Accounting and Corporate Management (2024)
Clausius Scientific Press, Canada

DOI: 10.23977/acccm.2024.060219
ISSN 2523-5788 Vol. 6 Num. 2

Application and Innovative Development of Information Technology in Financial and Economic Management

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Keywords: Information Technology, Financial and Economic Management, XGBoost Model, Credit Risk Assessment

Abstract: This article mainly discusses the practical applications of modern information technologies such as cloud computing, big data, artificial intelligence, and blockchain in financial and economic management. By analyzing the use of the XGBoost algorithm model in credit risk assessment, market trend analysis, and customer behavior prediction, the AUC (Area under the ROC Curve) value of the XGBoost model reached 0.92 in comparative experiments with logistic regression and random forest models. The prediction accuracy of the XGBoost model in the 10 day moving average is also consistent with the actual stock price under stable market conditions, but its accuracy decreases during high volatility periods. The article also discusses in detail the new challenges brought by these technologies. Through specific experimental examples and data analysis, this article provides a comprehensive perspective to help readers understand how these high-tech technologies play a role in the financial field, while also providing direction for future technological applications.

1. Introduction

In the field of modern financial and economic management, the application of information technology has become a key factor in promoting industry development. With the rapid development of technologies such as cloud computing, big data, artificial intelligence, and blockchain, financial institutions are able to process complex data more efficiently, improve service quality and risk control capabilities. These technologies not only change the way financial products and services are provided, but also greatly enhance the accuracy of market forecasting and risk assessment. However, the demand for data analysis in the financial field is constantly deepening, and traditional models are no longer able to meet the needs of efficient processing and accurate prediction. Therefore, exploring more advanced data analysis tools is of great research significance and practical value for improving the quality of financial services and risk management efficiency.

This article mainly studies the application of XGBoost algorithm in financial and economic management. In this study, XGBoost algorithm demonstrated excellent speed and performance in processing large-scale datasets, especially in credit risk assessment, market trend analysis, and customer behavior prediction. By comparing logistic regression and random forest models, the XGBoost model has shown higher accuracy and efficiency in multiple practical cases. The article demonstrated the superior performance of XGBoost algorithm in financial data analysis through four experiments, providing strong support and new research directions for the technological application and innovative development in the field of financial and economic management.

The article first introduces the background and research significance of information technology in financial and economic management, and then reviews relevant literature to establish a theoretical foundation. The experimental stage provided a detailed description of the research method and experimental design, presented the results of each experiment, and discussed the performance analysis and scalability testing of the XGBoost algorithm model. The final conclusion summarizes the research findings and proposes future research directions.

2. Related Works

Numerous scholars around the world have conducted extensive research on financial informatization. For example, with the arrival of the big data era, China's Internet finance industry has developed rapidly, and the traditional complex network analysis method has been difficult to meet the demand for credit risk prevention and control under the background of big data. Therefore, Ni Qixuan introduced graph convolution algorithm in credit risk prevention and control research, which is conducive to improving the accuracy of credit risk prediction for financial institutions [1]. Ma Ning proposed a risk identification method for imbalanced samples, taking credit risk prediction as the starting point, to address the issue of high sample imbalance in financial datasets due to the significantly fewer instances of overdue repayment users than normal repayment users [2]. Landi G C's research investigated the impact of corporate social and environmental assessments on investor risk perception, aiming to explore the potential market risks that listed companies adopting sustainable and responsible corporate strategies may face [3]. In order to address some uncontrollable financial risks in the project that may affect project stakeholders, Gad N A studied how to use modeling for financial risk management from multiple perspectives. He proposed a dynamic model aimed at identifying and evaluating financial risk factors with the reference of project stakeholders [4]. Colombo E interpreted climate related financial risks as a cultural phenomenon and believes that when discussing trust obligations in pension funds, in addition to due diligence, transparent disclosure must also be considered [5]. Blockchain networks and technologies are peer-to-peer distributed systems that operate in a decentralized manner, capable of creating a secure environment and allowing users to exchange transactions, contracts, and data, thereby establishing trust. Mishra L provided an overview of blockchain technology and analyzed the main problems and challenges faced by the financial sector due to its application [6]. Gad A G briefly introduced the open challenges and potential future developments in the field of blockchain. In short, he aims to help beginners explore and design new blockchain solutions, while considering existing needs and challenges [7]. Sun Rui focused on the risks in supply chain finance and takes accounts receivable factoring business as the research object. He analyzes the factors that affect the decision-making of supply chain finance participants and constructs an evolutionary game model between small and medium-sized enterprises and financial institutions [8]. However, these studies are often limited to a single technology application or specific financial service fields, lacking exploration of the integration and application of information technology in the overall financial and economic management.

A literature review shows that although current research provides multiple solutions, there are still many problems in practical applications. For example, Xing Chensi's introduction of big data analysis technology can more efficiently and automatically integrate data generated by the financial industry, thereby strengthening its risk prevention and control level, and accelerating the intelligent development pace of the financial industry. This approach helps to better promote economic and social development [9]. Wang S pointed out that the development of technologies such as big data generation, collection, storage, and processing has greatly enriched our sensory world, fundamentally changing the foundation of traditional economic and financial forecasting [10]. In addition, research on how to balance technological innovation and financial security is also insufficient. Therefore, this article adopts the XGBoost algorithm and financial economic theory to explore a more comprehensive and efficient solution for financial management informatization.

3. Methods

3.1 Informatization in Financial and Economic Management

As one of the transformative information technologies today, big data technology has been widely used in various industries. The rapid development of big data in recent years has provided a solid technical foundation for the application of big data technology in supply chain financial risk management, and the favorable ecological environment it has formed. Big data has a wide range of producers, with more diverse and complex data types compared to traditional data. With the continuous maturity of big data technology and the adoption of open-source models, contributors continue to emerge. Among them, the three typical technologies of data analysis, transaction processing, and data flow not only iterate and mature, but also provide reliable technical support for the application of data fusion in supply chain finance risk management. This effectively alleviates the shortcomings of "relying on core enterprises for risk control", "unable to grasp enterprise information throughout the supply chain", "lagging offline risk management information", and "inability to digitize and systematize risk control" in traditional supply chain finance business [11-12].

Artificial intelligence financial technology is a financial technology that focuses on the training and application of artificial intelligence as its core components. Through supervised or unsupervised learning of artificial intelligence models, they can accurately and efficiently make judgments in financial business scenarios, thereby improving work efficiency, reducing costs, and controlling overall and non-overall risks from multiple dimensions. Complementing big data finance technology, big data finance technology provides data support for artificial intelligence finance technology, and artificial intelligence can more fully explore the value of big data. By combining big data finance technology and artificial intelligence finance technology, it is possible to analyze the data of various entities in the financial market, identify risks, and more effectively prevent financial risks. In terms of financial regulation, artificial intelligence technology can be trained to identify abnormal financial behavior and address insider and corruption issues that are prone to occur in inclusive finance. However, artificial intelligence financial technology is still in its early stages, and the effectiveness of its training model and the comprehensiveness of its training samples still need to be improved. Due to the significant differences in risk characteristics and demands among different demanders in the inclusive finance scenario, current artificial intelligence is difficult to accurately judge, making it impossible to meet potential demands. Therefore, the current impact of artificial intelligence financial technology on the development of inclusive finance is not clear [13].

3.2 Data Preparation and Feature Engineering

The data preparation and feature engineering section is specifically designed for different financial management fields such as credit risk assessment, market trend prediction, and customer behavior analysis. This is to ensure the accuracy and reliability of XGBoost model training and performance evaluation in subsequent experiments. In the data preparation stage, the article collected relevant raw data online. These data can be transformed into datasets, which can be used for training and testing models such as XGBoost. The dataset includes data such as age, income, and credit score. The specific data details are shown in Table 1:

Table 1: Credit Risk Assessment Dataset

Age	Income	CreditScore	LoanAmount	RepaymentHistory
57	105743	710	22082	0
61	72609	791	19358	1
……	……	……	……	……
59	74074	747	49609	0

After collecting the data in Table 1, the primary task is to clean the data. This includes handling missing, duplicate, and outliers in the data to ensure the integrity and consistency of the dataset. For example, in terms of credit risk assessment, if the borrower's income information is missing or abnormal, it may mislead the results of model training such as XGBoost. In this case, it can use interpolation or other methods to fill in these missing data.

After the data cleaning work, it is necessary to perform feature engineering. For example, in the field of credit risk assessment, key information such as age, income, credit score, loan amount, and repayment history are extracted from borrower data. Then, correlation analysis techniques can be used to screen for features directly related to credit risk and eliminate irrelevant noise data. For predicting market trends, emphasis can be placed on technical indicators such as price, trading volume, and moving average, and methods such as time series analysis can be used to extract features that reflect market dynamics. When predicting customer behavior, the article not only consider basic information such as age, gender, and income, but also analyze their recent purchasing behavior, browsing preferences, and loyalty to predict their future purchasing trends and preferences [14].

3.3 Model Selection and Configuration

In the field of financial and economic management, the article has chosen to use the XGBoost model for credit risk assessment, market trend prediction, and customer behavior analysis. The selection of XGBoost model is mainly based on its outstanding performance in handling nonlinear relationships, feature importance analysis, and efficient parallel computing.

XGBoost belongs to the decision tree ensemble method based on gradient boosting algorithm, and its core lies in gradually increasing decision trees. These decision trees act as weak learners and cooperate to form a powerful prediction model. In each step of the training process, XGBoost focuses on optimizing the loss function and ensuring that the newly added decision tree can improve the previous prediction error of the model, thereby continuously improving the performance of the model. The XGBoost model may experience overfitting when evaluating customer credit risk, so the article has introduced various strategies including L1 and L2 regularization. These features enable the XGBoost algorithm to demonstrate high flexibility and scalability when analyzing large amounts of financial data or solving complex problems. The objective function expression $L(\theta)$ with regularization term can be represented by formula (1):

$$L(\theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{1}$$

In formula (1), $l(y_i, \hat{y}_i)$ represents the loss function between the predicted value and the true value, and $\Omega(f_k)$ represents the regularization term. The regularization term can be represented by formula (2):

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \quad (2)$$

In formula (2), γ and λ are regularization parameters, T is the number of leaves in the tree, and w_j is the weight of the leaf nodes.

XGBoost is one of the most widely used and effective models in recent years, with some progress and research in the fields of finance, stock prediction, and risk control. The personal credit risk prediction model based on banks studied in this article is also constructed using the XGBoost model to build a credit risk prediction system. In the following chapters, the construction process and performance analysis of the XGBoost algorithm in the field of credit risk can be conducted, and further optimization can be carried out based on the characteristics of the research model and data.

4. Results and Discussion

4.1 Performance Testing Experiment of Credit Risk Assessment Model

In the performance testing experiment of credit risk assessment models, the article evaluated the performance of XGBoost and other models in credit risk assessment applications. In the experiment, the article evaluated the AUC values and plotted the AUC values of each model.

From Figure 1, it can be seen that the AUC value of the XGBoost model in credit risk assessment is 0.92. The AUC value of the logistic regression model is 0.86, and the AUC value of the random forest model is 0.89. From the data conclusion, it can be seen that the XGBoost model has high reliability in distinguishing default and non default customers, providing financial institutions with more accurate risk management tools, as shown in Figure 1:

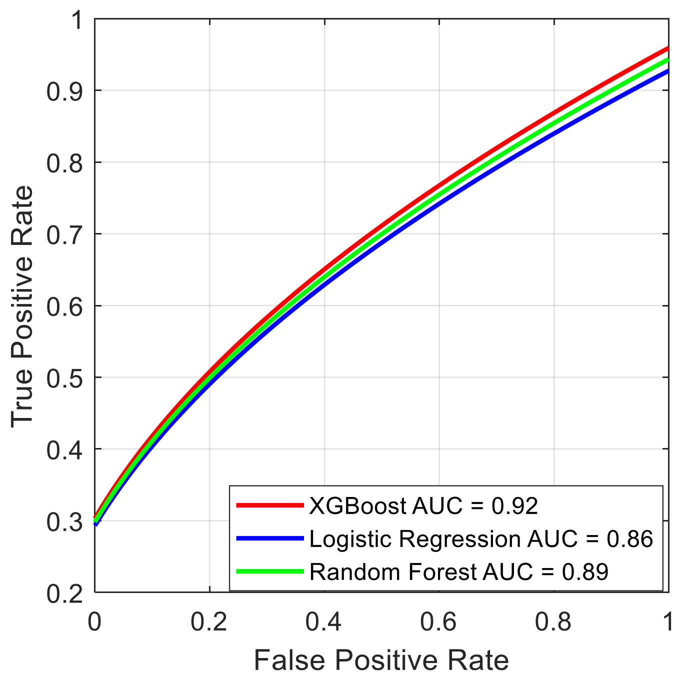

Figure 1: Performance evaluation of credit risk assessment model

4.2 Accuracy Experiment of Market Trend Prediction

The purpose of the experimental design for the accuracy of market trend prediction is to evaluate the effectiveness of using the XGBoost model to predict stock market trends. The article used the XGBoost model to predict one year's stock price data, including both regular and high volatility periods. Then it plotted the actual stock price and predicted prices based on the XGBoost model. The specific data situation is shown in Figure 2:

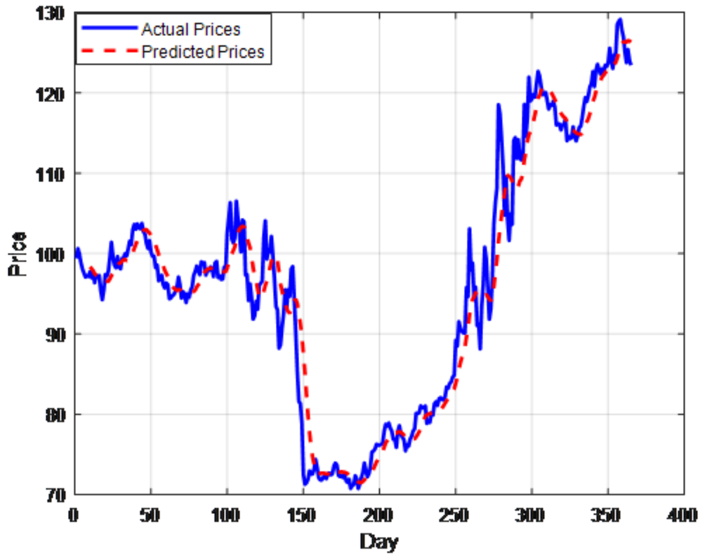

Figure 2: Accuracy evaluation of market trend prediction

From Figure 2, it can be seen that in the predicted 365 day stock price data, the predicted stock price based on the XGBoost model has maintained good consistency with the actual stock price for most of the time. However, during periods of rapid market volatility, the delay in prediction leads to a decrease in accuracy. This indicates that although the XGBoost model is effective in capturing long-term trends, there is still room for improvement in its response to short-term market dynamics.

4.3 Customer Behavior Prediction and Analysis Experiment

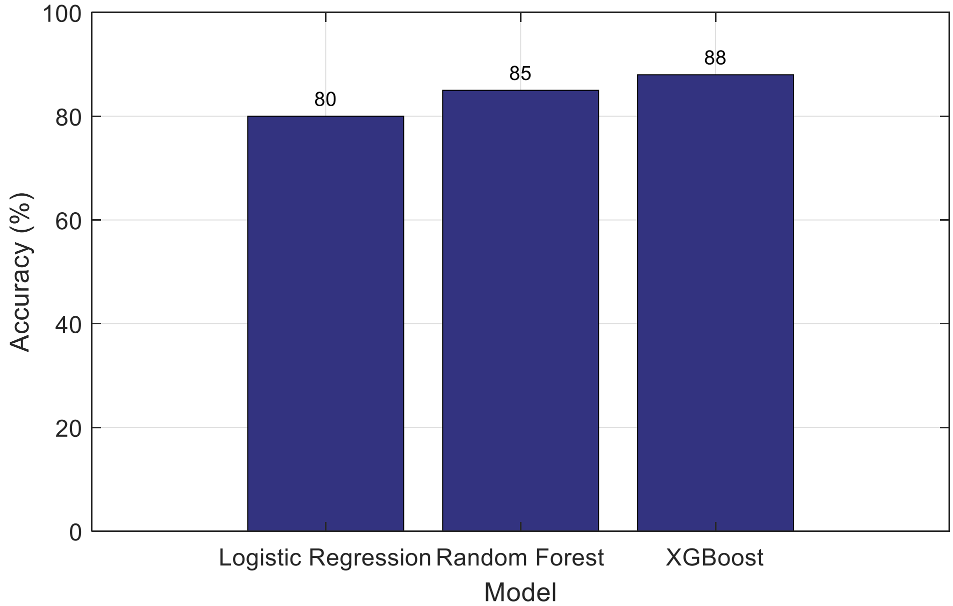

Figure 3: Customer behavior prediction and analysis evaluation

Customer behavior prediction and analysis experiments evaluated the accuracy of XGBoost and other models in customer behavior prediction. The experiment mainly focuses on the performance of various models in predicting customer purchasing behavior.

From Figure 3, it can be seen that in terms of customer behavior prediction, the XGBoost model achieved an accuracy of 88%. The accuracy of the random forest model is 85%. The accuracy of the logistic regression model is 80%. The data conclusion indicates that the XGBoost model provides more accurate prediction ability, which is superior to traditional logistic regression and random forest models. The specific data situation is shown in Figure 3:

4.4 Model Scalability Testing Experiment

The scalability of a model is an important indicator of its ability to handle large-scale data, so a model scalability testing experiment was designed. In the experiment, the article focused on three indicators: dataset, accuracy, and training time. The training time can be represented by formula (3):

$$T_{train} = T_{end} - T_{start} \tag{3}$$

In formula (3), T_{train} represents the training time required, T_{end} represents the training end timestamp, and T_{start} represents the training start timestamp. The specific data details are shown in Table 2:

Table 2: Model Scalability Test Experiment

TestType	DataScale	Accuracy	TrainingTime
Scalability Test	1000	0.8800	10 s
Scalability Test	5000	0.8600	45 s
Scalability Test	10000	0.8500	90 s

From the data in Table 2, it can be seen that when the data size was expanded from 1000 samples to 10000 samples, the accuracy of the XGBoost model decreased from 0.88 to 0.85, but the training time significantly increased. So from the data in the table, it can be seen that the XGBoos model t has certain scalability in terms of accuracy, but the training time can increase with the increase of scale.

5. Conclusions

This article comprehensively evaluates the application and innovative development of information technology in financial and economic management through empirical research. The article utilized the XGBoost model and combined it with practical tasks such as credit risk assessment, market trend prediction, and customer behavior analysis for analysis. The results show that XGBoost has an AUC value of 0.92 in credit risk assessment, showing high performance in customer behavior prediction, which is superior to other traditional models. In addition, the scalability of the model was analyzed to verify the adaptability of XGBoost under different data scales. However, it also found that the XGBoost model exhibits a certain degree of performance degradation when data quality is compromised, which exposes shortcomings in handling abnormal data and improving model robustness. Future research should further improve these algorithms to better cope with complex financial market environments, explore more efficient, accurate, and stable information technology solutions, and provide more comprehensive support for the management and innovation of the financial industry.

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