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List-wise probabilistic matrix factorization for recommendation

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ABSTRACT

Matrix factorization based recommendation methods gain great success due to their efficiency and accuracy. But optimizing the objective function in conventional matrix factorization based recommendation methods, which is the sum-of-square of factorization errors with regularization terms, does not ensure that the obtained recommendation results are consistent with the preference orders of the users. To address this problem, in this paper, we improve the model of probabilistic matrix factorization (PMF) and propose list-wise probabilistic matrix factorization (ListPMF). In ListPMF, we take the preference orders of the users indicated by observed ratings as a whole instance, and we maximize the log-posterior over the predicted preference order with the observed preference orders. By this way, the proposed method is able to get recommendation results more consistent with the user preferences. The proposed method is computationally efficient and can be applied to very large dataset. Experimental results on two real world datasets show that our method outperforms most of the compared state-of-the-art approaches.

1. Introduction

Recently, recommender systems have received great attention due to their commercial value in today's online business world [1,15,27]. Recommender systems are used to recommend music [17], groups [10], products [20], research resources [29], people and resources in Google Wave [34] and so on. In rating based recommender systems, users are allowed to assign ratings to items, which are collected to predict the interests of the users. Recommendation methods are generally divided into collaborative filtering (CF) methods and content-based (CB) methods [1]. In content-based recommender system, recommended items are similar to the items that the user liked in the past. Collaborative filtering methods try to recommend items to a particular user by analyzing the preferences of other similar users. The underlying assumption of collaborative filtering is that similar users have similar tastes.

In rating based recommender system, matrix factorization is one of the most popular collaborative filtering methods in recent years [15]. It is assumed that each user and item can be represented by a small number of unobserved features. Formally, supposing there are M users and N items, $M \times N$ matrix R is the observed rating matrix. Let D denote the dimension of user feature and item feature, $D \ll M,\ N$. Matrix factorization based methods find $M \times D$ user latent feature matrix U and $N \times D$ item latent feature matrix V, and minimize the difference between the predicted rating matrix $\widehat{R} = UV^T$ and the observed rating matrix R.

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Probabilistic matrix factorization (PMF) [33] is proposed to solve this problem. It is assumed that the distribution of the observed rating matrix R, user latent feature matrix U and item latent feature matrix V are Gaussian distribution, and the log-posterior over predicted rating matrix $\widehat{R}$ with the observed rating matrix R and fixed parameters θ is maximized:

$$\max\{\ln p(\widehat{R} \mid R, \theta)\} \tag{1}$$

where θ are the distribution parameters of R, U and V. It is equivalent to minimizing the sum-of-squares of factorization errors with regularization terms. Most of the recommendation methods based on matrix factorization use this kind of objective function.

Matrix factorization based recommendation methods gain great success in collaborative filtering. However, optimizing the sum-of-squares of factorization errors, the objective function in traditional matrix factorization based recommendation methods, cannot guarantee that the predicted ratings are agree with the preference orders of the users. For an example, suppose a user rated 4, 3 and 2 stars for the item A, B and C, separately, as illustrated in Fig. 1. By sorting these ratings, we can get the preference order of this user: A > B > C. There are two predictions for these ratings. Prediction 1 is 3, 4 and 3 stars. Prediction 2 is 3, 2 and 1 stars. The sum-of-squares of factorization errors of these two predictions are same. But the preference orders suggested by these two predictions are different. It can be observed that the preference order suggested by prediction 2 is same as the preference order of the user. In practice, users care more about the order of the recommended items than the absolute predicted rating values. Using prediction 2, the recommender system can give more satisfied recommendation result to the user, so it is a better prediction. Because the sum-of-squares of prediction errors cannot reflect the disagreement between the preference order of a user and its prediction, this metric is seldom used to evaluate a recommendation list. Instead, the recommendation results are evaluated through the measures in learning to rank (LTR) or information retrieval (IR), such as Mean Reciprocal Rank (MRR) [4], Mean Average Precision (MAP) [2], Expected Reciprocal Rank (ERR) [5] and Normalized Discounted Cumulative Gain (NDCG) [14]. These metrics can measure the agreement between the preference order of a user and the recommendation list. For example, the NDCG and ERR of prediction 1 in Fig. 1 are 0.9265 and 0.4148. The NDCG and ERR of prediction 2 are 1.0000 and 0.5398. According to NDCG and ERR, prediction 2 is better than prediction 1, which cannot be judged by the sum-of-squares of prediction errors. So, in order to give more satisfied recommendation results to the users, the objective function of the conventional matrix factorization methods should be changed to make it be able to measure the agreement between the preference orders of the users and the recommendation results.

To overcome the drawback of the conventional matrix factorization based methods, in this paper, we improve the model of probabilistic matrix factorization and propose list-wise probabilistic matrix factorization (ListPMF). In our framework, we take the user preference orders π as a whole instance, which can be got by sorting the observed rating matrix R. In order to make the predicted ratings consistent with the preference orders of the users as much as possible, we maximize the log-posterior over the predicted preference order $\hat{\pi}$ with the observed preference order π and fixed parameters θ:

$$\max\{\ln p(\hat{\pi} \mid \pi, \theta)\} \tag{2}$$

where the predicted preference order $\hat{\pi}$ is inferred by sorting the predicted rating matrix $\widehat{R}$. Our model represented by formula (2), taking the preference orders of the users into consideration, is different from the model of PMF represented by formula (1). By maximizing formula (2), our method can recommend a list of items more consistent with the preferences of the users. Same as the traditional matrix factorization based methods, the proposed method can be extended to integrate side information conveniently, such as social relation and tag information, by adding the regularization terms to the objective function. The proposed model is learned by gradient descent. Because the computational complexity of calculating the gradients is linear with respect to the number of the observed ratings, the proposed method is computationally efficient, and can be applied to large-scale real life datasets. We evaluate our method on Eipinions dataset [25] and MovieLen dataset [11]. The recommendation performance is measured by NDCG and ERR, which are the popular measures in information retrieval and learning to rank. The experimental results show the accuracy of our method outperforms most of the compared state-of-the-art approaches based on matrix factorization.

Fig. 1. Prediction 1 and prediction 2 are the predictions for user ratings with the same sum-of-squares of prediction errors. But only the preference order suggested by prediction 2 is agree with the preference order of the user.