Credit card fraud detection using machine learning

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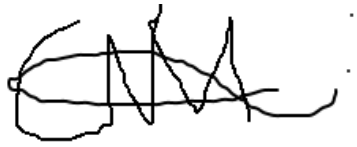
Abstract

Technological improvement has led people into using their credit cards in almost all the transactions they make daily. This rise of credit card use has, in turn, led to the rise of fraud activities by fraudsters thus leading financial institutions into increasingly large losses. In this essay, we will use machine learning algorithms to detect fraudulent transactions made. The dataset is highly imbalanced as we have 492 fraudulent transactions out of 284,807 observations and this is dealt with using several resampling approaches, Synthetic Minority Over-Sampling Technique (SMOTE), Tomek Links Removal, Edited Nearest Neighbor (ENN), Condensed Nearest Neighbor (CNN) and Nearmiss approach. We create the model using four classifiers, Random Forest, K-Nearest Neighbor (K-NN), Support Vector Machine (SVM) and Naive Bayes. We will evaluate the classifiers using the metrics, recall, precision and F1 score. Experimental results showed that Random Forest used with the resampling technique SMOTE and Tomek Links Removal gave good results as it had a precision of 86%, a recall of 87% and an F1 score of 86%. When used with ENN and CNN, Random Forest gave the same results of 84% for, precision, recall and F1 score.

Keywords: Credit card fraud detection, Random Forest, K-NN, Naive Bayes, SVM, SMOTE, Nearmiss, ENN, Condensed Nearest Neighbor (CNN), Tomek Links Removal.

Declaration

I, the undersigned, hereby declare that the work contained in this research project is my original work, and that any work done by others or by myself previously has been acknowledged and referenced accordingly.



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1. Introduction

1.1 Background

E-commerce is one of the fastest-growing sectors worldwide. Due to this growth, Kurien and Chikkamannur (2019) shows that usage of credit cards is standing out as the easiest and convenient means of payment for the online transactions. As credit card usage increases over the years, so do fraudulent activities. Figure 1.1 shows the rise in frauds in USA from the year 2014 to 2018.

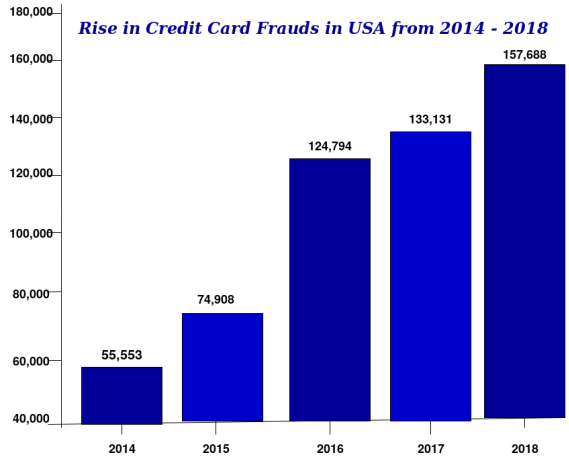

Figure 1.1: Credit Card fraud report for $2014 - 2018$

In an analysis by Anderson et al. (2013), there are 24.26 billion in 2018 which were lost due to fraudulent transactions made using credit cards worldwide. According to Renjith (2018), frauds recorded in 2019 were approximately 70 trillion dollars. The frauds associated with credit card stand out to be the highest over the years. A comparison of credit card related fraud and other types of fraud (Figure 1.2). We notice that from Figure 1.2 we have the credit card frauds standing out at 41% of the total frauds recorded.

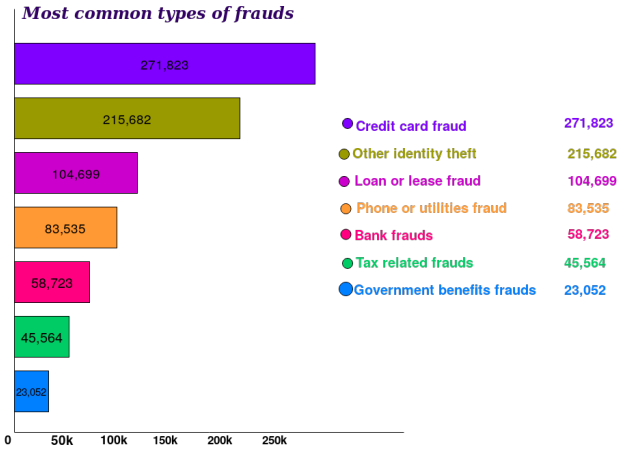

Figure 1.2: Reports on different types of frauds

The fraudsters use different methods to perform this crime which includes stolen cards, duplicating credit cards, and card not present. The most common technique used is the card not present and holds the highest percentage of (81%) (Anderson et al., 2013). Fraud detection is carried out by many financial institutions to reduce the losses they incur from this crime. Maes et al. (1993) defines fraud detection as the process of identifying from a group of transactions those that are legitimate and those that are fraudulent.

Researchers identify these fraudulent transactions using the fraud detection models. Creating these models is not an easy task as there are many challenges associated with the process. Firstly, the researchers have problems getting the data as the credit card transaction data is very confidential and institutions are not willing to give it to the public due to privacy policies (Dal Pozzolo et al., 2014). The other problem is class overlapping where we find that some of the transactions classified as fraudulent are legitimate transactions (Holte et al., 1989). The other main problem is the highly imbalanced dataset where the number of fraudulent cases is very few compared to the non-fraudulent cases (Baader and Krcmar, 2018).

The class imbalance can be very problematic especially when dealing with the traditional classifiers during their training (Japkowicz and Stephen, 2002). Thus, for any researcher, this becomes the first problem they have to tackle otherwise the results obtained will be inaccurate as they will favor the class with the many observations. Many researchers have carried out experiments to try and identify models that can detect these fraudulent activities.

1.2 Existing Work

Perantalu and BhargavKiran (2017) performed predictive modeling of credit card fraud detection. The authors used two machine learning classifiers, Logistic Regression, and Decision Trees. For the attribute selection they used information gain and used accuracy as the evaluation metric. Perantalu and BhargavKiran (2017) found out that the Decision Trees performed better than the Logistic Regression in detecting any fraudulent transaction.

Pun and Lawryshyn (2012) performed a study of whether a meta classifier performs better than the Falcon based fraud prediction performance. The data used was a neural network filtered dataset from a Canadian bank. The multi-based classifier algorithm used 3 classifiers, Naive Bayesian, K-Nearest Neighbor(K-NN), and Decision Trees. Naive Bayesian algorithm was used as the final classifier to combine the other classifiers. Pun and Lawryshyn (2012) concluded that the meta-classifier improved in saving money and in fraud detection.

In a study by Shakya (2018) using Random Forest, Logistic Regression and XGBoost showed that Random Forest performed better than the other two classifiers. He said the reason was because of the ensemble nature of Random Forest. The class imbalance problem was solved using Synthetic Minority Over-Sampling Technique (SMOTE). The combination of Random Forest and SMOTE gave the best results in detecting fraudulent transactions.

Wiese and Omlin (2009) performed a study on fraud detection using three different machine learning techniques, Conventional Feedforward Neural Networks, Support Vector Machine(SVM), and Long Short Term Memory Recurrent Neural Networks(LSTM). In his studies he took account of a sequence of transactions instead of individual transactions and so making this a time series problem. He concluded that LSTM outperformed the other two techniques reason been that it can deal with the noises in the data unlike the other techniques.

1.3 Aims and Objective

In this study, we aim to detect any fraudulent transactions made from all the transactions made using a credit card in the given dataset. This aim will be met by accomplishing the following objectives:

- Performing a predictive analysis using traditional machine learning classifiers such as Random Forest, SVM, Naive Bayes and K-NN.
- Resample, train and test the data.
- Evaluate the efficiency of the classifiers using different evaluation metrics.

1.4 Contribution

The main problem that researchers face when researching in this area is a class imbalance. The contribution in this research is to test different resampling techniques that have not been used in credit card fraud detection research but have worked well in other researches that involve a highly imbalanced dataset. The resampling techniques are NearMiss that have worked well with SVM and the hybrid techniques SMOTE and Tomek Links , ENN and CNN that work very well with Random Forest classifier.

1.5 Structure of the Essay

The essay will be structured as follows: Chapter 2 will have the literature review on past work, the machine learning techniques and resampling techniques. Chapter 3 will give the methodology used and the different evaluation metrics. Chapter 4 we will have the results from the four classifiers. Chapter 5 will present the conclusion, challenges faced in the essay and future work.

2. Literature Review

2.1 Introduction to Machine Learning

In this section, we will have an explanation of how machine learning works and the different types of traditional classifiers that can be used in detecting whether a transaction is fraudulent or legitimate. We will also have an explanation of different ways to deal with the challenge of class imbalance in the dataset.

2.1.1 Machine Learning.

Shabbir and Anwer (2018) defines machine learning as part of artificial intelligence which involves the computer implementing different algorithms to solve certain problems without a human being performing any programming. Machine learning is categorized into, Supervised learning, Unsupervised learning and Reinforcement learning.

2.1.2 Supervised Learning.

According to Mohri et al. (2012), the goal of supervised learning is to have a model that can predict a label when it is given a vector of features. In supervised learning, it contains labeled features that are used to predict a target value (Kotsiantis, 2007). The features can be categorical or continuous. Under supervised learning we can have two types of problems depending on the nature of the label we are predicting.

- **Regression**-This is when the label is continuous for example if we want to predict the stock prices in a given period.
- **Classification** - When the problem is a classification problem then we want to predict a categorical target. For example spam detection, credit default of a loan, fraud detection among many more.

In this essay, we will focus on supervised learning and specifically the classification problem.

2.1.3 Unsupervised Learning.

In the unsupervised learning, unlike the supervised learning here we only have the input variables but no output variable, Usama et al. (2019) refers to the data as unlabeled. In this learning, the algorithm learns by itself the pattern and the structure of a given data and then it comes up with a conclusion. There are two types of unsupervised learning:

- **Clustering** - The algorithm learns the patterns of a given data and groups it according to this pattern (Jain et al., 1999). For example, a certain group of customers likes buying these types of products.
- **Association** - This is also an important type of unsupervised learning where it checks the relation between one group with another. For example, if this customer buys wine and chocolate then they are also likely to buy some kinds of pasta.

2.1.4 Reinforcement Learning.

This is a less commonly used machine learning technique. In this technique, François-Lavet et al. (2018) shows that we have both the input and output variables and the algorithm tries to learn from its mistakes by maximizing the rewards of a certain situation and minimizing the mistakes.

2.2 Techniques to Solve Class Imbalance

Ling and Sheng (2010) defines class imbalance as, given a classification problem, the number of observations under one class is far less than those in the other class. In this essay, this is the main problem as the number of fraudulent transactions are very few, 0.0173% of the whole dataset. We have different approaches used to solve the class imbalance problem.

2.2.1 Ensemble Approaches.

Rokach (2005) explains that these approaches combines different weak classifiers and makes a better classifier that can deal with this class imbalance problem. This approach uses two different methods:

- **Bagging** - The method uses weak classifiers separately and then combines their results by either taking the average or by taking a vote (Breiman, 1994). The most common classifier that works this way is the Random Forest.
- **Boosting** - On the other hand, Freund and Schapire (1999) shows that this is different from the bagging since we work with the weak classifiers together in a way that the performance of one classifier depends on the other classifier.

2.2.2 Resampling Approaches.

We now discuss the different approaches under the resampling approaches as this is the approach that this essay focusses on.

- **Under-sampling** The majority class is reduced to have the same number of observations as the minority class (He and Garcia, 2009), (Figure 2.1). The disadvantage of this method is that when we reduce the majority class we are likely to lose some information and thus not making a good analysis. We can have many undersampling approaches that we will discuss below.

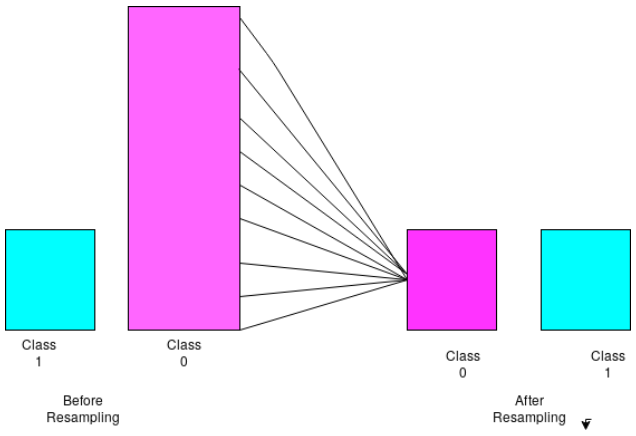

Figure 2.1: Undersampling approach

1. **NearMiss** An undersampling method where we take the distance between each majority class observations and minority class observations and depending on the approach of nearmiss used we delete the majority class observations that are not needed appropriately. There are 3 types of the NearMiss methods that can be used.
    - **NearMiss-1** Yen and Lee (2006) explains this as where we take the observations from the majority class that have a minimum average distance with the 3 nearest observations from the minority class.

- **NearMiss-2** this takes observations from the majority class that have the minimum average distance with the 3 furthest observations from the minority class and removes the other observations.
- **NearMiss-3** We take the majority class observations that have a minimum distance with each of the minority class instance (Zhang and Mani, 2003).

We use the Euclidean distance metrics to calculate this distance between the majority class instances and the minority class instances. In this essay we will use Nearmiss-3 since it works well with the highly imbalanced data (Zheng, 2004). Also since the dataset is highly dimensional, NearMiss-3 will be convenient compared to the other two methods. Figure 2.2 illustrates how NearMiss-3 works.

Figure 2.2: Nearmiss-3 Approach

2. **Edited Nearest Neighbor (ENN)** -This is also an undersampling method that we take an instance and check its 3 nearest neighbor (Alejo et al., 2010). If the instance is from the majority class and the other 3 neighboring instances are from the minority class then we remove this one instance from the majority class. On the other hand, if the instance is from the minority class and the 3 neighbors are from the majority class, then we remove the three instances from the majority class (Batista et al., 2004).
3. **Tomek Links Removal** This is another undersampling method where in a given dataset, we look for the observations from the majority and minority class that is close to each other and we remove those instances from the majority class (Tomek, 1976). Figure 2.3 shows how Tomek Links Removal works.

Figure 2.3: Tomek Links Removal

4. **Condensed Nearest Neighbor(CNN)** According to Hart (1968), this is referred to as the Hart algorithm. It is mostly used with the K-Nearest Neighbor(K-NN) classifier and works as follows:

- Given a training set X we take all those instances x close to each other but they are from the different labels and put them in the set S.
- Repeat the selection until no more instances can be added in S.
- Use the set S for classification instead of the training set X.

CNN helps in saving space and time used for training.

- **Over-sampling** This is the opposite of the undersampling where we take the minority instances and duplicate them until they are the same numbers as the majority class (Rahman and Davis, 2013). We have different oversampling techniques but we will focus on one of them in this essay, SMOTE. Figure 2.4 illustrates oversampling.

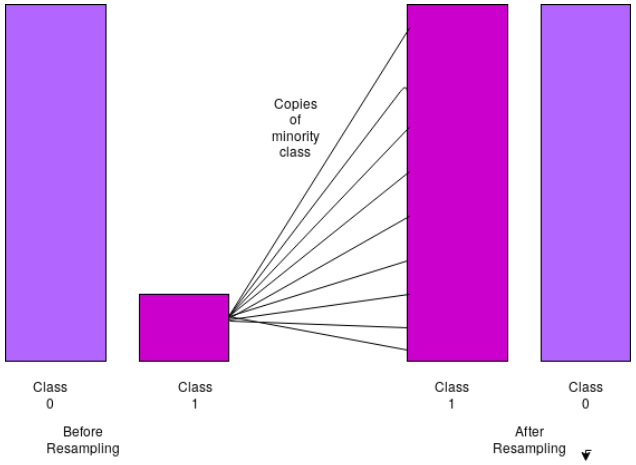

Figure 2.4: Oversampling

1. **Synthetic Minority Oversampling Techniques(SMOTE)** this is an oversampling technique where new instances are synthetically created from the existing minority class observations (Bunkhumpornpat et al., 2009). It works as follows:
   - Take the difference between the feature vector of an instance and the nearest neighbor say 1 nearest neighbor's feature vector.
   - Then multiply this difference by a value between 0 and 1 and not by the two numbers.
   - Then add the result to the instance's value and this becomes the new instance.

   The red dots are the synthetic instances created (Figure 2.5).

Figure 2.5: SMOTE

In this essay, we are going to use the above discussed resampling techniques together with different classifiers that we will discuss in the next section.

2.3 Machine Learning Classifiers

We have many traditional machine learning classifiers that can be used to solve a classification problem but we will focus on the four main ones.

2.3.1 Random Forest.

Given a dataset $D = \{(\mathrm{x}_1, \mathrm{y}_1), (\mathrm{x}_2, \mathrm{y}_2), \ldots, (\mathrm{x}_n, \mathrm{y}_n)\}$ where $i \in \mathbb{R}^+$, let x_i be the i^{th} observation and y_i the output given by the i^{th} element in D. The Random Forest which is an ensemble classifier of a number of decision trees is defined by Biau (2010) as:

$$H_{rf}(x) = \{h_1(x), h_2(x), \ldots, h_k(x)\} \tag{2.3.1}$$

$$\text{where} \quad 1, 2, \ldots, k \quad \text{are the number of trees}$$

To have an understanding of the Random Forest we look into the decision trees. $H_1(x)$ is the function representing the first decision tree $(i = 1)$ which is made by making different decisions just as the name suggests.

The decision tree is made by making splits. The top node in the tree is called the root node and when we split it we make decision nodes. The lowest node is called the terminal/leaf node (Breiman, 2004). We represent the features in the decision trees as the set

$$\Omega = \{\theta_1, \theta_2, \ldots, \theta_m\} \tag{2.3.2}$$

When we do the split, we have to consider which feature is more important and this can be done using two methods (Hjerpe, 2016):

- Information entropy
- Gini Index

The information entropy of a feature (attribute) is defined by Shannon (1948) as the information that will be needed to make any classification, say, is a transaction made fraudulent or legitimate. It is mostly used when the attributes are categorical. It is calculated as follows:

$$\text{entropy} = -\sum_{i=1}^{n} p_i \log p_i$$

The higher the entropy the better to use that attribute as the best split. On the other hand, the Gini index is defined by Han et al. (2012) as a representation of the cost incurred in making the wrong classification so we take the attribute with the lower index (Liu and Haig, 2018). It is mostly used when the attributes are continuous and when the data is highly imbalanced. It is calculated as:

$$\text{Gini} = 1 - \sum_{i=1}^{n} (p_i)^2 = \sum_{i=1}^{n} p_i(1 - p_i),$$

$$\text{where} \quad p_i = \text{probability of event i}$$

In this case, since our attributes are continuous and we are working on a highly imbalanced dataset, we will use the Gini index. So at each split in the decision tree the attribute with the lowest Gini index is selected.

Having an understanding of how the decision trees work, we focus on the Random Forest which is just a collection of many decision trees. And this is how the Random Forest works.

- We create with replacement resamples $\{c_1, c_2, \ldots, c_m\}$ from the dataset D by randomly choosing a given number of features mostly if we have n features we choose $k < n$ features where, $k = \sqrt{n}$.
- For each bootstrap resample, grow a tree using the Gini index for the best split.
- When we have a grown tree, we assign either 0 or 1 at each terminal node to represent a legitimate or fraudulent transaction.
- Having a group of m trees $T_M, M = 1, 2, \ldots, m$ each with a predicted value, we perform the following: for regression problem, Biau and Scornet (2016) suggests that we average all the predicted value from the trees. For classification, we do the voting and choose the highest voted class (Biau and Scornet, 2016).
- For regression, let $h_i(x), i = 1, 2, \ldots, m$ be the result of the i^{th} tree then the final result is given as:
$$H_{rf}(x) = \frac{1}{M}\sum_{i=1}^{m} h_i(x)$$
- For classification, let $c_i(x), i = 1, 2, \ldots, m$ be the class prediction of the i^{th} tree, then
$$C^i_{rf}(x) := \text{argmax}\{c_i(x)\}$$
- If we have 100 trees we have 100 results for a given observation, for example x_{20}, so we perform a vote on the one with the highest votes. If for example, in the case where 80 came out as a fraudulent transaction and 20 as a legitimate transaction then we vote that the observation is a fraudulent transaction.
- The more the trees the better but the slower the process as it has to do the voting from all the trees.

2.3.2 Support Vector Machine(SVM).

SVM is used in both classification and regression problems. When dealing with a regression problem we use the support vector regression (SVR) and when dealing with a classification problem we use the support vector classifier (SVC). In most cases, it is used in classification problems (Dheepa and Dhanapal, 2012).

When we have an n-dimensional space, the hyperplane is the line that separates the data points of one class from the other if we have two classes. The hyperplane can be represented by the equation:

$$wx + b = 0, \tag{2.3.3}$$

where w is the weight vector and is normal to the hyperplane $w = \{w_1, w_2, \ldots, w_n\}$

In a simple way, SVM creates a hyperplane such that given two classes, all the points from one class satisfy the equation $wx+b > 0$ and the points from the other class satisfy the equation $wx+b < 0$. More specifically, suppose we have a dataset $D = \{(\mathrm{x}_1, \mathrm{y}_1), (\mathrm{x}_2, \mathrm{y}_2), \ldots, (\mathrm{x}_n, \mathrm{y}_n)\}$ where $x_i \in \mathbb{R}^n$ represent the i^{th} observation which is a feature vector and $y_i \in \{-1, 1\}$ is the label associated to that instance.

The main focus of SVM is to maximize the distance between the hyperplane and the closest points to the hyperplane (Maimon and Rokach, 2005). These closest points are called the support vectors. Maimon and Rokach (2005) proposes that a hyperplane with a wide margin can handle a noisy dataset.

If we make the assumption that the observations from the two classes are separable, then we end up with a hyperplane that satisfiies the equation:

$$y_i(wx_i + b) \geq 1, \quad i \in \{1, \ldots, n\} \tag{2.3.4}$$

Since we will have many hyperplanes that can separate the two classes, we need to find the one that maximizes the margin. The margin is given as $\frac{1}{\|w\|}$ and so maximizing the margin is the same as minimizing the $\| w \|$. Kroon and Omlin (2004) converts this from a maximization problem to a constrained optimization problem by solving the equation:

$$\text{minimize} \quad \frac{1}{2} \| w \|^2, \quad \text{subject to} \quad y_i(wx_i + b) \geq 1 \quad i \in \{1, \ldots, n\}, \tag{2.3.5}$$

To deal with the constraint 2.3.4, Wiese and Omlin (2009) introduces the lagrangian multipliers α_i, $i \in \{1, \ldots, n\}$ and we get the primal form equation by multiplying the constraints by the lagrangian multipliers and subtracting it from the objective function:

$$\mathcal{L}_p(w, b, \alpha) = \frac{1}{2} \| w \|^2 - \sum_{i=1}^{n} \Big(\alpha_i (y_i(wx_i + b) - 1) \Big) \tag{2.3.6}$$

When we are dealing with an optimization problem, Kroon and Omlin (2004) shows that the solution lies on the saddle points of 2.3.6 which we have to minimize with respect to (w, b) and maximize with respect to α_i. We maximize by taking its partial derivative with respect to the variables w and b.

$$\frac{\partial \mathcal{L}(w, b, \alpha)}{\partial w} = w - \sum_{i=1}^{n} a_i x_i y_i = 0 \implies w = \sum_{i=1}^{n} a_i x_i y_i \tag{2.3.7}$$

$$\frac{\partial \mathcal{L}(w, b, \alpha)}{\partial b} = -\sum_{i=1}^{n} a_i y_i = 0 \tag{2.3.8}$$

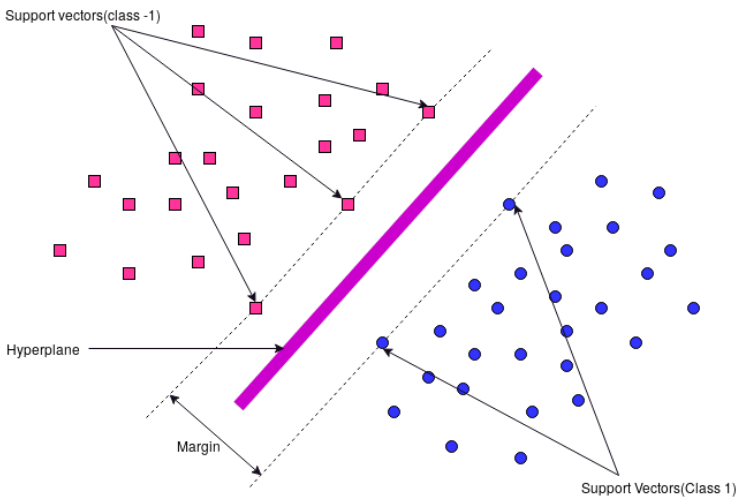

Figure 2.6: Support Vector Machine classifier

The Figure 2.6 above shows the hyperplane, the support vectors and the margin.

Using Karush-Kuhn-Tucker(KKT) conditions, we check any relationship between the lagrangian multipliers and the constraints and in this case we have:

$$\alpha_i(y_i(wx_i + b) - 1) = 0, \quad i \in \{1, \ldots, n\} \tag{2.3.9}$$

Using 2.3.9 we can either have $\alpha_i = 0$ or $y_i(wx_i + b) - 1 = 0$ meaning that for the support vectors $\alpha_i > 0$ and for the other instances that are not the support vectors, $\alpha_i = 0$.

Substituting 2.3.7 and 2.3.8 in the primal problem 2.3.6 we convert it into a dual maximization problem:

$$\mathcal{L}_D(\alpha) = \frac{1}{2}\left[\left(\sum_{i=1}^{n}\alpha_i x_i y_i\right).\left(\sum_{j=1}^{n}\alpha_j x_j y_j\right)\right] - \left[\left(\sum_{i=1}^{n}\alpha_i x_i y_i\right).\left(\sum_{j=1}^{n}\alpha_j x_j y_j\right)\right] + \sum_{i=1}^{n}\alpha_i y_i b + \sum_{i=1}^{n}\alpha_i$$

$$\mathcal{L}_D(\alpha) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j x_i x_j y_i y_j, \quad \text{subject to} \quad \alpha_i \geq 0 \quad \text{and} \quad 2.3.8 \tag{2.3.10}$$

To solve the dual maximization problem 2.3.10, we let α^* to be the maximizing solution and w^* and b^* the parameters of the hyperplane. In case we have a new instance x that need to be classified, the decision function used is:

$$\text{sign}(w^*x + b^*) = \text{sign}(\sum_{i=1}^{n}\alpha_i^* x_i y_i.x + b^*) \tag{2.3.11}$$

In most cases, the data points are not linearly separable so we use the kernel trick where we transform the low dimension input space to a higher dimensional feature space which can make the data points to be linearly separable.

When using the kernel trick we map the low dimension input space G into a higher dimension feature space F, i.e, $\psi : G \longmapsto F$ where we transform the data points into $\psi(x_1), \ldots, \psi(x_n)$ which are now linearly separable. According to the kernel trick, we have $\psi(x)\psi(y) = K(x, y)$ where K is the kernel function. When we replace the inner products in 2.3.10 with the kernel function we obtain 2.3.12 which we maximize to get the solution to our problem

$$\mathcal{L}(\alpha) = \sum_{i=1}^{n}\alpha_i - \frac{1}{2}\sum_{i,j}\alpha_i\alpha_j y_i y_j K(x_i x_j) \tag{2.3.12}$$

When we maximize 2.3.12 the decision function 2.3.11 becomes:

$$\begin{aligned}
&\text{sign}(w^*\psi(x) + b^*) \\
&= \text{sign}\left(\left(\sum_{i=1}^{n}\alpha_i^* y_i \psi(x_i)\right).\psi(x) + b^*\right) \\
&= \text{sign}\left(\sum_{i=1}^{n}\alpha_i^* y_i \psi(x_i).\psi(x) + b^*\right) \\
&= \text{sign}\left(\sum_{i=1}^{n}\alpha_i^* y_i K(x_i, x) + b^*\right)
\end{aligned} \tag{2.3.13}$$

Sometimes even with the kernel trick it is still not possible to separate the data points into two groups and so we use the soft margin. To deal with this non-separability, Jakkula (2006) introduces slack variables $\xi = (\xi_1, \ldots, \xi_n)$ this helps in case our data has noises such as outliers and thus preventing an overfitting of the model. We end up with the constraints as:

$$y_i(wx_i + b) \geq 1 - \xi_i, \quad i \in \{1, \ldots, n\}, \quad \xi \geq 0 \tag{2.3.14}$$

Including the slack variables the objective function becomes:

$$\min \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} \xi_i \tag{2.3.15}$$

from 2.3.15 Maimon and Rokach (2005) defines $C \in \mathbb{R}$ as a hyperparameter that represents the cost incurred when the constraint 2.3.4 is violated. We introduce the lagrange multipliers $\alpha > 0$ to deal with the constraints and we use another lagrange multpliers $\beta = \beta_1, \ldots, \beta_n$ to take care of the introduced slack variable constraint in 2.3.15. This gives us a primal optimization problem 2.3.16:

$$\mathcal{L}(w, b, \xi, \alpha, \beta) = \frac{1}{2} \parallel w \parallel^2 + C \sum_{i=1}^{n} \xi_i - \sum_{i=1}^{n} \Big(\alpha_i (y_i (w x_i + b) - (1 - \xi_i)) \Big) - \sum_{i=1}^{n} \beta_i \xi_i \tag{2.3.16}$$

To minimize 2.3.16, Jakkula (2006) differentiate it with respect to w,b and ξ_i

$$\frac{\partial \mathcal{L}(w, b, \xi_i)}{\partial w} = w - \sum_{i=1}^{n} a_i x_i y_i = 0 \implies w = \sum_{i=1}^{n} a_i x_i y_i \tag{2.3.17}$$

$$\frac{\partial \mathcal{L}(w, b, \xi_i)}{\partial b} = \sum_{i=1}^{n} a_i y_i = 0 \tag{2.3.18}$$

$$\frac{\partial \mathcal{L}(w, b, \xi_i)}{\partial \xi_i} = C - \alpha_i - \beta_i = 0 \implies C = \beta_i + \alpha_i \tag{2.3.19}$$

Replacing 2.3.17 and 2.3.19 in 2.3.16 we have:

$$\begin{aligned} \mathcal{L}(w, b, \xi_i) = \frac{1}{2} \Big((\sum_{i=1}^{n} a_i x_i y_i)(\sum_{i=1}^{n} a_i x_i y_i) \Big) + C \sum_{i=1}^{n} \xi_i - \sum_{i,j} \alpha_i x_i y_i \alpha_j x_j y_j \\ - b \sum_{i=1}^{n} \alpha_i y_i + \sum_{i=1}^{n} \alpha_i (1 - \xi_i) - \sum_{i=1}^{n} (C - \alpha_i) \xi_i \end{aligned} \tag{2.3.20}$$

solving 2.3.20 and replacing 2.3.18 we have:

$$\mathcal{L}(w, b, \xi_i) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i,j} \alpha_i \alpha_j x_i x_j y_i y_j \tag{2.3.21}$$

Equation 2.3.21 is similar to 2.3.12 even with the modification of the objective function, the dual problem is still the same. The only changes is on the constraints. In the separable case, we have the two constraints, $\alpha \geq 0$ and $\sum_{i=1}^{n} \alpha_i y_i = 0$ and in the non-separable case we have $\alpha \geq C$ from 2.3.19 and $\beta \geq 0$. After maximizing 2.3.21 and obtaining α^*, we can get the other parameters w^* and b^* in both cases, separable case and the non-separable case.

2.3.3 K-Nearest Neighbor (K-NN).

Fix and Hodges (1952) defines K-NN as a non-parametric, simplest and commonly used classifier. Non-parametric means that we do not need to know the probability distribution of the data. The classifier assumes that for a given data point, its nearest neighbors are similar to it. The classifiers take distance between the test data point and each training data point (Dasarathy, 1991).

Given a dataset $D = \{(\mathrm{x}_1, \mathrm{y}_1), (\mathrm{x}_2, \mathrm{y}_2), \ldots, (\mathrm{x}_n, \mathrm{y}_n)\}$ and we have a new data point X that we want to classify to which class it belongs, we denote the set of the k nearest neighbors of X as S_x where

$$S_x \subseteq D \quad \text{s.t} |S_x| = k \quad \text{and} \quad \forall (x_i, y_i) \in D \backslash S_x :$$

$$\text{dist}(x, x_i) \geq \max \text{dist}(x, x') \tag{2.3.22}$$

From 2.3.22 it means that the distance from the test data point and other training data points apart from those in the set S_x is greater than that with those in the set S_x.

We need to know how to calculate this distance by identifying the right distance metric to use.

There are different metrics that can be used:

- **Minkowski Distance** (Boriah et al., 2008), this metric is calculated as follows:

$$\text{distance} = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{\frac{1}{p}}$$

  And from this, we can have other distance metrics depending on the value of p

$$p = 1, \text{Manhattan distance}$$

$$p = 2, \text{Euclidean distance}$$

$$p = \infty, \text{Chebychev distance}$$

- **Manhattan Distance** Wilson and Martinez (2000) defines manhattan distance as the distance between two points when the value of $p = 1$ and is given as:

$$\text{d} = \sum_{i=1}^{n} |x_i - y_i|, i = 1, 2, \ldots, n$$

$$\text{d} = (x_1 - y_1) + (x_2 - y_2) + \cdots + (x_n - y_n)$$

- **Euclidean Distance** (Wilson and Martinez, 2000) To measure the distance between 2 points x_1 and x_2, we let them to be represented by the feature vectors:

$$x_1 = (x_{11}, x_{12}, \ldots, x_{1m})$$

$$x_2 = (x_{21}, x_{22}, \ldots, x_{2m})$$

  where m is the dimension of the feature vector

  To calculate the distance between the two points using the normalized Euclidean metric we use the following:

$$\text{d}(x_1, x_2) = \sqrt{\frac{\sum_{i=1}^{m} (x_{1i} - x_{2i})^2}{m}}$$

The value of k is not a constant value and it depends on the dataset one is working on but in most cases an odd number is considered and Chomboon et al. (2015) proposes, $k = 5$ or $k = 7$ are the common values used. Some researchers use $k = odd\sqrt{m}$ where m is the number of features. The value k is taken to be an odd value to make it possible for the voting.

Once the distance between the points is measured, according to Chomboon et al. (2015), the most common label in S_x is voted for as the label of the new instance (2.3.23)

$$h(x) = \text{mode}(\{y' : (x', y') \in S_x\}) \tag{2.3.23}$$

The Figure 2.7 below shows that after voting, the new green instance will be a blue triangle since we have two blue triangles versus one purple diamond.

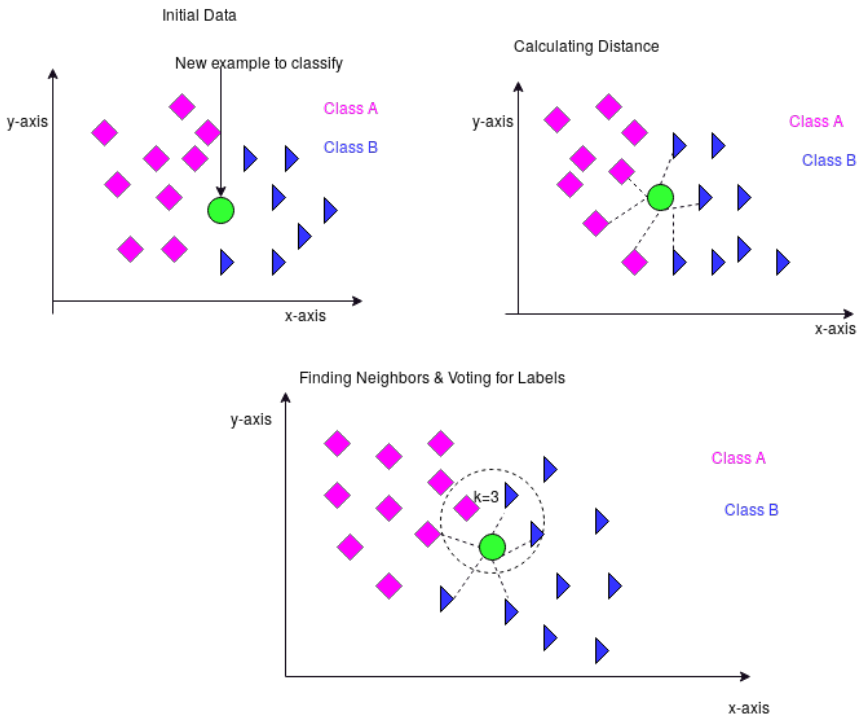

Figure 2.7: How KNN classifies the new instance

2.3.4 Naive Bayes.

The Naive Bayes classifier is based on the Bayes theorem (Berrar, 2018). Taheri and Mammadov (2015) shows that the classifier makes a naive assumption that the features are independent. Given two random variables A and B, Bayes theorem is given as:

$$\mathrm{p}(A|B) = \frac{\mathrm{p}(B|A)\mathrm{p}(A)}{\mathrm{p}(B)} \tag{2.3.24}$$

where

p(A|B) - is the probability of event A occurring given that event B has already occurred. It is called the posterior probability.

p(A) and p(B) - are the prior probabilities of events A and B occurring.

p(B|A) - is the probability of event B occurring given that event A has already occurred. It is called the conditional probability.

In Naive Bayes we want to classify a new observation X which is a feature vector $X = \{x_1, x_2, \ldots, x_n\}$, into one class $c_i \in C$. We use 2.3.24 to calculate the conditional probability $\mathrm{p}(c_i|x_1, x_2, \ldots, x_n)$ as follows:

$$\mathrm{p}(c_i|x_1, x_2, \ldots, x_n) = \frac{\mathrm{p}(x_1, x_2, \ldots, x_n|c_i)\mathrm{p}(c_i)}{\mathrm{p}(x_1, x_2, \ldots, x_n)} \tag{2.3.25}$$

We can rewrite the numerator of 2.3.25 using the relation $\mathrm{p}(A|B)\mathrm{p}(B) = \mathrm{p}(A, B)$ as:

$$\mathrm{p}(x_1, x_2, \ldots, x_n|c_i)\mathrm{p}(c_i) = \mathrm{p}(x_1, x_2, \ldots, x_n, c_i) \tag{2.3.26}$$

Taheri and Mammadov (2013) simplifies 2.3.26 using the chain rule of probability

$$\begin{aligned}
\mathrm{p}(x_1, x_2, \ldots, x_n, c_i) &= \mathrm{p}(x_1|x_2, \ldots, x_n, c_i)\mathrm{p}(x_2, \ldots, x_n, c_i) \\
&= \mathrm{p}(x_1|x_2, \ldots, x_n, c_i)\mathrm{p}(x_2|x_3, \ldots, x_n, c_i)\mathrm{p}(x_3, \ldots, x_n, c_i) \\
&\vdots \\
&= \mathrm{p}(x_1|x_2, \ldots, x_n, c_i)\mathrm{p}(x_2|x_3, \ldots, x_n, c_i) \ldots \mathrm{p}(x_{n-1}|x_n, c_i)\mathrm{p}(x_n|c_i)p(c_i)
\end{aligned}$$

$$\mathrm{p}(x_1, x_2, \ldots, x_n, c_i) = \mathrm{p}(x_1|x_2, \ldots, x_n, c_i)\mathrm{p}(x_2|x_3, \ldots, x_n, c_i) \ldots \mathrm{p}(x_{n-1}|x_n, c_i)\mathrm{p}(x_n|c_i)p(c_i) \tag{2.3.27}$$

But since Naive Bayes assumes that the features are independent of each other then it means that what happens on one feature does not affect the other feature and so 2.3.27 becomes:

$$\mathrm{p}(x_1, x_2, \ldots, x_n, c_i) = \mathrm{p}(x_1|c_i)\mathrm{p}(x_2|c_i) \ldots \mathrm{p}(x_{n-1}|c_i)\mathrm{p}(x_n|c_i)p(c_i) \tag{2.3.28}$$

but we can write the joint probability 2.3.28 as a product of the conditional probabilities of the features given the classes as

$$\mathrm{p}(x_1, x_2, \ldots, x_n, c_i) = \prod_{j=1}^{n} \mathrm{p}(x_j|c_i)p(c_i) \tag{2.3.29}$$

Replacing 2.3.29 in 2.3.25

$$\mathrm{p}(c_i|x_1, x_2, \ldots, x_n) = \prod_{j=1}^{n} \mathrm{p}(x_j|c_i)\frac{p(c_i)}{\mathrm{p}(x_1, x_2, \ldots, x_n)} \tag{2.3.30}$$

using maximum a posteriori (MAP) we have 2.3.30 as

$$\begin{aligned}
C_{\mathrm{MAP}} &= \operatorname{argmax} \quad \mathrm{p}(c_i|x_1, x_2, \ldots, x_n) \\
&= \operatorname{argmax} \quad \frac{\mathrm{p}(x_1, x_2, \ldots, x_n|c_i)\mathrm{p}(c_i)}{\mathrm{p}(x_1, x_2, \ldots, x_n)} \\
&= \operatorname{argmax} \quad \mathrm{p}(x_1, x_2, \ldots, x_n|c_i)\mathrm{p}(c_i) \\
C_{\mathrm{MAP}} &= \operatorname{argmax} \quad p(c_i) \prod_{j=1}^{n} \mathrm{p}(x_j|c_i)
\end{aligned} \tag{2.3.31}$$

Given the training dataset, we classify the observations according to which class they belong. For example, in this essay, we classify the observations that are fraudulent transactions and those that are legitimate and then get the probability of each class $p(c_i)$. We then multiply $p(c_i)$ by the product of the conditional probability of the new instance given that it belongs to class c_i 2.3.29. The class with the maximum of 2.3.31 is taken to be the class of the new instance that we want to classify Ng and Jordan (2002).

3. Methodology

In this chapter, we have the steps followed when carrying out the predictive analysis. This will include an explanation on data description, preprocessing the dataset, how the data is split, the methods used for hyperparameter fine tuning and evaluation metrics used.

3.1 Data Description

In this essay, we will use data collected in 2013 from transactions made by a European bank cardholders for two days. The dataset is available in Kaggle website [1]. The dataset contains $284,807$ observations of which only 492 were recorded as fraudulent transactions and the rest were legitimate transactions this means the dataset is highly imbalanced as we have 0.173% of the data as the fraudulent transactions.

We have 30 features and due to privacy policy from the bank, 28 of them are transformed using Principle Component Analysis (PCA). They are labeled V1-V28 and the features "Amount" and "Time" are not transformed. The feature "Time" represents the time between the first transaction and the other transactions.

Figure 3.1 shows a representation of the two classes in the dataset.

Figure 3.1: Legitimate and fraudulent transactions

We now check whether the features are correlated to each other as this will affect the analysis. We will do this by using a correlation matrix (Figure 3.2).

We see that from the correlation matrix Figure 3.2, there is no correlation between the features V1-V28. The variable "Amount" is negatively correlated with features V2 and V5 and positively correlated with the variables V7 and V20. The variable "Time" has a negative correlation with the variable V3. This is good since there is no high correlation with the features. We can proceed to preprocess our data to make it ready for creating a model.

[1] Credit Card Fraud Detection Dataset

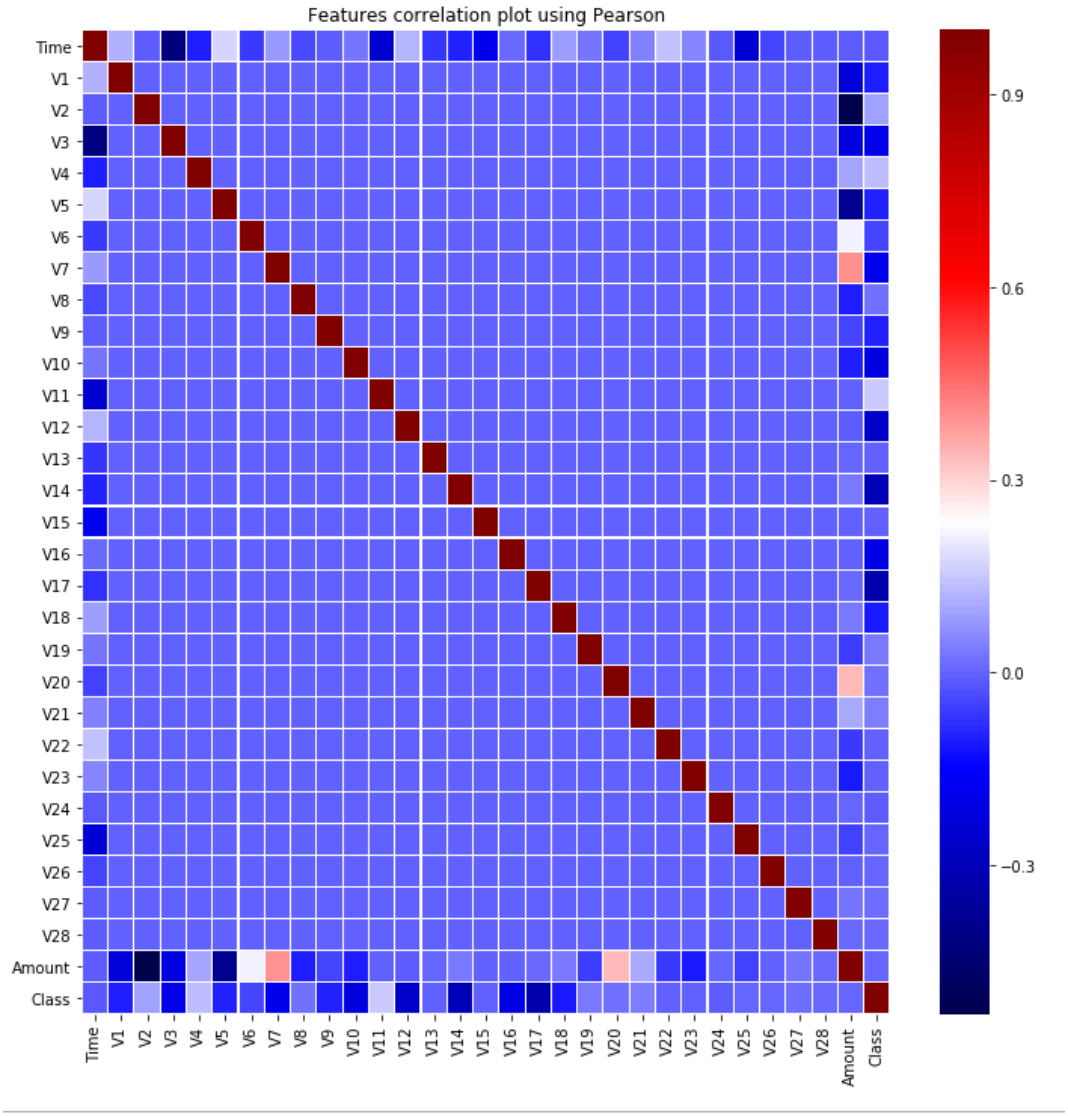

Figure 3.2: Correlation Matrix

3.2 Preprocessing the Dataset

We perform standardization on the feature "Amount" which is done by taking the observation and subtracting the mean then dividing by the standard deviation as follows:

$$z = \frac{x - \mu}{\sigma} \tag{3.2.1}$$

Standardization helps to keep the observations to be within a given range. We remove the feature "Time" since it is not important in detecting whether a transaction is legitimate or fraudulent.

3.3 Splitting Data

We split the data into training and testing data. The data we have is shuffled such that when we split we are not likely to face the challenge of having one class in the test data. The training data is used to

train the model and the test data is used to check whether the model can be able to work well on data that it has not met before. In this case, we will split the data into 70% for training and 30% for testing.

3.4 Resampling Techniques

We should make sure that we split the dataset before applying any resampling technique otherwise some examples appearing in the training set will also appear in the test data and so the model won't be efficient. In this essay we are going to use the following techniques and compare how they work with different classifiers.

- NearMiss
- Synthetic Minority Oversampling Technique(SMOTE) and Tomek links
- Edited Nearest Neighbor and Condensed Nearest Neighbor

3.5 Fine-Tuning Hyperparameters

When creating any model we need to identify the parameters and the hyperparameters. The parameters are those variables that are internal with the model and as a practitioner, we don't change them (Shakya, 2018). A hyperparameter is a configuration that is external to the model and whose value cannot be estimated from the training data (Shakya, 2018). The hyperparameters can be changed by the practitioner to fit the model and make them work well and this is what is called hyperparameter tuning or hyperparameter optimization.

There are three main methods to use when performing the hyperparameter tuning, namely:

- **GridSearchCV**- In this method, we give the values of the hyperparameters as a list and the model goes through all the values in the list and chooses the best values (Bergstra and Bengio, 2012).
- **RandomizedSearchCV**- when tuning hyperparameters using a randomized search, the model randomly picks the values provided in the list and from the most important ones the best hyperparameters are chosen (Bergstra and Bengio, 2012).
- **Manual Search**- This is where the practitioner chooses the hyperparameters from past experience and tries a range of them and picks the ones that work well with the given dataset and the classifiers used.

We are going to perform hyperparameter tuning for the three classifiers, K-NN, Random Forest and SVM since the Naive Bayes does not have any hyperparameter to tune. We will use the Manual Search because the dataset is very high dimensional and so it needs a lot of time and resources to tune using the first two tuning methods.

3.5.1 Hyperparameter optimization in Random Forest.

In Random Forest we are going to focus on tuning two main hyperparameters. The n_estimator which is the number of trees making the Random Forest and the max_feature which is the number of features used when doing the splitting on the decision trees.

3.5.2 Hyperparameter tuning in K-Nearest Neighbor (K-NN).

The main hyperparameter in the K-NN classifier is n_neighbor which is the number of neighboring points considered when classifying a new instance.

3.5.3 Hyperparameter tuning in Support Vector Machine.

We are going to tune two main hyperparameters, the kernel and C which is the cost penalty of misclassification.

3.6 Evaluation Metrics

Since our data is highly imbalanced, we will not use the accuracy as our evaluation metrics since it will always favor the legitimate class and so give high accuracy which is a misleading measure. We will consider the following evaluation metrics:

3.6.1 Confusion Matrix.

This is the most important metric as from it we can get other metrics. It gives an overview of how the model is working by looking how the values are distributed in it. It is represented as follows:

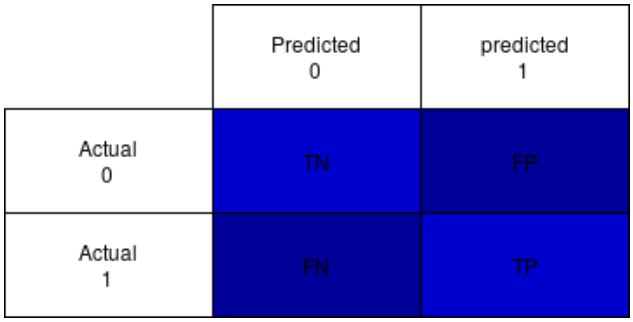

Figure 3.3: A Confusion Matrix

- **True Positive(TP)**- This represents all those observations that we predicted to be positive and that was true. In our case, those predicted to be fraudulent turned out to be fraudulent.
- **False Negative(FN)** - These are those observations taken to be negative but they are positive. For example transactions misclassified as legitimate when they are fraudulent.
- **True Negative(TN)**-This shows all the observations that were taken to be negatives and they were negative. In our case, all the transactions classified as legitimate and they were legitimate.
- **False Positive(FP)**- These are observations that were negative but they were misclassified as positive. For example a legitimate transaction classified as a fraudulent classification.

3.6.2 Recall.

This is an evaluation metric that checks how well can the model detect the true positives. In our case, it will show how well can a model detect when a transaction made is fraudulent. This will be our main focus since the essay is about fraud detection. A high recall is preferred. It is calculated as:

$$\text{Recall} = \frac{\text{True positive}}{\text{True Positive} + \text{False Negative}}$$

3.6.3 Precision.

The metric shows how true is the classification made by the model. In this essay, it will tell us how true is it when a model classifies a transaction to be fraudulent. We will also focus on the precision since we don't want to misclassify the transactions as this comes at a cost to the financial institutions. We calculate it as follows:

$$\text{Precision} = \frac{\text{True positive}}{\text{True Positive} + \text{False Positive}}$$

3.6.4 F1-Score.

This is a weighted average of both the precision and the recall. We calculate it as follows

$$\text{F1-score} = 2\left(\frac{\text{Precision * Recall}}{\text{Precision} + \text{Recall}}\right)$$

4. Results

In this section, we will have the results obtained from the four classifiers using the three resampling approaches. Due to page limitations, the numbers in the confusion matrices may need some zooming in to be visible.

4.1 Random Forest

4.1.1 NearMiss.

- **The best hyperparameters were n_estimators=400 and max_features=sqrt.**

From Table 4.1 we see the evaluation of Random Forest and NearMiss where the recall is at 86% and the precision is 34% meaning that when we resample the dataset using NearMiss, the model can detect 86% of the fraudulent transactions but we can only be 34% sure that these transactions are actually classified correctly as fraudulent. This is not a good thing because the percentage of misclassification is very high. This is seen in the confusion matrix Figure 4.1 where 229 legitimate transactions are classified as fraudulent transactions.

Table 4.1: Evaluation on Random Forest and Nearmiss

Evaluation Metrics	
Precision	0.34
Recall	0.86
F1-score	0.49

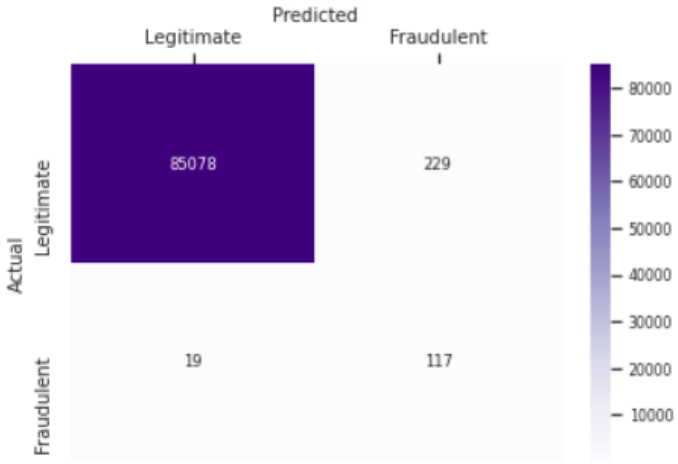

Figure 4.1: Confusion matrix-RF and Nearmiss

4.1.2 Edited Nearest Neighbor(ENN) and Condensed Nearest Neighbor(CNN).

- **The best hyperparameters were n_estimators=400 and max_features=sqrt.**

From Table 4.2 we see that the recall decreased from 86% to 84% which means that now our model can detect 84% of the fraudulent transactions. The precision increased from 34% to 84% so this means that the transactions classified as fraudulent are 84% true. This is a good model as seen in Figure 4.2 but the research is more interested in detecting the fraudulent transactions so we want a higher recall.

Table 4.2: Evaluation Metrics on RF-ENN+CNN

Evaluation Metrics	
Precision	0.84
Recall	0.84
F1-score	0.84

Figure 4.2: Confusion Matrix-Rf and ENN+CNN

4.1.3 Sythetic Minority Oversampling Technique(SMOTE) and Tomek Links Removal.

- **The best hyperparameters were n_estimators=400 and max_features=sqrt.**

Table 4.3 shows that when using SMOTE and Tomek Links Removal, the recall and precision increase to 87% and 86% respectively meaning now the model can detect 87% of the fraudulent transactions with 86% certainity. This is a good model since from the confusion matrix Figure 4.3, we see that only 20 legitimate transactions are misclassified as fraudulent.

Table 4.3: Evaluation Metrics on RF-SMOTE and Tomek Links Removal

Evaluation Metrics	
Precision	0.86
Recall	0.87
F1-score	0.86

Figure 4.3: Confusion Matrix-RF and Smote and Tomek Links Removal

4.2 K-Nearest Neighbor(K-NN)

4.2.1 NearMiss.

- **The best hyperparameter was n_neighbors=7.**

The Table 4.4 shows that when we use K-NN and NearMiss, 81% of the fraudulent transactions are detected and we are 45% sure that these transactions are truly fraudulent. This is not a good model as

we can see from Figure 4.4 that 136 of the legitimate transactions are wrongly classified as fraudulent transactions.

Table 4.4: Evaluation Metrics on KNN-Nearmiss

Evaluation Metrics	
Precision	0.45
Recall	0.81
F1-score	0.58

Figure 4.4: Confusion Matrix-KNN and Nearmiss

4.2.2 SMOTE and Tomek Links Removal.

- **The best hyperparameter was n_neighbors=5.**

From the evaluation metrics seen in Table 4.5, the model can detect 90% of the fraudulent transactions but with only 45% certainity. This is not a good model since from Figure 4.5 152 of the legitimate transactions are misclassified as fraudulent transactions.

Table 4.5: Evaluation Metrics on K-NN-SMOTE+Tomek links

Evaluation Metrics	
Precision	0.45
Recall	0.90
F1-score	0.60

Figure 4.5: Confusion Matrix-KNN and Nearmiss

4.2.3 ENN and CNN.

- **The best hyperparameter was n_neighbors=5.**

The evaluation metrics in Table 4.6 shows that when KNN is used together with ENN and CNN the model is able to detect 83% of the fraudulent transactions with 82% certainity. This is a good model

since from Figure 4.6 we have only 22 of the non-fraudulent transactions are misclassified as fraudulent transactions.

Table 4.6: Evaluation Metrics on KNN-ENN+CNN

Evaluation Metrics	
Precision	0.82
Recall	0.83
F1-score	0.83

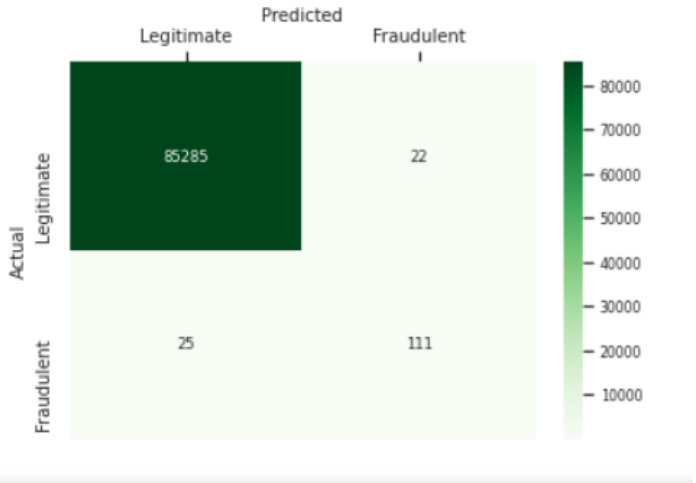

Figure 4.6: Confusion Matrix-KNN and ENN+CNN

4.3 Naive Bayes

4.3.1 NearMiss.

The results when using Naive Bayes and NearMiss (Table 4.7). The model is not good as the recall is at 57% meaning it can only detect 57% of the fraudulent transactions and from the precision, we are only 12% sure that these fraudulent transactions are truly in the right classification. Figure 4.7 shows that we have 554 legitimate transactions classified wrongly as fraudulent. The F1 score is very poor 20%.

Table 4.7: Evaluation Metrics on Naive Bayes-Nearmiss

Evaluation Metrics	
Precision	0.12
Recall	0.57
F1-score	0.20

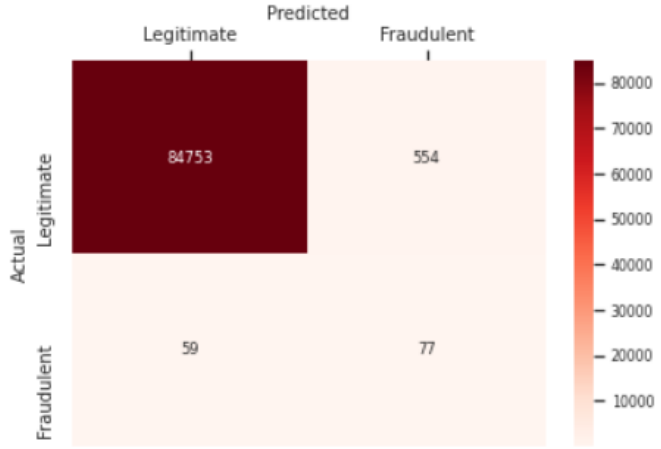

Figure 4.7: Confusion Matrix-Naive Bayes and Nearmiss

4.3.2 ENN and CNN.

From Table 4.8, we see that the recall has improved from 57% to 85% meaning that now our model can detect 85% of the fraudulent transaction but with only 6% of this been true which is half certainty compared to the NearMiss. This is a poor model since from Figure 4.8, 1865 of the non-fraudulent transactions are misclassified.

Table 4.8: Evaluation Metrics on Naive Bayes-ENN + CNN

Evaluation Metrics	
Precision	0.06
Recall	0.85
F1-score	0.11

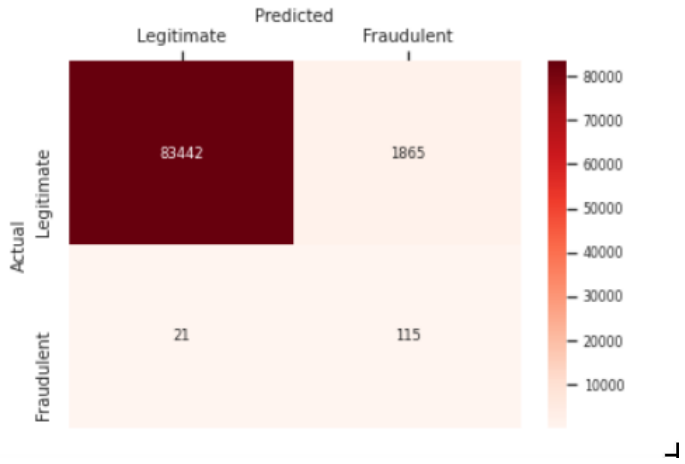

Figure 4.8: Confusion Matrix-Naive Bayes and ENN+CNN

4.3.3 SMOTE and Tomek Link Removal.

The model works well in terms of recall (Table 4.9). The model can detect 88% of the fraudulent transactions but the possibility of this being true is only 6% and this is not a good model given the very low F1 score of 11%. The model misclassify 2012 legitimate transactions as fraudulent transactions (Figure 4.9).

Table 4.9: Evaluation Metrics on Naive Bayes-SMOTE+Tomek links

Evaluation Metrics	
Precision	0.06
Recall	0.88
F1-score	0.11

Figure 4.9: ConfMat-NB and SMOTE+Tomek

4.4 Support Vector Machine (SVM)

4.4.1 SMOTE and Tomek Links.

- **The best hyperparameters were kernel=linear, C=0.01.**

Table 4.10 shows the evaluation metrics when using the SVM and SMOTE and Tomek links. The model is able to predict a very high number of the fraudulent transactions as seen in the recall 93% but the certainity that these transactions are actually fraudulent is very low 6%. The moodel is not good (Figure 4.10), 2138 of the legitimate transactions are misclassified as fraudulent transactions.

Table 4.10: Evaluation Metrics on SVM-SMOTE+Tomeklinks

Evaluation Metrics	
Precision	0.06
Recall	0.93
F1-score	0.11

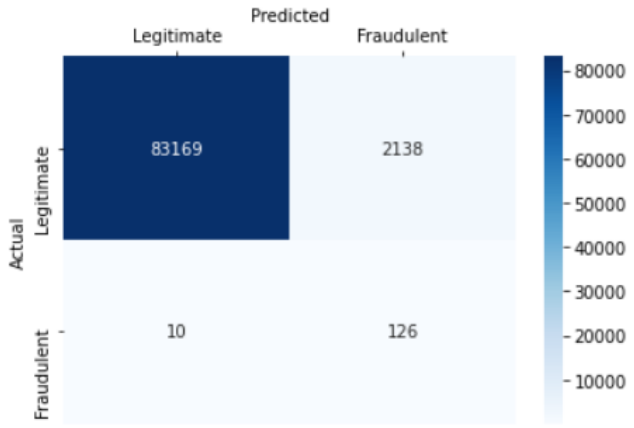

Figure 4.10: ConfMat-SVM and SMOTE+Tomek

4.4.2 Nearmiss.

- **The best hyperparameters were kernel=linear, C=0.001.**

Table 4.11, we see that both the recall and the precision are high which means this is a good model. The recall is at 82% implying that the model can detect 82% of the fraudulent transactions and from the precision, we are 80% certain that the detected fraudulent transactions are true. From Figure 4.11 we see that only 28 of the legitimate transactions are misclassified.

Table 4.11: Evaluation Metrics on SVM-Nearmiss

Evaluation Metrics	
Precision	0.80
Recall	0.82
F1-score	0.81

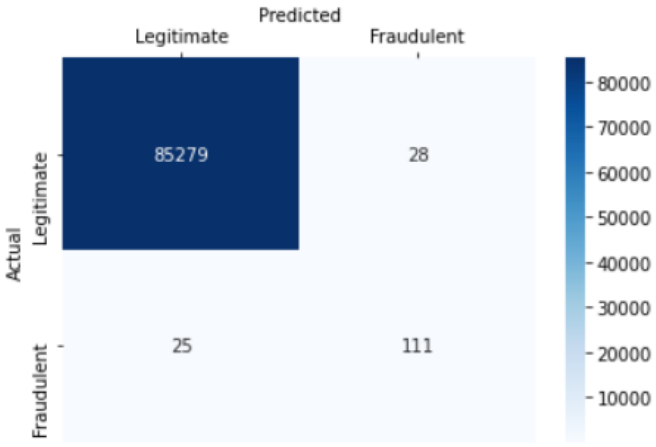

Figure 4.11: Confusion Matrix-SVM and Nearmiss

4.4.3 ENN and CNN.

- **The best hyperparameters were kernel=linear, C=0.01.**

Table 4.12, we see that the recall has increased from 82% to 83%. Now the model can detect 83% of the fraudulent transactions but the precison has decreased to 78% so we are less certain compared to the nearmiss approach and the number of misclassified legitimate transactions have increased from 28 to 31 but it is still a good model (Figure 4.12).

Table 4.12: Evaluation Metrics on SVM-ENN+CNN

Evaluation Metrics	
Precision	0.78
Recall	0.83
F1-score	0.81

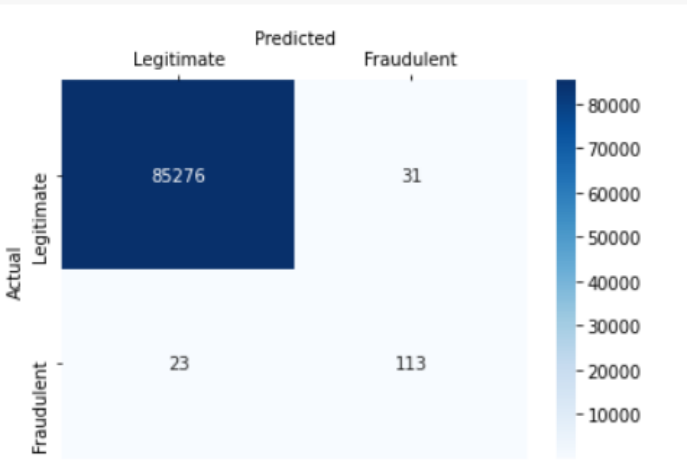

Figure 4.12: Confusion Matrix-SVM and ENN+CNN

4.5 General Discussion

Table 4.13: Summary on the evaluation of the four classifiers

Classifier	Resampling Approach	Precision	Recall	F1 score
Random Forest	Nearmiss	0.34	0.86	0.49
	SMOTE and Tomek links	0.86	0.87	0.86
	ENN and CNN	0.84	0.84	0.84
KNN	Nearmiss	0.45	0.81	0.58
	SMOTE and Tomek links	0.45	0.90	0.60
	ENN and CNN	0.82	0.83	0.83
Naive Bayes	Nearmiss	0.12	0.57	0.20
	SMOTE and Tomek links	0.06	0.88	0.11
	ENN+CNN	0.06	0.85	0.11
SVM	Nearmiss	0.80	0.82	0.81
	SMOTE and Tomek links	0.06	0.93	0.11
	ENN+CNN	0.78	0.83	0.81

Table 4.13 above shows a summary of the evaluation of the four classifiers. We see that all of them have high recall meaning that they can detect any fraudulent transaction easily. On the other hand, the precision is low for some classifiers meaning that even though they can detect the fraudulent transactions most of them are a misclassification of the legitimate transactions. The code for the obtained results is available on GitHub (here)[1].

Random Forest works well with SMOTE and Tomek Links as well as ENN and CNN. Because of its ensemble nature, Random Forest can deal with imbalanced data so when some resampling is done the classifier performs very well. NearMiss does not work well with Random Forest because Random Forest works well with a large dataset.

[1] All the codes used to perform the experiment is provided here: https://github.com/Njoki/Credit-Card-Fraud-Detection-Model.git

The K-NN is a nearest neighbor approach and that is why it works well when it comes to ENN and CNN since they are also nearest neighbor resampling approaches. Though in the other two approaches the recall is high, the misclassification rate is also likely to happen as seen in the low precision. Naive Bayes does not work well with any of the resampling approaches. This is because of the naive assumption it makes of feature independence which is not likely to happen in real data.

SVM works well with a small dataset and that is why Nearmiss and ENN and CNN work well because they are undersampling techniques. Another reason is that the classifier looks for the hyperplane with the maximum margin that separates the two classes and using the two resampling approaches, they make this easy and thus giving very good results.

5. Conclusion and Future Work

This research was carried out to detect fraudulent transactions when payments are made using credit cards by carrying out a predictive analysis using machine learning algorithms. The dataset used is from Kaggle dataset website which is taken from a European bank in 2013. The main objective was to deal with the highly imbalanced data and evaluate the best models from the four classifiers, Random Forest, Support Vector Machine (SVM), K-Nearest Neighbor (K-NN) and Naive Bayes that best detects these fraudulent transactions. The resampling techniques used were Nearmiss, Synthetic Minority Oversampling Technique (SMOTE) and Tomek links as well as Edited Nearest Neighbor (ENN) and Condensed Nearest Neighbor (CNN). The four classifiers were evaluated using the metrics, recall, precision and F1 score.

When using NearMiss, SVM performed better than all the other classifiers. It had a recall of 82%, a precision of 80% and an F1 score of 81%. Random Forest worked well with the hybrids of SMOTE and Tomek Links Removal and also ENN and CNN but SMOTE and Tomek Links Removal worked well as it had a recall of 87%, a precision of 86% and an F1 score of 86% compared to the latter which had 84% for all the three evaluation metrics.

K-NN works well with ENN and CNN with a recall of 83%, a precision of 82% and an F1 score of 83%. Naive Bayes performed poorly in all three resampling approaches due to the naive assumption of features been independent.

In conclusion, Random Forest recorded the best results compared to the other four classifiers and this is because it is an ensemble classifier and so it can deal with the imbalance nature of the data.

In the future, when we have computational resources such as high-performance computers (HPC), we can perform hyperparameter tuning using advanced methods that are likely to improve the performance of these classifiers. They will also save on the time spent when training the models. Also, we can include the cost-sensitive approaches to solve the class imbalance that will take care of misclassification costs as this is important to financial institutions.

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