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Adaptive Feature Interaction Model for Credit Risk Prediction in the Digital Finance Landscape

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Abstract:
The rapid evolution of online financial markets and shifting personal consumption patterns have led to an increasingly complex landscape of credit options. This expansion has heightened the necessity for robust credit risk assessment models, particularly in the face of rising defaults caused by economic downturns and unemployment. This study evaluates various credit risk models, proposing an adaptive feature interaction model to address limitations in conventional frameworks, such as feature interaction oversight and noise interference. Leveraging techniques like a SENET-based gating mechanism and an attention-augmented Multilayer Perceptron (MLP), the proposed model captures deeper feature interactions, yielding improved prediction outcomes. Experimental results reveal the model's superiority across key performance metrics, including AUC, accuracy, and geometric mean, highlighting its potential in enhancing credit risk forecasting. The findings demonstrate a promising application of advanced deep learning techniques in financial risk management, offering more accurate and reliable predictions.

Keywords:

Credit risk assessment, deep learning models, Internet finance

1. Introduction
With the continuous development of the Internet industry and the improvement of people's material living standards, personal consumption concepts are changing rapidly, and the financial market is constantly changing with the user’s needs [1]. Credit forms are emerging in an endless stream, and a large number of Internet credit transaction methods are gradually emerging in my country's consumer credit market [2].
Credit has become one of the current mainstream financing channels with its unique and convenient financing methods [3] and has been widely integrated into people's daily lives. As a result, the Internet financial industry has experienced rapid growth in a short period, leading major banks and credit institutions to compete to launch various consumer financial products, such as consumer loans, mortgages, and car loans. Although individuals and loan companies can benefit from Internet financial credit activities, due economic recession, rising unemployment, personal credit, and life changes, it is accompanied by many potential default risks, such as default, arrears, and bankruptcy. These risks will not only bring huge economic losses to financial institutions and investors but may also have an impact on the entire financial system, inducing unstable situations such as economic recession and market fluctuations.
In recent times, the incidence of borrower defaults has emerged as a significant challenge for financial institutions engaged in lending operations. Regulatory bodies in various regions have intensified their oversight of lending platforms, prompting these entities to enhance their risk management practices. Credit

platforms contribute to economic expansion by extending loans, thereby boosting institutional profitability and exploring diversification into additional business sectors. Concurrently, these platforms aim to ensure that borrowers meet their repayment obligations to mitigate default risks.

Consequently, developing effective methods to forecast the likelihood of borrower defaults has become a central concern in establishing robust financial risk control systems. Traditional approaches to financial risk management have long relied heavily on the expertise and intuition of internal personnel, such as loan officers and financial analysts, who base their decisions on historical data and personal experience. However, this reliance on human judgment has inherent drawbacks, including susceptibility to subjective biases and limitations in manual processing capabilities, which can lead to inconsistent results and consume considerable time and human resources. Moreover, the increasing volume, velocity, and variety of data that modern financial institutions must contend with exacerbate these issues, making traditional methodologies increasingly strained and less effective. The growing complexity of financial risks, coupled with the rapid pace of global economic changes, further necessitates the adoption of more advanced solutions that can process vast amounts of data quickly and accurately. Advanced analytics, machine learning algorithms, and artificial intelligence-driven models offer promising alternatives that can mitigate the shortcomings of traditional methods, providing more objective and timely assessments of creditworthiness and helping financial institutions to make better-informed decisions about lending practices.

To address the limitations of overlooked feature interactions and informational noise in conventional credit default prediction frameworks, an adaptive feature cross-compression model for predicting defaults has been developed [6]. This model employs a SENET-like gating mechanism to mitigate data noise, generating adaptively weighted embedding features. It employs a specialized component to better understand the interactions between basic categorical data and its adjusted form, leading to an enhanced portrayal of categorical information for individuals [7].

Additionally, an MLP (Multilayer Perceptron) incorporating an attention mechanism is deployed to achieve adaptive weighting of the integrated features. The MLP network is also utilized to model interactions among continuous features, thereby augmenting the non-linear modeling capabilities. Experimental outcomes indicate that this model outperforms existing default prediction models, delivering a notable enhancement in prediction accuracy [8].

2. Method

To deeply explore the interrelationships among attributes, the dynamic feature integration system separately handles nominal and quantitative data. The design of this system includes three main parts: the nominal data handling module, the quantitative data handling module, and the forecasting and learning module [9].

The discrete feature processing component utilizes a SENET-inspired gating mechanism to filter out data interference and adaptively extract feature importance. An attention mechanism is integrated to dynamically learn features, thereby strengthening the interactivity among them. For the continuous feature processing component, a multi-layer MLP is directly employed for interaction modeling. This boosts the nonlinear processing power of the normalized quantitative attributes [10]. The forecasting and learning element combines the processed representations of categorical and numerical data after their respective treatments and merges these with the predictive task to determine the probability of a loan applicant defaulting. The complete architecture of the model is shown in Figure 1.

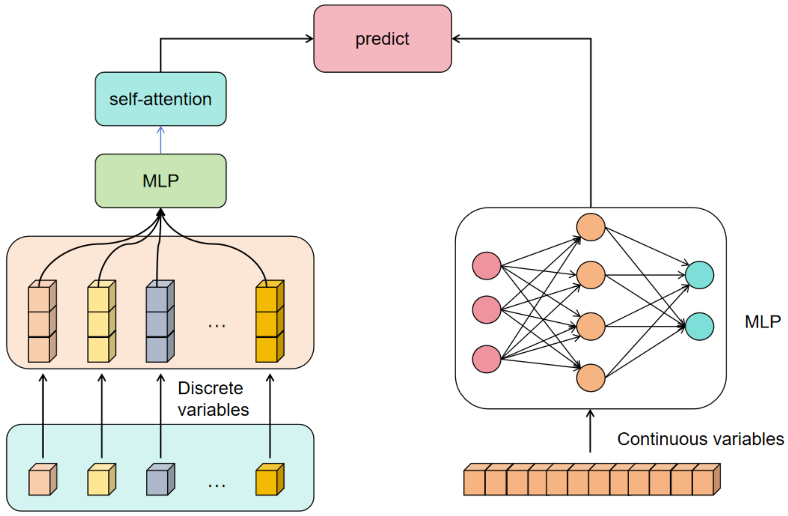

Figure 1 Overall network architecture

In the network architecture, the most important layer is the adaptive gating filter layer. This layer is responsible for screening and filtering the input features, retaining important feature information, and suppressing unimportant features. By learning feature weights, effective information is highlighted before feature interaction, and importance is adaptively assigned to the original embedding vector. The embedding vector E is subjected to weighted activation to generate the feature importance A, and the formula for this calculation is as follows:

$$A = \sigma_{\alpha}(W^{T} \cdot E + b)$$

Where A is the feature importance vector, σ_{α} is the activation function, W is the weight vector, E is the embedding vector, and b is the bias term. In the reduction layer, average pooling is used to decrease the input feature dimensions. This process condenses the information from each importance vector into a single value, acting as a summary of the statistical data for the importance vector. The operation conducted by global average pooling can be described as follows:

$$A_{GAP} = \frac{1}{n}\sum_{i=1}^{n} \sigma(W_i^{T} \cdot E + b_i)\ \alpha e_i = \alpha_i \circ \theta$$

Finally, we give the network structure of the entire adaptive gating layer, which is shown in Figure 2.

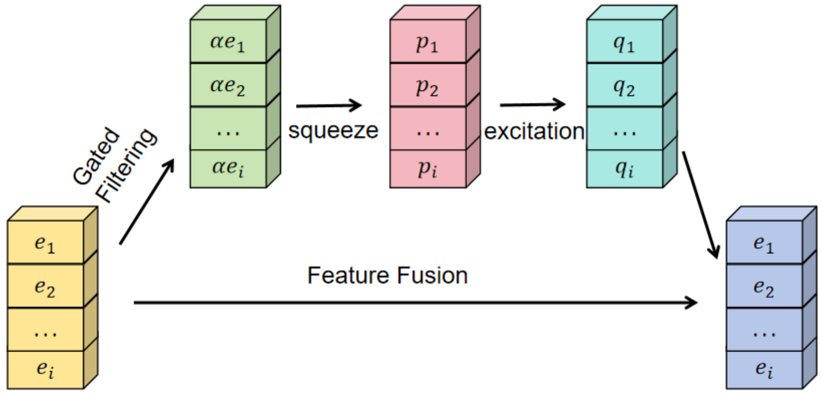

Figure 2 The architecture of the adaptive gating filter layer

As shown in Figure 2, the data obtained F through $E=\{e1,e2,...,e3\}$, and W composed of $ae1$, p, and q obtained more favorable features for network training and analysis. Finally, A_{GAP} was obtained through the above calculation process, realizing the process of adaptive weight weighting.

3. Experiment

3.1 Datasets

The dataset used in this experiment is the "Home Credit Default Risk" dataset, which is a widely used resource designed to help understand and predict the risk of personal loan defaults. The dataset is contributed by Home Credit Group and covers a variety of characteristics, such as applicant age distribution, income level, occupation type, credit history, and repayment behavior. These rich data points not only provide deep insights into the credit status of individual borrowers but also allow data scientists to build complex machine learning models to assess potential credit risks, thereby supporting a more accurate credit decision-making process.

By analyzing the detailed customer information in the "Home Credit Default Risk" dataset, researchers can explore how different variables affect the default rate and design more robust risk management strategies based on this. This dataset is suitable for financial institutions that want to improve the quality of their credit portfolios, reduce bad debt losses, and enhance overall business stability.

To facilitate the experiment, we first reduced the dimension of the dataset and combined RF with Filter feature selection for feature screening. We ranked the importance of the feature set according to the RF method, determined the feature importance threshold after multiple experiments with the base model, and finally selected 16 features with feature importance greater than 0.002. Finally, the selected features and their importance in the dataset are shown in Table 1.

Table 1 Features in the dataset and their importance ranking

Feature	Importance	Ranking
isDefault	0.8637	1
subGrade	0.0199	2
interestRate	0.0185	3
grade	0.0173	4

loan_Term	0.0167	5
avg_interestRate	0.0152	6
term	0.0149	7
dti	0.0137	8
rest_revol	0.0136	9
ficoRange_mean	0.0125	10
end_year	0.0111	11
issueDate	0.0105	12
all_installment	0.0103	13
rest_money_rate	0.0095	14
differ_areas_annual_mean	0.0093	15
rest_money	0.0081	16

3.2 Experimental Results

This paper chose ten representative classification prediction models were selected for comparison. These included individual deep learning models such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory Networks (LSTM); ensemble deep learning models like Stacked Autoencoders (SAE), Hybrid Boosting Networks (HBN), and Deep Residual Learning (ResNet); and other advanced deep learning models including Attention-based Recommendation Model (ARM), Neural Collaborative Filtering (NCF), AutoInt, and Variational Autoencoders (VAE). The best parameter configurations for each of these models were identified through a grid search procedure and are outlined in Table 2. This thorough evaluation aims to highlight the robustness and superior performance of the AFCC model compared to these benchmarks.

Table 2 Experimental Results

Model	**Parameter settings**
CNN	L= 0.001, O=adam
RNN	L= 0.001, O=adam
LSTM	L=0.003， O=adam
SAE	L=0.003， O=adam
HBN	L=0.003， O=adam
RESNET	L=0.003， O=adam
ARM	L=0.005， O=adam
NCF	L=0.005， O=adam
VAE	L=0.005， O=adam

The performance metrics for the proposed model and the comparative models on the dataset utilized in this study are presented in Table 3.

Table 3 Experimental Results

Model	**Auc**	**Acc**	**KS**	**G-mean**
CNN	0.7021	0.8012	0.3875	0.4633

RNN	0.7069	0.8037	0.4033	0.5756
LSTM	0.7089	0.8041	0.4172	0.5946
SAE	0.7144	0.8043	0.4257	0.6213
HBN	0.7198	0.8057	0.4369	0.6522
RESNET	0.7215	0.8066	0.4475	0.6813
ARM	0.7233	0.8067	0.4569	0.6819
NCF	0.7247	0.8071	0.4872	0.6977
VAE	0.7269	0.8079	0.4813	0.7013
Ours	0.7418	0.8096	0.5243	0.7062

The comparative analysis of the deep learning models highlights the proposed model's superior performance across all evaluated metrics. In terms of AUC, which gauges a model's ranking capability, the proposed model leads with a score of 0.7418, significantly outperforming alternatives such as CNN at 0.7021, RNN at 0.7069, and even more advanced models like SAE at 0.7144 and HBN at 0.7198. Accuracy (ACC) further supports this trend, with the proposed model achieving 0.8096, followed closely by VAE at 0.8079, and the lowest being CNN at 0.8012, indicating consistent yet varying levels of correctness across the models. Additionally, the proposed model excels in the KS statistic, achieving 0.5243, which denotes a better separation of distributions between classes, and in G-mean, scoring 0.7062, suggesting a balanced detection rate for both positive and negative instances. Other models, such as NCF, while competitive with a KS of 0.4872 and G-mean of 0.6977, do not match the proposed model's performance, reinforcing its robustness and effectiveness in the given classification task.
Our model achieves the best results on all four evaluation metrics, especially leading other models on the AUC and KS metrics, which shows that our model not only has stronger discriminative ability in general but also in dealing with the most difficult It also performs well when identifying minority class samples, showing the potential of this model in credit risk assessment. This result supports the use of more advanced algorithms to improve the validity and reliability of credit risk prediction.
In order to further demonstrate the experimental results, this paper gives a bar chart of the experimental results

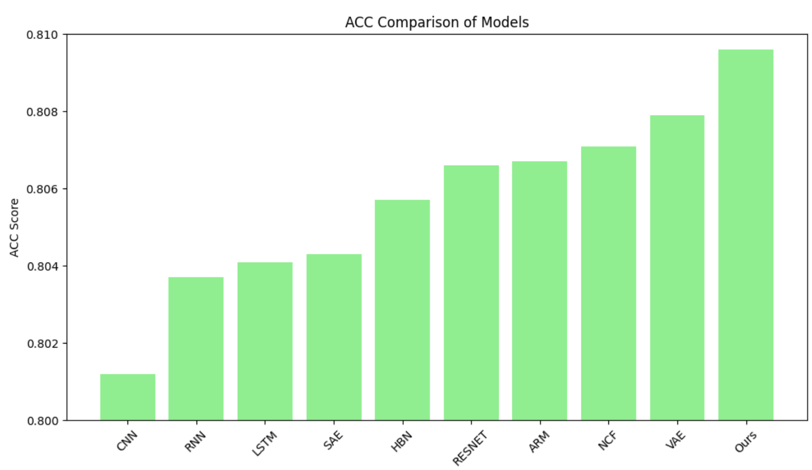

Figure 3 Accuracy Histogram

From the accuracy (ACC) histogram, it becomes clear that our model delivers outstanding results. The histogram provides a detailed comparison, showcasing the enhanced performance of our model over others. This graphical depiction clearly indicates the model's effectiveness, emphasizing its superiority through the visual presentation of accuracy scores.

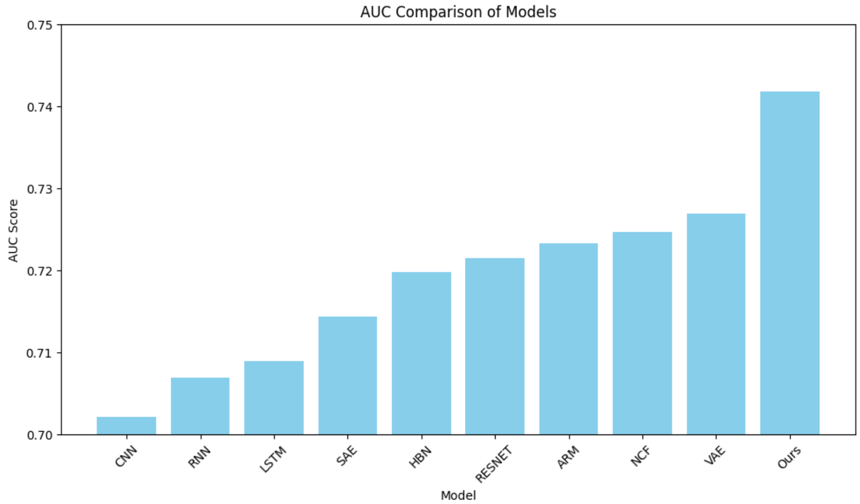

Figure 4 AUC Histogram

Similarly, to further substantiate our findings, we present the AUC histogram, which visually reinforces the quantitative data. This graphical representation vividly illustrates the performance differences among the models, making the proposed model's superiority unmistakable. The histogram clearly shows the proposed model's peak standing taller than those of CNN, RNN, LSTM, and other deep learning models, emphasizing its exceptional ability to distinguish between different classes effectively.
The AUC histogram serves as a powerful tool for conveying the robustness of the proposed model, as it visually encapsulates the disparity in performance metrics. By comparing the heights of the bars, it becomes immediately clear that the proposed model achieves notably higher AUC scores, demonstrating its strength in critical indicators such as classification accuracy and discrimination power. This visual aid not only simplifies the complex numerical data but also makes it strikingly evident that the proposed approach delivers enhanced results across the board, thereby validating its practical advantages over existing models.

4. Conclusion

Through the research conducted in this paper, it is evident that in the domain of credit risk assessment, the performance of predictive models generally improves as the model complexity escalates. Starting from simpler models such as traditional decision trees and factorization techniques, there is a progressive enhancement when moving towards ensemble methods, including random forests, gradient boosting techniques, and extreme gradient boosting. Further advancement into deep learning architectures, such as Deep Factorization Machines and Field-aware Interaction Networks, continues to elevate model performance. Notably, these models exhibit superior handling of imbalanced datasets, particularly in terms of metrics like AUC and G-mean, which reflect better discrimination and processing capabilities. Ultimately, the adaptive feature interaction model proposed in this study surpasses others across multiple evaluation metrics, underscoring its effectiveness and reliability in tackling credit risk assessment challenges. This progression from basic models to more sophisticated ones illustrates the evolving capabilities in addressing complex financial risk scenarios, with the final model demonstrating significant improvements in predictive accuracy and robustness.

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