Machine Learning Engineer Nanodegree

Capstone Project

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1. Definition

1.1 Project Overview

Fraud Detection is a very important research area for businesses and banks since it has a direct impact on their profits. There are many industries that have an interest in detecting fraudulent behaviour as early as possible: Banks need to identify criminal transactions that are drawn illegally from their customers' accounts, telecommunication companies need to know if the customer is trustworthy for a device payable by instalment and insurance companies desire to reveal insurance fraud.

The European Central Bank estimated that in 2012 the total value of credit card fraud was about to be 1.33 € billion in 2012, which represents an increase of almost 15% compared to the previous year (European Central Bank, 2014). This example illustrates that fraud is a very important issue that companies and banks are highly interested in fixing. Therefore different data mining and machine learning methods are in use, such as classification, regression, clustering or prediction techniques in order to detect fraudulent cases (Dal Palozzo, 2015).

The data for the analysis are credit card transactions generated by European credit cardholders. The dataset contains 0.172% cases of fraud. It was released by a research collaboration of Worldline and the Machine Learning Group of the University of Bruxelles (ULB) (Caelen, Dal Pozzolo, Johnson, & Bontempi, 2015). The datset is downloadable from kaggle under https://www.kaggle.com/dalpozz/creditcardfraud.

The aim is to classify whether a transaction is fraud or not. Therefore I am going to apply different supervised learning methods and compare the results to each other in order to find out which one performs best.

1.2 Problem Statement

A bank institute is interested in identifying credit card fraud as early as possible in order to avert damage from its customers and from themselves. The aim is to predict for a transaction whether it is fraud or not. Therefore they can apply machine learning and data mining methods that use past data which is already classified in fraud and non-fraud cases. This data should have one dependent variable (1=fraud/0=no fraud) that is going to be predicted and several independent variables such as amount of transaction, timestamp of transaction, target destination/country, country of transaction origin, frequency of transactions of card holder, ratio of foreign transations of card holder and so on. The quality of the model depends also on the quality of the predicting variables.

With using supervised learning methods such as regression, decision trees, neural networks, SVM or Bayes Learning it is possible to train a model that will predict whether a case is fraud or non-fraud when given new, previously unseen data. After examination whether the prediction was right or not, those cases can be used to update the algorithm and to make it better (this is the machine learning part).

The objective of the project is to build a model that is able to predict whether a transaction is fraud or not. I am going to implement different supervised learning methods:

- Logistic Regression (this will be the benchmark model)
- Support Vector Classifier
- Decision Tree
- Random Forest Classifier

1.3 Metrics

There are classic accuracy measurements such as

- Accuracy = (TP+TN)/Total
- Precision = TP/(TP+FP)
- Recall = TP/(TP+FN)

True Class ↓Predicted Class→	Fraud (1)	Non Fraud (0)
Fraud (1)	TP = true positive	FN = False negative
Non Fraud (0)	FP = false positive	TN = True negative

In our case it is important to maximize the number of true positive labelled cases and to minimize the false negative labelled cases. The false positive cases are not as bad for the business as the false negative cases, because the latter will cause tremendous harm to the business. The false positive cases will probably result in extra work for manually checking whether it is really fraud or not. This makes *Recall* an important metric to examine. Accuracy is not the measurement of choice because the data is highly imbalanced and precision does not take the worst case of false negatives in account (Descoins, 2013).

The authors of the dataset already point out the difficulty due to the imbalance of fraud and non-fraud cases and therefore recommend using the *Area Under the Precision-Recall Curve* (Caelen, Dal Pozzolo, Johnson, & Bontempi, 2015; Dal Palozzo, 2015). The Precision-Recall Curve is calculated as plotting a set of pairs of precision and recall for a number of thresholds and connections those dots with a line. Then the area under the curve can be calculated as definite integral (Richardson & Domingos, 2006).

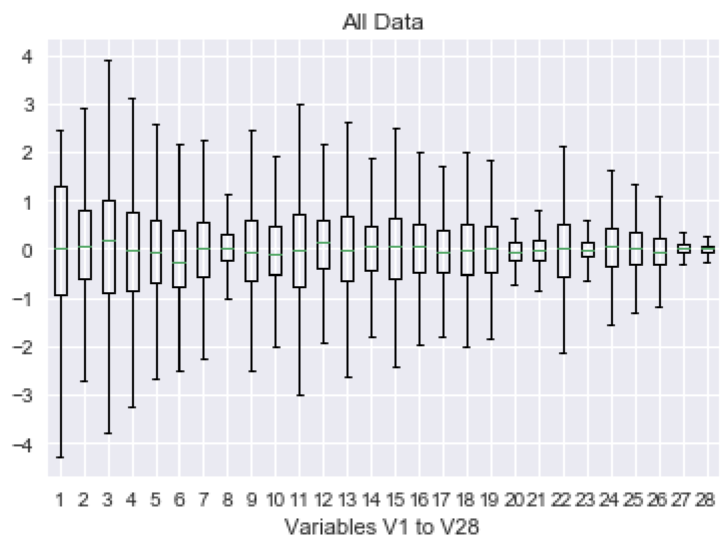
I am going to consider both recall and area under the precision recall curve.

2. Analysis

2.1 Data Exploration and Visualization

The dataset used for my analysis contains 284,807 credit card transactions of European credit cardholders whereof in 492 cases fraud was detected, which is only 0.172%. The variables of the dataset are all transformed by a PCA transformation and unfortunately there is no meta data that explains the meaning of the variables (due to confidentiality). There are 2 variables that are not transformed: “time” and “amount”, whereas the latter is the amount of the transaction and the first is the time between each transaction and the first transaction in seconds. The variable “Class” is the response variable (1=fraud, 0=no fraud). The dataset is real world data that was published by a research collaboration of Worldline and the Machine Learning Group of the University of Bruxelles (ULB) (Caelen, Dal Pozzolo, Johnson, & Bontempi, 2015).

To get a graphical overview I plotted all 28 variables as boxplots into one graph:



Even though the data is already transformed by a PCA there is still a lot of variance between the variables. For example, variables 27 and 28 have a small variance and variable 3 has a big variance, which can be seen when looking at the size of the box and the range of the whiskers. For variable 27 and 28 the box is very short, the upper and lower quartiles are quite close to each other and the whiskers are not too far apart. For variable 3 the box is much taller, which means that upper and lower quartiles (which include 50% of the data) are far apart as well as the whiskers. The median (the middle line of the box) is for all variables very close to zero.

The following table shows the statistics for the data:

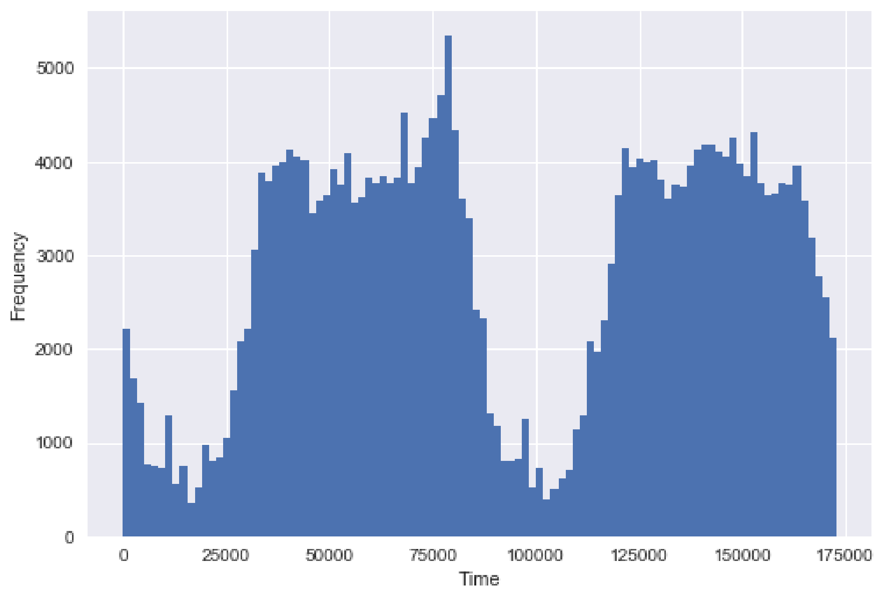
	Time	V1	V2	V3	V4	V5	V6	V7	V8	V9
count	284807	284807	284807	284807	284807	284807	284807	284807	284807	284807
mean	94813.86	0	0	0	0	0	0	0	0	0
std	47488.15	1.959	1.651	1.516	1.416	1.38	1.332	1.237	1.194	1.099
min	0	-56.41	-72.72	-48.33	-5.683	-113.74	-26.16	-43.557	-73.22	-13.434
25%	54201.5	-0.92	-0.599	-0.89	-0.849	-0.692	-0.768	-0.554	-0.209	-0.643
50%	84692	0.018	0.065	0.18	-0.02	-0.054	-0.274	0.04	0.022	-0.051
75%	139320.5	1.316	0.804	1.027	0.743	0.612	0.399	0.57	0.327	0.597
99%	170560.9	2.237	3.802	2.728	4.248	3.425	4.2	2.696	2.076	2.987
max	172792	2.455	22.058	9.383	16.875	34.802	73.302	120.59	20.007	15.595

	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19
count	284807	284807	284807	284807	284807	284807	284807	284807	284807	284807
mean	0	0	0	0	0	0	0	0	0	0
std	1.089	1.021	0.999	0.995	0.959	0.915	0.876	0.849	0.838	0.814
min	-24.588	-4.797	-18.68	-5.792	-19.21	-4.499	-14.13	-25.163	-9.499	-7.214
25%	-0.535	-0.762	-0.406	-0.649	-0.426	-0.583	-0.468	-0.484	-0.499	-0.456
50%	-0.093	-0.033	0.14	-0.014	0.051	0.048	0.066	-0.066	-0.004	0.004
75%	0.454	0.74	0.618	0.663	0.493	0.649	0.523	0.4	0.501	0.459
99%	3.254	2.291	1.699	2.514	2.15	1.926	1.875	2.29	2.069	2.263
max	23.745	12.019	7.848	7.127	10.527	8.878	17.315	9.254	5.041	5.592

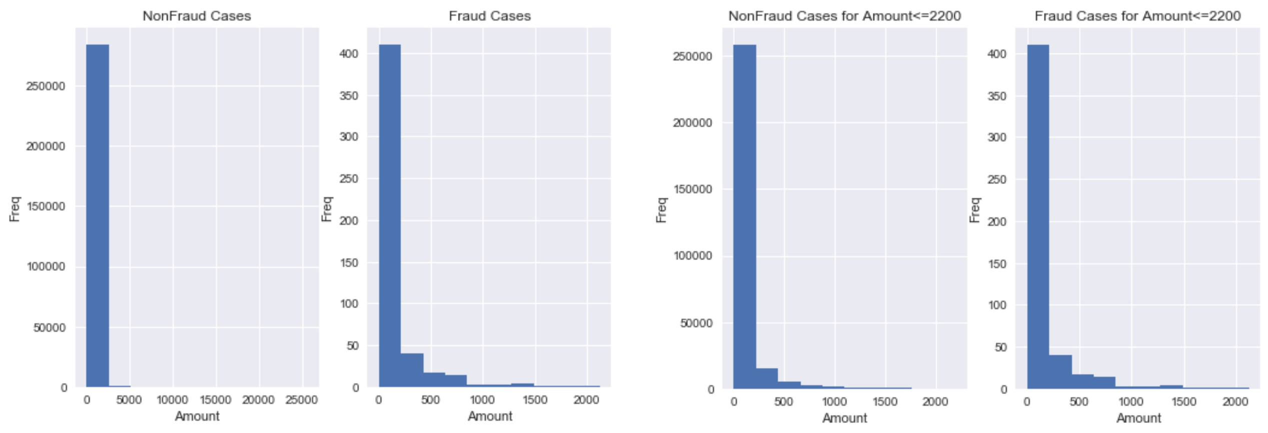
	V20	V21	V22	V23	V24	V25	V26	V27	V28	Amount
count	284807	284807	284807	284807	284807	284807	284807	284807	284807	284807
mean	0	0	0	0	0	0	0	0	0	88.35
std	0.771	0.735	0.726	0.624	0.606	0.521	0.482	0.404	0.33	250.12
min	-54.498	-34.83	-10.93	-44.81	-2.837	-10.295	-2.605	-22.566	-15.43	0
25%	-0.212	-0.228	-0.542	-0.162	-0.355	-0.317	-0.327	-0.071	-0.053	5.6
50%	-0.062	-0.029	0.007	-0.011	0.041	0.017	-0.052	0.001	0.011	22
75%	0.133	0.186	0.529	0.148	0.44	0.351	0.241	0.091	0.078	77.165
99%	2.412	1.932	1.53	1.509	1.064	1.204	1.159	0.931	0.541	1017.97
max	39.421	27.203	10.503	22.528	4.585	7.52	3.517	31.612	33.848	25691.2

All variables have 284,807 values, which is also the number of records and means that there are no missing values. All variables are numerical, except the target variable “Class” which is categorical with 0 meaning non-fraud and 1 meaning fraud. Variables V1 to V28 are already transformed which can be seen by looking at mean, which is 0 for all variables, and standard deviation, which is close to 1. As already seen in the boxplots there is nevertheless some variance since the maximum and the 99% quartile have a huge range, e.g. for variable 10. Therefore I am going to set all values above the 99% quartile to the value of the 99% quartile.

The variables Time and Amount are not standardized. Since 'time' represents the seconds between the first transaction in the dataset and each transaction it has not much analytical value and can therefore be eliminated.



The variable “Amount” has a mean of 88 and the maximum is for the fraud data different than for the nonfraud data: Fraud data has a maximum amount of 2,125 and normal data has a maximum amount of 25,691. The first two graphs show the amount for non-fraud and for fraud cases. The third and fourth graphs are zoomed in for amount less than 2,200. This shows that the distribution is similar for both. Therefore I am going to normalize the amount variable since this has not been done before and not scaling would result in overweighting the variable with the larger scale.



2.2 Algorithms and Techniques

As benchmark model I'm going to use a logistic regression. Logistic regression models are very common in real world industries for use cases such as Credit Scoring. They are used to predict whether an individual customer is likely to commit fraud and not to be able to pay the monthly amount. It can be used when the dependent variable is binary (which is the case in this analysis) and when the aim to predict the probability that a person is going is going to do something. The assumptions of linear regressions, e.g. normal distribution of residuals, can be violated. The only necessary assumption is that there exists a smooth linear decision boundary and after transformation it can even handle non-linear decision boundaries. It is quite robust against outliers. It is easier to interpret especially when you have a lot of independent variables. With a lot of independent variables running time is still quick and the estimation is still reliable. It gives insights into the impact of the predictors and its significance (Logodds resp. odds ratio) (Rae, Krishnan, Kolluru, & et al.)

For the challenging models I am going to implement a SVM , a decision tree and a Random Forest Classifier.

SVM is suitable for classification and for regression problems. It avoids overfitting, since not all data points are relevant for the decision boundary. It is possible to set a penalty parameter for dealing with data that has a location violating the decision boundary. By using the kernel trick you can use SVM also for non-linearly separable data. Also with using the kernel trick you can take advantage of domain knowledge. It performs well when there are lots of input variables. But with having more observations and more variables running time can get quite large. It is not intuitive and not easy to interpret. It is necessary to do data preparation beforehand and to tune the parameter by an expert (OracleHelpCenter, Support Vector Machines; Support Vector Machine).

Similar to logistic regression, decision trees can be applied in marketing in order to predict a customer's probability to buy/to churn or for Credit Scoring in order to predict fraud. Decision Trees are simple to understand and easy to interpret. Variables that are numerical or categorial can be handled. Also extensive data preparation is not necessary. They are robust and quick in computing time even with large datasets. It is possible to validate decision trees. All of this plus the fact that they are using a white box model it makes it easy to use. On the other hand they tend to overfit and get too complex – especially when you have a lot of independent variables. In this case they do not generalize will - but you can fix this by pruning earlier. It is possible that you get a local optimum instead of the global optimum. Further, in specific settings it can happen that trees are not robust, which means that a small change in training data causes a huge change in the tree. There are also problems that are not well represented by trees, such as XOR. If you have categorial variables with many levels it might happen that the tree is biased and prefers those variables with many levels (Decision tree learning).

Since SVM avoids overfitting and since decision trees have the risk to overfit this is a nice contrast to make sure that there is no overfitting.

The third challenging model will be a Random Forest Classifier, which computes many decision trees and gives the mode of the classes back. As pointed out before, a single decision tree is sensible to overfitting - but a random forest is not. It is efficient and quick even on large dataset (Breimann & Cutler).

2.4 Benchmark

A very simply heuristic model could be predicting "non-fraud" in 100% of test cases and that would lead to an accuracy of 99.83% which is already quite high. This is due to fact that the dataset has only 492 cases of fraud and is thereby imbalanced. With regard to the business background this is not meaningful since just one fraud case can already cause a lot of damage to the business. Therefore a bank has a very strong interest in detecting every single fraud case.

This makes it clear that a heuristic model is not adequate. The benchmark model for this problem is a logistic regression which can in most cases deliver robust predictions and is well-known and well in use in many companies.

As explained in the following chapter, I split the data into 70% training / 30% testing set and then do undersampling in order to get a balanced dataset and. This results in 690 training samples with 50% frauds and 85,443 testing samples with the original 0.713% rate of fraud.

I implemented a logistic regression model using *LogisticRegression* from *sklearn.linear_model.* It has the following performance:

```
Performance of Prediction by Logistic Regression
Confusion Matrix
[[83030  2266]
 [   15   132]]

False negative: 15
False positive: 2266

Area under the precision recall curve: 0.477
Recall: 0.898
```

So there are 15 false negatives of 147 fraud cases in the testing set. The model was trained on the sampled data and now it was tested on the unsampled data, which contains the real percentage of fraud and thereby too many false positives were generated. Recall is 0.898 and the area under the precision recall curve is 0.477. This is going to be the benchmark for the following models.

3. Methodology

3.1 Data Preprocessing

After having examined the statistics of the dataset and the graphs, there is to conclude that not too much preprocessing is needed because the data was already transformed by a PCA. A PCA is also a method to reduce dimensions.

First I will transform the variable “amount” using *StandardScaler* from sklearn preprocessing package, which gives a mean of 0 and a standard deviation of 1.

Then I am going to take care of outliers and will set the values that are above the 99.9% percentile to the value of the corresponding 99.9% percentile. This is necessary because some variables have extreme values, e.g. V7 has a maximum of 120,589 while its mean is 0, its standard deviation is 1.332 and the 99.9% percentile is 7.97.

Next I will divide my sample into a training and test sample using *train_test_split* from *sklearn.cross_validation* and splitting into 70% training data/ 30% testing data.

Then I am going to do undersampling of my sample which means that I’m going to take all the fraud data and draw randomly the same amount of non-fraud cases. I will then have a balanced sample of 50% fraud and 50% non-fraud. Therefor I am going to use the package *RandomUnderSampler* from *imblearn.under_sampling*. This is the result:

Training data Undersampling	*Test data*
690 cases	85,443
345 fraud cases = 50%	147 fraud cases = 0.173%

Similar to undersampling the data I try oversampling which does replicate synthetically the minority class and will result in a balanced dataset as well. I am going to use the package *smote* from *imblearn.oversampling.*

Training data Oversampling	*Test data*
398,038 cases	85,443
199,019 fraud cases = 50%	147 fraud cases = 0.173%

After fitting the model and testing with the test data, I will also test against the whole data set. The whole dataset contains also the data that was used for fitting, which could be a problem for overfitting.

3.2 Implementation

To compare the models I implemented a function that calculates the area under the precision recall curve and the recall. It is called *performance_metric* and I used the library *metrics* from *sklearn* for the **confusion matrix** and the **area under the precision recall curve** as well as **recall**. Then I implemented each model by using the relevant library. First I initialize the model, second I fit it and then I make the prediction. The prediction can then be evaluated using the function *performance_metric*. This makes it possible to compare the performance of all models.

First I tried Support Vector Classifier using *sklearn.svm.SVC* and got the following results:

```
Performance of Prediction by SVM
Confusion Matrix
[[81347  3949]
 [   11   136]]

False negative: 11
False positive: 3949

Area under the precision recall curve: 0.479
Recall: 0.925
```

The SVC reaches almost the same value for the area under the precision recall curve, which is very low with 0.479 and the number of false positives is even higher than before. Recall is very good with 0.925 and also the number of false negatives decreased.

Second I tried a Decision Tree using *sklearn.tree.DecisionTreeClassifier:*

```
Performance of Prediction by Decision Tree
Confusion Matrix
[[78017  7279]
 [   17   130]]

False negative: 17
False positive: 7279

Area under the precision recall curve: 0.451
Recall: 0.884
```

The Decision tree has more false negatives than the two models before (17). Also the area under the precision recall curve and recall are worse than for the benchmark model.

Third model was the Random Forest Classifier (*sklearn.ensemble.RandomForestClassifier*):

```
Performance of Prediction by Random Forest Classifier
Confusion Matrix
[[83245  2051]
 [   14   133]]

False negative: 14
False positive: 2051

Area under the precision recall curve: 0.483
Recall: 0.905
```

The random forest classifier is slightly better than the benchmark model in all metrics.

After checking with all the data the area under the precision recall curve improves slightly as well as recall but the number of false positives increases dramatically:

```
Performance of Random Forest Classifier when tested with whole (unbalanced) dataset
Confusion Matrix
[[277314   7001]
 [    17    475]]
```

```
False negative: 17
False positive: 7001

Area under the precision recall curve: 0.515
Recall: 0.965
```

Summary of the Undersampled data results:

Undersampled Data	Area under the precision recall curve	Recall	False negative / false positives
Logistic Regression Benchmark	0.447	0.898	15 / 2266
SVM	0.479	**0.925**	11 / 3949
Decision Tree	0.451	0.884	17 / 7279
Random Forest	**0.483**	0.905	**14 / 2051**

In the next step I tried oversampling of data, which replicates the minority class and provides bigger samples than the undersampling algorithm and obtained the following results, presented as summary:

Oversampled Data	Area under the precision recall curve	Recall	False negative / false positives
Logistic Regression Benchmark	0.487	**0.917**	47 / 7438
SVM	Too long running time		
Decision Tree	0.592	0.782	32 / 171
Random Forest	**0.863**	0.816	**27 / 12**

With oversampled data I was able to improve the area under the precision recall curve for the Random Forest Classifier. This one had a good recall and a good value for the area under the precision recall curve. Also it had the best portion of false negatives and false positives. The number of false negatives is very important, because that are not identified fraud cases which are very harmful in real life. But also the number of false positives should not increase too much, because every single case has to be checked by an employee within a short amount of time. If that increases up to 7000 cases (as it does by the Logistic Regression) then the model is not practicable for real life applications. Also the SVM had a very long running time which would not be suitable for that as well. Therefore I consider the Random Forest Classifier as the best model compared to the other ones.

4. Results

I checked the as best considered final model and let it run with the whole data. This is the result:

```
Confusion Matrix
[[284299     16]
 [    28    464]]

False negative: 28
False positive: 16

Area under the precision recall curve: 0.955
Recall: 0.943
```

On the whole dataset, which contains 0.173 or 492 cases of fraud, the model was able to identify 464 correctly. It missed on 28 observations and it misclassified 16 samples. Both metrics were very good with recall at 0.943 and the area under the precision recall curve at 0.955.

The model was chosen after comparing it to the other ones implemented, which performed worse on the metrics as discussed in the previous chapter.

5. Conclusion and Reflection

The challenge of this analysis was to deal with the unbalanced data set. Therefore I tried two approaches: Undersampling and Oversampling. I used the rebalanced dataset only for training and the unbalanced dataset for testing. This resulted in a high number of false positives, since in the training set the fraud ratio was much higher than in the testing set. Therefore I tried a number of different models to find the one that could deal with it the best. Random Forest performed best compared to the logistic regression, SVM and Decision Tree.

The next thing to do would be to challenge the model with new, previously unseen data from the following bank working days. One problem of the model could be that the final validation was done on the same data as the training and testing of the model beforehand. Therefore the model could be improved by having more data available.

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