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Recommendation in feature space sphere

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ABSTRACT

Recently, recommendation algorithms have been widely used in many e-commerce platforms to recommend items to users on the basis of their preferences to improve selling efficiency. Matrix factorization methods which extract latent features of users and items by decomposing the rating matrix have achieved success in rating prediction. But almost all of these algorithms are designed to fit the rating matrix directly to get the latent features and ignore the user-item relationship in feature space. To this end, in this paper, we propose a recommendation in feature space sphere (RFSS) which takes into account the relationship between users and items in feature space. Different from the conventional latent feature based recommendation algorithms, the proposed algorithm supposes that if a user likes an item, the user is close to the item in feature space. Meanwhile, the closer a user and an item are in feature space, the higher the predicted rating will be. And an adaptive user-dependent coefficient is introduced to map the user-item distances to the predicted ratings. Extensive experiments on four real-world datasets have been conducted, the results of which show that our proposed method outperforms the state-of-the-art recommendation algorithms.

1. Introduction

Due to the rapid growth of online markets/services, an increasing amount of merchandises/services can be sold/provided in these platforms nowadays. This makes it difficult for users to find something interesting or useful in a short time. As a consequence, recommendation algorithm emerges as required and has been widely used in many online markets/services like Amazon (Linden et al., 2003), YouTube (Davidson et al., 2010), Twitter (Elmongui et al., 2015), Tmall (Zhong et al., 2015) and Yahoo! (Koenigstein et al., 2011), to improve selling efficiency and enhance user experience. The function of recommendation algorithm is to recommend items to target users they are most likely interested in based on the huge amounts of data about user behaviour. Recommendation algorithm usually predicts the ratings to non-purchased items and presents the recommendation lists to the target users in the descending order of the predicted ratings (Guo et al., 2014). On the whole, the traditional recommendation algorithms can be classified into three types: collaborative filtering, content-based recommendation and hybrid recommendation (Jannach et al., 2013). Among them, collaborative filtering, one of the most successful technologies in personalized recommendation, can be separated into memory-based methods and model-based methods. And the basic idea of collaborative filtering is that a user prefers the items liked by the users with similar interest. In particular, matrix factorization is one of the most common model-based collaborative filtering algorithms.

Over the past decade, matrix factorization has attracted an increasing amount of attention. Matrix factorization technique usually learns the latent features of both users and items from the user-item rating matrix, and then predicts the ratings to non-purchased items according to user and item latent features. The most remarkable matrix factorization algorithm is probabilistic matrix factorization (PMF) (Salakhutdinov and Mnih, 2007). Another remarkable method is Non-negative Matrix Factorization (NMF) (Lee and Seung, 2000), where the constraint that all the features should be positive is applied. A sparse linear method (SLIM) (Ning and Karypis, 2011) uses sparse aggregation coefficient to make Top-N recommendation with high quality and efficiency concurrently.

Although matrix factorization methods have achieved remarkable success, there are some deficiencies. Matrix factorization methods focus on users and items in feature space and get the latent feature vectors of users and items by decomposing the rating matrix. But almost all of these algorithms are designed to fit the

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matrix directly to extract latent features and have not considered the user-item relationship in feature space. However, this relationship is useful in recommendation. This is because, different users will give different ratings to the same item and we can infer whether the user likes the item according to the rating. If a user gives a high rating to an item since the user likes the item, the user should be close to the item in feature space and vice versa. Another deficiency is that, although most of existing recommendation algorithms use inner product to fit real rating, this method lacks interpretation about why inner product can be used to predict rating. So, we develop a new prediction method based on similarity, which can explain that the predicted rating is associated with the relationship between user and item in feature space.

To address the above issues, we present a recommendation in feature space sphere (RFSS). This algorithm considers the relationship between users and items in feature space which is measured by Euclidean distance with rating as weight. If a user likes an item, the weight will be large and the user will be close to the item in feature space. And if a user is close to an item in feature space, the predicted rating will be high. Additionally, a user-dependent coefficient which is self-adaptive is used to map the relationship between user and item in feature space.

The contributions are summarized as follows:

1. A regularization term that measures the user-item relationship in feature space by Euclidean distance will be considered in the objective function.
2. An adaptive user-dependent coefficient is introduced to map the cosine-based similarities between users and items to the predicted ratings.
3. Complexity and convergence analysis is conducted to show the convergence property of the proposed method.
4. We conduct experiments on four real world datasets and the results show that the proposed RFSS algorithm outperforms the state-of-the-art recommendation algorithms.

2. Related work

Many efforts have been made in matrix factorization algorithms to improve the performance. Bayesian probabilistic matrix factorization (BPMF) (Ruslan and Andriy, 2008) uses bayesian treatment on the probabilistic matrix factorization to introduce Gaussian-Wishart priors on the hyperparameters of the user and item feature vectors. For improving singular value decomposition (SVD), the biases of users and items are integrated into SVD so as to better fit ratings (Paterek, 2007). In Wen et al. (2014), Cosine Matrix Factorization (CosMF) utilizes cosine similarity to replace inner product for sparse users and items to address the sparsity problem without auxiliary data. But it just considers the angle between two latent feature vectors and ignores their lengths. As an improved version, the expected risk minimized matrix approximation method (ERBMMA) (Li et al., 2017) uses expected risk to achieve better tradeoff between optimization error and generalization error. Chen et al. proposed a cross-domain recommendation algorithm (Chen et al., 2013) which uses PARAFAC tensor decomposition to extract the knowledge from the auxiliary domain and makes use of the knowledge in the target domain to increase user acceptance rate in recommendation lists. Kang et al. proposed a matrix factorization algorithm (Kang et al., 2016) that fills user-item matrix based on the low-rank assumption and keeps the original information at the same time for Top-N recommendation. But the above algorithms do not take the relationships between latent feature vectors into consideration.

Recently, the relationship about users and items in feature space has been considered to improve the performance of matrix factorization recommendation algorithm. Matrix factorization to asymmetric user similarities (MF-AMSD) (Pirasteh et al., 2015) gets the user features by decomposing the asymmetric user similarity matrix, so the similar users are also similar in feature space. Although these user features are used to predict ratings, the processes of feature extraction and rating prediction are independent which will cause error propagation. Recommender Systems with Social Regularization (SR) (Ma et al., 2011) supposes that a user should be close to his trusted users in feature space while the algorithm needs the data in trust network which may not be suitable for universal cases. On the contrary, the algorithm proposed by Paterek (2007), considering the item relationship in feature space, uses the item-item similarity learned as a product of two low-rank vectors to make a rating prediction. But the algorithm only considers item relationship and ignores user relationship in feature space. Following Paterek, Koren proposed a method (Koren, 2008) which combines matrix factorization and the traditional neighborhood based model to learn the latent features of users and items simultaneously, but the drawback is that the relationship between users and items in feature space has not yet been considered. Sparse covariance matrix factorization (SCMF) (Shi et al., 2013) uses sparse covariance prior to find the correlation between latent features. The algorithm connects users and items by placing the same prior to latent feature vectors which however cannot ensure a user will be close to the item he prefers in feature space.

To address the above issues, we propose a recommendation in feature space sphere (RFSS) which can improve the quality of recommendation by considering the user-item relationship in feature space.

3. The proposed algorithm

In recommendation algorithms, a user-item rating matrix $R = [r_{ij}]_{m\times n}$ is used to represent the rating relation between m users and n items. Each entry r_{ij} denotes the rating of user i to item j within a certain numerical interval $[R_{min}, R_{max}]$ which will vary in different datasets and if user i does not rate item $j, r_{ij} = 0$. I_{ij} is the indicator function that is equal to 1 if user i has rated item j or 0 otherwise. In the matrix factorization recommendation algorithms, α_i and β_j are d-dimensional vectors representing the latent features of user i and item j respectively.

3.1. Objective function

Different from the conventional latent factor based recommendation algorithms (Gao et al., 2013), in our proposed algorithm, we suppose that all the latent feature vectors are laying on the unit sphere surface in the feature space, so $\alpha_i\alpha_i^T = 1$ for $i = 1,\dots,m$ and $\beta_j\beta_j^T = 1$ for $j = 1,\dots,n$. As we will see below, the advantage of unit constraint is that the similarity between user and item in feature space can be calculated easily. Besides, the Euclidean distance can be confined to a certain range which can avoid some extreme conditions.

Therefore, the user latent feature vectors and item latent feature vectors are in the same feature space. All the items have their own features and the features of users can been represented by the features of items they have rated. In the feature space, if user i likes item j, the user is close to the item, i.e. their latent feature vectors are similar. So, Euclidean distance is suitable to measure user-item relationship. The kind of user-item relationship can be reconstructed by minimizing the term $\sum_{i=1}^{m}\sum_{j=1}^{n} r_{ij}\|\alpha_i - \beta_j\|_2^2 I_{ij}$ under the constraint of unit sphere surface representation, in which the rating r_{ij} can be viewed as a weight and *the higher the rating is, the closer user i and item j will be enforced to be.* Besides, this term can be viewed as a regularization term when learning the latent