Credit Card Fraud Detection

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Introduction

- Why is credit card fraud a problem?
  - Significant Financial costs
    - Global costs of $15 billion in 2014
  - Increase in online transactions
    - Losses expected to increase to $30 billion by 2020

Previous Work

- Significant Amount of research has been done
    - Focus is on champion-challenger approach
    - Most papers use Random Forest and Naïve-Bayes models.

Credit Card Fraud: Problem Constraints

- Real time processing required
- The cost of predicting false negatives versus false positives
- Data sets are difficult to find
- Fraudsters adjust, constant retraining required
- Data set imbalance

Our Work

- Examined a real-world dataset
- Selected 2 established Machine Learning algorithms
  - Random Forest, Naïve-Bayes Classifier
- Performed 3 feature selection methods
  - Correlation Filtered, Backwards Selection: Random Forest and Naïve-Bayes
- Compared the results of the 6 models built

Our expectation is that Random Forest and Naïve-Bayes will have similar results. Models built with backwards selected features should also perform better.

Dataset

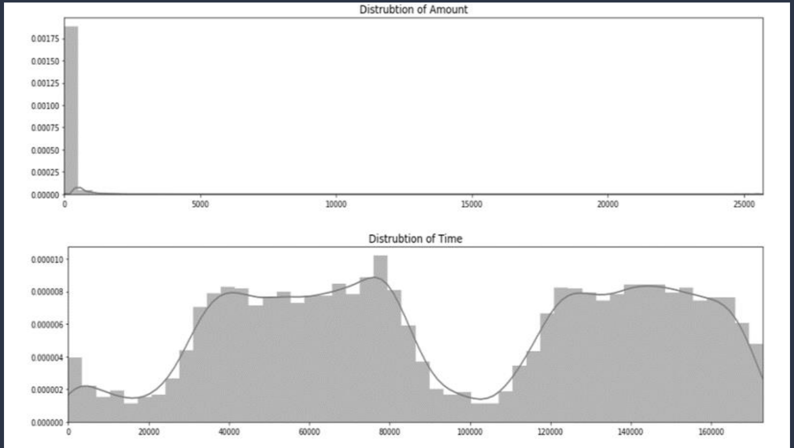
- 284,807 transactions from September 2013 by European cardholders
- 31 Features
  - Amount, Time, v1-v28, Class
  - Features v1-v28 are anonymized and transformed to numeric values for confidentiality

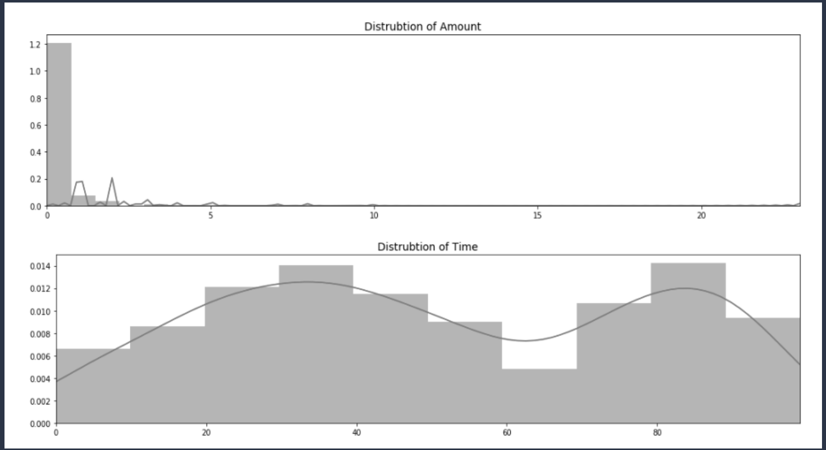
Time	V1	V2	V3	.. V26	V27	V28	Amount	Class
0	-1.35981	-0.07278	2.536347	-0.18911	0.133558	-0.02105	149.62	0
0	1.191857	0.266151	0.16648	0.125895	-0.00898	0.014724	2.69	0
1	-1.35835	-1.34016	1.773209	-0.1391	-0.05535	-0.05975	378.66	0
1	-0.96627	-0.18523	1.792993	-0.22193	0.062723	0.061458	123.5	0
2	-1.15823	0.877737	1.548718	0.502292	0.219422	0.215153	69.99	0
2	-0.42597	0.960523	1.141109	0.105915	0.253844	0.08108	3.67	0

Methodology and Tools

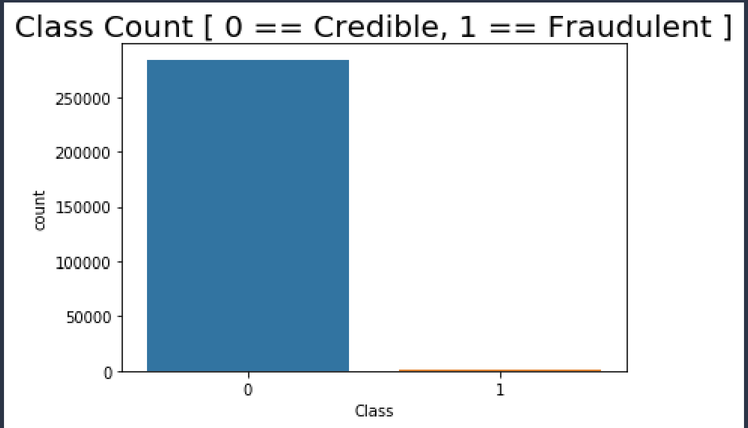
- Data Preprocessing
  - Binning
  - Undersampling
  - Feature Selection
    - Correlation
    - Backwards

Binning: Before and After



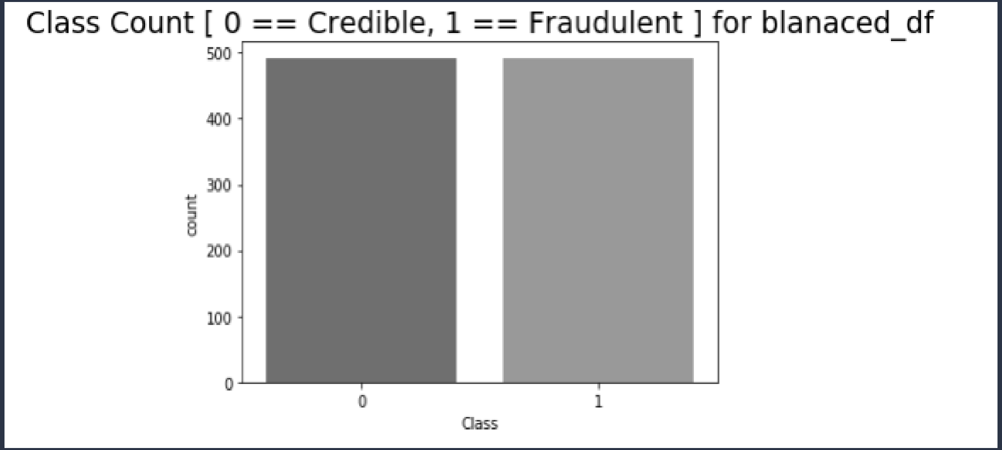


Data Imbalance



- 284,807 Transactions
- 492 Fraudulent transactions
    - 0.17% of all transactions
- Undersampling will be used to correct this

Undersampling



- Creatures a new, relatively small, and balanced data set
    - 984 total Entries
    - 492 Fraudulent Transactions
    - 492 Credible Transactions

Methodology and Tools

- Feature Selection
  - Correlation Filter Feature Selection
    - Features with correlation>0.5 with target feature
  - Backward Feature Selection
    - Build full model and remove features

Methodology and Tools: Machine Learning Algorithms

- Random Forest Algorithm
  - 20 Decision Trees
  - Easy to understand and implement

- Naive-Bayes Algorithm
  - Probability assuming independent features
  - Suitable for real time predictions

Methodology and Tools

- Measures of success
  - False Negatives minimized
  - F1score:
    - Recall = (TP) / (TP + FN)
    - Precision = (TP) / (TP + FP)
    - F1Score = 2 * (Precision * Recall) / (Precision + Recall)
  - Accuracy:
    - Accuracy = (TP + TN) / (TP + TN + FP + FN)

Methodology and Tools

- Tools
  - Python
  - Pandas
  - sklearn/matplotlib/seaborn/mlxtend
  - Jupyter/Anaconda
  - Kaggle

Results:
Feature Selection Outputs

Feature Selection Model:	Selected Features:
Filtered correlation selection	'V3', 'V4', 'V9', 'V10', 'V11', 'V12', 'V14', 'V16', 'V17'
Random Forest Backwards selection	'V4', 'V7', 'V13', 'V14', 'V17', 'V18', 'V21', 'V26', 'V27'
Naïve-Bayes Backwards Selection	'V4', 'V6', 'V7', 'V13', 'V14', 'V19', 'V23', 'V25', 'bin_time'

Results:
Model and Feature Set Combinations

Model No.	Model:	Dataset features:
1	Random Forest	Filtered correlation selected
2	Naïve-Bayes	Filtered correlation selected
3	Random Forest	Random Forest backward selected
4	Naïve-Bayes	Random Forest backward selected
5	Random Forest	Naïve-Bayes backward selected
6	Naïve-Bayes	Naïve-Bayes backward selected

Results: Raw Data

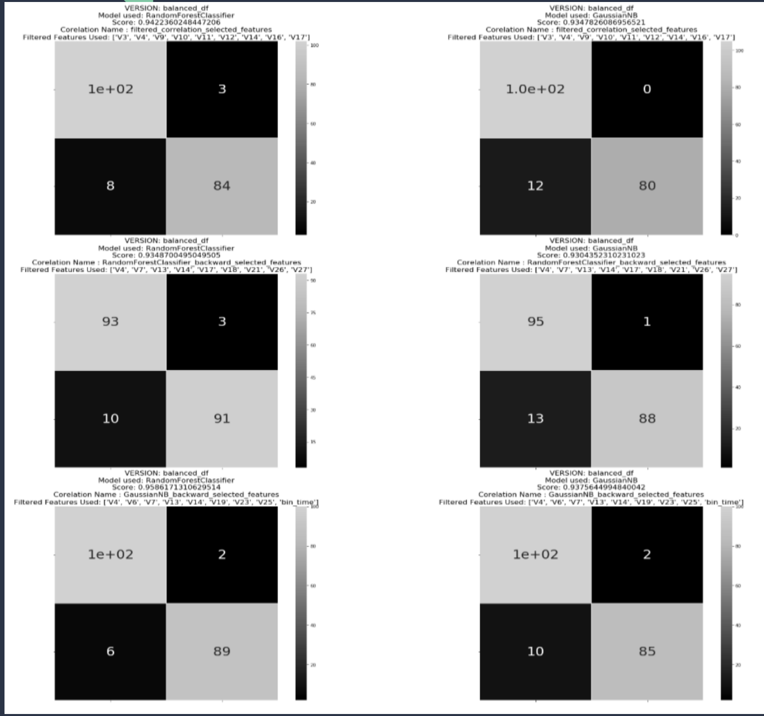
TABLE 3 NUMBER OF CLASSIFICATIONS

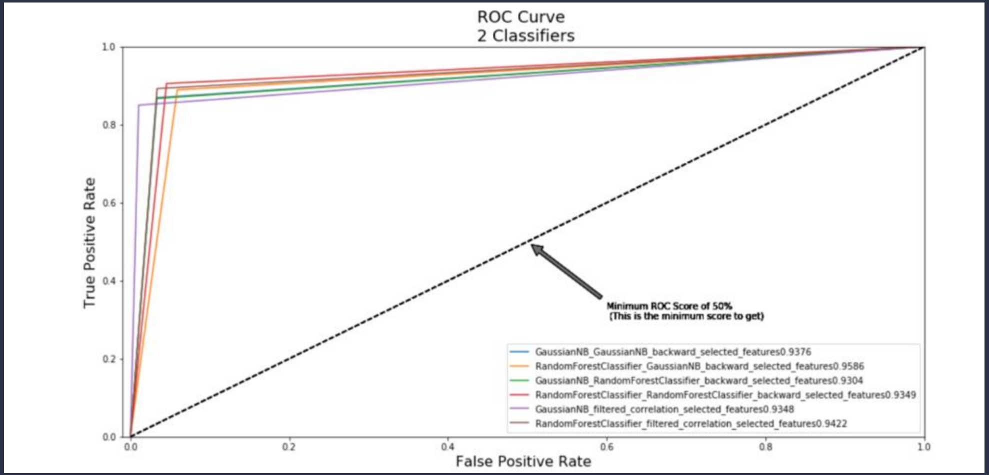
Model	TN	FN	TP	FP
1	84	3	102	8
2	80	0	102	12
3	91	3	93	10
4	88	1	95	13
5	89	2	100	6
6	85	2	100	10

TABLE 4 CLASSIFICATION RATES

Model	TPR	TNR	FPR	FNR
1	.97	.91	.09	.03
2	1.0	.87	.13	0.0
3	.97	.90	.10	.03
4	.99	.87	.13	.01
5	.98	.94	.06	.02
6	.98	.89	.11	.02

Results: Visualization





Results: Scoring

TABLE 5 CLASSIFICATION SCORING

Model	Recall	Precision	F1-score	Accuracy
1	.91	.97	.94	.94
2	.87	1.00	.93	.94
3	.90	.97	.93	.93
4	.87	.99	.93	.93
5	.94	.98	.96	.96
6	.89	.98	.93	.94

Conclusion

- Best model was: Model 5 (Random Forest with Naive-Bayes backwards selected features)
  - FNR: 0.02 F1Score: 0.96 Accuracy 0.96
- All models performed extremely well
- Both Random Forest and Naïve-Bayes suitable algorithms
  - Effect of Algorithm vs Feature Selection

Future work:

- Training/Processing Time
  - Over half a million cards in circulation
- Include Cost-analysis
  - Amount omitted during feature selection
- Thresholding
- More Algorithms

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