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Application of Deep Learning in Financial Credit Card Fraud Detection

BAO, Qiaozhi [1*] WEI, Kuo [2] XU, Jiahao [3] JIANG, Wei [4]

[1] North Carolina State University, USA
[2] Independent Research, China
[3] University of Southern California, USA
[4] Xidian University, China

***** BAO, Qiaozhi is the corresponding author, E-mail: qiaozhbao6@gmail.com***

Abstract: Credit cards play an important role in our daily life, and the emergence of Internet finance makes credit card payment face more fraud risks. Therefore, it is of great significance to build an efficient credit card fraud detection model and continuously improve the fraud detection accuracy for improving the market system, promoting the healthy development of economy, maintaining the stability of national economy and ensuring financial security.This paper proposes a BERT model for credit card fraud detection to address the challenges posed by imbalanced and high-dimensional datasets. Leveraging BERT's pre-training to capture semantic similarity, the model enhances fraud detection accuracy. Through extensive data preprocessing and model training, the proposed approach achieves a remarkable 99.95% accuracy in detecting fraudulent transactions. The study underscores the importance of leveraging advanced deep learning techniques like BERT to combat evolving fraud tactics in the internet finance industry.

Keywords: Credit card fraud detection, BERT model, Imbalanced dataset, Deep learning, Data preprocessing

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1 Introduction

With the rapid development of Internet finance, the credit card issuance of domestic banks is also increasing at a very fast rate every year, which greatly facilitates the transaction between users and merchants, making it fast and convenient. [1,2] In this context, it also brings serious problems such as credit card fraud, fraud will cause great losses to banks and users, so accurate detection of credit card fraud is an important link to protect the healthy development of the Internet finance industry. In the current field of credit card fraud detection, there are far more non-fraudulent transactions than fraudulent transactions in the data set, which has the problem of extreme imbalance and high dimension, resulting in low classification accuracy and poor prediction performance of the existing model. Meanwhile, the fraudulent means of criminals will change over time, and the characteristics of credit card fraud will also change. In order to solve the above problems, this paper proposes the BERT model to detect credit card fraud and reduce the loss of credit card fraud of financial institutions. This model has shown its applications in various domains such as robotic control areas [3]. The specific research in this paper includes:

Aiming at the problem of extreme imbalance and high dimensionality in credit card data set, the data were preprocessed by correlation analysis, balancing data set by combining undersampling and oversampling, and various transformations. In the BERT model, the pre-training of BERT layer is used to represent the data as dense vectors, which capture the semantic similarity of the data, so that the BERT model can better understand the meaning of the input, provide more accurate detection of fraud and non-fraud classification problems, and solve the problem of unbalanced data sets and high dimensions [4-6].

Aiming at the problem of credit card fraud detection, this paper reviews and learns the existing credit card fraud detection models and methods at home and abroad, proposes to conduct credit card fraud detection based on [7] BERT model, and conducts model prediction experiments aiming at the problem that credit card fraud data will change over time, so as to analyze the practical problems of credit card fraud detection and improve ideas.

2 Related Work

2.1 Credit card fraud detection

In the last decade, many studies have explored the effectiveness of several active learning strategies in the context of real credit card fraud detection using streaming data. The goal of the study was to determine which strategies were most effective at detecting fraudulent transactions in real time. The study compared four different active learning strategies: random sampling, uncertain sampling, committee voting [8,9] (OBC), and marginal sampling. The results show that both uncertain sampling and marginal sampling are superior to committee voting and random sampling and query in terms of efficiency and effectiveness. YvanLucas proposed automatic feature engineering of credit card fraud detection using multi-view Hidden Markov model (HMM). [10] By analyzing multiple perspectives or factors and using HMM to automate the feature engineering process to improve the effectiveness of machine learning algorithms in detecting fraud. Eunji Kimal proposed a Champion challenger framework. This approach combines integrated methods (bagging and boosting) with deep learning (convolutional neural networks and recurrent neural networks) [11,12]. The final results show that combining different methods can achieve better performance in complex tasks such as fraud detection. Van Vlasselaer uses a model that takes into account a variety of factors, such as cardholders' spending habits and the geographical location of transactions, and uses web-based extensions to further improve accuracy. Andrea DalPozzoloa designed a framework for real-time credit card fraud detection, SCAFF, based on the open source distributed computing system Apache Spark. The framework is designed to be highly scalable and can process large numbers of credit card transactions with low latency. The method used in SCARFF is based on a machine learning algorithm that detects anomalies in credit card transaction data and alerts interested parties while minimizing false positives [13]. The team at EN.Osegil9 compared artificial neural networks (ANN) in simulated annealing training with hierarchical temporal memory (HTM). The advantage of ANN's approach is that it can consider a large number of parameters, thus achieving high accuracy [14-15]. The downside is that it can be slower than other algorithms. N Sanaz proposes a cost-sensitive method for payment card fraud detection based on dynamic random forests and K-nearest neighbors. They aim to address the problem of data imbalance in fraud detection by assigning different misclassification costs to normal and fraudulent transactions. The dynamic random forest algorithm is used to select and optimize features, while the K-nearest neighbor algorithm is used to detect fraud. The proposed method is evaluated on real data sets and compared with other traditional and cost-sensitive algorithms, and the results are satisfactory [16]. AA Taha et al. investigated a smart credit card fraud detection method based on an optimized Light Gradient Boosting Machine. Specific research content includes how to use data preprocessing and feature engineering methods to design feature sets for training and testing machine learning models; How to use cross-validation and other evaluation metrics to evaluate the performance of classifiers; How to select and optimize hyperparameters for lightweight gradient enhancement machine algorithms.

2.2 Credit card fraud risk

The use of credit cards involves a variety of transactions and cooperation, from individual application to bank card issuance to merchant and individual transactions, and even there is fraud risk in the process of credit card transportation. From this point of view, credit card fraud risk mainly involves three aspects: merchants, third parties and cardholders.

The fraud risk of credit card merchants refers to the behavior of merchants using the loopholes or illegal means in credit card transactions to obtain illegal benefits from credit card institutions through false transactions. One of the more typical cases is the malicious closure of merchants after obtaining the authorization of credit card institutions, merchants quickly obtain a large number of transaction lines in a short period of time, and soon after declaring bankruptcy or bankruptcy, so as to evade debts, so that the acquiring institutions bear the relevant refund or error losses.

Third-party risks mainly come from the risk of data leakage. If the user data of credit card institutions or third-party payment platforms is exposed, hackers or criminals may use these data to commit credit card fraud.

Cardholder risk refers to the risk that cardholders use false information or other means to profit from fraudulent credit card transactions. There are mainly fake invitations and fake card fraud. False application refers to the cardholder providing false information or tampering with true information to obtain a credit card, such as forging identification, salary proof, etc. This behavior will lead to loopholes in the bank's credit evaluation process, increasing the risk of overdue credit cards and bad debts. Fraudulent card fraud means that criminals can obtain other people's credit card information through various ways, such as cracking the database of the merchant, peeping at others to enter the password. This information can then be used to forge credit cards or make purchases directly in places such as online shopping. Or some illegal division may use the device that can read and store the magnetic stripe information and cardholder information, installed in the bank POS machine or ATM, by stealing the card information, and then use the invalid or blank deposit card to reproduce the magnetic stripe information, in order to create a forged card, this fraud is also known as side recording cloning card.

2.3 BERT detection model

BERT is a pre-trained language model based on Transformer encoder architecture. Unlike traditional language models, BERT considers not only contextual information, but also bidirectional information of sentences [17]. It uses a multi-layer Transformer encoder that enables it to learn context-sensitive word vector representations in a bidirectional manner [18]. BERT contains two versions: Bert-Base and Bert-Large, where Bert-Base contains 12 encoder layers. BERT-large contains 24 encoder layers.

BERT's input is a sequence of tokens that, after being embedded in [19-22] WordPiece, are passed to a bidirectional Transformer encoder in the form of a positional embed. In this encoder, the token vectors at each location are passed through a series of operations such as self-attention, feedforward neural networks, and residual connections. Among them, the self-attention mechanism allows the model to focus on words at different locations in the input sequence, so that it can capture more rich semantic information at the last encoder layer of BERT, and the output vector of each token is passed to a fully connected layer for fine-tuning downstream tasks. The main steps of BERT used in this paper include three steps: pre-processing, pre-training and fine-tuning.

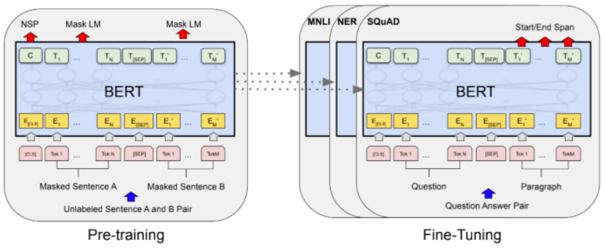

Figure 1.BERT model architecture diagram

BERT's main model architecture is the Transformer encoder. Transformer was proposed by Ashish equals in 2017 for Google machine translation, including Encoder (Encoder) and Decoder (Decoder).

The BERT model uses two pre-training objectives to learn text content features.

Masked Language Model [23] (MLM) can predict masked words by masking words and learning their contextual features

Next Sentence Predication [24] (NSP) predicts whether two sentences are next to each other by learning the relationship between sentences

In BERT model, text preprocessing is segmented according to the smallest unit. [25] For example, the pre-processing of English text uses Google's wordpiece method to solve the problem of unknown words.

The object covered in MLM is mostly a subword, not a full word; For Chinese, it is directly segmented according to the word, and directly covers the single word. This masking strategy leads to incomplete learning of word information in the model. In response to this shortcoming, most researchers have improved the MLM [26-27] masking strategy. In the BERT-WWM model subsequently released by Google, the way of full word coverage is proposed.

BERT uses word segmentation to cover all the words that make up a complete word at the same time.

ERNIE extends the whole word masking strategy to cover Chinese word segmentation, phrases and named entities.

SpanBERT adopted geometric distribution to randomly sample the masked phrase fragments, and used Span boundary word vectors to predict the masked words

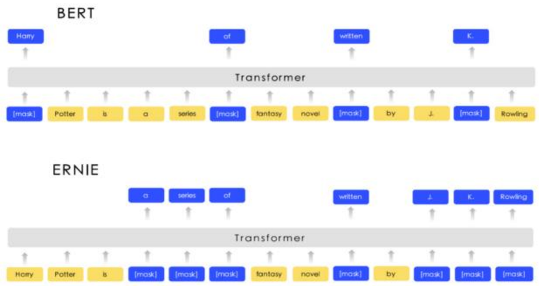

Figure 2. The different masking strategy between BERT and ERNIE

Aiming at the credit card fraud detection task in this paper, the model construction is to construct a specific network, including a fully connected layer, and take the output vector of the pre-trained model as the input of the network [28]. Initial network weights are used to initialize task-specific network weights, which can be randomly initialized. Training is to use the training set to train the network, adjust the weight of the network through the backpropagation algorithm, so that it can better adapt to the requirements of the task. Validation is to use validation set to verify the performance of the model on the task, and evaluate the performance of the model according to the loss function and accuracy of the validation set. Adjusting hyperparameters is to adjust hyperparameters, such as learning rate regularization parameters, according to the performance of the verification set. Finally, the test set is used to test the performance of the model on the task, so as to obtain the final performance evaluation result.

3 Methodology

In our experiments, we adopted from Kaggle data sets (link: https://www.kaggle.com/mlg-ulb/creditcardfraud). The data set records real banking transactions by European cardholders in 2013, including both normal and fraudulent transactions. For privacy and security reasons, the raw data has been processed for feature transformation using PCA (Principal Component Analysis), resulting in a dataset with 29 feature columns and 1 category column (indicating whether a transaction is fraudulent).

To further improve the accuracy and efficiency of fraud detection, we will introduce BERT (Bidirectional Encoder Representations from Transformers) model [29-31]. BERT is a pre-trained deep learning model with powerful natural language processing capabilities, but it can also be applied to other areas of sequential data analysis, such as the transaction data covered in this article.

	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9	...	V21	V22	V23	V24	V
0	0.0	-1.359807	-0.072781	2.536347	1.378155	-0.338321	0.462388	0.239599	0.098698	0.363787	...	-0.018307	0.277838	-0.110474	0.066928	0.1285
1	0.0	1.191857	0.266151	0.166480	0.448154	0.060018	-0.082361	-0.078803	0.085102	-0.255425	...	-0.225775	-0.638672	0.101288	-0.339846	0.1671
2	1.0	-1.358354	-1.340163	1.773209	0.379780	-0.503198	1.800499	0.791461	0.247676	-1.514654	...	0.247998	0.771679	0.909412	-0.689281	-0.3276
3	1.0	-0.966272	-0.185226	1.792993	-0.863291	-0.010309	1.247203	0.237609	0.377436	-1.387024	...	-0.108300	0.005274	-0.190321	-1.175575	0.6473
4	2.0	-1.158233	0.877737	1.548718	0.403034	-0.407193	0.095921	0.592941	-0.270533	0.817739	...	-0.009431	0.798278	-0.137458	0.141267	-0.2060
5	2.0	-0.425966	0.960523	1.141109	-0.168252	0.420987	-0.029728	0.476201	0.260314	-0.568671	...	-0.208254	-0.559825	-0.026398	-0.371427	-0.2327
6	4.0	1.229658	0.141004	0.045371	1.202613	0.191881	0.272708	-0.005159	0.081213	0.464960	...	-0.167716	-0.270710	-0.154104	-0.780055	0.7501
7	7.0	-0.644269	1.417964	1.074380	-0.492199	0.948934	0.428118	1.120631	-3.807864	0.615375	...	1.943465	-1.015455	0.057504	-0.649709	-0.4152
8	7.0	-0.894286	0.286157	-0.113192	-0.271526	2.669599	3.721818	0.370145	0.851084	-0.392048	...	-0.073425	-0.268092	-0.204233	1.011592	0.3732
9	9.0	-0.338262	1.119593	1.044367	-0.222187	0.499361	-0.246761	0.651583	0.069539	-0.736727	...	-0.246914	-0.633753	-0.120794	-0.385050	-0.0697

10 rows × 31 columns

Figure 3. Data set

By introducing [32] BERT model into our experiment, we expect to be able to use the context information and sequence features learned by Bert model to further improve the ability to identify fraudulent transactions. In the following experimental part, we will introduce our method and results of credit card fraud detection based on BERT model in detail.

3.1 Data preprocessing and model

```
Data columns (total 31 columns):
 #   Column  Non-Null Count   Dtype
---  ------  --------------   -----
 0   Time    284807 non-null  float64
 1   V1      284807 non-null  float64
 2   V2      284807 non-null  float64
 3   V3      284807 non-null  float64
 4   V4      284807 non-null  float64
 5   V5      284807 non-null  float64
 6   V6      284807 non-null  float64
 7   V7      284807 non-null  float64
 8   V8      284807 non-null  float64
 9   V9      284807 non-null  float64
 10  V10     284807 non-null  float64
 11  V11     284807 non-null  float64
 12  V12     284807 non-null  float64
 13  V13     284807 non-null  float64
 14  V14     284807 non-null  float64
 15  V15     284807 non-null  float64
 16  V16     284807 non-null  float64
 17  V17     284807 non-null  float64
 18  V18     284807 non-null  float64
 19  V19     284807 non-null  float64
 20  V20     284807 non-null  float64
 21  V21     284807 non-null  float64
 22  V22     284807 non-null  float64
 23  V23     284807 non-null  float64
 24  V24     284807 non-null  float64
 25  V25     284807 non-null  float64
 26  V26     284807 non-null  float64
 27  V27     284807 non-null  float64
 28  V28     284807 non-null  float64
 29  Amount  284807 non-null  float64
 30  Class   284807 non-null  int64
dtypes: float64(30), int64(1)
```

Figure 4. Data preprocessing results

When doing data preprocessing, first we need to import the data set. You can easily do this using the pandas module in Python. With the following command, we can load the data into a DataFrame object named data. Once the data has been successfully loaded, we need to process and understand the data. Before analyzing the data, we may notice an important problem: the unevenness of the data set. In concrete terms, this means that the vast majority of normal transactions in the data set and a small percentage of fraudulent transactions. [33] This imbalance may have an impact on our subsequent modeling and analysis, as models may tend to predict major categories better and ignore smaller ones. Therefore, we need to take appropriate measures to solve this problem.

Based on the count of each column, we have no null values. In addition, you can try to apply feature selection methods to check whether the results are optimized.

I observed 28 features in the data that are transformed versions of PCA [34], but the field "Amount "is raw. When checking the minimum and maximum values, I found that the differences were large and could deviate from our results.

3.2 Result

It achieves 99.95% accuracy in credit card fraud detection. While this number may not come as much of a surprise, it's important to note that our dataset was for one category. This means that our model focuses primarily on one type of fraud, and may be less accurate on other aspects. However, this is still an encouraging achievement and shows that our model performs very well when dealing with specific types of fraud.

Another striking result is that, according to our F1-Score, the BERT model is the winner in our case. The BERT model is known for its excellent natural language processing capabilities, and the previous experiment shows excellent performance on this particular task [35]. However, it is important to note that the data we used to train the model used a transformed version of PCA, which may have had some impact on the model's performance. This shows the impact of data preprocessing on the performance of the model, and the processing we chose seems to have a positive impact on the performance of the BERT model.

4 Conclusion

Credit cards play an important role in our daily life, and the emergence of Internet finance makes credit card payment face more fraud risks. Therefore, it is of great significance to build an efficient credit card fraud detection model and continuously improve the fraud detection accuracy for improving the market system, promoting the healthy development of economy, maintaining the stability of national economy and ensuring financial security.

For the challenge of low classification accuracy and poor prediction performance of the existing model due to the phenomenon of high imbalance and multiple dimensions in the fraud data, this paper uses BERT model to segment the input words with special marks, then converts the sequence after word segmentation into vectors, and adopts WordPiece embedding to split the words into subunits, the previous research has also demonstrated this point [36]. These subunits are then converted into dense vectors using WordPiece embedding. Each vector is represented as the addition of its corresponding WordPiece's embedding vector and position embedding vector. Feature extraction is carried out by stacking Transformer encoders, each with multiple self-attention layers and forward-transfer layers. Through each self-attention layer is used to capture correlations in the input sequence, and each position can interact with other positions in the sequence. The forward transfer layer can map each position in the sequence to a higher-dimensional space, and then learn the language representation by maximizing the language model and the mask language model to form a pre-trained model. In this way, the BERT model can better understand the meaning of the input to solve the problem of unbalanced data sets and high dimensions [37,38].

In conclusion, the integration of artificial intelligence, particularly through models like BERT, holds immense potential for enhancing credit card fraud detection accuracy. As AI technology evolves, its application in financial markets is poised to drive efficiency, transparency, and innovation, paving the way for a more secure and resilient industry.

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The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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Author Contributions

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About the Authors

BAO, Qiaozhi

Statistics, North Carolina State University, NC, USA

WEI, Kuo

Computer Science, Individual Contributor, Shenzhen, China

XU, Jiahao

Master of Science in Financial Engineering, University of Southern California, CA, USA

JIANG, Wei

Computer Science, Xidian University, Xian, China

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