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ORIGINAL ARTICLE

Personalized recommendation of film and television culture based on an intelligent classification algorithm

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Abstract

Personalized recommendation of film and television culture is an important content to meet people's daily cultural needs and social information. Promoting the personalized recommendation of film and television culture is conducive to promoting the more efficient use of network resources. However, in recent years, the film and television culture industry has developed rapidly, and the production of film and television culture has also increased year by year. How to quickly and accurately find the user's favorite film and television culture in the massive film and television cultural data has become an urgent problem to be solved. Aiming at the shortcomings of the film and television culture recommendation system, this paper proposes a new personalized recommendation algorithm for film and television culture based on an intelligent classification algorithm. Based on the preliminary screening results of the traditional collaborative filtering recommendation algorithm, the user data and video data are used as input and the video score as output, which is further filtered by a convolutional neural network. Finally, selecting the film and television culture recommendation set that is most suitable for the current user can also make up for the cold start problem of collaborative filtering at the beginning of the system operation. The simulation experiment is carried out. The experimental results show that the personalized recommendation algorithm based on an intelligent classification algorithm improves the scoring accuracy by 0.15, which indicates that the designed film and television culture recommendation system has a good application effect.

Keywords Film and television culture · Personalized recommendation · Classification algorithm · Convolutional neural network

1 Introduction

With the popularity of the Internet, it has gradually become an information society, and more and more information is published on the Internet, resulting in information overload. Traditional information search has been unable to meet people's needs, and personalized recommendations have gradually become the core of people's search information.

Wei [1] uses network analysis technology to mine the network common node set, improve the Spark Streaming stream, integrate the Louvain algorithm to improve, capture community information, and apply its information to the field of personalized information recommendation. Lin et al. [2] implemented the personalized recommendation system using the MyMediaLite platform and elaborated its implementation plan, laying the foundation for the research based on the MyMediaLite recommendation library algorithm. Liao [3] elaborated on the concept of personalized recommendation and the significance of a collaborative filtering algorithm to design a personalized recommendation system for film and television. Zhang [4] carried out research on the personalized fast recommendation algorithm of traditional digital libraries and proposed the construction method of the book intelligent recommendation system based on data mining technology, which provides theoretical reference for the application of data mining software in the library. Zhao and Pan [5] designed an offline recommendation module based on the IRGAN algorithm model and an online recommendation module based on online user behavior data collection and processing and implemented a movie recommendation system based on the IRGAN model and Hadoop. Niu et al. [6] proposed a project score prediction algorithm based on the co-occurrence latent semantic vector space model (CLSVSM) based on the traditional project-based recommendation algorithm (IBCF). Xu

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et al. [7] successfully applied artificial intelligence technology to recommendation technology by analyzing the advantages and disadvantages of several typical collaborative recommendation internal accounting methods, displaying the platform vision part of acquiring a large number of data samples, and demonstrating the dynamic sorting part of object-based pictures or user face information recognition. Shao [8] conducted research on data information protection under the personalized recommendation system to ensure that users can protect the information under the premise of using personalized recommendation. Liu and Liu [9] aimed at the WeChat public platform article, using algorithmic intelligence to sort, and, combined with the reader's interest, targeted articles to individuals, thus saving retrieval time. Jin et al. [10] proposed a new method of personalized recommendation using the method of preference feature construction, which uses the preference feature combined with machine learning to classify, thus realizing hotel personalized recommendation. Li et al. [11] used the time factor to optimize the user information recommendation function for microblog information and realized the novelty and pertinence of information recommendation.

This paper puts forward a model of personalized recommendation system for film and television culture based on an intelligent classification algorithm, expounds the architecture, technical path, and function realization of the model, and illustrates the application effect of the personalized recommendation system for film and television culture through practical case analysis, in order to provide a scientific reference model and basis for the establishment of personalized recommendation technology for film and television culture.

2 Review of related algorithms

In the process of data mining, a classification algorithm is of great significance as an indispensable algorithm. Classification models can be constructed based on statistical methods, decision trees, machine learning, and neural network models.

The core of the decision tree is the inductive algorithm, which uses the method of reasoning to determine its representation from a set of disorganized elements to determine its classification rules [12]. The top-down research method is used to compare and classify the internal elements of the decision tree by recursion, so as to determine the classification and gradually branch from the node according to the specific classification [13]. In the decision tree, a path from the root to the leaf represents a category, and the entire decision tree represents a set of expression rules. In order to adapt to the processing requirements of big data, the decision tree is continuously improved, and SLIQ and SPRINT are more representative decision tree classification algorithms [14]. The decision tree schematic is shown in Fig. 1.

The Bayesian classification algorithm is a typical statistical algorithm, and its core is to use the method of probability and statistics to classify. In the case of more classifications [15], the accuracy of Bayesian algorithm classification can be compared with that of classification algorithms such as decision trees and neural networks and even has its advantages. In the context of big data, the Bayesian algorithm is used for classification. The method is simple, the accuracy is high, and the classification speed is fast [16]. However, because the Bayesian algorithm needs to assume that an initial attribute value directly affects the value of other attributes, it will lead to a decrease in classification accuracy [17]. The schematic diagram of the Bayesian classification algorithm is shown in Fig. 2.

The artificial neural network is composed of a large number of neurons with certain rules interrelated, and the sample is trained and learned by means of thinking similar to the brain, so that the obtained information is stored in the "brain" [18]. Backward neural networks, feedforward neural networks, and self-organizing networks are currently the three main neural networks [19]. The feedforward neural network is a kind of neural network commonly used in classification. This paper uses a convolutional neural network to intelligently recommend film and television culture [20]. The schematic diagram of the neural network is shown in Fig. 3.

3 Demand analysis of individualized recommendations for film and television culture

3.1 Overview of the film and television culture personalized recommendation system

With the development of society, the popularity of the Internet has enabled people to obtain a large amount of information to meet the needs of the information age. However, with the continuous popularization of the network, the amount of online information has also increased dramatically, making people face a lot of information. When you do not get completely useful information, the efficiency of using information is reduced, which is the information overload problem.

The film and television culture personalized recommendation system is a potential method to solve the information overload problem. It is a personalized information recommendation system that recommends interesting information and products to users according to their information needs and interests. Compared with search engines such as Baidu and Google, the recommendation system first collects information such as movies and TV that users usually watch and uses personalized calculations to guide users to find their own demand for film and television culture. A good recommendation system not only provides users with personalized services but

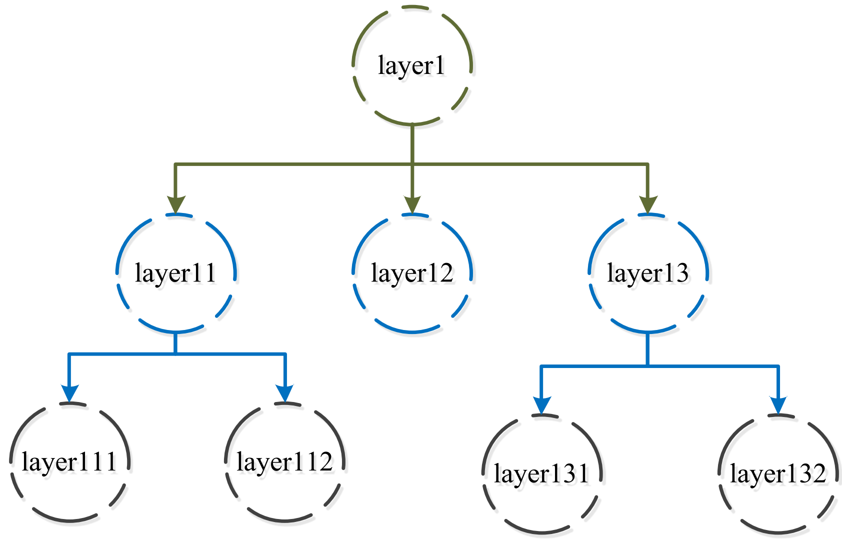


Fig. 1 Decision tree

also establishes close contact with users, allowing users to gradually rely on recommendations [21].

Personalized recommendation systems have been widely used in many fields, the most promising of which is the field of film and television culture. At the same time, research in the field of film and television personality recommendation has received much attention in the academic community.

3.2 Film and television culture personalized recommendation system framework

The personalized recommendation system mainly has three frameworks: the algorithm modeling module, the film and television recommendation modeling module, and the user personalized modeling module, as shown in Fig. 4, which is the classic model of the film recommendation system [22]. The recommendation system uses the user personalized modeling module to collect the user personalized viewing information, uses the algorithm modeling module to calculate the user personalized and then uses the recommendation modeling module to collect the database, and finally recommends the personalized viewing information to the user.

The algorithm modeling module is the core and most critical part of the whole recommendation system, which largely determines the quality and performance of the recommendation system. A large number of papers and work have focused on algorithm modeling modules. At present, there are many recommended strategies for algorithm modeling modules. There is no uniform standard for classification; however, the generally accepted recommendation strategies include recommendations for combinations of film and television content, knowledge, and networks [23].

The film recommendation modeling module is used to generate a user's interest preference for the film, thereby

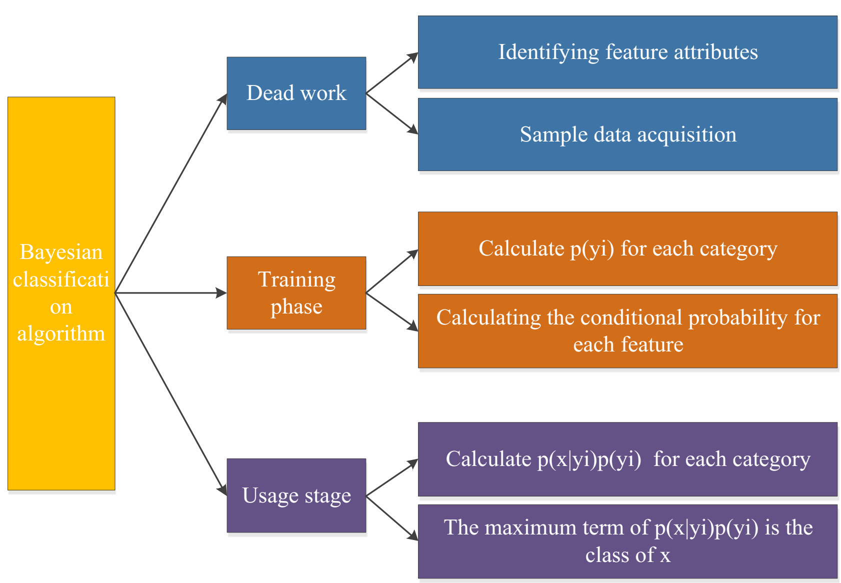
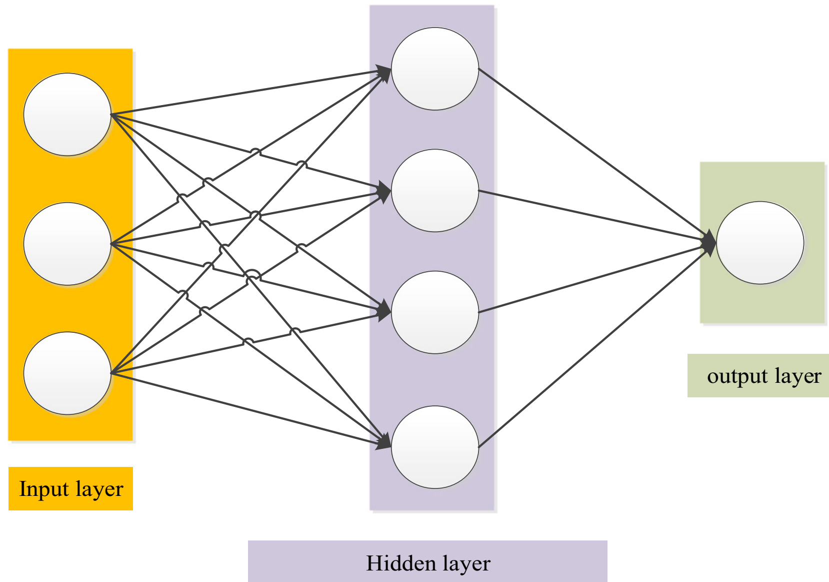


Fig. 2 Bayesian classification algorithm

Fig. 3 Neural network structure



providing data for the user's personalized calculation. In the process of recommending movies to users, it is necessary to pay attention to the videos that the user has watched or the films that are too similar are not recommended, so they need to be modified in the model [24].

The user personalized modeling module provides a personalized service for the user, and the recommendation system should be able to access the interest reflecting the user preferences of various dynamic changes. The recommendation system is necessary for creating the user model, and the model can store and identify the user information, understand the user's personal information, better understand the user, understand the needs of users and tasks, and better implement the function [25]. The user personalized modeling schematic is shown in Fig. 5.

After a period of development, some key and difficult problems related to the recommendation have emerged, which has aroused the attention of researchers and become a hot issue in future research.

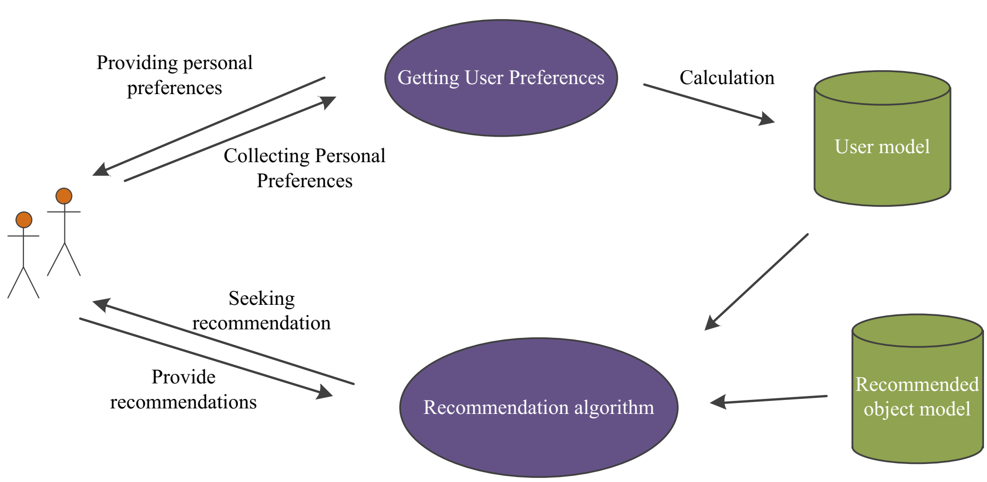
(1) Research on a user interest extraction method and film extraction method

The current recommendation system actually uses the functionality of fewer users and referrals; i.e., the most widely used collaborative recommendation uses user ratings. The main problem is that the method of obtaining user interests and preferences and the method of extracting the characteristics of the recommended objects are not suitable. It is necessary to introduce more precise and applicable user and object characteristics.

(2) Research on the security of the personalized recommendation system

When conducting collaborative recommendation, it is necessary to grasp user information such as the user's interests and hobbies; however, users are worried that personal data cannot be effectively protected and are not willing to disclose

Fig. 4 Recommended system model



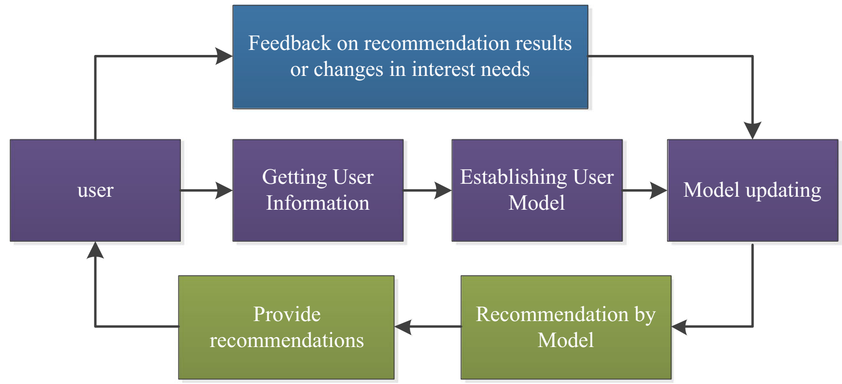


Fig. 5 User personalized modeling

personal information. This is a long-standing collaborative recommendation problem. Improving the performance of the recommendation system by obtaining user information and effectively protecting user information will be the research direction of the future recommendation system. At the same time, in order to increase or decrease the recommendation probability of some objects, some illegal users maliciously fabricate user rating data to achieve this purpose, which is also a security problem of the recommendation system, called recommendation attack. Detecting and preventing recommended attacks are also the future direction of research.

4 Design and implementation of the personalized recommendation system for film and television culture based on an intelligent classification algorithm

4.1 Introduction to convolutional neural networks

Artificial neural networks were called a computational model in the early days, and their history is even earlier than the history of computers. As one of the classifications of artificial neural networks, the discovery of convolutional neural networks originated in the field of biology. In 1962, biologists Hubei and Wiesel experimented and found that some of the neurons in the animal's brain only responded to the edges of the brain's structure in certain directions. The idea that specific members of the system can accomplish a specific task is also well applied to machine learning, which is also the basis of convolutional neural networks [20, 26, 27]. At present, the convolutional neural network has become the focus of research in many hot fields because of its non-linear mapping and high parallel processing ability. Its advantage lies in its suitability for processing data with similar local attributes. Therefore, it has a high research and application value in data feature extraction and prediction. The particularity of convolutional neural networks is manifested in two aspects: the neurons in the neural network are only partially connected, and some of the neurons share weights. Its weight sharing feature reduces the complexity of the network model and reduces the total number of weights in the neural network. This feature avoids complex feature extraction and data reconstruction processes in traditional neural networks when extracting multidimensional data from the network [28–31].

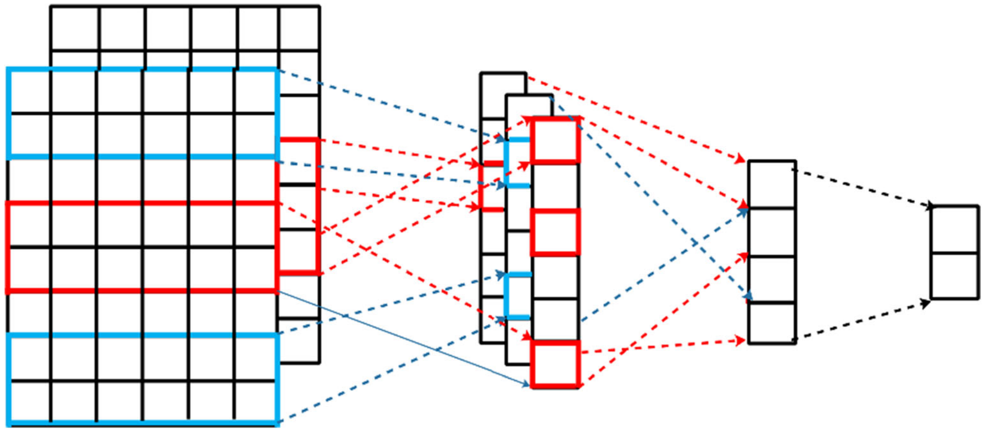
Convolutional neural networks generally consist of an input layer, a convolutional layer, a pooled layer, and a fully connected layer. The input layer is the initial data input, and each convolution layer is generally connected to a pooled layer. This unique two-layer feature structure allows the network to have high tolerance to input samples [32]. The convolutional layer and the pooling layer continuously repeat the feature extraction of the input data. After the final layer completes the feature extraction of the original data, the vectorization of the feature data is completed according to the fully connected layer and finally connected to the corresponding classifier. In the film and television culture score prediction algorithm, there are input layer, convolution layer, and fully connected layer [33]. The hierarchical structure of convolutional neural networks is shown in Fig. 6.

4.2 Data collection and processing

4.2.1 Data collection

The project uses the Movielens-1M dataset to provide an anonymous score of 6900 users for 3900 film and television cultures, with a total of 1,000,209 records. The dataset contains a total of three tables: user information table, film and television cultural information table, and user's score sheet for film and television culture. The user table includes the user ID, that is, the number information of the registered user, the gender, the age, the occupation, and the attribute of the user's region. The fields in the film and television culture information table mainly include the ID of the film and television culture, the release time of the film and television culture, the type of the film and television culture, and the name of the film and television culture. The user behavior table is the user's scoring information about the film and television culture, including the user's ID, the film and television culture

Fig. 6 Convolutional neural network hierarchy diagram



ID, the user's score on the film and television culture, and the time of scoring. The score histogram is shown in Fig. 7.

Figure 7 shows the proportion of different types of film and television culture scores [34]. The scores of different ages and different occupations and users in different regions also show high differences.

4.2.2 Receipt processing

In order to facilitate post-analysis, the data is processed as follows: user ID, occupation, and movie ID do not change. In the gender field, it is necessary to convert "F" and "M" to 0 and 1. The age field is to be converted into 8 consecutive numbers 1~8. The genre field is a categorical field that you want to convert to a number. First, the categories in genres are converted into a dictionary of strings to numbers and then, the genre field of each film culture is converted into a list of numbers, because some film cultures are a combination of multiple genres. In title field, the processing method is the same as the genre field. First, a text-to-number dictionary is created, and then, the description in the title is converted into a list of numbers. In addition, the year in the title also needs to be removed. The genre and title fields need to be uniform in length so that they are easy to handle in the neural network.

(1) User data

User data has fields such as user ID, gender, age, occupation ID, and postal code. Age processing data are shown in Table 1.

Some occupational processing data are shown in Table 2. Occupation is chosen from the choices shown in Table 2:

User D, gender, age, and occupation are all category fields.

(2) Film and television culture data

The film and television cultural data includes fields such as film and television culture ID, film and television culture name, and film and television culture style. Some codes of film and television culture types are shown in Table 3.

The film and television culture name codes are similar and are not described here, where movie ID is the category field, title is the text, and genre is also the category field.

Fig. 7 Dataset of film and television culture type and the corresponding number of ratings

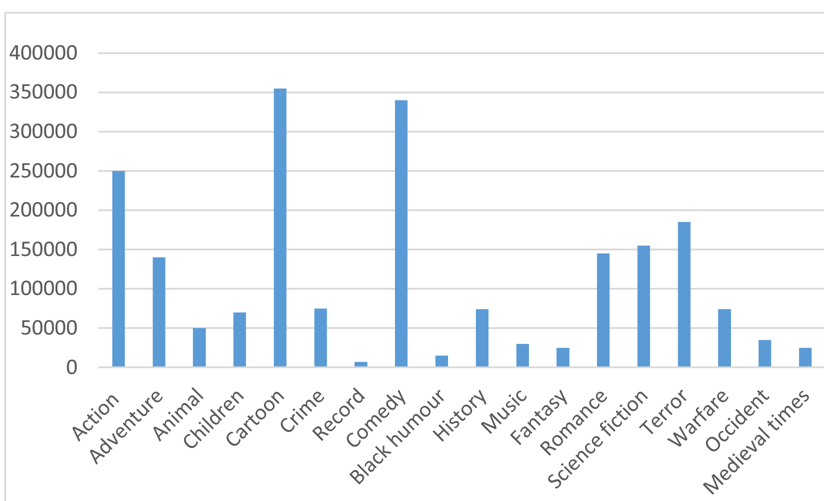


Table 1 Age processing data

Number	Age	Number	Age
1	Under 18	5	36–42
2	18–23	6	43–49
3	24–29	7	50–56
4	30–35	8	56+

Table 3 Part of the film and television culture type code table

Film style	Coding	Film style	Coding
Action	0147	Crime	0863
Adventure	1473	Documentary	4214
Animation	1425	Fantasy	4512
Comedy	1502	Horror	0427

4.3 System model establishment

The main function of the film and television culture recommendation model is to calculate the user's preferences through the user's behavior data, thereby recommending the film and television culture that satisfies the user's preferences to the user. The film and television culture score prediction algorithm, which is the core of the film and television culture recommendation model, is essentially a classifier. The input data is a combination of user information and film and television culture information, and the returned result is the user's prediction of the film culture.

4.3.1 Recommended film and television culture primary election

At present, the more common recommendation techniques are mainly divided into collaborative filtering recommendations. Collaborative filtering technology is based on the algorithm of sociological research. Collaborative filtering can bypass the bottleneck of information itself and analyze the similarity between users, so that the recommended information is more extensive. At present, collaborative filtering technology has been widely used, and many large-scale Internet systems use collaborative filtering as the primary technology for recommendation systems [35]. In the collaborative filtering research, it can be divided into user-based collaborative filtering and project-based collaborative filtering. User-based collaborative filtering finds neighbor users by analyzing the similarity between users, and similar users can recommend related projects. When there are a large number of users, there will be too many recommended items, which is also a major bottleneck of collaborative filtering [36]. Project-based collaborative filtering calculates the similarity between projects through a scoring matrix to recommend appropriate projects for users.

Table 2 Part of the occupational processing data

Number	Career	Number	Career
0	Other	4	College
1	Academic/educator	5	Customer service
2	Artist	6	Doctor/health care
3	Clerical/admin	7	Farmer

Collaborative filtering inevitably faces the similarity of the recommended project's merit level, which is also a major deficiency of collaborative filtering [37]. The method was verified by the data of this paper. It was found that the results with similar advantages in the recommended results generally reached 40–50. It is obviously not feasible to use all of these as recommended results; however, this paper found that the probability of including the correct result in the 40–50 recommendation results is 95.3%, so this article uses it as the primary selection result.

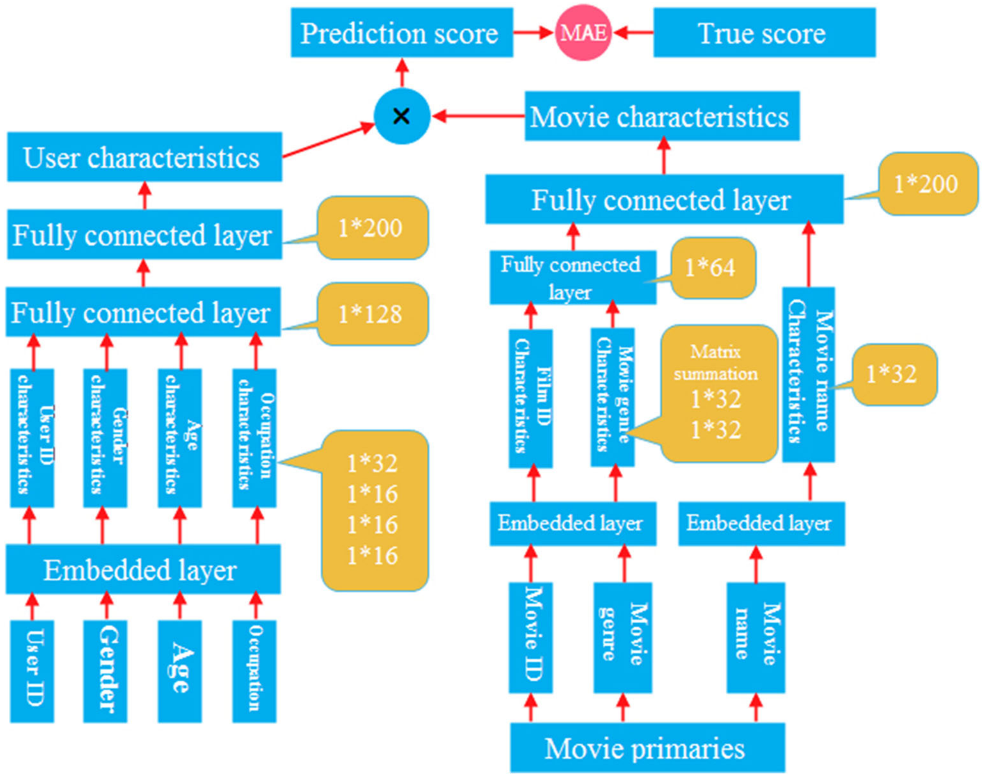
4.3.2 Film and television culture score prediction algorithm based on the convolutional neural network

The film and television culture score prediction is the core part of the film and television culture recommendation. The film and television culture score prediction uses the combination of user attributes and film and television culture attributes to estimate the user's score on film and television culture through calculation. After summarizing the above contents, the film and television culture score prediction algorithm based on the convolutional neural network is as follows:

A neural network is constructed for the scoring dataset of film and television culture. The size and dimension of the neural network data matrix are determined, and the number of layers of the convolutional layer, the number of convolution kernels, the step size of the movement during the convolution operation, the activation function, the calculation method of the loss function, and the number of iterations and the learning rate M are defined and initialized. The occupational characteristics, age characteristics, gender characteristics, ID in the user data, name, style, and ID characteristics in the film and television cultural data are taken as input, and the score of the film and television culture as the output. The algorithm flow is as follows:

(1) Initial values are assigned to the weights and offsets of the convolutional neural network using random values.
(2) The clustered data is divided into a training set and a test set according to the selected verification method. The 80% input sample in the dataset and the corresponding output are selected as the training set:

Fig. 8 Algorithm flow chart



$$X(n) = (x_1(n), x_2(n)\cdots, x_k(n))$$

$$D(n) = \left(d_1(n), d_2(n)\cdots, d_q(n)\right)$$

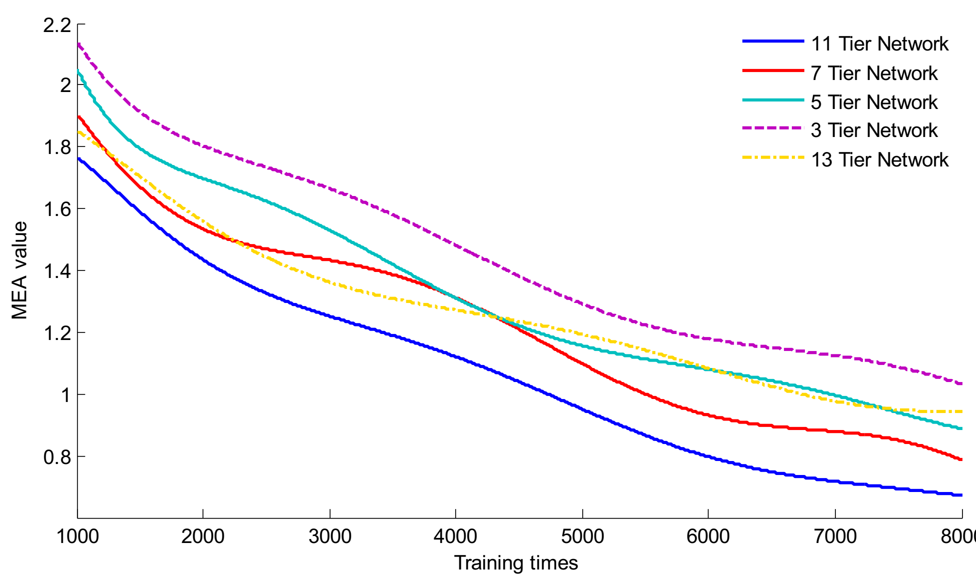
(3) Part of the data of the training set is selected as input data, and the output is calculated according to the input of each layer of neurons until reaching the fully connected layer.

The input and output of each layer of neurons are calculated by the following formula:

$$f_{in}(n) = \sum_{i=1}^{n} (p_i, w_i + b_n)$$

$$f_{\text{out}}(n) = \max(0, f_{in})$$

Fig. 9 Training error map



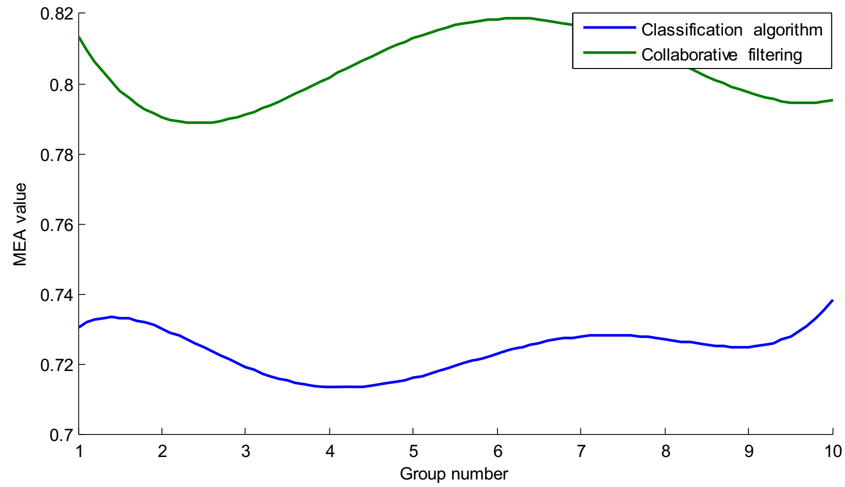


Fig. 10 MAE value comparison chart

(4) After the final results are obtained by the neural network, the weights and biases of each layer of the convolution layer corresponding to the convolution core are adjusted by using the results of the training set and output and the partial derivatives of weights and biases are obtained by the loss function.

$$e = \frac{1}{2}\sum_{o=1}^{q}\left(d_o(k) - f_{\text{out}}(n)\right)^2$$

(5) The training ends when the calculation result of the neural network and the actual result of the dataset are within a reasonable range or the number of iterations reaches the maximum number of iterations. Otherwise, return to step (3).

(6) The test set is entered for testing and the algorithm ends.

Table 4 MAE and response time table

Dataset	Intelligent algorithm MAE	Response time (ms)
1	0.73	1835
2	0.735	1942
3	0.71	1792
4	0.72	1854
5	0.72	1936
6	0.71	1794
7	0.735	1954
8	0.72	1834
9	0.72	1729
10	0.73	1834

By studying the field types in the dataset, this article finds that some are category fields and the usual processing is to convert these fields into one hot encoding. But fields like user ID and movie ID will become very sparse, and the input dimensions will expand dramatically. This is something that I do not want to see in this article. Because of the limited processing power of computers, too high dimension can make calculations slow, so these fields are converted to numbers when preprocessing data. This paper uses this number as the index of the embedded matrix, using the embedded layer in the first layer of the network, and the dimensions are (N, 32) and (N, 16). There are many steps to deal with the types of film and television culture. Sometimes a film and television culture has many types of film and television culture. Therefore, indexing from the embedded matrix is a (n, 32) matrix. Because there are many types, this paper will sum this matrix into (1, 32) vectors. After indexing the features from the embedded layer, each feature is passed to the fully connected layer, the output is again passed to the fully connected layer, and finally the two feature vectors of the user feature and the film culture feature are respectively obtained. The flow chart of the algorithm is shown in Fig. 8.

Since different parameters will have a greater impact on the final result in the process of training the neural network, various combinations are used to verify the actual effect of the algorithm. It includes the learning rate, the number of convolution layers, the number of convolution kernels, the number of pooling layers, the number of iterations, and the step size. However, in actual situations, the number of convolution layers is often the parameter that has the greatest impact on accuracy. Therefore, the network is trained by different convolution layers such as 3, 5, 7, 11, and 13, respectively. The training results are shown in Fig. 9.

It can be seen from the layer that the 11-layer convolutional neural network has the smallest error under the same training times, so the 11-layer convolutional neural network can be used in this paper.

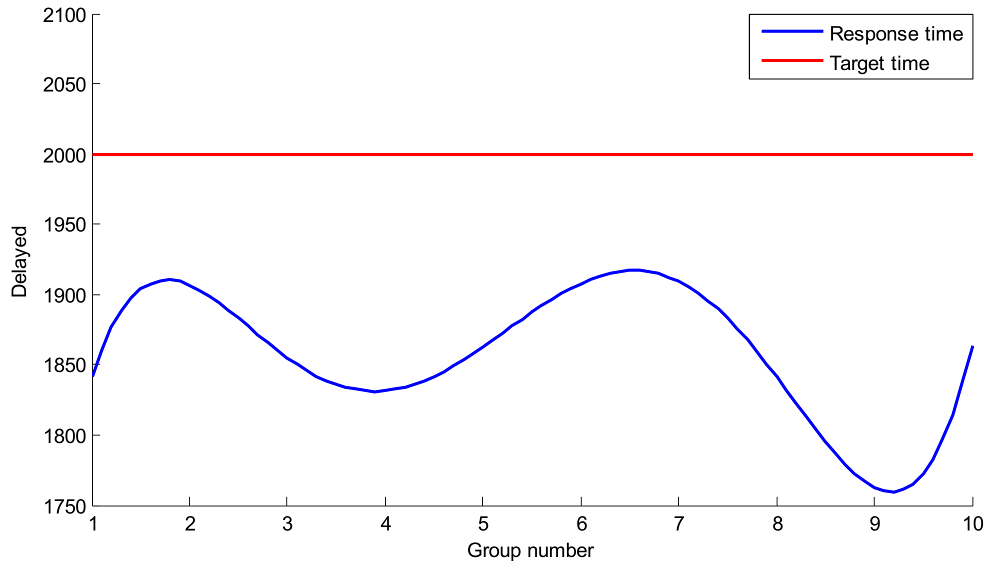


Fig. 11 Delay time

5 System application evaluation and analysis

5.1 System test environment

The experiment was carried out in 64-bit Windows 7. The central processor of the computer used is Intel i7-8750HQ, and the system memory was 8 G. The development language is python3.6.

5.2 Analysis of test results

Suppose that during the experiment, the recommended set of ratings predicted by the user is

$$A = \{p_1, p_2, \cdots p_n\}$$

The corresponding actual score set results are

$$B = \{q_1, q_2, \cdots q_n\}$$

The average absolute deviation can be expressed as

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |p_i - q_i|}{n}$$

The MAE average absolute deviation represents the average absolute difference between the predicted value and the actual value. The MAE can accurately measure the

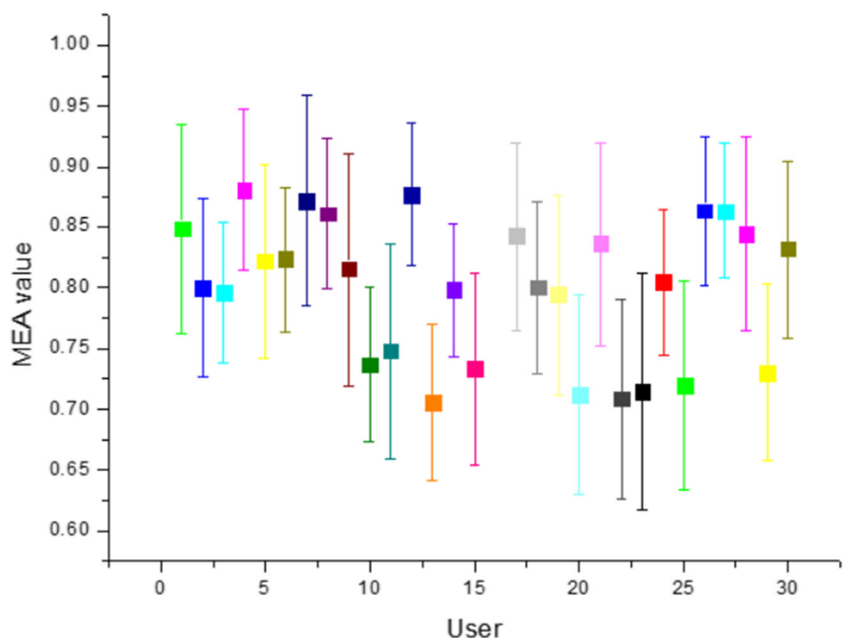


Fig. 12 MAE error limits

recommended quality. The smaller the value, the better the recommended effect. The data is divided into 10 parts, and the MAE comparison between the film and television culture personalized recommendation algorithm based on an intelligent classification algorithm and the film culture recommendation engine based on single collaborative filtering is performed.

As shown in Fig. 10, the MAE comparison between the film and television culture personalized recommendation algorithm based on the intelligent classification algorithm and the recommendation engine based on the single collaborative filtering recommendation algorithm is compared with the intelligent classification algorithm based on the intelligent classification algorithm. The recommendation score based on a single collaborative filtering recommendation engine is accurate to 0.15.

For the above data, the data volume of each group is in the original dataset of 6000 evaluation records of 6000 users and 3000 film cultures. Table 4 lists the MAE values for the 10 calculations and the time consumption of the system.

The delay time is shown in Fig. 11.

As can be seen from Table 4 and Fig. 11, it takes about 1.9 s from the time when the user requests the personalized recommendation service to the recommendation information to the user. The time consumption of this recommendation system is within the target range. For large data volumes, the system delay will not be much different. For large data volume calculations, the 1.9-s calculation delay is the calculation time, and for the time complexity, high calculations are not perceived by users. In order to further verify the accuracy of the system, this paper randomly selected 30 users, collected the required information in the form of questionnaires, and brought them into the model for verification. The error limit diagram is shown in Fig. 12.

It can be seen from the figure that most MAE errors do not exceed 0.2, further illustrating the superiority of the model.

6 Conclusion

The personalized recommendation algorithm of film and television culture based on an intelligent classification algorithm is based on collaborative filtering. On the basis of its preliminary screening, the user's favorite film and television culture is further selected by the convolutional neural network, which solves the problem that the priority difference of collaborative filtering of the sparse matrix is too small. At the same time, due to the high efficiency of the convolutional neural network, the score obtained by data preprocessing is more accurate, which makes up for the cold start problem of collaborative filtering at the beginning of the system operation, and increases the number of recommended film and television culture projects. The improved recommendation algorithm improves the traditional collaborative filtering algorithm in terms of quality and efficiency and satisfies the user's demand for diversified information recommendation.

The direction of future improvement should be based on the integration of recommendation algorithms and cross-domain information based on deep learning, in order to achieve more than just accurate recommendations. For cross-domain recommendation research, the main research methods currently include collaborative filtering, transfer learning, and tensor decomposition. However, these methods fuse specific types of information in different fields, and their adaptability is very limited. In the future, the recommendation of cross-domain information fusion through the construction of deep learning models will be the focus of academic and industrial research.

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