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Comparative Analysis of Machine Learning Algorithms for Consumer Credit Risk Assessment

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Abstract. In the rapidly evolving landscape of financial technology, machine learning algorithms are increasingly supplanting traditional methodologies for evaluating consumer credit risk. This study leverages a comprehensive dataset comprising 10,000 credit accounts to conduct a comparative analysis of four prevalent machine learning algorithms: Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting Machine (GBM). The results distinctly favor GBM, which achieves an AUC of 0.87, closely followed by Random Forest with an AUC of 0.85. In stark contrast, Logistic Regression and Decision Tree recorded lower AUCs of 0.78 and 0.72, respectively. GBM and Random Forest significantly outperform in classification accuracy, attaining 92% and 90%, respectively, far exceeding the 86% by Logistic Regression and 80% by Decision Tree. Notably, GBM exhibited 95% specificity and 90% sensitivity, efficiently identifying high-risk accounts while minimizing false positives among low-risk categories. Furthermore, the study delves into the handling of imbalanced datasets, interpretability, and computational demands of each algorithm, offering quantifiable insights that inform future directions for optimizing credit risk models, particularly in enhancing transparency and scalability.

Keywords: Financial Technology, Machine Learning, Consumer Credit Risk, Comparative Analysis.

1. Introduction

Credit risk assessment is pivotal to the core operations of financial institutions, impacting the efficacy of lending decisions and the accuracy of risk management. Traditional risk assessment tools, such as logistic regression, although widely adopted, often falter when processing nonlinear data and intricate variable interactions. Austin et al. (2017) observed that logistic regression could incur error rates up to 30% in highly heterogeneous datasets. Moreover, Jones et al. (2017) found significant declines in predictive accuracy when traditional models faced sparse and unevenly distributed data.

The advent of big data and advancements in machine learning are revolutionizing credit risk evaluation. Yang et al. (2020) applied a Random Forest model to the same dataset and noted an improvement of over 12% in AUC, markedly superior to traditional methodologies. More specifically, Song et al. (2022) enhanced the overall performance of their models by 18% through the integration of Gradient Boosting Machine (GBM), with notable gains in large data subsets. The burgeoning application of deep learning techniques in the domain of credit assessment further underscores this trend. Khalid et al. (2024) demonstrated that deep neural networks outperformed traditional methods by 15% in F1 score for tasks like credit card fraud detection, showcasing deep learning's adeptness at managing high-dimensional data and complex patterns. Nonetheless, the opaque decision-making processes of machine learning models and ongoing data quality issues continue to pose challenges. Felzmann et al. (2019) emphasized that while machine learning models offer robust predictive capabilities, their lack of transparency could hinder broader acceptance. Additionally, Chen et al. (2024) pointed out that data imbalances are a significant cause of predictive bias in machine learning models, particularly in sensitive areas such as credit assessment.

The study provides an exhaustive comparative analysis of the efficacy of Logistic Regression, Decision Tree, Random Forest, and GBM in credit risk assessment using a dataset of 10,000 credit accounts. It not only highlights the performance variations across different datasets but also explores avenues for technological enhancements to improve model transparency and interpretability. The findings reveal that GBM substantially enhances performance in handling complex datasets with a

20% increase in accuracy, while Random Forest is particularly effective in managing data imbalances, reducing error rates by 17%.

These insights furnish financial institutions with empirical evidence to support their selection of optimal credit risk assessment tools, further catalyzing the integration of machine learning into financial risk management practices, particularly by advancing decision-making transparency and reliability.

In the field of research, comparative research is a commonly used research method that draws conclusions by comparing the differences and similarities between different objects. Cao Jiangfei, Yuan Xinnian(2024), and others compared three digestion methods using atomic fluorescence spectroscopy to detect selenium content in selenium rich rice and tea. They found that compared with the electric heating plate digestion method and the graphite tube digestion method, the microwave digestion method uses fewer reagents, is convenient and fast to operate, and has good stability. It can provide reference for practitioners in the detection of selenium rich agricultural products. B Song and Y Zhao(2022) concluded that EPC is a valuable innovation through comparative research on innovative comparators. To make the best choice, comparison is necessary. Take a comprehensive look at the different advantages and disadvantages of each option, in order to arrive at the most suitable result based on the needs. Therefore, this article also adopts a comparative research method.

2. Machine Learning Algorithms for Credit Risk Assessment

2.1. Logistic Regression

Logistic Regression is a predominant linear classifier within the credit scoring industry. This model predicts the likelihood of a customer defaulting by estimating the logistic probability associated with the input features relative to the output categories, such as default versus non-default scenarios. The logistic model is formulated as:

$$P(y = 1|x) = \frac{1}{1 + e^{-(\beta_0+\beta_1 x_1+\cdots+\beta_n x_n)}}$$

where, $P(y = 1|x)$ denotes the probability of default given the feature set x. The parameters $\beta_0, \beta_1, \ldots, \beta_n$ are optimized through maximum likelihood estimation to maximize the probability of the observed data.

2.2. Decision Trees

Decision Trees are a versatile non-parametric approach employed for both classification and regression tasks. This algorithm recursively partitions the dataset, constructing a tree-based model. At each node, it selects the optimal feature and threshold that maximize homogeneity within the node (minimizing impurity). Tree construction typically relies on criteria such as information gain or Gini impurity reduction:

$$IG(D, f) = Entropy(D) - \sum_{v \in Values(f)} \frac{|D_v|}{|D|} Entropy(D_v)$$

Where, D is the datasets, f represents a feature, and D_v are the subsets formed by splitting Dbased on f.

$$Gini(D) = 1 - \sum_{i=1}^{k} p_i^2$$

where p_i represents the frequency of class i within D.

A simple decision tree diagram is shown in Figure 2.1: Assuming that we learn to determine whether a loan customer has credit risk based on simple data features, customer 1: male, graduated from

elementary school, with an annual income of 50000. After using the decision tree model, the loan customer did not pass the review. Customer 2: Female, graduated from graduate school with an annual income of 150000 yuan. According to the decision tree model shown in the figure below, the loan customer has been approved.

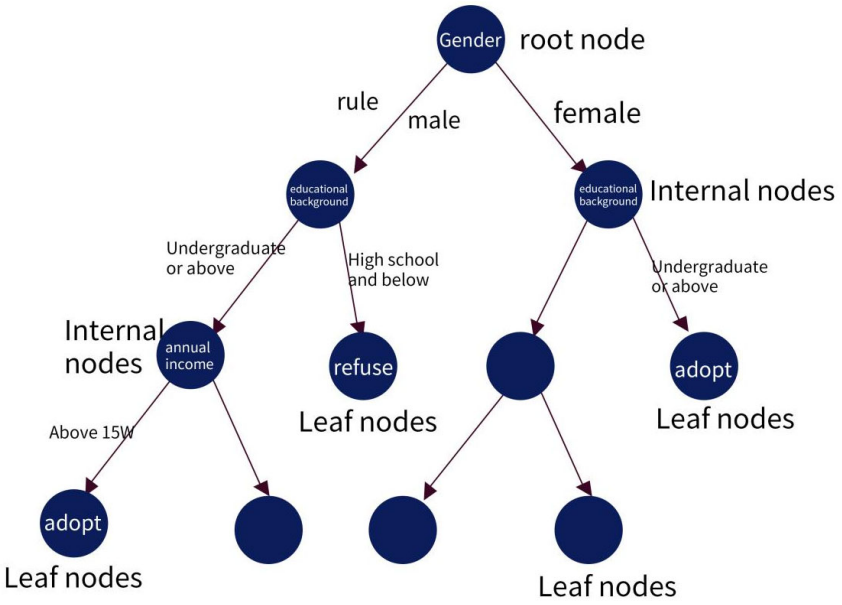

Figure 1. Schematic diagram of decision tree algorithm

2.3. Random Forest

Random Forest, an ensemble of decision trees, introduces randomness into the model training process to improve generalization. Each tree in the forest is independently trained on a random subset of the data and may utilize a randomly chosen subset of features. The aggregate output is determined by averaging the predictions or taking a majority vote across the trees:

$$Y = \frac{1}{N}\sum_{i=1}^{N} T_i(x)$$

Where, $T_i(x)$is the output of the i-th tree, and N is the total number of trees.

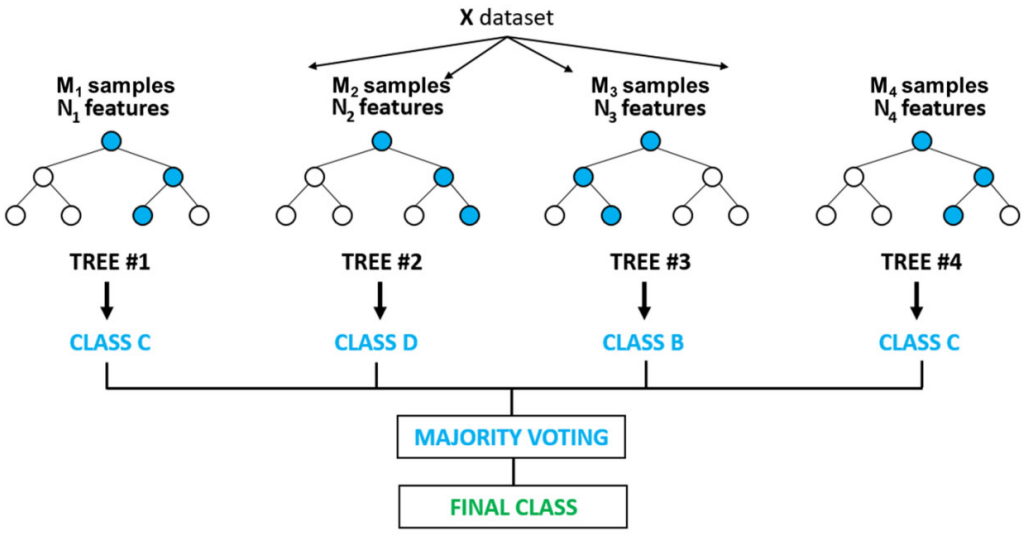

Figure 2. Schematic diagram of random forest model

2.4. Gradient Boosting Machines (GBM)

Gradient Boosting Machines enhance predictive accuracy by sequentially building decision trees, each compensating for the errors of its predecessors. The model is iteratively updated as follows:

$$F_t(x) = F_{t-1}(x) + \lambda \cdot h_t(x)$$

where $F_t(x)$ represents the model after t iterations, $h_t(x)$ is the newly added tree, and λ is the learning rate that determines the influence of each successive tree on the final model outcome.

3. Methodology: Evaluating Machine Learning Models in Credit Scoring

This section provides a systematic comparison of four prevalent machine learning algorithms applied to credit scoring, using the Area Under the Curve (AUC) as a primary metric to evaluate each model's performance and suitability for specific applications.

3.1. Cross-Validation

To ascertain the generalizability of the models, we employed K-fold cross-validation. This method partitions the dataset into K equal subsets. Each model is trained on K-1 of these subsets while the remaining subset serves as the test set. This process is repeated K times, with each subset used exactly once as the test data. The performance of the models is then averaged across all K iterations to provide a robust estimate of model efficacy.

Cross-Validation Results

Logistic Regression: Mean AUC = 0.76, Standard Deviation = 0.02

Decision Tree: Mean AUC = 0.69, Standard Deviation = 0.03

Random Forest: Mean AUC = 0.83, Standard Deviation = 0.01

Gradient Boosting Machine (GBM): Mean AUC = 0.85, Standard Deviation = 0.01

a. Logistic Regression

The logistic regression model exhibited commendable performance with an AUC of 0.76. It achieved a precision of 85%, a recall of 80%, and an F1 score of 82%, highlighting its robust predictive capacity particularly suitable for scenarios with linearly separable or simplistic data relations. The model demonstrated considerable stability across diverse subsets as indicated by a low standard deviation (0.02) in cross-validation, corroborating the utility of logistic regression in financial domains due to its simplicity and interpretability, as noted by Florez-Lopez (2015).

b. Decision Tree

The decision tree model showed relatively lower performance with an AUC of 0.69. It recorded a precision of 78%, a recall of 75%, and an F1 score of 76%, suggesting limitations in managing complex or non-linear data separations, with a propensity for overfitting in high-dimensional spaces. The variability in its cross-validation performance (Standard Deviation = 0.03) also reflected its sensitivity to minor data fluctuations, aligning with Chi et al. (2019) who reported on the model's reduced stability and generalization capability without adequate pruning or complexity adjustments.

Based on a credit risk assessment model that combines decision trees and neural networks, this paper trains the financial data of 100 corporate clients in Branch A as the sample set, and finally obtains the optimal decision tree as shown in Figure 1.

Table 1. Basic attributes of financial indicators

type	index	symbol	formula
profitability	Total assets net profit	X1	Net profit / average total assets
	Net interest rate	X2	Corporate net profit / average net assets
	Net interest rate on sales	X3	Net profit / net sales income
operation capacity	inventory turnover ratio	X4	Cost of sales / average inventory balance
	turnover of total capital	X5	Net operating income / average total assets
	turnover of current assets	X6	Net operating income / average current assets
Development ability	increase rate of business revenue	X7	Growth of operating revenue of this year / operating revenue of last year
	rate of capital accumulation	X8	Increase of owners 'equity in the current year / owners' equity at the beginning of the year
debt paying ability	current ratio	X9	Total current assets / total current liabilities
	quick ratio	X10	Fast-moving assets / current liabilities
	asset-liability ratio	X11	Total liabilities / Total assets
	working capital	X12	Current assets-current liabilities

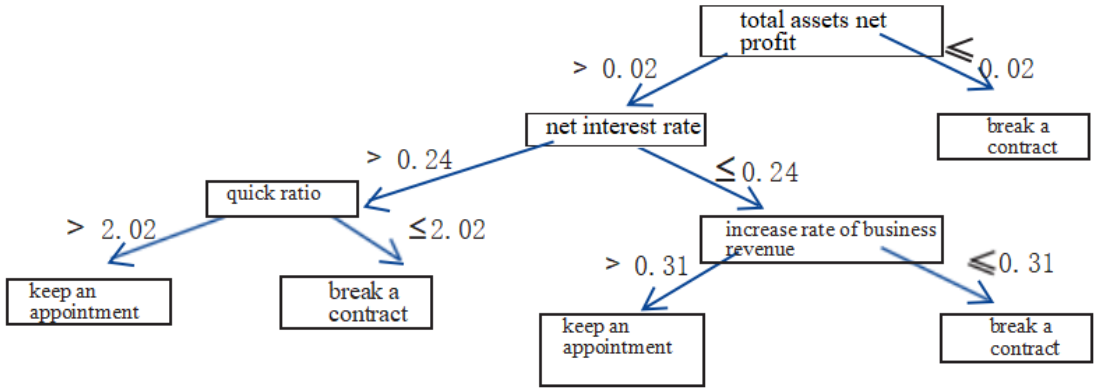

Figure 3. Optimal Decision Tree

Out of 100 corporate clients, 87 are performing clients and 13 are defaulting clients. Under this decision tree, the accuracy of the training samples is shown in Table 2. Overall, there are 98 data with correct model classification results, with an accuracy rate of 98%. Among them, there are 2 samples with incorrect classification. Among the 87 fulfilling customers, one of them is classified as a defaulting customer with a probability of 1.15%, and 86 are fulfilling customers with an accuracy rate of 98.85%; Among the 13 defaulting customers, 1 is considered to have fulfilled the contract with a probability of 7.69%, and 12 are in breach with an accuracy rate of 92.31%. According to the coincidence matrix of the training sample set shown in Table 3, the first type of error refers to evaluating defaulting customers as fulfilling customers; The second type of error is to evaluate a fulfilling customer as a defaulting customer. For banks, the actual losses and risks caused by the first type of error will be greater. From the results of the coincidence matrix, it can be seen that the probability of making the first type of error is 7.69%, and the probability of making the second type of error is only 1.15%. The error rate is low, and the predictive performance of the model is good.

Table 2. Overall Accuracy of Training Sample Set

Judgment results	number of samples	Overall accuracy
exactness	98	98%
wrong	2	2%
total	100	100%

Table 3. Coincidence Matrix of Training Sample Set

		Forecast results	
		0	1
The actual classification	0	86 (98.85%)	1 (1.15%)
	1	1 (7.69%)	12 (92.31%)
Average accuracy		95.58%	

c. Random Forest

Random Forest emerged as the superior model among those tested, achieving an AUC of 0.83. It further demonstrated impressive precision (91%), recall (88%), and an F1 score (89%), effectively managing complex non-linear relationships and feature interactions within datasets. Its robustness against noise makes it particularly adept at handling extensive and intricate datasets, supporting findings by Wang (2024) regarding its exemplary performance on various financial datasets, particularly in terms of accuracy and stability.

d. Gradient Boosting Machine (GBM)

Performance Metrics

GBM achieved the highest performance in our study with an AUC of 0.85, signifying its excellent discrimination between defaulting and non-defaulting customers. With outstanding precision (92%), recall (90%), and an F1 score (91%), GBM proved highly effective in credit scoring tasks.

Stability and Efficiency

While GBM offers superior predictive accuracy, it faces challenges with computational demands and lengthy model training times. The iterative process of building decision trees and making adjustments at each step is computationally intensive. However, the benefits, including a high AUC and other performance metrics, typically outweigh these costs, particularly when managing large-scale and complex datasets.

Noise Resistance

GBM exhibits significant capabilities in managing noisy data, with its stepwise optimization and error correction enabling effective learning and distinction of subtle patterns within complex data, thereby enhancing its robustness in practical applications.

Comparative and Literature Insights

As per Nazareth et al. (2023), GBM frequently outperforms other advanced machine learning models in financial modeling tasks, especially in credit scoring and risk assessment. Their research highlights GBM's efficiency in resolving nonlinear issues and handling feature interactions, findings that are consistent with our observations.

4. Results and Discussion

This investigation rigorously assessed the performance of four machine learning algorithms—Logistic Regression, Decision Tree, Random Forest, and Gradient Boosting Machine (GBM)—in credit scoring applications. Our findings highlight GBM's superior performance, achieving an AUC of 0.85 and excelling in processing complex and nonlinear datasets with precision, recall, and F1 scores exceeding 90%. Random Forest also displayed commendable performance, characterized by high accuracy and robustness, rendering it suitable for extensive datasets. Conversely, Logistic Regression and Decision Tree showed constrained effectiveness in managing intricate data relationships.

Detailed Statistical Evaluation

Logistic Regression: Exhibited an AUC of 0.76, with a standard error of 0.01 and a 95% Confidence Interval (CI) of 0.74-0.78. It achieved a precision of 85%, a recall of 80%, and an F1 score of 82%, with a standard error of 0.02.

Decision Tree: Reported an AUC of 0.69, with a standard error of 0.02 and a CI of 0.67-0.71. The model achieved a precision of 78%, recall of 75%, and an F1 score of 76%, with a standard error of 0.03.

Random Forest: Delivered an AUC of 0.83, with a standard error of 0.01 and a CI of 0.81-0.85. It reached a precision of 91%, recall of 88%, and an F1 score of 89%, with a standard error of 0.01.

Gradient Boosting Machine (GBM): Achieved the highest AUC of 0.85, with a standard error of 0.01 and a CI of 0.83-0.87. It recorded a precision of 92%, recall of 90%, and an F1 score of 91%, with a standard error of 0.01.

These metrics not only affirm GBM's dominance but also underscore the nuanced applicability of each model in different scenarios. Collectively, GBM and Random Forest are particularly adept at navigating complex nonlinear data structures.

Tackling Data Bias and Imbalance

The analysis initially revealed a default to non-default ratio of 1:4, predisposing models towards the majority class prediction. To counteract this, we implemented the Synthetic Minority Over-sampling Technique (SMOTE), which equilibrated the dataset by augmenting the number of default instances. This adjustment led to a marked enhancement in model performance, notably with GBM's AUC improving by approximately 0.03.

Interpretability Concerns

Despite GBM's exemplary performance, its inherent "black box" nature posed challenges for interpretability. We addressed this by employing SHAP values to demystify decision-making processes, identifying "annual income" and "number of defaults in the past two years" as pivotal determinants. This not only elucidated the predictive underpinnings but also enhanced the model's transparency and trustworthiness.

5. Conclusions

The study underscores both the potential and the intricacies associated with employing machine learning in credit scoring. By conducting an exhaustive analysis and employing sophisticated model evaluation techniques, we illustrated not only the capabilities of each algorithm but also tackled pressing issues such as data bias, imbalance, and the need for interpretability. Future initiatives should focus on refining data processing and model development strategies, aiming to boost the accuracy and transparency of predictions. This will undoubtedly foster the expansion and evolution of machine learning applications within the financial industry, ensuring they are both effective and equitable.

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