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RBPR: A hybrid model for the new user cold start problem in recommender systems

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ABSTRACT

The recommender systems aim to predict potential demands of users by analyzing their preferences and provide personalized recommendation services. User preferences can be inferred from explicit or implicit feedback data. Most existing collaborative filtering (CF) methods rely heavily on explicit feedback data. However, these methods perform poorly when rating data is sparse. In this paper, we deal with the extreme case of sparse data, i.e., the new user cold start problem. In order to overcome this problem, we propose a novel CF ranking model, which combines a rating-oriented approach of Probabilistic Matrix Factorization (PMF) and a pairwise ranking-oriented approach of Bayesian Personalized Ranking (BPR) together. Therefore, our proposed model makes full use of the explicit and implicit feedback data. Experiments on the constructed new user cold start datasets based on four public datasets demonstrate the effectiveness of the proposed model for cold start recommendation. Code for the proposed method is available in https://gitee.com/xia_zhaoqiang/recomender-systems-rbpr.

1. Introduction

With the explosive growth of information, recommender systems (RSs) [1] are widely applied to online systems such as the e-commerce system Amazon [2], e-shops Taobao [3], the DVD rental system Netflix [4], TV shows [5], Google News [6], tourism [7] and cultural heritage systems [8], guiding users to find the information of their interests. In RSs, recommendation algorithms are the key content of systems [9,10], which are used to predict user preferences by analyzing their historical behavior data. In general, recommendation algorithms can be roughly divided into three classes [1]: content-based recommendation, collaborative-filtering (CF) recommendation, and hybrid recommendation. Among them, collaborative filtering [11,12] has become one of the most popular recommendation technologies due to its effectiveness and scalability. The CF recommendation algorithm draws on the basic idea that normally a user is likely to purchase products that have been purchased or highly rated by users who have the same or similar preferences as this user. The basic assumption of the CF recommendation algorithm is that the information requirements of users with the same or similar interest preferences are also similar.

Since the CF recommendation algorithm recommends items for users mainly based on the user's historical ratings, an important issue in collaborative filtering RSs is the cold start problem [13–16]. This problem will occur when few ratings can be obtained, as it is difficult to make reliable recommendations. The cold start problem is usually divided into three kinds [17]: new community, new item, and new user. This paper focuses on the cold start problem for a new user with small number of ratings. In the case of a cold start, if RSs cannot provide satisfactory personalized recommendation results for a new user, it is easy to lose the user confidence in these RSs and cause the loss of user resources. Therefore, it is imperative to solve the new user cold start problem in the RSs.

To address the cold start problem, many personalized recommendation approaches have explored user feedback data including explicit and implicit feedback [18–20]. Explicit feedback mainly refers to user ratings on items they purchased or viewed in the past. However, explicit feedback data is not available in the case of user cold start. Compared to explicit feedback, implicit feedback such as browsing history, purchase and click-through activity, which indirectly reflects user preference, is richer and easier to collect. However, the majority of previous research on the cold start problem is devoted to either explicit feedback data or implicit feedback data separately rather than incorporating them into a ranking model. Hence, we propose a novel CF model called Rating Bayesian Personalized Ranking (RBPR),

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which combines the rating-oriented model PMF [21] and the ranking-oriented model BPR [22] to further improve the ranking performance. The proposed model integrates both explicit feedback and implicit feedback to fully use the feedback information. Specifically, we first use the Singular Value Decomposition (SVD) [23] model to preprocess the unrated items to increase the density of explicit feedback data. Then, we integrate the PMF and BPR models to extract explicit and implicit features respectively. Finally we fuse the extracted features jointly as the final user and item feature matrices.

The main contributions are summarized in three aspects:

1. We propose a novel ranking model, which unifies two types of recommendation models including a ranking-oriented model and a pairwise ranking-oriented model together. The proposed model makes full use of the users' feedback information of rating data and implicit data to obtain accurate information representing the characteristics of users and items.
2. To further improve the ranking accuracy of the proposed model, we jointly integrate the PMF model and the BPR model to exploit their complementary advantages. BPR is used to extract the implicit features of users and items from the implicit feedback data while PMF is used to extract the explicit features of users and items from the rating data. To ensure the accuracy of the explicit feature extraction, the user rating data are also pre-processed.
3. Compared to existing methods of addressing the new user cold start problem, the proposed model aims to improve the recommendation quality of RSs by extracting common latent features of users and items. The excessive noise that the existing methods introduce in the process of extracting user and item features is effectively suppressed. The model is comparatively evaluated on extensive experiments.

The rest of our paper is organized as follows. Section 2 summarizes some previous related research. Section 3 introduces the Preliminaries of the proposed model, including the approaches of PMF and BPR. Section 4 describes our proposed model in detail. Section 5 presents the experiments and discusses the experimental results. Finally, Section 6 gives a high level description of the conclusions and future work.

2. Related work

In RSs, collaborative filtering recommendation algorithms can be classified into two categories: rating-oriented CF algorithms and ranking-oriented CF algorithms. If a CF recommendation algorithm first predicts the user ratings on unrated items and then generates the ranking recommendation lists, this type is referred to as a rating-oriented CF recommendation algorithm [24]. If a recommendation approach directly generates the recommendation lists based on the predicted ranking scores, which are not necessarily related to ratings, this type is called as a ranking-oriented CF recommendation algorithm [25]. In this section, we briefly review the recent work related to the rating-oriented CF algorithms, the ranking-oriented CF algorithms and the approaches to the new user cold start problem.

2.1. Rating-oriented CF algorithms

SVD [23] is a typical rating-oriented algorithm. This model focuses on the explicit feedback and is optimized by the stochastic gradient descent (SGD) approach. To integrate implicit feedback data and improve the recommendation accuracy, Koren [23] proposed the SVD++ model, an extension of the SVD model. However, the computational complexity of this algorithm is too high to apply on large datasets. Beyond that, Guo et al. took into account the user-trus implicit influence and designed a trust-based model called TrustSVD in [26], which is built on SVD++. In [18], to fully exploit the heterogeneous explicit feedback such as 5-star grade scores and like/dislike binary ratings problem, Pan et al. proposed a generic-mixed factorization based transfer learning framework algorithm for collaborative recommendation. In a recent work, Chen et al. [19] proposed a latent factor model based on probabilistic matrix factorization combined with the explicit and implicit feedback data. The explicit and implicit feedback matrices were first divided into a user latent factor matrix and an item latent factor matrix with both of they sharing the same user matrix subspace. Then, a gradient descent algorithm was used to optimize the latent factor vectors.

2.2. Ranking-oriented CF algorithms

Ranking-oriented CF algorithms can be generally divided into three categories according to different inputs: pointwise, pairwise and listwise. The pairwise and listwise approaches garner more attention than the pointwise ones for their higher recommendation accuracy.

The pairwise approach focuses on relative preferences rather than absolute ratings. BPR [22] is the first pairwise method, which is directly optimized for ranking. The item pairs in the BPR model are sampled from observed positive feedback and unobserved negative feedback, respectively. The BPR ranking algorithm achieves great success in dealing with the one-class collaborative filtering (OCCF) problem. As a result, plenty of algorithms have been proposed based on BPR. To exploit multiple feedbacks simultaneously, Loni et al. [27] designed the Multi-feedback Bayesian Personalized Ranking (MF-BPR) method. In addition, to improve the individual and independence assumptions of BPR, Pan et al. [28] proposed Group Bayesian personalized ranking (GBPR), which introduced richer interactions among users. Moreover, Pan et al. proposed adaptive Bayesian personalized ranking (ABPR) [29] to solve the heterogeneous and implicit feedback recommendation problem. Two types of implicit feedback including users' transaction records and examination records are exploited. Recently, a Bayesian personalized ranking method was proposed in [30] to incorporate heterogeneous and implicit feedback (BPRH) such as views and likes into a unified model for online service systems.

The listwise approach directly optimizes the item ranking list. Take the Collaborative Less-is-More Filtering (CLiMF) model [31] for example. The well-known information retrieval metric, e.g., Mean Reciprocal Rank (MRR), is directly maximized to learn the user and item latent factors of the model and improve the performance of top-k recommendations. Shi et al. [32] proposed a unified recommendation model (URM), which combined PMF and a list-wise learning-to-rank with matrix factorization (ListRank) model, and shared the same user and item latent factors. In a recent work, a unified OCCF (UOCCF) method [33] was proposed, which incorporated CLiMF model with the PMF model to optimize the rank of the items and the ratings together. To exploit the explicit and implicit influence of user-trust and item ratings simultaneously, Li et al. proposed a social personalized ranking model (SPR_SVD++) [20] based on xCLiMF and TrustSVD by optimizing ERR.

2.3. Approaches to the new user cold start problem

In recent years, various works have been done to handle the new user cold start problem. Ann [34] proposed a heuristic similarity measure to alleviate this problem. The proposed measure was composed of three similarity factors, including Proximity,

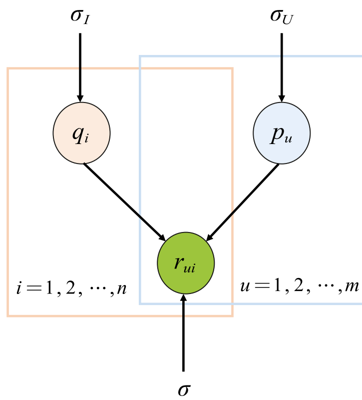


Fig. 1. PMF probability graph model.

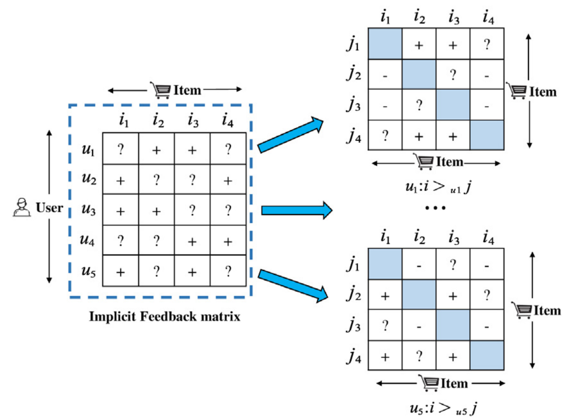


Fig. 2. An example of generating a set of pair items input by BPR from implicit feedback data.

Impact and Popularity. Hence, the proposed measure was named as PIP. On the basis of PIP, Liu et al. [35] proposed an improved measure Proximity-Significance-Singularity (PSS), which was also composed of three similarity factors, namely, Proximity, Significance and Singularity. Considering the proportion of the co-rated items and the global rating preference of the user at the same time, the new heuristic similarity model (NHSM) was proposed to improve the recommendation performance in the case of the cold user. In [36], three measures were proposed to address the new user cold start problem in different scenarios, including personality-based CF, personality-based active learning and personality-based cross-domain recommendation.

3. Prerequisites

In this section, we will mainly introduce the notations used in this paper and the related PMF and BPR models.

3.1. Notations

In this paper, we assume that m and n represent the number of users and items respectively. $U = \{u_1, u_2, \ldots, u_m\}$ and $I = \{i_1, i_2, \ldots, i_n\}$ are used to represent the set of users and items, respectively. The user–item rating matrix is $R = [r_{ui}]^{m\times n}$, where r_{ui} indicates the rating of user u on item i.

3.2. PMF [21]

PMF is a matrix decomposition model, which is commonly used in CF recommendation algorithms. The model introduces the idea of probability on the basis of matrix decomposition. The graph model of PMF is shown in Fig. 1.

Through Fig. 1, we can see that the PMF model tries to use two low-rank matrices U and V to represent the user–item rating matrix R. Assuming that the matrices R, U and V follows a Gaussian distribution, the conditional distribution over these three matrices are defined as:

$$p\left(R|U,\ I,\ \sigma^2\right) = \prod_{u=1}^{m}\prod_{i=1}^{n}\left[\mathcal{N}\left(r_{ui}|p_u^T q_i,\ \sigma^2\right)\right]^{I_{ui}} \tag{1}$$

$$p\left(U|\sigma_U^2\right) = \prod_{u=1}^{m}\mathcal{N}\left(p_u|0,\ \sigma_U^2\mathbf{I}\right) \tag{2}$$

$$p\left(I|\sigma_I^2\right) = \prod_{i=1}^{n}\mathcal{N}\left(q_i|0,\ \sigma_I^2\mathbf{I}\right) \tag{3}$$

Here, $\mathcal{N}\left(\mu,\ \sigma^2\right)$ represents the Gaussian distribution with the mean μ and variance σ^2. I_{ui} is the indicator function. If the user u rated on the item i, I_{ui} is true, and 0 otherwise. $\mathbf{I}$ is the identity matrix with dimension of f. The posterior probabilities of U and V derived by the Bayesian formula can be formulated as follows:

$$E = \arg\min_{u,i}\frac{1}{2}\sum_{u=1}^{m}\sum_{i=1}^{n}I_{ui}\left(r_{ui} - p_u^T q_i\right)^2 + \frac{\lambda_U}{2}\|p_u\|^2 + \frac{\lambda_I}{2}\|q_i\|^2 \tag{4}$$

In the equation above, $\lambda_U = \frac{\sigma^2}{\sigma_U^2}$ and $\lambda_I = \frac{\sigma^2}{\sigma_I^2}$ are regularization coefficients, which are used to reduce over-fitting.

3.3. BPR [22]

The BPR model offers a user with a personalized ranking list only based on implicit feedback such as view history, transaction and click-through activity. The BPR model is constructed on the assumption that the user prefers item i to item j $(u : i >_u j)$ if a user u prefers a rated item i to an unrated item j, $(i \in N(u)\ and\ j \in \bar{N}(u))$. Moreover, the model further considers the relative order between a pair of items, rather than merely the user–item pairs. If all items in a pair are all marked by one user or both of them are not marked, no conclusion about user preference can be inferred. Fig. 2 shows an example of the BPR model. The implicit feedback matrix is shown on the left side of the figure. On the right side, the plus signal represents that the user prefers item i to item j. On the contrary, the minus signal indicates the user prefers item j to item i, and no conclusion about the two items can be inferred from the question signal.

The generic optimization criterion of BPR for personalized ranking is listed below

$$BPR - Opt = \sum_{(u,i,j)\in D_S}\ln\left(\sigma\left(\hat{r}_{uij}\right)\right) - \lambda_\Theta\|\Theta\|^2 \tag{5}$$

Here, $D_S = \left\{(u, i, j)\,|i \in N(u)\ \ and\ j \in \bar{N}(u)\right\}$, and D_S is the training dataset. $\hat{r}_{uij}$ captures the special relationship between the user and two items, which is defined as $\hat{r}_{uij} = \hat{r}_{ui} - \hat{r}_{uj}$. The predicted ranking score $\hat{r}_{ui} = q_i^T p_u + b_i$. $\sigma(x)$ applies the logistic sigmoid function and $\sigma(x) = \frac{1}{1+e^{-x}}$. The constant λ_Θ controls the regularization of the model. The parameter vector of the model is represented by $\Theta = \left\{b_u, b_j, p_u, q_i, q_j\right\}$, and these parameters are learned through the gradient descent technique.

4. Proposed model

In this section, we first introduce the proposed model with mathematical formalization in detail. Thereafter, we adopt an

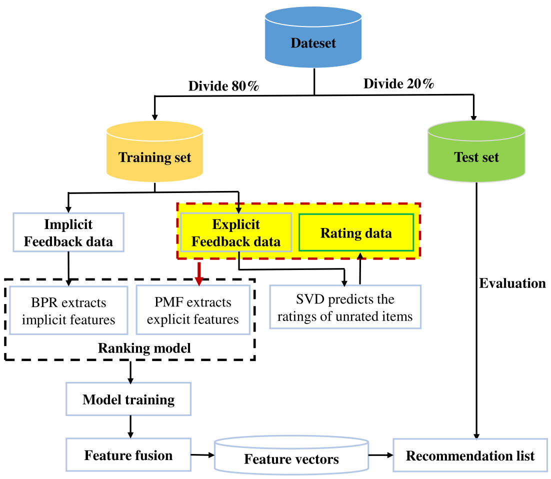


Fig. 3. Schematic visualization of the proposed model.

efficient learning algorithm to solve the optimization problem for the proposed model.

4.1. The framework

Fig. 3 shows the framework of the proposed RBPR model, which aims to integrate the explicit and implicit feedback data into one model for achieving complementary advantages and further improving the ranking performance. Initially, we exploit the explicit rating data and implicit feedback data of users, respectively. Since the historical ratings of users are very scarce under the condition of a cold start and the implicit feedback information is relatively rich, we use the BPR model to extract implicit features of users and items. In order to extract explicit features, the PMF model is adopted. Considering that the rating data is not enough for the PMF model to extract explicit features accurately, we choose to add a pre-processing step before feature extraction for increasing the number of ratings, in which the SVD model is used to predict the users' unrated items based on the historical ratings. The predicted ratings together with the historical ratings are taken as the data source of the PMF model. Then, the objective functions of the BPR and PMF models are linearly combined by a trade-off parameter. When the latent feature dimensions of the BPR model and the PMF model are the same, the two models above will share the user and item feature spaces. The trade-off parameter is used to control the relative contribution of PMF and BPR. Finally, the implicit features extracted by the BPR model and the explicit features extracted by the PMF model are fused. After the model training, the fused user and item feature matrices can be obtained and then the ranking scores of unmarked items can be predicted. At the same time, the performance of the proposed model can be evaluated based on the actual item ranking of the test set.

4.2. Combining PMF and BPR

The proposed model RBPR is a linear combination of the PMF and BPR models. Since the amplitude value of predicted ranking scores in Eq. (5) is unknown and the predicted ratings in Eq. (4) needs to be limited to the users' rating range, the predicted scores are computed as $\hat{r}_{ui} = q_i^T p_u$ in the proposed model. We use Sigmoid function to process $\hat{r}_{ui}$ and normalize them to (0,1), limiting them to the users' rating range in the proposed model. The formula of PMF after limiting the amplitude is given as follows:

$$E = arg\,\min_{u,i} \frac{1}{2}\sum_{u=1}^{m}\sum_{i=1}^{n}\left(r_{ui} - \omega\sigma\left(\hat{r}_{ui}\right)\right)^2 + \frac{\lambda_U}{2}\|p_u\|^2 + \frac{\lambda_I}{2}\|q_i\|^2 \tag{6}$$

where $\sigma(x)$ denotes the Sigmoid function and ω is a amplitude control parameter. The purpose of setting this parameter is to convert the predicted score into the users' rating range. Therefore, $\omega = r_{\max}$, $r_{\max}$ represents the maximum user rating on the dataset. Hence, the formula above can be transformed into Eq. (7).

$$E = arg\,\min_{u,i} \frac{1}{2}\sum_{u=1}^{m}\sum_{i=1}^{n}\left(r_{ui} - r_{\max}\sigma\left(\hat{r}_{ui}\right)\right)^2 + \frac{\lambda_U}{2}\|p_u\|^2 + \frac{\lambda_I}{2}\|q_i\|^2 \tag{7}$$

Since the number of users' ratings is very small in the case of a cold start, PMF cannot accurately extract explicit features based on the historical ratings. Therefore, before extracting features, we add a pre-processing step by SVD to predict the users' unrated items based on the historical ratings, which can effectively relieve the sparsity problem [37]. Then the historical and predicted ratings are used as the input data source of PMF. Consequently, the loss function of the PMF model after pre-processing is shown in Eq. (8).

$$\begin{aligned} E = &\frac{1}{2}\left(\sum_{(u,i)\in T}\left(r_{ui} - r_{\max}\sigma\left(\hat{r}_{ui}\right)\right)^2 + \sum_{(u,i)\in T'}\left(\tilde{r}_{ui} - r_{\max}\sigma\left(\hat{r}_{ui}\right)\right)^2\right) \\ &+ \frac{\lambda_U}{2}\|p_u\|^2 + \frac{\lambda_I}{2}\|q_i\|^2 \end{aligned} \tag{8}$$

where T represents the set of historical ratings, and T' represents the set of predicted ratings obtained by the SVD model. $\tilde{r}_{ui}$ indicates the predicted rating of user u on unrated item i based on SVD model.

In this paper, we exploit the explicit and implicit latent features simultaneously by combining the PMF and BPR models. We further propose the RBPR ranking model, which shares common latent features of users and items in the PMF and BPR models. The Eq. (8) calculates the minimum value of the PMF loss function, and the Eq. (5) calculates the maximum value of the BPR loss function. Then, the RBPR can be formulated with the loss function below.

$$\begin{aligned} F = &-\frac{\alpha}{2}\frac{\left(\sum_{(u,i)\in T+T'}\left(r_{ui} - r_{\max}\sigma\left(\hat{r}_{ui}\right)\right)^2 + \sum_{(u,j)\in T+T'}\left(\tilde{r}_{uj} - r_{\max}\sigma\left(\hat{r}_{uj}\right)\right)^2\right)}{2} \\ &+ (1-\alpha)\sum_{(u,i,j)\in D_S}\ln\left(\sigma\left(\hat{r}_{uij}\right)\right) - \lambda_\Theta\|\Theta\| \end{aligned} \tag{9}$$

In the equation above, $\Theta = \left\{p_u, q_i, q_j\right\}$. α is the trade-off parameter, and $\alpha \in [0,1]$, which is used to control the relative contribution of PMF and BPR. When $\alpha = 0$, the proposed model degenerates to BPR; when $\alpha = 1$, the proposed model degenerates to PMF. The value of α is determined by experiments.

4.3. Optimization

The SGD method [38] is adopted to optimize the loss function of RBPR. The gradients for each parameter are shown in the following, which can be derived by calculating the partial derivative of each parameter in Eq. (9), respectively.

$$\begin{aligned}\frac{\partial F}{\partial p_u} =& \frac{\alpha\cdot r_{\max}}{2}\left(r_{ui}-\left(r_{\max}\sigma\left(\hat{r}_{ui}\right)\right)\sigma'\left(\hat{r}_{ui}\right)q_i\right.\\ &\left.+\left(\tilde{r}_{uj}-r_{\max}\sigma\left(\hat{r}_{uj}\right)\right)\sigma'\left(\hat{r}_{uj}\right)q_j\right)\\ &+(1-\alpha)\left(1+e^{-\hat{r}_{uij}}\right)\sigma'\left(\hat{r}_{uij}\right)\left(q_i-q_j\right)-\lambda p_u\end{aligned}\tag{10}$$

$$\begin{aligned}\frac{\partial F}{\partial q_i} =& \frac{\alpha\cdot r_{\max}}{2}\left(r_{ui}-r_{\max}\sigma\left(\hat{r}_{ui}\right)\right)\sigma'\left(\hat{r}_{ui}\right)p_u\\ &+(1-\alpha)\left(1+e^{-\hat{r}_{uij}}\right)\sigma'\left(\hat{r}_{uij}\right)p_u-\lambda q_i\end{aligned}\tag{11}$$

$$\begin{aligned}\frac{\partial F}{\partial q_j} =& \frac{\alpha\cdot r_{\max}}{2}\left(\tilde{r}_{uj}-r_{\max}\sigma\left(\hat{r}_{uj}\right)\right)\sigma'\left(\hat{r}_{uj}\right)p_u\\ &-(1-\alpha)\left(1+e^{-\hat{r}_{uij}}\right)\sigma'\left(\hat{r}_{uij}\right)p_u-\lambda q_j\end{aligned}\tag{12}$$

where $\sigma'(x)$ represents the derivative of $\sigma(x)$. λ denotes the regularization coefficient. Based on the gradient formula above, the update rule for the RBPR parameters is shown in Eq. (13)

$$\Theta=\Theta+\gamma\frac{\partial F}{\partial\Theta}\tag{13}$$

where γ is the rating rate.

5. Experiments and evaluation

This section first introduces the datasets and evaluation metrics, then, we explore the impact of parameters in RBPR. Along with this, a series of experiments are conducted to compare the performance of our proposed model with some other baseline approaches for verifying the effectiveness of our approach. Finally, we test the influence of different degrees of cold start problems on the performance of our model.

5.1. Datasets

Four publicly available dataset are employed to demonstrate the validity of the proposed model including Movielens 100k, Movielens 1M, FilmTrust and Ciao.

- The Movielens 100k dataset [35] contains 100,000 ratings rated by 943 users on 1682 movies. In this dataset, each user has rated at least 20 movies. The scores are integers and range from 1 to 5. The score value 1 indicates that the user feels the movie is bad, and the score value 5 means that the user feels the movie is perfect.
- The Movielens 1M dataset [35] contains 1,000,209 anonymous ratings rated by 6040 users on 3706 movies. The scores are integers and range from 1 to 5.
- The FilmTrust dataset [39] is a small public dataset. The data obtained from the FilmTrust website contains 35,497 anonymous rating records, which are rated by 1508 users on 2071 movies. The scores are the multiple of 0.5, ranging from 0.5 to 4.0.
- The Ciao dataset [40] comes from a DVD website, which contains 72,665 ratings rated by 17,615 users on 12,121 items. All ratings are integers and the values are between 1 and 5.

Fig. 4 shows the number of users' historical ratings in four different datasets. In Movielens 100k and Movielens 1M datasets, users rated at least 20 movies, and most users rated more than 40 movies. Therefore, the new user cold start problem will not appear in these two datasets. Different from these two datasets, the data marked in the FilmTrust and Ciao datasets are relatively small, especially in the Ciao dataset. Most users in the Ciao dataset rated less than 10 items, which is difficult for RSs to provide accurate recommendations. It can be inferred that the user cold start problem is likely to appear in the FilmTrust and Ciao datasets. Based on the analysis, since it is uncertain whether the target user is a cold start user or not, it is necessary to construct user cold start datasets to evaluate the performance of the proposed RBPR model at the beginning of experiments. According to the rule of constructing artificial cold start conditions, a user whose ratings are no more than 20 will be selected as the cold start user. Thus, we delete several users' ratings in the four datasets, so that the number of each user's rating is less than 20. Finally, in the following experiments, each constructed dataset of cold start is divided into two sets, i.e., a training set and a test set. 80% randomly selected samples are used for training and the remaining for testing. The corresponding implicit feedback datasets in the experiments are the datasets obtained by setting all explicit scores to 1 in the training set.

5.2. Evaluation metrics

In this paper, four widely used ranking-oriented metrics, i.e., Precision [33], Recall, mean average precision (MAP) [30] and MRR, are adopted to evaluate the preference and recommendation accuracy of the proposed model. The larger these four evaluation metrics, the better the performance of the recommendation.

In terms of precision and recall, we suppose the parameter N is the size of the recommendation list and is a positive integer. The *Precision@N* and *Recall@N* are defined as:

$$Precision@N=\frac{\sum_{u\in U^T}\left|I_u^N\cap I_u^T\right|}{N\left|U^T\right|}\tag{14}$$

$$Recall@N=\frac{1}{\left|U^T\right|}\sum_{u\in U^T}\frac{\left|I_u^N\cap I_u^T\right|}{\left|I_u^T\right|}\tag{15}$$

Here, I_u^N represents the recommendation list of items recommended by RSs, and $\left|I_u^N\right|=N$. I_u^T is the ranking list of actual items in the test dataset. U^T is the set of users in the test dataset.

MAP is more sensitive to position. In the recommendation list, the higher the ranking position of the item that the user is interested in, the larger the value of MAP and the better the ranking performance. MAP is defined as

$$MAP=\frac{1}{\left|U^T\right|}\sum_{u\in U^T}\sum_{N=1}^{\left|I_u^T\right|}\frac{1}{N}\sum_{k=1}^{N}\delta\left(i_u^k\in I_u^T\right)\tag{16}$$

where $\delta(x)$ is an indicator function. When x is true, $\delta(x)=1$; in other cases, $\delta(x)=0$. i^k represents the item located at the ranking position of k.

MRR mainly considers the position of the first matching recommendation item in the recommendation results. The higher the first matching position, the greater the MRR and the better the performance of the algorithm. MRR is given by

$$MRR=\frac{1}{\left|U^T\right|}\sum_{u\in U^T}\frac{1}{\min_{i_u^k\in I_u^T}k}\tag{17}$$

5.3. Baselines

To verify the effectiveness of the proposed RBPR, the experiments will be conducted on four different new user cold start datasets constructed by Movielens 100k, Movielens 1M, FilmTrust and Ciao. The corresponding implicit feedback datasets in the experiments are the datasets obtained by setting all explicit scores to 1 in the above-mentioned datasets. We compare the

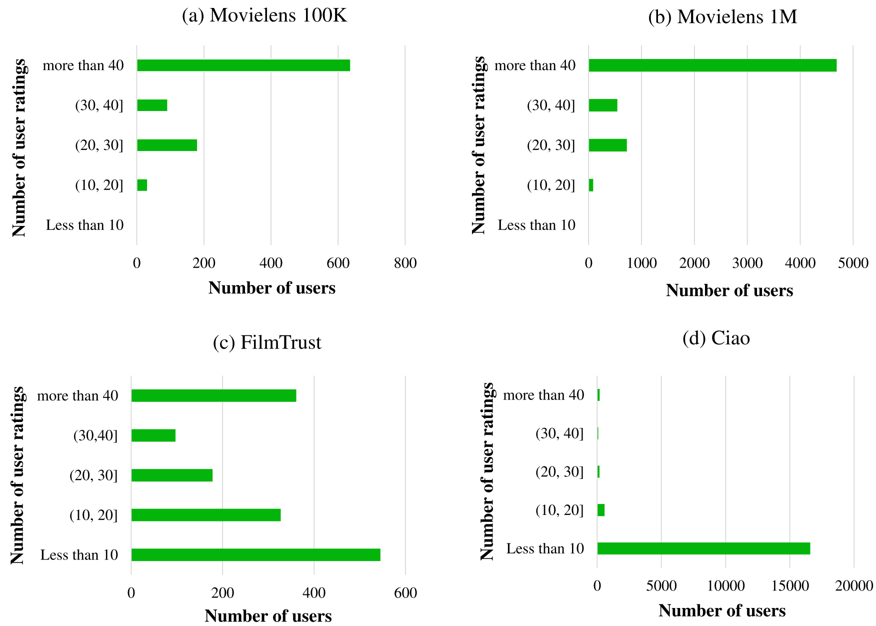


Fig. 4. Comparison of user historical ratings in four different datasets.

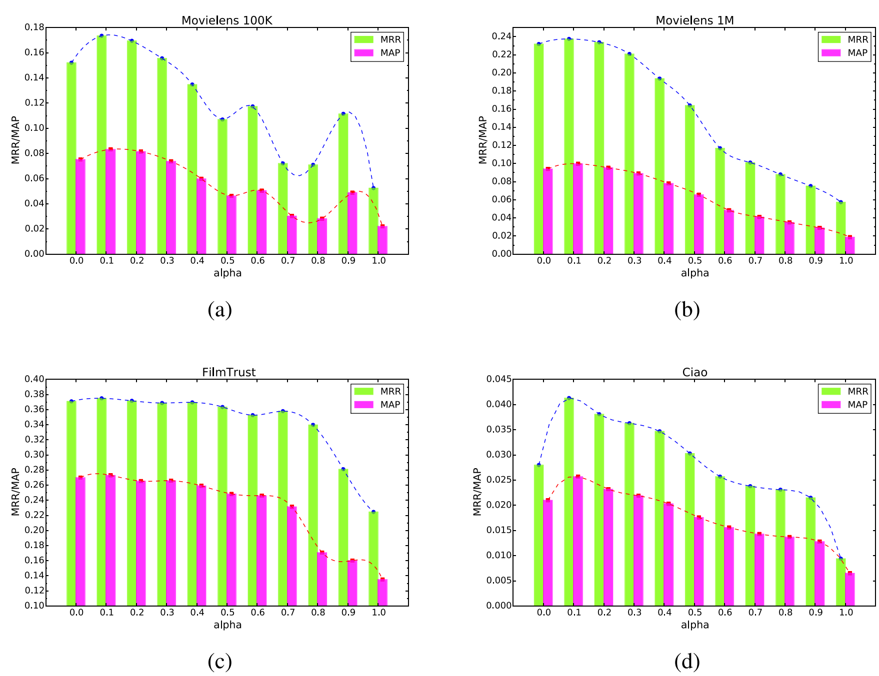


Fig. 5. The curve of the performance of the RBPR with the trade-off parameter on four different new user cold start datasets.

performance of RBPR with other seven baseline algorithms, which are listed as follows:

- **PMF** [21] is a state-of-the-art rating-oriented CF method, which introduces the idea of probability on the basis of matrix factorization. PMF is equivalent to the proposed RBPR when α is set to 1.
- **SVD** [23] is a widely used matrix factorization model, and its user and item feature matrices are learned by minimizing the root mean square error (RMSE).
- **BPR** [22] is the first pairwise ranking model for implicit feedback data. The essential idea is to treat the noted items as positive feedbacks and all unnoted items as negative feedbacks.
- **GBPR** [28] introduces richer interactions among users via group preference on the basis of BPR, and the group preference of users can be estimated from individual preferences. Compared with the BPR model, the GBPR model inherits the advantages of the BPR model ranking, while not increasing the time complexity of the model. The size of the user group is fixed as $|\mathcal{G}| = 3$, and the tradeoff parameter ρ is set to $\rho = 0.5$.
- **CoFiSet** (Collaborative filtering via learning pairwise preferences over item-sets) [41] defines the preference of one user on a set of items (item-set) instead of on a single item and generalizes the pairwise BPR assumption by defining the preference between two item-sets instead of two items.

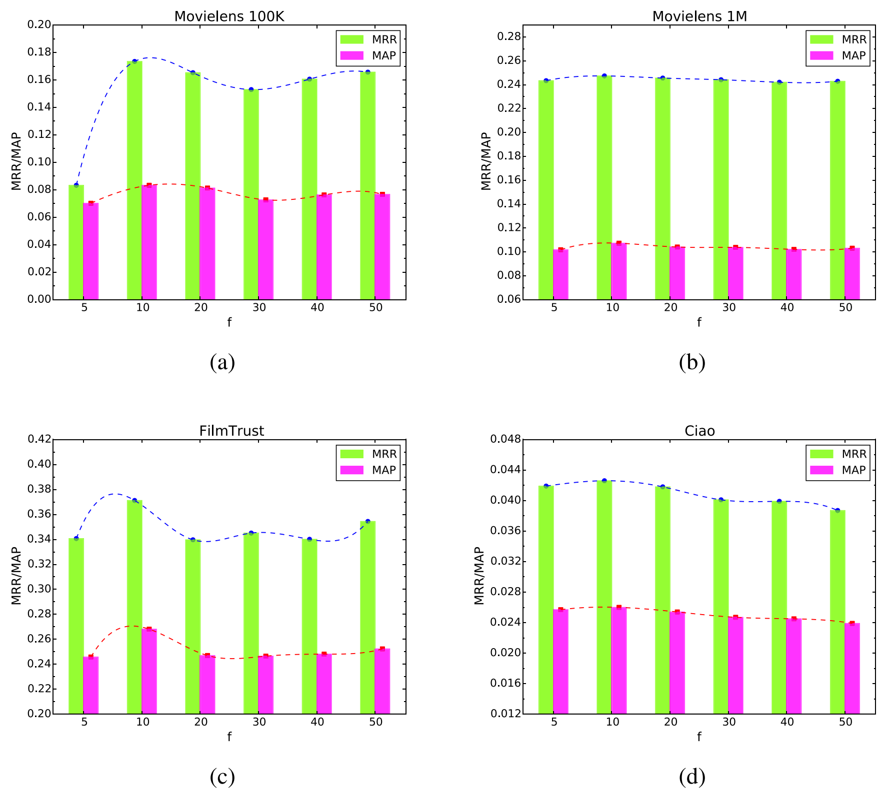


Fig. 6. The curve of the performance of the RBPR with different latent feature dimensions on four new user cold start datasets.

- **CLiMF** [31] is a listwise ranking CF approach for implicit feedback data, which learns the model parameters by optimizing the MRR. The time complexity of CLiMF is linear by introducing a lower bound of smoothed reciprocal rank metric.
- **UOCCF** [33] combines CLiMF and PMF models together, which benefits from the ranking-oriented and rating-oriented perspectives by sharing common latent features of users and items in CLiMF and PMF. In the following experiments, the tradeoff parameter ρ is fixed as $\rho = 0.1$ for achieving the best performance.

5.4. Parameter analysis

Since the performance of the model RBPR is affected by parameters such as the trade-off parameter α, latent feature dimension, iterations, learning rate and regularization parameter, this section mainly discusses the influence of the first four parameters on the performance of the proposed model, while the latter two parameters are fixed as 0.01.

5.4.1. Impact of trade-off parameter α

From Eq. (9) we know that the trade-off parameter α directly affects the performance of RBPR. In this section, we evaluate the impact of α on four different new user cold start datasets constructed by Movielens 100k, Movielens 1M, FilmTrust and Ciao, separately. The MAP and MRR are used to evaluate the performance of RBPR. During the experiments, α ranges from 0 to 1, and the step size of α is set to 0.1. Since the performance of the model is affected by both the latent feature dimension and the number of iterations, to minimize the impact of the above two factors, the latent feature dimension f of the model is set to 10, and the number of iterations is set to 1000. Fig. 5 illustrates the results of recommendation quality in terms of trade-off parameter α on four different new user cold start datasets. Note that the RBPR is equivalent to PMF if the trade-off parameter $\alpha = 1$ and is equivalent to BPR if $\alpha = 0$. As the results showed, the recommendation performance has an improvement compared to BPR and PMF. This observation proves the effectiveness of combining two types of models, i.e., the rating-oriented and ranking-oriented models.

It can be noticed from Fig. 5(a) that the trade-off parameter α has a great influence on RBPR. When $\alpha = 0.1$, the MAP and MRR reach the maximum values at the same time, and the performance of RBPR is optimal. With the increase of α, the MAP and MRR begin to decrease until $\alpha = 0.5$. When $\alpha > 0.5$, the performance curve of RBPR fluctuates. When $\alpha = 1$, the values of MRR and MAP reach the minimum. In this case, the performance of RBPR becomes the worst. It can be noted from Figs. 5(b)–5(d) that the performance curves of RBPR change relative-smoothly without severe fluctuations. With the increase of α, the MRR and MAP of RBPR reach the maximum when $\alpha = 0.1$, and the performance of the proposed model reaches the best. Based on the analysis above, we can conclude that the performance of RBPR is optimal when $\alpha = 0.1$. It means that the ranking-oriented model makes the major contribution to the performance of the proposed approach. Therefore, the value of the trade-off parameter α is set to 0.1 in the following experiments.

5.4.2. Impact of the latent feature dimension

Since the RBPR model is optimized with SGD, the performance of RBPR is affected by the latent feature dimension f. This section determines the optimal value of f through experiments on four new user cold start datasets constructed by Movielens 100k, Movielens 1M, FilmTrust and Ciao. The MAP and MRR are the evaluation metrics we used. $f = \{5, 10, 20, 30, 40, 50\}$. The reason why the dimension value is relatively low is that the training time of the model increases with the increase of f. In this set of experiments, the trade-off parameter α is set to 0.1, and the

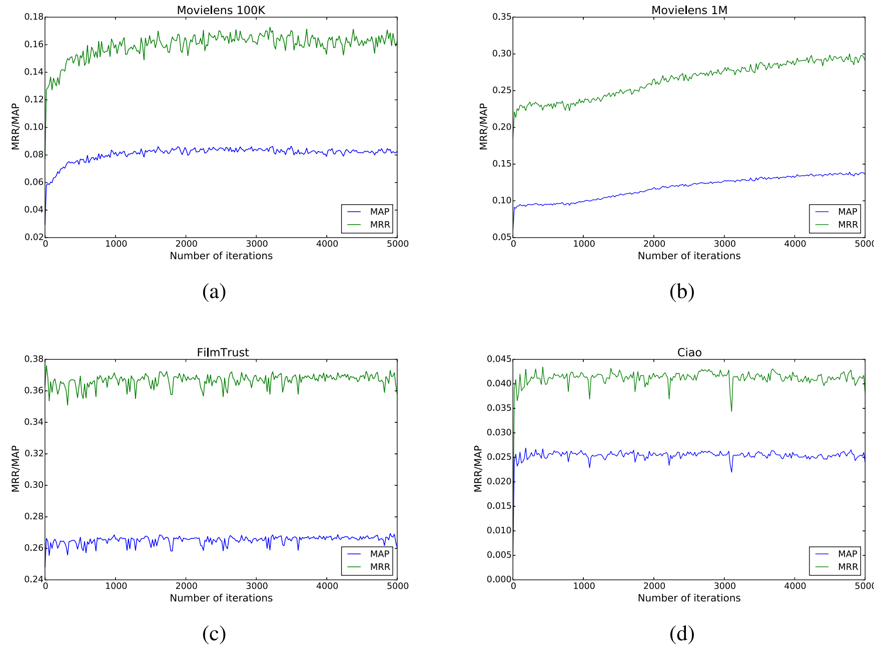


Fig. 7. The curve of the performance of the RBPR with the iterations on four different new user cold start datasets.

number of iterations is set to 1000. The results are illustrated in Fig. 6.

Fig. 6 reveals the performance of RBPR with different latent feature dimensions on four datasets. We notice from Fig. 6 that the best performance of RBPR is achieved when $f = 10$ on four datasets within the whole range of the latent feature dimensions we selected. In Fig. 6(a), the worst performance is achieved when $f = 5$. When the latent feature dimension is greater than 20, the MAP and MRR of RBPR model increase with larger f, and the growth rate is constantly slowing down. The possible reasons for this phenomenon are that, within a certain range of dimensions, the higher the dimension of the latent feature, the more information can be stored. So the hidden features of users and items can be tapped to a greater extent. The performance of RBPR will increase with the increase of the latent feature dimension. However, the larger the dimension of the latent feature, the larger the interference received by the error, which leads to the performance degradation of the model. In Figs. 6(b) and 6(d), we can see that the performance change of the model is relative gentle over the whole range of dimensions. In Fig. 6(c), the values of MAP and MRR fluctuate within a small range when $f > 10$. The possible reason for this phenomenon is that the dataset is relatively small and sparse. Since the datasets with new user cold start problem are extremely sparse, the dimension of the latent feature should not be too large. Therefore, f is set to 10 in the following experiments.

5.4.3. Impact of the iterations

As the performance of the proposed model will be affected by the number of iterations during the training process, this section conducts experiments on four different new user cold start datasets. MAP and MRR are also used as the evaluation metrics. The value range of the iteration number is from 0 to 5000, and the step size is set to 20. Due to the previous experiments, the trade-off parameter α is set to 0.1, and the latent feature dimension is set to 10. The performance curve of RBPR with the iteration number is shown in Fig. 7.

As can be seen from Fig. 7(a), MRR and MAP have an increasing trend with the number of iterations increases while both of them fluctuates within a certain amplitude range (the latter has a smaller fluctuation range). When the iteration number is less than 1000, the increasing trend of MRR and MAP become more obvious with the increase of iteration number. When the number of iterations is greater than 1000, MRR and MAP have a tendency to increase slowly as the number of iterations increases. When the number of iterations is greater than 2000, MAP is approaching stable and the growth of MRR is not obvious. In Fig. 7(b), we can see that with the iteration number increasing, the values of MAP and MRR have an upward trend when the variable value is less than 4000. When the iteration number is greater than 4000, the performance improvement will slow down. It can be seen from Figs. 7(c) and 7(d) that the best performance of RBPR remain basically unchanged when the iteration number is greater than 1000. Since the model converges at different speeds in different datasets, the iteration number is set to 2000 in the datasets constructed by Movielens 100k, FilmTrust and Ciao and is set to 5000 in the dataset constructed by Movielens 1M in the following experiments.

5.5. Algorithm performance comparison

In the section, the experiments are conducted on four different new user cold start datasets. Precision, Recall, MAP and MRR are chosen to evaluate the performance of RBPR and baseline algorithms. The number of $Top - N$ recommendations is set to 3 and 5, which are commonly used in CF recommendation filed. The trade-off parameter α in the proposed model is set to 0.1. For fair comparison, we set the dimension of latent features to 10 for all matrix factorization models, and the iteration number is set to 2000 for Movielens 100k, FilmTrust and Ciao datasets, and 5000 for Movielens 1M dataset. The learning rate and the regularization parameter are fixed as 0.01, respectively.

The experimental results of RBPR and the baseline approaches on the four datasets are shown in Table 1, from which we can have the following observations:

(1) The performance of pairwise ranking models (BPR, GBPR, CoFiSet and RBPR) is better than the listwise ranking models (CLiMF and UOCCF). The performance of matrix factorization models (PMF and SVD) is the worst. Although the UOCCF algorithm combines the explicit feedback model PMF and the

Table 1
Test results of several models on the new user cold start datasets.

Algorithms	Dataset: Movielens 100k					
	Precision@3	Recall@3	Precision@5	Recall@5	MAP	MRR
PMF	0.0157	0.0118	0.0150	0.0192	0.0164	0.0537
SVD	0.0254	0.0190	0.0254	0.0346	0.0317	0.0844
BPR	0.0582	0.0468	0.0544	0.0696	0.0608	0.1327
GBPR	0.0585	0.0462	0.0548	0.0715	0.0793	0.1548
CLiMF	0.0496	0.0382	0.0507	0.0653	0.0621	0.1322
CoFiSet	0.0485	0.0383	0.0438	0.0567	0.0556	0.1261
UOCCF	0.0424	0.0318	0.0420	0.0525	0.0511	0.1194
RBPR	**0.0629**	**0.0563**	**0.0575**	**0.0773**	**0.0833**	**0.1735**
Algorithms	Dataset: Movielens 1M					
	Precision@3	Recall@3	Precision@5	Recall@5	MAP	MRR
PMF	0.0163	0.0123	0.0163	0.0215	0.0188	0.0574
SVD	0.0231	0.0183	0.0246	0.0322	0.0340	0.0834
BPR	0.0983	0.0793	0.0829	0.1098	0.1049	0.2319
GBPR	0.0995	0.0801	0.0830	0.1103	0.1050	0.2328
CLiMF	0.0616	0.0512	0.0541	0.0746	0.0662	0.1530
CoFiSet	0.0816	0.0660	0.0698	0.0928	0.0903	0.2036
UOCCF	0.0767	0.0573	0.0674	0.0843	0.0833	0.1953
RBPR	**0.1243**	**0.0977**	**0.1078**	**0.1415**	**0.1388**	**0.3004**
Algorithms	Dataset: FilmTrust					
	Precision@3	Recall@3	Precision@5	Recall@5	MAP	MRR
PMF	0.0345	0.0356	0.0334	0.0556	0.0449	0.0970
SVD	0.1135	0.1232	0.1232	0.1833	0.1297	0.2660
BPR	0.1702	0.1851	0.1528	0.2690	0.2568	0.3603
GBPR	0.1643	0.1804	0.1477	0.2640	0.2492	0.3491
CliMF	0.1253	0.1297	0.1215	0.2129	0.2009	0.2846
CoFiSet	0.1595	0.1712	0.1483	0.2574	0.2518	0.3496
UOCCF	0.1047	0.1353	0.0934	0.1923	0.1746	0.2501
RBPR	**0.1728**	**0.2085**	**0.1571**	**0.3057**	**0.2702**	**0.3734**
Algorithms	Dataset: Ciao					
	Precision@3	Recall@3	Precision@5	Recall@5	MAP	MRR
PMF	0.0027	0.0055	0.0023	0.0077	0.0065	0.0094
SVD	0.0045	0.0069	0.0048	0.0117	0.0104	0.0150
BPR	0.0087	0.0186	0.0081	0.0282	0.0214	0.0289
GBPR	0.0089	0.0201	0.0091	0.0342	0.0256	0.0322
CliMF	0.0058	0.0111	0.0052	0.0162	0.0114	0.0171
CoFiSet	0.0079	0.0164	0.0083	0.0301	0.0250	0.0323
UOCCF	0.0050	0.0105	0.0056	0.0154	0.0106	0.0158
RBPR	**0.0128**	**0.0203**	**0.0113**	**0.0350**	**0.0263**	**0.0410**

implicit feedback model CLiMF, the performance is mainly determined by the CLiMF model. Moreover, the available explicit feedback data is scarce under the condition of new user cold start. Thus, the performance improvement of UOCCF is not very obvious compared with CLiMF.

(2) *Recall*@5 is higher than *Recall*@3 across all algorithms on the four new user cold start datasets. The performance of GBPR is better than BPR on the new user cold start datasets constructed by Movielens 100k, Movielens 1M and Ciao, however, the performance of GBPR is slightly worse than BPR on the new user cold start dataset constructed by FilmTrust, which demonstrates that the group preference introduced by GBPR are effective in most cases.

(3) The proposed RBPR model outperforms the seven baseline approaches in terms of all evaluation metrics on the four datasets, which demonstrates the effectiveness of the proposed method. The experimental results show that using the PMF model can explore the user preference in the explicit ratings, combining BPR model to explore the latent features of users and items for achieving better ranking performance and improving the recommendation accuracy.

(4) Compared to BPR, the improvement of the proposed model RBPR varies greatly in terms of all evaluation metrics on the four datasets. The performance improvement on the new user cold start datasets constructed by Movielens 100k and Movielens 1M is higher than the other two datasets. That is because the users have few rated items on the latter datasets of FilmTrust and Ciao (the sparseness of the above datasets is relatively high). Although the prediction ratings generated by SVD pre-processing step can enrich the explicit rating data, the prediction accuracy of SVD is low due to the sparse datasets, which leads to introducing too much noise into the model and reduces the recommendation accuracy.

5.6. Cold start analysis

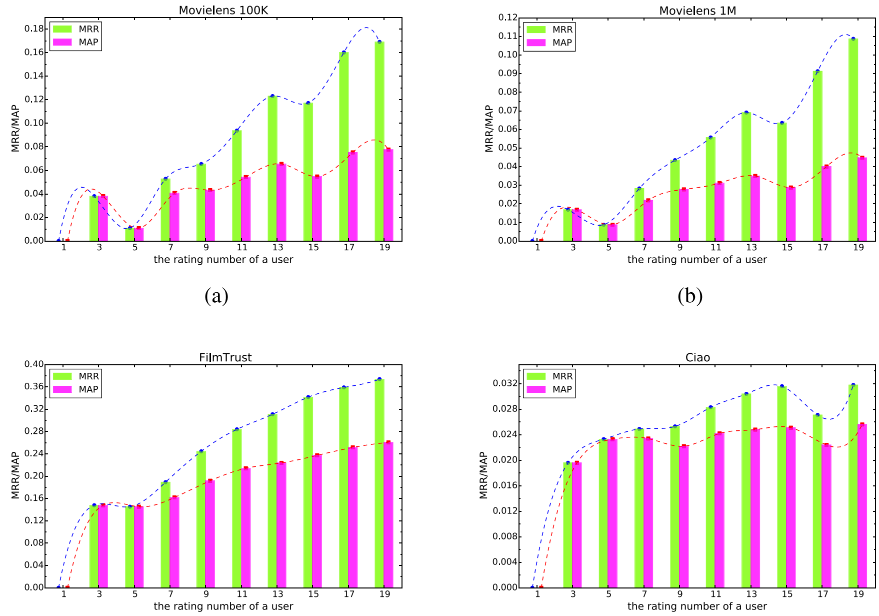
In the previous experiments, we choose users whose rating number is less than 20 as the cold start users. To investigate the performances of RBPR model in dealing with different degrees of new user cold start problem, we conduct new user cold start datasets on four original datasets including Movielens 100k, Movielens 1M, FilmTrust and Ciao artificially. The rating number of a user is increased from 1 to 19, and the step size is set to 2. Datasets with different user ratings are constructed from the original datasets. The less the number of user ratings, the more serious the cold start problem. For example, 3 indicates that users rated at most 3 items in this dataset. MAP and MRR are chosen as the evaluation metrics. The trade-off parameter α in the proposed model is set to 0.1. The latent feature dimension is set to 10. The iteration number is set to 2000. Both learning rate and regularization parameter are set to 0.01. The experiment results are shown in Fig. 8.

From Fig. 8, we can see that with the increase of the rating number of one user, the performance of RBPR is continuously improving, except for very few cases. When the rating number of one user is not more than 1, our RBPR model cannot make effective recommendations according to the existing data. In Figs. 8(a) and 8(b), with the increase of the rating number of one user, the values of MAP and MRR change relatively quickly and the changes of the two evaluation metrics are relatively gentle in Figs. 8(c) and 8(d). To summarize, our proposed model can alleviate the cold start problem even under extremely sparse conditions.

6. Conclusion and future work

To alleviate the new user cold start problem, we presented a novel ranking model RBPR, which combines explicit ratings and implicit feedbacks into one model. The proposed method first adopted a pre-processing step by SVD to increase the density of explicit ratings. Then, PMF and BPR are jointly unified together. PMF was used to explore the explicit features of users and items from explicit ratings while BPR was used to explore the implicit features of users and items from implicit feedback data. Finally, the common latent features of users and items extracted from both models were taken as the final features of users and items. We experimentally verified that the recommendation performance of RBPR were mainly contributed by the ranking-oriented approach BPR and further improved by the rating-oriented approach PMF. Experimental results on practical new user cold start datasets indicated that our proposed method RBPR outperforms most existing rating-oriented and ranking-oriented approaches in terms of different evaluation metrics.

For future work, we first plan to use the CF recommendation algorithm based on multi-score fusion to alleviate the new user cold start problem in the RSs. Second, we will consider adding the additional content information to the proposed RBPR model for improving the recommendation accuracy in the subsequent research.



(a) (b)

(c) (d)

Fig. 8. The curve of the performance of the RBPR with different rating number of a user on four datasets.

CRediT authorship contribution statement

Junmei Feng: Data curation, Methodology, Software, Writing - original draft. **Zhaoqiang Xia:** Conceptualization, Software - reviewing and sharing preparation, Writing - review & editing. **Xiaoyi Feng:** Writing - review & editing. **Jinye Peng:** Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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