Matrix factorization recommendation algorithm based on deep neural network

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***Abstract*—Collaborative filtering is the most classical technology in recommendation system. Compared with memory-based collaborative filtering technology, matrix factorization has good scalability and recommendation effect, which makes it widely used. On the basis of matrix factorization model, deep neural network is introduced to improve the accuracy of scoring prediction and the quality of recommendation. Experiments on MovieLens dataset show that the proposed method improves the accuracy and quality of recommendation algorithm.**

Keywords—matrix factorization, deep neural network, recommendation algorithm

I. INTRODUCTION

With the advent of the Internet era, the scale of information expands, the amount of data increases sharply, and the problem of information overload becomes increasingly serious. How to reduce information interference and enable users to effectively obtain the information they really need has become an important part of current research.

The recommendation system uses interactive information among users and items to mine user's behavior preferences in depth, so as to predict user's interest preferences and recommend the most suitable projects to the specific users who need the project. The goal of recommendation algorithm is to find out the relevant information that users really need from the massive data information, so as to solve the problem of information overload.

Since the birth of personalized recommendation, it has been widely concerned. In this era of information explosion, in order to meet the personalized needs of users and provide personalized information for each user, personalized recommendation algorithm has been widely used in online platforms such as e-commerce, social networks and real-time news.

Collaborative filtering recommendation algorithm [1] is currently the most widely used recommendation algorithm. Collaborative filtering recommendation algorithms can also be divided into neighborhood-based [2] collaborative filtering recommendation algorithm and model-based collaborative filtering recommendation algorithm. Neighbor-based collaborative filtering recommendation algorithm calculates the similarity between user and user or between items by cosine similarity, Euclidean distance and Pearson correlation coefficient based on the rating of existing items by existing users.

Model-based recommendation algorithms include clustering-based [3], Bayesian classifier-based[4], latent factor model[5], graph model[6] and so on. The model-based collaborative filtering recommendation algorithm trains the recommendation model through the user-item scoring matrix. The model trained can predict the user's unknown items, then rank the predicted scores, and recommend the items with higher scoring to the user. Among the numerous collaborative filtering recommendation algorithms, matrix factorization has become one of the most popular recommendation algorithms and has attracted wide attention. Singular value decomposition (SVD) is the most classical recommendation algorithm based on matrix factorization [7]. SVD decomposition first fills the matrix, then decomposes the matrix to reduce the dimension, which leads to the high complexity of SVD decomposition and is not suitable for large-scale matrix processing. Simon Funk proposed the Funk-SVD decomposition. Instead of decomposing the matrix into three matrices, it was decomposed into two low rank matrices, which effectively reduced the complexity of SVD decomposition. Koren proposed BiasSVD[8] decomposition, adding user and item bias items, taking into account the influence of user preferences and inherent attributes of items. In addition to user's explicit rating, SVD++ adds implicit feedback information for user preference modeling. The above-mentioned recommendation algorithms based on matrix decomposition are widely used in the field of recommendation algorithms. However, the recommendation model based on matrix decomposition models the interaction between users and objects through simple vector inner product, which affects the effect of recommendation to some extent.

On the basis of the recommendation algorithm model based on matrix factorization, this paper proposes to replace simple vector inner product with deep neural network (DNNS) to build a non-linear model of complex user-item interaction function[9], which further improves the accuracy of the prediction results of the recommendation model based on matrix decomposition in scoring prediction. Experiments on MovieLens dataset show that the proposed algorithm effectively improves the accuracy and quality of recommendation.

II. PROBLOM STATE

Rating prediction is one of the common tasks in personalized recommendation tasks. Suppose there are m users $U = \{u_1, u_2, \dots, u_m\}$ and n items $I = \{i_1, i_2, \dots, i_m\}$, the user's score on the item is recorded with $R_{m\times n} =$

$[r_{ui}]_{m \times n}$,, where the row represents the user, the column represents the item, and the r_{ui} represents the specific rating user u has on the item i. In the current Internet era, the data scale of online platforms such as e-commerce and social media is very large, and the scale of users and items is often tens of millions or even more. However, the interaction between users and items is very small, which leads to the extremely sparse rating matrix $R_{m \times n}$. Rating prediction task learns the existing rating r_{ui} that user u has on item i and obtains the rating prediction model. For each user $u \in U$ and each item $i \in I$, if user u has no score on item i, then the prediction rating of user u on item i can be obtained by rating prediction model. The predicted ratings of item i obtained by each user u is sorted, and the items with higher rating are recommended to users, and personalized recommendation is made to users.

III. OUR PROPOSED MODEL

A. Matrix factorization

Fig 1. Example of Matrix Factorization

The idea of matrix factorization[10] is to decompose the rating matrix obtained from the interaction information between users and items , and get the user-feature matrix and the item-feature matrix. The user's behavior and the inherent attributes of objects will cause deviation in the score. Recommendation based on the characteristics of users and items can avoid the influence of the user's behavior difference and the inherent attributes difference of items.

Matrix factorization model maps users and items to k-dimensional joint latent feature space. Suppose that for a given user U , $p_u \in R^k$ is the latent feature vector of the user, indicating the user's preference for the latent feature attributes of the item; for a given item I, $q_i \in R^k$ is the latent feature vector of the item, indicating the degree of the attribute possessed by the item. $p_u {q_i}^T$ is the inner product of user latent feature vector and item latent feature vector which represents the general preference degree of the user u for the item i characteristics. The rating that user U has on item I can be expressed as $\hat{r}_{ui}$,

$$\hat{r}_{ui} = p_u {q_i}^T \quad (1)$$

An objective function is constructed to minimize the square error on the known rating data to learn the latent feature vector of users and items.

$$min \sum_{(u,i)\in\kappa} (r_{ui} - p_u {q_i}^T)^2 \quad (2)$$

κ is a set that contains each pair of user-item corresponding to the known rating r_{ui} in the training set.

In order to prevent the objective function from over-fitting, the regularization term is added to the objective function as follows.

$$min \sum_{(u,i)\in\kappa} (r_{ui} - p_u {q_i}^T)^2 + \lambda(\|p_u\|^2 + \|q_i\|^2) \quad (3)$$

B. Matrix Factorization with Deep Neural Network(DNN-MF)

By using matrix factorization technique, the rating matrix of interaction information between m users and n items can be decomposed into user latent feature matrix $P = \{p_1, p_2 \ldots, p_m\}^T \in R^{m \times k}$ and item latent feature matrix $Q = \{q_1, q_2 \ldots, q_n\}^T \in R^{n \times k}$. User latent feature matrix and item latent feature matrix are input into deep neural network[11]. At each layer of the neural network, each input vector is mapped to a new vector space. Usually, x represents input vector and y represents output vector, and the middle layer is represented by $l_i (i = 1, \ldots, N-1)$. The weight matrix of layer i is expressed by W_i , the bias term of layer i is expressed by b_i, and the output of the neural network is expressed by h :

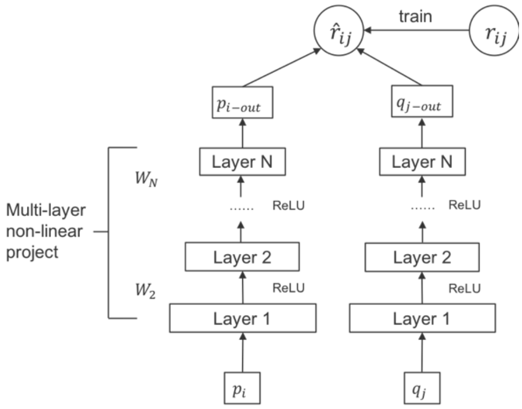

Fig 2. The architecture of DNN-MF

$$l_1 = W_1 x$$

$$l_i = f(W_{i-1} l_{i-1} + b_i), i = 2, \ldots, N-1 \quad (4)$$

$$h = f(W_N l_N + b_N)$$

In the hidden layer and the output layer $l_i(i = 2, \ldots, N\text{-}1)$, we use ReLU as an activation function:

$$f(x) = \max(0, x) \quad (5)$$

Two multi-layer networks are used to transform the representation of potential features of users and items. Through the neural network, the potential features of users and items are mapped to low-dimensional vector space.

$$p_{u-out} = f_{\theta_N^U}(\ldots f_{\theta_3^U}\left(W_{U_2} f_{\theta_2^U}(p_i W_{U_1})\right)\ldots) \quad (6)$$

$$q_{i-out} = f_{\theta_N^I}(\ldots f_{\theta_3^I}\left(W_{I_2} f_{\theta_2^I}(q_j W_{I_1})\right)\ldots) \quad (7)$$

Here $W_{U_1}$and W_{I_1}represents the weight matrix of user U and item I in the first layer of the neural network respectively, W_{U_2} and W_{I_2} represent the weight matrix of user U and item I in the second layer respectively, and so on.

$\hat{r}_{ui}$ is predict ratings of user U on item I :

$$\hat{r}_{ui} = p_{u-out} {q_{i-out}}^T \quad (8)$$

The objective function is:

$$L(R,P,Q) = min \sum_{(u,i)\in\kappa}(R_{ui} - P_u Q_i^T)^2 + \lambda(\|P_u\|^2 + \|Q_i\|^2) \quad (9)$$

Usually, the user latent feature P and the item latent feature matrix Q are initialized, which obey the Gauss distribution with the mean value of 0 and the standard deviation of 0.01. During training, P and Q are updated by stochastic gradient descent.

$$P_u' = P_u - \gamma_1 \frac{\partial L}{\partial P_u} \quad (10)$$

$$Q_i' = Q_i - \gamma_2 \frac{\partial L}{\partial Q_i} \quad (11)$$

Here, learning rate of $\gamma_1(\gamma_1 > 0)$ and $\gamma_2(\gamma_2 > 0)$ is learning rate. In order to reduce the complexity of the model, we set γ_1=γ_2.

IV. Experiments

A. Datasets

Through the above-mentioned matrix decomposition recommendation algorithm based on deep neural network, experiments are carried out on Movie Lens (ML) open data sets. The MovieLens data set is a standard data set commonly used in recommendation algorithms. It is provided by the University of Minnesota Group Lens Research Group. It contains five datasets of different sizes: 100k, 1M, 10M, 20M and Movielens-latest. Among them, the Movie Lens-latest-small data set contains 610 users'100,836 rating data for 9742 movies. These data are real ratings collected from the movie website. The rating range is 1-5, the number of movie ratings per user is not less than 20, and the user's label information for movies.

B. Evaluation for Recommendation

As a commonly used evaluation method of recommendation algorithm, Root mean square error (RMSE) is the square root of the ratio of the square of the deviation between the predicted score and the real score. The smaller RMSE is, the higher the recommendation quality is.

$$RMSE = \sqrt{\frac{\sum_{u=1}^{M}\sum_{i=1}^{N}(R_{ui}-\hat{R}_{ui})^2}{n}} \quad (12)$$

C. Performance Comparison

In order to verify the effectiveness of the proposed DNN-MF algorithm, the traditional matrix factorization recommendation algorithm is added to the comparison:

1) Basic MF: Basic Matrix factorization Recommendation Algorithms.

2) DNN-MF-2: Two-layer neural network is added to the basic matrix factorization recommendation algorithm.

3) DNN-MF-3: Three-layer neural network is added to the basic matrix factorization recommendation algorithm.

4) DNN-MF-4: Four-layer neural network is added to the basic matrix factorization recommendation algorithm.

5) DNN-MF-5: Five-layer neural network is added to the basic matrix factorization recommendation algorithm.

D. Experients Analysis

In this experiment, the data set is randomly divided into training set and test set according to 7:3. The training set contains 70585 data and the test set contains 30251 data.

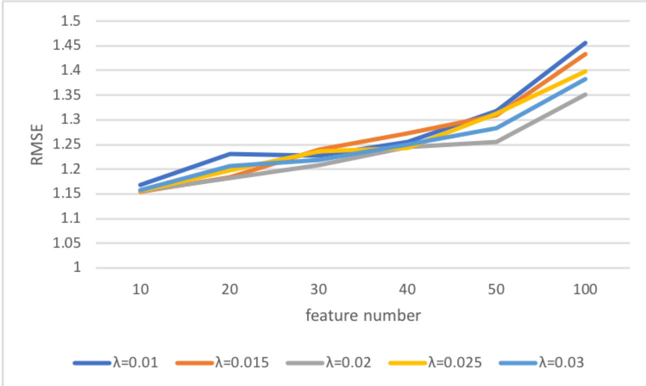

Fig 3. Experiments on Matrix Factorization

In the first group of experiments, the basic MF was tested at a learning rate $\gamma = 0.01$, and the regularization coefficients of different sizes of λ were compared with each other when the number of features was 10, 20, 30, 40, 50 and 100. The experimental results show that RMSE increases with the increase of the number of features. When the number of features is 10 and λ= 0.02, the RMSE of Basic MF is the best, and the error between predict rating and real rating is the smallest, which is about 1.15.

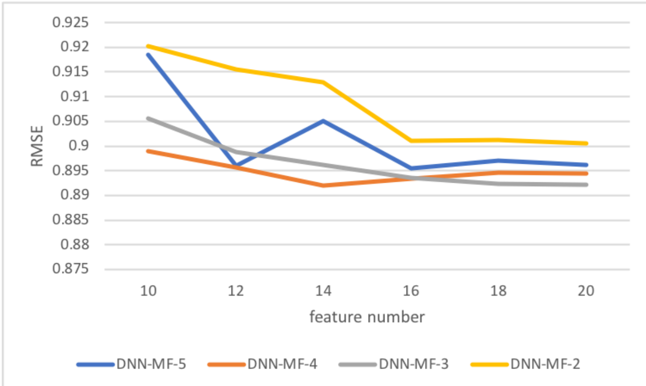

Fig 4. Experiments on different layers of DNN-MF

The second group of experiments maintained regularization coefficient $\lambda = 0.02$, learning rate $\gamma = 0.001$, only changed the number of features k, and the number of features was the dimension of output layer. The number of features selected was 10, 12, 14, 16, 18 and 20, respectively. The number of neurons in each layer was 1/2 of that in the previous layer.

The experimental results show that the matrix factorization algorithm DNN-MF based on deep neural network is superior to Basic MF. At the same time, when using different layers of neural network, using three-layer neural network and four-layer neural network is superior to other layers of neural network. When the number of features is small, the network structure of four-layer neural network is superior to the network structure of three-layer neural network, when the characteristics are small. When the number of networks increases, the network with three layers of neural network structure is better than the network with four layers of neural network structure. The error between predict rating and real rating of DNN-MF with different layers fluctuates between 0.891 and 0.916.

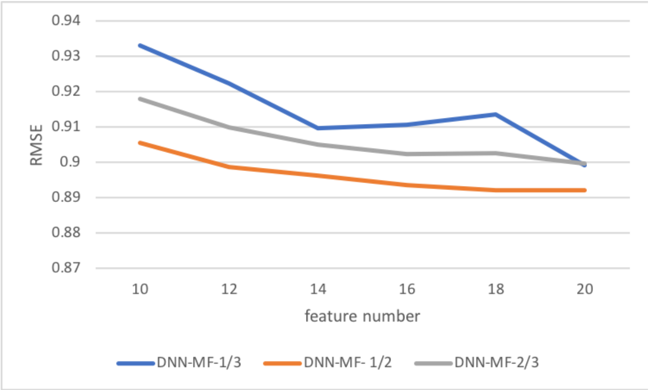

Fig 5. Experiments on different unit on each layer

The third group of experiments used three layers of neural network to compare the experiments under different number of hidden layer nodes. The number of neurons in each layer is 1/3, 1/2 and 2/3 of the previous layer, and the dimensions of the output layer are 10, 12, 14, 16, 18 and 20, respectively. The experimental results show that when the number of neurons in each layer is 1/2 of that in the previous layer, the error between the predict rating and the real rating is the smallest.

V. Conclusion And Future Work

Matrix factorization algorithm has become one of the most popular recommendation algorithms because of its scalability and accuracy. In this paper, the deep neural network is introduced into the basic matrix factorization model, and a matrix factorization recommendation algorithm based on the deep neural network is proposed. Through the powerful learning ability of the neural network, the latent feature of users and items are learned from the rating information of users and items. The experimental results show that the proposed algorithm is much better than the basic matrix factorization algorithm in rating prediction.

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