

# RoboGarden Bootcamp Capstone Project

Credit Card Fraud Detection  
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(update Oct 2019)

<https://github.com/dvbckle>

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## Credit Card Fraud Project

### **Description:**

- 284,807 credit card transactions made by European cardholders in September 2013

### **Features:**

- Time: seconds since first transaction
- V1 – V28: Anonymous data – Confidentiality
- Amount: Transaction value (Unspecified currency)
- Class (T/F): fraudulent / genuine

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**Available:** Data World & Kaggle: <https://data.world/raghu543/credit-card-fraud-data>

**File:** creditcard.csv

**Reference use of dataset:** Dal Pozzolo, Olivier Caelen, Reid A. Johnson and Gianluca Bontempi. Calibrating Probability with Undersampling for Unbalanced Classification. In Symposium on Computational Intelligence and Data Mining (CIDM), IEEE, 2015

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## Credit Card Fraud Project Dataset

• <i>normal amount total</i>	<b>25,043,410</b>
• <i>fraud amount total</i>	<b>58,591 (0.25%)</b>
• <i># transactions over 2 days</i>	<b>284,807</b>
• <i># fraud transactions</i>	<b>492 (0.17%)</b>
• <i># non-fraud duplicates</i>	<b>1062 (0.4 %)</b>
• <i># fraud duplicates</i>	<b>19 (4.0 %)</b>
• <i># zero amount normal transactions</i>	<b>1798 (0.6%)*</b>
• <i># zero amount fraud transactions</i>	<b>27 (5.5%)*</b>

\* Retained zero amount transactions. Insufficient information to remove them.

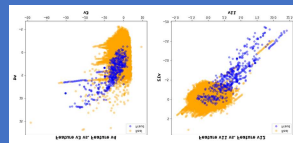
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## Work Process

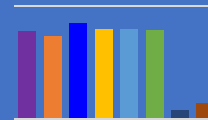
Clean Data

Remove Duplicates

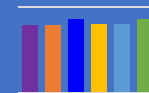
Visualize Data



Screen 8 Classifiers

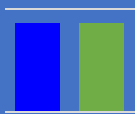


Optimize 6 Classifiers  
All Features

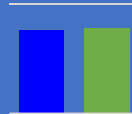


Optimize RF & MLP on  
10 Features

Feature Importance



Optimize RF & MLP on  
Undersampled Dataset  
All Features

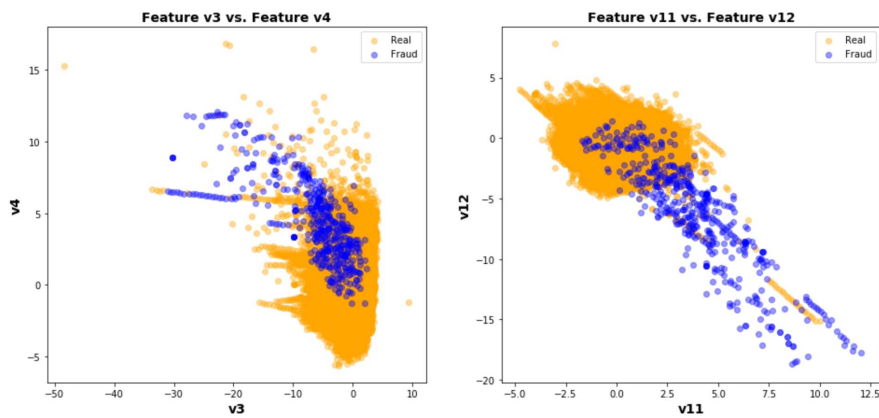


Run Autoencoders on  
10 Features  
4 Features



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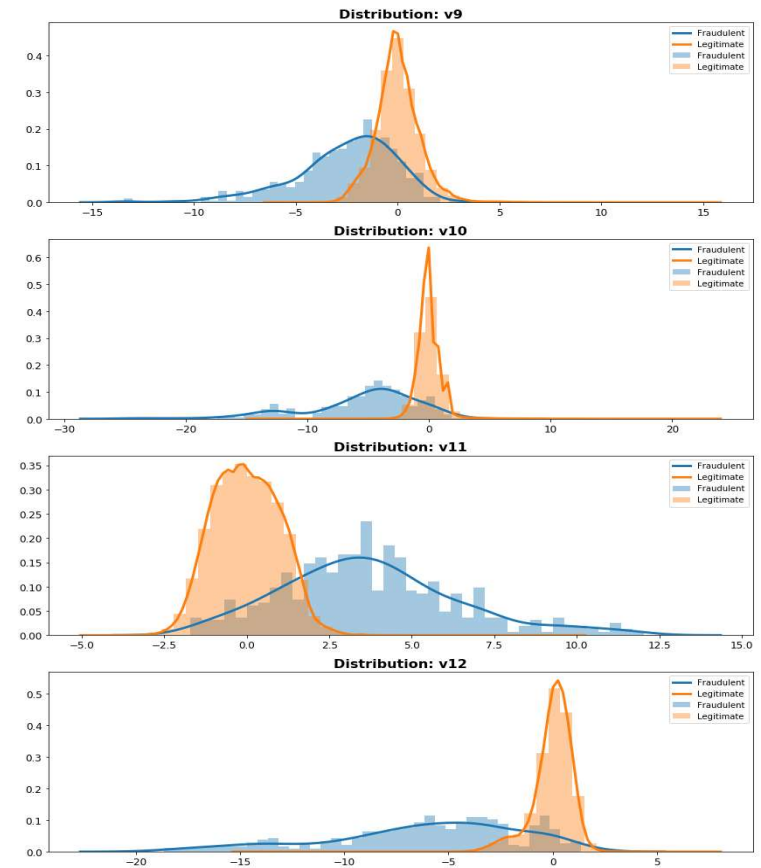
## Visualization Examples



- 2D Scatter plots show some overlap & separation.

Showing 4 of 28 Features: Fraud vs. Normal Histograms

- Several have distinctive range differences.
- Some distributions are aligned, (not shown).

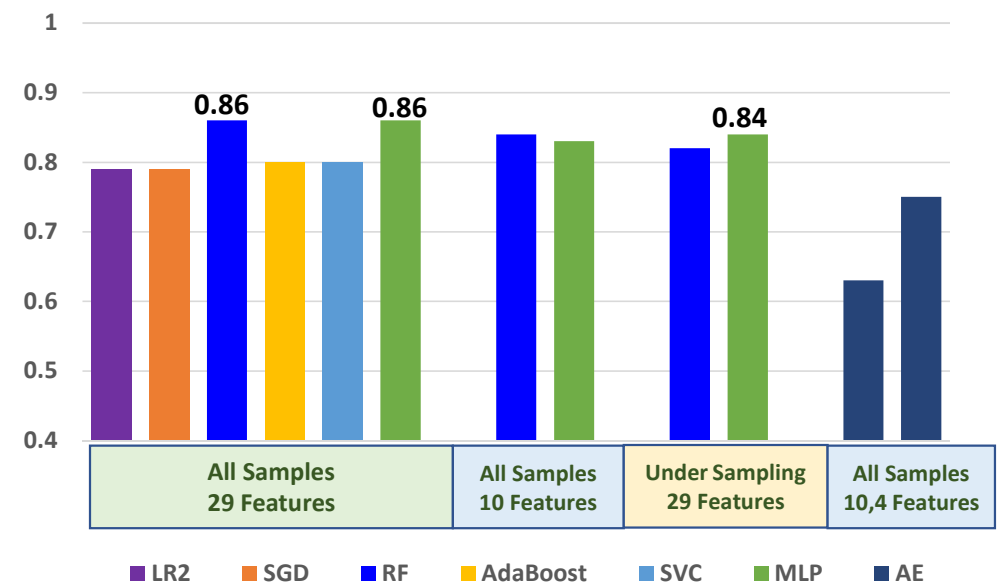


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## Modelling Results

Model	Application	Features	Scores			TP	FP	FN
			AU-ROC	AU-PRC*	F-1			
LR	All Samples	29	0.98	0.79	0.69	65	5	53
SGD	All Samples	29	0.98	0.79	0.79	83	7	35
RF ★	All Samples	29	0.96	0.86	0.86	92	4	26
SVC	All Samples	29	0.95	0.80	0.78	77	3	41
AdaBoost	All Samples	29	0.97	0.80	0.80	84	8	34
MLP ★	All Samples	29	0.99	0.86	0.86	92	5	26
RF	All Samples	10	0.95	0.84	0.85	90	4	28
MLP	All Samples	10	0.98	0.82	0.83	88	6	30
RF **	Undersampling	29	0.99	0.82	0.85	91	6	27
MLP **	Undersampling	29	0.98	0.84	0.82	90	11	28
AE	All Samples	10	0.97	0.57	0.58	66	45	52
AE	All Samples	4	0.96	0.75	0.78	83	11	35

Area Under Precision-Recall Curve



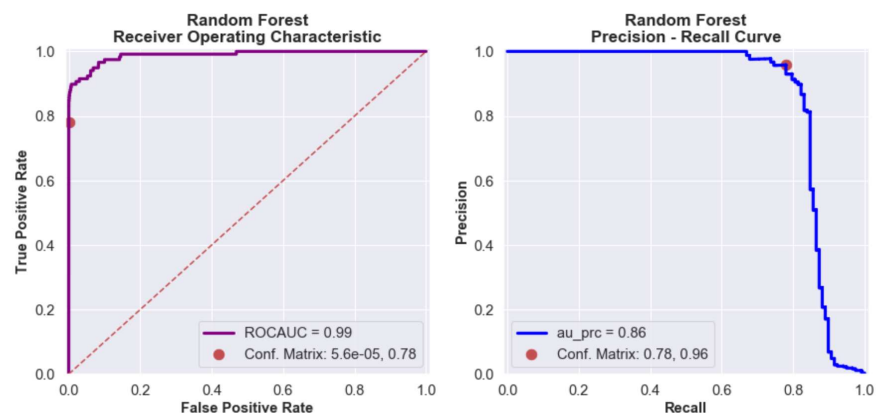
★ Model results shown on following slides, Highest AU-PRC and Highest amount of fraud found

\* AU-PRC: Area under the Precision-Recall Curve is the recommended measure of accuracy stated by the dataset provider due to the imbalance in the dataset.

\*\*Under Sampling applies calibration to the sample probabilities.

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## Random Forest Results

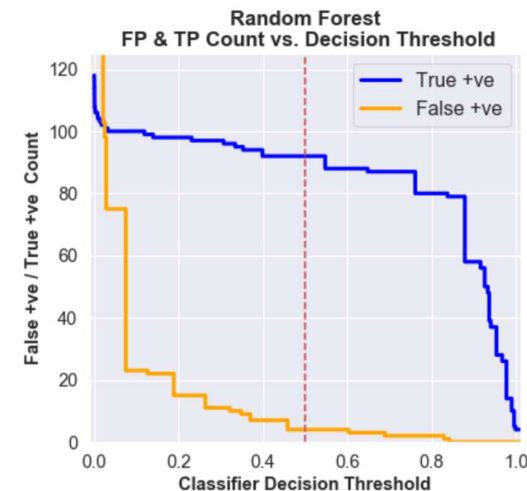
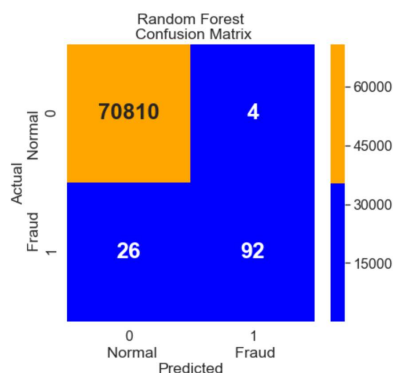


Random Forest trained on the full dataset \*:

- Found 78% of frauds at 0.5 decision threshold.
- Has a low false positive rate.
- 67% of frauds have a classification probability over 0.8.

ROC and Precision-Recall Curves:

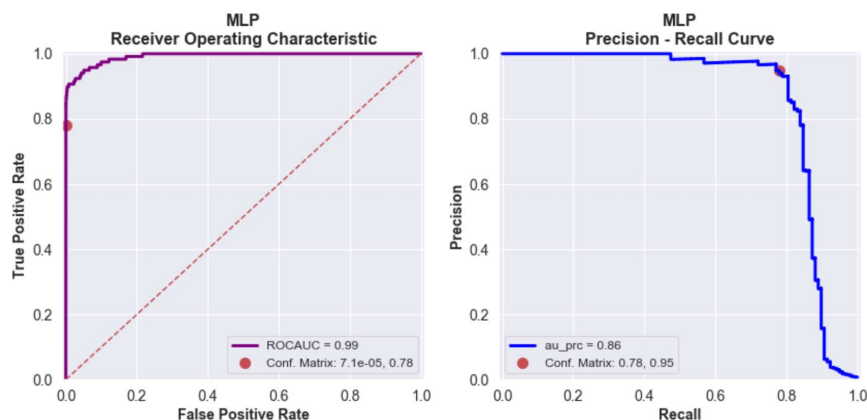
- Area under Precision-Recall of 0.86.
- Area under ROC of 0.96.
- Confusion Matrix corresponds to markers on ROC & PRC and decision threshold line on the FP & TP Count plot.



\*Trained on 29 Features: Amount + Features v1 to v28 (time was dropped)

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## MLP Results

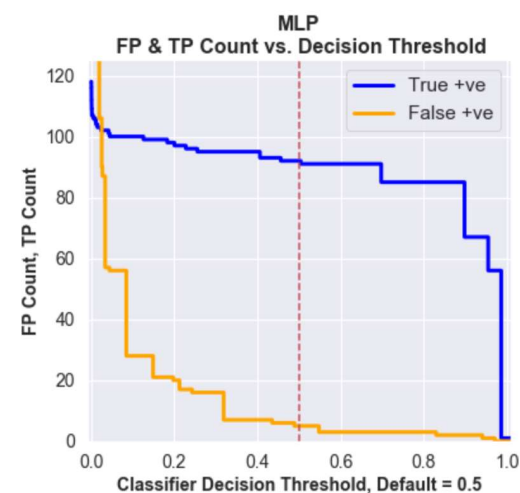
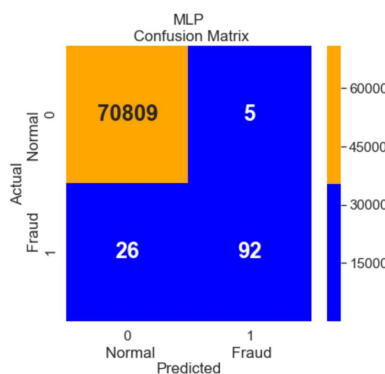


MLP trained on the full dataset \*:

- Found 78% of frauds at 0.5 decision threshold.
- Has a low false positive rate.
- ~71% of frauds have a classification probability over 0.8.

ROC and Precision-Recall Curves:

- Area under Precision-Recall of 0.86.
- Area under ROC of 0.99.
- Confusion Matrix corresponds to markers on ROC & PRC and decision threshold line on the FP & TP Count plot.



*\*Trained on 29 Features: Amount + Features v1 to v28 (time was dropped)*



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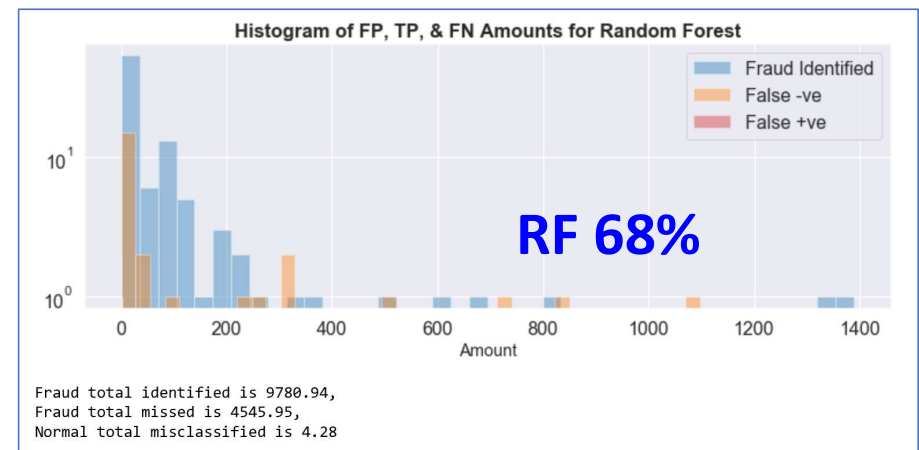
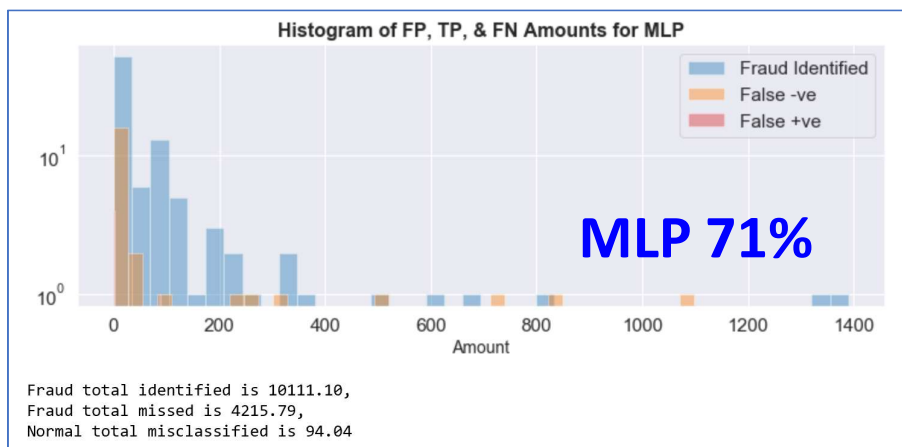
## Fraud Value Identified in Test Set (25% of Dataset)

**96 Frauds & 71% of value\***

**5 FP's – 6.5% of the total Fraud value**

**92 Frauds & 68% of value\***

**4 FP's – .03% of the total Fraud value**



- Random Forest identified a slightly lower fraud amount, but misclassified a lower amount than the MLP Classifier. \*All total percentages will vary with new data and the breakdown of amounts related to other features (e.g. zero or low value transactions vs larger amounts.)

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## Conclusions / Future Work

### Conclusions:

- Despite the extreme unbalanced nature of the dataset, Random Forest classified 78% of the fraudulent transactions with few false positives (4% of frauds identified).
- The undersampling technique did not improve the area under the Precision-Recall Curve score but identified a slightly higher value of frauds for the same number of transactions identified. The MLP model identified a higher value amount of frauds for all features, reduced features and undersampling but also misclassified a higher value amount of legitimate transactions.
- Performance degraded when features were dropped except for the Autoencoder model which improved with fewer more distinct features.

### Future Work:

- Include more model parameters in a broader optimization search.
- Use time feature by setting it to time of day vs. time from first transaction.
- Investigate a hybrid classifier by combining multiple classifiers.