# CREDIT CARD DEFAULT PREDICTION


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## Abstract

Aiming at the problem that the credit card default data of a financial institution is unbalanced, which leads to unsatisfactory prediction results, this paper proposes a prediction model based on *k*-means SMOTE and BP neural network. In this model, *k*-means SMOTE algorithm is used to change the data distribution, and then the importance of data features is calculated by using random forest, and then it is substituted into the initial weights of BP neural network for prediction. The model effectively solves the problem of sample data imbalance. At the same time, this paper constructs five common machine learning models, KNN, logistics, SVM, random forest, and tree, and compares the classification performance of these six prediction models. The experimental results show that the proposed algorithm can greatly improve the prediction performance of the model, making its AUC value from 0.765 to 0.929. Moreover, when the importance of features is taken as the initial weight of BP neural network, the accuracy of model prediction is also slightly improved. In addition, compared with the other five prediction models, the comprehensive prediction effect of BP neural network is better.


## 1. Problem Statement

Can we reliably predict who has is likely to default? If so, the bank may be able to prevent the loss by providing the customer with alternative options (such as forbearance or debt consolidation, etc.). We will use various machine learning classification techniques to perform my analysis.

## 2. Data

Source, classic dataset from UC Irvine's machine learning repository: [https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients](https://archive.ics.uci.edu/ml/datasets/default+of+credit+card+clients)
Target: Did the customer default? (Yes=1/Positive, No=0/Negative)
Features:

1. Credit Limit: Amount of the given credit (in dollars): it includes both the individual consumer credit and his/her family (supplementary) credit

2. Sex (1=male; 2=female)

3. Education (1=graduate school; 2=university; 3=high school; 4=other)

4. Marital Status (1=married; 2=single; 3=others)

5. Age (years)

6. History of past payment: The measurement scale for the repayment status is: -1 = pay duly; 1 = payment delay for one month; 2 = payment delay for two months; . . .; 8 = payment delay for eight months; 9 = payment delay for nine months and above

7. Amount of bill statement (dollars) for past 6 months

8. Amount of previous payment for the past 6 months

# 3. Introduction

Recently, the state vigorously promotes the economic construction of large- and medium-sized cities, which not only improves people's living standards but also changes people's consumption concept and consumption mode. People are more and more inclined to spend ahead of time and mortgage their "credit" to the bank to enjoy certain things in advance. However, when consuming, people often lack rational thinking and overestimate their ability to repay loans to banks in time. On the one hand, it increases the loan risk of banks; on the other hand, it increases the credit crisis of consumers themselves [1]. With a large number of banks selling credit cards, the phenomenon of credit card default emerges one after another. It is very important for banks to effectively identify high-risk credit card default users. Generally speaking, compared with the credit card customers who have not paid their loans overdue, there are fewer overdue repayments [2, 3]. This variable feature of overdue and overdue loan repayment is called "two classifications" in machine learning prediction. In the prediction of "two classifications," a few categories are called positive examples (default), and most categories are called counterexamples (nondefault). However, most of the credit card loan data are unbalanced. We can see that the problem of category imbalance is mainly solved from the following two perspectives: the first perspective is to balance the data by changing the number of samples. This method can also be divided into three aspects. On the one hand, it is to improve the oversampling method. On the other hand, it is based on the principle of undersampling to change the data distribution. On the third hand, it is the method of combining oversampling and undersampling. The second perspective is to improve the classifier algorithm to improve the prediction performance of the model and at the same time use relevant evaluation indicators to evaluate the prediction results. Under normal circumstances, since undersampling will lose information, oversampling is the most widely used technique, and smote is the more common method. However, we have found that most scholars cannot reduce the imbalance between and within the sample categories at the same time when using the improved version of the smooth method, and the applicability of the improved version of the classifier is also limited. Therefore, this paper proposes an improved version of the smooth algorithm with better applicability, which combines the *k*-means algorithm. This method clusters all samples using the *k*-means unsupervised learning algorithm, finds clusters with more samples in the minority class, and then uses the smote method that synthesizes new samples in the cluster to change the data distribution. It can not only reduce the imbalance between the categories but also reduce the imbalance within the categories. At the same time, it combines the BP neural network method to predict the credit card default situation to help the bank to identify credit card risks effectively.applicability of the improved version of the classifier is also limited. Therefore, this paper proposes an improved version of the smooth algorithm with better applicability, which combines the *k*-means algorithm. This method clusters all samples using the *k*-means unsupervised learning algorithm, finds clusters with more samples in the minority class, and then uses the smote method that synthesizes new samples in the cluster to change the data distribution. It can not only reduce the imbalance between the categories but also reduce the imbalance within the categories. At the same time, it combines the BP neural network method to predict the credit card default situation to help the bank to identify credit card risks effectively.

## 4. Basic Theory

- **PCA**

The main idea of the principal component analysis (PCA) method is to transform the *n*-dimensional feature variable through the coordinate axis and the origin to form a new *m*-dimensional feature (usually, *m* is less than *n*) [11]. This *m*-dimensional feature is also called principal component. Its essence is to replace a series of related sample features with newly generated comprehensive features that are irrelevant to each other. When analyzing the data, you can set the cumulative variance ratio determination factor in advance.

- **Feature Importance Calculation of Random Forest**

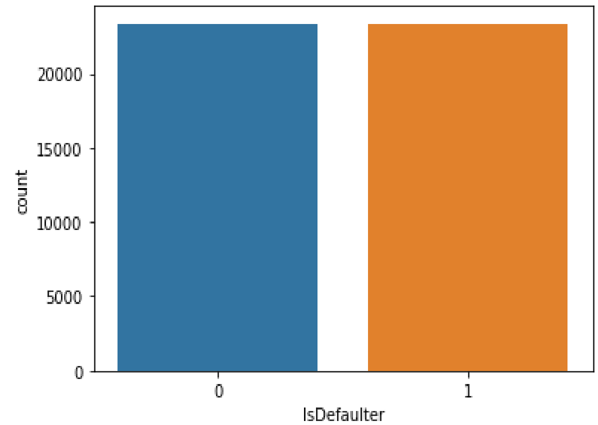
Random forest is a relatively basic machine learning algorithm, which is widely used in predictive analysis [12], data labeling [13], tag ranking [14], feature importance calculation [15], and other fields. The principle of the algorithm is as follows: using bootstrap method to randomly construct *n* decision trees, each decision tree is split and pruned and finally combined to form a random forest. In this paper, random forest is used to calculate feature importance, which is used as the initial weight of BP neural network.

- **BP Neural Network**

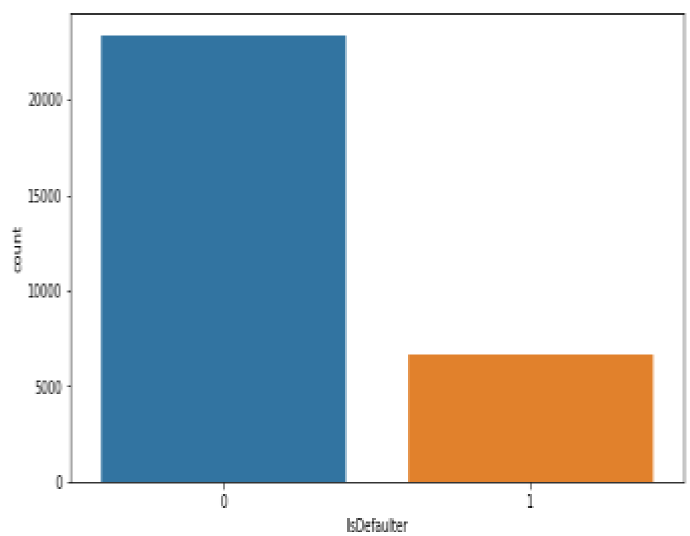
The prediction model used in this paper is the BP neural network algorithm, which is a feed-forward neural network for error backward update. It is often used for bank risk analysis [16], geological disaster monitoring [17], image and handwritten digit recognition [18, 19], and other fields. BP neural network consists of three parts: input layer, middle layer, and output layer. In the model, data samples enter the input layer through a weighted combination of different weights, then pass through the middle layer, and finally get the result from the output layer. Different weights and activation functions make the output of the model very different.

## 5. K-means SMOTE Algorithm

We know that smote is a method for synthesizing new samples and solving data imbalance proposed by Chawla et al. [20] and is widely used in various fields. Smote is an improved method of random oversampling technology. It is not a simple random




sampling, repeating the original sample, but a new artificial sample generated by a formula. But the smote algorithm will also increase the imbalance between the positive and negative classes of the sample to a certain extent. Therefore, according to the problem of imbalance of credit card sample categories, this paper uses




an improved smote algorithm called *k*-means SMOTE algorithm.

This algorithm can reduce the

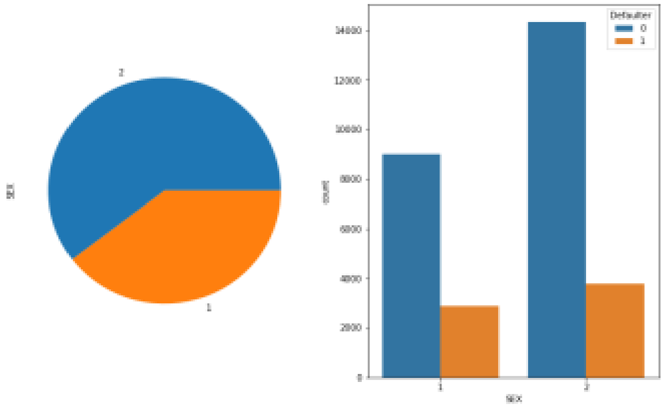
imbalance between categories on the one hand and reduce the imbalance within categories on the other hand. In this experiment, we first cluster all samples (30,000), then use *k*-means method to filter clusters with more minority categories, select clusters with more minority categories after filtering, and finally perform smote oversampling in the filtered clusters.

# 6. Experimental Data and Preliminary Analysis

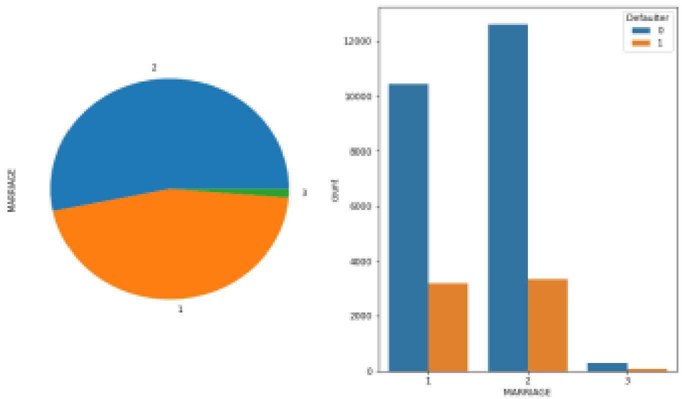
- **Preliminary Analysis of Data**

Credit Limit by Sex. The data is evenly distributed amongst males and females.

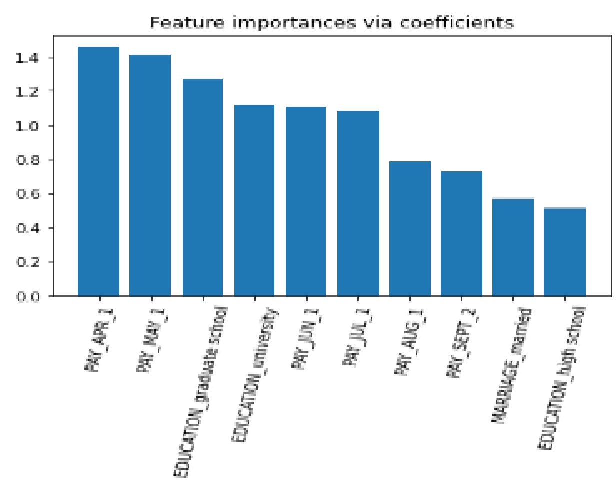
Distribution of target classes is highly imbalanced, non-defaults far outnumber defaults. This is common in these datasets since most people pay credit cards on time (assuming there isn't an economic crisis).



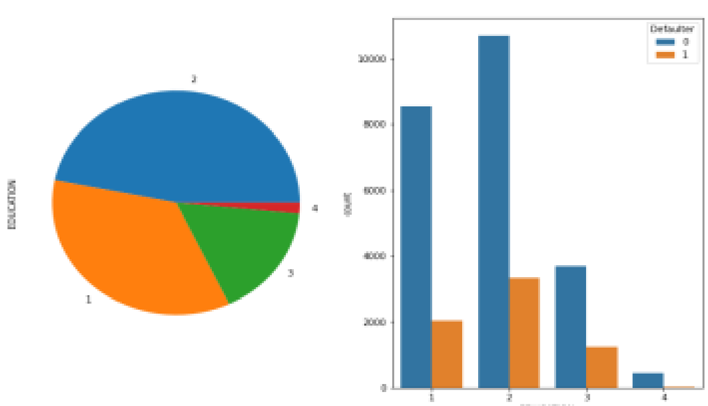

Marriage, age, and sex. The dataset mostly contains couples in their mid-30s to mid-40s and single people in their mid-20s to early-30s




## 7. Model Prediction and Comparative Analysis.




Credit Limit by Education. The data is evenly distributed amongst males and females.



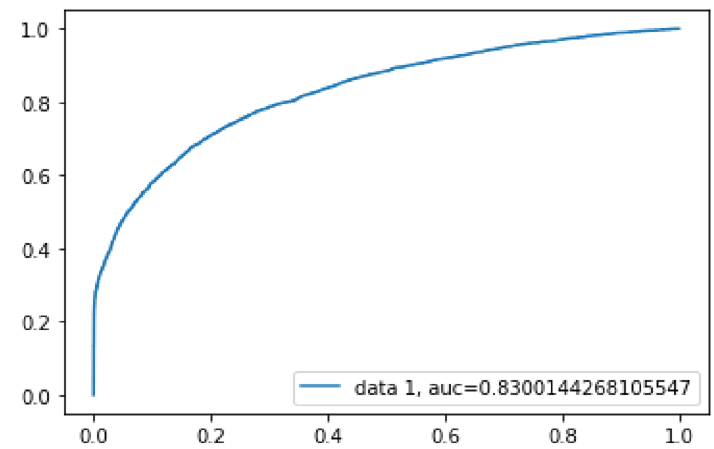
- **Model Evaluation Method**

According to the actual situation, for unbalanced data, we should use the evaluation index of unbalanced data [21], but because at the beginning of the experiment, we have balanced the number of positive and negative classes in the sample. And we are still using the two-class evaluation indicators commonly used in the past: hybrid matrix, recall, precision, f1-score, AUC value, and so on.

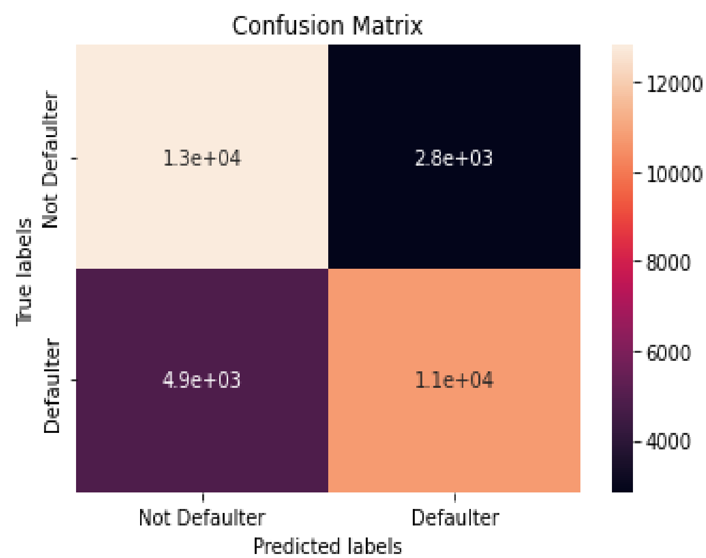
## 8. Implementing Logistic Regression

Logistic Regression is one of the simplest algorithms which estimates the relationship between one dependent binary variable and independent variables, computing the probability of occurrence of an event. The regulation parameter C controls the trade-off between increasing complexity (overfitting) and keeping the model simple (underfitting). For large values of C, the power of regulation is reduced and the model increases its complexity, thus overfitting the data.

We have implemented logistic regression and we getting f1-sore




approx. 73%. As we have imbalanced dataset, F1- score is better parameter. Let's go ahead with other models and see if they can yield better result.




## 9. DECISION TREE:

Decision tree is the most powerful and popular tool for classification and prediction. A Decision tree is a flowchart like tree structure, where each internal node denotes a test on an attribute, each branch represents an outcome of the test, and each leaf node (terminal node) holds a class label.

## 10. RANDOM FOREST:

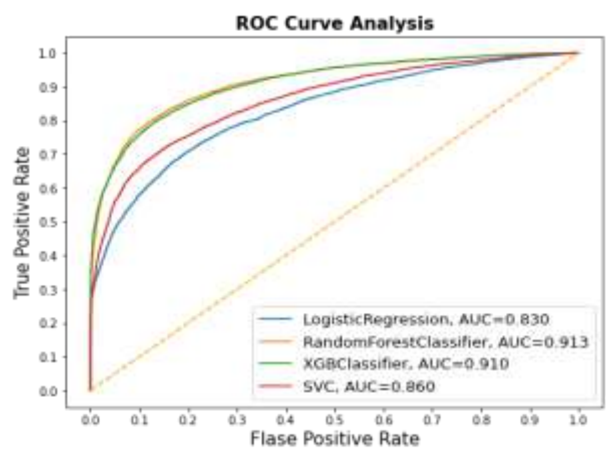
Random Forest is a bagging type of Decision Tree Algorithm that creates a number of decision trees from a randomly selected subset of the training set, collects the labels from these subsets and then averages the final prediction depending on the greatest number of times a label has been predicted out of all.

## 11. GRADIENT BOOSTING:

The term gradient boosting consists of two sub-terms, gradient and boosting. We already know that gradient boosting is a boosting technique. Let us see how the term ‘gradient’ is related here. Gradient boosting re-defines boosting as a numerical optimization problem where the objective is to minimize the loss function of the model by adding weak learners using gradient descent. Gradient descent is a first-order iterative optimization algorithm for finding a local minimum of a differentiable function. As gradient boosting is based on minimizing a loss function, different types of loss functions can be used resulting in a flexible technique that can be applied to regression, multi-class classification, etc.

## 12. ROC Curve

The area under the ROC curve tells us how well the model separates the different classes in the dataset. It plots true positive rate against false positive rate




## 13. Conclusion

In the method used in this study, features related to transaction flow had the highest importance weight, showing that the transaction flow data could effectively predict credit card default. Second, in the process of XGBoost modeling, the accuracy of default prediction mainly depended on feature extraction. It takes a lot of time to understand the specific meaning of each transaction type, but only when there is a deep understanding of the credit card business background can transaction types be correctly classified and useful features extracted. Third, when applying LSTM to process transaction flow data, it was only necessary to complement and splice the data, without any feature extraction work, which again confirms that the advantage of deep learning is that it does not require manual feature extraction. Finally, the XGBoost-LSTM fusion model combined basic, billing, and installment information, as well as PBOC branch and transaction flow, and it obtained extremely good test accuracy. This study shows that LSTM is an effective method for dealing with credit card transaction flow data.Data categorical variables had minority classes which were added to their closest majority class

## 14. **REFERENCES:**


- https://book.akij.net/eBooks/2018/May/5aef50939a868/Data Science_for_Bus.pdf
- Hands-On Exploratory Data Analysis with Python Perform EDA techniques to understand, summarize, and investigate your data by Suresh Kumar Mukhiya, Usman Ahmed (z-lib.org)
- https://bunker2.zlibcdn.com/dtokend/01c5fc197a94283bfb0c0943bd5b2d0c
- .S. Fan, Y. Shen, and S. Peng, "Improved ML-based technique for credit card scoring in internet financial risk control," *Complexity*, vol. 2020, Article ID 8706285, 14 pages, 2020.View at: Publisher Site | Google Scholar