FYS-STK3155/4155 Project 3: Comparisons of machine learning techniques for credit card fraud detection

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Abstract

In this paper we have looked at credit card transactions for a 48 hour period to see if we can train models using machine learning techniques to detect fraudulent transactions. Our dataset was very imbalanced, where the fraudulent transactions was only 0.0172 % of all transactions. We decided to undersample the dataset, where we removed random parts of the legitimate transactions, so we can train and test the models with more balanced data. We decided to try different ratios for the fraudulent to legitimate transactions ratio, which were 1:1 and 1:100, where the format is frauds:non-frauds. We also decided that the recall score was the main focus for our project, because we wanted our methods to find all of the frauds.
We tested four methods in this project, which were Logistic Regression, Neural Network, Decision Tree and Random Forest. Here we saw that Neural Network performed the best with a recall score of 0.9355 for 1:1, also having both a good cross-validation score and test score in both ratios, but was time-consuming. Logistic regression came in second, but took a lot less time and was unstable for ratio 1:100. Random Forest and Decision tree was ranked third, as they were prone to overfitting at oversampled values, although they performed well at the ratio 1:1.
Based on these result we recommend Neural Network as the best classifier in this case, but Logistic Regression is better if you want a less time-consuming method.

The material for this project can be found in our GitHub-repository at:
https://github.com/michaesb/machine_learning_3.git

1 Introduction

In this paper we look at fraud detection in credit card data. Today, credit cards are susceptible to fraudulent transactions and this can charge customers for items they did not purchase. Credit card companies need to recognize these frauds, but because of the sheer number of transaction that happen, they become needles in a haystack. This makes it a big task to investigate manually, but machine learning techniques can help us perform the data analysis. Machine Learning is today a growing field with numerous breakthroughs, which can offer high accuracy identifiers to find the fraudulent transactions. This allow banks to better handle frauds and consequently prevent the cost for the customers. We will here look at credit card transactions for a 48-hour period and create a model of the frauds and non-frauds using four machine learning methods and compare their performance.

We will first go through the theory of some of the methods and the score functions and present the dataset and the results of the methods. Then, we discuss the results in and come with our conclusion.

2 Theory

Credit Card data

We got the credit card transactions data from the Kaggle site. The data was collected over two days in September 2013 and it's specified that this is European cardholders. The datasets contains features which is the information around the transaction and whether the transaction is fraudulent or not.

Classification Methods

A regression method is a method using a statistical process to determine the output based on the relationship between one or multiple input parameters. We will in this paper utilize four methods, but we will explain the function only for decision tree and random forest.

For more information on how Logistic Regression and Neural Network works, we invite the reader to check out a previous report on Regression Methods and Neural Network [5].

Logistic Regression

We will not go into the workings of Logistic Regression, but we will mention the different parameters it needs to function. Logistic regression is a simple, yet

powerful method for creating classifiers with a good prediction. The parameters for Logistic Regression include a learning rate, which defines how much it varies the parameters to find the best minimum point. It also includes two different options for the penalty called L1 and L2 and we can also put a limit on the number of iterations the function performs. Note that it is the parameters for `Scikit-Learn` that is our focus in this assignment.

Neural Network

As with Logistic Regression, we will mainly focus on the parameters given to the Neural Network.

Neural Network has a great deal of parameters, from the number of layers in the network, number of neurons in a layer, penalty choice, and limit to the iterations. Neural network has an almost infinite amount of permutations and is difficult to find the best solution for our data.

Decision Tree

Decision Tree is one of the easier methods to understand and is less of a black box compared to other machine learning algorithms. It bases on sorting information and by using a condition, for example $x_1 < 10$, it then decides if it moves to the "false" node or the "true" node. This process continues until it reaches the bottom node or also called leaf. Here it will be classified and can give an output based on which leaf the sample ended at. In order to find a good Decision Tree, the algorithm must decide if the tree should split into two branches and what feature should cause the split. To do this we use a gini index, see formula (1). The p in the formula is the probability of it being classified to a particular class. The gini index tells us how important each feature is. This let's us find the best divides for the branches. An example of an algorithm that calculates this, is the CART-algorithm[1], which can be used both for classification and regression.

$$G = 1 - \sum_{i=1}^{n} (p_i)^2. \tag{1}$$

See graph 6 for an example of a Decision Tree.

Random Forest

Decision trees have some drawbacks that sometimes make it difficult to obtain a stable predictive performance. This is especially the fact that Decision Trees are really prone to overfitting data. It depends a lot on many factors such as the size and balance of the dataset, number of features and if features are continuous or categorical and so forth. This can be avoided by using other methods such as boosting, bagging and random forests. What these other methods have in common is that they create several trees instead of one, and improves the performance of the model.

Random forest is a form of bagging, and it creates a jungle or forest of trees, in order to avoid overfitting to the training set. The drawback of creating a multitude of trees with this algorithm, instead of using the Decision Tree, is that we again return to a black box. It is not as easy to interpret the model as for the diagram created from the decision tree.

The random forest method creates several bootstrapped training samples and then builds trees from those training samples. A difference from the decision tree to random forest is when creating the splits in the trees. When creating a split, we randomly choose m of the total p features, and then choose one of these features to create the new branches. Normally we choose the sub-sample m to be

$$m = \sqrt{p}.$$

The reason for choosing only between m of the p features is that there might be some predictors that are more important than the others, causing the splits to often use the same predictors, thus making many of the generated trees similar. Limiting the choice of feature for splitting then generates a forest of trees that are different, increasing the search in the fitness space of the dataset.

Methods in Scikit-Learn

For this whole project, we decided on using `Scikit-Learns` machine learning methods. The methods in `Scikit-Learn` are tested and proven, so that the the work in this project goes to finding good parameters and comparing the results of the different methods.

We used `Scikit-Learn's LogisticRegression`, `MLPClassifier`[2], `DecisionTreeClassifier` and `RandomForestClassifier`. Each of these methods have a multitude of different parameters that we can adjust to create a good classifier, so we need a method for choosing the values for the parameters.

Grid search is one method for finding parameter-values that optimize the score of our choosing. Grid search is a very simple algorithm that structurally goes through every parameter chosen by the user, creates a model and predicts the output. It then lets us see what parameters caused the best score. The `GridSearchCV` method we chose in `Scikit-Learn` uses cross-validation to improve the scores. This method also allows us to choose the score function we'd like to optimize.

[1] Classification and Regression Trees

[2] MLP: Multi Layered Perceptron. A version of neural networks.

Testing the models

In order to test our models, we use multiple score functions to determine different properties for each of the models.

	Actual 1	Actual 0
Predict 1	TP-True Positive	FN-False Negative
Predict 0	FN-False Positive	TN-True Negative

Table 1: Confusion Matrix to display the different outcomes possible when comparing the model to the actual result.

We will look into an accuracy function as a way to determine how accurate it is to predict both legitimate transactions and frauds. See formula (2). This will measure the general performance of the model.

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

We also look at the precision, which is defined as how many of our predicted frauds are actual frauds. See formula (3).

$$\text{Precision} = \frac{TP}{TP + FP} \tag{3}$$

We also have a measure of its ability to detect frauds, called recall score. See formula (4). Much like precision, it focuses only on one type of prediction and ignore the other.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

3 Results

Data processing

For the dataset we chose, most of the features are made up from anonymous data, due to privacy of the users, so we don't get any information on what those features mean in a practical sense. There are 30 features in total, and the only two features that aren't anonymous data is the "Time" and the "Amount" feature. The time feature just states when, in time, the transactions took place after the first transaction. The amount feature says how large the transactions were.

Although 28 of the features are unknown, the description specified that the unknown parameters are the result of a PCA (Principal Component Analysis) dimensionality reduction. This means that the only features that hasn't been transformed by PCA are the "Time" and "Amount" features. Since 28 of the 30 features are transformed, we decided not to perform any more PCA reduction on the features.

Because of the unknowns in the features, we decide to not focus on which parameter is most important, but on the performance of the methods.

The dataset has a total of 284 807 transaction, with only 492 of them being fraudulent, as you can see in figure 1. This fact makes this dataset highly imbalanced, where 99.827 % of the dataset are zeros, e.g. regular non-fraudulent transactions.

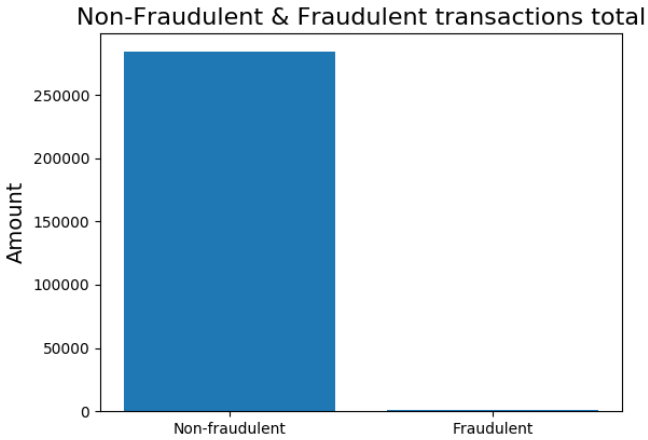

Figure 1: Here you can see the distribution of non-frauds and frauds in the dataset. As you can see the dataset is imbalanced, which can make it difficult for the methods to process.

To deal with the highly imbalanced classes, we make use of undersampling techniques in order to even out the two classes. We used a simple randomized undersample where we just randomly pick out the same amount of non-fraudulent samples as there are fraudulent samples. With this we end up with a much smaller, but balanced dataset, as you can see in figure 2. This dataset now only has 984 samples, and a possible solution to the now small dataset, would be to not undersample with a 1:1 ratio, but rather 1:2, 1:4, or 1:10. This would give us more data to work with, while we still have enough fraudulent transactions in the dataset.

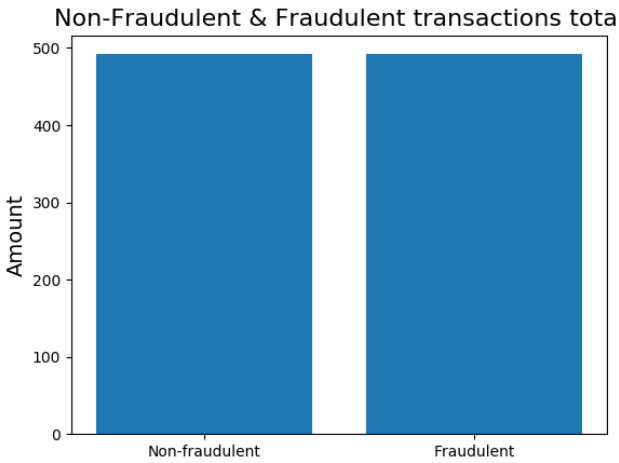

Figure 2: Here we have performed undersampling on our data with a ratio 1:1 and display that amount is equalized

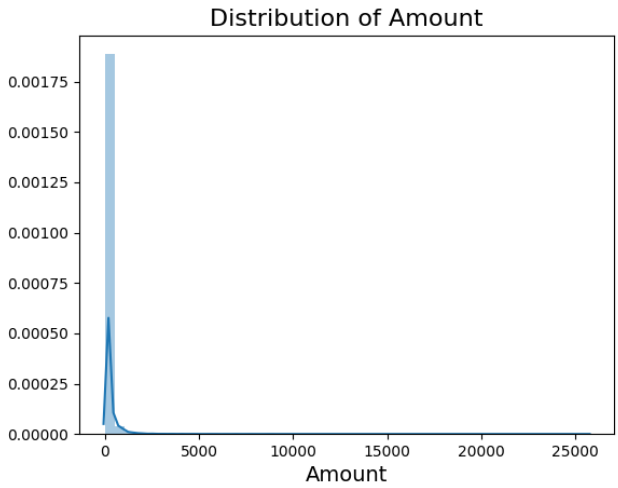

Figure 4: Distribution of the amount. Most of the amounts below 250, but there are a few larger amounts, the highest being 25691. The dataset doesn't specify which currency is used, but considering this being in Europa, we can guess this is in Euros.

We continued to look deeper at the dataset, and made two distribution plots for the "Time" and "Amount" features, as you can see in figures 3 and 4. This plot creates a histogram to give us more info on how the inputs are distributed. In the time-distribution plot, we can tell now it took place in a 48-hour window and we can see there are two big "centers" in time where most of the transactions took place during the day.

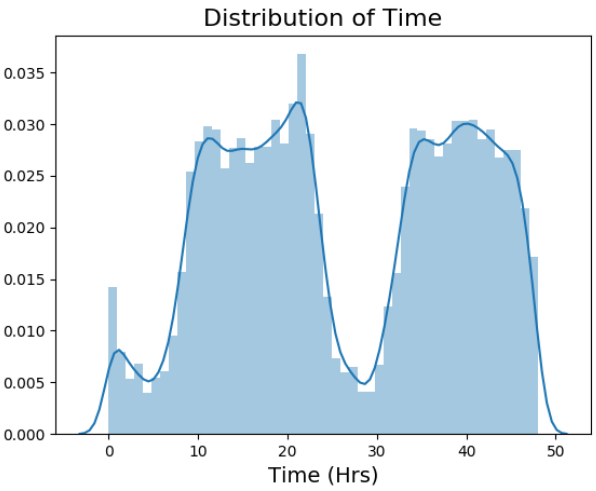

Figure 3: Here we see the distributions of transactions as functions of time. We see the two peaks in the middle of the day, which showed that most of the transactions happened during the day.

Finally, we used `Scikit-Learn`'s `StandardScaler` to scale the data. Time and amount were the only features that needed scaling.

We plotted the performance on decision tree as to see how the scores behaved at different ratios. This can be seen in graph 5. We choose to do this with decision tree, because it's a lighter method compared to the others, and we wanted to get a grasp of different ratios affected the score functions.

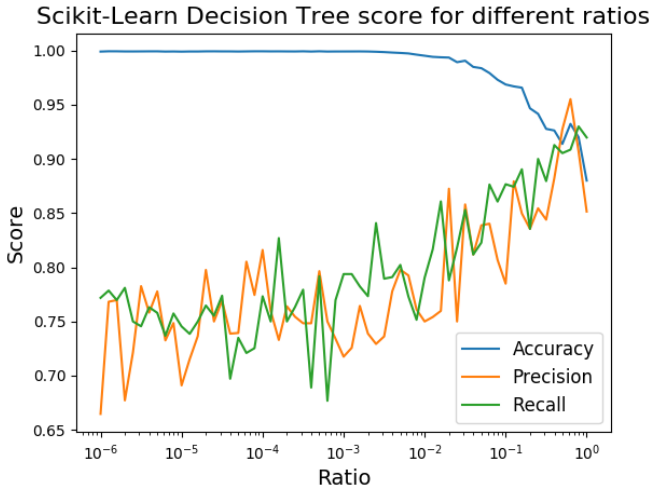

Figure 5: Plotted the accuracy, precision and recall score as functions of the ratio between the number of frauds and non-fraudulent transactions. The smallest dataset with a 1:1 ratio is at the far right, and the dataset is increasing as the graph moves to the left.

We see two interesting areas in graph 5 at ratio

1:100 and higher, where it seems to be quite constant, and ratio 1:1, where the accuracy and precision + recall meet. From ratio 1:100 and higher, it seems saturated, we decide to look at ratio 1:100, as it's the smallest ratio that still seem saturated. We are also interested in the ratio 1:1, where the recall and precision is at its best. These are the ratios we will look into with our methods in our reports, and we present the scores for these ratios in table 2 and 3.
In this project, we have decided to focus on the recall score. The reason for this is that we think that it's more important to reduce the number of frauds being classified as legitimate (False Positives), than classifying a legitimate transactions as fraud (False Negatives). We think that our algorithm is best used as a way to identify frauds, but should be checked by someone or something else. Because of this, our model should be used to bring fourth candidates for the investigators, where it will tag too many transactions, but few frauds will be missed by the model. Therefore we will focus on creating a model where the recall is at its best, but not ignoring accuracy and precision. We have adjusted the grid search to find the best value of recall when we have looked for the best model.

Logistic Regression

The first machine learning method we tried for this dataset is logistic regression.

To start, the logistic regression in `Scikit-Learn` takes a lot of parameters, but we choose to optimize the parameters "penalty" and "C", while using the solver "liblinear". The penalty can be chosen to be "l1", "l2", "elasticnet" or "none", and it specifies which norm to use in the penalization. By using the "liblinear" solver, we can use "l1" or "l2" penalty. The parameter "C" specifies the strength of the penalization, or regularization. More accurately, it is the inverse of the regularization strength.

With our grid search method, we found that the best parameters for the logistic regression are `C = 0.01` and `penalty = "l1"`. This gave a score of

CV Recall Score: 0.9496.

Neural Network

The second method we used is the neural network in `Scikit-Learn` called `MLPClassifier`.

The parameters of the `MLPClassifier` are many and sometimes difficult to understand. For our neural network we chose to use an adaptive learning rate, with an initial rate of 0.001, and a tolerance of 10^{-4}. The parameters we optimize with our grid search is the activation function, the regularization parameter "alpha", the number of neurons and layers, the maximum iterations in the algorithm and finally which solver to use. Most of the parameters we used are self-explanatory, but some are not. The solver, for example, is the solver deciding the weight optimization, using different versions of gradient descent and so forth.

The grid search found the best parameters to be the sigmoid/logistic activation function, `alpha = 0.1`, 4 hidden layers with 30 neurons in each, a maximum iteration of 500 and the solver "lbfgs". With these parameters we got a score of

CV Recall Score: 0.9555,

Decision tree

We also tried using a decision tree for classification because of its simplicity and interpretability. The exact method we use is `Scikit-Learn`'s `DecisionTreeClassifier`. It also has a bunch of different parameters to choose from, and we ended up optimizing the criterion of a split, the maximum depth of the tree, the leaf node minimum samples, the minimum number of samples to create a split and the number of features for creating a split. When using the grid search we found the best parameters to be the splitting criterion gini, maximum depth of 20, maximum features of 30, minimum sample leaf of 1 and a minimum samples for split of 2. This gave us the score of

CV Recall Score: 0.9367.

The decision tree we ended up with for the parameters above, can bee seen in figure 6

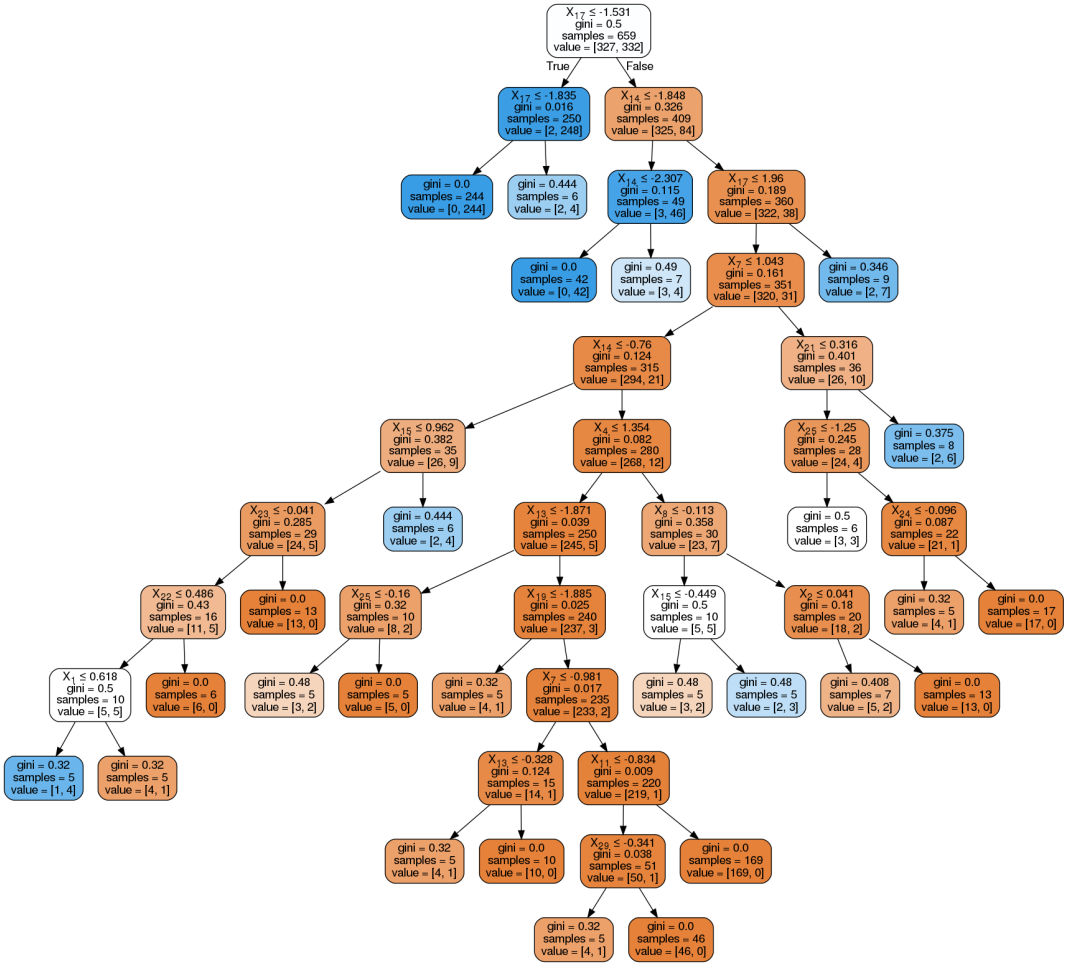

Figure 6: Here you can see how a decision tree check data at each node and redirects the data to one of the two branches all the way down to the final node called the leaf. This decision tree that was used in our project.

Random Forest

Lastly, we made a model using a random forest method. This method is part of `Scikit-Learns` ensemble methods, and is called `RandomForestClassifier`. As all the other methods, it takes a lot of parameters and can be very much tuned. For optimization with grid search, we chose the parameters for maximum tree depth, maximum features considered for a split, minimum samples required for split, minimum samples at a leaf node, splitting criterion, and the number of estimators, i.e. the number of trees in the forest. When using the grid search we found the parameters that optimized the recall score are the splitting criterion gini, a maximum depth of 15 nodes, maximum features of 30, minimum samples for a leaf of 1, a minimum samples for split of 10 and using 10 decision trees. With these parameters we got a score of

CV Recall Score: 0.9371.

Comparison

Method	CV Recall Score	Test Recall Score	Test Precision Score	Test Accuracy
Logistic Regression	0.9496	0.9226	0.8994	0.9138
Neural Network	0.9555	0.9355	0.9062	0.9231
Decision Tree	0.9367	0.9250	0.8970	0.9108
Random Forest	0.9371	0.9138	0.9464	0.9262

Table 2: Here we have presented the scores for the different methods with a ratio of 1:1. When running these methods, the neural network and random forest took the longest running grid search, and decision tree and logistic regression needed less time.

Method	CV Recall Score	Test Recall Score	Test Precision Score	Test Accuracy
Logistic Regression	0.7882	0.8373	0.9329	0.9977
Neural Network	0.8342	0.8434	0.8434	0.9968
Decision Tree	0.8416	0.7927	0.9848	0.9978
Random Forest	0.8537	0.7953	0.9577	0.9975

Table 3: Here we have presented the scores for the different methods with a ratio of 1:100. When running these methods neural network and random forest took the longest running grid search, and decision tree and logistic regression needed less time. Since this was a larger dataset than the other ratio in table 2, therefore it took longer to run.

4 Discussion

We decided that the main focus of this projects was to test different machine learning methods for a specific dataset and try to find which parameters optimized the score for each of the methods. As stated earlier in the report, we decided to optimize the method parameters to maximize the recall score in (4). The recall score basically tells us how many of the total fraudulent transactions our prediction models manages to classify correctly. We decided its more important to classify all of the fraudulent transactions and maybe then some, rather than classifying all the non-fraudulent transactions correctly.

The method we used to optimize this recall score was the grid search method, which uses brute force, to test all the different permutations for the parameters. This grid search can be very time-consuming for a large number of parameters, and there exists another method called randomized search, that lets you go through a bigger variety of parameters to obtain a good score without being so time-consuming.

What also would be very interesting to take a look at in this project, is testing our models, trained on the undersampled dataset, on the full imbalanced dataset of 284807 samples. We would recommend trying this for getting more practical and useful scores for the different models.

Logistic Regression

Logistic regression is a simple, yet trustworthy method for classification problems. It performs surprisingly well on classifying the fraudulent transactions in the dataset provided, with a cross-validation recall score of 0.9496 for the undersampled, now balanced, dataset.

In this project, we decided on using the solver "liblinear" for our logistic regression. The other options were "newton-cg", "lbfgs", "sag" and "saga". The documentation states that the "liblinear" solver is good for small datasets with binary classification, while still having the capability to use both L1 and L2 penalties. This is why we went for the "liblinear" solver, but we would recommend also trying out the different solvers, especially if you have larger datasets.

Neural Network

Neural networks are good at finding a good model for complex data, but not always as good, when using simple data, compared to the other simpler methods. Still, neural networks seem to perform well across a large variety of examples, when tuned correctly. A downside of using a neural network over other methods is the vast amount of parameters that can be tuned, as stated in the results section of this report. It is difficult to find the best parameters because of how many parameters there are, and our grid search method took a really long time going

through all the different permutations of parameters. This is why we again suggest using the randomized search for finding these parameters.

One disadvantage of the `MLPClassifier` from `Scikit-Learn` is that you can not choose different activation functions for different layers, and it would be interesting to test with different activation functions using for example `TensorFlow`.

Decision Tree

The perks of using decision trees is without a doubt the interpretability of the method. As stated, they create a visual tree, as in figure 6, you can inspect and actually understand, compared to the black box models of the other methods. In this method there also are a lot of parameters that can be tuned, but luckily the fitting process of this method is rather quick, so you can search through many parameters to obtain a good prediction. The disadvantage of decision trees is that they unfortunately tend to overfit to the training dataset, causing poor predictions for the test set. Also, you can see in figure 5 how the decision tree performs for different undersampling ratios. We see that the recall and precision performs best at the 1:1 ratio of fraudulent and non-fraudulent transactions. This might be because the methods can't make good models for predicting fraudulent transactions when there aren't a bigger percentage of fraudulent transactions in the dataset

Random Forest

The random forest method tweaks the decision tree method to create a more stable method, less prone to overfitting. The random forest creates a bunch of different decision trees, and uses a randomized feature choice for splitting the branches. Because of the many different decision trees in the random forest, it manages to circumvent the problem of overfitting, but it brings along a new problem; readability. The cost of avoiding overfitting is that it is now again more difficult to read and interpret the resulting model. Random forest works well, but for this dataset it didn't perform any better than the decision tree model.

Comparison

We see in table 2 and 3 a comparison of the methods. In the first table we have the different scores for an undersampling ratio of 1. That means there are as many fraudulent as there are non-fraudulent transactions, while in the second table there are 100 times more non-fraudulent than fraudulent transactions. As stated before we decided we are most interested in a good recall score, which will be our main focus. We see that for a 1:1 undersampling, the neural network has the best recall score for both cross-validation and the test set, while logistic regression comes in at a good second place. Random forest seems to get the best precision score, which means it is good at predicting correct frauds, but not getting all of them. For the 1:100 undersampling ratio, it is still the neural network that is overall performing best. And the other methods follow the same rank as for 1:1 ratio, and this makes it easy to see that the neural network was the best method for prediction in this dataset.

5 Conclusion

We have compared four methods in this paper with focus on their ability to detect fraudulent transactions. To find the best model we used a score function called recall score. We tested these methods for two datasets, one with the same amount of fraudulent and legitimate transactions and one where there were 100 times more legitimate transactions than fraudulent transactions.

For both datasets, we have ranked method as such:

1. Neural Network
2. Logistic Regression
3. Random Forest + Decision Tree

Neural Network was however quite a time-consuming model to train although it was stable, so Logistic Regression could be preferable in some cases.

We saw that although Random Forest is known to be better at overfitting than Decision Tree, we see that in ratio 1:100, it did not perform better than Decision Tree in this case here, when the dataset is quite unbalanced. We have put them in equal third place, because although Random Forest performed better than Decision tree, it took a lot longer, so we ranked them equally in this project.

There are many machine learning methods that we haven't tested for this e.g. Boosting methods, support vector machines, and bayesian algorithms and we suggest trying them in order to see if they perform better than the methods tested here.
We also recommend trying the same methods with more data, so we can train and test our models better.
We also suggest testing randomized search from `Scikit-Learn` in order to find a better model and do a more thorough searches of the fitness space.
We used `Scikit-Learn` in this project, but `TensorFlow` is worth looking into, where one can adjust the activation function for the different layers.

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Due to request from data holder Machine Learning Group - ULP, we have cited the works below.

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