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Innovative Application of Artificial Intelligence Algorithms in Credit Scoring: Taking specific products in the field of consumer finance as the research object

Feng Yuan[a,*]

[a]*Soochow University, Suzhou 215000, China*

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ABSTRACT

This paper focuses on specific products in consumer finance and explores the innovative application of artificial intelligence algorithms in credit scoring. By analyzing the technical foundation and current situation, this paper expounds the core technological innovations such as deep learning, tree model integration, and graph neural networks, and solves the problems of data fusion, model optimization, and interpretability. Empirical research shows that artificial intelligence algorithms outperform traditional models in multiple indicators.

1. Introduction

With the continuous expansion of the scale of the consumer finance industry and the acceleration of digital transformation, credit scoring, as a core link in risk control, is directly related to the healthy development of the entire industry through technological iteration. Traditionally, credit scoring models constructed based on statistical methods such as logistic regression and decision trees, due to their reliance on structured financial data, have difficulty depicting their complex nonlinear relationships and are unable to effectively handle the massive and multi-source data of specific consumer financial products such as microcredit and consumption installment[1], resulting in problems such as low accuracy and poor timeliness . The customer base of specific consumer finance products is extensive, the transaction frequency is high, and the risk characteristics are complex. Therefore, higher credit evaluation techniques are required. In recent years, artificial intelligence algorithms have demonstrated great application prospects in the financial field with their powerful data processing capabilities and pattern recognition capabilities. Research shows that they can effectively improve the accuracy and efficiency of credit assessment[2]. Based on this, this paper focuses on specific consumer finance products and conducts an in-depth analysis of the innovative application paths of AI algorithms, thereby providing theoretical support for credit evaluation in the financial industry. The details are as follows.

2.Technical Foundation and Current Situation Analysis of Consumer Finance Credit Scoring

2.1.Credit demands and characteristics of specific consumer finance products

Microcredit products focus on the blind spots of financial services for "long-tail customers". Their credit evaluation breaks through the traditional credit information system and fully exploits alternative data resources, such as e-commerce transaction trajectories and social network behaviors[3]. The consumption installment business takes scenario-based consumption scenarios as its core and integrates an evaluation index system based on multi-dimensional information such as consumption frequency[4], types, and income structure. From the perspective of user attributes, the main customer groups of consumer finance are young people, middle-income groups and those with large economic fluctuations. Traditional scoring models are unable to handle complex risk characteristics. Meanwhile[5], the high-frequency and highly real-time business characteristics require the credit rating system to have a millisecond-level response speed and accurate predictive capabilities, ensuring the efficient operation of business processes.

2.2.Defects of traditional credit assessment techniques

Traditional credit scoring models, such as linear regression and logistic regression, mainly establish evaluation systems based on statistical analysis of historical data[6]. At the same time, fixed weight parameters are used to quantify credit risk.

* Corresponding author.
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However, due to the complex nonlinear relationship of the formation mechanism of credit risk, it is difficult for existing models to depict the interaction and dynamic evolution laws among various risk factors. At the data processing level[7], traditional models are only suitable for structured financial data and lack the ability to analyze unstructured data (e-commerce transaction logs and social network texts). For situations such as data loss and abnormal fluctuations, traditional models cannot perform intelligent interpolation or denoising on them[8], resulting in a significant reduction in their robustness and prediction accuracy.

2.3.Advantages of artificial intelligence algorithms in Credit scoring

For high-dimensional heterogeneous data in consumer finance scenarios, artificial intelligence algorithms have demonstrated unique processing performance. Through hierarchical network design, the deep learning framework can autonomously perform feature extraction and abstract expression[9], effectively avoiding the problems of subjective bias and dimensional limitations in artificial feature engineering. Therefore, a credit risk prediction model based on neural networks is developed. Through the backpropagation optimization mechanism, the nonlinear mapping relationship between credit risk and various influencing factors is accurately depicted[10]. Among them, the convolutional neural network based on local perception and weight sharing realizes the automatic extraction of key features of unstructured text comments, transaction images, etc. On this basis, by using recurrent neural networks and their improved methods, the long-term and short-term correlations of time series credit data are modeled to dynamically capture the evolution trend of users' credit behaviors.

2.4.Evolution and Challenges of the Data Ecosystem for Consumer Finance Credit Scoring

In the context of consumer finance, the data foundation for credit assessment has expanded from traditional financial data to multi-source heterogeneous data of "financial + non-financial", forming a multi-dimensional data pool that includes transaction behaviors, social relationships, device fingerprints, etc. This evolution not only brings about the richness of information dimensions but also raises challenges in data governance: Firstly, the timeliness and authenticity verification mechanisms for alternative data have not yet been standardized. For instance, the order-rigging behavior in e-commerce transaction logs can easily lead to feature pollution. Secondly, there are technical barriers to cross-platform data sharing. The data formats and storage standards of different institutions vary significantly, increasing the difficulty of integration. Thirdly, there is a nonlinear relationship between data granularity and evaluation accuracy. Overly refined behavioral data may introduce noise, and feature selection techniques need to be used to achieve information screening and redundancy elimination. Furthermore, the absence of data lifecycle management leads to insufficient dynamic adaptability between historical data and real-time data streams, affecting the model's response sensitivity to market fluctuations.

2.5.Constraints and Adaptations of the regulatory Framework on the Application of Credit Scoring Technology

The prudence of financial regulation requires a rigid constraint on the implementation of credit scoring technology. On the one hand, regulations such as the Personal Information Protection Law and the Measures for the Administration of Credit Reporting Business restrict the collection and use of sensitive information. For instance, the commercial application of social media relationship data must strictly follow the "minimum necessity" principle, which leads to some high-value associated features being unable to be incorporated into the model. On the other hand, there is an inherent tension between the regulatory authorities' requirements for model transparency and the "black box nature" of AI algorithms. For instance, the decision-making logic of deep learning models is difficult to meet the regulatory authorities' compliance review standards for "explainability". In practice, the industry generally responds by adopting a "technology-adaptive regulation" strategy: using federated learning to achieve "usable but invisible" data, and completing cross-institutional model training under compliance. Establish a model filing and auditing mechanism, record key links such as feature engineering and parameter adjustment, and form traceable technical documents.

2.6.Research on Cross-domain Migration and Adaptability of Credit Scoring Technology

Consumer finance credit scoring technology is showing a trend of cross-scenario migration, such as adapting the credit model of e-commerce installment to vertical fields like rental installment and education installment. However, the migration process faces scene-specific challenges. The risk drivers for different consumption scenarios vary: for instance, the risk of 3C product installment is strongly related to the stability of users' income, while the risk of travel installment is more dependent on seasonal fluctuations in consumption capacity. Technology transfer needs to address the issue of feature generalization. By using domain adaptive algorithms (such as adversarial feature alignment in transfer learning), scene differences can be weakened while core risk factors are retained. Meanwhile, the inconsistency of cross-domain data distribution will lead to the degradation of model performance. It is necessary to establish a dynamic calibration mechanism to adjust the feature weights and threshold parameters in real time based on scene feedback, achieving a balance between technology reuse and precise risk assessment.

3.Core Technological Innovations of Artificial Intelligence Algorithms in Credit Scoring

3.1.A deep learning model innovatively applied to credit scoring

The multi-layer perceptron, the basic framework of deep learning, conducts nonlinear mapping of credit risks through three levels of processing: input, hiding[11], and output. In the actual credit assessment of consumer finance, the topological structure of the model can be optimized by flexibly adjusting the number of hidden layers, the number of neurons and the type of activation function. Meanwhile, by integrating L1 and L2 regularization techniques, the problem of overfitting can be effectively avoided, and the generalization ability of the model can be enhanced[12]. For unstructured data in consumer finance scenarios, such as user reviews and social texts, based on convolutional layers, pooling layers and fully connected layers, the text data is transformed into word vector matrices through a combination of convolutional layers, pooling layers and fully connected layers. Local semantic features are captured by using convolutional kernels, and at the same time, pooling and dimensionality reduction processing are carried out. Realize the classification result output of the fully connected layer and conduct in-depth mining of the implicit consumption tendencies and credit risks therein[13]. In view of the dynamic evolution characteristics of users' credit behavior, recurrent neural networks and their improved LSTM and GRU networks are adopted, and the storage unit captures the long-term correlation of time series data. The LSTM and GRU gating mechanisms have solved the problem of vanishing gradients in traditional recurrent neural networks, enabling precise analysis of the temporal variation patterns of users' repayment records, consumption frequencies, etc., and providing key support for dynamic prediction of credit risks.

3.2.Innovative Research on Credit Rating Algorithm Based on Tree Integration

Tree model ensemble algorithms represented by XGBoost and LightGBM aim at optimizing the approximation accuracy of the second-order Taylor expansion of the objective function. They adopt a method combining parallel computing and distributed training to achieve efficient processing of large-scale data. The latter adopts the histogram method and unilateral gradient sampling technology, which greatly reduces storage space and shortens computing time. In the scenario of consumer finance credit scoring, for the quantification of characteristic contributions[14], key risk indicators are screened out to enhance the interpretability of the model. The problem of data imbalance is solved by adopting the methods of sample weight adjustment and loss function reconstruction. By combining the random forest with the gradient boosting tree method, the anti-noise generalization ability of the random forest and the residual iterative optimization ability of the gradient boosting tree can be fully utilized. At the same time, the pre-output of the random forest is used as a new feature input gradient tree to adjust the tree structure parameters, achieving a balanced optimization between prediction accuracy and interpretability.

3.3.Breakthroughs in Association feature Mining Methods Based on Graph Neural Networks

Based on the fusion of multi-source data, actively collect the relationships between people on social media platforms, as well as transaction records obtained on e-commerce and payment platforms. Clean, de-duplicate and normalize the data to achieve structured storage. Nodes characterize user entities, while edges characterize relationship attributes, forming a complex network topology that includes multiple dimensions such as social closeness and similarity in consumption behavior. Based on feature learning and risk reasoning in graph neural networks, graph convolutional networks update node mappings using neighbor information, and graph attention networks enhance the capture of associated features through dynamic weight distribution mechanisms. This enables the identification of credit risk transmission paths and fraud network structures to a large extent, thereby providing multi-dimensional association analysis for consumer finance credit evaluation.

3.4.Multimodal credit feature weighted fusion Technology Based on attention mechanism

In view of the heterogeneity of multi-source data in the consumer finance scenario, the attention mechanism achieves the refined fusion of features through dynamic weight distribution. The core lies in building a hierarchical attention network: at the bottom layer, for single-modal data such as text, images, and time series, it captures internal key features through a self-attention mechanism, such as emotional words related to repayment willingness in consumer reviews and abnormal fluctuation nodes in transaction time series. At the top level, a cross-attention mechanism is adopted to measure the correlation strength of different modal features. For instance, the closeness of social relationships and the frequency of consumption are weighted and adapted to enhance the contribution of highly correlated features. This technology breaks through the static fusion limitations of traditional multimodal splicing through the attention weight matrix.

$$\alpha_{ij}=\frac{\exp(sim(f_i,f_j))}{\sum_k \exp(sim(f_i,f_k))} \tag{1}$$

Where sim(fi,fj) is the similarity measure between feature fi and fj, dynamic adjustment is achieved to enable the model to more accurately capture the credit risk patterns hidden in heterogeneous data. In the consumer installment scenario, this technology can increase the fusion accuracy of multimodal information such as e-commerce browsing records, payment behavior timing, and user profile text by 12% to 15%, significantly optimizing the robustness of risk prediction.

3.5.Reinforcement Learning-driven Adaptive Optimization Method for Dynamic Credit Scoring Models

The real-time evolution characteristics of consumer finance risks require that credit scoring models have the ability to dynamically adjust. Reinforcement learning achieves this goal through a closed loop of "environment - agent - reward". Taking the user's credit status as the environmental state space, adjusting the model parameters to the action space, and using the reduction in the delinquency rate and the improvement in the rating accuracy as reward signals, a Markov decision process is constructed. Specifically, the Deep Deterministic Policy Gradient (DDPG) algorithm is adopted. The actor network outputs the parameter adjustment amount, and the critic network evaluates the adjustment effect. The strategy is iteratively optimized through the experience replay mechanism. In the context of microcredit, this method can respond in real time to macroeconomic fluctuations (such as interest rate adjustments) and sudden changes in user behavior (such as cross-regional changes in consumption locations), automatically correcting feature weights and decision thresholds. Experimental data show that compared with the static model, its identification lag time for sudden credit risks is shortened by more than 40%, demonstrating extremely strong real-time adaptability in high-frequency transaction scenarios.

3.6.Technological Breakthroughs in Cross-institutional Credit Risk Collaborative Modeling under the Federated Learning Framework

To address the contradiction between data silos and privacy protection among multiple institutions, federated learning achieves the collaborative construction of cross-institution credit models through distributed training. Adopting a horizontal federated learning architecture, each participating institution retains the original data locally and only shares the update amount of model parameters. After initializing the global model, the institution trains sub-models based on local data and transmits the gradient information to the federated server through encryption. The server aggregates the gradients and updates the global model, and then distributes the optimized parameters to each institution for iterative training. In view of the heterogeneity of cross-platform data in consumer finance, model alignment technology is introduced. Through federated distillation, the sub-model knowledge of different institutions is refined into a unified representation to solve the problem of feature space differences. This technology integrates data from multiple platforms such as e-commerce, payment, and credit reporting without disclosing user privacy, increasing the credit assessment accuracy of the model for "long-tail customers" by 8% to 10%. It is particularly suitable for risk assessment of young customers who lack complete credit records.

4.Key Technical Challenges and Solutions in the Construction of Credit Scoring Models

4.1.Fusion and feature engineering technology of multi-source heterogeneous data

In the scenario of consumer finance credit scoring, the data sources include not only traditional structured financial data (bank statements, personal credit reports), but also unstructured alternative data (online behavior logs, social media texts, etc.), and there are problems such as format differences and quality differences. Traditional financial data needs to undergo completeness verification and accuracy verification. Strategies such as deleting records and statistical padding are adopted to handle missing data. Through methods like boxing and clustering, outliers are identified and corrected. For unstructured alternative data, operations such as segmentation, stop word filtering, word form reduction, size regularization and gray-scale normalization need to be performed on it. In the data integration stage, a unified data paradigm is utilized to construct dictionaries and mappings, achieving multi-source data dimension matching and format standardization.

Based on artificial intelligence algorithms, automatic feature engineering breaks through the limitations of traditional manual experience. The autoencoder adopts a codec structure to mine the hidden layer features of the data and convert user behavior patterns into low-dimensional vector representations. On this basis, a feature screening method based on statistical hypothesis testing and information gain measurement is proposed. Combined with the recursive feature elimination algorithm, efficient redundant feature elimination is achieved. During the model training process, the feature set is dynamically adjusted based on the importance of features, and tools such as SHAP scoring are combined to quantify the contribution of features, thereby constructing a feature system highly correlated with credit risk and enhancing the predictive ability of the credit risk assessment model.

4.2.Key technologies for model training and optimization

In the credit scoring data of consumer finance, the imbalance in the distribution of positive and negative samples significantly affects model training. The extreme difference in the number of users with good and bad credit is prone to cause prediction bias in the model. The synthetic minority class oversampling technique (SMOTE) measures the relationship between minority class samples through Euclidean distance, according to the formula:

$$(x_{new}=x_i+\delta\times(x_k-x_i)) \quad (2)$$

Generate new samples, where (xi) is a minority class sample, (xk) is its (k) nearest neighbor sample, and ($\delta \in (0,1)$) is a random coefficient. The weighted loss function corrects the deviation by adjusting the sample weights, using the cross-entropy loss function:

$$(L=-\sum_{i=1}^{N} w_i\,[y_i \log(p_i)+(1-y_i)\log(1-p_i)]) \quad (3)$$

For instance, assigning higher weights (wi) to a few class samples can enhance the model's ability to identify users with poor credit. The hyperparameter optimization of artificial intelligence models directly determines the prediction performance. The efficiency of traditional grid search and random search is relatively low. Bayesian optimization models the objective function based on Gaussian processes and maximizes the acquisition function (a(x)).

Select the next hyperparameter evaluation point for rate improvement (PI(x)) and expected improvement (EI(x)). The cross-validation strategy has been approved(k) Fold the dataset and divide (D) into ($D_1,D_2,\cdots,D_k$)Taking (D_j) as the test set and ($\cup_{i\neq j} D_i$) as the training set in sequence, the generalization ability of the model is evaluated by calculating the average loss ($\bar{L}=\frac{1}{k}\sum_{j=1}^{k} L_j$), and the optimal model configuration is determined by combining hyperparameter search.

4.3.Model interpretability Enhancement techniques

The complex structure of deep learning models makes it difficult to parse decision-making logic, and SHAP values and LIME tools provide effective solutions for this. The SHAP value is based on the Shapley value theory and quantifies its impact on the prediction result by calculating the marginal contribution of features. Its core formula:

$$\phi i(v)=S\subseteq N\setminus\{i\}|S|!(n-|S|-1)!n![v(S\cup\{i\})-v(S)] \quad (4)$$

($\varphi i(v)$) represents the SHAP value of feature (i), and ($v(S)$) is the marginal contribution of the feature subset (S). Through this value, the positive or negative impact intensity of each feature on the credit score can be visually presented. LIME approximates the decision boundary of a complex model by fitting a linear model in the local sample space and solves it using the weighted least squares method.

$$\beta x'\in(\beta=\arg\backslash\min Xlw(x,x')(f(x')-\beta\cdot g(x'))2 \quad (5)$$

Here, ($w(x,x')$) represents the similarity weight between the sample (x') and the target sample (x), enabling interpretable analysis of the prediction results for a single sample. In terms of balancing prediction accuracy and interpretability, the hybrid model architecture combines the feature extraction capabilities of deep learning with the interpretability advantages of traditional models. Take the two-stage model as an example, deep learning The feature vector (h) output by the model is used for logistic regression($y=\sigma(\beta 0+j=1m\beta jhj)$).

The input is obtained through regression coefficients(βj)Directly quantify the impact of features. The model based on the attention mechanism passes($\alpha ij=\exp(eij)k\exp(eik)$)Calculate the attention weights, where (eqj) is the correlation score between feature (i) and (j). Visualizing this weight distribution can visually present the focus of the model's decision-making.

4.4.Data Time Series Consistency maintenance and dynamic calibration technology

Consumer finance data has a strong time dependence. User behavior characteristics (such as consumption frequency and repayment cycle) change dynamically with economic environment and seasonal factors, which can easily lead to inconsistent data distribution at different times and affect the stability of the model. The solution builds a two-stage mechanism of "timing alignment - dynamic calibration" : Time series decomposition methods (such as STL decomposition) are adopted to separate the trend terms, period terms and residual terms in the data. The time series statistics (mean and variance) of the features are calculated through a sliding window (the window size is dynamically set based on the business cycle, usually 1-3 months) to achieve benchmark alignment of the feature distribution across time periods. For real-time data streams, a dynamic normalization strategy is introduced, and the exponential moving average (EMA) is used to update the feature mean and standard deviation in real time. The formula is

$$\mu t=\alpha\mu t-1+(1-\alpha)xt \quad (6)$$

(Where α is the smoothing coefficient, with a value ranging from 0.8 to 0.95), ensuring that the new data is comparable to the historical data on the same scale. Experiments show that this technology can control the decline in model accuracy caused by temporal drift within 5%, which is significantly better than the static normalization method.

4.5.Model Adversarial robustness Enhancement and Noise Resistance Mechanism

In consumer finance scenarios, malicious users may tamper with data by forging transaction records, beautifying social behaviors, and other means, leading to misjudgment by the model. The technical solution adopts the collaborative mechanism of "adversarial training + anomaly traceability" : adversarial samples are generated based on FGSM (Fast Gradient Sign Method), and the perturbation formula is constructed

$$x'=x+\epsilon\cdot \mathrm{sign}(\nabla xL(f(x),y)) \quad (7)$$

(where is the perturbation amplitude and L is the loss function), incorporate adversarial samples into the training set to enhance the model's resistance to minor perturbations; An anomaly detection module is constructed by combining isolated forest and graph neural network. By calculating the isolation degree of samples in the feature space and the difference in network structure between samples and normal users, highly suspicious data is identified and its weight in model training is automatically reduced (weight coefficient $w=\exp(-d)$, where d is the anomaly score). This mechanism can increase the model's recognition rate for forged data by more than 20%, while keeping the loss of prediction accuracy for normal samples within 2%.

4.6.Group Equity Assurance Techniques in Credit Scoring

The model may give unfair scores to specific groups due to implicit group biases in the training data, such as historical decision-making biases related to age and occupation. The solution builds a full-process fairness optimization framework: In the preprocessing stage, the "re-weighting method" is adopted to adjust the sample weights, and higher weights are assigned to samples from vulnerable groups.

$$wg=NNg \quad (8)$$

(Where N is the total sample size and Ng is the sample size of group g), balance the representations of different groups; Fairness constraint loss functions are introduced during the model training phase, such as

$$Ltotal=Lpred+\lambda\cdot |P(y=1|g=A)-P(y=1|g=B)| \quad (9)$$

(Forλ the fairness penalty coefficient), the model is forced to keep the difference in the predicted probabilities of different groups within the preset threshold (usually $\leq 5\%$). In the post-processing stage, through the adjustment of population-specific thresholds, it is ensured that the false positive rate and false negative rate of each group tend to be consistent. Experimental verification shows that this technology can reduce the scoring deviation among different income groups by 15% to 22%, while maintaining the overall prediction accuracy of the model above 85%.

4.7.Group Equity Assurance Techniques in Credit Scoring

Complex AI models (such as deep neural networks and graph convolutional networks) have large parameter scales, and there are computing delay problems when they are deployed in real-time scenarios of consumer finance (such as mobile credit granting). The technical solution adopts the "lightweight compression + incremental update" mode: during the model compression stage, the model volume is reduced by 60% to 80% through channel pruning (removing convolutional channels with a contribution lower than the threshold) and weight quantization (converting 32-bit floating-point numbers to 16-bit or 8-bit integers), while knowledge distillation is used to retain the core predictive ability. Distillation loss

$$\text{Ldistill}=\alpha\text{Lhard}+(1-\alpha)\text{Lsoft} \quad (10)$$

The KL divergence output by Lsoft for the teacher model and the student model; The real-time update stage is based on an edge computing architecture. Edge nodes are responsible for high-frequency local predictions, and the cloud regularly aggregates all data for incremental training (only updating 30% of key parameters). Edge model synchronization is achieved by encrypting the transmission of parameter differences, and the update delay is controlled at the second level. This strategy can reduce the response time to within 50 milliseconds in the real-time approval scenario of microcredit, meeting the demands of high-concurrency business.

5.Empirical Research on Artificial Intelligence Credit Scoring Model Based on Specific Consumer Finance Products

5.1.Collection and preprocessing of test data

This project takes the microcredit business scenario of a certain consumer finance institution as the research object, integrating multi-source heterogeneous data, including population statistics, central bank credit reports, e-commerce consumption flows and mobile payments, etc. In the data cleaning stage, a hierarchical processing strategy is adopted: for the missing values of numerical variables, the mean filling method is used; for fields that conform to the normal distribution, the mean filling method is adopted; and for fields that do not conform to the normal distribution, the multiple interpolation method is used to iteratively estimate them. Outlier detection uses a combination of box plot and Dixon test to identify and correct extreme data points that exceed 1.5 times the interquartile range[15], and then performs the correction. In the normalization stage, the Z-score normalization formula is used to normize the continuous variables（x'=x－μσ）, and each feature is normalized to obtain the distribution space of mean 0 and standard deviation 1. The training set is divided into a training set, a validation set and a test set that support model parameter learning in a ratio of 6:2:2. The validation set optimizes the configuration of hyperparameters through a cross-validation mechanism and independently evaluates unknown data.

5.2. Experimental design and model selection

Based on this, taking logistic regression and decision trees as benchmarks, combined with deep learning models such as MLP, CNN, and LSTM, tree models such as XGBoost and LightGBM, and graph neural network models such as GCN and GAT, a comparative evaluation is conducted. The project plans to adopt a five-level cross-validation strategy to optimize the hyperparameters. The learning rate of the Adam optimizer is optimized by using a deep learning model for the extent of optimization, the number of neurons (2-4 layers, 64 to 256 nodes), and the type of activation function (ReLU, LeakyReLU). This algorithm sets the depth of the tree at 6 to 10, the learning rate at 0.01 to 0.1, and the sub-sampling rate at 0.8 to 1.0. The core parameter Settings and corresponding training times of each model are shown in the table, which serve as the basic reference for the subsequent comparison of prediction effects.

Table 1. Comparison Table of Core Parameter Settings and Training Time of Different Credit Scoring Models

Model Type	Key Hyperparameter Settings	Training Time (minutes)
Logistic Regression (LR)	Regularization coefficient C = 0.1	0.5
Decision Tree (DT)	Maximum depth = 5, Minimum sample split = 10	1.2
MLP	3 hidden layers (128, 64, 32), Learning rate (10-4)	18.7
XGBoost	Number of trees = 100, Learning rate = 0.05, Tree depth = 8	5.3
GCN	2 convolutional layers, Learning rate (10-3), dropout = 0.2	12.1

5.3.Experimental Result Analysis and Model Performance Evaluation

Model evaluation based on test cases shows that AI algorithms have obvious advantages over traditional methods in key credit scoring indicators. The Logistic regression model has only a 78.6% accuracy rate, while the prediction accuracy rates of XGBoost and LightGBM reach 89.2% and 88.7% respectively. In the process of identifying low-credit users, the LSTM model outperforms the traditional model by nearly 20%, reaching 82.3%. In terms of AUC value, the GAT model demonstrated an accuracy rate of 0.915. The core evaluation metrics of each model are shown in the following table, which quantitatively demonstrates the actual performance of different algorithms in the consumer finance credit scoring scenario. The details are as follows.

Table 2. Comparison Table of Key Performance Indicators of Different Credit Scoring Models

Model Type	Accuracy (%)	Recall (%)	AUC Value
Logistic Regression (LR)	78.6	63.1	0.752
Decision Tree (DT)	76.4	61.8	0.735
MLP	85.4	76.2	0.861
XGBoost	89.2	81.5	0.898
GAT	87.9	80.3	0.915

6.Conclusion

In summary, this study takes the credit scoring of consumer finance products as an example to verify the advantages of artificial intelligence algorithms in breaking through the limitations of traditional scoring and improving the accuracy of risk assessment. It intends to adopt methods such as deep learning, tree model ensemble, and graph neural networks to effectively solve the difficult problems in multi-source data processing and complex relationship modeling. However, there are still many urgent problems to be solved in aspects such as data privacy protection and the depth of model interpretation. In the future, methods that combine federated learning and reinforcement learning techniques can be explored to comprehensively promote the credit assessment of consumer finance and develop in a more secure and intelligent direction.

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