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Effect of Rating Time for Cold Start Problem in Collaborative Filtering

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Abstract Cold start is one of the main challenges in recommender systems. Solving sparsechallenge of cold start users is hard. More cold start users and items are new. Sine many general methods for recommender systems has over fittingon cold start users and items, so recommendation to new users and items is important and hard duty. In this work to overcome sparse problem, we present a new method for recommender system based on tensor decomposition that use time dimension as independent dimension. Our method uses extra information of sequence of rating time which specify time duration of ratings. We test our method on dataset of Each Movie with 2 data types. One type has cold start users and items and another hasn't cold start users and items. Result shows that using time dimension has more effect on cold start users and items than others.

Keywords: Cold Start Problem, Collaborative Filtering, Time Dimension, Dynamic Recommendation.

Introduction

A collaborative recommender system helps the users to identify the right product during purchasing [1]. The collaborative recommender system identifies the similar users based on other ratings [2,3]. One of the main problems of recommender systems is the cold start problem, which can be divided into cold start items and cold start users. These users or items have low ratings. They are usually new users and new items [4]. Because of this, it is important that we have right recommendations to them. General methods for recommender systems don't have efficient suggestions for new users and in these methods, they usually give in over fitting [5,6]. In other words because of low ratings for new users and items, the recommender systems methods recommend mistake recommendations. Some methods have been presented for cold start problem [7, 8]. In [7], it proposes a method which derives from explicit ratings. The proposed method first predicts actual ratings and subsequently identifies prediction errors for each user and the npre-computed models for

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error-error information. In [8] a privacy protected model has been developedto solve the cold start problem. In other research, Probabilistic neural network (PNN) is used to calculate the trust between users based on rating matrix. Using the calculated trust, sparse rating matrix is smoothened, by predicting the rating values of the nonrated items in the matrix. Using this smoothened rating matrix, the trust is calculated for online active users. The calculated trust is used to recommend product [9]. Using association rule mining for solving cold start problem has existed [10].Association rules use as a source of information to expand a user profile for avoiding this problem. Special methods for cold start problem usually use non-cold start users and items for solving cold start users and items. Using sequence of rating for cold start users or on cold start items can help to having better results. Some methods map concept to construct an attribute-aware matrix factorization model for item or user recommendation from implicit, positive-only feedback [11]. Using rating time has extra information for recommender systems [6, 12]. This information is more information for cold start users and items than others. We prove it in this paper. In [13] solve optimization problem of matrix factorization in recommender system via Kull Back Leibler. Matrix and tensor factorization are the best methods for recommender system. Solving cold start problem with these methods has better results [14].We present our method that use time dimension as independent dimension. Using time dimension which is time of rating on items has more effect on cold start prediction rating than non-cold start. Our general algorithm because of using time dimension can use for cold start problem with high accuracy. Time dimension in our method is independent dimension and consider to sequence of ratings. Then in result we prove our idea conceptually. Conclusion and references arethe last section of this paper.

Time dimension as independent dimension

We have proposed a method for recommendation system [6] that use time dimension as independent dimension. Time has been used in some recommender systems but it hasn't been considered as a separate dimension. In this method, we present a method that uses 3 dimension user-item-time for recommender system. It is presented based on tensor decomposition which use HoSVD algorithm. In fact we transform HoSVD algorithm for recommender system that have 3 dimensions user-item-time.

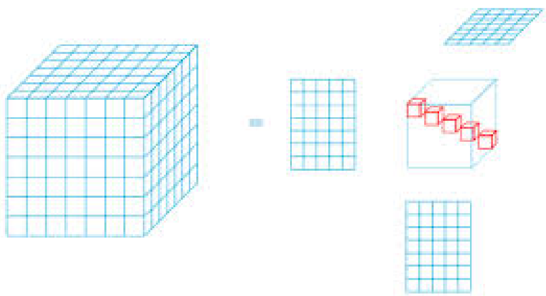

Fig. 1 tensor decomposition of HoSVD for recommender system

This method is shown as:

$$R \approx (U, I, T).S \qquad (1)$$

$$U_{k1} \in R^{m*k1}, I_{k2} \in R^{n*k2}, T_{k3} \in R^{l*k3}, S \in R^{k1*k2*k3}$$

when $U \in R^{m*m}, I \in R^{n*n}, T \in R^{l*l}, R \in R^{m*n*l}$. In which U is the user vectors matrix, I is the item vectors matrix and T is the time vectors matrix. If q_i is equal to the row "I" of I matrix, and P_u is equal to the row "u" of the U matrix and γ_t is equal to the row "t" of the T matrix, then the recommendation for user "u" on item i in time "t" by tensor decomposition will be as below:

$$\overline{r_{uit}} = \sum_m \sum_n \sum_l (u_{um} i_{in} t_{tl}) S_{uit} \quad (2)$$

The above formula can be reformulated and simulated as below:

$$r_{uit} = (u^T{}_u, i^T{}_i, t^T{}_t).S \quad (3)$$

So in tensor model, we are helped from the HoSVD decomposition problem with minimization problem and the result will be appropriate. The formula follows:

$$Min \sum_{(u,i,t)\in k} [(r_{uit} - (U_u^T, I_i^T, T_t^T).S) + \lambda(\|U_u\|^2 + \|I_i\|^2 + \|T_t\|^2)]^2 \quad (4)$$

In the above formula we have 2 sections. The first section is square error of real rating and discriminate rating. We add the second section for avoiding of mutation in optimization steps. Time dimension in this method uses sequence of rating for prediction new ratings. Because of this, cold start problem has less challenge in this method.

Another method that we use hasn't used time dimension and has presented based on 2 dimensions user-item [15]. This method is based on SVD algorithm. Indeed it presented method in [6] uses time dimension and has better result indeed when we don't use time dimension. Cold start users and items have better improvement in this method than non-cold start users and items.

We show that of other general method our general method can be used for cold start problem because of time dimension. Time dimension creates extra information about sequence of rating time, and it avoid from cold start users' over fitting.

Result

We test our proposed method on 2 types of datasets. In type 2, we have new users and items named cold start users and items. The other type of dataset has no cold start users and items. For considering effect of time dimension on cold start problem we calculate RMSE for 2 methods that have been presented in [6,15]. Evaluation of method based on RMSE shows that effect of using time dimension which exist sequence of rating time has more effect on cold start users and items than non-start users and items. The RMSE method has been used according to the below formula:

$$RMSE = \sqrt{\frac{\sum_{(u,i,t)} \left(r_{u,i,t} - \hat{r}_{u,i,t}\right)^2}{n}} \quad (5)$$

That n is number of rating. We evaluate our method on each movie dataset has 200 users, 200 items, 20 duration of time and 1534 rating. Sparse of this dataset is 1534/200*200*20 for tensor decomposition which has time dimension and 1534/200*200 for matrix decomposition method.

We give RMSE for some number of hidden features for tensor decomposition. Below figure show that RMSE for type 1 of dataset which hasn't cold start user and item is less that type 2.

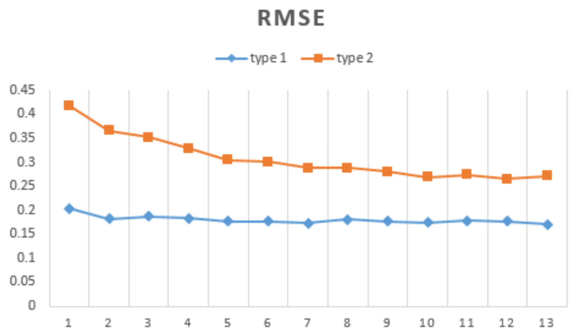

Fig. 2 RMSE for tensor decomposition

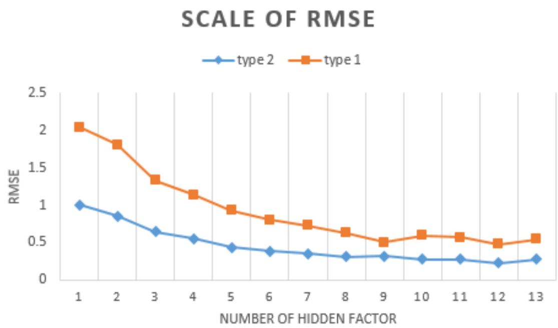

Fig. 3 scale of RMSE

In above figure, it is scale of RMSE in both types of datasets. We divide RMSE of tensor decomposition which has 3 dimension user-item-time on matrix decomposition which has 2 dimension user-item. We evaluate this compassion on some number of hidden factor (1-13). Figure shows that scale of RMSE for type 2 of dataset is less than type 1 of dataset. This means that effect of time dimension on cold start users and items has more information. Our method uses sequence of time of ratings for all users and items and so has extra information. In other words, our method that is a general method for recommender systems can be used for cold start problem which isn't right for many methods.

Conclusions and future work

We have presented a general method for recommender systems based on tensor decomposition in [6]. In this method we use time dimension as independent dimension which add extra information of sequence of ratings. Sequence of rating in our method considers duration of rating time. Many methods on recommender systems that have presented generally don't efficient for cold start problem and trouble in over fitting. Our method because of features of time dimension that use in it is a confidence method for cold start problem. We evaluate our method on 2 types of datasets and result show that effective and extra information of time dimension on cold start users and items has more than non-cold start users and items. Also it shows that if a user has more rating time dimension has less information for he/she than a user that has less rating. In other words, for cold start users and items which many of them are new users and items, we can use time dimension as independent dimension for having better prediction and better suggestion to them. In future we can consider scale of effective of time dimension on cold start problem. Also we can have a preprocessing for cold start users and items. This preprocessing will have better prediction for cold start users.

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