Deep Learning for Predicting Credit Card Defaults

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Abstract

This report presents the findings of analyzing credit card default prediction using artificial neural networks (ANNs). The main findings include the effectiveness of ANNs in predicting credit card defaults, the impact of hyperparameter settings on model performance, and insights into credit risk management practices.

1 Introduction

The aim of this report is to investigate the application of artificial neural networks (ANNs) in predicting credit card defaults. The problem involves developing a predictive model that accurately identifies individuals at risk of defaulting on their credit card payments. Previous research has shown the potential of deep learning approaches, including ANNs, in credit risk prediction due to their ability to capture complex patterns in data. Ma and Lv (2019) conducted a comprehensive study to compare the performance of the XGBoost algorithm with logistic regression for identifying bad customers who do not pay money back from good customers. Their results show that the XGBoost algorithm outperformed logistic regression significantly [1].

The report begins with an overview of the problem, highlighting the importance of credit risk management in the financial industry. We discuss the suitability of different deep learning approaches for credit card default prediction and provide a brief review of related work in the field. The achievements of this report include the development of a predictive model using ANNs and the analysis of its performance.

The report is organized as follows: Section 2 describes the proposed methodology, including the pre-processing phase. Section 3 presents the experimental results, detailing the hyperparameter settings, evaluation process, and obtained results. Section 4 summarizes the main findings of the report and discusses their implications for credit risk management practices.

2 Proposed Method

In this section, we outline the methodology employed to predict credit card defaults using an Artificial Neural Network (ANN). The process involves several steps, including data preprocessing, model architecture design, compilation, training, and evaluation.

2.1 Data Preprocessing

Firstly, we load the dataset from an Excel file (`CCD.xls`), where the header is specified as the second row. The initial row, which contains column names, is dropped to ensure consistency in data handling. The dataset is then split into features (`X`) and the target variable (`y`).

Subsequently, the dataset is divided into training and testing sets using the `train_test_split` function from `sklearn.model_selection`. This division ensures that the model is trained on one subset of the data and evaluated on another, thus providing an unbiased estimate of its performance.

Furthermore, feature scaling is applied to standardize the range of the input features. This is achieved using the `StandardScaler` from `sklearn.preprocessing`, which transforms the data to have a mean of 0 and a standard deviation of 1.

2.2 Model Architecture

The ANN model is constructed using the `Sequential` class from `keras.models`, allowing for the sequential stacking of layers. The model comprises an input layer, two hidden layers, and an output layer. Each hidden layer consists of six neurons and utilizes the ReLU activation function [2], which introduces non-linearity to the model and enables it to capture complex patterns in the data. The output layer, which contains a single neuron, employs the sigmoid activation function [2] to produce binary predictions (0 or 1) representing the likelihood of credit card default.

2.3 Compilation and Training

Before training the model, it needs to be compiled using the `compile` method. Here, we specify the optimizer, loss function, and evaluation metric. We utilize Stochastic Gradient Descent (`SGD`) as the optimizer and binary cross-entropy as the loss function, which is well-suited for binary classification tasks. The model is trained using the `fit` method, with a batch size of 10 and 100 epochs. Additionally, we include the validation data to monitor the model's performance on unseen data during training.

2.4 Evaluation

Upon completion of training, the model is evaluated using the test set to assess its performance. We compute the accuracy score and construct a confusion matrix to analyze the model's predictive capabilities. The accuracy score represents the proportion of correctly classified instances, while the confusion matrix provides insight into the model's performance across different classes (default or non-default).

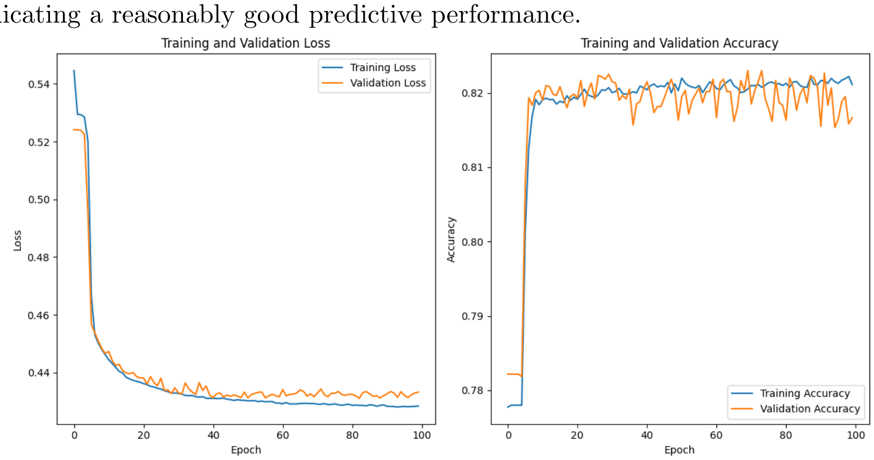
Overall, the proposed methodology aims to leverage the power of Artificial Neural Networks to accurately predict credit card defaults, thereby assisting financial institutions in managing credit risk effectively.

3 Experimental Results

In this section, we present the experimental results obtained from training and evaluating the proposed Artificial Neural Network (ANN) model for predicting credit card defaults.

3.1 Model Performance

The trained ANN model achieved an accuracy of approximately 81.67%. This metric represents the proportion of correctly classified instances in the test set, indicating a reasonably good predictive performance.



3.2 Confusion Matrix

The confusion matrix provides a detailed breakdown of the model's predictions compared to the actual labels. For the credit card default prediction task, the confusion matrix is as follows:

$$\begin{bmatrix} 4372 & 321 \\ 779 & 528 \end{bmatrix}$$

Here, the rows represent the actual classes (non-default and default), while the columns represent the predicted classes. [3] The values in the matrix denote the number of instances classified accordingly.

The confusion matrix reveals that the model correctly predicted 4372 instances of non-defaults and 528 instances of defaults. However, it misclassified 321 non-default instances as defaults and 779 default instances as non-defaults.

3.3 Discussion

The obtained results demonstrate that the ANN model can effectively classify credit card defaults with reasonable accuracy. However, further analysis and optimization may be required to reduce misclassifications, particularly false negatives and false positives, which are critical in financial risk assessment.

Overall, the experimental results suggest that the ANN model shows promise as a tool for credit risk prediction, but continued refinement and evaluation are necessary to enhance its performance and reliability in real-world scenarios.

4 Summary

In this report, we presented an investigation into the use of an Artificial Neural Network (ANN) for predicting credit card defaults. The aim was to develop a predictive model capable of accurately classifying credit card users as either default or non-default, based on various features such as demographic information and payment history.

The proposed method involved preprocessing the dataset, splitting it into training and testing sets, and scaling the features using standardization. We then constructed an ANN architecture consisting of input, hidden, and output layers. The model was trained using the Stochastic Gradient Descent (SGD) optimizer and binary cross-entropy loss function.

Experimental results revealed that the trained ANN model achieved an accuracy of approximately 81.67% on the test set. The confusion matrix provided insights into the model's performance, highlighting the number of correct and incorrect classifications for default and non-default instances.

Despite its relatively good performance, the model exhibited misclassifications, particularly in distinguishing between non-default and default instances. Further analysis and optimization may be necessary to enhance the model's accuracy and reliability, particularly in the context of financial risk assessment.

In summary, the experimental findings suggest that the ANN model holds promise as a tool for credit risk prediction. However, ongoing refinement and evaluation are essential to improve its performance and ensure its suitability for real-world applications.

References

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