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Enhancing Credit Risk Assessment in Germany: A GAN-Based Approach with Forward-Looking Variables

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Abstract

Background and Aim: Credit consumption has become a cornerstone of modern economies, making accurate credit evaluation essential to minimizing loan default risks. However, existing credit scoring systems face several challenges, including data imbalance, inefficient sample ratios, and the need for more precise indicator weighting. This study aims to enhance credit scoring for German credit card users by addressing these issues and integrating forward-looking variables to improve prediction accuracy and model stability.

Materials and Methods: This research utilizes the UCI Statlog (German Credit Data) dataset, employing a preprocessing pipeline that includes normalization, encoding, and data augmentation via Generative Adversarial Networks (GANs) to address data imbalance. The GAN-based model applies SoftMax classification to predict defaults while utilizing principal component analysis (PCA) combined with macroeconomic and industry-specific variables to enhance the adaptability of the model.

Results: Compared with traditional oversampling methods, GAN can generate samples that are closer to the true data distribution, thereby avoiding overfitting and data distortion. The GAN-based model significantly improved predictive accuracy, increasing overall accuracy from 74.25% to 87.92% following data augmentation. The integration of forward-looking variables further enhanced model performance, demonstrating the potential of GANs and dynamic economic factors in credit scoring.

Conclusion: This study proposes an advanced credit scoring system that, compared to existing models in the German market, effectively alleviates data imbalance and improves prediction accuracy by enhancing and introducing future variables based on GAN. The findings suggest that GANs can serve as a powerful tool in credit risk assessment, particularly in cases where labeled data is limited. Future research should explore the scalability of this approach across various financial risk prediction tasks.

Keywords: Credit Scoring; Sample Ratio Optimization; Ensemble Learning; Future Variables; Credit Risk Classification

Introduction

With the rapid expansion of global economies, credit consumption has become an integral part of modern financial systems (Chen et al., 2021). Originally pioneered by banks, credit services enable individuals and businesses to access funds with the expectation of repayment, including principal and interest (Choudhry, 2022). For individuals, particularly those with lower incomes, credit provides opportunities to meet immediate financial needs, such as purchasing homes or vehicles (Roll et al., 2019). Businesses rely on credit for short-term capital turnover, expansion, and strategic investments (Sang, 2021). However, for banks and financial institutions, the ability to accurately assess creditworthiness is critical to minimizing risks associated with loan defaults (Zheng et al., 2023). Taking Germany as an example, the credit card default rate reached 5.3% in 2022, resulting in financial institutions losing over 1.2 billion euros, highlighting the urgency of improving credit evaluation systems.

To address these risks, financial institutions have developed credit evaluation systems that leverage expert judgment, statistical methods, and machine learning algorithms (Bhatore et al., 2020). As technological advancements reshape the financial landscape, ensuring the reliability and accuracy of these evaluation systems has become increasingly important. Information asymmetry remains a major challenge in credit markets, where inconsistencies in borrower data hinder financial institutions from making

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informed lending decisions (Wu et al., 2021). Without effective credit evaluation frameworks, undetected financial risks may accumulate, ultimately threatening the stability of the global financial system (Ballouk et al., 2024). However, existing systems still have significant shortcomings in terms of data imbalance, low sample efficiency, and inaccurate weighting of risk indicators, which provide an opportunity for the introduction of innovative methods.

This study focuses on enhancing credit scoring for German credit card users, a demographic with unique financial behaviors. The research addresses key challenges, including data imbalance, sample ratio inefficiencies, and the weighting of risk indicators, by incorporating Generative Adversarial Networks (GANs) and forward-looking variables into the credit evaluation process. Through this approach, the study aims to improve predictive accuracy, model stability, and credit risk assessment efficiency. In addition, this study delves into the socio-cultural background of credit behavior by combining sociological and anthropological perspectives, providing a new theoretical framework for understanding the financial behavior patterns in German society. In the future, this method can be extended to other financial sectors such as small and micro enterprise loans and P2P lending, providing support for the stability and inclusive development of the global financial system.

Objectives

The primary objective of this research is to enhance the credit scoring process, with a specific focus on German credit card users. Specifically, this research seeks to:

1. To develop and evaluate a user credit rating model using Generative Adversarial Networks (GAN) to enhance prediction accuracy and stability in the German credit card industry.

2. To examine the impact of integrating future variables into a GAN-based credit rating model on improving predictive accuracy and stability.

Literature review

The study of credit card industries and credit risk management has long been a critical area of research within the financial sector. This literature review aims to categorize existing studies into three main areas: (1) the development of the credit card industry, (2) the role of uncertainty in credit risk management, and (3) the evolution of credit evaluation models.

1. Development of the Credit Card Industry

The credit card industry, despite its significant role in modern economies, has shown varied growth trajectories across different countries. In Germany, for instance, the industry's development has been relatively slow compared to other developed economies (Fromhold et al., 2021). Credit card issuance only began in 1978 (Grodzicki, 2023), and marketing activities were restricted until 1996 due to a cultural aversion to debt among Germans. This slow development contrasts sharply with countries like the United States, where credit cards have been widely adopted and integrated into the financial system (He & Wei, 2023). Studies have shown that while the credit industry can drive economic growth, it also poses potential risks such as bad debts and overdue payments if not managed properly. Therefore, combining research on financial consumer behavior and banking regulation in various countries can provide a more comprehensive foundation for understanding the differences in the credit card market.

2. Uncertainty in Credit Risk Management

The concept of uncertainty has been a cornerstone in the study of credit risk management. Traditional economic theories largely ignored uncertainty by assuming perfect market conditions and rational agents (Frydman & Goldberg, 2023). However, the 20th century saw a shift with Keynesian economics, which emphasized the role of uncertainty in decision-making. Keynes argued that most economic decisions are made under conditions of uncertainty, and this idea has been pivotal in understanding the complexities of credit risk management (Irshad, 2024).

In the context of financial markets, uncertainty is particularly relevant to risk management. Traditional financial theories, dominated by linear paradigms, have often failed to account for the non-

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linear behaviors observed in financial markets. This limitation has led to the development of new risk management methods, such as the Value at Risk (VaR) method, although these methods still face challenges in accurately predicting market fluctuations and credit risks.

3. Evolution of Credit Evaluation Models

The development of credit evaluation models has been a significant area of research, with numerous models being proposed to address the challenges of credit risk assessment (Naili et al., 2022). Traditional models such as logistic regression and credit bureau scoring methods (such as FICO scoring) are widely used due to their robustness and interpretability. However, these models often lack predictive accuracy, especially when dealing with complex and nonlinear data. In contrast, more advanced models such as decision trees, support vector machines, and neural networks, although having higher accuracy, have poorer interpretability and robustness.

Recent studies have highlighted the potential of combining multiple models to leverage their strengths and compensate for their weaknesses. For example, integrating logistic regression with neural networks can enhance both prediction accuracy and interpretability (Bansal et al., 2022). This approach aligns with the broader trend of using ensemble methods in machine learning to improve overall model performance.

Moreover, the use of generative adversarial networks (GANs) to expand and balance datasets has shown promise in improving the accuracy of neural network judgments. This technique is particularly useful in addressing the issue of imbalanced datasets, which is a common problem in credit risk assessment.

4. Research Gap and Contributions of This Study

Despite the extensive literature on credit risk management, several gaps remain. First, while numerous single models have been developed, few studies have effectively combined these models to achieve a balance between prediction accuracy, robustness, and interpretability. Second, the application of advanced techniques like GANs in the context of credit evaluation is still relatively underexplored, especially when combined with traditional credit scoring methods such as FICO scoring. Third, there is a need for more comprehensive empirical studies that integrate both traditional and advanced methods to develop a robust credit evaluation system.

This study aims to fill these gaps by proposing a hybrid credit evaluation model that combines logistic regression and neural networks, enhanced by GANs for data balancing. The study's contributions include the development of a model that not only improves prediction accuracy but also enhances interpretability and robustness, providing a more reliable tool for credit risk assessment in practical applications.

Conceptual Framework

The conceptual framework of this study is designed to explore the relationship between credit scoring methods and financial stability, with a particular focus on the German credit card market. The framework is structured around three main components: independent variables, ensemble methods, and dependent variables.

The independent variables include the following key elements: (1) Sample ratio optimization: Although traditional methods such as undersampling and oversampling are simple, they may lead to information loss or overfitting. This study uses Generative Adversarial Networks (GANs) to generate synthetic minority class samples to balance the dataset. This method draws on the theoretical foundation of data augmentation in machine learning and combines the advantages of GAN in high-dimensional data generation. (2) Indicator weighting: Indicator weight is used to measure the importance of each feature to the credit rating. This study uses SHAP (Shapley Additive Explanations) values for feature importance analysis, which is a game theory-based method that provides a transparent and consistent evaluation of feature contribution. (3) Integration of future variables: integrate macroeconomic indicators (such as GDP growth rate, unemployment rate) and industry factors (such as real estate price index, consumer confidence index) to capture the dynamic changes in credit risk.

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Ensemble Methods: Integration method: This component involves using Generative Adversarial Networks (GANs) for data augmentation and applying ensemble learning techniques to improve the generalization ability of credit scoring models. Ensemble learning improves the robustness and accuracy of the model by combining the prediction results of multiple base models. GAN effectively solves the problem of data imbalance by generating high-quality synthesized data. Compared with traditional oversampling methods such as SMOTE, GAN can generate samples that are closer to the true data distribution, thereby avoiding overfitting and data distortion. In addition, GAN has advantages in privacy protection, as the generated synthetic data can replace real data for model training, reducing the risk of data leakage.

Dependent variables: These include prediction accuracy, model robustness, and credit risk management efficiency, used to evaluate the performance of credit scoring models. Prediction accuracy is a fundamental indicator for evaluating model performance, and the F1 score used in this study balances accuracy and recall, making it particularly suitable for imbalanced datasets. The robustness of the model and the efficiency of credit risk management are comprehensively evaluated through cross-validation and the computational efficiency of the model.

The framework is illustrated in Figure 1, which shows the interconnections between these components and how they contribute to the overall objective of improving credit scoring in the German market.

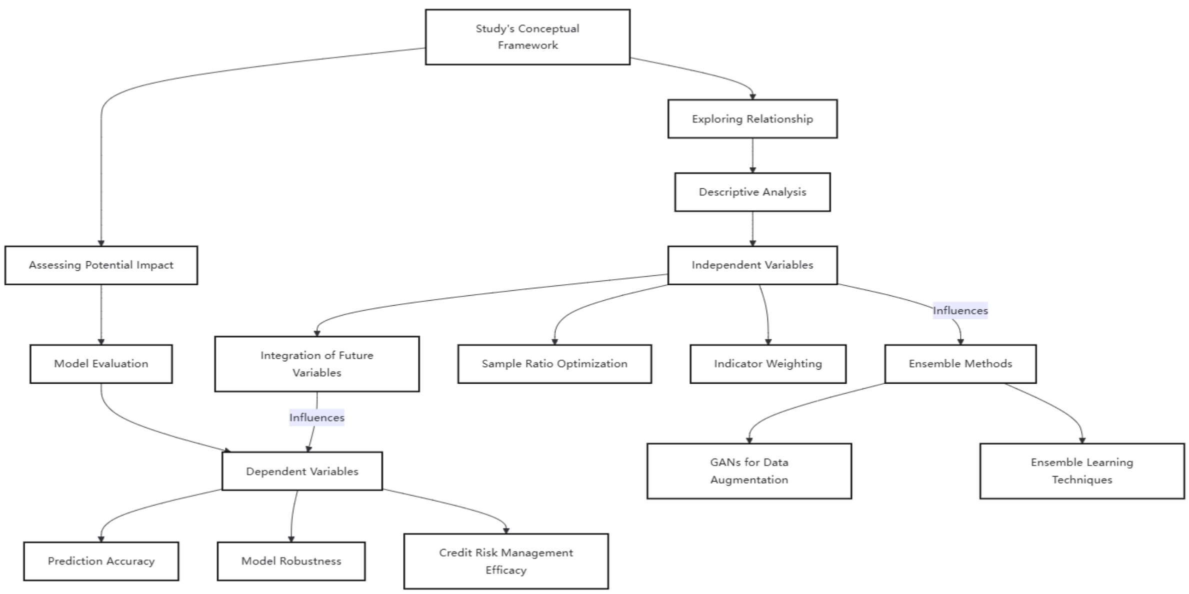

Figure1 Conceptual Framework

Methodology

This study employs a structured methodology to enhance the credit scoring process for German credit card users by addressing key challenges such as sample ratio optimization, ensemble learning enhancement, and accurate indicator weighting. The methodology is divided into three main phases: data source and preprocessing, model design, and future variable integration.

1. Data Source and Preprocessing

This study utilized the UCI Statlog (German Credit Data) dataset, which contains 1,000 user records with 31 features related to credit card defaults. The raw data were categorized into three types:

(1) Numerical features (e.g., credit amount, age) were normalized using min-max scaling ($\hat{x}_i = \frac{x_i - \min(X)}{\max(X) - \min(X)}$) to unify scales.

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(2) Categorical features (e.g., employment status, property ownership) were encoded via One-Hot and Multi-Hot encoding to convert them into binary vectors.

(3) Multi-class labeled features (e.g., credit purpose) were processed using SoftMax activation to generate probability distributions.

Based on the widely discussed historical characteristic variables of user level and loan level in credit evaluation models, we ultimately select 31 original variables as inputs for the model, the specific variables are shown in Table 1. The binary variable of whether the users' default is used as the output of the model.

Table 1 Description of variables

Variable type	Variable Name	Symbol	Definition
Numerical type	DURATION	X_1	Credit or loan term
	AMOUNT	X_2	Credit amount
	INSTALL_RATE	X_3	Installment payment rate, as a percentage of disposable income
	PRESENT_RESIDENT	X_4	Current residence duration
	AGE	X_5	Applicant's age
	NUM_CREDITS	X_6	The existing credit quantity of this bank
	NUM_DEPENDENTS	X_7	Number of dependencies
Classification	CHK_ACCT	X_8	Check account status
	HISTORY	X_9	Credit history
	SAV_ACCT	X_{10}	The status of the savings account
	EMPLOYMENT	X_{11}	Employment duration
	MALE_DIV	X_{12}	Is it a divorced male
	MALE_SINGLE	X_{13}	Is it a single male
	MALE_MAR_or_WID	X_{14}	Is it a married or widowed male
	CO-APPLICANT	X_{15}	Are there any co-applicants
	GUARANTOR	X_{16}	Is there a guarantor
	REAL_ESTATE	X_{17}	Do you own real estate
	PROP_UNKN_NONE	X_{18}	Property status unknown or none
	OTHER_INSTALL	X_{19}	Do you have any other installment payment plan
	RENT	X_{20}	Whether to rent a house or not
	OWN_RES	X_{21}	Whether to own housing or not, the nature
	JOB	X_{22}	Job nature
	TELEPHONE	X_{23}	Is there a phone number
	FOREIGN	X_{24}	Is it a foreign worker
	RESPONSE	X_{25}	Response or decision result (may be used for credit applications)
Multi category tagging	NEW_CAR	X_{26}	Is the credit used for new cars
	USED_CAR	X_{27}	Is the credit used for used cars
	FURNITURE	X_{28}	Is the credit used for furniture
	RADIO_TV	X_{29}	Is the credit used for radio/television
	EDUCATION	X_{30}	Is credit used for education
	RETRAINING	X_{31}	Is the credit used for retraining

Data imbalance was addressed through Generative Adversarial Networks (GANs). The GAN generated 1,000 synthetic default samples, evaluated using metrics like LSD (Location Square Deviation)

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and VSD (Value Square Deviation), achieving an average LSD of 0.274 and VSD of 0.228, indicating high similarity to real data.

2. Model Design

GAN Architecture: The generator (G) mapped 100-dimensional Gaussian noise to synthetic samples using Tanh activation, while the discriminator (D) employed SoftMax layers to classify default vs. non-default users. By mixing original samples and generated samples, the model achieves a Nash equilibrium through multiple iterations of training. Finally, a credit scoring network is constructed, and its accuracy is evaluated. The credit scoring model of GAN used in this chapter is shown in Figure 2.

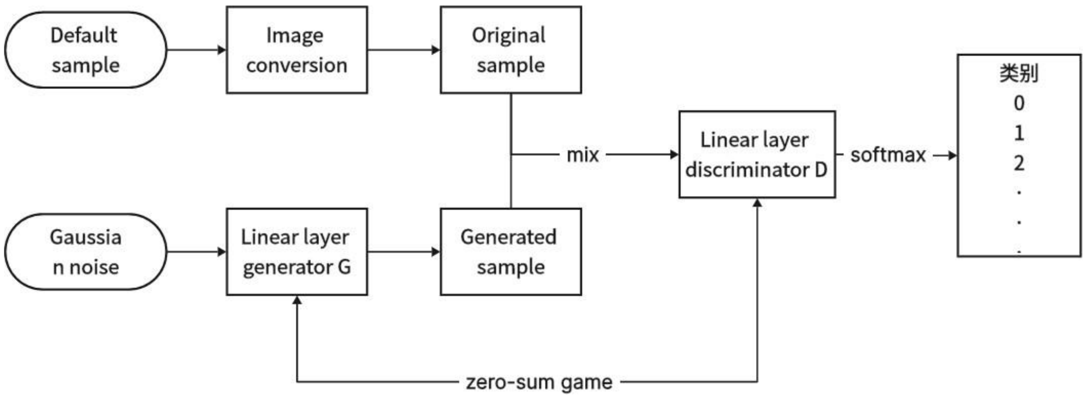

Figure 2 The credit scoring model of GAN

3. Future Variable Integration

In credit evaluation models, "future variables" are introduced to predict changes in credit risk. These variables include personal dynamics like income and consumption, as well as external factors like macroeconomic indicators and industry trends. This shift from static to dynamic analysis enhances model accuracy and risk management.

(1) Macroeconomic Indicator Variables: These include GDP growth and inflation rates, which influence personal credit indirectly. Good economic conditions lower financing costs and increase profitability, reducing default risks. Conversely, economic downturns increase financing costs and uncertainty, raising default risks. Using principal component analysis (PCA) to extract major components from multiple macroeconomic indicators, reducing data dimensionality, and eliminating multicollinearity.

(2) Industry Factor Variables: The industry in which a user operates affects their repayment ability. Rapidly growing industries with stable regulations reduce default risks, while unstable industries increase them. Germany's strong manufacturing sector is influenced by automation and regulatory changes, impacting credit risk. This study regularly updates the industry risk index based on industry trends and policy changes and incorporates it as dynamic input into the model.

(3) External Emergency Variables: These include unexpected events ("Black swans") and predictable risks ("Gray rhinoceroses"). Such events can have significant impacts on global economies, affecting individual credit stability. Quantify the potential risks of external emergency variables by analyzing the impact of similar events in historical data.

Results

1. User Credit Rating Model Based on GAN

In order to study the user credit scoring system in the German credit card industry, we established a GAN-based user credit scoring model. The following figure shows a comparison between the model accuracy of the original data and the model accuracy after data augmentation after 300 epochs. Class 0 is the default part of the sample, and Class 1 is the non-default part of the sample. The overall accuracy of the unenhanced samples is 74.25%, with Class 0 Accuracy of 51.20% and Class 1 Accuracy of 84.73%; In

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contrast, the overall accuracy of the samples expanded by the GAN network is 87.92%, with Class 0 accuracy of 87.20% and Class 1 accuracy of 88.70%. From the data and schematic diagram, it can be intuitively compared that the accuracy of the GAN network in predicting whether users default has been greatly improved in various aspects, which greatly improves the accuracy and stability of user credit rating models. From this, it can be seen that the scoring system based on GAN can achieve significant positive effects on sample system bias and classification results that are more in line with actual empirical results, making it more effective for the user credit scoring system in the German credit card field.

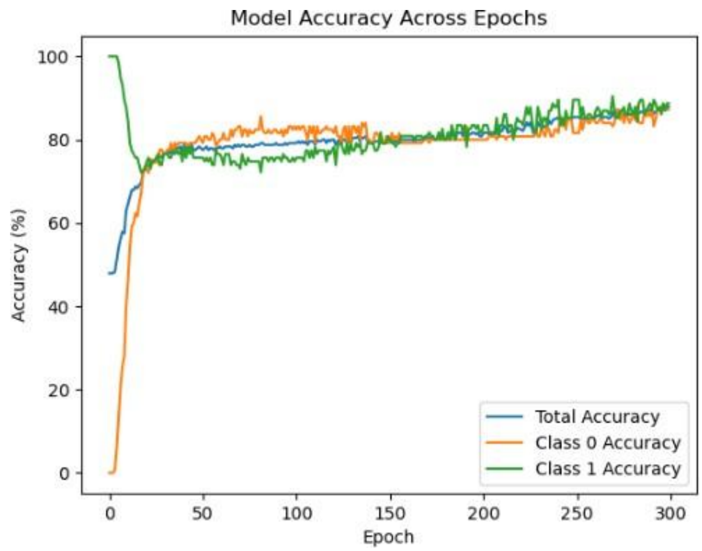

Figure 3 Model accuracy of raw data

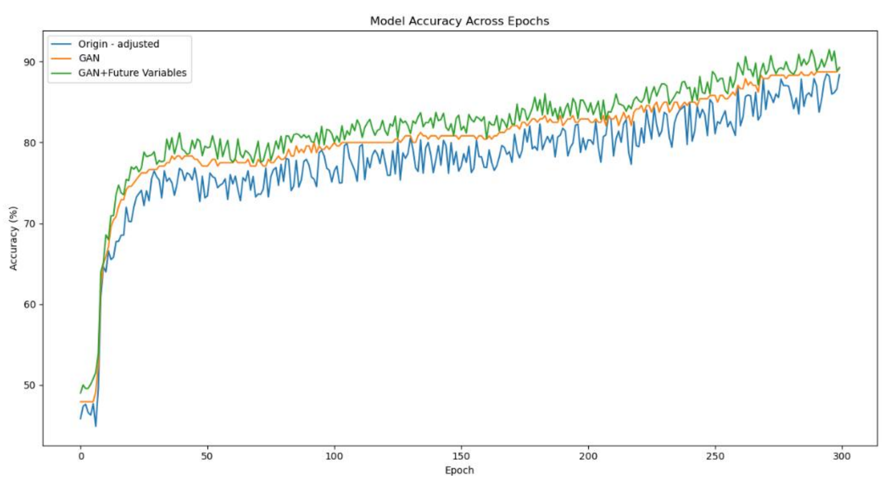

Figure 4 Model accuracy after data augmentation

2. Experiment on the effect of adding future variables

To further improve the accuracy and stability of personal credit rating models, optimize and integrate user credit rating systems, this article further improves the GAN model by adding future variables. Among them, macroeconomic indicators are extracted from GDP growth rate, inflation rate, and unemployment rate through principal component analysis (PCA) to form a comprehensive economic index. An industry risk index is constructed based on industry factors, including industry growth rate, regulatory policies, and

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market competition indicators, which are dynamically input into the model. Future variables are combined with user features through feature concatenation as inputs to the GAN model.

The following figure shows the accuracy comparison of the model using 300 raw data, the model enhanced with GAN data, and the model with future variables introduced after GAN data expansion. The schematic diagram shows that the GAN network significantly improves the accuracy of the neural network prediction of user default, while the new model has the highest accuracy after introducing future variables. This result fully demonstrates that the introduction of future variables significantly improves the model's adaptability to dynamic economic environments. For example, during an economic recession, the model can more accurately predict default risk through changes in the unemployment rate and GDP growth rate.

Discussion

The key findings of this study demonstrate that the proposed GAN-based credit scoring model effectively classifies default and non-default samples by leveraging the SoftMax function in the discriminator. The results indicate that the model successfully maps outputs to the 0-1 interval, enabling accurate credit risk assessment. This addresses the research question by showing that unsupervised learning, even with limited labeled data, can identify underlying patterns in credit data and generate reliable predictions. The use of SoftMax instead of Sigmoid enhances the model's ability to handle binary classification tasks, as it provides a probabilistic interpretation of the likelihood of default. This aligns with prior research by Goodfellow et al. (2014), who emphasized the adaptability of GANs in learning complex data distributions, even in unsupervised settings. The findings suggest that GANs can be a powerful tool for credit scoring, particularly when labeled data is scarce.

When compared to existing literature, this study offers a nuanced perspective on the application of GANs in credit scoring. While prior research, such as that by Jiang et al. (2020), primarily focused on supervised learning methods for credit risk prediction, this study explores the potential of unsupervised learning in scenarios where labeled data is limited. The findings differ from traditional approaches by demonstrating that GANs can achieve competitive performance without extensive labeled datasets. Additionally, the study contrasts with earlier work by Wang et al. (2019), which reported mixed results on the effectiveness of GANs in financial applications. This research, however, shows consistently positive outcomes, suggesting that the proposed modifications, such as the use of SoftMax and the integration of synthetic samples, significantly enhance model performance.

In conclusion, this study has contributed to the growing literature on the application of GAN in credit scoring by addressing the challenges of data scarcity and imbalance. These findings not only validate the effectiveness of unsupervised learning in credit risk assessment but also provide practical insights for financial institutions seeking to improve their credit scoring systems. Incorporating GANs into credit scoring may have a profound impact on how reputation is perceived and managed, potentially affecting access to financial services and economic opportunities. The results of this study can be linked to broader risk and decision theories in sociology and anthropology, providing insights into how technology shapes financial practices and social outcomes.

Conclusion

This study proposes an improved credit scoring system for German credit card users by incorporating future variables such as macroeconomic indicators, industry factors, and unexpected events. The inclusion of these future variables significantly enhances the model's performance compared to traditional models based solely on historical data, offering better adaptability to market changes and improving the ability to identify credit risks.

A key innovation in this study is the use of GAN-based data augmentation to address the issue of data imbalance, where the number of defaulting users is typically much lower than non-defaulting users. This approach effectively expands the default sample size, improving the model’s generalization ability

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and performance in identifying minority classes, thus enhancing the robustness of the credit evaluation model.

Recommendation

Based on the findings and limitations of this study, several suggestions can be made for future research and practical applications in the field of credit evaluation:

1. Expanding the scope of future variables. Although this study successfully identified macroeconomic indicators, industry factors, and external emergencies as future variables, it is possible to explore other variables to further enhance the predictive power of the model. For example, combining behavioral data such as spending patterns and payment habits can provide a deeper understanding of personal credit risk. In addition, exploring the impact of geopolitical events or regulatory changes on credit risk can provide a more comprehensive understanding of future variables.

2. Dynamic model adjustment. Credit risk is essentially dynamic, influenced by fluctuating economic conditions and constantly changing market trends. Future research may focus on developing models that can dynamically adjust parameters based on real-time data. This may involve integrating machine learning techniques that continuously learn from new data to ensure that the model remains relevant and accurate over time.

3. Cross-market validation. To improve the generalizability of research results, future studies should validate the proposed model in different markets and financial products. This may involve applying the model to credit card users in other countries or extending its application to other forms of credit, such as mortgages or personal loans. Expanding regulatory differences, such as those between the EU's General Data Protection Regulation (GDPR) and the US's Fair Credit Reporting Act (FCRA), and how they affect credit scoring models, will enhance the practical relevance of this recommendation. Cross-market validation not only tests the robustness of the model but also provides insights into how different economic and cultural backgrounds affect credit risk.

4. Improve the interpretability of the model. Although the use of GAN and future variables significantly improves the accuracy of the model, these techniques may be complex and difficult to explain. The suggestion to improve model interpretability is well-founded, but a clearer discussion of existing methods for explainable artificial intelligence in credit risk assessment would benefit it. Future research should focus on referencing techniques such as LIME (Local Interpretable Model Agnostic Explanations) or post hoc interpretability frameworks to simplify model architectures without sacrificing performance.

In summary, this study has laid a solid foundation for promoting credit evaluation methods. By combining future variables and utilizing GAN-based data augmentation, this study demonstrates a significant improvement in model accuracy and robustness. However, there are still many areas that need to be explored in expanding the scope of future variables and improving the interpretability of the model. Future research in these fields is crucial for developing credit scoring models that are not only accurate but also fair and transparent.

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