Research on Movie Recommendation Algorithm Based on Stack De-noising Auto-encoder

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Abstract. Focused on the problems that the randomness of the noise-adding operation in the de-noising auto-encoder (DAE), and the data matrix does not consider the impact of trusted users on the deep preferences of target users, this paper proposes a recommendation algorithm based on stack de-noising auto-encoder (SDAE) which integrates the preferences of trusted users. Firstly, the score vector is used as the input of the auto-encoder, and the mask vector is designed to train the potential preference of the target user. Secondly, the deep preference of the target user and the trusted user is obtained by the weighted fusion of the features of the two hidden layers of the auto-encoder. Thirdly, in order to reduce the impact of noise on the prediction accuracy, the cascaded auto-encoder model is constructed and trained according to the greedy training method layer by layer training. Finally, SDAE model is compared with other models on different data sets. The experimental results show that SDAE model has better recommendation performance.

1. Introduction
With the advent of 5G era, the phenomenon of information overload is becoming more and more prominent. In the face of massive data, how to quickly find the information that you are interested in a limited time becomes more and more difficult [1]. Information retrieval technology represented by search engine is one of the effective means to solve this problem, but users need to accurately describe what they need. When the user needs are not clear or cannot be described in a simple language, the search engine can do nothing. Therefore, personalized recommendation system emerges as the times require, and is widely used in online shopping, online news, online social networking and other fields.

The core of recommendation system is recommendation algorithm. At present, the main recommendation algorithms are divided into collaborative filtering algorithm, model-based recommendation algorithm and hybrid recommendation algorithm [2]. Especially with the development of deep learning technology, it brings new opportunities and challenges for the research of recommender system. In reference 3, the improved weighted Slone one method is combined with auto-encoder r to learn the deeper features of the dataset and improve the quality of recommendation. In reference 4, aiming at the problem that the randomness of the noise adding operation in the traditional de-noising auto-encoder affects the prediction accuracy, and the problem that the data matrix ignores the user specific scoring information, a multi de-noising auto-encoder (MDAE) model combined with user scoring is proposed. The experimental results show that the model can obtain better recommendation results. In reference 5, the additional information is spliced into the original input layer by using a semi-automatic encoder, and the extracted features are those that have considered the additional information.
The present method has achieved satisfactory results, but there are still several factors to consider to improve the performance of the algorithm. Firstly, for the data sparsity problem of the original scoring matrix, the potential preferences of the user's unsatisfied items are not deeply learned. Secondly, the deep preference characteristics of trusted users are not mined out, and most of them use shallow model to model trust relationship directly. Finally, for the randomness of noise adding operation, it is impossible to judge whether the original data feature representation is affected in the process of noise adding. In order to solve the above problems, this paper proposes to use deep learning technology to fuse the deep preferences of trusted users. The experimental results show that the proposed algorithm can improve the accuracy of prediction.

2. Movie Recommendation Algorithm Based on Stack De-noising Auto-encoder

2.1. Feature learning of movie score

According to the real data, the user movie scoring data set is obtained, which is composed of user's scoring records of movies. Assuming that R= \{(u, i, r)\} represents the scoring set of all users, then each element (u, i, r) represents a scoring record, which represents the user's rating r of movie i. The details are shown in Table 1.

| Movie 1 | Movie 2 | Movie 3 | Movie 4 | Movie 5 |
|---------|---------|---------|---------|---------|
| User A  | 5       | -       | 2       | 4       | -       |
| User B  | 2       | 4       | -       | 3       | -       |
| User C  | 3       | -       | -       | 3       | -       |
| User D  | 4       | 2       | 3       | 2       | -       |
| User E  | 1       | 1       | 4       | 4       | -       |

The user's rating information of all movies is taken as the user's rating vector, which is input into the auto-encoder in turn for reconstruction, and the hidden potential preferences of each user can be obtained. The reconstruction process is shown in Figure 1.

The red mark in the input vector of the auto-encoder is the Unrated movie. Because the preference of users' UN rated movies is unknown, a mask vector is designed in order to avoid interfering with the calculation of users' potential preference in practice. The length of mask vector is the same as that of user rating vector. The items that users rated excessively are set to 1, and the items that are not rated are set to 0. The back-propagation error of each output neuron will be multiplied by the mask of the corresponding input position, which eliminates the interference of the user's unsatisfied item error on the network.
2.2. Preference characteristics of fusion trust users

In order to effectively simulate the influence mechanism of friend users, two auto-encoders are used to learn the rating data of users and friend users respectively, and the low dimensional preferences of users and their friend users are obtained. The two hidden layers of automatic encoders are cascaded to balance the importance of hidden layer representation and effectively model the deep interaction of user preferences. Cascade auto encoder can mine the potential preferences of target users from additional social information, and then improve the recommendation performance.

Let $R_u$ denote the rating data of target user $u$, $S_u$ denote the set of trusted users of user $u$, $N_u$ denote the number of trusted users of user $u$, and $T$ denote the data of user trust value obtained from social trust network, which are usually two values of 0 and 1, then the rating data of trusted users is given by the following formula:

$$R_u = \frac{\sum_{i \in S_u} R_{iT}}{N_u} \tag{1}$$

Using the above formula, social network information can be transformed into more dense score vector, which is convenient for neural network to learn characteristics. All the user preferences in the target user's trust list can reflect part of the target user's preferences to a certain extent. In order to improve the target user's score prediction accuracy through the influence of the trusted user, the potential influence of the trusted user on the target user is modeled through the feature weighted fusion of two auto encoder hidden layers. The specific model is shown in Figure 2. The model consists of two stages: encoding and decoding. The input data is de-noised before encoding.

![Figure 2. model structure diagram of integrating trust user preferences](image.png)

In the coding stage, in order to extract the potential features of target users and trusted users, the target users and trusted users' rating data are first processed with noise to get the noisy data. Then, the coding layer is used to map the input of target user rating and friend user rating to low dimensional space, and the coding formula is given

$$h^R_u = f(W^R \tilde{R}_u + a) \tag{2}$$

$$h^X_u = f(W^X \tilde{X}_u + b) \tag{3}$$

Among them, $\tilde{R}_u$ and $\tilde{X}_u$ respectively represent the scoring data of target users and their trusted users after noise processing. $h^R_u$ and $h^X_u$ represent the potential preferences of target users and their trusted users respectively. Parameters $W^R$, $W^X$, $a$ and $b$ are the weight parameters and bias of network coding layer.

In order to further integrate the rating data and potential preferences of trusted users, this paper uses noise reduction self encoder to model the potential impact of trusted users on target users through weighted fusion of hidden layer features.
Let $F$ be the output of weighted hidden layer, which is used to fuse the indirect influence of trust user preference

$$
F_u = \beta h_u^R + (1 - \beta) h_u^X
$$

(4)

Among them, $\beta$ is the weight factor to balance the influence of trust users.

Finally, two decoder layers are used to reconstruct the original input data,

$$
\hat{R}_u = f(W^{\prime R}F_u + a')
$$

(5)

$$
\hat{X}_u = f(W^{\prime X}F_u + b')
$$

(6)

Among them, $\hat{R}_u$ and $\hat{X}_u$ are the prediction values of user $u$ score data and its trust user score respectively, and the parameters $W^{\prime R}, W^{\prime X}, a', b'$ are the weight parameters and bias of the decoding layer.

By using the above formula, the decoder layer reconstructs the representation of low dimensional space into input, and automatically fills in the missing values. $u$ refers specifically to a user. The final objective function is defined as:

$$
L = l(R, \hat{R}) + l(X, \hat{X}) + \Omega(W^R, W^X, W^{\prime R}, W^{\prime X}, a, b, a', b')
$$

(7)

In this paper, $l(*)$ mean square error (MSE) is used to represent the network loss function, $N$ is used to represent the number of matrix elements, and l2 normal form is used

$$
l(R, \hat{R}) = \frac{1}{N} \sum_{i=1}^{N} \left\| R_i - \hat{R}_i \right\|^2
$$

(8)

2.3. Formatting author affiliations

DAE to the randomness of the noise, it is difficult to guarantee all the characteristics of the original data. Therefore, this paper constructs a cascaded de-noising auto encoder model (SDAE). SDAE is similar to the DAE model, but different from the DAE model, by increasing the number of hidden layers, the proposed cascaded noise reduction auto encoder is formed. In SDAE model, the output of the previous hidden layer is taken as the input of the next layer. In this way, each layer is treated as a simple auto decoder for pre training, and then stacked, and the training efficiency will be greatly improved. The flow of recommendation algorithm based on SDAE model is as follows:

Step 1: Feature learning is performed on the film scoring matrix, and the corresponding predicted values are filled into the original matrix to form a new scoring matrix.

Step 2: Combines the new target user rating matrix with the trust user rating matrix as the input of the de-noising self encoder for training.

Step 3: Judge whether the training result has the best trust user influence weight. If not, adjust the trust user influence weight and return to step 2. If so, form a preliminary score prediction and go to step 4.

Step 4: Input the initial score prediction into the stack de-noising auto encoder (SDAE).

Step 5: According to the greedy training layer by layer, the cascaded self encoder is trained, and the relevant parameters of the model are obtained by continuously optimizing the loss function.

Step 6: According to the trained model, reconstruct the score matrix on the training set to get the score prediction value.

Step 7: Compares the predicted score with the original score and calculates the mean absolute error (MAE) and root mean square error (RMSE).

3. Experiment and result analysis

3.1. Evaluating indicator

The evaluation standard used in this paper is prediction accuracy, which is also the most important evaluation index of recommendation system. The smaller the value of mean absolute error (MAE) and
root mean square error (RMSE), the closer the evaluation score is to the actual score, and the more accurate the prediction result is. The formula is as follows:

\[ MAE = \frac{1}{N} \sum_{i=1}^{N} |r_i - \hat{r}_i| \quad (9) \]

\[ RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (r_i - \hat{r}_i)^2} \quad (10) \]

Where \( r_i \) is the actual score of movie \( i \) given by the target user, \( \hat{r}_i \) is the prediction score given by the recommendation algorithm, and \( N \) is the number of samples in the test set. The lower the MAE, the more accurate the prediction is. RMSE increases the penalty for the movie item with wrong prediction, so the evaluation of recommendation algorithm is more strict. By selecting the above two indicators, the experimental results can be evaluated at the standard level and under more stringent conditions.

3.2. Analysis of experimental results

Due to the serious data sparsity problem in the original score matrix, if the cascade de-noising auto encoder recommendation algorithm (SDAE) is directly applied to the original score matrix, the recommendation accuracy will be reduced. Therefore, the original score data is taken as the input of the auto encoder, and a mask vector is designed to multiply the back propagation error of each output neuron. After deep training, the score of the ungraded movie is not only 0, so that the influence of the ungraded movie error on the network is eliminated, and the prediction accuracy of the recommendation is improved.

During the experiment, several representative recommendation algorithms are selected and compared with SDAE algorithm. They are user based collaborative filtering algorithm (U-CF), user based auto encoder recommendation algorithm (U-AE), de-noising auto-encoder recommendation algorithm (DAE) with a hidden layer.

3.2.1. MAE values

Figure 3 shows the comparison of MAE values of SDAE algorithm and other algorithms on movielines-100k data set. It can be seen from the figure that the accuracy of U-CF algorithm in predicting scoring is lower, which may be due to less scoring items in user movie scoring matrix. The other algorithms all use auto encoder and deep learning technology. At the same time, the prediction accuracy of de-noising auto encoding (DAE) is lower than that of U-AE. This is because the data scale is relatively small and the original data is damaged after adding noise. As a result, the less obvious features in the data are not trained and extracted, and the robustness of the model is not strong enough. SDAE model has more hidden layers, so it can learn deeper features.

3.2.2. RMSE values

Figure 4 shows the comparison of the RMSE values of SDAE algorithm and other algorithms on movielines-100k data set. The right figure shows that the RMSE value of U-CF is the largest and the prediction accuracy is poor. In addition, the RMSE values of several other algorithms have little
difference, which indicates that the prediction accuracy can not be significantly improved when the data dimension is low. Although the prediction accuracy of SDAE has been improved, it is not obvious.

As can be seen from figure 8, with the increase of data size, the MAE values of various algorithms have decreased significantly, which indicates that expanding the data set to a certain extent can improve the accuracy of algorithm recommendation. Compared with other algorithms, the recommendation accuracy of U-CF algorithm is the lowest, but with the expansion of the data set, DAE algorithm is significantly better than U-AE algorithm, which indicates that the addition of noise enhances the robustness of the algorithm and achieves certain results. SDAE algorithm still has the highest recommendation accuracy compared with other algorithms.

As can be seen from Figure 6, the recommendation accuracy of u-ae algorithm is almost the same as that of DAE algorithm, but the advantage of noise addition is obvious, and SDAE algorithm still has the highest recommendation accuracy.

4. Conclusion
Aiming at the problem of low recommendation accuracy of DAE model, this paper introduces auto encoder in the data preprocessing stage to conduct deep training of user preferences; through the combination of two de-noising auto encoders, the preference information of learning features is trained and learned from the data of target users and trusted users. In addition, in view of the problem that the data characteristics are affected by the process of adding noise in the DAE model, this paper uses the stack de-noising auto-encoder model for multiple noise reduction. Experimental results show that the algorithm is effective. With the continuous research and development of recommendation system, more and more extra information will be integrated into the recommendation model to further improve the accuracy of recommendation.

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