

RESEARCH ARTICLE

Dual Auto-Encoder Based Rating Prediction Recommendation Algorithm

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ABSTRACT Collaborative filtering is the most widely used method in recommendation algorithms, but it still faces the serious problem of data sparsity. Traditional collaborative filtering uses matrix decomposition to learn the latent features of users and items. As an extension model of matrix decomposition, Funk-SVD model has attracted wide attention due to its good scalability and easy implementation, but it is difficult to extract the latent features of users and items from sparse rating information because it essentially learns the linear relationship between users and items. To solve this problem, we propose a Dual auto-encoder based Rating Prediction Recommendation Algorithm (DRPRA) model. The DRPRA model uses the strong ability of deep learning in feature learning, which combines double auto-encoders with Funk-SVD. First, the auto-encoder captures the latent features of users and items respectively. Then, the Funk-SVD combines the user features with item features to reconstruct the rating matrix. After that, we minimize the error between original rating matrix and reconstructed rating matrix, and to alleviate the problem of data sparsity and improve the accuracy of rating prediction effectively. We conducted extensive experiments on Movielens-100K, Movie Tweeting-10k, and Film Trust datasets, and the results show that the rating prediction model based on dual auto-encoders has a superior recommendation performance.

INDEX TERMS Recommendation algorithm, auto-encoder, Funk-SVD, sparsity.

I. INTRODUCTION

Nowadays, the exponential growth of information on the Internet has created the problem of information overload, which makes it difficult for users to obtain valuable information from the mass of content. Recommendation algorithms mine the user's historical interaction with the item, predict the user's preference for the item, and then recommend the content that the target users may be interested in, and to alleviating the information overloading [1].

The most widely used recommendation algorithm is collaborative filtering (CF). In general, CF can be divided into three types: user-based, item-based and model-based [2]. User-based CF assumes that similar users have the same

preferences, so they may be interested in the same item. By calculating the similarity between users, the historical data of similar with high similarity to target users are used for prediction [3]. Item-based CF is based on the similarity between items and determines the similar items of historical items according to the historical ratings, and recommends the items with high similarity to target users [4]. Model-based CF relies on matrix factorization (MF), Funk-SVD and other machine learning models, uses existing sparse data to predict missing user-item ratings, and recommends the items with the highest predicted ratings to users [5]. Funk-SVD learns the linear relationship between users and items. In fact, the relationship between users and items is complex and non-linear, so it is difficult for Funk-SVD to capture the complex interaction relationship between users and items.

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Collaborative filtering has a good recommendation effect to some extent, but it has limitations in dealing with sparse data. To alleviate the problem of low accuracy caused by sparse data in rating prediction, some deep learning methods such as MLP [6], CNN [7], [8], RNN [9], [10] GAN [11], [12] and AE [13], [14] have been applied to recommendation systems due to their advantages in feature learning. Based on the above, we propose a rating prediction model combined with dual auto-encoder (DRPRA). The DRPRA model integrates rating, user attributes and item attributes, which enriches the feature space and alleviating the problem of low rating prediction accuracy caused by sparse data. Dong *et al.* [15] proposed the HCRDa model which combines MF with deep learning model for rating prediction. HCRDa model combines the latent features of users and items with MF to reconstruct the rating matrix, but the reconstructed rating matrix may not conform to the original rating matrix, which affects the accuracy of rating prediction.

To solve these problems, we propose a rating prediction recommendation algorithm with dual auto-encoders, which integrates the rating and user-item attribute features. Dual auto-encoders capture the latent features of users and items respectively. The Funk-SVD is used to reconstruct the rating matrix to predict the missing values in the original rating matrix. The error between the reconstructed rating matrix and the original rating matrix is minimized to ensure the accuracy of rating prediction. The advantages of deep learning in feature learning and the enhanced attribute features of users and items overcome the defects of sparse data processing by MF and improve the accuracy of rating prediction. We conducted extensive experiments on three real datasets, and the results show that the DRPRA model has better performance than other methods. The contributions of this paper are as follows:

- We propose a DRPRA model, which integrates the rating and user-item attributes, further expands the feature space, alleviates the problem of data sparsity and improves the accuracy of recommendation.
- The powerful feature learning capability of the auto-encoder can fully learn the latent features of users and items, and the introducing of Funk-SVD makes the reconstructed prediction rating matrix fit better with the original rating matrix, which improves the accuracy of rating prediction.
- The DRPRA model has been extensively tested on Movielens-100K, Movie Tweetings-10k and Film Trust datasets, and the results show that the DRPRA model is superior to other methods in rating prediction.

The remainder of this article is as follows. In section 2, we describe how researchers have gone about mitigating the data sparsity problem, and the application of self-encoders to recommender systems. In section 3, we first defined the problem and then focused on the DRPRA model, which includes the overall structure of the model, the design of the loss function, etc. In section 4, the details of the experiments,

the results of the experiments, and the analysis of the results are presented. In section 5, we summarize the whole paper and elaborate on some issues that need to be addressed in the future.

II. RELATED WORK

Excellent recommendation algorithms can help users find items of their interest among numerous items, and therefore, the research on recommendation algorithms is of great importance. We introduce the work related to the research of recommendation algorithms.

A. APPLICATION OF AUXILIARY INFORMATION IN RECOMMENDATION ALGORITHM

Nowadays, to solve the problem of low accuracy of rating prediction in recommendation algorithms, researchers have added user and item features as auxiliary information in the matrix decomposition, such as age and gender of users; item production year and attributes of items, etc., and obtained good rating prediction results. Moradi *et al.* integrate cooperation relationships contained in social networks into the matrix co-decomposition model to improve the prediction accuracy [16]; Yorke-Smith *et al.* add ratings as the main factor into the matrix co-decomposition model [17]; Bostanci *et al.* use the method of calculating user-item ratings into the matrix co-decomposition model. The method of calculating and quantifying the similarity values of different users is proposed to weight the identification of multiple neighboring users, and the identified and calculated neighboring users are applied to the rating prediction task of the matrix decomposition model [18]; Al-Shamri *et al.* argue that an unknown user rating value can be directly predicted without finding and weighting similar users [19]. The above models introduce objective features of users or items as auxiliary information and search for possible associations between users based on objective features, which improves the rating prediction accuracy. PKER [20] introduces knowledge graphs for item representation and feeds them as auxiliary information into an extensible self-encoder to alleviate the data sparsity problem; Agrec [21] treats the rating matrix as a graph and extracts graphical features of items as higher-level feature representations to improve recommendation accuracy; GraphRec [22] uses user-item symbiotic graphs (bipartite graphs) to construct generic user and item attributes that do not require external information to alleviate the sparsity problem and obtain higher recommendation results. This graph does not require external information to alleviate the sparsity problem and obtain higher recommendation results; CAPR [23] uses autoencoders with graph regularization to extract user features to construct higher-level features to obtain better user-item interaction features.

In this paper, we also use dual autoencoders to extract user item features for recommendation, but we introduce more important user item attributes, such as user zip code (which contains the user's geographic information), item name, and

item topic (an important attribute to analyze the degree of association between items). The introduction of more important attributes can further extract user item features to obtain better user item features and eventually find quality user item interaction features to recommend more interesting items to users.

B. APPLICATION OF DEEP LEARNING IN RECOMMENDATION ALGORITHM

Since traditional collaborative filtering cannot extract non-linear features, deep learning shows strong performance in feature learning. Therefore, we apply deep learning to recommendation algorithm to improve the accuracy of rating prediction of recommendation algorithm. Sedhain *et al.* [24] combined auto-encoders with collaborative filtering recommendation and proposed the AutoRec model, which utilizes a single-layer hidden auto-encoder to encode and decode the rating matrix and reconstruct the user's predicted ratings of items, which is the first combination of auto-encoder and recommendation system; Wang *et al.* [25] proposed CDL to extract potential features of items from text information using stacked noise reduction auto-encoder and combined with PMF for recommendation, which solved the problem of low recommendation accuracy of rating prediction algorithm when data is sparse; Subsequently, Wu *et al.* [26] proposed to recommend items to users using RNN and applied it to NetEase with good results; subsequently, Zhang *et al.* [27] proposed an semi auto-encoder based HRSA model that introduces exploit auxiliary information for rating prediction and Top-k recommendation; Zhu *et al.* [28] proposed exploit dual auto-encoders in recommendation algorithms, employing dual auto-encoders for multi-label feature learning, which achieves robust global feature learning by concatenating two different types of auto-encoders to obtain different features from the data; Wu *et al.* [29] proposed the CDAE algorithm to solve the Top-k recommendation problem, which is similar to the model structure of AutoRec, but the key difference is that CDAE introduces a user feature for each user to improve the recommendation effect. Zhuang *et al.* [30] proposed to use dual auto-encoders to learn the potential feature information of users and items separately, and then obtain the prediction values by the inner product of the potential feature vectors of users and items to improve the recommendation effect.

III. DRPRA MODEL

A. PROBLEM DEFINITION

In this section, before presenting the proposed dual auto-encoder based rating prediction recommendation algorithm, introduce the rating prediction problem and the commonly used parameters.

Given M users and N items, $R \in \mathbb{R}^{M \times N}$ represents the rating matrix, $r^{ui} \in R$ as the rating of user $u \in \{1, \dots, M\}$ for item $i \in \{1, \dots, N\}$, $r^u \in \{R_{u1}, \dots, R_{uN}\} \in \mathbb{R}^N$ as the user's rating vector, and the overall rating vector of all

M users is denoted as $R^U \in \mathbb{R}^{M \times N}$; the item rating vector is denoted as $r^i \in \{R_{1i}, \dots, R_{Mi}\} \in \mathbb{R}^M$, and the overall rating vector of all the overall rating vector of N items is denoted as $R^I \in \mathbb{R}^{M \times N}$; Each user and item has unique attribute features, such as the time of movie release, the time and type of song composition; the age and occupation of the user, etc. We take full account of the user and item attribute features by one-hot coding them. The attribute feature vector of item i is denoted as $A^I \in \mathbb{R}^{W \times N}$, and the attribute feature vector of user u is denoted as $A^U \in \mathbb{R}^{M \times Y}$.

To refer to the auxiliary feature information, we fuse the overall item rating vector R^I with the attribute feature vector A^I of the item as the input of an auto-encoder to learn the latent features of item i . The overall user rating vector R^U is fused with the user's attribute feature vector A^U as the input of another auto-encoder to learn the latent features of user u . The fusion of the overall item rating vector and the item attribute feature vector as the overall feature vector of the item is defined as $cat(R^I; A^I)$; the fusion of the overall user rating vector and the user attribute feature vector as the overall feature vector of the user is defined as $cat(R^U; A^U)$. As shown in Eq.(1) and Ep.(2):

$$cat(R^I; A^I) = \text{concatenation of } R^I \text{ and } A^I \quad (1)$$

$$cat(R^U; A^U) = \text{concatenation of } R^U \text{ and } A^U \quad (2)$$

B. THE PROPOSED DRPRA MODEL

In recent years, as deep learning has demonstrated powerful performance in feature learning, MLP, CNN, RNN, and AE have been applied to recommendation algorithms, etc. To further alleviate the data sparsity problem and improve the accuracy of recommendation algorithms when performing rating prediction tasks, we designed Dual auto-encoder based Rating Prediction Recommendation Algorithm framework is shown in Figure 1. we utilize auto-encoders to learn potential features of both users and items, and minimize the bias of the training data through the user and item representations learned by FUNK-SVD.

We combine the overall rating vector R^I of items with the item attribute feature vector A^I as the input to the auto-encoder to learn the implicit special of item i . We denote $cat(R^I; A^I) \in \mathbb{R}^{(M+W) \times N}$ as the item features of R^I and A^I in series, where R^I denotes the rating vector of all N items and A^I denotes the attribute feature vector of the items. Using $cat(R^I; A^I)$ as the input to the auto-encoder, the implicit features of the learned items are denoted p_i . The purpose of the auto-encoder is to approximate the initial input, where we use the auto-encoder to make the output approximate the rating part of the input, while extracting the implicit features of the items p_i . The loss function of this part, as well as the encoding and decoding are shown in Eq.(3) Eq.(4) and Eq.(5) are shown.

$$p_i = g \left(cat(R^I, A^I)^T \cdot Q_i + b_i \right) \quad (3)$$

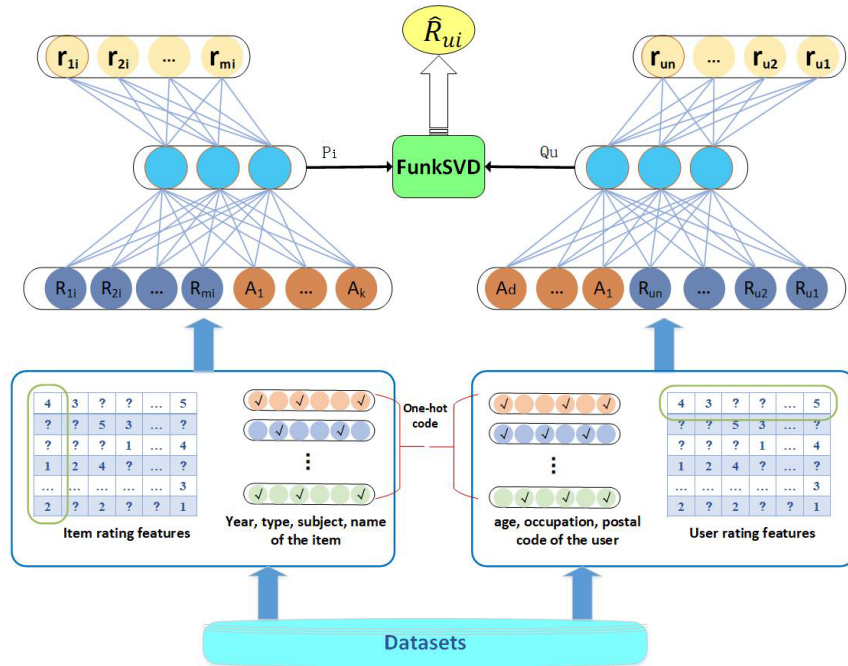


FIGURE 1. The above figure shows the Dual auto-encoder based rating prediction recommendation algorithm.

$$\hat{R}_i = f(p_i \cdot Q'_i + b'_i) \quad (4)$$

$$\mathcal{L}_i = \underset{Q_i, Q'_i, b_i, b'_i, r^{ui}}{\arg \min} \|R_i - \hat{R}_i\|^2 \quad (5)$$

In the above equation, $Q_i \in R^{(M+W) \times H}$ and $Q'_i \in R^{H \times M}$ are used as the weight matrix, $b_i \in R^H$ and $b'_i \in R^M$ are the bias term, $g(\cdot)$ and $f(\cdot)$ are the activation functions, where the activation function $g(\cdot)$ uses Sigmoid and $f(\cdot)$ uses Identity.

Here, the overall rating vector R^U of the item is combined with the user attribute feature vector A^U as the input of the auto-encoder to learn the latent features of user u . The $cat(R^U; A^U) \in R^{M \times (N+Y)}$ is represented as the user features of R^U and A^U in series, where R^U denotes the rating vector of all M users, and A^U denotes the attribute feature vector of users. Using $cat(R^U; A^U)$ as the auto-encoder input, the potential features of the user q_u are learned. the purpose of the auto-encoder is to approximate the original input, and we use the auto-encoder to make the output approximate the rating part of the input, extracting the user implicit features q_u . The loss function of this part, as well as the encoding and decoding, is as in Eq.(6) Eq.(7) and Eq.(8) are shown.

$$q_u = g(cat(R^U, A^U) \cdot Q_i + b_u) \quad (6)$$

$$\hat{R}_u = f(q_u \cdot Q'_u + b'_u) \quad (7)$$

$$\mathcal{L}_u = \underset{Q_u, Q'_u, b_u, b'_u, r^{ui}}{\arg \min} \|R_u - \hat{R}_u\|^2 \quad (8)$$

Above equation, $Q_u \in R^{(N+Y) \times H}$ and $Q'_u \in R^{H \times N}$ are used as the weight matrix, $b_u \in R^H$ and $b'_u \in R^N$ are the bias term, $g(\cdot)$ and $f(\cdot)$ are the activation functions, where the activation function $g(\cdot)$ uses Sigmoid and $f(\cdot)$ uses Identity.

Algorithm 1 DRPRA

Require: The rating matrix $R \in R^{M \times N}$, the number of hidden neurons h , and the dimension of user and item attribute vector.

Ensure: The prediction matrix $\hat{R}_{ui} = q_u^T \cdot p_i$
 1: Get the attribute information vector a_u for each user;
 2: Get the attribute information vector a_i for each item;
 3: Get the splicing vectors (R^U, A^U) and (R^I, A^I) of the attribute vectors of the users and the items and the corresponding rating vectors;
 4: Initialize Q_u, Q'_u, Q_i, Q'_i by truncating a normal-distributed random number, and set p_i, q_u to 0 vectors.
 5: Input $(R^U, A^U), (R^I, A^I)$ to two semi-autoencoders;
 6: Minimize Eq. (11) using a stochastic gradient descent algorithm until the algorithm converges;
return $\hat{R}_{ui} = q_u^T \cdot p_i$

Here, the potential features of users and items are obtained separately using auto-encoder, and the high-dimensional sparse data are mapped to the low-dimensional potential space by the auto-encoder model, and the prediction rating matrix $q_u^T \cdot p_i$ is reconstructed in the low-dimensional space

using the potential features of users and items using the Funk-SVD technique, so that the final prediction matrix $q_u^T \cdot p_i$ has the lowest deviation from the original rating matrix, where the loss function is shown in Eq.(9)

$$\mathcal{L}_F = \left\| R_{ui} - \hat{R}_{ui} \right\|^2 + \gamma \left(\|p_i\|^2 + \|q_u\|^2 \right) \quad (9)$$

The overfitting problem is a common problem in the training process of recommendation algorithm models, and to avoid this problem, we introduce the regularization term of the auto-encoder weight matrix. As shown in Eq.(10).

$$\mathcal{L}_{norm} = \|Q_i\|^2 + \|Q'_i\|^2 + \|Q_u\|^2 + \|Q'_u\|^2 \quad (10)$$

From this we obtain the loss function of the DRPRA model, as shown in Eq.(11).

$$\mathcal{L} = \mathcal{L}_F + \alpha \cdot \mathcal{L}_i + \beta \cdot \mathcal{L}_u + \gamma \cdot \mathcal{L}_{norm} \quad (11)$$

Considering the problem of model overfitting, and utilize the regularization term of the weight matrix here and regularize the weight matrix to ℓ_2 parametric as the fourth term of the objective function, α , β , γ as the weight parameters. Among them, α and β are used as the weight parameters of the auto-encoder to learn potential features to control the importance of potential features of users and items, and when the value is larger, it indicates that we pay more attention to the learning of the auto-encoder; γ is used as the weight parameter of the regularization term to avoid overfitting of the model. In this algorithm, we use the auto-encoder to learn both user and item potential features, and we can also use SGD to training the parameters and optimize the objective function. When the model converges, the predictive rating matrix \hat{R}_{ui} is obtained, as shown in Eq.(12). The pseudo code for this article is shown in Algorithm 1.

$$\hat{R}_{ui} = q_u^T \cdot p_i \quad (12)$$

IV. EXPERIMENT

In this section, the proposed Dual auto-encoder based Rating Prediction Recommendation Algorithm is experimented on three real datasets and compared with other algorithms to verify recommendation effect of the DRPRA model. Here we use three datasets, MovieLens-100K, Movie Tweetings-10K, and Film Trust, which have different sparsity, so that we can analyze the accuracy of the algorithm under different evaluation metrics in the face of datasets with different sparsity. We first present specific information on the dataset and evaluation metrics, and secondly analyze the experimental comparison of the DRPRA algorithm with other algorithms on different datasets.

A. DATASET AND EVALUATION INDICATORS

1) DATASETS

We used three datasets with different sparsity, MovieLens-100K, Movie Tweetings-10K and Film Trust. As shown in Table 1, specific information about the dataset is presented in detail. In these datasets, we use not only the

rating matrix of the user's project, but also the user's age, gender, occupation, zip code (which implicitly contains the user's location information), year, type, theme, and name of the project (these are the key factors influencing the user's preferences and play an important role in the training).

TABLE 1. The table shows the statistics for the three datasets.

Dataset	Items	Users	Ratings	Density (%)
MovieLens-100K	1682	943	100000	6.30
Movie Tweetings-10K	123	3096	2233	0.59
Film Trust	2071	1508	35497	1.14

MovieLens-100K includes 100000 ratings for 1682 movies from 943 users. The user data provides demographic data for three domains: gender, age, and occupation; movie data includes movie title and genre; and the rating data includes the user ID of each rating, the movie ID of the rating, and the timestamp, with a rating range of 1 to 5.

The Movie Tweetings-10K dataset is an extremely sparse dataset with ratings ranging from 1 to 10. In the experiments, the dataset we processed to retain users with at least 10 items, and this dataset contains only item attribute information, and without user attribute information.

Film Trust dataset contains 35497 ratings of 2071 movies by 1508 users, with ratings ranging from 0.5 to 4. There are no attribute features of users and items in this dataset, so we exploit rating information in advance, while comparing the proposed algorithm with the trust-based algorithm model.

2) EVALUATION INDICATORS

In recommendation Algorithms, the evaluation criteria of the recommendation algorithm as an important concern in assessing the accuracy of the prediction. The accuracy evaluation criteria measured by the root mean square error (RMSE) and the mean absolute error (MAE), revealing the deviation between the predicted values of the values in the experimental results and the corresponding values in the validation dataset. Thus minimizing the error value and thus making the best prediction performance, which is calculated as shown in Eq.(13) and Eq.(14).

$$RMSE = \sqrt{\frac{\sum_{(u,i) \in R} (R_{u,i} - R'_{u,i})^2}{|R|}} \quad (13)$$

$$MAE = \frac{\sum_{(u,i) \in R} |R_{u,i} - R'_{u,i}|}{|R|} \quad (14)$$

Above formula, $R_{u,i}$ is the global rate matrix, and $R'_{u,i}$ the prediction matrix. Obviously, the values of MAE and RMSE are the smallest and the algorithm recommends the best performance.

B. THE METHOD OF COMPARISON

This section, contrast the DRPRA model with the following baseline methods to verify its recommended accuracy:

NMF [31] Evaluation and prediction based on non-negative matrix decomposition.

PMF [32] Probability matrix Factorization algorithm.

BPMF [33] Probability matrix decomposition of rating prediction.

SVD++ [34] The algorithm uses explicit and implicit feedback data together and supplements the set of item hidden factors over evaluated by users with their hidden factors.

ReDa [30] Based on the representation learning model of double auto-encoders.

HRSA [27] An algorithm for rating prediction and top-k recommendation using semi-auto-encoder.

HCRDa [15] A novel dual auto-encoder to learn user and item features.

TrustMF [35] Matrix decomposition technique based on user ratings and social trust network data.

TrustSVD [36] A trust-based matrix decomposition technique.

C. EXPERIMENTAL RESULTS

We randomly sampled the dataset according to a certain proportion, divided the dataset into train sets and test sets, and repeatedly verified them through multiple experiments, and all the experimental results were conducted five times independently, and the average value was taken as the final experimental results, as shown in Tables 2-4, which are the experimental results of the DRPRA model on Movielens-100K, Movie Tweetings-10K, and Film Trust datasets for comparison respectively.

TABLE 2. The table shows rmse and mae on movielens-100K.

Datasets Metrics	Movielens-100K					
	RMSE			MAE		
	90%	80%	70%	90%	80%	70%
NMF	0.966	0.963	0.962	0.766	0.758	0.760
PMF	0.923	0.932	0.932	0.729	0.733	0.740
BPMF	1.103	1.127	1.153	0.863	0.811	0.904
SVD++	0.924	0.931	0.950	0.722	0.726	0.704
HRSA	0.894	0.897	0.910	0.705	0.707	0.718
HCRDa	0.794	0.865	0.915	0.619	0.676	0.723
DRPRA	0.724	0.807	0.854	0.555	0.623	0.671

TABLE 3. The table shows rmse and mae on movie tweetings-10K.

Datasets Metrics	Movie Tweetings-10K					
	RMSE			MAE		
	90%	80%	70%	90%	80%	70%
NMF	1.724	1.852	1.831	1.237	1.376	1.363
PMF	1.752	1.863	1.894	1.341	1.398	1.426
BPMF	1.710	1.756	1.754	1.289	1.368	1.341
SVD++	1.529	1.621	1.628	1.139	1.226	1.230
HRSA	2.718	2.838	2.848	2.298	2.475	2.462
HCRDa	1.467	1.446	1.556	1.057	1.022	1.183
DRPRA	1.297	1.273	1.343	0.917	0.983	1.034

In the experiments about parameter settings, we set the learning rate to $lr = 1E - 4$, the regularization parameter $\gamma = 0.5$ for three datasets, the number of hidden layer neurons is 512, and the optimization method in this paper

TABLE 4. The table shows RMSE and mae on film trust.

Datasets Metrics	Film Trust					
	RMSE			MAE		
	90%	80%	70%	90%	80%	70%
NMF	0.853	0.859	0.871	0.647	0.648	0.653
PMF	0.922	0.953	0.982	0.694	0.703	0.722
SVD++	0.804	0.801	0.810	0.624	0.615	0.624
TrustMF	0.828	0.827	0.835	0.634	0.631	0.640
TrustSVD	0.764	0.791	0.799	0.618	0.613	0.620
HRSA	0.810	0.831	0.832	0.625	0.632	0.636
HCRDa	0.722	0.791	0.836	0.552	0.602	0.644

TABLE 5. The table shows impact of auxiliary information on MOVIELENS-100K.

Dataset Metric	Movielens-100K					
	RMSE			MAE		
	90%	80%	70%	90%	80%	70%
DRPRA (without feature)	0.813	0.871	0.929	0.637	0.682	0.729
DRPRA-user	0.802	0.860	0.913	0.621	0.673	0.716
DRPRA-item	0.767	0.849	0.904	0.595	0.663	0.706
DRPRA	0.724	0.807	0.854	0.555	0.623	0.671

is a small batch SGD with a batch size of 128. As shown in Figure 2 and Figure 3, we use a histogram to show the experimental results of the data DRPRA algorithm more visually.

Here, we tested the effect of the parameters α , β and γ in Eq.(11) on the dataset by subjecting the dataset to a random sampling at a ratio of 80%. Initially, $\alpha = 0.5$, $\beta = 0.5$ and $\gamma = 1$. Next, we utilized the control variable method to Choose optimal parameters of the model, specifically, all three parameters α, β and γ were sampled from 0.001, 0.005, 0.01, 0.05, 0.1, 0.5, 1, 5 to test one parameter, and the remaining two parameters were kept constant. As shown in Figure 4, we analyse the effects of the parameters α , β , and γ on the dataset.

D. PERFORMANCE ANALYSIS OF DRPRA

From the above experiments and comparisons, the following conclusions are drawn:

- The experiments were carried out on three datasets with different sparsity, in which the deep learning-based algorithms ReDa, HRSA and HCRDa were able to obtain better results than the traditional models, indicating that the deep learning-based models have powerful feature learning ability, and meanwhile, the DRPRA algorithm proposed was able to achieve better results compared with other algorithms.
- The sparsity of Movielens-100K, Film Trust and Movie Tweetings-10K datasets used during the experiment decreases sequentially, and the DRPRA model achieves good results on all three datasets with different sparsity, which also proves that the DRPRA model can solve the problem of poor recommendation accuracy due to data sparsity.
- Since Film Trust does not contain attribute features of users and items, comparing DRPRA with trust-based

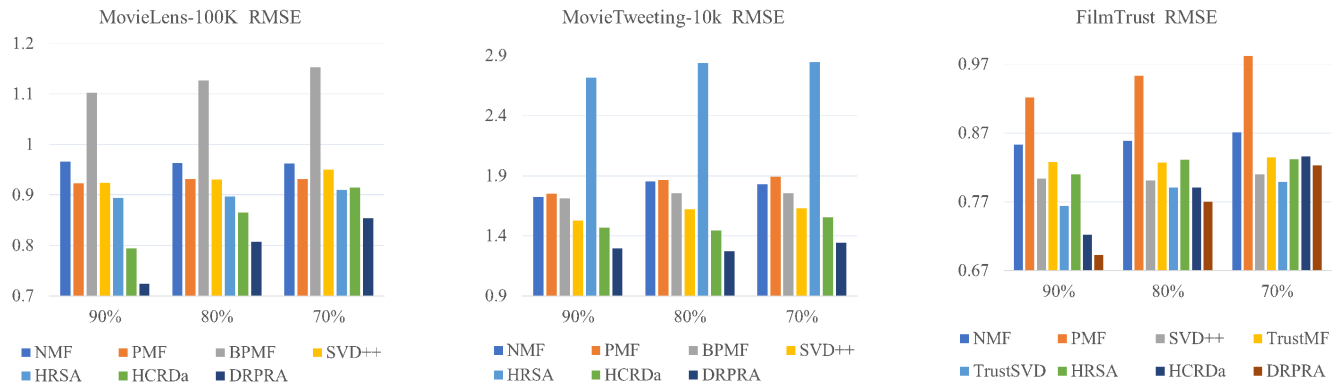


FIGURE 2. Which shows the RMSE at Moviелens-100K, movie tweetings-10K and film trust.

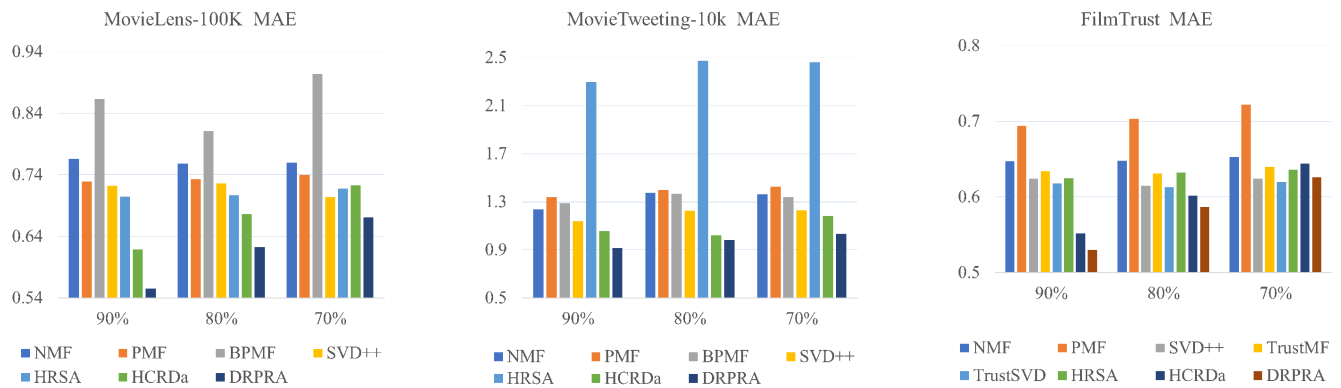


FIGURE 3. Which shows the mae at movielens-100K, movie tweetings-10k and film trust.

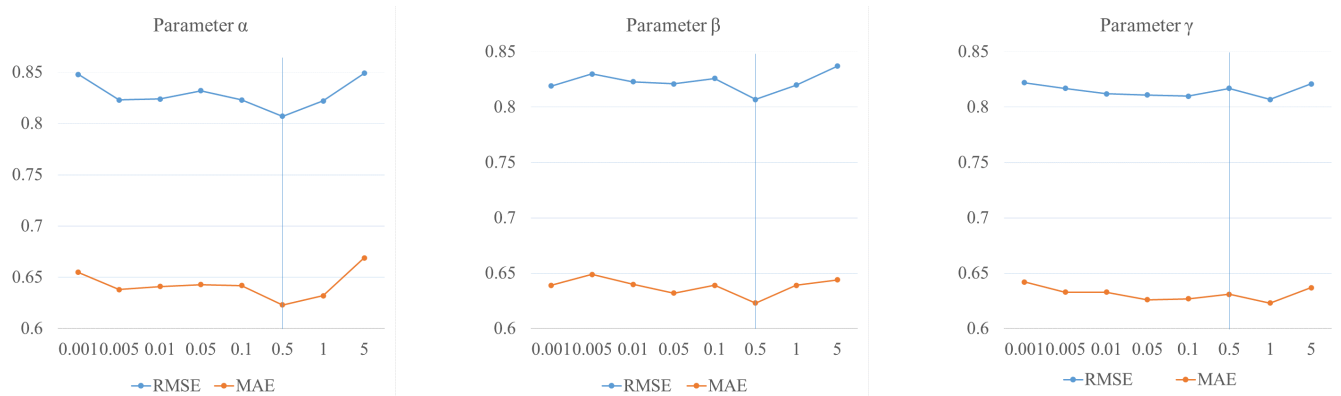


FIGURE 4. Which shows the the impact of parameter.

collaborative recommendation algorithms, DRPRA is less effective compared with the traditional trust-based model TrustMF and TrustSVD when the percentage of training set in the dataset is low, which may be due to the fact that deep learning models require massive data to enrich the training of the models.

- As shown in Table5, we compare the addition of auxiliary information with and without the addition of

auxiliary information. The experimental results show that DRPRA can achieve better results when auxiliary information is utilized, indicating that utilizing user and item attribute features as auxiliary information to the model can alleviate the data sparsity problem and improve the recommendation performance of the algorithm. Since only Moviелens-100K contains both user and item attribute features in the three datasets,

the comparison experiments are conducted on the Movielens-100K dataset only.

- Overall, the comparison experiments demonstrate that the recommendation performance of the DRPRA model outperforms other algorithms.

V. CONCLUSION

In this paper, we review the collaborative filtering-based rating prediction recommendation algorithm, and provide a detailed introduction to the traditional collaborative filtering recommendation algorithm and deep learning-based recommendation algorithm in recommendation systems, and then propose a dual auto-encoder based rating prediction recommendation algorithm, where the attribute features of users and items are fused with the rating features, and the low-dimensional nonlinearities of users and items are extracted by the auto-encoder respectively features, and in addition, we introduce the Funk-SVD model in the objective function to minimize the difference between the reconstructed rating matrix and the original rating matrix. This not only solves the problem that the traditional collaborative filtering algorithm cannot extract the potential features of users and items well, but also solves the problem of low recommendation accuracy due to sparse data to a certain extent, so that the performance of the recommendation algorithm can be improved. We have conducted rich experiments on Movielens-100K, Movie Tweetings-10K and Film Trust datasets, and found that the DRPRA model can achieve better effect through comparison experiments. Next step, we can utilize multiple dimensions of evaluation metrics, such as prediction accuracy, item recall, and other evaluation metrics in the subsequent research.

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