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Financial accounting intelligence management of internet of things enterprises based on data mining algorithm

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Abstract. With the introduction of the information age, enterprise financial management has been challenged as never before, and the application of Internet of Things (IoT) technology can effectively improve the efficiency of financial accounting management and realize the informationization of financial management. In order to solve the problem of enterprise financial accounting data processing, a data mining algorithm is constructed, which uses data mining technology to obtain massive information data and cluster analysis processing to realize the fusion of multiple uncertainty information processing models. Firstly, the financial information cloud platform is designed by using the IoT technology. The financial risk index coefficient of the enterprise is judged by the association rules. Finally, the research sample is divided into the risk group and the normal group according to the ST classification standard, and the 296 financial indicators of the two groups are correlated. The research results show that if the enterprise with a score below 40 points has financial risk, the accuracy rate is 70.9%, which is slightly lower than the financial risk warning model of the decision tree. Through the research of this paper, it has enlightenment to the financial accounting management of IoT enterprises. The data mining technology is applied in the processing of massive data information of accounting, which is more efficient.

Keywords: data mining algorithm, enterprise, financial accounting, smart management

1. Introduction

At the same time of rapid development, modern enterprises are always faced with financial risks. The existence of financial risks not only has a negative impact on the survival and growth of modern enterprises, but also may cause huge economic losses to stakeholders [1]. Therefore, how to provide early warning to enterprises with financial risks has become an urgent problem for modern enterprises. Data mining technology has the function of discovering potential laws and knowledge from a large amount of historical data. It is feasible and important to construct a financial risk early warning model by using a large number of enterprise historical financial data as a research sample through data mining clustering and the practical significance of classification algorithms [2].

Data mining is a technique for analyzing each data and finding its regularity from a large amount of data. First, the required data is selected from the relevant data sources and integrated into a data set for data mining. Secondly, the data set is formed by some method. The rules are found out, and finally the rules found in the user-understandable way (such as visualization) are represented by Yusuf R et al. [3].

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Association rules and decision tree algorithms are one of the main intelligent algorithms in data mining algorithms [4]. By highly automated analysis of big data, inductive reasoning, and mining potential models, companies, businesses, and users can adjust market policies, reduce risks, rationally face the market, and make correct decisions [5]. Therefore, this paper studies the financial accounting intelligence management of IoT enterprises by constructing association rules and decision tree data mining algorithms.

The research in this paper is divided into three parts. One is to elaborate on the previous studies and summarize them. The second is to elaborate on the enterprise financial accounting wisdom management method based on data mining, including the IoT financial information cloud platform. The structural design, the construction of the financial accounting information management model used in the data mining method, etc., the third is the specific application of the design method.

2. Related work

Data mining, also known as knowledge discovery in databases, is intended to extract hidden, potentially valuable information from a large number of noisy, fuzzy and random application data. At present, scholars have carried out research on it, and there are many researches on applying data mining in enterprise management. Honghui L I proposed the algorithm for manufacturing enterprise network intelligent fault diagnosis technology and applied it to the financial system of the enterprise [6]. Zhou Y proposed the financial risk early warning modeling method based on data mining method. The research content is mainly the comparison experiment between artificial neural network and logistic regression method [7]. Xue Y expounded the basic principles of data mining, analyzes the process and main functions of data mining, introduces the characteristics of data mining tools, and studies some applications of data mining technology in financial forecasting [8]. Yu M proposed to design the IoT massive data mining system based on the association rule Apriori algorithm, and quickly analyze process, store and mine the massive business data of the IoT. The research results realized the rapid extraction of valuable information and served it, which is IoT enterprise management decision-making [9]. Gao J improved the traditional Apriori algorithm, so that all the frequent itemsets can be retrieved, as long as the transaction database is scanned once. The Apriori algorithm is Map/Reduce, and the effectiveness of the improved Apriori algorithm is verified by experiments. Research shows that the use of distributed parallel computing in cloud computing is feasible for cloud computing-based IoT data mining [10]. Lin Y proposed a new association rule improved algorithm for the problems that traditional methods could not solve. Applying these algorithms to the research of enterprise financial risk analysis and crisis early warning, this paper puts forward the enterprise financial risk concept hierarchy tree model and time series dynamic maintenance. The financial crisis early warning model shows that using this algorithm to construct an early warning model greatly improves the efficiency of data mining [11]. Liu X proposed a method of interactive mining of association rules, selecting financial indicators in multiple aspects, and mining the rules between all financial indicators to finally determine the more representative financial risk indicators. The results show that the algorithm only needs to be added. The database is mined, the associated association rules are effectively maintained, and the efficiency of the algorithm is improved. The research shows that the algorithm can filter the target of financial early warning indicators, which is conducive to the construction of financial early warning model [12]. Luo R constructed a time series financial data mining model, using time series incremental mining and interactive mining strategy to carry out dynamic maintenance mining of association rules. The research found that the algorithm can help enterprises find the rules between financial indicators and predict the development of crisis enterprises [13]. Wei S used the Logistic algorithm of data mining to analyze and predict the possibility of financial crisis in listed companies. A sample of 15 listed companies that are specially dealt with due to financial problems in 2009 was selected. At the same time, 15 normal listed companies are selected as paired samples. The results of the analysis are used to establish a financial crisis warning model for listed companies. Finally, the model feasibility is verified by experiments [14]. Kumar RR introduced SPRINT algorithm as the customer classification modeling algorithm, and discussed several major stages such as preprocessing, optimal segmentation and execution splitting in the design process of SPRINT algorithm. Finally, combined with the actual situation of a newspaper company, the decision tree modeling of customer classification was implemented, and the design of the business architecture and functional modules of the CRM system was completed [15].

All in all, after more than 20 years of development, data mining has a variety of analytical methods such as classification, prediction, clustering, correlation, estimation, and many excellent algorithms such as C5.0, K-Means, SVM, Apriori, and KNN. The current data mining research has entered the stage of applicability research and empirical research, and is widely used in more than 50 fields such as finance, network, sales, user behavior, and customer relationship [16, 17]. With the advent of the IoT era, how to effectively extract and process massive amounts of data in corporate financial accounting management is very important. The data mining algorithm can effectively solve this problem, which provides the possibility for the realization of enterprise financial accounting wisdom management construction.

3. Enterprise financial accounting wisdom management method based on data mining

3.1. Structure design of IoT financial information cloud platform

From the perspective of the history of accounting development, accounting is a discipline that keeps pace with the times. It continues to improve and develop with the deepening and refinement of economic activities [18]. The emergence of the IoT will greatly change and improve peoples' production and life. The real-time and stereoscopic perception of objects and objects, objects and people, and people in the IoT will greatly solve the problem of information asymmetry. The performance of the responsibility, the owner can get relevant information in real time, in this case, the financial report will need more information to reflect the useful information. Therefore, in this context, the research on the possible impact of financial accounting activities of IoT enterprises, based on data mining algorithms to explore the intelligent management of financial accounting of IoT enterprises, the improvement of accounting activities of IoT enterprises is explore in the new environment.

The financial information traceability information sharing platform website combines JAVAEE technology and SSH structure, and then researches and discusses the platform. Struts is a module of SSH structure, which greatly regulates the integrity and simplicity of the code, and is conducive to the expansion and maintenance of the program [19, 20]. Hibernate used the class method to write the database module part, so that users can easily call the program. String is the container framework in the SSH framework. It mainly maintains the relationship between objects and objects. Objects can be any object (including business layer, data source, etc.). Enterprise users need to complete user registration and login, and can publish relevant data in time, and can also operate related data. At the same time, the administrator can manage the users in a unified manner, prevent illegal operations by ordinary users, and some improper operations, so as not to affect the platform, and also increase the security factor of the platform to ensure the normal operation of the follow-up work. The node mode of the IoT is shown in Fig. 1.

3.2. Construction of data mining method used in financial accounting information management model

Decision tree is a classification algorithm in data mining, including: ID3, C4.5, C5.0. The decision tree algorithm divides the attributes of the sample into two categories: conditional attributes and decision attributes. A condition attribute is a condition for judging a decision attribute, that is, a category that the final decision tree needs to be divided.

The ID3 algorithm is the most classical decision tree algorithm. The information entropy and information gain are used to select the attributes of the decision tree preferentially down-classified. Let the decision attribute S have a total of k values in the sample set, which are respectively $S_1, S_2 \dots S_k$, and the probability of taking each value is $p_1, p_2 \dots p_i$. Then, the information of the decision attribute S is calculated by Entropy as shown in the formula (1):

$$Entropy(S) = -\sum_{i=1}^{k} p_i \log_2(p_i) \tag{1}$$

Let condition attribute A have a total of n values in the sample set, which are $A_1, A_2 \dots A_n$, and the probability of each value is $p_1, p_2 \dots p_i$. Then, the information of each value in the attribute A can be calculated as Entropy, and the information gain Gain of the condition attribute A relative to the decision attribute S is calculated as the formula (2):

$$Gain(S, A) = Entropy(S) - \sum_{v=1}^{n} P_V Entropy(A_V) \tag{2}$$

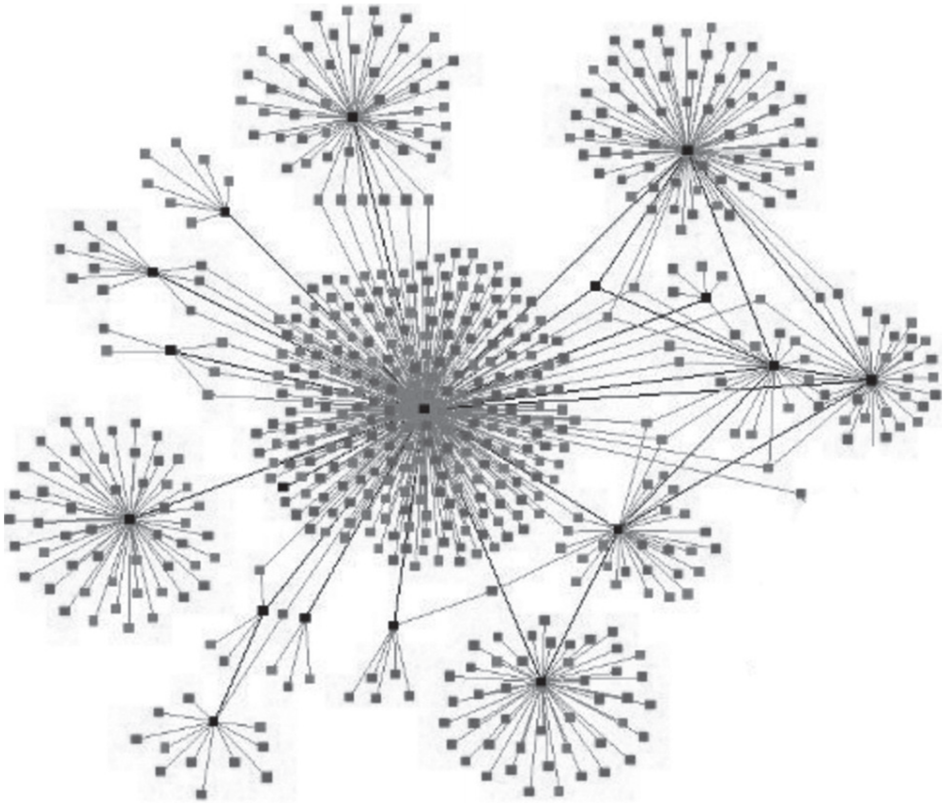

Fig. 1. Node distribution of Internet of things.

The decision tree algorithm prioritizes the splitting of the tree by selecting the conditional attribute with the largest information gain Gain. The ID3 algorithm is an algorithm for processing discrete data. When dealing with continuous values, it is necessary to pre-process the continuous value discretization. The C4.5 algorithm is the improvement of this, and C5.0 belongs to C4.5. The core concept of the Apriori algorithm is support and confidence. Let A be an item in the association rule sample set. The sample set contains a total of N records. Among the N records, there are M records containing item A. Then, the calculation method of the support degree Support of the item A is as shown in the formula (3):

$$Support(A) = \frac{M}{N} \quad (3)$$

Similarly, the support degree of the multiple items A and B associated with each other is the number of records including A and B in total, divided by the total number of records. The pattern of the form "A->B" belongs to the association rule, A is the rule front item, B is the rule back item, and its meaning is the probability that the rule item B also occurs when the rule front item A occurs. This probability is called confidence for each association rule, such as the confidence of the rule "A->B" is calculated as shown in Equation (4):

$$confidence(A \to B) = \frac{Support(A \cup B)}{Support(A)} \quad (4)$$

To build a financial risk early warning model through association rules, it is needed to set the early warning indicator as the rule front item, set the risk indicator as the rule back item, and filter out the trusted association rules by setting the minimum support degree and the minimum confidence value. Through credible association rules, it can be judged that when the warning indicators are in the interval, the enterprise will have financial risks.

3.3. Financial indicator screening method

The traditional financial risk early warning analysis is more subjective when selecting early warning indicators, and it is easy to ignore potential early warning indicators. With the development and improvement of database technology, researchers can easily obtain large-scale financial indicator data, and have the conditions to screen reasonable early warning indicators from large-scale financial indicators. The vast amount of information brought about by the IoT will aggravate the contradiction between financial report information users and financial report providers, increase the individualized needs of information users and lead to changes in financial report content. In addition, the application of IoT technology to enterprises will lead to closer linkages between enterprises, which will lead to the internal control risks of enterprises extending from the inside of the enterprise to the outside of the enterprise. The internal control environment of the enterprise is more complicated and the control risks are intensified.

Therefore, this paper first needs to conduct screening of early warning indicators, which mainly includes the following steps: preliminary screening of 296 financial indicators obtained, and eliminating indicators with vacancy values of 5% or more. At the same time, the indicator library also contains a large number of similar indicators, such as: total return on assets A, total return on assets B, total return on assets C. It can be concluded from the data dictionary that there are only slight standard deviations in the calculation formula, so only one need to be retained. This article uniformly retains the "B" standard-an international standard, and eliminates other similar indicators.

The variance test is performed on the remaining indicators to find out the indicators that there were significant differences between the risk group and the normal group. It is believed that if there is no significant difference between an indicator and a normal group, it indicates that the financial risk has no impact on the indicator and is therefore not suitable as an early warning indicator.

Correlation tests are performed on the remaining indicators in order to keep only one financial indicator with strong correlation, such as asset-liability ratio and equity ratio with strict positive correlation, or other potentially strong correlation indicator groups. Based on the correlation analysis results, a reservation is selected between any two indicators whose absolute value is greater than 0.8. The general steps of the association rule algorithm are shown in Fig. 3:

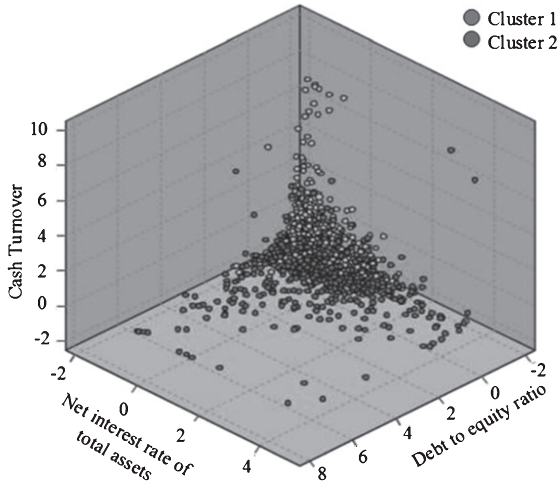

Fig. 2. Clustering effect under three indicators.

4. Experimental design and analysis

4.1. Data selection and processing

The sample data studied in this paper is derived from the relevant table of Guotai An CSMAR Financial Indicators Analysis Database. The basic tables involved mainly include: solvency sheet, disclosure financial indicator table, ratio structure table, operating capacity table, profitability table, cash flow. Eight tables including analysis table, risk level table and development capability table, a total of 296 financial indicators are obtained, and the time interval is from December 31, 2014 to December 31, 2016.

According to the needs of the experiment, this paper divides all sample data into two categories:

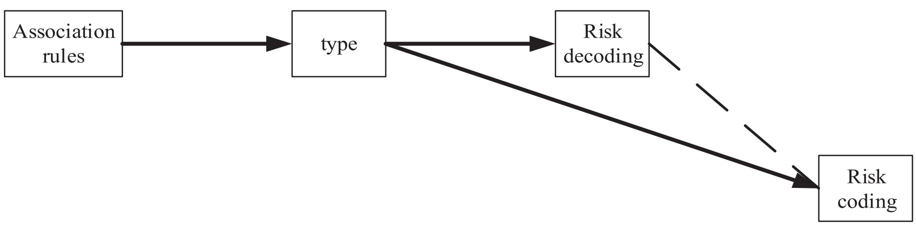

Fig. 3. The financial risk early warning modeling process based on association rules.

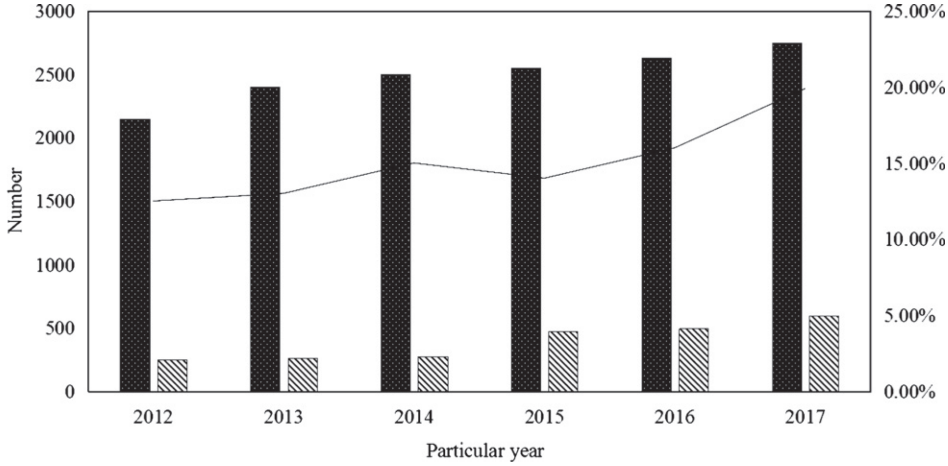

Fig. 4. Number of deficit enterprises in different years.

"risk group" and "normal group". The classification criteria refer to the ST classification method. Combined with the hysteresis characteristics of financial data and the release time of actual financial statements, the classification rules are defined as: "After the year after the current accounting cycle of the enterprise is marked as ST enterprise, the financial indicator data of the current accounting cycle of the enterprise is classified into the risk group". For example, if XXX enterprise is marked as ST on December 31, 2015 (or January 1, 2016), the annual report data released by XXX Enterprise on December 31, 2014 will be divided into risk groups, and a risk identification column will be added, marked as "1". At the same time, the risk identification column of the normal group sample is marked as "0".

There are several ways to get information about whether a company is marked as ST. It is more common to directly obtain a list of ST companies published by the stock exchange. However, ST companies announced by the stock exchange mainly include two types of enterprises: the first category is a company with negative net profit for two consecutive years; the second category is special treatment caused by other special reasons. It is believed that the first category of special treatment caused by financial situation should be the focus of our research. The special treatment enterprises caused by the special causes of the second category may interfere with the experimental results and need to be eliminated. In the end, 350 sample companies are selected as the "risk group" samples from the 2631 sample companies, and the rest are compared as "normal group" samples.

4.2. Continuous evaluation algorithm performance experiment

The F-score model is based on the Z-score scoring model of the Chinese scholars in the 1990s. Based on the Chinese financial data, the financial risk early warning model based on logistic regression is the basic research method. After the continuous development of informatization construction, the F-score model has undergone several important changes. At present, the discriminant formula of the latest F-score model is shown in Equation (5):

$$F = -0.1774 + 1.1091X_1 + 0.1074X_2 + 1.9271X_3 + 0.0302X_4 + 0.4951X_5 \quad (5)$$

The calculation formula of each variable is shown in Table 1.

The critical value of the F-score is 0.0274. When the F-value calculated by the relevant financial data of a certain enterprise is less than 0.0274, it is considered to have financial risk; if the F-value is greater than 0.0274, there is no financial risk. One of the most striking features of the F-score model is that it enhances the role of "cash" in corporate finance. The previous Z-score model and related research results did not focus on the cash position of the company. X1 in the F-score model is an indicator of the companys' discounting ability; X3 is an indicator of cash solvency; X5 is about total assets. The indicators of creating cash ability all reflect the importance of cash flow in controlling corporate financial risks. Because the F-score model is intuitive, easy to operate, and has high prediction accuracy, and is modeled by Chinese

Table 1
Formulas for calculating variables in F fractional mode

Variable	Measure aspect	Calculation formula
X1	Discounting ability	(end of current assets - end of current liabilities) / final total assets
X2	Profitability	End of term retained earnings / end assets
X3	Solvency	(after tax net income+depreciation) / average total liabilities
X4	Financial structure	Market value / final liabilities of end shareholders' equity
X5	Profitability	(after tax net income+Interest+depreciation) / average total assets

Table 2
Early warning accuracy of financial risk in F score mode

	Enterprises without financial risk (Practical)	Enterprises with financial risks (Practical)
Enterprises without financial risk (forecast)	2101(accuracy rate 92.1%)	108(error rate 30.9%)
Enterprises with financial risks (forecast)	180(error rate 7.9%))	242(accuracy rate 69.1%)
	2281	350

Table 3
Main index and weight table of enterprise comprehensive performance evaluation

Evaluation content	Index name	Weight	Calculation formula
Profitability	Return on net assets	20	Net profit / net assets
Profitability	Total assets return rate	14	(gross profit+interest expense) / total assets
Asset quality	Turnover of total assets	10	Sales revenue / total assets
Asset quality	Accounts receivable turnover rate	12	Sales revenue / accounts receivable
Debt risk	Asset liability ratio	12	Total liabilities / total assets
Debt risk	Interest coverage	10	(gross profit+interest expense) / interest expense
Business growth	Sales growth rate	12	Sales revenue grew year-on-year
Business growth	rate of capital accumulation	10	Net assets increased by+1

companies, it is more suitable for the financial situation of enterprises in Chinas' economic environment. Therefore, the F-score model is analyzed on financial websites and bank credits. Areas such as evaluation have been widely used.

Compare the accuracy of the warning, and use the financial annual report data of the listed company disclosed on December 31, 2015 to test the early warning accuracy of the F-score model, and the warning result will be marked as ST on January 1, 2017. For comparison, the following warning accuracy matrix is obtained, as shown in Table 2.

The "Detailed Implementation Rules for Enterprise Comprehensive Performance Evaluation" is officially promulgated by China State-owned Assets Supervision and Administration Commission in 2004. The financial performance evaluation part includes 22 financial indicators and their weights, including eight main indicators and fourteen revised indicators. The impact on the scoring results is small, and some of the indicators are not available to external report users. Therefore, in order to simplify the operation, only eight main indicators can be used for evaluation, as shown in Table 3. Each 4-6 years will issue a version of each indicator to obtain a range of values for different scores, generally referred to as the "standard value", the most recent standard value was issued in 2014. Through the scoring rules of the "Comprehensive Rules for the Evaluation of Corporate Comprehensive Performance Evaluation", each company can obtain a 100-point scoring result to represent the financial risk status of the enterprise. At present, the "Detailed Implementation Rules for Enterprise Comprehensive Performance Evaluation" is widely used in the field of financial evaluation, and has important guiding significance for financial risk assessment.

The "Detailed Implementation Rules for Enterprise Comprehensive Performance Evaluation" has strong practicality. First, in the "standard value", the division of the enterprise scale is carried out, the operation is refined, and the old data is eliminated in time, so that the applicability continued to maintain a high level with the passage of time. Secondly, the indicators involved are more comprehensive and can measure all aspects of the financial situation of

Table 4
Evaluation results of financial risk enterprises by implementing rules for comprehensive performance evaluation of enterprises

Scoring range	Sample size	Occupation ratio
[0, 20)	59	16.3%
[20, 40)	197	54.6%
[40, 60)	86	23.8%
[60, 80)	19	7.3%
[80, 100]	0	0%

the enterprise. The setting of the weight can highlight the key points and have certain guiding significance.

From the indicators involved, the indicators of the "Comprehensive Rules for the Comprehensive Performance Evaluation of Enterprises" are comprehensive, basically involving the four main aspects of profit, turnover, liabilities and development, although the financial risk warning indicators based on data mining are basically It comes from these angles, but it is more focused. For example, there are more indicators related to profitability and development, and it is more important when discriminating. Only the "net" in the indicator system of the "Comprehensive Rules for Enterprise Performance Evaluation" The return on assets has a higher weight, and the rest is not clearly differentiated.

Since the evaluation result of the "Comprehensive Rules for the Evaluation of Enterprise Comprehensive Performance Evaluation" is a percentage system score, the two-category early warning result of the enterprise financial risk early warning model based on decision tree cannot directly compare the accuracy rate, so the distribution of the scores of the sample can be observed. Since the relevant model has higher warning accuracy rates for enterprises that do not actually have financial risks, this part is no longer tested. Taking the enterprise marked as ST on January 1, 2017 as the research object, the financial annual report released on December 31, 2015 was selected and evaluated according to the "Detailed Implementation Rules for Enterprise Comprehensive Performance Evaluation". The standard value refers to the 2014 edition and observes it. Whether the evaluation results have an early warning effect. The final evaluation results are shown in Table 4:

According to the evaluation results, it can be seen that the scores of enterprises with financial risks are more than half of the scores obtained in [20, 40), and the distribution of scores of normal enterprises should be more compatible with the normal distribution, so the with financial risks as a whole, the score is at a lower level. If the enterprise with a score below 40 points has financial risks, the accuracy rate is 70.9%, which is slightly lower than the financial risk early warning model of the decision tree, and slightly higher than the financial risk early warning model of the association rules. If a company with a score below 60 points has financial risks, it can identify 94.7% of financial risk companies.

To sum up, in terms of using the financial annual report data of listed companies disclosed on December 31, 2015 to predict the financial risk level of enterprises at the end of 2016, the financial risk early warning model based on decision trees is compared with the "Comprehensive Rules for Comprehensive Performance Evaluation of Enterprises". The selected financial indicators are more targeted. At the same time, in the early warning of financial risk enterprises, the accuracy rate of early warning is basically the same as the proportion of enterprises with scores below 40. The "Comprehensive Rules for the Comprehensive Performance Evaluation of Enterprises" has more standardized operability, and its weighted summation scheme is more acceptable to users.

5. Conclusion

With the development of the IoT and the maturity of technology, the application of IoT technology can not only strengthen the data management of enterprise financial accounting, but also promote the development of enterprise accounting information. Based on this, this paper takes the historical financial data of Chinas' listed enterprises in the Guotaian database from 2014 to 2015 as the research sample, and divides the research sample into risk group and normal group according to the ST classification standard, and makes 296 financial indicators for the two groups of samples, factor analysis of variance and correlation analysis. 25 financial indicators are screened out suitable for constructing financial risk early warning models, and pexisting industries are aggregated into "profitable industries" and "operating industries" through K-means cluster analysis algorithm. The decision tree algorithm and the association rule algorithm are used to construct the financial risk early warning model for the two types of industries. The study found that the decision tree algorithm has stronger stability when constructing the financial risk early warning model. At the same time, the early warning indicators of "profitable industries" and "operating industries" are very different.

Compared with the financial risk early warning model based on the logistic regression, the financial risk early warning model based on data mining has higher warning accuracy. Compared with the current corporate financial performance evaluation methods, the financial risk early warning model based on data mining provides simpler operations and more intuitive early warning results for external report users.

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