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Report on practical training on the topic: “Combining Machine Learning with Data-balancing methods for credit scoring”

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Introduction

Forecasting the abilities of customers to fulfill their financial obligations is a critical issue in banking activities. To address this problem, financial services companies try to assess the probability of defaulting through credit scoring process, aimed at classifying the applicants into categories corresponding to good and bad credit quality, according to their capability to meet financial obligations.

Credit scoring is defined as statistical model aimed to determine the creditworthiness of customers, I.e. to estimate the probability of defaulting [1].

Since costumers with bad creditworthiness have high probability of defaulting, the accuracy of credit scoring system is critical to financial institutions profitability such that even a one percent improvement in the accuracy of credit scoring of "bad" customers may significantly decrease the losses of a financial institutions[2] .Also From the economic point of view, inaccurate estimates of creditworthiness in the banking sector were one of the key determinant of the two worst economic crises of modern times (i.e., the Great Depression of 1929 and the Great Recession of 2008) [3][4]. The latter in particular was triggered by the so-called subprime mortgage crisis, where underestimation of default probabilities and easy credit conditions had catastrophic economic consequences.

In general, there are two approaches to design automatic credit scoring systems; I.e., statistical techniques and AI techniques [5]. Several statistical techniques are applied to design automatic credit scoring systems, However, a common weakness of most statistical approaches is that some assumptions must be made, such as assuming specific data distributions [6]. On the other hand, many studies have shown that AI methods such as artificial neural networks are effective tools for credit scoring and unlike statistical approaches, AI techniques can be used to design credit scoring systems without assuming specific data distributions [7].

Additional issues when dealing with credit scoring systems are "dimensionality" and "imbalanced dataset". To address dimensionality often feature selection techniques are used, which aimed to extract the most relevant features from the feature space, resulted in overfitting decrease and accuracy improvement as well as reducing training costs. And to address the problem of imbalanced dataset, various sample-modifying techniques are used, which usually help prevent the model from becoming biased towards more representative classes.

Since there is no best overall AI technique, and it depends on the details of problem [8], this report attempts to answer following question:

> Which combinations of ML models, feature selection and sample-modifying techniques are the most effective for credit scoring system?

Methods

ML models

Random forest

The random forest classifier consists of a combination of tree classifiers where each classifier is generated using a random vector sampled independently from the input vector, and each tree casts a unit vote for the most popular class to classify an input vector [9]. The random forest classifier consists of randomly selected features or a combination of features at each node to grow a tree. Bagging, a method to generate a training data set by randomly drawing with replacement *N* examples, where *N* is the size of the original training set [10], was used for each feature combination selection. Examples are classified by taking the most popular voted class from all the tree predictors in the forest [11] . There are many approaches to the selection of attributes used for decision tree induction and most approaches assign a quality measure directly to the attribute. The most frequently used attribute selection measures in decision tree induction are Information Gain Ratio criterion and Gini Index [12] . The random forest classifier uses the Gini Index as an attribute selection measure, which measures the impurity of an attribute with respect to the classes. For a given training set T, selecting one case at random and saying that it belongs to some class C_i, the Gini index can be written as:

$$\sum \sum_{j \neq i} \frac{(f(C_i,T)}{|T|} \frac{(f(C_j,T)}{|T|}$$

where $\frac{f\,(C_i,T)}{|T|}$ is the probability that the selected case belongs to class C_i.

Neural Network

Neural networks take as input features $x_1, \ldots, x_d$ and construct a nonlinear function $f(x)$ aimed at predicting the dependent variable y. The peculiarity of the method is the procedure followed to obtain $f(x)$. The most common type of neural network consists of three layers of units: the input, hidden, and output layers. Such a structure is usually called a multilayer perceptron. A layer of "input" units is fed to a layer of "hidden" units, which is finally connected to a layer of "output" units [13] .

Gradient boosted tree

Gradient boosting is typically used with decision trees of a fixed size as base learners. For this special case, a modification is proposed to gradient boosting method which improves the quality of fit of each base learner.

Generic gradient boosting at the $m - th$ step would fit a decision tree $h\_m(x)$ to pseudo-residuals. Let J_m be the number of its leaves. The tree partitions the input space into J_m disjoint

regions $R_{1m}, \ldots, R_{J_m m}$ and predicts a constant value in each region. Using the indicator notation, the output of $h_m(x)$ for input *x* can be written as the sum:

$$h_m(x) = \sum_{j=1}^{J_m} b_{jm} \mathbf{1}_{R_{jm}}(x)$$

Where b_{jm} is the value predicted in the region R_{jm} .

Then the coefficients b_{jm} are multiplied by some value γ_m , chosen using line search so as to minimize the loss function, and the model is updated as follows:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x), \quad \gamma_m = arg\,min_\gamma \sum_{i=1}^{n} L\big(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)\big)$$

A modification is proposed to modify this algorithm so that it chooses a separate optimal value γ_{jm} for each of the tree's regions, instead of a single γ_m for the whole tree. This modified algorithm is called Tree Boost. The coefficients b_{jm} from the tree-fitting procedure can be then simply discarded and the model update rule becomes [14] [15] :

$$F_m(x) = F_{m-1}(x) + \sum_{j=1}^{J_m} \gamma_{jm} b_{jm} \mathbf{1}_{\boldsymbol{R_{jm}}}(x), \quad \gamma_{jm} = arg\,min_\gamma \sum_{x_i \in R_{jm}} L(y_i, F_{m-1}(x_i) + \gamma)$$

Logistic regression

the basic setup of logistic regression is as follows: A dataset is given containing *N* points. Each point i consists of a set of *m* input variables $x_{1,i}$,..., $x_{m,i}$ (also called independent variables), and a binary outcome variable y_i (also known as a dependent variable), i.e. it can assume only the two possible values 0 (often meaning "no" or "failure") or 1 (often meaning "yes" or "success"). The goal of logistic regression is to use the dataset to create a predictive model of the outcome variable.

As in linear regression, the outcome variables y_i are assumed to depend on the explanatory variables $x_{1,i}$,..., $x_{m,i}$ [16] .

Feature selection techniques

L1 based feature selection with support vector machine

In this study support vector machines are used with linear kernels. The prediction obtained had the general form $pred(x) = sign(b + \sum_{i=1}^{d} \alpha i K(x, xi))$. If the kernel was linear (i.e., $K(x, v) = x^T v$), then the prediction became $sign(b + wTx)$ for $w = (w1, \ldots, wd)^T$ $=(\alpha_1 x_1, \ldots, \alpha_d x_d)^T$, where w is a vector of weights that can be computed explicitly. This

technique classifies a new observation (y^*, x^*) by testing whether the linear combination $w_1 x_1^* + \cdots + w_d x_d^*$ of the components of x^* is larger or smaller than a given threshold b [17] . Hence, in this approach, the jth feature is more likely to be important if its weight w_j is above the threshold. This type of feature weighting has some intuitive interpretation, because a predictor with a small $|w_j|$ value has a minor impact on the predictions and can be ignored [18] .

Random forest recursive feature elimination

Recursive feature elimination (RFE) is a greedy algorithm based on feature-ranking techniques. The algorithm measures the classifier performance by eliminating predictors in an iterative manner. In a first step, RFE trains the classifier with all d features, and then it calculates the importance of each feature via the Information Gain method or the mean reduction in the Gini index [19] [20] . Subsequently, subsets of progressively smaller sizes $m = d, d - 1, \ldots, 1$ are created by iterative elimination of the features. The model is retrained within each subset, and its performance is calculated. Hence, RFRFE is a feature selection method that combines RFE and random forests [21] .

Sample-modifying techniques

Random oversampling

One of the common approaches to address the problem of imbalanced datasets is to use resampling techniques to make the dataset balanced. Resampling techniques can be applied either by under-sampling or oversampling the dataset. Under-sampling is the process of decreasing the amount of majority target instances or samples. Oversampling can be performed by increasing the amount of minority class instances [22] [23] .

The basic idea consists of resampling the original dataset, either by oversampling the smallest class or under-sampling the largest class until the sizes of the classes are approximately the same. Since under-sampling may discard some important information and consequently worsen the performance of the classifiers, oversampling tends to be preferred [24] .

Random oversampling is one of the simplest methods, as it increases the minority class through randomly repeated copies of the minority class. A possible disadvantage is that if the dataset is large, it may introduce a significant additional computational burden. Moreover, since it yields exact copies of the minority class, it can increase the risk of overfitting [25] .

Synthetic minority oversampling technique (SMOTE)

The synthetic minority oversampling technique (SMOTE) oversamples the minority class by synthetically creating new instances rather than oversampling with replacement, as random oversampling does. The SMOTE forms new minority examples by interpolating between several minority class observations that are close to each other [26] .

More particularly, the minority class is oversampled by taking each minority class sample and introducing synthetic examples along the line segments joining any/all of the k minority class nearest neighbors. Depending upon the amount of over-sampling required, neighbors from the k nearest neighbors are randomly chosen.

Synthetic minority oversampling technique with Tomek links (SMOTETomek)

SMOTETomek performs SMOTE oversampling technique along with Tomek Links under-sampling technique. In Tomek Links technique, the majority class is under-sampled by randomly removing majority class observations until the minority class reaches some specified percentage of the majority class. In more detail, the Tomek Links discard observations from the most represented class that are close to the least represented class in order to obtain a training dataset with a more clear-cut separation between the two classes [27] .

Synthetic minority oversampling technique with one sided selection (SMOTEOSS)

Similar to SMOTETomek, SMOTEOSS performs SMOTE oversampling technique along with One-Sided Selection (OSS) under-sampling technique. OSS technique combines Tomek Links and the Condensed Nearest Neighbor (CNN) Rule [28] . Specifically, Tomek Links are ambiguous points on the class boundary and are identified and removed in the majority class. The CNN method is then used to remove redundant examples from the majority class that are far from the decision boundary [29] .

In more details, first CNN procedure occurs in one-step and involves first adding all minority class examples to the store and some number of majority class examples (e.g., 1), then classifying all remaining majority class examples with K nearest neighbors (*k=1*) and adding those that are misclassified to the store.

Criteria

The performance of the models was evaluated based on the standard measures in the fields of credit scoring. These measures are as follows:

- Area Under the Curve of the Receiver Operating Characteristics (AUC-ROC) [30]
- Accuracy
- Sensitivity
- Specificity

Where these measures are described as follows:

ROC is a probability curve and AUC represents the degree or measure of separability. It shows how much the model is capable of distinguishing between classes.

Consider the following figure (figure 1) known as confusion matrix, we define Accuracy, Sensitivity and Specificity as specified below:

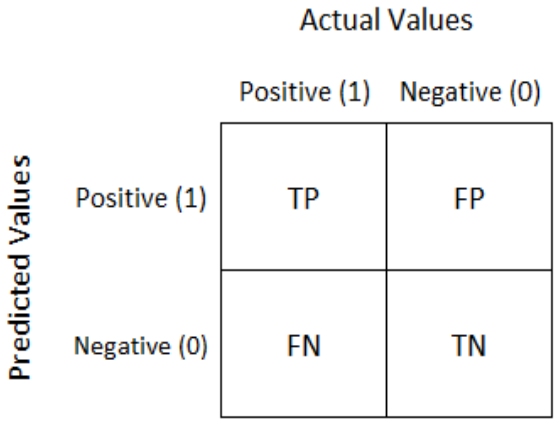


Figure 1, confusion matrix

$$Accuracy = \frac{\sum TP+TN}{\sum TP+FP+FN+TN}$$

$$Sensitivity = \frac{\sum TP}{\sum TP+FN}$$

$$Specificity = \frac{\sum TN}{\sum TN+FP}$$

Data

For this study two data sets are used [31] [32] . Both of them consists of information about customers of financial institutions. In the following table description of the data sets is shown:

Data set	Number of examples	Numbers of features	Imbalance ration
UCI Credit Card	30000	24	3.50
Default	10000	4	29.02

Where imbalance ratio is the ratio of the number of examples in majority class to the number of examples in minority class.

In the analysis “UCI Credit Card” dataset is considered as the main dataset and after conducting the experiment on it, analysis on “Default” dataset is conducted, in order to show the accordance of results of the main dataset. Notice that “Default” dataset is n an extremely imbalanced dataset, therefore analysis on it can show the effect of balancing techniques on the performance.

As the table above is shown the main data set consists of 30000 examples, with 24 features, which consist of financial and non-financial (age, education, gender, …), with one target and imbalance ratio of 3.5.

The main data set is split into testing set and training set, where testing set consist of 30% of the main data set.

Experiments

Methodology

To analyze the data set, first the data set is split into training and testing sets, then considering the testing set, first feature selection method (L1 based feature selection with support vector machine) is used to extract the relevant features, then all data balancing techniques are used respectively (oversampling, SMOTE, SMOTETomek, SMOTEOSS) to balance the testing set. Thereafter classifier algorithms (Random Forest, Neural network, boosted tree, Logistic regression) are trained on them. The classifiers are also trained on imbalanced training set. After all the performance of classifiers trained on different data sets are measured using the criteria (Accuracy, Sensitivity, Specificity, AUC-ROC) and then their performance is compared to find best combination of data balancing techniques and classifier algorithms. Then all the steps are repeated for the second feature selection method (Random Forest feature elimination) and compare the results.

It is worth to mention that a neural network consisting of one hidden layer is used with sigmoid function as activation function for hidden layer and input layer and linear function as activation function for output layer. Also, XGBoost implementation is used for gradient boosted tree.

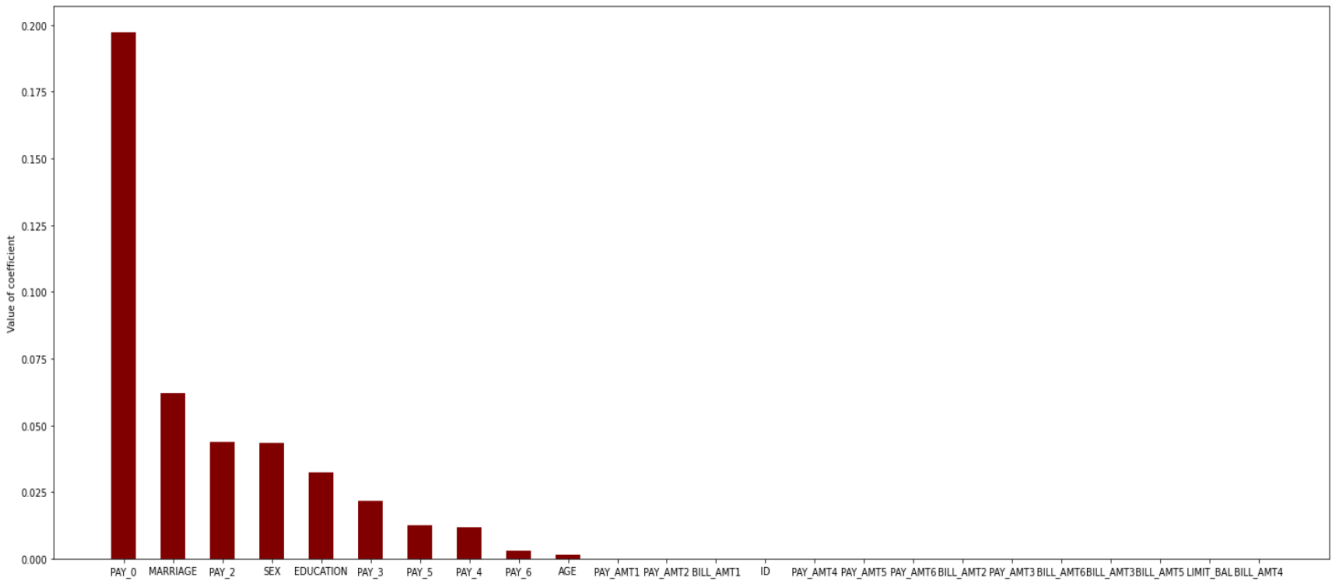
Results

Before considering the result of experiments, first let's overview the features of the main data set[1]:

[1] -The code of the experiment is available in [33] [34]

```
---   ------
 0    ID
 1    LIMIT_BAL
 2    SEX
 3    EDUCATION
 4    MARRIAGE
 5    AGE
 6    PAY_0
 7    PAY_2
 8    PAY_3
 9    PAY_4
 10   PAY_5
 11   PAY_6
 12   BILL_AMT1
 13   BILL_AMT2
 14   BILL_AMT3
 15   BILL_AMT4
 16   BILL_AMT5
 17   BILL_AMT6
 18   PAY_AMT1
 19   PAY_AMT2
 20   PAY_AMT3
 21   PAY_AMT4
 22   PAY_AMT5
 23   PAY_AMT6
```

First the L1 based feature elimination with support vector machine feature selection is run, and 13 numbers of features are eliminated. The following figure shows the features based on their coefficients (or importance):



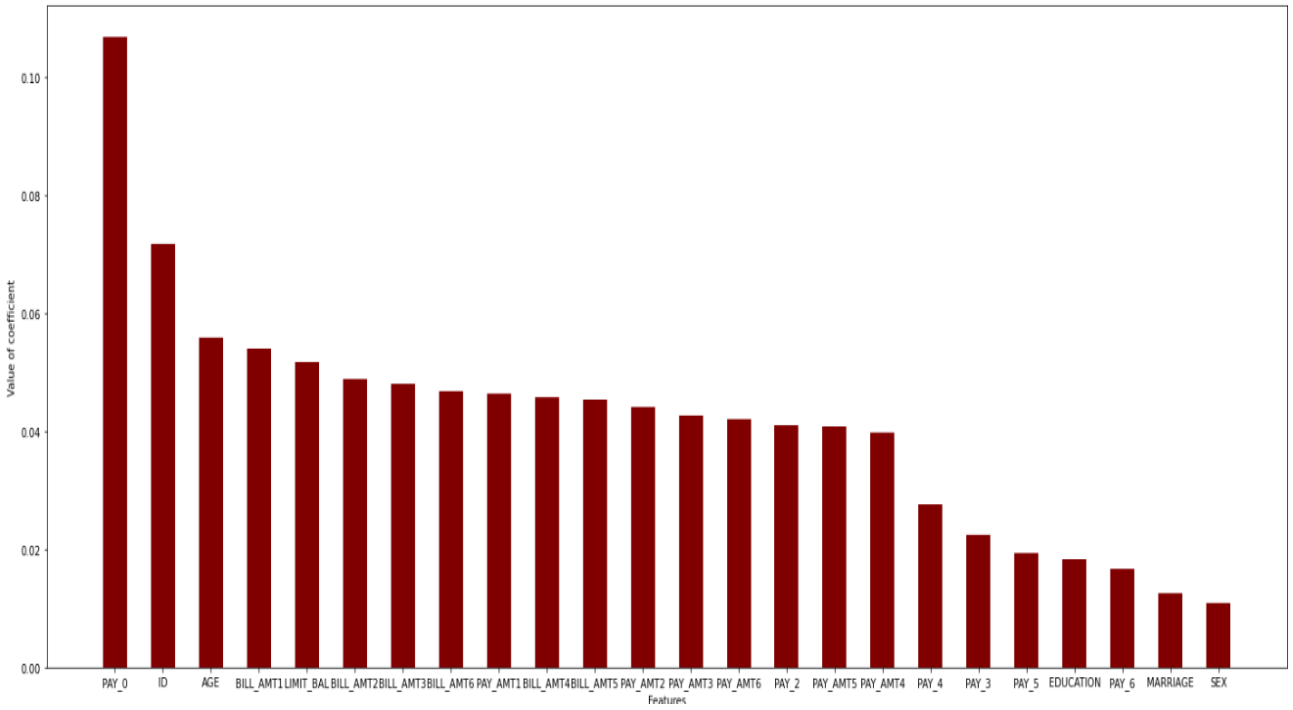
As it is shown above, the feature selection procedure eliminates less important features (features with lower coefficient).

Conducting experiment on the main data set, after performing above-mentioned feature selection technique, the followings results are obtained:

Models	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
RF-imbalanced	0.784	0.509	0.906	0.627
RF-Random-Oversampling	0.730	0.394	0.812	0.691
RF-SMOTE	0.768	0.462	0.879	0.625
RF-SMOTETomek	0.769	0.464	0.881	0.624
RF-SMOTEOss	0.769	0.463	0.881	0.624
NN-imbalanced	**0.816**	0.380	0.939	0.747
NN-Random-Oversampling	0.763	0.592	0.811	**0.749**
NN-SMOTE	0.765	0.585	0.815	0.742
NN-SMOTETomek	0.779	0.563	0.839	0.740
NN-SMOTEOss	0.763	0.580	0.814	0.740
XGB-imbalanced	0.813	0.632	0.943	0.647
XGB-Random-Oversampling	0.768	0.473	0.827	0.691
XGB-SMOTE	0.813	0.623	0.937	0.655
XGB-SMOTETomek	0.810	0.608	0.932	0.654
XGB-SMOTEOss	0.811	0.612	0.935	0.654
LR-imbalanced	0.808	**0.688**	**0.972**	0.596
LR-Random-Oversampling	0.736	0.422	0.787	0.671
LR-SMOTE	0.740	0.428	0.791	0.675
LR-SMOTETomek	0.736	0.422	0.786	0.672

LR-SMOTEOss	0.744	0.433	0.797	0.672

Second Random Forest Recursive Feature Elimination selection is run and 11 number of features are eliminated. The following figure shows the features based on their coefficients (or importance):



As it is shown above, the feature selection procedure eliminates less important features (features with lower coefficient).

Conducting experiment on the main data set, after performing above-mentioned feature selection technique, the followings results are obtained:

Models	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
RF-imbalanced	**0.813**	0.632	0.943	0.647
RF-Random-Oversampling	0.807	0.581	0.915	**0.685**
RF-SMOTE	0.806	0.580	0.917	0.663
RF-SMOTETomek	0.809	0.582	0.916	0.667

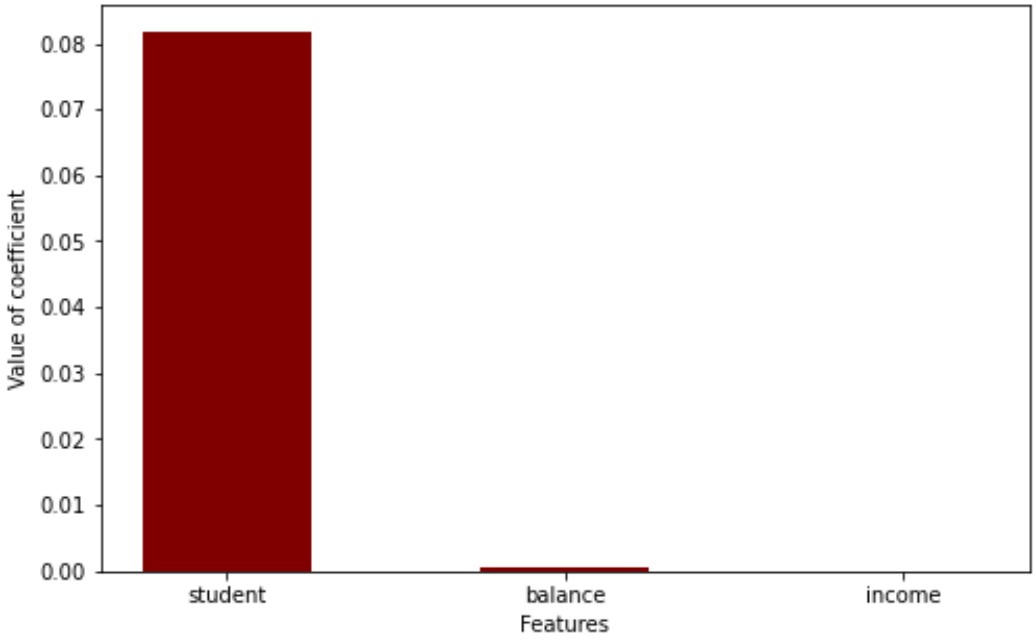
RF-SMOTEOss	0.781	0.593	0.922	0.667
NN-imbalanced	0.563	0.001	**1.000**	0.508
NN-Random-Oversampling	0.551	**0.636**	0.543	0.624
NN-SMOTE	0.540	0.629	0.530	0.613
NN-SMOTETomek	0.575	0.632	0.514	0.579
NN-SMOTEOss	0.807	0.596	0.568	0.579
XGB-imbalanced	0.763	0.608	0.939	0.638
XGB-Random-Oversampling	0.805	0.464	0.823	**0.685**
XGB-SMOTE	0.807	0.582	0.924	0.651
XGB-SMOTETomek	0.809	0.595	0.930	0.647
XGB-SMOTEOss	0.781	0.606	0.933	0.647
LR-imbalanced	0.560	0.000	**1.000**	0.500
LR-Random-Oversampling	0.606	0.290	0.523	0.609
LR-SMOTE	0.606	0.300	0.609	0.604
LR-SMOTETomek	0.560	0.291	0.521	0.611
LR-SMOTEOss	0.593	0.300	0.577	0.611

Now considering the second data set, lets first overview the features:

```
0   default
1   student
2   balance
3   income
```

Now let’s repeat the experiment for the second data set:

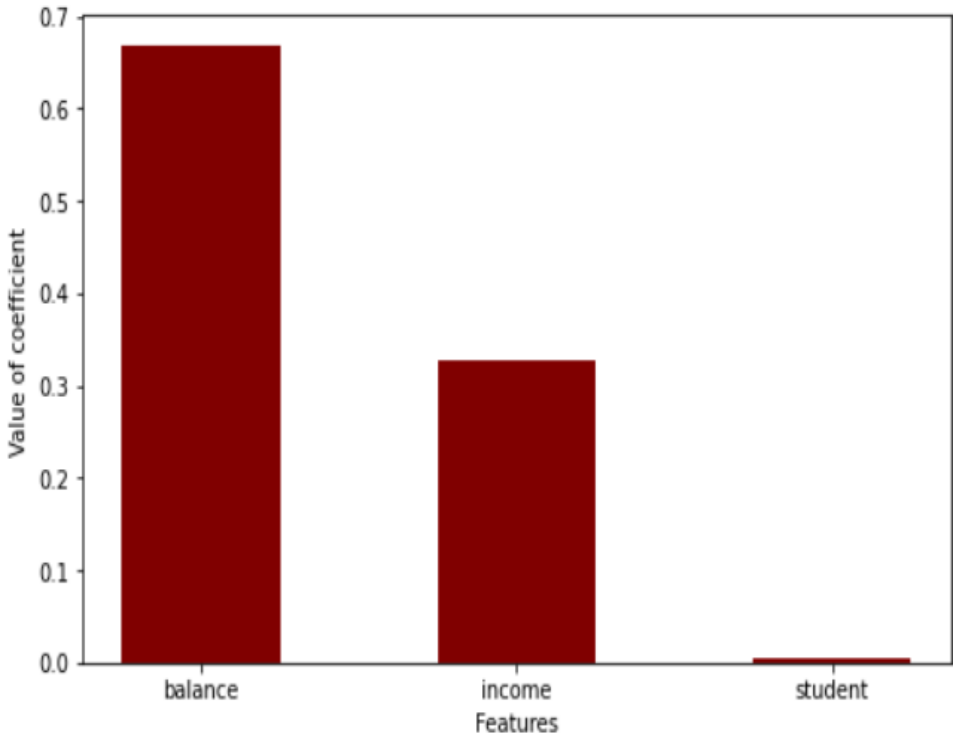
First the L1 based feature elimination with support vector machine feature selection is run, and 2 numbers of features are eliminated.



Models	**Accuracy**	**Sensitivity**	**Specificity**	**AUC**
RF-imbalanced	0.956	0.302	0.977	0.643
RF-Random-Oversampling	0.956	0.302	0.977	0.643
RF-SMOTE	0.892	0.146	0.905	0.703
RF-SMOTETomek	0.896	0.161	0.907	0.730
RF-SMOTEOss	0.912	0.171	0.926	0.730
NN-imbalanced	0.969	0.000	**1.000**	0.947
NN-Random-Oversampling	0.692	**0.979**	0.683	0.946
NN-SMOTE	0.756	0.968	0.749	**0.948**
NN-SMOTETomek	0.693	**0.979**	0.683	0.947
NN-SMOTEOss	0.897	0.809	0.900	0.947

XGB-imbalanced	0.971	0.564	0.992	0.661
XGB-Random-Oversampling	0.936	0.259	0.948	0.756
XGB-SMOTE	0.917	0.202	0.929	0.741
XGB-SMOTETomek	0.914	0.208	0.924	0.770
XGB-SMOTEOss	0.926	0.233	0.937	0.770
LR-imbalanced	**0.974**	0.743	0.997	0.637
LR-Random-Oversampling	0.867	0.179	0.866	0.885
LR-SMOTE	0.870	0.183	0.869	0.887
LR-SMOTETomek	0.869	0.182	0.868	0.886
LR-SMOTEOss	0.883	0.194	0.884	0.886

Second Random Forest Recursive Feature Elimination selection is run and 3 numbers of features are eliminated.



Models	Accuracy	Sensitivity	Specificity	AUC
RF-imbalanced	0.955	0.294	0.975	0.647
RF-Random-Oversampling	0.955	0.294	0.975	0.647
RF-SMOTE	0.842	0.132	0.846	0.785
RF-SMOTETomek	0.858	0.142	0.863	0.783
RF-SMOTEOss	0.873	0.150	0.881	0.783
NN-imbalanced	0.969	0.000	**1.000**	0.500
NN-Random-Oversampling	0.761	**0.926**	0.756	**0.944**
NN-SMOTE	0.872	0.862	0.873	**0.944**
NN-SMOTETomek	0.844	0.904	0.842	**0.944**
NN-SMOTEOss	0.872	0.872	0.872	**0.944**
XGB-imbalanced	0.973	0.633	0.994	0.662
XGB-Random-Oversampling	0.936	0.263	0.948	0.761
XGB-SMOTE	0.871	0.164	0.874	0.820
XGB-SMOTETomek	0.870	0.164	0.874	0.820
XGB-SMOTEOss	0.892	0.187	0.897	0.820
LR-imbalanced	**0.975**	0.737	0.997	0.647
LR-Random-Oversampling	0.862	0.169	0.862	0.867
LR-SMOTE	0.864	0.172	0.864	0.868
LR-SMOTETomek	0.859	0.168	0.859	0.871
LR-SMOTEOss	0.887	0.194	0.889	0.871

Discussion and conclusion

Considering the result of the experiment, it can be concluded that using Random Forest or Neural Network classifiers with Random Forest Recursive Feature Elimination together with random oversampling can outperform the other models. However, combination of Neural Network classifier with random oversampling also can results a good performance even with L1 based feature elimination with support vector machine.

As it is expected the performance of Logistic Regression algorithm worsens as the data set becomes more skewed. Also considering the experiment on the second, more imbalanced data set it is clear that using data balancing techniques improves the performance of models especially for Logistic Regression which is more under the effect of imbalance of data set.

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