into two categories: content-based filtering and collaborative filtering. Content-based filtering approaches analyzing the content information associated with items and users, such as product descriptions and user profiles. These approaches extract user features from item descriptions and extract item features from user profiles. Then, the feature representations of users and items are matched to obtain the recommendation results. Collaborative filtering approaches are mostly domain-independent and entail no content information of users or items. These approaches assume that similar users tend to prefer similar items. Collaborative filtering works by mining the correlation between users and items. The similarity of users is measured based on their commonly rated items in terms of certain metrics, such as the Pearson correlation coefficient [2]. The collaborative filtering approaches can be divided into two subcategories: memory-based approaches and model-based approaches. In this paper, we mainly focus on the model-based approach. We adopt one of the most popular model-based approaches, the matrix factorization technique [3]. Matrix factorization has been widely applied to various recommendation systems and exhibits powerful capability in recommendation tasks.

With the recent development of online social media, social network-based recommendation technologies have attracted increasing attention from both industry and academia. The related methods are called social recommendation methods [4]. Social networks describe user relationships, which have a significant influence on user preferences. Traditional social recommendation approaches focus on the rating prediction scenario and obtain better performance than nonsocial recommendation approaches. However, traditional social recommendation approaches still have much room for improvement in the ranking accuracy of recommended items, although they have improved the accuracy of rating prediction. For example, Yang et al. [5] utilized user groups in online social networks with richer information to solve the problem of cold-start video recommendation. Liu [6] proposed constructing trust-based social networks to measure the quality of a friends recommendations in different contexts. These two studies have demonstrated that user groups and trust relationships can largely contribute to recommendation accuracy. Inspired by these works, we intend to take advantage of user groups and trust relationships in item recommendations within the learning-to-rank scenario.

Learning to rank, as a series of state-of-the-art ranking methods, seeks to optimize the ranking of documents or web pages, which has been widely used in various information retrieval tasks. Recommendation systems have also adopted learning-to-rank methods for ranking-oriented recommendations. Recommendations based on learning to rank transforms the query-document pairs to the user-item pairs and yields ranking lists of items for certain users [7]. Learning-to-rank recommendation methods have proven to be effective in optimizing item rankings for users. However, the learned ranking models still have much room for improvement due to data sparsity, which can be complemented using additional user information, such as social information.

In this paper, we propose a group-enhanced social recommendation method based on learning to rank. In our method, we first compute the trust values between users based on the following relationship of users. Then, we adopt a group-enhanced ranking method to address the user trust relationship. We incorporate the trust values as weights into the loss function for model optimization and add a social regularization term to the original listwise recommendation method to avoid overfitting. We evaluate our method on the two datasets in comparison with several state-of-the-art baseline methods. Experimental results show that our proposed model outperforms the baseline methods for more accurate recommendations.

We summarize the contributions of this paper as follows.

(1) We propose incorporating trust relationships between social network users using a graph-structured social matrix for item recommendation. The trust-based matrix is used to assign weights between trustworthy users in the optimization and construction of recommendation models.
(2) We propose a novel group-enhanced ranking loss function to integrate the social trust relationships of users to accurately recommend items. The proposed loss function treats a certain user and his or her trustworthy

friends as group samples to better model the user relationship in recommendations.

(3) We conduct adequate experiments on two real datasets to examine the effectiveness of the proposed methods. Experimental results show that our method is effective in ranking-based social recommendations, outperforming other state-of-the-art recommendation models.

The rest of the paper is organized as follows. Related Work reviews the related work. Problem Formulations provides a formal definition of the focused problem. Methods details the proposed algorithm. Experiments and Analysis reports the experimental results and analysis of the results. Conclusions and Future Work concludes the paper and presents future research directions.

Related Work

In this section, we review related work from three lines: basic matrix factorization, social and trust-based recommendations, and learning-to-rank-based recommendations.

Basic Matrix Factorization

Matrix factorization techniques have been widely applied to collaborative filtering-based recommendation systems and proven to be effective in rating prediction tasks [8–12]. Models based on matrix factorization aim to learn the $d \times m$ user-specific feature matrix $\mathbf{U}$ and $d \times n$ item-specific feature matrix $\mathbf{V}$, where $\mathbf{U}$ and $\mathbf{V}$ are low-rank matrices subject to $d \ll m$ and $d \ll n$. The predicted rating of user i to item j is the inner product of feature vector U_i of user i and vector V_j of item j, namely, $\hat{R}_{ij} = U_i^T V_j$. $\mathbf{U}$ and $\mathbf{V}$ can be learned by minimizing the observed rating prediction loss in terms of evaluation metrics, such as root mean squared error (RMSE). A general form of the loss function can be formulated as follows.

$$L(\mathrm{U}, V) = \sum_{i=1}^{M} \sum_{j=1}^{N} I_{ij}(R_{ij} - g(U_i^T V_j))^2 + \frac{\lambda}{2}(||U||_F^2 + ||V||_F^2) \tag{1}$$

where M is the number of users and N is the number of items. I_{ij} is the indication function. A rating of user i on item j indicates $I_{ij} = 1$; otherwise, $I_{ij} = 0$. The rating value of user i on item j is given by the entries R_{ij} in $\mathbf{R}$. $\mathbf{U}$ and $\mathbf{V}$ are the latent feature matrices of users and items, where $\mathbf{U} \in R^{d\times m}$ and $\mathbf{V} \in R^{d\times n}$. The i^{th} row in $\mathbf{U}$ represents the feature vector representation of user i. The j^{th} row in $\mathbf{V}$ represents the feature vector representation of item j. The second term in Eq. (1) is the regularization term, where $\frac{\lambda}{2}$ is the regularization hyperparameter. $||U||_F^2$ and $||V||_F^2$ are the Frobenius normalization factors of $\mathbf{U}$ and $\mathbf{V}$, respectively.

The constraints $d \ll m$ and $d \ll n$ in matrix factorization reduce the high-dimensional user-item rating matrix to a low-dimensional user feature matrix and item feature matrix. Based on probabilistic estimation theory, Salakhutdinov et al. [8] proposed a probabilistic matrix factorization model (PMF) and introduced Markov chain Monte Carlo (MCMC) to estimate the parameters [10]. Probabilistic matrix factorization models have been successfully used in recommendation systems and improved recommendation accuracy. For example, Ren et al. [11] integrated the interest, geographical, and categorical relevance scores of users into a probabilistic matrix factorization model for location-based point-of-interest recommendation. Hernando et al. [12] presented a novel technique for predicting the tastes of users in recommendation systems based on collaborative filtering by considering the probabilistic meaning of components in the matrix. Matrix factorization provides a new way to predict user preferences for certain items. Recommendation approaches based on matrix factorization can be further enhanced by integrating abundant user information, such as social information.

Social and Trust-based Recommendation Approaches

Social networks have improved the accuracy and interpretation ability of recommendation systems [13–22]. Most social network-based recommendation approaches are based on the matrix factorization framework and exhibit high scalability and effectiveness in predicting user-item ratings. For example, Ma et al. [23] proposed a social regularization method (SoRec) by considering the constraints of social relationships. They modified the probabilistic matrix factorization method to simultaneously factorize the rating matrix and the social matrix. Jamali et al. [24] proposed a new matrix factorization model by adding a social regularization term to make feature vectors of associated users nearer. Wu et al. [25] proposed adding a novel regularization term based on user trust and item tags in the basic matrix factorization model. The obtained model ensured that trustworthy users had similar user-specific feature vectors, and items with similar tags had similar item feature vectors. These social recommendation approaches have proven that matrix factorization with social information outperforms matrix factorization without social information.

In recent years, the trust relationship of users, as a crucial factor in social network-based recommendation, has been investigated by many researchers [26–30]. For example, a new collaborative filtering approach was proposed under the belief function framework to incorporate trust in recommendations [31]. Azadjalal et al. [32] proposed a trust-based collaborative filtering method based on Pareto dominance and confidence concepts to identify implicit trust relationships. Guo et al. [33] proposed three factored similarity models based on social trust for top-N item recommendation. Enhanced context-aware social recommendation using a Gaussian mixture model with individual trust among users. Park et al. [34] addressed top-k recommendation by modeling user relationships as trusters and trustees to improve the recommendation accuracy. Generally, the trust relationship in a social network with m users can be modeled as a trust matrix $T \in \mathbf{R}^{m \times m}$, where t_{uk} is the trust value of user u with respect to user k. A larger value of t_{uk} indicates a larger influence of user k on user u. Namely, the trust value will increase if user k follows a large number of users and decrease if user u follows a large number of users. Therefore, the trust value t_{uk} can be formalized as follows.

$$t_{uk} = F(d^{-}(v_k), d^{+}(v_u)) \tag{2}$$

where $d^{-}(v_k)$ is the indegree of the user k. $d^{+}(v_u)$ is the outdegree of user u, and F is a nonlinear mapping from the network degrees to trust values. Existing studies have shown that the trust relationship of social network users is useful for item recommendation, particularly in the top-k recommendation scenario. However, few studies have incorporated trust relationships in learning-to-rank-based recommendations, although learning to rank has exhibited promising performance for top-k recommendations.

Learning-to-Rank-based Recommendation Approaches

Learning to rank in information retrieval has been widely used to optimize the document ranking for given queries. Since ranking is a general problem in natural language processing tasks, learning to rank has also been applied in tasks such as recommendation systems and question answering. In recommendation systems, learning-to-rank methods seek to predict an ideal ranking list of items for different users, which overcomes the difficulty in predicting the accurate rating of each user to each item. Learning-to-rank-based recommendation approaches focuses on optimizing the ranking performance of items and provides users with more accurate top-k recommendation results. Most real-world applications fall into the top-k recommendation scenario.

Ranking-based recommendation approaches can be divided into three types: the pointwise approach, the pairwise approach and the listwise approach. Rating-oriented approaches fall into pointwise rank-based approaches. The pairwise rank-based approaches take a pair of items as a learning instance for model training. For example, Liu and Yang [35] proposed a pairwise rank-based algorithm EigenRank, which measured the similarity between users based on their pairwise ranking preferences. Rendle et al. [36] proposed a Bayesian personalized ranking approach by modeling binary relevance data and optimizing binary relevance metrics. They randomly selected observed items as positive samples and unobserved items as negative samples to generate item pairs and estimated the parameters by maximizing Bayesian posterior probability using stochastic gradient descent. Proposed a pairwise rank-based model based on RankNet [37]) to adapt the loss function to a matrix factorization framework. Liu et al. [38] adapted the Bradley-Terry model [39] to the loss function designed for pairwise preferences and incorporated it into an existing matrix factorization model. The listwise approaches take an item ranking list as a learning instance. For example, Weimer et al. [40] proposed minimizing a convex upper bound of the normalized discounted cumulative gain (NDCG) [41, 42] loss through matrix factorization. Shi et al. [43] proposed ListRank-MF to optimize the listwise ranking probability distribution based on the loss function of ListNet [44].

Our previous work focused on cognitive computation methods for user attribute classification [45]. The difference between this study and previous works lies in the tasks and methods. In this work, we focus on learning-to-rank-based recommendations, whereas our previous work focused on other NLP tasks. Since we address different tasks in these studies, we design different computational models in consideration of task-specific characteristics. Even though learning-to-rank methods can contribute to improving the performance of recommendations, few studies have attempted to integrate the social information of users into learning to rank to further enhance performance. In this study, we consider the trust relationship of users based on social networks and incorporate trust values of users into the loss function of learning to rank to optimize the recommendation process.

Problem Formulations

For a collaborative filtering recommendation system with m users $\{u_1, u_2, ..., u_m\}$ and n items $\{v_1, v_2, ..., v_n\}$, user ratings on items constitute a $m \times n$ rating matrix $\mathbf{R}$, where r_{ij} represents the rating that user u_i assigned to item v_j. The value of ratings ranges from 1 to 5, indicating user preferences for certain items.

With the development of social networks, many studies have focused on modeling user relationships based on social networks to enhance collaborative filtering recommendation systems. For a social network-based recommendation system, a graph based on a social network is integrated to model the relationship of users. In this graph, each node represents a user, and each edge represents the social relationship of two users. Typically, the social graph is modeled as a $m \times m$ social matrix $\mathbf{S}$. A positive value of an element in the matrix indicates that there exists a social relationship between two users. For a directed social network, if user u_i follows user u_j, s_{ij} is a nonzero positive value. For an undirected social network, the social matrix is symmetrical. Generally, the values of elements in the social matrix are 1 or 0. Different methods have been proposed to address the recommendation problem in consideration of the social relationships of users.

In this study, we introduce learning-to-rank methods for integrating a social network-based graph into a collaborative filtering recommendation system. The task of social recommendation is then transformed as a learning-to-rank problem and solved from an information retrieval perspective. Formally, given the user-item ratings matrix $\mathbf{R}$ and the user social graph-based matrix $\mathbf{S}$, we measure trust values between each pair of users and obtain a user-user trust matrix $\mathbf{T}^{m\times m}$. We incorporate the trust matrix into the loss function of learning to rank to predict the item ranking list π_i for each user u_i.

Methods

In this section, we introduce the proposed model in detail. We first define and compute trust values between users from online social networks in Trust Value in Social Networks. We then present the learning-to-rank-based social recommendation model in Group-enhanced Ranking for Social Recommendation and introduce the model training process in Model Training.

Trust Value in Social Networks

Online social networks model the relationship of users as a graph-structured social matrix. Abundant information about users is implicitly encoded in the matrix, including the trust relation between users. Intuitively, a trustworthy user is more likely to recommend preferred items to his or her friends. Therefore, the measurement of trust values is important for explicitly modeling the trust relationship of users. The trust value between users can be reflected based on the preference influence between users. The influence between users can be modeled based on the following and followed relationships in social networks. The influence of trust is always directed regardless of whether the social network is directed or undirected.

Specifically, for a social network with m users, we model the trust relationship as a trust matrix $T \in \mathbf{R}^{m\times m}$, where t_{uk} is the trust value of user u with respect to user k. A larger value of t_{uk} indicates a larger influence of user k on user u. Similar to the Web link adjacency graph in [46], the trust value will increase if user k follows a large number of users and decrease if user u follows a large number of users. Based on this idea, we formulate the trust value t_{uk} as follows.

$$t_{uk} = \sqrt{\frac{d^{-}(v_k)}{d^{+}(v_u) + d^{-}(v_k)}} \tag{3}$$

where $d^{-}(v_k)$ is the indegree of the user k. $d^{+}(v_u)$ is the outdegree of the user u. Particularly, in undirected social networks such as Renren[1] and Facebook[2], $d^{-}(v_u) = d^{+}(v_u) = d(v_u)$.

Due to the social influence in social networks, the preference of users will be influenced by the friends they follows. The latent feature vector of a certain user u will be influenced by his direct trusted neighbors [47]. We formulated the social influence as follows.

$$\hat{U}_u = \frac{\sum_{v\in N_u} t_{uv} U_v}{\sum_{v\in N_u} t_{uv}} \tag{4}$$

where N_u is the direct trust user set of user u. U_v represents the latent feature vector of user v based on the definition in Eq. (1). Namely, we integrate the feature vectors of neighbors of user u with the corresponding trust values of its neighbors to produce the preference vector of u. We normalize the obtained vectors in the trust matrix to ensure that $\sum_{v\in N_u} t_{uv} = 1$.

Group-enhanced Ranking for Social Recommendation

We propose a group-enhanced ranking method to fully capture user relationships for social recommendations. In our method, we incorporate trust relationships from social networks into learning-to-rank-based recommendation algorithms. Our method is adapted from ListRank-MF [43]; we name our method social group rank matrix factorization (SGroupRank-MF) and introduce details on our method in the following subsections.

Group-enhanced Learning to Rank

Group-enhanced learning to rank was proposed to improve the ranking performance by resampling documents with diverse ground truth labels as groups [48]. It is based on the divide-and-conquer strategy of extending the sampling space of learning to rank for improving the effectiveness and robustness of the ranking model. Specifically, a group sample constitutes one document with greater relevance and several documents with less relevance. In the training process, ranking loss is accumulated based on groups of documents to highlight the relevant documents and reduce the weights of irrelevant documents. The learned ranking model

[1] www.renren.com

[2] www.facebook.com

can therefore rank the highly relevant documents at the top of the document ranking list.

In this study, we introduce the group-enhanced ranking method in social network-based recommendations to address the trust relationships of users. In the original presentation of group-enhanced learning to rank, documents with diverse ground truth relevance labels are taken as groups for training. Instead of grouping documents, we treat one user and his or her trustworthy friends as a group sample to extend the sample space of recommendation. In model training, we accumulate the ranking loss at the group level to capture the trust relationships of users for item recommendations. In the following subsections, we adopt the top-one permutation probability to transform ranking scores into a probability and employ cross entropy to measure the ranking loss at the group level.

Top-one Permutation Probability

In our method, we adopt a widely used permutation probability model named the Plackett Luce model [39] to transform the permutations of rated items into a probability distribution. The permutation probability model assumes that each permutation of items corresponds to a probability, indicating the possibility that the permutation takes place. More accurate permutations have higher permutation probabilities and tend to rank the items with larger ranking scores at the top of the ranking list. Since the computation of all the permutations for a set of items is an NP hard problem, the top-one permutation probability has been applied in ranking tasks to simplify this problem. In our method, we also adopt the top-one permutation probability and formalize the top-one probability for social recommendations as follows.

$$P_{l_i}(R_{ij}) = \frac{\phi(R_{ij})}{\sum_{k=1} K\phi(R_{ik})} \tag{5}$$

where R_{ij} is the rating value that user i assigned to item j in the user-item rating matrix. l_i is the item ranking list for the user i. $P_{l_i}(R_{ij})$ is the top-one probability of an item with the rating value R_{ij} to be ranked to the top-one position in the ranking list l_i. We assume that each item has the probability of being ranked to the first position. $\phi(x)$ is a monotonically increasing and strictly positive function. In this paper we use the exponential function $\phi(x) = exp(x)$. An item with a higher rating will have a higher top-one probability and be more preferable to users. The item, therefore, will be more likely to rank toward the top-one position. Based on the definition of top-one probability, we model the item ranking list as a probability distribution for the computation of ranking loss.

Cross Entropy-based Ranking Loss

Cross entropy is commonly used to measure the similarity between two probability distributions in information theory. A smaller value of cross entropy means that the two probability distributions are closer to each other. In our method, we employ cross entropy to estimate the ranking loss by measuring the similarity between the top-one probability distribution of the ground truth item list and the predicted item ranking list. For a recommendation system with M users and N items, the cross entropy-based loss function can be formulated as follows.

$$L(\mathrm{U}, \mathrm{V}) = \sum_{i=1}^{M} \{-\sum_{j=1}^{N} I_{ij} P_{l_i}(R_{ij}) log(P_{l_i}(g(U_i^T V_j)))\} \tag{6}$$

where U is the matrix of users and V is the matrix of items, subject to $\mathrm{U} \in \mathbf{R}^{d\times m}$, $\mathrm{V} \in \mathbf{R}^{d\times n}$. I_{ij} is the indication function. If user i rated item j, I_{ij} is set to 1; otherwise, it is set to 0. $P_{l_i}(R_{ij})$ is the top-one probability of the rated item list of user i for item j. $g(x)$ is the logistic function to bound the range of $U_i^T V_j$. For example, if our method is applied in a 5-scale rating system, $g(x) = 5/(1 + e^{-x})$.

In social networks, trust relationships of users reflect user preferences and tastes for certain items. Trustworthy users often have similar interests, and users with greater trust values tend to have more influence on each other. Based on these assumptions, we modify the basic cross-entropy loss function by treating a user and his or her trustworthy users as a group. We assign weights within the groups of users and measure the ranking loss based on user trust values. We formulate the new loss function as follows.

$$L(\mathrm{U}, \mathrm{V}) = \sum_{i=1}^{M} \sum_{k\in N_i} T_{ij} \{-\sum_{j=1}^{N} I_{ij} P_{l_i}(R_{ij}) log(P_{l_i}(g(U_i^T V_j)))\} \tag{7}$$

where N_i is the set of trustworthy users for user i. T_{ij} is the trust value of user i for user j. We assign weights T_{ij} within the trustworthy users for user i to capture the trust relationship of different users. In addition, we add two regularization terms to the loss function to avoid overfitting. One is the user trust regularization term, and the other is the traditional regularization term. The final loss function can be formulated as follows.

$$\begin{aligned} L(\mathrm{U}, \mathrm{V}) = {} & \sum_{i=1}^{M} \sum_{k\in N_i} T_{ij} \{-\sum_{j=1}^{N} I_{ij} P_{l_i}(R_{ij}) log(P_{l_i}(g(U_i^T V_j)))\} \\ & + \frac{\lambda_u}{2} \sum_{i=1}^{M} (||U_i - \sum_{j\in N_i} T_{ij} U_j||_F^2) + \frac{\lambda}{2}(||U||_F^2 + ||V||_F^2) \end{aligned} \tag{8}$$

where $\frac{\lambda_u}{2}$ is social trust penalty coefficient. $\frac{\lambda}{2}$ is the regularization coefficient to avoid overfitting. T_{ij} is the trust value of

Table 1 Social Group Ranking Algorithms

Input: training data **U** and **V**, hyper parameters λ_u, λ and d,
user trust matrix T, the number of iterations *iteration*
learning rate η

Constructing group samples from the training data.
Initialize parameter U and V.
for $t = 1$ to *iteration* do
 Compute gradient for each $\triangle \mathrm{U_i}$, $\triangle \mathrm{V_j}$
 $\triangle \mathrm{U_i} = \frac{\partial L(\mathrm{U,V})}{\partial U_i}$, $\triangle \mathrm{V_j} = \frac{\partial L(\mathrm{U,V})}{\partial V_j}$
 Update $U_i = U_i - \eta \times \triangle \mathrm{U_i}$, $V_j = V_j - \eta \times \triangle \mathrm{V_j}$
end for
Output Social Group Ranking Recommendation Model

user i with respect to user j. $||U||_F^2$ and $||V||_F^2$ are the Frobenius normalization of **U** and **V**, respectively.

Model Training

We train the proposed model, SGroupRank-MF, by minimizing the cross entropy loss function defined in Eq. (7). Since we use learning to rank for item recommendation, the goal of the training is to obtain the optimal ranking list of items for different users instead of predicting the exact ratings of items.

The hyperparameters of our model include the social regularization coefficient λ_u, regularization coefficient λ and dimensionality d of the user and item matrix. Given the hyperparameters, we seek to find the minimum of the loss function in Eq. (7) by performing gradient descent on U_i and V_j for each user u and each item j. We formulate the training process of our model in the following algorithm (See Table 1).

To obtain the optimal **U** and **V**, we iteratively update the parameters with a learning rate η. Since the loss function is not convex jointly over **U** and **V**, we use gradient descent to update **U** and **V** in the algorithm.

After our model learned the optimized user latent feature matrix **U** and item latent feature matrix **V**, the ranking score of a specific user i with respect to a specific item j is assigned by the inner product of the user feature vector and item feature vector. The final recommendation result is generated by ranking items with the ranking score in descending order.

Experiments and Analysis

We conduct experiments on two publicly available datasets to evaluate the proposed SGroupRank-MF model. In this section, we first provide the experimental settings and then compare our model with the state-of-the-art approaches. Finally, we discuss the parameter selection for our model.

Table 2 Statistics information of Epinions and BaiduMovies datasets

Statistics	Epinions	Baidu Movies
#users	40,163	9,722
#items	139,738	7,889
#ratings	664,824	1,256,998
rating density	0.01%	1.64%
#follow	442,979	7,898
follow density	0.03%	0.01%

Dataset

We evaluate our model on two datasets: Epinions and BaiduMovies. Epinions is an online social item rating website. Users in Epinions can rate their items of interest and follow other users with similar interests. Therefore, we can obtain rating information and social information of users from Epinions, which is suitable for evaluating our model. In our experiments, we crawl data from Epinions, which contains approximately 665k rating records. The data involve ratings from 40,163 users on 139,738 items. The BaiduMovies dataset was released by Baidu Company in 2013 and is used in the Baidu movie recommendation competition. The dataset involves user ratings on movies, user-following relationships and movie tags. There are a total of 1,256,998 ratings by 9,722 users of 7,889 movies. In both datasets, the range of ratings is from 1 to 5, indicating user preferences from low to high. Social relations of users in these two datasets are directed. The distribution of the number of ratings for each user follows a long-tailed distribution. Namely, more popular items are rated by more users. The rating density of Epinions is approximately 0.01%, and the rating density of BaiduMovies is approximately 1.64%. The rating density is relatively sparse in both datasets, which is commonly data distribution in recommendation tasks. The user-following relationship is also sparsely distributed in these two datasets. The relatively low density of user ratings and following makes this task challenging. The proposed method aims to meet the challenge by predicting the rating given a user relationship. We list the statistical information of the datasets in Table 2, including the sparsity of user ratings on items and the following relationship among users.

Evaluation Metrics

For rank-based recommendation approaches, standard evaluation metrics, such as the mean absolute error (MAE) or root mean squared error (RMSE), are not suitable for evaluating the ranking performance. Similar to previous work on learning-to-rank-based recommendations, we employ the normalized discounted cumulative gain (NDCG) [41, 42] as the evaluation metric. NDCG is one of the most popular metrics in information retrieval for evaluating ranking performance with graded relevance judgments.

In evaluating recommendation performance, item ratings assigned by users can serve as relevance judgments. The NDCG metric is evaluated over the top-k items in the ranking list. We formulate the NDCG at the k^{th} position with respect to the set of users Q as follows.

$$NDCG(Q,k) = \frac{1}{|Q|}\sum_{u\in Q} Z_u \sum_{p=1}^{k} \frac{2^{R_{u,p}-1}}{log(1+p)} \tag{9}$$

where Q is the set of users in each dataset. $R_{u,p}$ is the rating score assigned by user u on the item at the p^{th} position in the ranking list. Z_u is a normalization factor to control the *NDCG* value in the interval from 0 to 1. The *NDCG* value is sensitive to the top-ranked items because the discounting factor $log(1+p)$ increases with the position in the ranking list. In our experiments, recommendation performances are measured by NDCG at the top-1, top-2, top-5 and top-10 ranking positions following the existing ranking-based studies. We denote these measures as NDCG@1, NDCG@2, NDCG@5 and NDCG@10, respectively.

Baseline Models

We choose two rating-oriented matrix factorization algorithms and four ranking-based algorithms as baseline models in our experiments. We introduce these methods as follows.

(a) Basic matrix factorization (Basic-MF) [8] adopted probabilistic matrix factorization to predict the user-item rating for item recommendations. This model is the basic model for other baseline models.
(b) Social influence-based matrix factorization (Social-MF) [13] integrated the social influences of users from a social network to additive coclustering for discovering user clusters and item clusters for recommendation accuracy.
(c) Matrix factorization based on the RankNet loss function (RankNet-MF) [?] treated rated positive item pairs as learning instances and learned the latent feature matrix of users and items by minimizing cross-entropy-based pairwise ranking loss.
(d) Matrix factorization based on the Bradley-Terry model (Bradley-Terry-MF) [38] adapted the Bradley-Terry model [39] to the loss function designed for pairwise preferences and incorporated it into the basic matrix factorization model.
(e) Bayesian personalized rank with implicit feedback (BPR) [36] modeled the binary relevance data by optimizing the binary relevance metrics and selecting observed and unobserved items as item pairs. The model estimated the parameters by maximizing Bayesian posterior probability using stochastic gradient descent.
(f) Matrix factorization based on the ListNet loss function (ListRank-MF) [43] optimized the listwise ranking probability distribution based on the loss function of ListNet [44]. The loss function is based on the cross entropy of the permutation probability of the predicted and the ground truth ranking lists.
(g) Trust-based social recommendation (CSIT) [?] considered the individual trust relationships of users in social matrix factorization, which is a strong baseline method for comparing the trust models in our experiments.

In addition, two versions of the proposed models are compared in our experiments. One is based on listwise matrix factorization in consideration of the user trust relationship, denoted as SListRank-MF. The other is based on the group-enhanced ranking with user trust values, denoted as SGroupRank-MF. To enhance the validity of the obtained experimental results, we conduct fivefold cross-validation for all the compared methods in our experiments. We divided each dataset into fivefold, in which threefold were used as the training set, onefold was used as the validation set and the remaining fold was used as the test set. The training set is used for model training, the validation set is used for parameter selection and the test set is used for model prediction. All models were trained and tested five times with the selected optimal parameters. Finally, we report the average performance of the five test folds in our comparisons.

Comparison and Analysis

In this section, we compare the proposed methods with the baseline methods in three respects. We first compare the listwise and pairwise learning-to-rank methods to examine the effectiveness of these two types of ranking approaches in social recommendations. Second, we examine the effectiveness of the proposed group sampling strategy in constructing the ranking models. Finally, we compare the proposed methods with other baseline methods involving social information to examine the effectiveness of our trust modeling method. We believe these three sets of experiments would accurately and completely evaluate the performance of the proposed methods.

Comparisons of Listwise and Pairwise Ranking Approaches

The first set of experiments is designed to compare the performance of listwise and pairwise ranking approaches. These two types of approaches incorporate pairwise and listwise ranking constraints to learn ranking models. The pairwise ranking constraint considers the preference order of each pair of items in the loss function for model

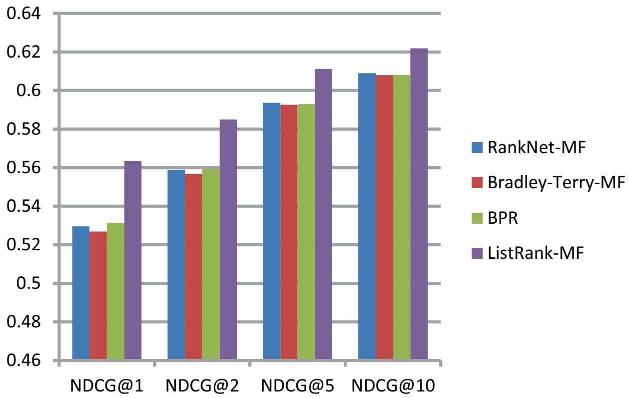


Fig. 1 Comparisons of listwise and pairwise ranking approaches on the Epinions dataset

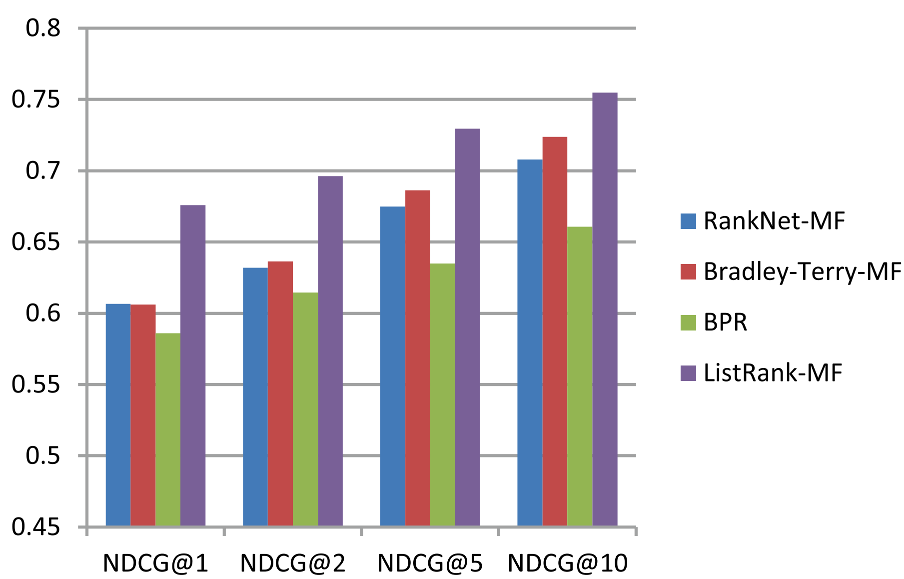
optimization, and the listwise ranking constraint considers the entire ranking list of items in computing the intermediate ranking loss. In the experiments, we compare three pairwise methods, RankNet-MF, Bradley-Terry-MF and BPR, with the listwise method ListRank-MF. RankNet-MF [?] adopted a widely used pairwise method RankNet to learn top-k item ranking by leveraging LDA-based topic models. We apply stochastic gradient descent to try to find a local minimum of its loss function with respect to user-specific and topic-specific latent factors as the settings in [?]. Bradley-Terry-MF [38] adopted the Bradley-Terry model involving pairwise preferences in a matrix factorization framework. We followed the maximum likelihood estimation of its training objective and solved via stochastic gradient descent. BPR [36] also considered item pairs in model training from implicit feedback. We followed the original version of this method by maximizing Bayesian posterior probability with stochastic gradient descent. The listwise method ListRank-MF [43] adopted the listwise version of RankNet by directly considering the divergence between the ground truth ranking list and the predicted ranking list. The loss function of ListRank-MF is also computed based on the listwise divergence and optimized using gradient descent. We illustrate the performance comparisons of pairwise and listwise approaches in Figs. 1 and 2.

The results show that Bradley-Terry-MF achieves a better performance than BPR, and RankNet-MF achieves a slightly better performance than Bradley-Terry-MF on both datasets. Furthermore, the listwise ranking approach ListRank-MF outperformed the pairwise ranking approaches RankNet-MF, Bradley-Terry-MF and BPR in general. This finding implies that the listwise learning-to-rank approach captures more useful information from matrix factorization for item recommendation, while pairwise ranking approaches focus on optimizing item pair classification error, partly ignoring the entire item ranking performance. Take BPR as an example. This model takes the unrated items as a negative sample regardless of the influence of the graded rating values, which may reduce recommendation accuracy. Therefore, we would like to achieve further improvement by modifying the listwise approach with group sampling and social information.

Evaluation on the Group Sampling Strategy

To further evaluate the proposed group sampling strategy, we compare the listwise method ListRank-MF and two proposed methods. We compare two versions of our methods: the method in consideration of the user trust relationship, denoted as SListRank-MF, and the method based on the group-enhanced ranking with user trust values, denoted as

Fig. 2 Comparisons of listwise and pairwise ranking approaches on the BaiduMovies dataset



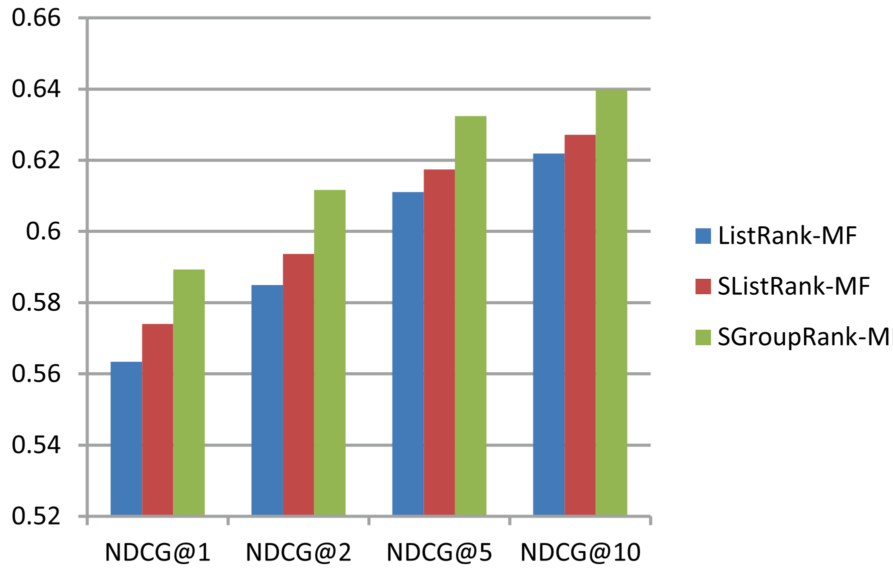


Fig. 3 Evaluation of the group sampling strategy using the Epinions dataset

SGroupRank-MF. We illustrate the results in Figs. 3 and 4 on the Epinions and BaiduMovies datasets.

From the illustrations, we observe a similar performance trend on both datasets: SListRank-MF achieves a slightly better performance than ListRank-MF, which indicates that social trust information of users contributes to improving the recommendation performance. Furthermore, SGroupRank-MF outperforms ListRank-MF, which demonstrates the effectiveness of the proposed group sampling strategy. This is because the group-enhanced ranking method further addresses the trust relationship of users by extending the sampling space of ranking. Therefore, SGroupRank-MF further optimizes the ranking model and produces better recommendation results.

Evaluation of the Effectiveness of Social Information

To further examine the effectiveness of social information used in our methods, we compare our methods with social-based recommendation baselines in this section. As mentioned above, we conduct fivefold cross validation for training, validating and testing on the models. Specifically, we randomly split each dataset into fivefold, in which threefold are used as the training set, onefold is used as the validation set and the remaining fold is used as the test set. We choose the optimal parameter for each algorithm based on the validation set and train different models on the training set. We report the average performance over all the testing sets in Tables 3 and 4.

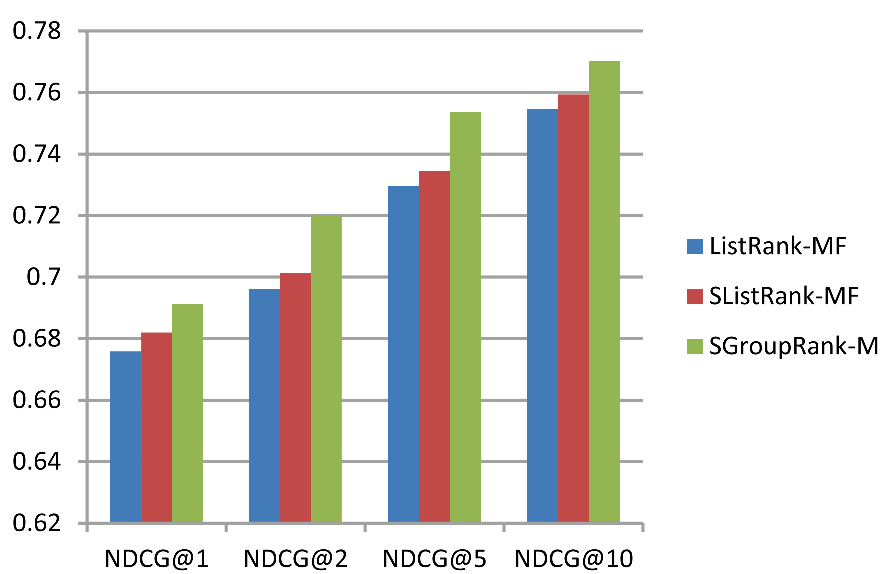


Fig. 4 Evaluation of the group sampling strategy using the BaiduMovies dataset

Table 3 Result comparison of different methods in Epinions dataset

Methods	NDCG@1	NDCG@2	NDCG@5	NDCG@10
Basic-MF	0.5440	0.5712	0.6033	0.6167
Social-MF	0.5595	0.5829	0.6102	0.6219
CSIT	0.5710	0.5869	0.6107	0.6195
SListRank-MF	0.5740	0.5937	0.6174	0.6272
SGroupRank-MF	**0.5893***	**0.6117***	**0.6324***	**0.6398***

Table 4 Result comparison of different methods in BaiduMovies dataset

Methods	NDCG@1	NDCG@2	NDCG@5	NDCG@10
Basic-MF	0.6695	0.6877	0.7031	0.7225
Social-MF	0.6705	0.6892	0.7112	0.7385
CSIT	0.6683	0.6815	0.7126	0.7378
SListRank-MF	0.6820	0.7013	0.7344	0.7594
SGroupRank-MF	**0.6913***	**0.7202***	**0.7536***	**0.7703***

From the experimental results on the Epinions dataset, we observe that the social influence-based models Social-MF and achieve better performance than the basic matrix factorization model, which implies that social information and user trust relationships are useful for item recommendation. This observance indicates the usefulness of social information in item recommendation. The proposed SGroupRank-MF model achieves the best performance among all the baseline models. This is because group-enhanced ranking samples based on user trust relationships contribute to more effective models with abundant social information, and we incorporate user trust relations as a constraint term to better model user interests. We observe a similar trend in the performance of the experimental results on the BaiduMovies dataset, which indicates the effectiveness of trust-based information in social recommendation. The experimental results show that the proposed model SGroupRank-MF outperforms other methods in predicting the item rankings of users. The trust relationship of users from social networks contributes to better performance in the top-k recommendation scenario. Group-enhanced ranking is more effective than the listwise and pairwise approaches in predicting the latent feature matrix of users and items.

Impact of Parameters

In this section, we investigate the influence of two parameters in our model, namely, λ and λ_u. λ is the regularization term to avoid overfitting, and λ_u controls the influence of the user trust relationship in the loss. A larger λ_u indicates more emphasis on the social relations of users. We fix one parameter to find the optimal value of the other parameter on the validation set.

Specifically, we fix the social penalty coefficient λ_u and switch different values for λ from 0.1 to 1.0 for model training. We report the performance of the learned models with different λ in Fig. 1. In the figure, performance is evaluated in terms of $NDCG@1$. We observe that the models with λ less than 0.3 tend to be overfitting, the model with $\lambda = 0.3$ yields the best performance, and the models with λ larger than 0.3 tend to be underfitting.

Similarly, we fix the optimal regularization coefficient λ as 0.3 and switch different λ_u from 0 to 0.2 to find the optimal value for the parameter. We report the performance of models with different λ_u in terms of $NDCG@1$ in Fig. 2. We observe that the model with $\lambda_u = 0.15$ yields the best performance, and a larger or smaller value can reduce performance. Therefore, we set $\lambda_u = 0.15$ and $\lambda = 0.3$ in our experiments (See Figs. 5 and 6).

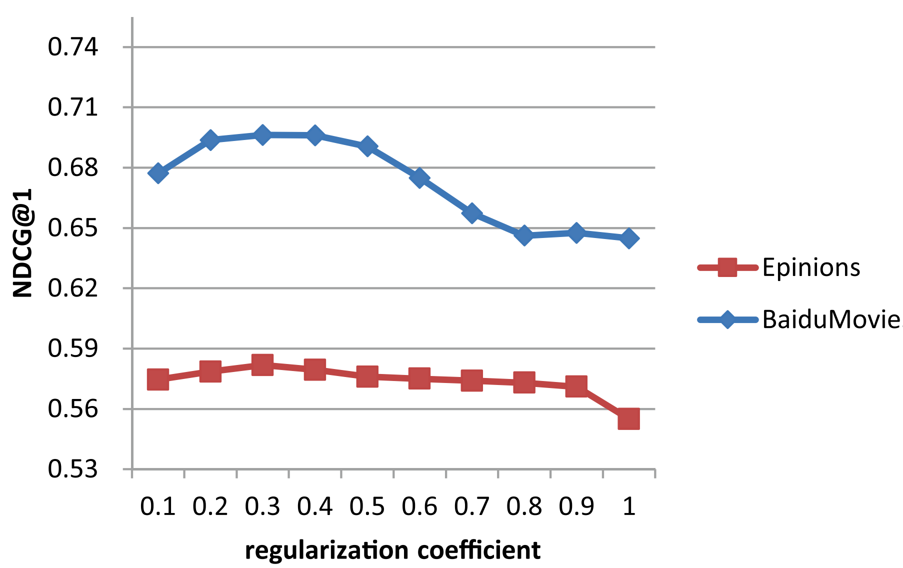
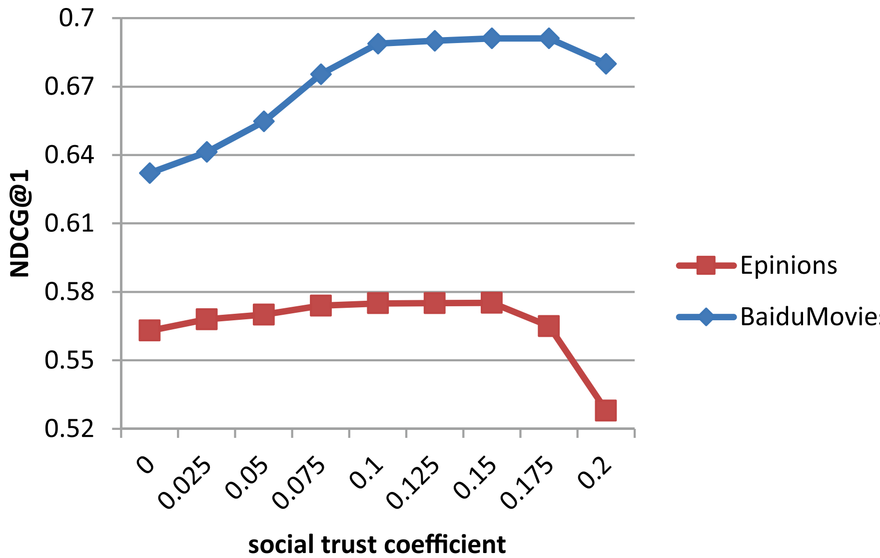


Fig. 5 Impact of regularization parameter λ

Fig. 6 Impact of regularization parameter λ_u



Conclusions and Future Work

In this study, we propose a novel learning-to-rank-based social recommendation method, SGroupRank-MF, for cognitive knowledge-aware item recommendation. Our method adopts the group-enhanced ranking framework to incorporate social trust information into the loss function. Furthermore, we address social trust information with a social trust term in the loss function. Our method comprehensively captures the trust relationship of users for modeling user preferences and recommending users with their items of interest. We evaluate the proposed method on two datasets to compare state-of-the-art baseline models. Experimental results show that the proposed SGroupRank-MF method significantly outperforms the other models. Future work could be carried out from several interesting research directions. First, since the proposed method in this paper is based on the directed relationship of users, we would like to develop effective methods for modeling undirected trust relationships of users. The obtained undirected trust models can also be integrated in the proposed framework to produce accurate recommendations. Second, classical problems in recommendation systems, such as cold start and data sparsity, could be further addressed in the proposed framework. For example, recommendation models could be trained with unbalanced data to simulate the cold start scenario, and effective strategies could be tailored to solve this specific problem, which would further enhance the generalization ability of our method.

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Declarations

Research Involving Human and Animal Participants This article does not contain any studies with human participants or animals performed by any of the authors.

Conflicts of Interest The authors declare that they have no conflicts of interest.

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