Book Recommendation Algorithm Based on Deep Learning

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Abstract

Research on book recommendation algorithms based on deep learning, in order to achieve better book recommendation results. This paper introduces the principle of user-based collaborative filtering recommendation algorithm, reveals the data sparse problem of traditional collaborative filtering recommendation algorithm, combines deep learning algorithm with matrix factorization, and proposes a new book recommendation algorithm to improve the experiment through actual book dataset. The algorithm alleviates the problem of data sparseness and improves the efficiency of book recommendation.

Keywords

Book recommendation, Matrix factorization, Deep learning.

1. Introduction

With the rapid growth of information, the problem of information overload is becoming more and more significant. The recommendation system is an important method to solve this problem, which can help users find information that can be effectively utilized from a large amount of data, thereby alleviating the problem of information overload. Today, most online services, such as e-commerce and social networking sites, use a recommendation engine to display items of interest to their users. According to[1], 60% of YouTube's video playback comes from its homepage recommendation, and 80% of Netflix's user views come from its recommendation system. In addition, the recommendation system adds 35% of profits to Amazon. Therefore, research in this field is very important, it is the key to some enterprises to effectively serve users and increase user satisfaction.

The traditional recommendation algorithms are divided into three types: content-based recommendation [2] and collaborative filtering-based recommendation[3] and hybrid recommendation [4]. The content-based recommendation is for a given user A, based on the set of items I like before A, to find an item with a certain similarity to the content of the set I, and then recommend it to A. This algorithm only requires historical preference information of User A and similarity information between Set I, Project, and the like. Recommendations based on collaborative filtering are based on the user's past recommendations for explicit or implicit behavior of the item. As matrix factorization (MF)[5] and SVD++[6] in the model-based collaborative filtering algorithm shine in the Netflix Prize recommendation system competition, matrix factorization methods are increasingly favored. The hidden features of the user or item are discovered by the implicit semantic model (LFM)[5], which can better explain the rating in the user-item rating matrix. However, it is not difficult to find that the matrix factorization essentially approximates the original matrix by one factorization. The level of feature mining is not deep enough, and the content information of the articles is not used, such as the category classification of books and the genre classification of music. The recommendation is not good when faced with sparse data. The hybrid recommendation algorithm combines collaborative filtering and content-based methods to take advantage of the long complements to solve the problem of the proposed algorithm model. However, this approach makes the complexity of the model larger.

For the above problems, this paper proposes a book recommendation model based on deep learning. The user-book rating matrix is input into the deep structure learning framework proposed in this paper, and the low-dimensional vector space representation of users and books is obtained respectively, and the inner product interaction is used to obtain the prediction rating. The experimental results on the actual data set show that the model can accurately predict the book rating.

2. Book Recommendation Model

The book recommendation algorithm based on deep learning proposed in this paper will be elaborated in this section. The model uses a neural network to process the user-book rating matrix to solve the sparse problem of the rating matrix. The rating matrix is input into the depth matrix factorization structure constructed in this paper to learn the hidden features of the user and the book hidden, so that the potential features learned can be used to approximate the rating of each user.

2.1 Deep matrix factorization

The rating matrix $X \in R^{m \times n}$ is used as the input of the deep neural network, and the deep user and book hidden features are learned through the network, and the high-dimensional vector space of the user and the book is mapped to the low-dimensional vector space. Figure 1 shows the model architecture presented in this paper.

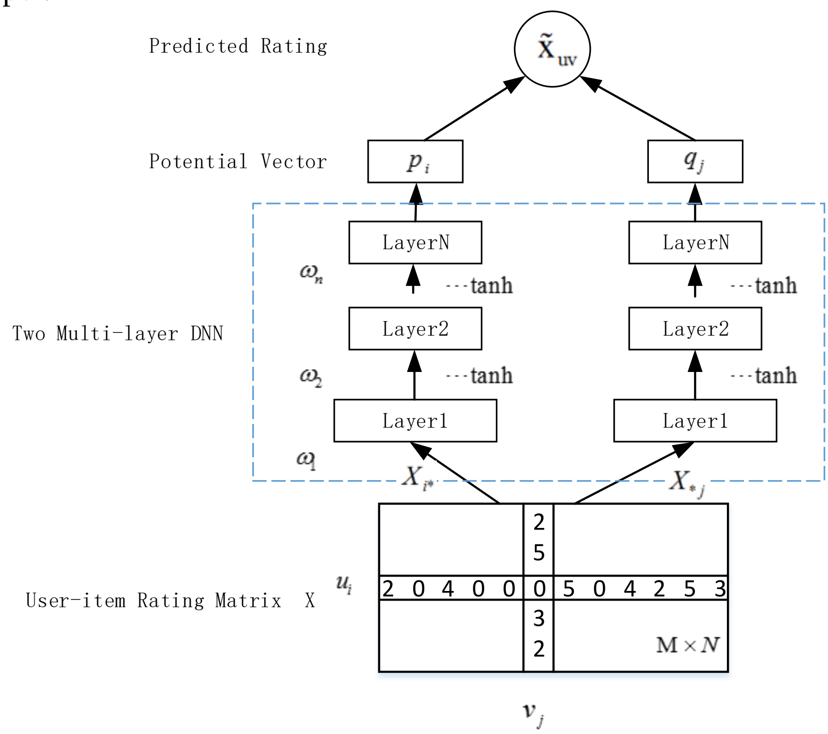

Fig. 1 Deep matrix factorization model architecture

The matrix X represents the user-book rating matrix, and x_{uv} represents the user u's rating of the book v. X_{i*} represents a high-dimensional vector of a user u_i, and X_{*j} represents a high-dimensional vector of a book v_j.

$$l_1 = \omega_1 x \tag{1}$$

$$l_i = f(\omega_{i-1} l_{i-1} + b_i), i = 2, \cdots, n-1 \tag{2}$$

$$h = f(\omega_n l_{n-1} + b_n) \tag{3}$$

l_i denotes the hidden layer, i = 1, …, n-1, ω_i denotes the i-th weight matrix, b_i denotes the i-th bias term, and h denotes the low-dimensional vector of the final output of the network. The tanh function is selected as the nonlinear activation function in the hidden layer and the output layer.

The model uses two multi-layer neural network networks to convert user and book representations, respectively. Through the neural network, the user u_i and the book v_j are finally mapped to low-dimensional vectors in the potential space, as shown in equations (4) and (5).

$$p_i = f_{\theta_n^u}(\cdots f_{\theta_3^u}(\omega_{u2} f_{\theta_2^u}(X_{i*}\omega_{u1}))\cdots) \tag{4}$$

$$q_j = f_{\theta_n^i}(\cdots f_{\theta_3^i}(\omega_{i2} f_{\theta_2^u}(X_{*j}^T\omega_{v1}))\cdots) \tag{5}$$

The predicted rating $\tilde{x}_{uv}$ is obtained by the vector inner product.

$$\tilde{x}_{uv} = \sum_f p_{if} q_{jf} \tag{6}$$

2.2 Model learning

For many recommended algorithm models, in order to further improve the model parameters, the objective function is generally constructed using a loss function such as point-wise loss or pair-wise loss. In this paper, use the point-by-point loss function:

$$L_{reg} = \sum_{(u,v)\in X} (\tilde{x}_{uv} - x_{uv})^2 \tag{7}$$

The value of the rating of the book v by the user u is actually expressed in the equation (7). $\tilde{x}_{uv}$ represents the rating predicted by the depth matrix factorization model.

In the TensorFlow framework, the loss function is optimized in the process of training the neural network model using a small batch gradient descent algorithm. In the optimization process of the model, regularization methods are often used to help prevent the model from over-fitting and improve the generalization ability of the model. In the model presented in this paper, L2 regularization avoids the occurrence of overfitting.

3. Experimental Data Processing and Result Analysis

Perform a number of experiments on actual book data sets to evaluate models using the latest methods. The experiment was implemented in Python under the deep learning Tenserflow framework developed by Google. This section first describes the data sets and evaluation metrics used for the experimental evaluation, and then compares the different matrix factorization methods to define the experimental setup and results analysis.

3.1 Dataset

Goodbooks-10k: The book rating data set contains 6 million ratings for 10,000 of the most popular (most rated) books. Also: books that are marked for reading by the user, book metadata (author, year, etc.), label/shelf/genre. It also ratings from 1-5 with a sparsity of 98.88%, and the data set is relatively sparse. As shown in Table 1.

Table 1 Three Scheme comparing

Data set	User number	Book number	Rating
goodbooks-10k	53424	10000	5976479

The experiment randomly divided the data set into an 80% training set and a 10% validation set and a 10% test set. To properly evaluate the experimental results, the experiment used the same data set to train the model and other recent model methods.

3.2 Experimental rating indicator

Mean absolute error (MAE) and root mean square error (RMSE) are commonly used in rating predictions in the recommended field.

$$MAE = \frac{\sum_{(u,v)\in N} |\tilde{x}_{uv} - x_{uv}|}{|N|} \tag{8}$$

$$RMSE = \sqrt{\frac{\sum_{(u,v)\in N} (\tilde{x}_{uv} - x_{uv})^2}{|N|}} \quad (9)$$

The lower the MAE and the lower the RMSE, the better the model predicts the rating and the better the performance. RMSE increases the penalty for predicting unacceptable ratings than MAE, and the system is more rigorous. Therefore, the evaluation index used in this paper is RMSE.

3.3 Different matrix factorization methods

Comparative experiment selection model probability matrix factorization (PMF)[7], collaborative subject regression (CTR)[8] and collaborative deep learning (CDL)[9], and the widely recognized most advanced convolution matrix factorization ConvMF+[10] and The recommended models in this paper are compared.

PMF[7]: The basic rating prediction model, which only uses user rating data as a data source.

CTR[8]: It combines collaborative filtering with topic models for rating prediction. The model uses rating data and ancillary information as a data source.

CDL[9]: It incorporates the deep learning model SDAE to extract textual information features to predict ratings. The model uses rating data and ancillary information as a data source.

ConvMF+[10]: In order to obtain the text information feature, the probability matrix is decomposed into the convolutional neural network. The model uses rating data and ancillary information as a data source.

3.4 Performance comparison

The performance results of the book recommendation model presented in this paper and the other matrix factorization methods mentioned in Section 3.3 are shown in Table 2. The model's RMSE on the dataset is better than PMF, CTR, CDL, and ConvMF+, with significant improvements.

Table 2 Performance comparison results

Model	Goodbooks-10k
PMF	1.4435
CTR	1.3523
CDL	1.2382
ConvMF+	1.2358
PaperModel	1.1426
Promotion	7.54%

The data set is very sparse and will even reach 99%. This data sparseness poses a great challenge to the method of rating prediction by collaborative filtering. It can be observed that the model and other methods in the category do not perform well due to the high sparsity of the data. This paper argues that the user potential vector of ConvMF+ learned by PMF represents that user characteristics are not very accurate in the data set. In contrast, the model in this paper has been improved, and the RMSE has improved slightly, by 7.54%. This significant gain indicates that the model works better than other methods on very sparse data sets.

4. Conclusion

In order to allow users to easily find books that may be of interest to them in a large number of books in the library, this paper proposes a matrix factorization model based on deep learning for book recommendation algorithm based on the traditional sparse problem of rating matrix data based on collaborative filtering algorithm. The experimental results show that the improved algorithm improves the sparseness of book rating data and improves the effect of personalized recommendation of books, which has practical research significance.

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