

Research Article

Research on English Movie Resource Information Mining Based on Dynamic Data Stream Classification

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Massive English film and television resources will provide people with a rich content, while it has become more and more difficult for people to find the resources and information they need. Through the analysis of massive amounts of film and television data, the application system can effectively push the works that users may like. In response to this problem, we can build an English film and television resource information mining model by combining fuzzy neural network algorithms and dynamic data stream classification technology. Firstly, we use dynamic data stream classification technology to preprocess and screen English film and television resource information. Secondly, we use the fuzzy neural network algorithm to conduct data mining on related film and television resource information. The experimental results verify the superior performance of the English film and television resource information mining model established in this paper. This model can help people to find the resources and information they need.

1. Introduction

In recent years, with the wave of big data, data-driven decision-making has been expanding and deepening in many industries, among which the film industry is very prominent [1–10]. After using machine learning technology to analyze many movie scoring data, the famous movie rental company Netflix can predict a user's scoring of a certain movie with a high degree of accuracy, and this indirectly becomes the core technology for recommending movies to users. Data-driven decision-making has been expanding and deepening in many industries. In the film industry, through the analysis of massive amounts of film and television data, the application system can effectively push the works that users may like. Recently, some film production companies have tried to use the results of data analysis to design castings and scripts, and their works have been very successful [11–18]. Movie data contains a wealth of information, but the current mining and analysis work for it often only focuses on specific information, which affects the integrity of the results to a certain extent.

On the other hand, a heterogeneous information network is an information network that contains multiple types of nodes, and there are multiple types of edges between nodes, which is very suitable for modeling data that contains rich information. In other scenarios, the system can help users to find works that may be of interest through the information related to the movie plot. After analyzing many users' movie-watching behavior data, the results of the analysis are used in script design, character selection, and so on. In 2012, it launched the popular TV series "House of Cards" [17]. In a paper published in the 2017 KDD conference [19], researchers even try to dig out some valuable patterns from a large amount of film and television data to guide multiple links in the film production process to improve the possibility of film success under a limited budget. In recent years, mining and analysis problems based on heterogeneous information networks have been extensively studied, and related experiments show that the algorithm has achieved better results after considering heterogeneous information [20]. In the work of this paper, the information contained in the video data is organized

through a heterogeneous information network, and the key information in it is effectively represented through network representation learning and text representation learning algorithms. On this basis, this paper proposes a set of query-driven mining and analysis scheme, which can efficiently complete a variety of different analysis tasks.

Logistics enterprise owns huge dynamic data during the long-term operating process. It is a common cognition to strengthen mining these data. Most of the related research articles discussed and analyzed the application of traditional data mining in logistics information analysis aimed at static data source, ignoring the dynamic feature of logistics data.

In recent years, there are many new strategies to realize the information mining in different kinds of industries. Many studies are carried out about the analysis and prediction methods of the technical and economic data [21–23]. Nguyen et al. [24] analyzed the prediction and interpolation methods of missing economic data of the mining enterprise, such as the mean method, the weighted average method, the linear regression method, the maximum expected method, and the multiple imputation method. Muthukrishna et al. [25] collected the borehole data and discovered the global trend and the aeolotropism existing in the data. The data are transformed to normal distribution, and the aeolotropism of the data is rejected, thus the interpolation precision is improved. Many research projects have recently focused on designing fast mining algorithms, whereby massive data streams can be mined with real-time response [26–28]. Similarly, many research projects have also focused on managing the data streams generated from these applications [29, 30]. However, the problem of supporting mining algorithms in such systems has, so far, not received much research attention [31]. Furthermore, static mining algorithms can also be written in procedural language using a cache mining approach that makes little use of DBMS essentials. However, online mining tasks cannot be deployed as stand-alone algorithms, since they require many DSMS essentials, such as I/O buffering, windows, synopses, and load shedding. Clearly, KDD researchers and practitioners would rather concentrate on the complexities of data mining tasks and avoid the complexities of managing data streams, by letting the mining system handle them. In short, while mining systems are a matter of convenience for stored data, they are a matter of critical necessity for data streams. Even though there are many new strategies to deal with the data mining, but there is not an effective scheme to the English movie resource information mining.

This paper proposes a new strategy to realize the English movie resource information mining. The main idea of this paper is to build an English film and television resource information mining model by combining fuzzy neural network algorithms and dynamic data stream classification technology. Firstly, we use dynamic data stream classification technology to preprocess and screen English film and television resource information. Secondly, we use fuzzy neural network algorithm to conduct data mining on related film and television resource information. The experimental simulation test results verify the superior performance of the English film and television resource information mining

model established in this paper. This model can help people find the resources and information they need.

The contributions of this paper can be summarized follows:

- (1) This paper proposes a new scheme which can realize resource and information mining. This paper combines dynamic data stream classification technology and fuzzy neural network algorithm, which can help to preprocess and screen English film and television resource information and conduct data mining on related film and television resource information, respectively.
- (2) We use this new scheme in English movie resource information mining, which is a difficult problem. Generally speaking, massive English film and television resources will provide people with richer content, but at the same time, it has become more and more difficult for people to find the resources and information they need. With this new scheme, we can solve this problem effectively.

This remainder of this paper is organized as follows. Section 2 presents some preliminary studies and related works. Section 3 is the research on English film and television resource information mining based on fuzzy neural network. Section 4 is the case verification of English film and television resource information mining based on dynamic data stream. Finally, Section 5 sums up some conclusions and gives some suggestions as the future research topics.

2. Summary of Related Technologies

In order to have a fuller understanding of the research problem, this chapter will review and comment on the research status of related technologies. First, we introduce the application scenarios of several types of film and television data mining and analysis and the algorithms used and then introduce the basic concepts of heterogeneous information networks and related research on heterogeneous information network analysis. At the same time, a similar concept, the semantic web, is simply introduced. Finally, we introduce the related content of representation learning, including reviewing several baseline network representation learning algorithms and representation learning for short text.

2.1. Research on Information Mining of English Film and Television Resources. Pushing movies to users by analyzing users' viewing data is the most common application scenario. The basic idea is that if the user's viewing preferences can be analyzed, the past videos will be more likely to be followed [32]. The user portrait composed of keywords is a symbolic representation, which is likely to cause the problem of sparse representation. To alleviate this, you can use component analysis-related techniques to extract the theme components of the plot, and you can even consider learning the distributed representation of the document. However, the user's viewing preferences may also be affected by some

factors outside the plot. For these factors outside the plot, a comprehensive and systematic analysis is more difficult. The collaborative filtering model is considered an excellent choice to solve this problem. At present, there are two main methods for data acquisition whether it is foreign or domestic IMDB or domestic Dougan platform [33–35]. One is to obtain data through the platform to provide a public application programming interface (API). The other is to obtain data through web crawlers. Although the data can be obtained directly based on the open API, its open permissions are quite restricted. There are many ways to practice this idea. The improved wireless communication structure of English video resource information mining scheme is shown in Figure 1 [36].

For example, you can start from the movie plot that the user has watched, extract keywords to generate a user portrait, and then further match and push the movie. For example, currently Dougan only opens a part of the interface, and many external data interfaces are not free, or directly not open to the outside world. Even if the API is open to the outside world, there are strict controls on the frequency and number of access data.

Since it is impossible to consider various factors, it is better to treat all users as a set of filters. When a user watches a certain movie, these filters can filter out suitable movies under this limited condition, that is, they have watched this movie. When you enter the movie page of Dougan Movicol, there will be a column “People who like this movie also like it,” that is, the coordination filtering model is used. Although this is the simplest and most direct implementation of the collaborative filtering model, it has already been able to complete a video recommendation with a certain value. One idea that can improve performance is to abstract the film into a set of potential influence factors. The reason for this is that in the previous implementation, if the target users watch very few movies, or the audience circle of the movies they watch is very small, it will cause great obstacles to the recommendation, which is simply extracting keywords from the plot.

2.2. Dynamic Data Stream Classification. With the development of information technology in recent years, the field of traditional data mining is facing unprecedented challenges. The biggest challenge comes from changes in data. From the traditional static data mining for the database, it becomes the real-time dynamic mining for the data stream. The characteristics of the data stream are massive (data cannot be saved in all), real-time (with certain requirements for processing speed), and instability (concept drift exists). At present, the hot research areas of data stream mining include credit card fraud monitoring, network security monitoring, sensor data monitoring, and grid power supply. The schematic diagram of dynamic data stream classification is shown in Figure 2 [37, 38].

Classification is an important branch in data mining. It refers to constructing a model that describes or distinguishes class labels or concepts of the object (data) to be processed based on the characteristics, attributes, and other factors of

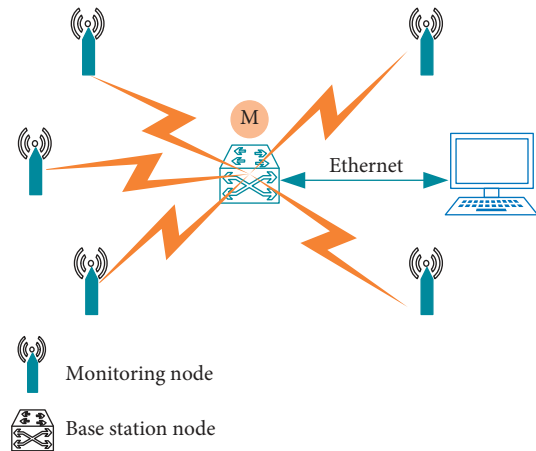


FIGURE 1: Improved wireless communication structure of English video resource information mining scheme.

the object to be processed so the model can be used to label unknown parameters, so that the predicted data can be effectively classified.

The process of analyzing the influence of program network media communication is as follows: grab data from portals and video websites, preprocess the data (data cleaning, data integration, data transformation, and data protocol), form a target database, and combine with the film and television media knowledge base, data analysis. The value of each dimension in the feature space describes an attribute or feature of the current dataset, that is, the essential attributes of the data. The classification process is to establish a mathematical model based on a given sample dataset and then use the established model to discriminate the category labels of data samples with unknown category labels. Mainly use association rule analysis and decision tree analysis to find out the correlation between high-click videos and the main attribute factors that affect movie program clicks and provide decision support for actual advertisers’ advertising, video website program introduction, and film and television creation.

3. Research on English Film and Television Resource Information Mining Based on Fuzzy Neural Network

Nowadays, no matter on the web or mobile, many products have the function of predicting users’ preferences. This kind of system can be called a recommendation system. At present, there are many algorithms and theories in recommendation technology, and there are some targeted algorithm theories for the research of movie recommendation technology. Although the data can be obtained directly based on the open API, its open permissions are quite restricted. There are many ways to practice this idea. For example, you can start from the movie plot that the user has watched, extract keywords to generate a user portrait, and then further match and push the movie. For example, currently Dougan only opens a part of the interfaces, and many external data interfaces are not free or directly not

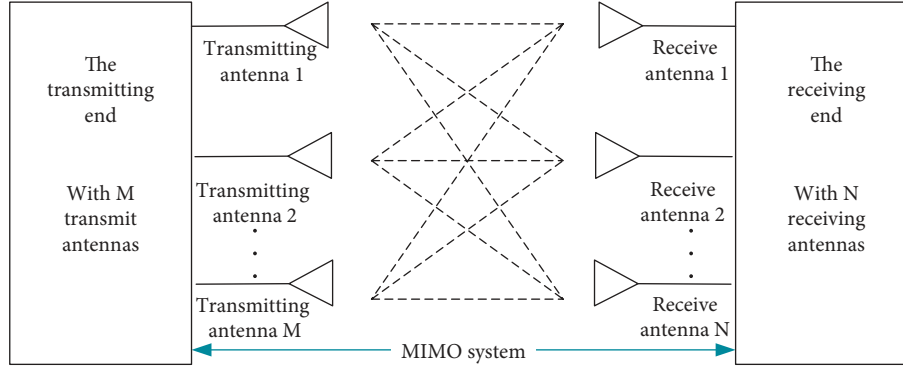


FIGURE 2: Schematic diagram of dynamic data stream classification.

open to the outside world. Even if the API is open to the outside world, there are strict controls on the frequency and number of access data. The research framework of English video resource information mining based on fuzzy neural networks is shown in Figure 3 [39].

The neural network that uses nonlinear prediction is usually a backpropagation neural model (BP model). The model uses a basic 3-layer topology, namely, the input layer, the hidden layer, and the output layer. The input layer has 7 nodes, which represent 7 relevant factors that affect the task price [16, 40]. Concept drift refers to the phenomenon that the concepts implicit in the data change over time. When concept drift occurs, the model needs to be adjusted to adapt to the new changes. Concept similarity is a supplement to concept drift. When the concepts between two datasets are similar, it is considered that concept drift has not occurred. Using such properties can simplify the complexity of data stream classification. In response to this problem, this chapter introduces the definition of conceptual similarity, the measurement of conceptual similarity, and the determination of similarity values. The output layer has a node to build the relationship with the model, the neurons in the middle layer are not connected to each other, and the neurons in the adjacent layer are connected by weights.

According to the profit maximization goal of the APP platform, the input layer and price-related factors are sorted by importance [41–43]; it can be denoted by the following formula:

$$v_{ij}^{e+1} = W + V_{IJ}^e + C_1 * R_1 * (pBest_{ij} - P_{ij}^e) + C_2 * R_2 * (gBest_{ij} - P_{ij}^e). \quad (1)$$

The unit connection weights from the input layer to the hidden layer, the connection weights from the hidden layer to the output layer, the threshold of the hidden layer unit, and the random value of the unit threshold of the output layer are respectively given:

$$\tilde{p}(n, m) = p(n, m) * h(n) = \sum_{L=-N_1}^{N_1} p(n-1, m)h(l). \quad (2)$$

Select the activation function sigmoid function to calculate the activation value of the hidden layer unit, which is

$$\delta_i^{(n_1)} = \frac{\partial}{\partial z_i^{(n_1)}} J(W, b; x, y). \quad (3)$$

Calculate the activation value of the output layer unit and calculate the error function. It can be calculated by

$$\delta_i^{(n_1)} = \frac{\partial}{\partial z_i^{(n_1)}} \frac{1}{2} \|y - h_{w,b}(x)\|^2 = -(yi - a_i^{(n_1)}) \cdot f'(z_i^{(n_1)}). \quad (4)$$

Adjust the unit connection weight between the hidden layer and the output layer unit:

$$\delta_i^{(l)} = \left(\sum_{j=1}^{S_{l+1}} W_{ji}^{(l)} \delta_j^{(l+1)} \right) f'(z_i^{(l)}). \quad (5)$$

Adjust the threshold of the output layer:

$$\tilde{P}_2 = s \cdot P_2 \cdot R + L. \quad (6)$$

Adjust the connection weight of the input layer to the hidden layer:

$$Pr[A(X) \in \hat{D}] \leq e^{[X, X']} Pr[A(X') \in \hat{D}]. \quad (7)$$

Adjust the implicit unit threshold:

$$s = \frac{\text{tr}(P_{K1}^T \cdot P_{k2} \cdot R)}{\text{tr}(P_{K2}^T \cdot P_{k2})}. \quad (8)$$

To calculate the global error, repeat Step 2 and Step 3; otherwise, the learning ends. It is

$$\left. \begin{aligned} \tilde{p}(0) &= h(-255)p(-255)+, \dots, +h(0)p(0)+, \dots, +h(255)p(255) \\ \tilde{p}(0) &= h(-255)p(-255)+, \dots, +h(0)p(1)+, \dots, +h(255)p(255) \\ \tilde{p}(0) &= h(-255)p(-255)+, \dots, +h(0)p(255)+, \dots, +h(255)p(255) \end{aligned} \right\} \quad (9)$$

Enter the prediction object in the system, then the system is connected to the corresponding database, model library knowledge base, and the neural network weight database called out is used for prediction, and the prediction results are displayed through dynamic reports. It can be denoted by

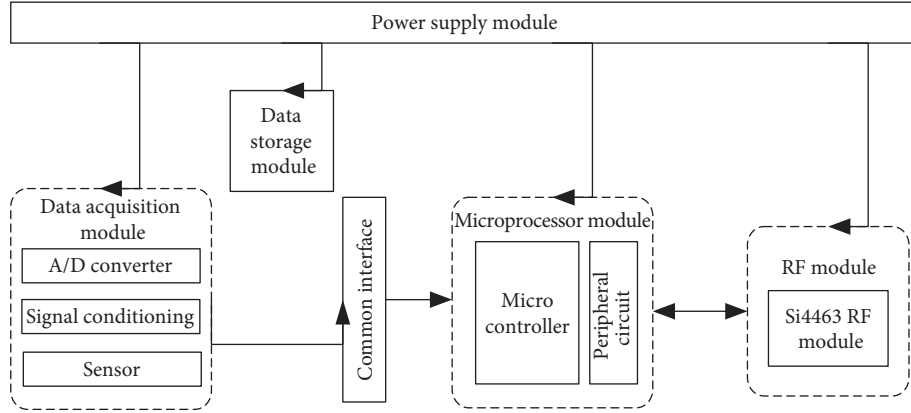


FIGURE 3: Research on English film and television resource information mining based on fuzzy neural network.

$$\begin{aligned}
 \delta_i^{(n_i-1)} &= \frac{\partial}{\partial z_i^{n_i-1}} J(W, b, x, y) \\
 &= \frac{\partial}{\partial z_i^{n_i-1}} \frac{1}{2} \|y - h_{w,p}(x)\|^2 \\
 &= \left(\sum_{j=1}^{S_{xj}} W_{ji}^{n_i-1} \delta_j^{(n_i)} \right) f'(z_i^{n_i-1}).
 \end{aligned} \quad (10)$$

Select the activation function sigmoid function to calculate the activation value of the hidden layer unit.

4. Case Verification of English Film and Television Resource Information Mining Based on Dynamic Data Stream

4.1. Sources of English Film and Television Resources. Building a high-quality film and television information network is an important foundation for subsequent mining and analysis. This chapter will introduce how to construct a network by obtaining film and television data from data sources. Firstly, we introduce the composition of film and television data and the mode of film and television information network. Then, it introduces how to extract the entities used to construct the information network, the relationships between entities, and attribute information from the obtained film and television data, including the extraction of plot keywords and the alias labeling of entities. Finally, we will introduce how to effectively store the film and television information network to make subsequent analysis work more efficient. In this experiment, the movie data were analyzed in a cluster of five multinodes to measure the overall performance of the recommendation system.

This article uses an open dataset about movie ratings provided by Group Lens. Movie Lens is an experimental dataset specifically aimed at researching related technologies. Because of the reliability and authenticity of the data, this article uses the Movie Lens dataset for various experiments. Group Lens currently provides datasets of different sizes, with thousands of users and ratings and even hundreds of thousands of movie ratings. In this paper, several

thousands to tens of thousands of datasets of different numbers are used to carry out related experiments and analysis, because the movie dataset provided by Group Lens is already a standard with a very standardized format.

4.2. Analysis of the Mining Effect of English Film and Television Resources. There are four relationships between directing, filming, and screenwriting. There is a corresponding reverse relationship from the film node to the filmmaker node. In addition, there is a two-way relationship between film and film tags that contains and is contained. It should be noted that in the knowledge graph, the two relationships between attributes and nodes are considered as data attributes and object attributes, respectively. The former points from the object domain to the literal range, and the latter points from the object domain to the object range.

Figure 4 gives the comparison of the response speed performance results of English film and television resource mining of the proposed scheme under different data nodes. We adopt four different data nodes ranging 1~16, 17~32, 33~47, and 48~63, which are denoted by test environment index 1, test environment index 2, test environment index 3, and test environment index 4, respectively. It can be seen from Figure 4 that the speedup ratio of the robust extreme support vector machine algorithm with forgetting factor approaches linear growth when the data node is between 1 and 16. This is because the part of the robust extreme support vector machine algorithm with forgetting factor that has the largest amount of calculation is highly parallel, so the algorithm has a good speedup. When the data node is greater than 16, the algorithm uses 64 MB as the unit when processing data due to the Hadoop environment. Data is divided. Here, for clarity of explanation and to reduce the involvement of the concept of subdivided fields, the first is simply called attributes, and the latter is called internode relations, but the implementation is still in accordance with the definition of the knowledge graph. After completing the above three steps, the network mode of the film and television information network is determined.

Figure 5 gives the comparison of results of concurrency tolerance of English film and television resource mining server of the proposed scheme under different data nodes. We adopt four different data nodes ranging 1~16, 17~32,

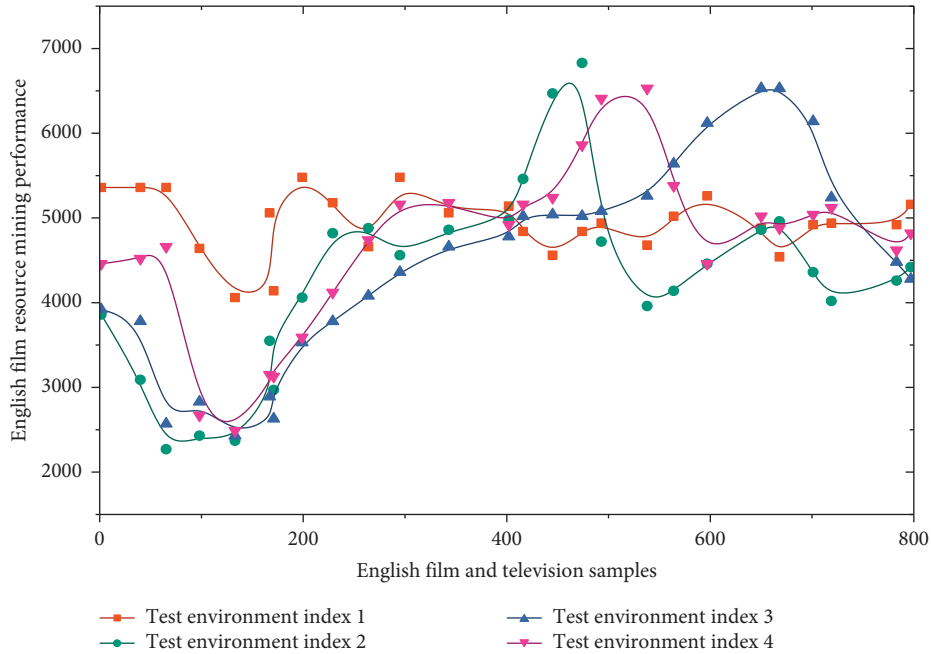


FIGURE 4: Response speed performance results of English film and television resource mining.

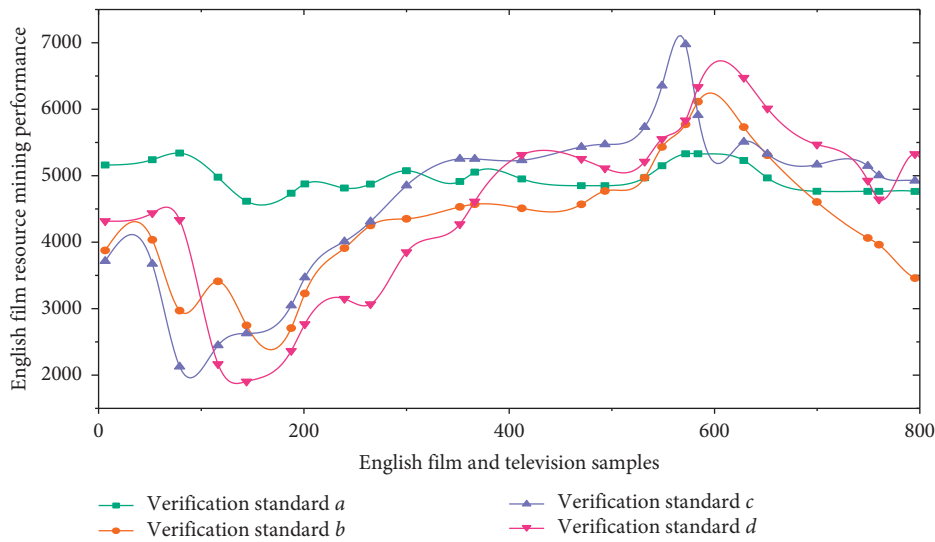


FIGURE 5: Results of concurrency tolerance of English film and television resource mining server.

33~47, and 48~63, which are denoted by verification standard *a*, verification standard *b*, verification standard *c*, and verification standard *d*, respectively. It can be seen from Figure 5 that when the number of nodes is greater than the number of data partitions, increasing the number of nodes has a limited increase in the efficiency of the algorithm, so currently the growth of the acceleration ratio tends to be flat. Under normal circumstances, the scalability of parallel algorithms shows a downward trend as the scale of nodes and data increases. Figure 5 shows that the scalability of robust extreme support vector machine algorithms with forgetting factors increases with the scale of nodes and data.

Figure 6 gives the comparison of the quality of the reconstructed signal in the analysis of the effect of the

mining of English film and television resources of different detection methods. There are four methods considered here, which are FDNDCA proposed in this paper, IGC proposed in [44], AAAR proposed in [45], and NEUMN proposed in [46], respectively. These four methods correspond to detection method 1, detection method 2, detection method 3, and detection method 4, respectively. Compared with other algorithms, the accuracy of the FDNDCA algorithm also has a significant advantage, and the improvement is between 1% and 13%. The FDNDCA algorithm is significantly better than the other three algorithms in classification accuracy.

Figure 7 gives the comparison of data mining quality of English film resources mining and reconstruction of different detection method. Similarly, there are four methods

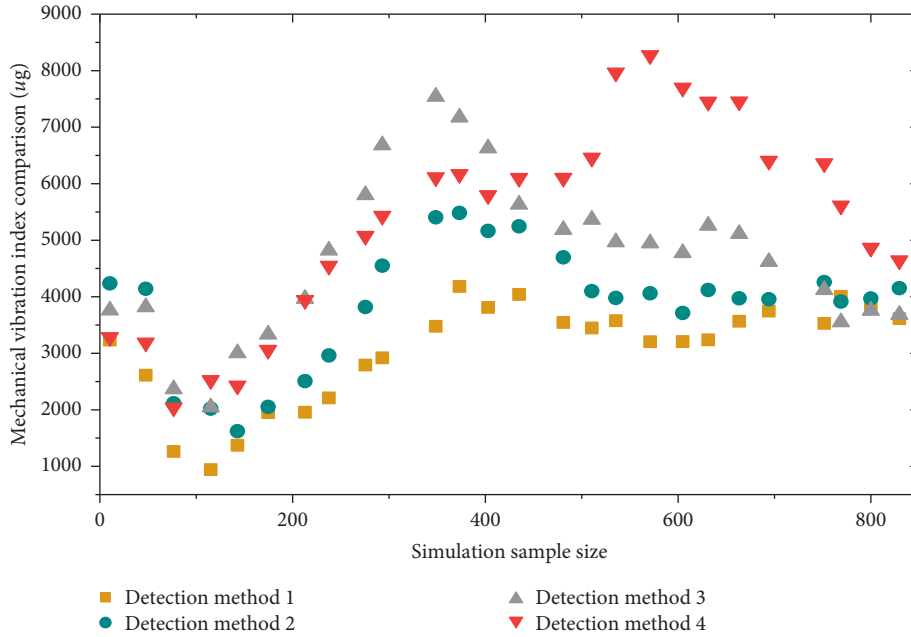


FIGURE 6: Comparison of the quality of the reconstructed signal in the analysis of the effect of the mining of English film and television resources.

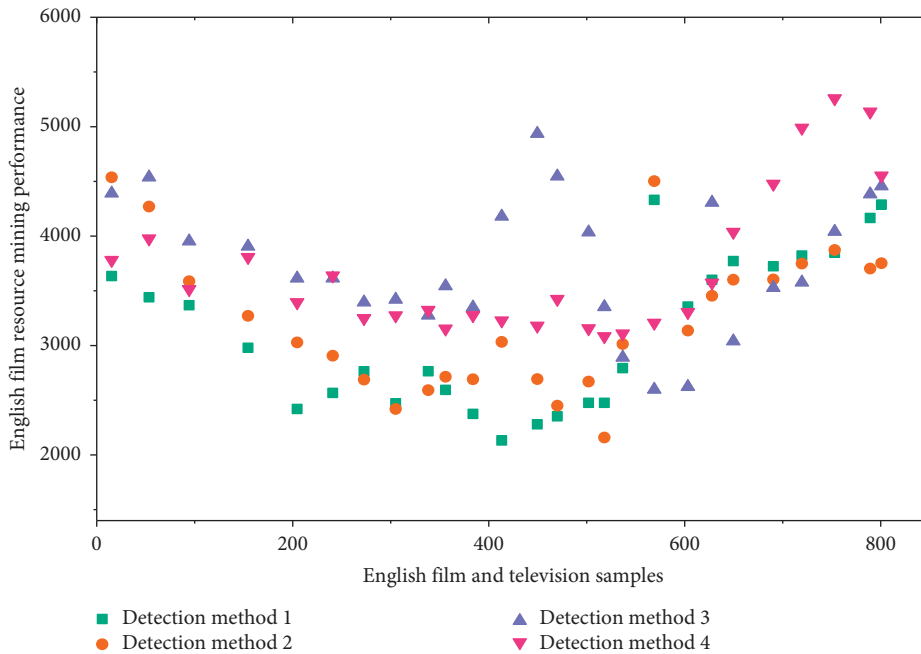


FIGURE 7: Comparison of data mining quality of English film resources mining and reconstruction.

considered here, which are FDNDCA proposed in this paper, IGC proposed in [44], AAAR proposed in [45], and NEUMN proposed in [46]. These four methods correspond to detection method 1, detection method 2, detection method 3, and detection method 4, respectively. As can be seen from Figure 7, when the amount of data is relatively small, in the stand-alone mode and the cluster architecture environment, the recommended accuracy is not much

different. But from 200 data to 700 data, the quality has a little obvious difference, but it is still not very large, and even the recommendation effect of the two can be considered the same to a certain extent. However, from 300 to 700, the fluctuations and changes in the value of the cluster mode are relatively stable so that there is not much change in the accuracy of the recommendation. Because in practical applications, as the amount of processed data continues to

increase, its recommendation accuracy and recommendation effect will decrease, because the movies rated by users are very sparse.

Above all, the proposed method can achieve a better performance than the other three methods. The reason might be that (1) we use dynamic data stream classification technology to preprocess and screen English film and television resource information, which can help to get an ideal classification effect. (2) We use fuzzy neural network algorithm to conduct data mining on related film and television resource information which can help to get the characteristics of the data.

5. Conclusion

Although the data can be obtained directly based on the open API, its open permissions are quite restricted. There are many ways to practice this idea. For example, you can start from the movie plot that the user has watched, extract keywords to generate a user portrait, and then further match and push the movie. For example, currently Dougan only opens a part of the interface, and many external data interfaces are not free, or directly not open to the outside world. Even if the API is open to the outside world, there are strict controls on the frequency and number of access data. With the help of the concept of heterogeneous information network, the paper organizes film and television data into a heterogeneous information network containing multiple types of nodes and multiple relationships between nodes and uses network representation learning and text representation learning algorithms to effectively deal with the key information in the film data said. In the work of this paper, the information contained in the video data is organized through a heterogeneous information network, and the key information in it is effectively expressed through network representation learning and text representation learning algorithms.

On this basis, this paper proposes a set of query-driven mining and analysis solutions, which can efficiently complete a variety of different analysis tasks. First, we use dynamic data stream classification technology to preprocess and screen English film and television resource information. Secondly, we use a fuzzy neural network algorithm to conduct data mining on related film and television resource information. The experimental simulation test results verify the superior performance of the English film and television resource information mining model established in this paper. This model can help people find the resources and information they need. In addition, a query-driven mining analysis framework is proposed, which can efficiently complete a variety of different analysis tasks. Based on the abovementioned research, we designed and implemented a Dougan film and television data analysis prototype system, which can effectively discover the important information hidden in the film and television data and can serve a variety of analysis scenarios. Looking to the future, there are many areas worthy of further improvement in the work of this article. The film and television data obtained in this article are not enough in terms of comprehensiveness and volume

of information. This also limits the depth and breadth of analysis to a certain extent. In fact, in addition to obtaining relevant data from professional movie websites such as Dougan movies, a lot of movie information can also be obtained from social networking sites and news-related websites, which can be used as a supplement to the former. In addition, it is worth trying to enrich the amount of information in the data by introducing an external knowledge base.

As for the proposed scheme, it can help to realize English movie resource information mining, and the experimental results show the effectiveness of this method. A large number of studies and experiments have proved that this method can show good performance when the amount of data is not large and there is a certain relationship between the data. When the amount of data is very large or the relationship between data is small, the performance of this method will be poor. So, the future research direction is to improve the performance of the algorithm in the case of large amount of data and small relationship between data.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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