Movie recommendation algorithm based on Deep Learning

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Abstract: Improving the recommendation performance of the recommendation system has been a very big challenge in the past, because both the accuracy of the recommendation results and the calculation time for calculating the recommendation results must be taken into account when making recommendations. Based on the above problems, in this paper we propose a recommendation algorithm based on deep learning, which uses deep learning methods to mine features of users and movies and train models to improve the accuracy of recommendation algorithms. At the same time, the features of users and movies are extracted through neural networks, rather than based on the user's rating matrix for movies, which solves the sparsity problem and cold start problem in the recommendation system. Finally, experiments are conducted on real data sets to verify the accuracy of the recommended algorithm.

1. Introduction

With the development of the Internet, the era of big data has arrived, and the phenomenon of information overload is becoming more and more prominent. how to mine valuable information from a large number of complex data and analyze it, so as to improve people's living standards is particularly important. there are two main ways to mine the data users need from massive data: one is through search engines, which requires users to accurately describe what they need; Second, through the recommendation system, the task of the recommendation system is to present the information that the user may want according to the user's preference or historical behavior, so as to help the user save valuable time [1].

The development of the recommendation system can be traced back to 1979. It started from cognitive science and gradually played an increasingly important role in life. At present, more and more e-commerce websites are beginning to access recommendation systems, such as Taobao and Amazon. The recommendation system helps them recommend products of interest to users, saving users' browsing time. In addition, there are NetEase cloud music recommendation system, Weibo social recommendation system, Netflix movie recommendation system, etc. The recommendation system helps users save time and at the same time helps the enterprise to bring benefits, so the recommendation system has been extensively studied [2].

At present, the mainstream recommendation algorithms are mainly divided into collaborative filtering recommendation algorithm, model-based recommendation algorithm and hybrid recommendation algorithm. The collaborative filtering algorithm mainly considers the user's historical behavior when making recommendations, calculates the similarity between users or items through the user's historical scoring matrix, and then recommends to the user. The model-based recommendation algorithm recommends other items similar to the items the user is interested in by analyzing the attributes of the items. Hybrid recommendation algorithm is a combination of collaborative filtering algorithm and content-based recommendation algorithm, and strive to get better recommendation effect [3].

The above traditional recommendation algorithms are currently facing some problems. The collaborative filtering algorithm relies heavily on the user scoring matrix, so it will face the problem of sparsity, that is, because the number of users who score items is small, the user scoring matrix will be very sparse and it is very difficult to find similar users. This is usually particularly prominent in systems where the number of items is higher than the number of users. At the same time, it also faces the problem of cold start, unless an item is scored by a user, it will not be recommended to the user. Although the model-based recommendation algorithm can improve the sparsity problem, it will lead to a reduction in recommendation accuracy\. Aiming at the problems often encountered in the current recommendation algorithm, this study proposes a deep learning-based recommendation algorithm, which uses the deep learning algorithm to fully mine the characteristics of users and items, build a model, and verify it on the MovieLens-1m dataset.

2. Model structure

2.1CNN text network structure

Convolutional neural network (CNN) is a variant of multi-layer perceptron (MLP). By adding a convolution layer and pooling layer to the neural network, it is possible to extract the local features of the sample, and at the same time, the extracted features are passed through the network. With the increase of the number of network layers, the characteristics of the samples have been continuously excavated. As shown in Fig.ure 1, by using convolutional layers to learn the pixel matrix, each computing unit responds to a small part of the input data, and can recognize colors, contours, and shapes in the image to train a classification model. In the past 10 years, CNN has become one of the most popular technologies for solving computer vision problems. A large number of computer vision applications are constructed using CNN, such as image classification, object detection, and facial recognition.

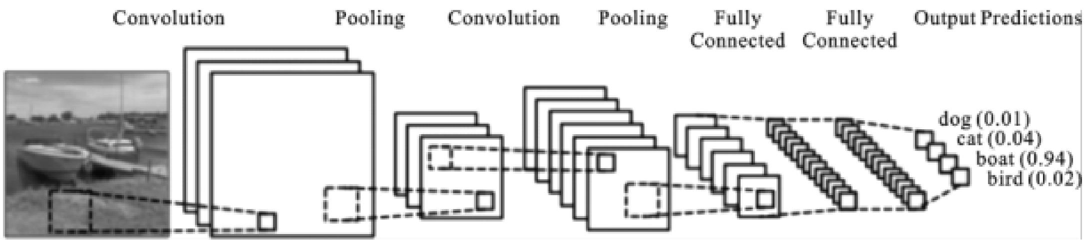


Fig. 1 Convolutional neural network model

The researchers found that CNN can also achieve better results when applied to text problems. RieJohnson applied CNN to the one-dimensional structure of text, and made each unit in the convolutional layer respond to a small area of the document, so as to learn the features of the document and realize the classification of the document. YuyunGong models the label recommendation task as a classification problem, proposes a CNN-based attention neural network recommendation model, adds weights to words by adding an attention layer, and then converts Weibo tags into fixed-length vectors. Bo's recommendation. CNN is not the same for text and images. The input of the network in the text is a word vector. For a sentence of 10 words embedded in 100 dimensions, we will have a 10 × 100 matrix as input. The width of the filter layer is 100, which is usually the same as the width of the input matrix, and the height is usually 25, that is, one sliding window is 25 words. Fig.ure 2 shows a text sliding window with heights of 2 and 3, respectively.

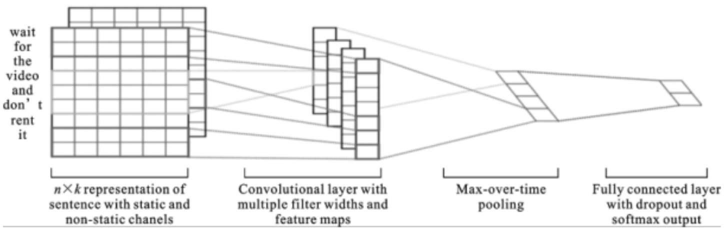


Fig. 2 Text convolution neural network model

2.2Recommendation algorithm model based on deep learning

In order to solve the sparseness of the scoring matrix generated by the traditional recommendation algorithm, this paper proposes a deep learning recommendation algorithm model based on the CNN text neural network, and uses the neural network to deeply mine the relationship between users and movie features to train the model To achieve movie recommendation.

First, preprocess the data to extract the basic attributes of users and movies, and convert the basic attributes into corresponding digital vector representations. Normally, the basic attributes are converted into one-hot form, but after conversion into one-hot, the feature dimension is very large, so for some basic attributes, you can directly use the numeric index instead.For example, the user's gender can be represented by a single digit 0, 1 instead of a two-dimensional vector [0, 1].The category of movies can be represented by the numbers 1, 2, ..., 17. Because a movie may correspond to many categories, the dimension of the movie category matrix is set to 17, and the category that does not exist is replaced by 18. The basic attribute vector of the user, the basic attribute vector of the movie and the text description vector of the movie are respectively expressed by matrices u, v and d.

$$u : \begin{bmatrix} u_{11} u_{12} \cdots u_{1m} \\ \vdots \;\; \cdots\cdots \;\; \cdots \\ u_{n1} \cdots\cdots u_{nm} \end{bmatrix}$$

$$v : \begin{bmatrix} v_{11} v_{12} \cdots v_{1m} \\ \vdots \;\; \cdots\cdots \;\; \cdots \\ v_{n1} \cdots\cdots v_{nm} \end{bmatrix}$$

$$[d_1, d_2, \cdots, d_i, \cdots, d_m]$$

After extracting the basic attribute vectors of the user and the movie, they are separately input into the embedding layer. One function of the embedding layer is to reduce the amount of data required for training.

$$\bar{u} = \text{embedding}(u)$$
$$\bar{v} = \text{embedding}\ (v)$$

For the movie description text, the text convolution neural network is used to process, and the convolution kernels with heights of 2, 3, 4, and 5 are used to learn the text features, and then the text feature vector is obtained by the pooling layer. The calculation formula is as follows, where Fi represents the convolution kernel and bi generation in the table, f represents the activation function. In this paper, the relu function is selected as the activation function.

$$\bar{d} = \max \text{Pooling}\left(f\left(F_i^* d + b_i\right)\right)$$

Each feature vector is input into the fully connected layer separately to obtain the prediction score y, the calculation formula is as formula below, W and b are the corresponding weight and bias terms.

$$\bar{y} = f\left(W_3\left(f\left(W_1\bar{u} + b_1\right) + f\left(W_2(\bar{v} + \bar{d}) + b_2\right)\right) + b_3\right)$$

Compare the output value with the real sample score, and use MSE to optimize the loss.

$$\text{loss} = \frac{\sum_{i=1}^{n}(y - \bar{y})^2}{n}$$

3. Experiment and Analysis

3.1 Experimental environment and data

In this paper, the experimental hardware conFig.uration is 2. 6GHzIntelCorei5 processor, 16GBRAM, the operating system is macOS. The TensorFlow framework was used to write the code for the experiment, and the MovieLens-1m real data set was used as the experimental data. TensorFlow is a machine learning platform developed by Google. It has various tools and can perform machine learning and deep learning experiments. MovieLens-1m is a data set provided by the GroupLens research group of the University of Minnesota, which is widely used in the research of recommendation algorithms. The data set contains 1000209 ratings of 3652 movies by 6040 users. It also contains additional information such as user age, occupation, movie name, movie category and so on. All scores are divided in a 4: 1 way, divided into training set and test set, the training set is used for model training, and the test set is used for testing.

3.2Model training and evaluation

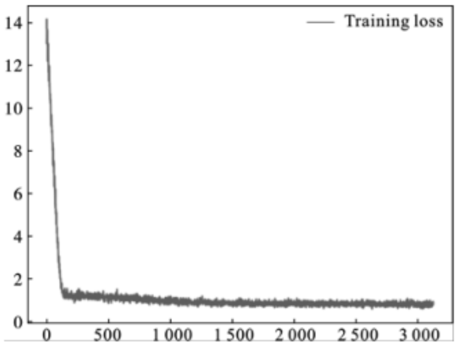


Fig. 3 training loss

Input user vectors and movie vectors into the model, use convolution kernel heights of 2, 3, 4, and 5 for convolution learning, and finally add a fully connected layer as the output layer, and return the output value to the real score. Function optimization loss. Adjust the learning rate and model parameters. After continuous learning, it is found that the model can quickly reach convergence by observing Loss. As shown in Fig.ure 3, the model is stable and can be used for movie recommendation.

Apply the model to the test data set, and use MAE to evaluate the recommended model. MAE refers to the average absolute error, which is usually used to indicate the degree of deviation from the accuracy of the recommendation. The calculation method is as follows:

$$\mathrm{MAE} = \frac{\sum_i^n |y_i - y_i'|}{n}$$

Among them, yi is the user's actual rating of item i, y'i is the model's true user rating of item i, and n represents the number of samples. The lower the MAE, the more accurate the model prediction. After iteration, the MAE of the model tends to be stable.

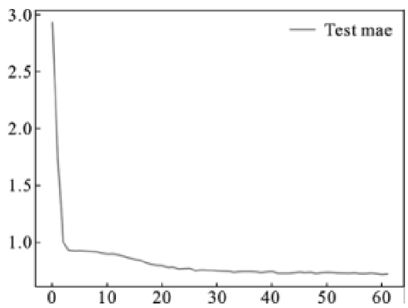


Fig. 4 MAE curve

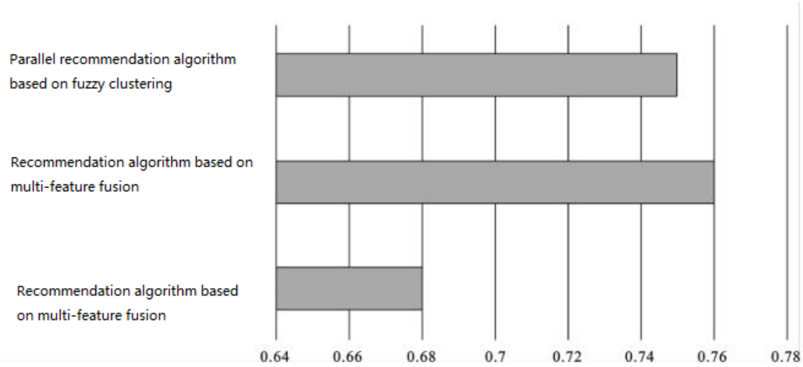
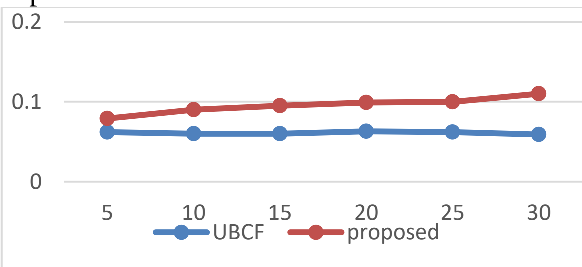


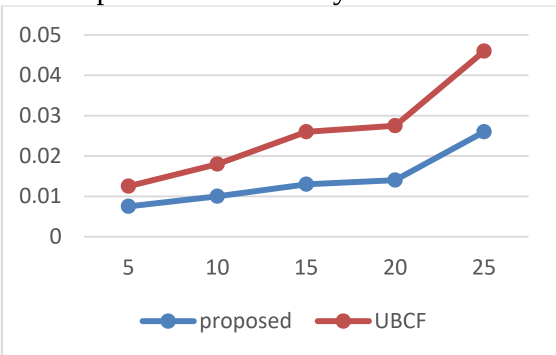
Fig. 5 Compare with MAE of other algorithms

Comparing the trained model based on the same data set with other recommendation algorithms is shown in Fig.ure 4. The recommendation algorithm based on deep learning proposed in this paper is significantly lower in MAE than the recommendation algorithm in the literature and the recommendation algorithm in the text. The accuracy of the recommendation algorithm proposed in this paper has been significantly improved. At the same time, the deep learning method is used to mine the features of users and movies, rather than mining association relationships based on the user rating matrix, so the sparsity problem is effectively alleviated.

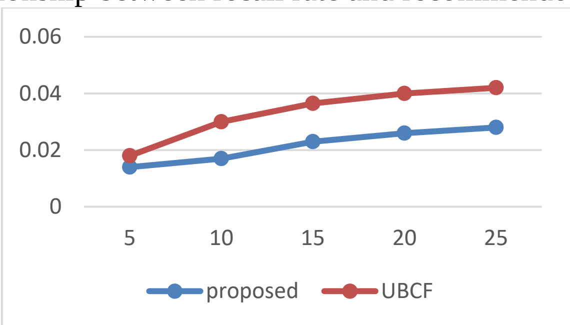
The test is recommended based on top-k, and the recall rate, accuracy rate and F1 value (F) are selected as the recommended performance evaluation indicators.



(a) The relationship between accuracy and recommended number



(b) Relationship between recall rate and recommended number



(c) Relationship between F1 value and recommended number

Fig. 6 Comparison of accuracy rate, recall rate and F1 value when the recommended number of items takes different values

Take different values for the recommended items and compare them with the traditional user-based recommendation algorithm (UBCF) on the three indicators of recall rate, accuracy rate, and F1 value. The experimental results are shown in Fig.ure 6. With the increasing number of recommendations, the recall rate and F1 value increase monotonically in both algorithms, and the algorithm proposed in this paper is always higher than the UBCF recommendation algorithm. The accuracy rate increases with the recommended items, then increases first and then decreases. As the number of recommended items increases, the denominator becomes larger, and the accuracy rate is likely to decrease. The algorithm proposed in this paper is always higher in accuracy than the UBCF algorithm. This shows that the recommendation algorithm proposed in this paper is superior to the UBCF algorithm in recommendation effect.

4. Conclusion

In this paper, a recommendation algorithm model based on deep learning is proposed. The recommendation algorithm uses neural networks and text volume set neural networks to fully mine the features of users and movies, thereby further learning the relationship between features, and finally calculating the user's rating of the movie, generating a recommendation list, and solving the scoring matrix existing in traditional recommendation algorithms Sparseness and cold start issues. Finally, experiments are conducted on real data sets. The results show that the recommendation algorithm model proposed in this paper has good accuracy and can improve the recommendation effect.

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