



Machine Learning Based Method for Mining Anomaly Features of Network Multi Source Data

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Abstract. Aiming at the problem that the current network multi-source data anomaly diagnosis is not effective, this paper proposes a method of network multi-source data anomaly feature mining based on machine learning. First of all, a multi-source data feature recognition model is built based on the multi-level structure of machine learning. Then, the network multi-source data feature classification algorithm is designed and optimized to identify and locate the abnormal data features based on the classification results. Finally, the network multi-source data abnormal data screening model is constructed to mine the abnormal characteristics. The experimental results show that this method has high practicability and accuracy, and fully meets the research requirements.

Keywords: Machine Learning · Network Multi-source Data · Abnormal Data · Data Mining

1 Introduction

With the rapid development of big data technology, the amount of data generated by people has increased exponentially, realizing the sharing and multi-purpose of large-scale data. However, in the process of data transmission, storage and interaction, information may be connected into a complex data network [1].

With the continuous expansion of data network scale, the number of multi-source target data is also increasing. The stability of the network can be guaranteed by analyzing the characteristics of multi-source data and mining the abnormal data [2]. Generally, in the process of analyzing and mining network multi-source data, it is necessary to establish a multi-source data fusion tracking model, and combine big data mining and information reconstruction methods to conduct data fusion detection and feature analysis, so as to improve the mining ability of abnormal data [3].

On the basis of existing research, this paper designs a new method for mining abnormal features of network multi-source data based on machine learning. The design idea is as follows:

Based on the principle of machine learning, a multi-source data feature recognition model is constructed.

Implement feature classification for network multi-source data, and identify and locate abnormal data based on classification results.

Build a network multi-source data abnormal data screening model and mine the abnormal features.

2 Network Multi-source Data Learning Abnormal Feature Mining

2.1 Construction of Multi-source Data Feature Recognition Model

Machine learning data mining is a key link in the process of network data anomaly feature mining. This study uses the multi-level structure of machine learning to achieve data collection. The model structure is shown in Fig. 1.

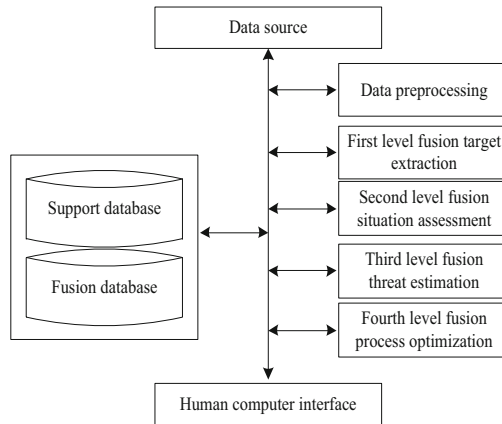


Fig. 1. Machine learning data collection model

Based on the model in Fig. 1, the element information is modeled according to the prior template structure in the knowledge base. Match the data observation behavior with the assumed template. If the matching degree is less than the set threshold, the data will be discarded, otherwise, the data behavior sequence will be interpreted with the assumption template. Figure 2 shows the principle of data feature mining.

Data mining technology is a process of discovering valuable and meaningful rules behind these data through some technical means from the massive information in the database. The function of the data mining model is to mine and analyze the feature information useful for command and decision-making from the massive and complex situation machine learning, and finally present the analysis results to the decision-maker as a situation visualization multi view. Therefore, this paper presents the corresponding data mining model functional framework, as shown in Fig. 3.

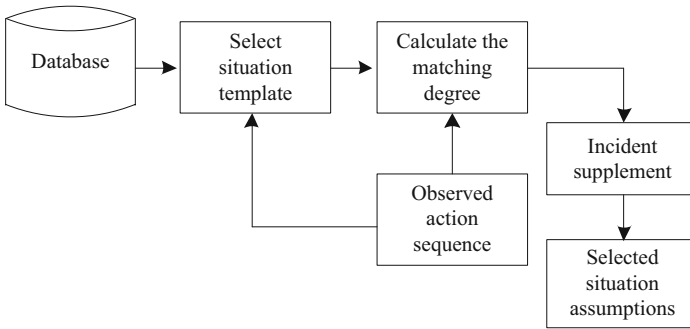


Fig. 2. The principle of multi-source data feature mining

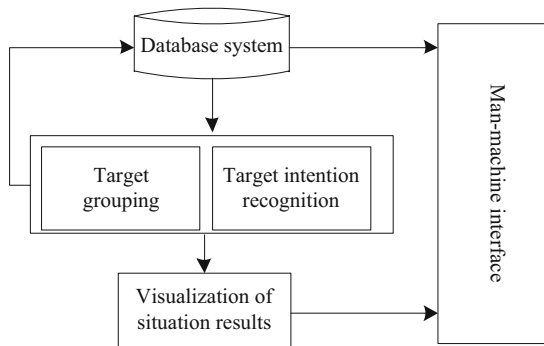


Fig. 3. Functional structure of the multi-source data feature evaluation model

The functional requirements of the model include: human-computer interaction interface design, mainly including user login and logout operations, selection of core functions within the model, real-time display of situational results, and query and display of feature results; core function design of machine learning data mining models, including data preprocessing operations such as cleaning, integration, specification, transformation, etc. for the absence, anomaly, format, and redundancy of situational machine learning; Mining and analysis of target groups The behavioral state of the target group is used to identify the target’s combat intention and establish a functional relationship view between the target objects: combine the former two to establish a target group interaction relationship view; feature mining data management function design, including situational machine learning and real-time storage of situational results, query, modify, delete and other operations.

2.2 Multi Source Data Feature Anomaly Recognition Algorithm

The data features mined above are unprocessed. At this time, the data may have different feature specifications, and the data cannot be compared together because of their different feature specifications. Machine learning can solve the problem of feature. The method of machine learning can be divided into region zoom *a* and standardization *A*. Before

standardization, it is required to have the characteristic value a of the phenomenon of normal distribution, or after normalization, it can meet the standard normal distribution r . The standardized formula is as follows

$$x' = \prod \frac{a - \bar{A}}{S} - r \quad (1)$$

Then the boundary information is used to shorten the range of features to a feature point. For some features that need to be quantified, the information contained in them is not numerical, but a literal interval. At this time, it needs to be transformed into quantitative characteristics. In addition, there is also the problem of large numerical range of some quantitative characteristics. At this time, you can set a threshold value. If it is greater than the threshold value, it is set as 1. If it is less than or equal to the threshold value, it is set as 0. The method is as follows:

$$x' = \begin{cases} 1, & a > \text{threshold} \\ 0, & a \leq \text{threshold} \end{cases} \quad (2)$$

The principle of collective outlier detection based on data distribution fitting is mainly divided into three steps. First, the sample data is fitted, and the distribution function obtained is regarded as the distribution structure of normal sequence data; Secondly, the actual data distribution is fitted, and the distribution function obtained is the mixed distribution structure of medium normal data and collective outliers. Finally, the parameter characteristics of the two distribution functions are compared to identify the collective outliers. The details are as follows: For sample data set f with normal labels, its distribution structure θ_s is simulated according to the formula. Parameter p represents the data distribution function, λ represents the parameters in the distribution function, and t represents the data instance.

$$D(n) = \lambda \sum tx' + f_s(p + \theta_s) \quad (3)$$

For the actual sequence data, according to formula (3), the data distribution $D(n)$ is fitted by the mixed distribution function model. The parameter φ represents the mixture distribution function, θ_s represents the distribution function of the collective outliers, θ_a represents the proportion of the collective outliers in the sequence data, B is the parameter in the mixture distribution function, and a is the parameter in the abnormal data distribution function. The distribution structure of the sample dataset is as follows:

$$\Delta D(n) = tx'[(1 - \varphi)f_s(p + \theta_s) + \lambda f_s(p + \theta_a)] \quad (4)$$

Further, the data series that are significantly different from the distribution structure $\Delta D(n)$ of the sample dataset in the actual sequence data are identified as collective outliers. Assume that the sample set $x = \{x_1, x_2, \dots, x_n\}$ of m data objects, the number of clusters is k , set $c = \{c_1, c_2, \dots, c_n\}$ is the known initial cluster center of the sample set, and $m < k$, the shortest distance from the sample point z in the sample set to the known initial cluster center set s is (x_j, c) , the shortest distance obtained from the sample set d_s is arranged in ascending order, and the shortest distance from the point to the set

is the probability:

$$p(x_i) = \frac{|\Delta D(n) - D(n) + m|^2}{k \sum_{x_j \in x} d_s(x_j, c)^2} \tag{5}$$

In the process of data mining, the sample points of machine learning are not rigidly divided into corresponding categories by 0 or 1, and the probability that the broken data points tend to different categories is introduced. Given a sample set of n data objects, u_{ij}^m and v_i are the number of clusters. By minimizing the objective function, the cluster center and the membership degree between the sample point and the cluster center are updated iteratively, and finally the similar sample points are as accurate as possible. The samples are divided into the same cluster, and the clusters composed of dissimilar sample points are divided as far as possible. The data feature mining objective function is defined as follows:

$$J = n \sum_{i=1}^c \sum_{j=1}^n u_{ij}^m d_{ij}^2 + \|p(x_i) - v_i\|^2 \tag{6}$$

If $v_i^{(r-1)}$ represents the fuzzy weighting coefficient, $m \in [1, +\infty)$, in general, $m = 2$. The membership matrix of cluster center η and sample points and cluster center is updated iteratively by using the Lagrange multiplier method, so that the objective function value $f(n)$ gradually decreases until it converges to the minimum value. The updating formula of the membership matrix is obtained by using the Lagrange multiplier method as follows:

$$u_{ij}^{(l)} = \frac{\|J - v_i^{(r-1)}\|^{-2/m-1}}{\|p(x_i) - v_i\|^2} - \eta \tag{7}$$

It can be seen that the machine learning method, after repeatedly updating U and V in turn, finally finds the most suitable result that meets the target. The calculation process of the machine learning method is simple, but there are still some shortcomings. The algorithm of the machine learning method is affected by the initial cluster center, and several methods of initializing the cluster center can be adopted.

2.3 Implementation of Network Multi-source Data Mining

Self organizing network will become an important technology of 5G. 5G will be a heterogeneous network with integrated and cooperative multi system coexistence Technically, the coexistence of multi-layer and multi wireless access technologies will lead to a very complex network structure. The relationship between various wireless access technologies and network nodes with various coverage capabilities is complex. The deployment, operation and maintenance of the network will become a very challenging work. In order to reduce the complexity and cost of network deployment, operation and maintenance, and improve the quality of network operation and maintenance, the future 5G network should be able to support more intelligent The unified SON function can

uniformly realize the joint self configuration, self optimization and self-healing of multiple wireless access technologies and coverage levels Recently, the SON technology for LTE, LTE-A, UMTS, and WiFi has been developed relatively well, and gradually began to be applied in the newly deployed network. However, the existing SON technologies are all oriented to their respective networks, and perform independent self-deployment and self-configuration, self-optimization and self-healing from the perspective of their respective networks, and cannot support the collaboration between multiple networks. SON technology for constructing network, such as node self-configuration technology based on wireless backhaul in heterogeneous network, self-optimization technology in heterogeneous system environment, such as coordinated wireless transmission parameter optimization, coordinated mobility optimization technology, and coordinated energy efficiency optimization technology, cooperative admission control optimization technology, etc., as well as cooperative network fault detection and location under different systems, so as to realize the self-healing function. The multi-source data mining of machine learning acquisition and analysis network is designed and implemented according to the combined prediction model based on machine learning and data features. Figure 4 shows the functional architecture of the model.

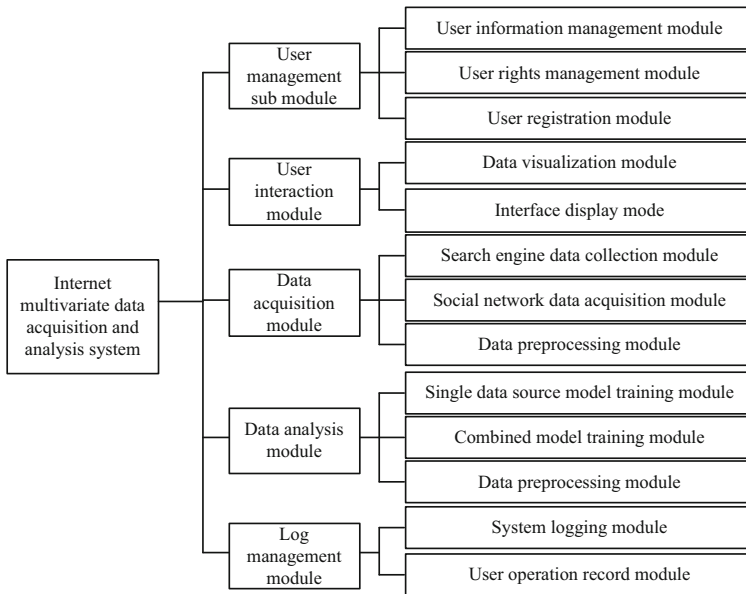


Fig. 4. Functional structure of machine learning network data feature model

In general, the model has designed three main functional modules, which are data acquisition module, data analysis module and user interaction module. User interaction module is mainly divided into data visualization sub module and interface presentation sub module. The data collection module is divided into search engine data collection module, social network data collection module, content filtering module and data preprocessing module. The data analysis module is divided into single data source model

training sub module, combined model training sub module and data preprocessing sub module. The model also includes log management sub-module and user management sub-module. The comprehensive index finally obtained by the feature analysis of the search engine data needs to construct the corresponding prediction model. The basic flow of the prediction model is shown in Fig. 5.

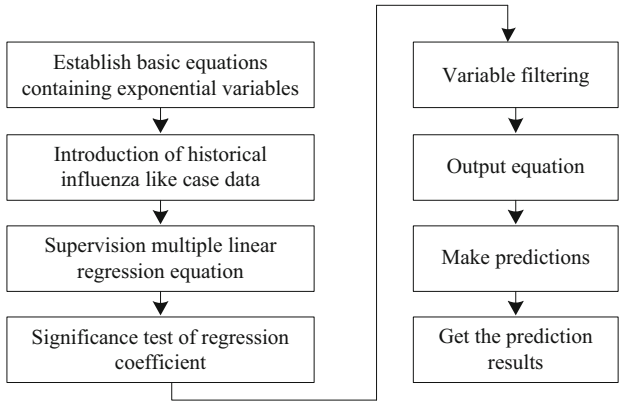


Fig. 5. Basic process of data feature recognition and classification

The data feature recognition and classification module is responsible for model training and data prediction. This module includes three sub modules: single data source model training module, combined model training module and data preprocessing module. Multi source cloud data architecture usually adopts C/S structure, B/S structure, and combination of C/S and B/S. However, these three framework connection methods all need to use cloud computing database as the main bearing container of multi-source isomers, and require that the database must use the core server as the basic installation background, and all big data to be connected must maintain a tight connection with the front processor. For the multi-source cloud data interface, every program file output from the cloud computing database must enter the central processing layer structure through this structure. In order to avoid the accumulation of cloud data, each multi-source cloud data interface is directly connected to the client processor, and under the promotion of an external power supply device, it provides continuous data support for cross-source scheduling of big data. When the basic connection form is not enough to meet the transmission requirements of multi-source heterogeneous big data bodies, some data will release the node information carried by itself before entering the cloud computing database, and transmit the information to SQL temporary storage through the multi-source cloud data interface structure to avoid the occurrence of scheduling efficiency reduction events due to data loss [4]. Traditional big data scheduling processes mostly use API interfaces, which can maintain the structural stability of big data multi-source isomers to the greatest extent. However, with the continuous increase of the total amount of data to be scheduled, such interfaces cannot maintain a long-term continuous working state, which is easy to cause data accumulation, and is not conducive to in-depth integration of underlying network traffic. Because the training data required by

the combined model training module needs to wait for the prediction data given by the single data source model training module, the multi-source heterogeneous data formats are divided into four categories for interpretation by using the data conversion system during data processing, namely: text files, mainly including text format files; Binary file class, mainly including binary format files; GDAL file class, mainly including NetCDF format file, GrADS format file, HDF format file, remote sensing image file; MATLAB file class, mainly including Mat format files. Therefore, during the processing of the data analysis module, the data shall be preprocessed first, then the single data source model shall be trained, and finally the combined model shall be trained. The overall processing flow of the module is shown in Fig. 6.

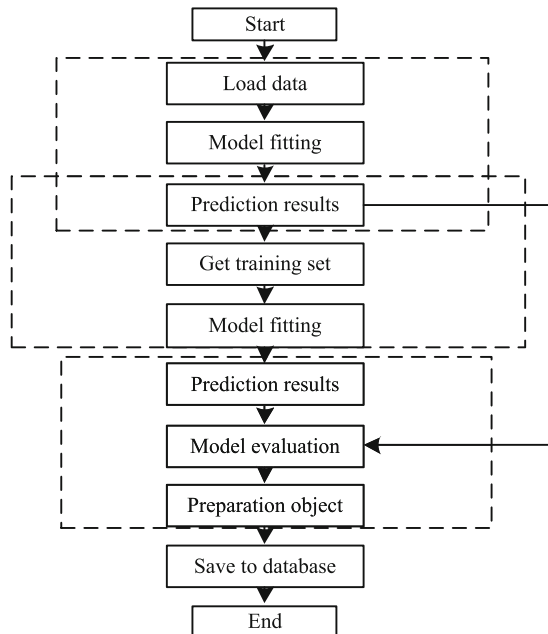


Fig. 6. Optimization of abnormal data screening and positioning process

According to the data selection criterion, the ant colony algorithm is used to fuse the active-active data to obtain the fusion solution. The specific steps are as follows:

- (1) Convert the data values collected by the two data centers into fuzzy values to obtain the local decision of the active-active data center;
- (2) Calculate the distance between active-active data centers;
- (3) Establish a distance matrix, thereby determining the matrix relationship;
- (4) According to the determined result, a directed graph can be obtained;
- (5) According to the directed graph, two active data centers can be merged into a new group, and the decision value can be calculated. Use this decision value to replace the fused active data, and return to step (2) until the distance between active data centers is 0, and the maximum active data connection group can be obtained. So

far, the integrated access to multi-source big data of the distribution communication network has been completed.

In the training module of single data source model, the prediction models used are the described prediction models based on search engine data, prediction models based on social network data, and prediction models based on official data. Multi source regression algorithm is used in the first two models, and autoregressive moving average model is used in the prediction model of official data. The training results and prediction results of the model will be stored in the database, and the data results will be input into the preprocessing module; The combined model training module uses the prediction results of a single data source model as the training set, which is used to train the gradient lifting decision tree algorithm. The final training results and prediction results will be stored in the database, and the data results will be input to the preprocessing module; the data preprocessing module is mainly used for data conversion between models. In addition, the evaluation criteria need to be calculated according to the training results and prediction results of each model. The evaluation results of the model will also be stored in the database to facilitate the display of subsequent interactive modules. In order to ensure the effectiveness of abnormal data mining of data nodes in the security resource pool, the abnormal data feature collection algorithm is optimized [3]. During the collection of abnormal features of data nodes in the security resource pool, its minimum support sequence vector set is: $A = \{A_1, A_2, \dots, A_n\}$. In the above set, n represents the number of items in the minimum support sequence vector set. If there is a characteristic value ε in the set, and ε is a special sequence parameter in the set [4]. If the data support degree in the set is ϖ , record the special sequence item value κ of abnormal features, and define the support degree of abnormal data feature sequence as Ra . Based on this, the least support frequent itemset L is calculated as follows.

$$L = \lim_{0 \rightarrow \infty} u_{ij}^{(l)} \sum \sum \frac{\varepsilon + \sqrt{(\varpi - \kappa)^{n-1}}}{A + Ra} \tag{8}$$

In the process of in-depth collection and query of data features, in order to ensure the effectiveness of data mining, it is necessary to further improve the automatic abnormal mining natural data center, so as to optimize the abnormal data mining process. Based on the above steps, the abnormal feature data of the data node is further mined. According to the initial clustering population value M collected by the data model, the individual characteristics of the optimal population are judged. If the number of characteristic clusters collected is j , the numerical algorithm for the dynamic adjustment range of abnormal data is:

$$\zeta = \lambda \bigcap^j - 1 / (L - M) \tag{9}$$

Before a node j fails, the operation data is dynamically transferred to other nodes $C_k(t)$ to ensure that the task is completed before that time. Requirement:

$$C_j(t) = (L + \zeta) + C_k(t)(d_i - \xi_j(t) - t_0) \geq \omega_i(t) \tag{10}$$

It is known from the failure prediction model that at the time of $\xi_j(t)$, node d_i will experience resource failure, and the end time of t_0 's operation data is $> \omega_i(t)$. Based on

the above algorithm, global optimization and mining processing are carried out for the differential node numerical operator of abnormal data. Based on the distributed resources of multiple targets, the real-time perception of data resources based on multi-target genetic algorithm is realized. Like the DAG parallel graph, there is a data dependency between running data. For example, T1 is the subsequent running data of a running data L2 and 3. You can arrange running data 1 to virtual machine resource n, and assign running data 2 and t3 to virtual machine resources $T_{predexec}(t_j)$ and $T_{pred eamm}(t_j)$. Then the data transmission between running data $T_{starl}(t_j, v_t)$ and $T_{starl}(t_j, v_t)$ should be completed by the communication link between virtual machine resources $T_{comm}(t_i)$ and $T_{exec}(t_i)$, Then the parallel running data planning problem can be described as follows: on virtual machine resource U, the reliability of the whole task is increased and the task schedule length is reduced

$$\begin{cases} \max C_j(t) \sum_{i=1}^m \text{Priority} \\ T_{starl}(t_j, v_t) \geq T_{predexec}(t_j) + UT_{pred eamm}(t_j) \\ T_{starl}(t_j, v_t) = \max\{UT_{comm}(t_i) | t_i \in \text{Pred}(t_j)\} \\ T_{prederec}(t_j) = \max\{UT_{exec}(t_i) | t_i \in \text{Pred}(t_j)\} \end{cases} \quad (11)$$

The absolute error average value filled with the distribution network data can better reflect the real filling deviation, and the less the average absolute error, the better the filling result. Here y_i represents the padded data and x_i represents the corresponding actual data, so the mean absolute error of n samples is defined as the following

$$\text{MAE}(y_i, x_i) = \frac{1}{n} \sum_{i=0}^{n-1} |T_{starl}(t_j, v_t) - T_{starl}(t_j, v_t) - T_{prederec}(t_j)| \quad (12)$$

Between the measured data and the measured data, the sample benchmark deviation is selected as the optimal prediction index. The smaller the mean value is, the more accurate the result is. Here, y_i represents the filled data, and x_i represents the corresponding real data. Therefore, the average error of n samples is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=0}^{n-1} |y_i - x_i|^2} \quad (13)$$

The normalization of the current multi-index, according to the characteristics of its indicators, can be attributed to two kinds of linear and nonlinear. This method can be used for both the anterior index and the reverse index, but the conversion index cannot be used to represent the correlation between the initial indexes. Ratio conversion: After conversion, convert the front and rear indices into a positive index. Although there will be different indices, it cannot well reflect the interaction between the reverse indices. Local abnormal feature numerical search based on machine learning principle is carried out for individual and group features of collected abnormal data. In order to further accelerate the speed of mining convergence, the above algorithms need to be processed iteratively. Because the automatic mining method of data node exceptions is relatively complex and a complete process, the mining steps are usually relatively tedious, time-consuming and

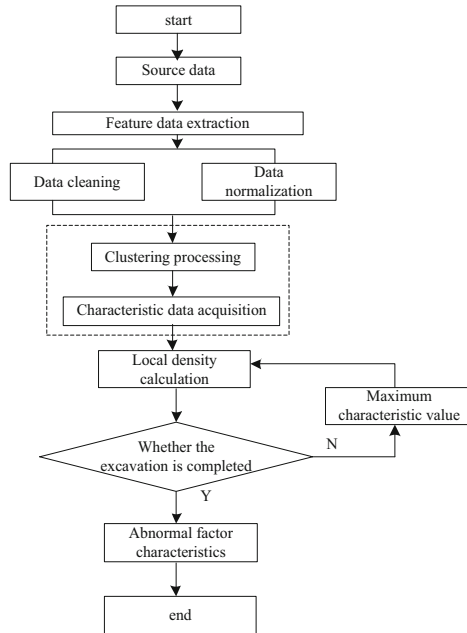


Fig. 7. Optimization of abnormal data feature mining steps

prone to deviation, Therefore, the process of abnormal feature data mining is optimized, and the specific steps are shown in Fig. 7.

In the process of data mining of abnormal features, in order to minimize the complexity of data mining, the mining steps are further improved, as follows:

1. Data preparation. Randomly collect characteristic values of data nodes in the security resource pool.
2. Select Feature Data. Mining the internal and external characteristic data information of the collected data.
3. Data preprocessing. The characteristic data is further analyzed and transformed, and a corresponding analysis model is established, and a corresponding data center is established.
4. Data mining. Combining the feature data and the data center detection value to realize automatic mining, obtain and output the data feature value.

Analyze and define the dimension boundary of the characteristic boundary of abnormal values. Based on constraint conditions and iterative processing method, the numerical mining method of abnormal data intrusion features in flow data is improved, as follows:

1. Feature mining algorithm optimization. By optimizing the data feature mining algorithm, the speed and accuracy of data mining are improved.
2. sdn data center structure optimization. In order to better expand the depth of data mining, the data features are clustered in combination with the CAF principle and data feature collection standards.

3. Data cleaning. In order to ensure the rationality of data mining, it is necessary to perform routine denoising processing on abnormal feature data to clean the data and ensure the effectiveness of data mining.

4. Data output. Output and store the collected and cleaned data, and check and repair the abnormal data by comparing the characteristic values of standard data.

Based on the above methods, we can effectively optimize the automatic mining method of security resource pool data node exceptions, so as to achieve the research goal of improving the accuracy and effectiveness of data mining.

3 Analysis of Experimental Results

In order to verify the practical value of the network multi-source data anomaly feature mining method based on machine learning designed in this paper, the following comparative experiments are designed.

Take two computers with the same configuration, one of which carries the traditional Bayesian multi-source data anomaly feature mining method as the control group; The other one carries the method of this paper as the experimental group.

Before starting the experiment, complete the experimental parameter setting according to Table 1.

Table 1. Experimental parameter setting table

| Experimental parameters | Experience group | Control group |
|-------------------------|-------------------|-------------------|
| TAD/(T) | 6.75×109 | 6.75×109 |
| DSI | 0.79 | 0.79 |
| DSR/(T/s) | 1.45×104 | 1.45×104 |
| Dmt/ (class) | IV | IV |
| KVS/(%) | 97.57 | 97.57 |
| AOT/(s) | 47.96 | 47.96 |

First of all, the performance indicators of the two methods are tested with correlation coefficient r , mean square error MSE, root mean square percentage error RMSE, and maximum absolute percentage error MAPE as indicators. The results are shown in Table 2.

Table 2. Evaluation results of application effects of different methods

| Evaluating indicator | Traditional methods | The method of this paper |
|---------------------------------------|---------------------|--------------------------|
| Pearson correlation coefficient | 0.4723 | 0.9845 |
| Root mean square error (%) | 1.1178 | 0.1088 |
| Root mean square percentage error (%) | 6.0133 | 1.4259 |
| Maximum absolute percentage error (%) | 5.0622 | 2.6311 |

It can be seen from Table 2 that compared with the traditional method, the method in this paper has better application effect in the test of Pearson correlation coefficient, root mean square error, root mean square percentage error, and maximum absolute percentage error.

On this basis, the mining time of abnormal data features of different methods is analyzed, and the results are shown in Fig. 8.

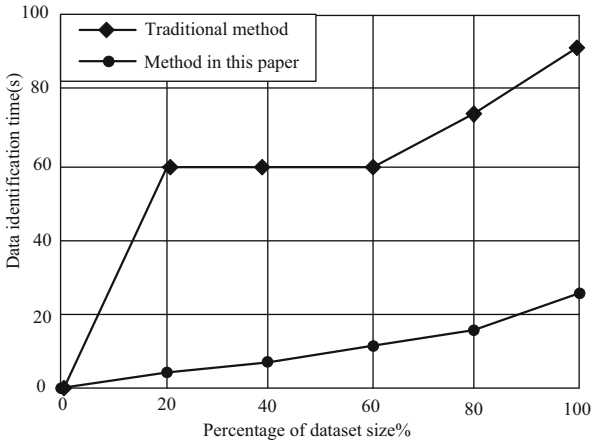


Fig. 8. Comparison of abnormal data mining time under different methods

It is not difficult to find out through analysis based on the above comparative detection results. Compared with the traditional methods, the method in this paper takes significantly less time to identify abnormal data in the actual application process.

The error of abnormal data mining of the two methods in the same environment is further compared for comparative detection. The specific detection results are shown in Fig. 9.

Based on the contrast detection results in Fig. 9, it is not difficult to find that compared with the traditional methods, the data anomaly feature mining method proposed in this paper has significantly lower error rate, and the overall mining accuracy is significantly better, fully meeting the research requirements.

Further compare the mining effects of different methods with the contour coefficient and standard mutual information as indicators, and the results are shown in Table 3.

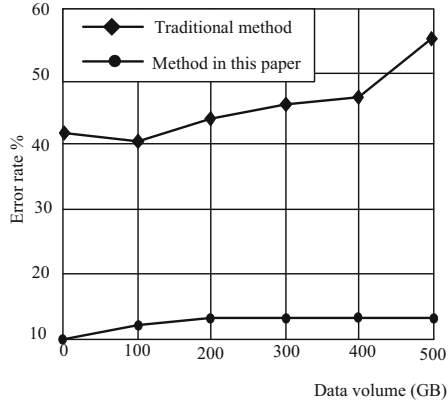


Fig. 9. Error detection results of abnormal data mining by different methods

Table 3. Comparison of the mining results of the two methods

| | Traditional methods | | The method of this paper | |
|-----------|---------------------|-----------------------------|--------------------------|-----------------------------|
| | Contour coefficient | Standard mutual information | Contour coefficient | Standard mutual information |
| Iris | Max | Min | Max | Min |
| Seeds | 0.688 | 0.598 | 0.833 | 0.768 |
| Survival | 0.699 | 0.606 | 0.846 | 0.816 |
| Knowledge | 0.679 | 0.589 | 0.928 | 0.748 |
| Perfume | 0.618 | 0.598 | 0.902 | 0.719 |

As shown in Table 3, compared with the traditional mining methods, the advantages of the method in this paper are that it first eliminates the randomness of the initial parameter selection, so that the clustering results are always unique, the clustering process is more stable, and the mining effect is better.

4 Conclusion

With the development of network technology, data sources are more complex and diverse, and there are fuzziness and uncertainty in them. Mining abnormal features from network multi-source data is very important for maintaining network security. For this reason, this research designs a method of mining abnormal features of network multi-source data based on machine learning. In this paper, a multi-source data feature recognition model is built based on machine learning principle, and then a network multi-source data anomaly feature screening model is built on the basis of multi-source data feature classification, and has achieved good application results.

In the future research, the research scope will be further narrowed and accurate mining will be carried out for data anomaly features in feature sources.

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