Credit Card Default Prediction

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Abstract: This project presents and discusses data-driven predictive models for predicting the defaulters among the credit card users. Data used include details like limit balance, age, sex, amount of bill statement, repayment status and amount of previous payment. The paper discusses which variables are the strongest predictors of default, and to make predictions on which customers are likely to default.

1. Problem Statement

This project is aimed at predicting the case of customers default payments in Taiwan. From the perspective of risk management, the result of predictive accuracy of the estimated probability of default will be more valuable than the binary result of classification - credible or not credible clients. We can use the K-S chart to evaluate which customers will default on their credit card payments.

• X1: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.

• X2: Gender (1 = male; 2 = female).

• X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).

• X4: Marital status (1 = married; 2 = single; 3 = others).

• X5: Age (year).

• X6 - X11: History of past payment. We tracked the past monthly payment records (from April to September, 2005) as follows: X6 = the repayment status in September, 2005; X7 = the repayment status in August, 2005; . .

• X 11= the repayment status in April, 2005. 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.

• X12-X17: Amount of bill statement (NT dollar). X12 = amount of bill statement in September, 2005; X13 = amount of bill statement in August, 2005; . . .; X17 = amount of bill statement in April, 2005.

• X18-X23: Amount of previous payment (NT dollar). X18 = amount paid in September, 2005; X19 = amount paid in August, 2005; . . .;X23 = amount paid in April, 2005.

2. Introduction

Credit risk has traditionally been the greatest risk among all the risks that the banking and credit card industry are facing, and it is usually the one requiring the most capital. This can be proven by industry business reports and statistical data. Despite machine learning and big data have been adopted by the banking industry, the current applications are mainly focused on credit score predicting.

The disadvantage of heavily relying on credit score is banks would miss valuable customers who come from countries that are traditionally underbanked with no credit history or new immigrants who have repaying power but lack credit history. The purpose of this project is to conduct quantitative analysis on credit card default risk by using interpretable machine learning models with accessible customer data, instead of credit score or credit history, with the goal of assisting and speeding up the human decision making process.

3. Exploratory Data Analysis

Data Preparation: This is the stage of the project where one decides on the data that one will use for analysis. The criteria used to make this decision includes the relevance of the data to the data mining goals, the quality of the data, and technical constraints such as limits on data volume or data types. For data preparation, number of outliers were checked and observed to have more number of outliers in some features.

- **Null values Treatment**
  Our dataset contains a large number of null values which might tend to disturb our accuracy hence we dropped them at the beginning of our project inorder to get a better result.

- **Encoding of categorical columns**
  We used One Hot Encoding to produce binary integers of 0 and 1 to encode our categorical features because categorical features that are in string format cannot be understood by the machine and needs to be converted to numerical format.

4. Variable involved :

LIMIT_BAL

LIMIT_BAL states the amount of given credit. This is the maximum amount a customer can spend with their credit card in a single month. The amount of balance limit is dependent on the bank's own screening processes and other unknown factors

AGE
This is the age of the customer which is stated in years. The mean and median of the age are 35 and 34 respectively. This is numerical column. There are no missing values in this column. There are some outliers in AGE column. The decline in number of customers starts from about 30 years among the non-defaulting group, while the number of customers of different ages stays much more constant from 25 to around 40 years. This indicates that likelihood of default among men grows with age. In box plot we can see many outliers which are considered here as extreme values.

SEX
This variable can obtain a value of 1 for male and 2 for female. In this study, sex and gender are used interchangeably to intend the same thing.

EDUCATION
The education level of a customer is represented as one of four values: 1 = Graduate school, 2 = University, 3 = High school, 4 = Other. For the purpose of analysing customer groups, this is assumed to indicate the highest level of education completed.

Bill_AMT
Amount of bill statement is recorded in this variable. It is represented in the data as 6 columns, one for each month. Data collected from 6 months, April to September.

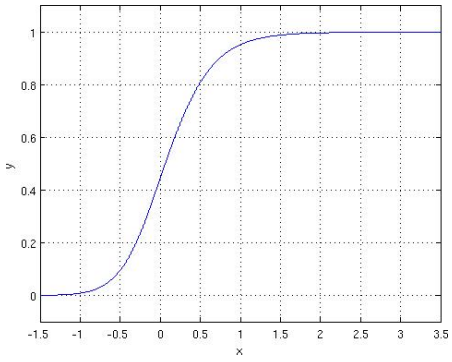
5. Fitting different models

For modelling we tried various classification algorithms like:

1. **Logistic Regression**
2. **Random Forest Classifier**
3. **XGBoost classifier**

5.1. Algorithms:

1. **Logistic Regression:**
   Logistic Regression is actually a classification algorithm that was given the name regression due to the fact that the mathematical formulation is very similar to linear regression.
   The function used in Logistic Regression is sigmoid function or the logistic function given by:
   f(x)= 1/1+e ^(-x)



The optimization algorithm used is: Maximum Log Likelihood. We mostly take log likelihood in Logistic:

$$\ln L(\mathbf{y},\beta)=\ln\prod_{i=1}^{n}f_i(y_i)=\sum_{i=1}^{n}\left[y_i\ln\left(\frac{\pi_i}{1-\pi_i}\right)\right]+\sum_{i=1}^{n}\ln(1-\pi_i)$$

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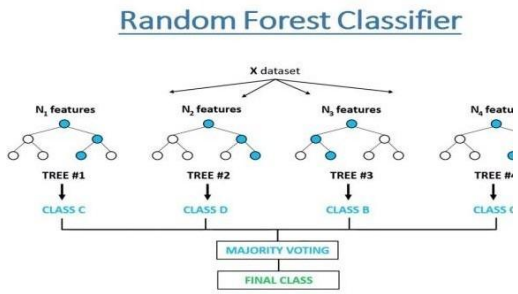
2. **Random Forest Classifier:**
   Random Forest is a bagging type of Decision Tree Algorithm that

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 most number of times a label has been predicted out of all.

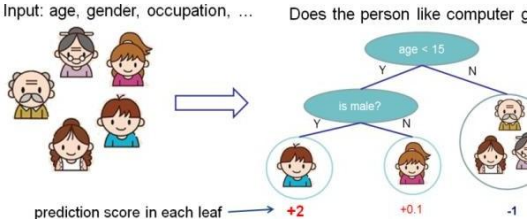


3. **XGBoost-**

To understand XGBoost we have to know gradient boosting beforehand.

- **Gradient Boosting-**

  Gradient boosted trees consider the special case where the simple model is a decision tree



In this case, there are going to be 2 kinds of parameters P: the weights at each leaf, w, and the number of leaves T in each tree (so that in the above example, T=3 and w=[2, 0.1, -1]).

When building a decision tree, a challenge is to decide how to split a current leaf. For instance, in the above image, how could I add another layer to the (age > 15) leaf? A 'greedy' way to do this is to consider every possible split on the remaining features (so, gender and occupation), and calculate the new loss for each split; you could then pick the tree which most reduces your loss.

XGBoost is one of the fastest implementations of gradient boosting. trees. It does this by tackling one of the major inefficiencies of gradient boosted trees: considering the potential loss for all possible splits to create a new branch (especially if you consider the case where there are thousands of features, and therefore thousands of possible splits). XGBoost tackles this inefficiency by looking at the distribution of features across all data points in a leaf and using this

information to reduce the search space of possible feature splits.

5.2. Model performance:

Model can be evaluated by various metrics such as:

1. **Confusion Matrix**-

The confusion matrix is a table that summarizes how successful the classification modelis at predicting examples belonging to various classes. One axis of the confusion matrix is the label that the model predicted, and the other axis is the actual label.

2. **Precision/Recall**-

Precision is the ratio of correct positive predictions to the overall number of positive predictions : TP/TP+FP

Recall is the ratio of correct positive predictions to the overall number of positive examples in the set: TP/FN+TP

3. **Accuracy**-

Accuracy is given by the number of correctly classified examples divided by the total number of classified examples. In terms of the confusion matrix, it is given by: TP+TN/TP+TN+FP+FN

4. **Area under ROC Curve(AUC)**-

ROC curves use a combination of the true positive rate (the proportion of positive examples predicted correctly, defined exactly as recall) and false positive rate (the proportion of negative examples predicted incorrectly) to build up a summary picture of the classification performance.

5.3. Hyper parameter tuning:

Hyperparameters are sets of information that are used to control the way of learning an algorithm. Their definitions impact parameters of the models, seen as a way of learning, change from the new hyperparameters. This set of values affects performance, stability and interpretation of a model. Each algorithm requires a specific hyperparameters grid that can be adjusted according to the business problem. Hyperparameters alter the way a model learns to trigger this training algorithm after parameters to generate outputs.

We used Grid Search CV, Randomized Search CV and Bayesian Optimization for hyperparameter tuning. This also results in cross validation and in our case we divided the dataset into different folds. The best performance improvement among the three was by Bayesian Optimization.

1. **Grid Search CV-**Grid Search combines a selection of hyperparameters established by the scientist and runs through all of them to evaluate the model's performance. Its advantage is that it is a simple technique that will go through all the programmed combinations. The biggest disadvantage is that it traverses a specific region of the parameter space and cannot understand which movement or which region of the space is important to optimize the model.

2. **Randomized Search CV-** In Random Search, the hyperparameters are chosen at random within a range of values that it can assume. The advantage of this method is that there is a greater chance of finding regions of the cost minimization space with more suitable hyperparameters, since the choice for each iteration is random. The disadvantage of this method is that the combination of hyperparameters is beyond the scientist's control

3. Model Analysis

Modelling: As the first step in modelling, one selects the actual modelling technique that one will be using. Although one may have already selected a tool during the business understanding phase, at this stage one may be selecting some specific modelling technique. If multiple techniques can also be applied. After treating the data, we performed various models on our data such as logistic regression, XG boost, svc, Random forest etc. Hyper parameter tuning was also performed.
This analysis uses 3 classification models - Logistic Regression, Random Forest and XG Boost.

Since Random Forest and XG Boost are tree based on algorithms, rescaling is only performed on Logistic Regression, not on these 2 models. For each model, we first try the model's default parameters, train each model without SMOTE and with SMOTE samplings. Then tune each model's hyper parameters to find the optimal performance. As mentioned earlier, this dataset has imbalanced classes, therefore we use precision and recall, instead of accuracy as the
performance metrics.

SMOTE Oversampling: In the initial model fitting, we start by using all models' default parameters. To compensate for the rare classes in the imbalance dataset, we use SMOTE(Synthetic Minority Over-Sampling Technique) method to over sample the minority class and ensure the sampling is not biased. What this technique does under the hood is simply duplicating examples from the minority class in the training dataset prior to fitting a mode. After SMOTE sampling, the dataset has equal size of 0s and 1s.

In order to verify if SMOTE improves models' performance, all 3 models are trained with SMOTE and without SMOTE. Below table shows the ROC_ AUC scores on training data improved significantly with all models after over sampling with SMOTE. This proves SMOTE is an effective method in sampling imbalanced dataset.

Compare within the 3 models . Logistic Regression has the highest recall but also the lowest precision. Random Forest outperforms Logistic Regression and XG Boost if measured on their F1 scores, which is the balance between precision and recall. XG Boost has a decent performance but it takes the most time to tune the model.

Conclusions

Based on the exploratory data analysis, we discover that human characteristics are not the most important predictors of default, the payment status of the most 2 months and credit limit

From the modeling, we are able to classify default risk with accessible customer data and find a decent model. Using a Logistic Regression classifier, we can predict with 73% accuracy, whether a customer is likely to default next month. Using a Random Forest classifier, we can predict with 92% accuracy, whether a customer is likely to default next month. Using a XG BOOST classifier, we can predict with 88% accuracy, whether a customer is likely to default next month.

If the balance of recall and precision is the most important metric, then Random Forest is the ideal model.

References-

1. Machine Learning Mastery
2. Geeks for Geeks
3. Analytics Vidhya