National Taiwan University

Financial Technology

Project 1: Credit Card Fraud Detection

Lecturer:
Che Lin (林澤)

Author: Tadeo Hepperle

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1 Introduction

In this project we use a dataset from Kaggle "Credit Card Fraud Detection" to predict fraudulent spendings on credit cards, given a range of features. For this task, we will compare classical machine learning models like logistic regression, support vector machines and random forests with deep neural networks and evaluate their performance.

1.1 Description of the data

The dataset was originally from Kaggle, named "Credit Card Fraud Detection" and contains 31 variables, grouped into 30 features and one class label. Two of these features are the time the transaction took place and the amount spent. The 28 remaining features were obtained by performing a principal component analysis on a larger dataset. The classlabel is either 0 (normal) or 1 (fraudulent) for each record. The entire data consists of 99999 independent transaction records. Of those only 223 are fraudulent, which amounts to only 0.22% and makes the data extremely unbalanced.

1.2 Description of methods

Besides deep neural networks, we also take a brief look at logistic regression, support vector machines and random forest models.

1.2.1 Logistic Regression

In Logistic regression we try to predict a binary response by using an array of numeric features. The model formula looks like this:

$$P(y = 1) = \frac{exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)}{1 + exp(\beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k)}$$

where $P(y = 1)$ represents the probability of class 1 (fraud in our case) and the $x_1, \ldots, x_k$ represent k predictors. The probability of the other class ($P(y = 0)$) is therefore $1 - P(y = 1)$. Because the derivative of the logistic

function is never 0 there is no closed form solution and methods like gradient descent need to be used for optimization. However if the data is linearly separable, these methods will never converge and will result in an "infinitely steep" probability curve.

1.2.2 Support Vector Machines

Support Vector Machines (SVM) aim to find a hyperplane that linearly seperates the data linearly into 2 homogeneous halfspaces. Because this is not always possible, two tricks can be applied. First, it is useful to use a soft margin instead of a hard one which allows some points of the wrong class to lie in the half space of the other class as long as they are still pretty close to the hyperplane. In some cases, like noisy data this can even give better classification results in cases where a hard margin could perfectly seperate the two classes. The second "Trick" that can be used to make Support Vector machines more useful is to use a certain kernel function to transform the input features to a different space domain. This can make even originally not linearly seperable data, seperable if the right transformations are used. In this project, we will not experiment with any kernel functions.

1.2.3 Random Forest Classifier

Random Forest is an ensemble method. That means it combines the power of an array of weak learners that on their own would perform poorly. Typically decision trees are used as the weak classifier, hence the name random "Forest". There are multiple ideas, how to let the individual trees learn and how to combine them. in Bootstrapping for example, we let each tree learn on a bootstrapping sample of the original data and later take a majority vote among all trees as the final decision. The bootstrapping sample is produced by randomly sampling objects from the data n times with put backs (where n is the number of objects in total). The sample is different for every tree and can therefore allow the trees to learn different aspects of the data. The problem with this approach is, that the bootstrapping samples are still highly correlated. Random Forest aims to solve this, by further diversifying and restricting what data can be used by each tree during learning. The

idea is simple: At each split to be made in a decision tree, not all features are considered, but only a subset of features is allowed to be used to make the split. Typically for k features, $\sqrt{k}$ randomly selected features are allowed in each split. This increases the variance among weak learners and can lead to classification improvements.

2 Results

With an 80-20 train-test split of the data, 3 models were trained: Logistic Regression, Support Vector Machine and Random Forest Classifier.

2.1 Confusion Matrices and Classification Metrics

As Figure 1 shows, all models are pretty good at classifying the non-fraud cases as non-fraud, which is non-surprising since these comprise the overwhelming majority of the training data. Taking a look at the classification metrics in Table 1 we can see that the SVM is overall performing best, also with highest accuracy. To judge the performance, I would use the F1-score as it provides a good middle ground between precision and recall, in both of which high values are desired. I think the F1 metric is most suitable on this dataset because it is not so much affected by the very imbalanced distribution of fraud vs. non-fraud cases in the data. Surprisingly Logistic Regression and Random Forest have the same performance in our case.

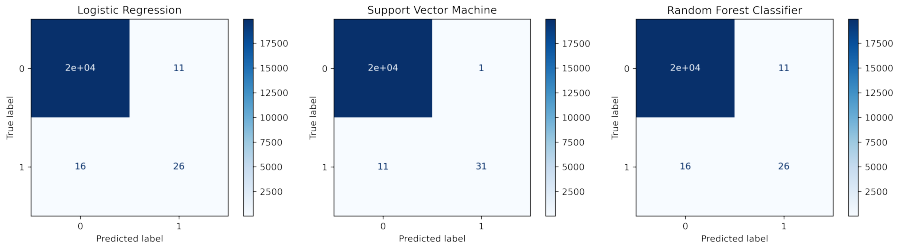


Figure 1: Confusion matrices for logistic regression, SVM and Random Forest on test data

Table 1: Accuracy, Precision, Recall and F1-Score for the 3 models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.9987	0.7027	0.6190	0.6582
Support Vector Machine	0.9994	0.9688	0.7381	0.8378
Random Forest Classifier	0.9987	0.7027	0.6190	0.6582

2.2 Constructing the Deep Neural Network

Secondly we construct a deep neural network and compare it to the methods previously presented. The network has an input layer with 30 nodes, one for each feature. Then there are d fully connected hidden layers, each consisting of k neurons. A ReLU layer is put in between each two neighboring hidden layers. In the end, there is one output node, to which a sigmoid function is applied, to convert scores to probabilities. If the output is greater or equal to 0.5 we classify a case as fraud, otherwise as non-fraud. The model is trained using the ADAM Optimizer, reducing the binary cross entropy loss function. The training uses mini-batch gradient descent. There are some parameters that we need to set in advance:

1. The number of hidden layers d.
2. The number of nodes in each hidden layer k.
3. The learning rate LR.
4. The $BATCHSIZE$, of batches used in the gradient descent.
5. number of $EPOCHS$ (how many times to go over the entire dataset before stopping training)

To perform a full grid search over all of these parameters would be very costly and take too much time, so we will try to figure out good parameters individually.

2.2.1 Learning Rate

For the learning rate the values $LR \in \{0.01, 0.001, 0.0001, 0.00001, 0.000001\}$ are considered while holding other values constant ($d = 4, k = 8, BATCHSIZE =$

$64, EPOCHS = 50$). Table 2 shows the results for the resulting confusion matrices on the test data after 50 epochs of training. It seems like a learning rate of 0.0001 is best. The others mostly just classified the entire dataset as non-fraud.

Table 2: Performance for different Learning Rates on the test set

LR	TN	TP	FP	FN	accuracy	F1	loss (train)	loss (test)
0.01	19958	0	0	42	0.9979	0	0.2263	0.2100
0.001	19958	0	0	42	0.9979	0	0.2263	0.2060
0.0001	19946	25	12	17	0.9986	0.6329	0.0062	0.0051
0.00001	19946	0	0	42	0.9979	0	0.0121	0.0107
0.000001	19948	0	10	42	0.9974	0	0.5478	0.5474

Next we will take a look at the influence of the size and amount of hidden layers: In the following Table 3 you can see the training outcomes for different configurations, keeping other values constant ($BATCHSIZE = 64, EPOCHS = 50, LR = 0.0001$). The configurations (d, k) = (hidden layer count, nodes per hidden layer) are set to $(1, 8)$, $(1, 16)$, $(4, 8)$, $(4, 16)$ and $(8, 8)$. Surprisingly having 4 hidden layers with 8 nodes each seems to be the best configuration.

Table 3: Performance for different Learning Rates on the test set

d	k	TN	TP	FP	FN	accuracy	F1	loss (train)	loss (test)
1	8	19958	0	0	42	0.9979	0	0.2252	0.2057
1	16	19954	0	0	46	0.9979	0	0.2216	0.2300
4	8	19946	25	12	17	0.9986	0.6329	0.0062	0.0051
4	16	19947	20	11	22	0.99835	0.5479	0.008	0.0065
8	8	19950	9	8	33	0.9974	0.3051	0.0115	0.0103

For the rest of this report we will consider a network with the following parameters:

1. The number of hidden layer $d = 4$.
2. The number of nodes in each hidden layer $k = 8$.
3. $LR = 0.0001$.
4. $BATCHSIZE = 64$
5. $EPOCHS = 50$

2.3 Characteristics of the DNN

Table 4 shows some characteristics of the deep neural network that was deemed best during the hyper parameter selection process:

Table 4: Performance of the strongest model

characteristic	train	test
TN	79790	19946
TP	114	25
FP	28	12
FN	67	17
Accuracy	0.9988	0.9986
Precision	0.8028	0.6757
Recall	0.6298	0.5952
F1	0.7058	0.6329
Loss	0.0062	0.0051

Figure 2 shows how accuracy and loss devoloped throughout the training period for both the train and test dataset. Figure 3 shows the confusion matrices on the train and test datasets after the model was trained for 50 epochs.

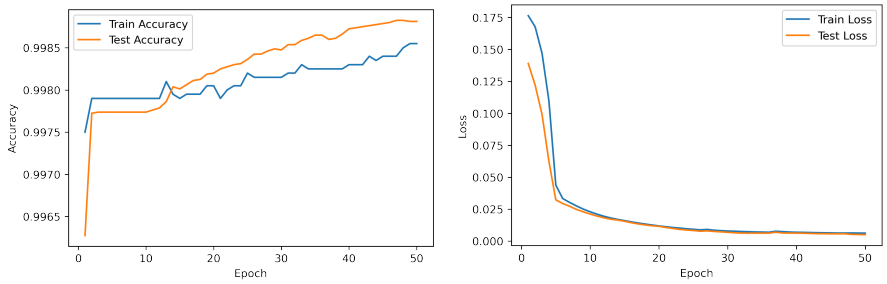


Figure 2: Accuracy and Loss over the training period

2.4 ROC and PRC curves

Figure 4 shows the ROC and PRC curves of the 4 different models and also provides the area under curve for each.

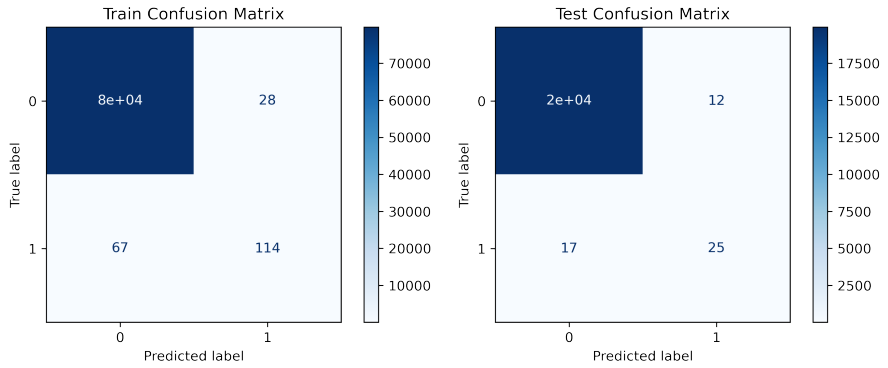


Figure 3: Confusion matrices for test and train data

Using the F1 score to compare the models, we find, that the Support Vector Machine is performing best ($F1 = 0.8378$). On the second and third place we have the Random Forest Classifier ($F1 = 0.6582$) and the Logistic Regression with $F1 = 0.6582$. They have exactly the same confusion matrix. Sadly the deep neural network performs worst with an F1 score of only $F1 = 0.6329$, though not much worse than the other methods. This is unexpected and is likely due to not enough data that is available in the fraud-class to have really good training.

3 Other ideas for the unbalanced data problem

Since out of our 99999 objects in the dataset only 223 represent fraud, we need to deal with the unbalanced data in a smart way. We can use under- or oversampling. However there are also other approaches.

3.1 Clustering

Instead of using undersampling, we could also cluster the majority class objects into n clusters, where n is the number of objects in the minority class and use the resulting cluster centers as "examples" for the majority

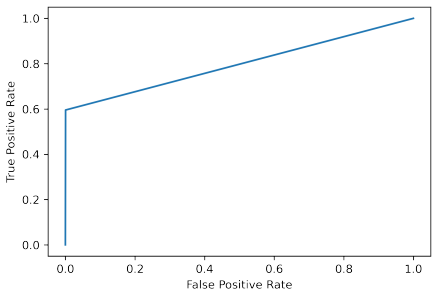
class in training. This way we have a balanced and relatively small dataset but still capture some information from each object from the original data, since each object has some influence on the resulting cluster centers.

3.2 Stronger Weights for Minority Class

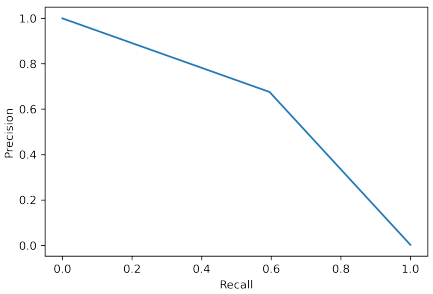
since there are so few fraud cases, it is easy for a machine learning algorithm to simple oversee them, and not recognize their influence. To avoid this, we could give a greater punishment to the misclassification of fraud cases and in this way force the model to consider them more strongly. We could do this by having an asymmetric loss function, which is steeper in the area where the fraud class would be misclassified.

3.3 Summary

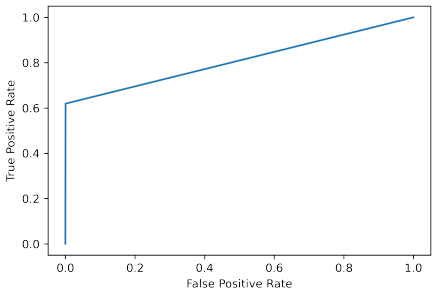
Bibliography



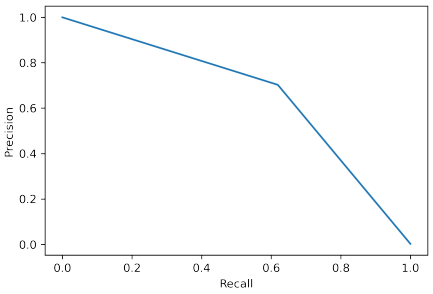
(a) ROC for DNN. AUC = 0.7973



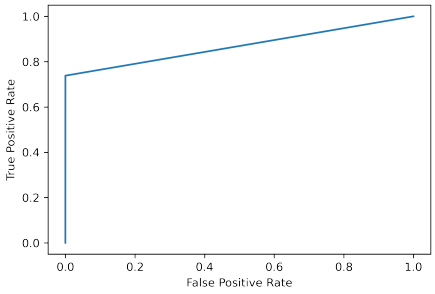
(b) ROC for DNN. AUC = 0.4030



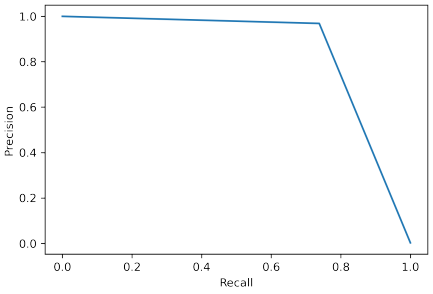
(c) ROC for Logistic Regression. AUC = 0.8092



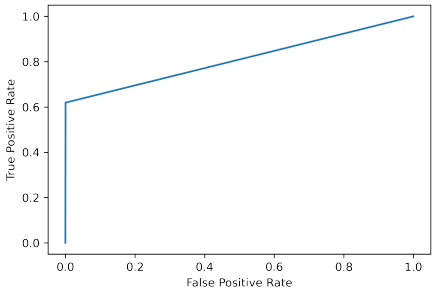
(d) PRC for Logistic Regression. AUC = 0.4358



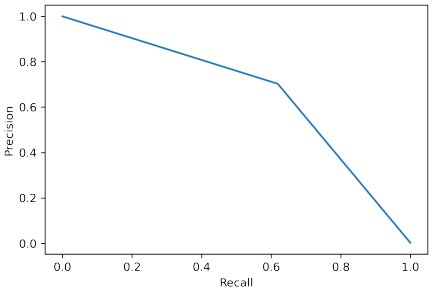
(e) ROC for Support Vector Machine. AUC = 0.869



(f) PRC for Support Vector Machine. AUC = 0.7156



(g) ROC for Random Forest Classifier. AUC = 0.8092



(h) PRC for Random Forest Classifier. AUC = 0.4358

Figure 4: ROC and PRC curves