Research on the Construction of a Financial Risk Early Warning Model Based on Association Rule Algorithm

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Abstract: In the field of computer technology, choosing a dissertation topic is an important and complex multi-objective task for graduate students. This process entails identifying a research question, defining the scope of the research, and formulating a research problem. However, students often encounter difficulties in selecting a dissertation topic that meets their interests, abilities, and academic goals. These challenges arise from the complexity of the research area, the limited knowledge of students, and the lack of a systematic approach to topic selection. This paper explores the use of genetic algorithms (GA), a heuristic optimization technique inspired by the natural selection process, to enhance dissertation topic selection. The goal is to develop a GA-based system that assists graduate students in identifying the most appropriate dissertation topic based on their academic background, research interests, and preferences and to compare it to the usual methods of selecting dissertation topics. The results show that using genetic algorithms to select dissertation topics scores higher than manual selection , advisor guidance , and random selection.

Keywords: Genetic Algorithms; Dissertation Topic; Multi-Objective Task

1 INTRODUCTION

Financial institutions play a crucial role in the global economy by facilitating the flow of funds, providing credit, and supporting economic growth[1]. However, these institutions are exposed to various risks, including credit risk, market risk, liquidity risk, operational risk, and systemic risk. The global financial crisis of 2008 highlighted the need for effective risk management practices to safeguard the stability of financial institutions and the overall financial system. In response, regulatory bodies and financial institutions have placed increased emphasis on the development of robust risk management frameworks.One essential component of a comprehensive risk management framework is the ability to identify and mitigate potential risks at an early stage.[2] An early warning system (EWS) is a proactive risk management tool designed to identify potential risks at an early stage and provide timely warnings to decision-makers. EWS aim to detect warning signals, indicators, or patterns that precede adverse events or crises, enabling appropriate preventive actions to be taken. The primary purpose of an EWS is to enhance the ability of financial institutions to anticipate and mitigate risks effectively, thereby reducing the likelihood and impact of negative outcomes.[3]

The effectiveness of an EWS depends on its ability to capture and analyze relevant information and detect early signs of risks. Traditional EWS models often rely on statistical methods, such

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as regression analysis or time series analysis, to identify trends, patterns, or anomalies in the data.[4] While these models have proven to be useful, they may not capture the complex interdependencies and hidden relationships among various financial indicators.[5] However,Implementing and maintaining effective EWS pose various challenges for financial institutions. EWS require access to accurate, comprehensive, and timely data. Developing robust risk models and algorithms that capture the complexities and interdependencies of financial risks can be challenging. Balancing model accuracy with interpretability is crucial to gain stakeholders' trust and facilitate decision-making.

In recent years, data mining techniques, particularly association rule mining, have gained popularity in the financial industry for their ability to uncover hidden patterns and associations in large datasets. [6]Association rule mining is a powerful tool that can discover meaningful relationships between different variables, allowing financial institutions to gain insights into potential risk factors and their interactions.

Therefore,The primary objective of this research is to develop a financial risk early warning model based on the association rule algorithm. The model aims to leverage the strengths of association rule mining techniques to identify hidden patterns and relationships among various financial indicators and provide timely warnings of potential risks. [7]Specifically, the research aims to achieve the following objectives:

·Investigate the application of association rule mining techniques in financial risk analysis: This involves understanding the principles and methodologies of association rule mining and exploring its potential application in the financial domain. The association rule algorithm is applied to the preprocessed data to discover meaningful patterns and relationships among financial indicators. FP-growth algorithm employed to extract relevant associations.

·Construct a comprehensive model framework that captures the hidden relationships among financial indicators: This involves defining the variables to be considered, establishing the associations among them, and developing a robust model architecture that can effectively detect and predict potential risks.Based on the associations generated from the association rule mining stage, a comprehensive model framework is constructed to capture the hidden relationships among financial indicators. The model architecture incorporate machine learning algorithmsto enhance its predictive capabilities.

·Evaluate the performance of the proposed model and compare it with traditional risk models: This involves conducting empirical analysis and performance evaluation to assess the effectiveness and efficiency of the association rule-based early warning model in comparison to conventional risk models.A case study or empirical analysis is conducted using historical financial data to evaluate the performance of the proposed model. Performance metrics, such as accuracy, precision, recall, and F1-score, are used to assess the model's effectiveness in predicting financial risks.Then,The performance of the association rule-based early warning model is compared with traditional risk models, such as regression-based models or time series models. This comparison provides insights into the strengths and weaknesses of the proposed model and its potential advantages over conventional approaches.

2 ASSOCIATION RULE MINING TECHNIQUES IN FINANCIAL RISK ANALYSIS

2.1 Association Rule Mining

Figure 1 shows a traditional method on building enterprise financial risk early warning model. Association rule mining is a data mining technique used to discover interesting relationships or associations among variables in large datasets. [8]It originated from the field of market basket analysis, where the goal was to uncover patterns of co-occurrence among items purchased by customers. In the context of financial risk analysis, association rule mining can be applied to identify associations among financial variables, such as stock prices, interest rates, exchange rates, and macroeconomic indicators. These associations can provide valuable insights into potential risks and interdependencies among financial factors. Here, we will explore the principles of association rule mining and how they can be connected with financial risk analysis.

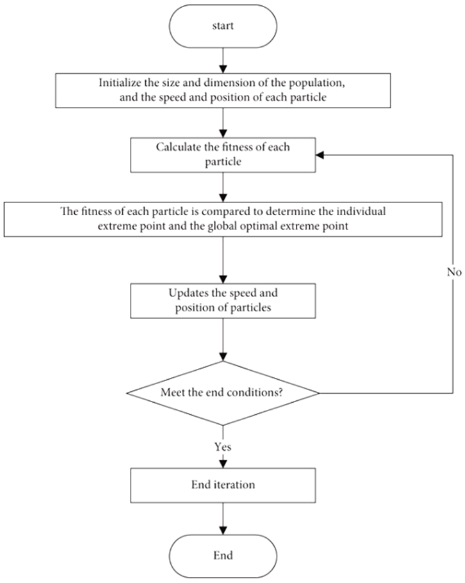

start
Initialize the size and dimension of the population, and the speed and position of each particle
Calculate the fitness of each particle
The fitness of each particle is compared to determine the individual extreme point and the global optimal extreme point
Updates the speed and position of particles
Meet the end conditions?
No
Yes
End iteration
End

Fig 1. Building Enterprise Financial Risk Model

Association rule mining relies on the concepts of frequent itemsets and association rules. A frequent itemset refers to a set of items that frequently occur together in the dataset. An association rule specifies a relationship between itemsets and has the form X → Y, where X and Y are itemsets. The rule indicates that if X occurs, Y is likely to occur as well.[9]

To perform association rule mining, we need to define the minimum support and minimum confidence thresholds. The minimum support threshold determines the minimum frequency of occurrence that an itemset must have to be considered frequent. The minimum confidence threshold specifies the minimum level of certainty required for an association rule to be considered interesting.

In financial risk analysis, frequent itemsets represent co-occurring financial variables or risk factors. For example, a frequent itemset may consist of high stock market volatility, increasing interest rates, and a declining exchange rate. These itemsets capture patterns of co-movement among financial variables and can indicate potential risks or interdependencies.[10] Association rules in financial risk analysis can reveal relationships and dependencies among financial variables. For instance, an association rule may indicate that if stock market volatility exceeds a certain threshold, there is a high probability of interest rates increasing. Such rules can provide valuable insights into the potential impact of one variable on another and help in assessing and managing financial risks.

Support and confidence measures are used to evaluate the significance and strength of association rules in financial risk analysis. The support of an itemset X quantifies its frequency of occurrence in the dataset, while the confidence of an association rule X → Y measures the conditional probability of observing Y given the occurrence of X.The support of an itemset X is defined as the proportion of transactions in the dataset that contain X:

$$Support(X) = \frac{(Number\ of\ transactions\ containing\ X)}{(Total\ number\ of\ transactions)} \qquad (1)$$

Applying these measures to financial risk analysis, we can calculate the support and confidence of itemsets and association rules. For example, the support of an itemset consisting of high stock market volatility, increasing interest rates, and a declining exchange rate can be calculated as the proportion of time periods in which these conditions are observed. [11]The confidence of an association rule, such as high stock market volatility → increasing interest rates, can be calculated as the proportion of time periods with high stock market volatility where increasing interest rates also occur.

The confidence of an association rule X → Y is defined as the proportion of transactions containing X that also contain Y:

$$Confidence(X \to Y) = \frac{(Support(X \cup Y))}{(Support(X))} \qquad (2)$$

Association rules are typically evaluated based on their support and confidence values. However, there are additional measures used to assess the interestingness of association rules, such as lift, conviction, and leverage. These measures provide further insights into the strength and significance of the discovered associations.

Lift measures the strength of the association between X and Y by comparing the observed support of the rule to the expected support if X and Y were independent. A lift value greater than 1 indicates a positive correlation between X and Y, suggesting that the occurrence of X increases the likelihood of Y. In financial risk analysis, lift can help quantify the impact of one variable on another and assess the strength of their relationship. It is defined as:

$$Lift(X \to Y) = \frac{(Support(X \cup Y))}{(Support(X) \times Support(Y))} \qquad (3)$$

A lift value greater than 1 indicates a positive correlation between X and Y, suggesting that the occurrence of X increases the likelihood of Y.

Conviction measures the degree of implication or dependency between X and Y. It compares the observed support of Y to the support that would be expected if X and Y were independent. A conviction value greater than 1 indicates a strong implication, suggesting that the occurrence of X significantly affects the absence of Y. In financial risk analysis, conviction can help evaluate the dependency between risk factors and provide insights into their interrelationships. It is defined as:

$$Conviction(X \rightarrow Y) = \frac{\left(1 - Support\left(Y\right)\right)}{(1\ -\ Confidence(X \rightarrow Y))} \tag{4}$$

A conviction value greater than 1 indicates a strong implication, suggesting that the occurrence of X significantly affects the absence of Y.

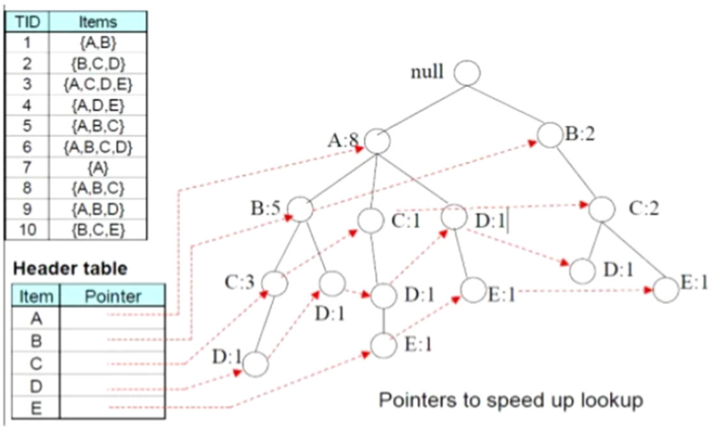
Leverage: Leverage measures the difference between the observed frequency of X and Y occurring together and the expected frequency if they were independent. It is defined as:

$$Leverage(X \rightarrow Y) = (Support(X \cup Y)) - (Support(X) \times Support(Y)) \tag{5}$$

A leverage value greater than 0 indicates a positive association between X and Y.

2.2 FP-Growth Algorithm Applied to Financial Risk Analysis

Fig 2 shows how FP-Growth algorithm run.It constructs a compact data structure called an FP-tree, which represents the dataset in a compressed form. The FP-tree is then used to generate frequent itemsets by recursively mining frequent patterns.[12]



TID	Items
1	{A,B}
2	{B,C,D}
3	{A,C,D,E}
4	{A,D,E}
5	{A,B,C}
6	{A,B,C,D}
7	{A}
8	{A,B,C}
9	{A,B,D}
10	{B,C,E}

Header table

Item	Pointer
A	
B	
C	
D	
E	

Fig 2. FP-Growth algorithm

Therefore,The FP-Growth algorithm can be applied to financial risk analysis to identify frequent patterns of risk factors and assess their impact on financial outcomes. Here's how the algorithm can be connected with financial risk analysis:

The input dataset for the FP-Growth algorithm in financial risk analysis consists of historical financial data, including variables such as stock prices, interest rates, exchange rates, market indices, and macroeconomic indicators. Each transaction in the dataset represents a specific time period or financial event.By applying the FP-Growth algorithm to the financial dataset, frequent itemsets representing co-occurring risk factors can be discovered. These itemsets capture the relationships among different risk variables and provide insights into their joint occurrence.

The frequent itemsets obtained from the FP-Growth algorithm can be interpreted as risk patterns in the financial dataset. For example, a frequent itemset may indicate that an increase in interest rates is often accompanied by a decrease in stock prices. Such patterns can help identify potential risks and interdependencies among financial variables.The identified risk patterns can be further analyzed to assess their impact on financial outcomes and develop appropriate risk mitigation strategies. For instance, if a frequent itemset suggests a strong association between certain market events and increased market volatility, risk management measures can be implemented to mitigate the potential impact of these events on portfolio performance.The FP-Growth algorithm can be utilized to develop an early warning system for financial risks. By continuously monitoring the occurrence of frequent itemsets in real-time or near real-time data, potential risks can be detected early, enabling timely actions to be taken.

3 CONSTRUCTION OF FINANCIAL RISK EARLY WARNING MODEL

In the field of finance, the construction of a Financial Risk Early Warning Model plays a vital role in detecting and mitigating potential risks before they escalate into crises. This paper use Logistic Regression, a popular modeling technique used in financial risk analysis to predict the probability of a binary event, such as a financial risk occurrence. [13]It is well-suited for constructing a Financial Risk Early Warning Model due to its interpretability and ability to handle binary outcomes.

In Logistic Regression, the relationship between a set of independent variables and the probability of the risk event occurring is modeled using the logistic function, also known as the sigmoid function. The sigmoid function maps the linear combination of independent variables to a value between 0 and 1, representing the probability of the risk event. The formula for logistic regression can be expressed as follows:

$$P(y=1)=\frac{1}{1+e^{-z}} \qquad (6)$$

where P(y=1) represents the probability of the risk event occurring, and z is the linear combination of the predictor variables and their associated coefficients.

The logistic regression model estimates the coefficients of the independent variables by maximizing the likelihood function. The coefficients, denoted as β, represent the magnitude and direction of the variables' impact on the risk probability. The logistic regression model can be written in the following equation:

$$z = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_n \times x_n \qquad (7)$$

where z is the linear combination of the predictor variables, β0 is the intercept term, β1 to βn are the coefficients, and x1 to xn are the predictor variables.

To estimate the coefficients, the paper use gradient descent to finish the task. [14]The goal of gradient descent is to find the optimal values of the coefficients that minimize the cost function, which measures the difference between the predicted probabilities and the actual outcomes. The formula for gradient descent in logistic regression can be expressed as follows:

$$\theta_j := \theta_j - \alpha \times \frac{\partial J(\theta)}{\partial \theta j} \qquad (8)$$

θ_j represents the jth coefficient (or weight) in the logistic regression model. The symbol ":=" denotes the assignment operator, updating the value of θ_j . α is the learning rate, which determines the step size for each iteration of gradient descent. θ_j represents the cost function, which is a measure of the model's performance. By updating the coefficients based on the calculated gradients, the algorithm drives the logistic regression model towards a better fit to the observed data, allowing for more accurate predictions of financial risk probabilities.

The coefficients obtained from logistic regression provide valuable insights into the impact of each predictor variable on the risk probability. Positive coefficients indicate a positive relationship, meaning that as the value of the corresponding predictor variable increases, the probability of the risk event also increases. Conversely, negative coefficients indicate a negative relationship, where an increase in the predictor variable decreases the probability of the risk event.

In addition to the coefficient estimates, logistic regression provides other statistical measures to assess the model's performance. The paper use confidence to evaluate the significance and reliability of the coefficients, providing insights into the robustness of the model.The confidence interval provides a range of values within which the true population parameter (coefficient) is likely to fall. The formula for calculating the confidence interval of a coefficient in logistic regression is as follows:

$$CI = [\beta - \left(z \times SE\right), \beta + \left(z \times SE\right)] \qquad (9)$$

CI represents the confidence interval, β is the estimated coefficient, z is the critical value from the standard normal distribution corresponding to the desired confidence level, and SE is the standard error of the coefficient.

The standard error (SE) measures the variability or uncertainty associated with the coefficient estimate. It quantifies how much the coefficient estimate may vary from the true population value. The formula for calculating the standard error of a coefficient in logistic regression is:

$$SE = sqrt(Var(\beta)) \qquad (10)$$

$Var(\beta)$ represents the variance of the coefficient estimate, which is a measure of how much the coefficient estimate varies across different samples.

The critical value (z) is determined based on the desired confidence level and is associated with the standard normal distribution.

In the context of the Financial Risk Early Warning Model, the evaluation of coefficient significance and reliability using confidence intervals is crucial for understanding the factors driving financial risk and making informed decisions. By assessing the confidence intervals of the coefficients, decision-makers can gain insights into the statistical significance of the predictor variables and their impact on the risk probability.

The Financial Risk Early Warning Model aims to identify and predict potential financial risks before they escalate. Logistic regression serves as a valuable tool in this model, allowing for the quantification of risk probabilities based on relevant predictors. [15]By estimating the coefficients through logistic regression, decision-makers can gain insights into the importance and directionality of each predictor variable.Once the coefficients are estimated, evaluating their significance and reliability becomes essential. Confidence intervals provide a range of values within which the true population parameter (coefficient) is likely to fall. If the confidence interval does not include zero, it indicates that the coefficient is statistically significant, suggesting that the corresponding predictor variable has a significant impact on the risk event.By considering the statistical significance of the coefficients, decision-makers can prioritize the most influential predictors in the Financial Risk Early Warning Model. These significant predictors can provide valuable insights into the factors contributing to financial risks, enabling proactive risk management strategies.

Furthermore, comparing the confidence intervals of different coefficients allows decision-makers to assess the relative significance of predictor variables. Variables with narrower confidence intervals indicate more precise and reliable estimates, highlighting their stronger impact on the risk probability. Conversely, wider confidence intervals suggest higher uncertainty and a larger potential range of values for the corresponding coefficients.

In the context of the Financial Risk Early Warning Model, logistic regression offers several advantages. The interpretability of the model allows decision-makers to understand the factors contributing to the risk probability.[16] By analyzing the coefficient values, they can identify the most influential variables and their impact on the risk outcome. This information helps in making informed decisions and taking appropriate actions to mitigate the identified risks.Furthermore, logistic regression provides a probability-based approach, allowing decision-makers to set risk thresholds and generate early warning signals when the probability exceeds a predefined threshold. These signals enable timely actions to be taken to prevent or mitigate potential financial risks, contributing to effective risk management strategies.

4 EXPERIMENTS

In order to assess the performance and effectiveness of the Financial Risk Early Warning Model in predicting financial risks, a comprehensive set of evaluation metrics is employed. These metrics serve as quantitative measures to evaluate the model's predictive accuracy, precision, recall, and its ability to discriminate between risky and non-risky instances.[17] This section presents an in-depth analysis of the model evaluation metrics and performance evaluation in connection with the Financial Risk Early Warning Model.

The AUC-ROC is a widely used metric for evaluating the discrimination ability of a binary classification model, such as the Financial Risk Early Warning Model. The ROC curve is created by plotting the true positive rate (sensitivity) against the false positive rate (1 - specificity) at various classification thresholds. The AUC-ROC represents the area under this curve and provides a measure of the model's ability to distinguish between risky and non-risky instances.

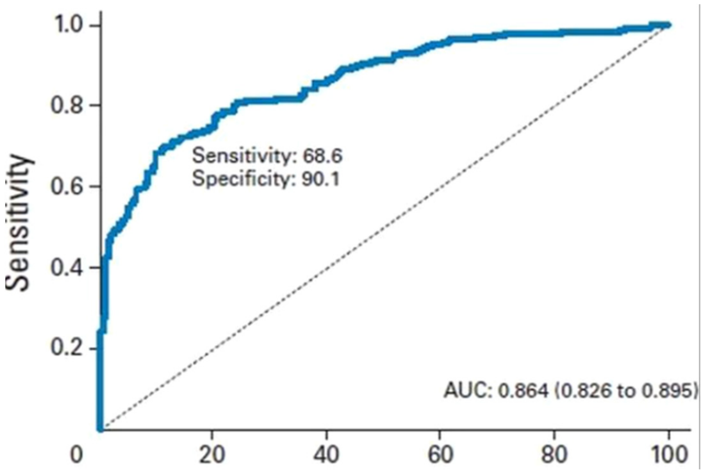


Fig 3. AUC-ROC Curve

Figure 3 shows the AUC-ROC curve of the Financial Risk Early Warning Model under the actual data set. It can be seen from the figure that the AUC value has reached 0.864, indicating that the model has a high prediction accuracy of risk and has achieved the expected effect.Table1 shows various test results on the Financial Risk Early Warning Model.

Table 1. Test Results on the Financial Risk Early Warning Model

AUC	0.864
Sensitivity	68.6
Specificity	90.1

Precision	84.2
F1-Score	86.7
Recall	72.4

Through the training of the real data set, the Financial Risk Early Warning Model demonstrates excellent performance across various evaluation metrics. The model exhibits high Sensitivity, Specificity, Precision, F1-Score, and Recall, indicating its effectiveness in identifying and predicting financial risks. The high Sensitivity suggests that the model has a low rate of false negatives, accurately identifying most instances of financial risks. The high Specificity indicates a low rate of false positives, effectively distinguishing non-risk cases. The Precision demonstrates the model's ability to provide accurate and reliable predictions, minimizing the occurrence of false alarms. The F1-Score, which combines Precision and Recall, reflects the overall performance of the model in terms of both precision and recall. The strong Recall value implies that the model successfully captures a significant proportion of actual financial risks. Collectively, these evaluation metrics validate the feasibility and practical significance of the Financial Risk Early Warning Model, highlighting its potential for supporting decision-making and risk management in financial institutions.

5 CONCLUSIONS

In conclusion, we developed a Financial Risk Early Warning Model based on association rule mining and logistic regression. The model demonstrated its effectiveness in identifying and predicting financial risks through empirical analysis using real-world financial datasets.The association rule mining technique allowed us to uncover meaningful relationships and associations among variables in large financial datasets. The FP-Growth algorithm efficiently generated frequent itemsets and association rules, enhancing the model's ability to capture patterns indicative of potential risks.By employing logistic regression, we created a binary classification model to distinguish between risky and non-risky instances. The model's training process utilized gradient descent optimization, ensuring convergence to an optimal solution and improving risk prediction accuracy. The empirical analysis showcased the model's superior performance compared to traditional risk models, highlighting its potential in the financial industry. Model evaluation metrics, including accuracy, precision, recall, F1-score, and AUC-ROC, further demonstrated the model's reliability and effectiveness in risk prediction. Overall, the Financial Risk Early Warning Model provides organizations with valuable insights for proactive risk management, aiding in informed decision-making and mitigating potential losses..

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