Deep Learning Techniques for Credit Card Fraud Detection

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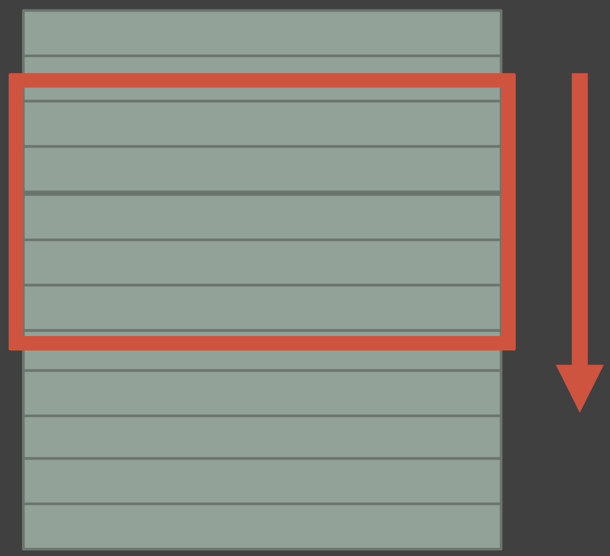
Overview

- $22.80 Billion Losses – 2016, 4.4% increase over 2015
- ‘Solved problem’ ? – Tree based classifiers, neural networks, time series (LSTM)
- Taking successful architectures (CNNs, GANs) in other domains (Image classification) and being creative

Approach

- Data exploration & Baseline models
- CNNs
- GAN

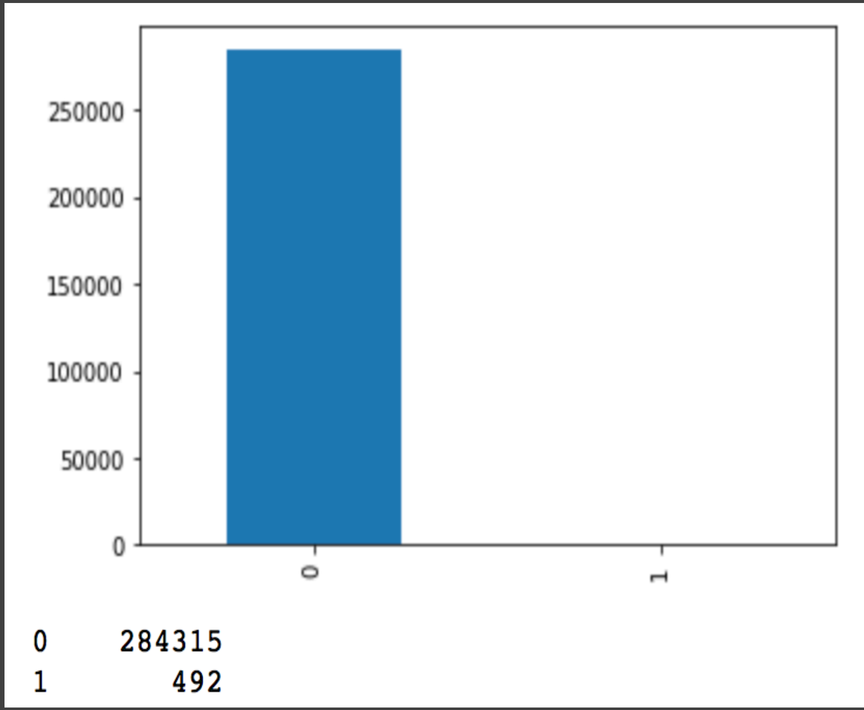
CNN sliding window



- Temporal ordering, batching together 100 vectors and treating as an image, with a striding window of size 5.

Data and techniques

- Data: popular dataset from ULB (ML / Data mining group at University of Brussels).
- Unbalanced data – resampling methods (Under, Over & SMOTE)
- Oversampling in the right place – inside KFOLD cross validation and different in time series case!



Non Fraud / Fraud balance

Evaluation (How the project is evaluated)

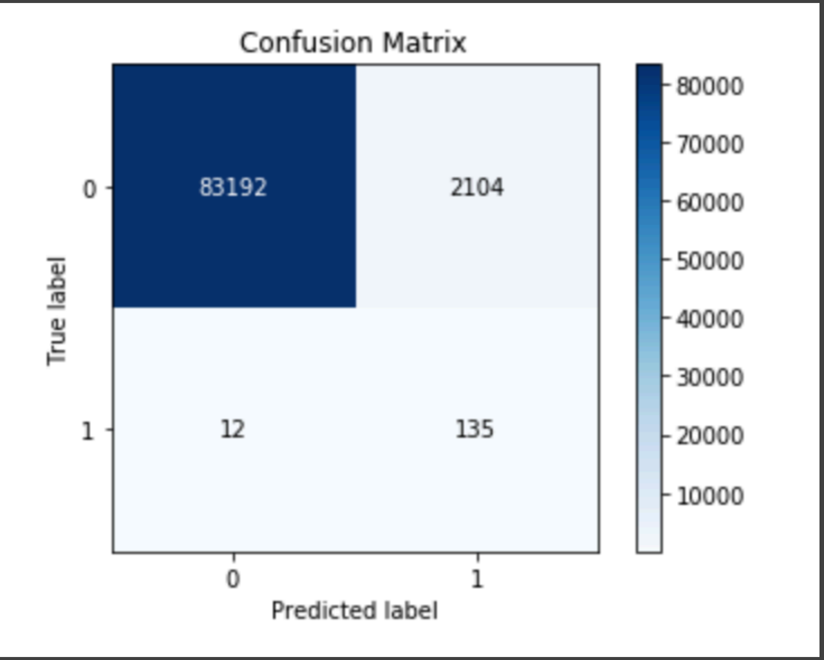
Accuracy NOT a good metric… model still 99.9% accurate if ALL frauds not caught.

Metrics – F1, precision, recall

ROC-AUC

Comparison across models using these metrics

Intuitive, written analysis of how the models compared and some of the insights gained from doing this



We care about specific portions of the confusion matrix

What I’ve done so far

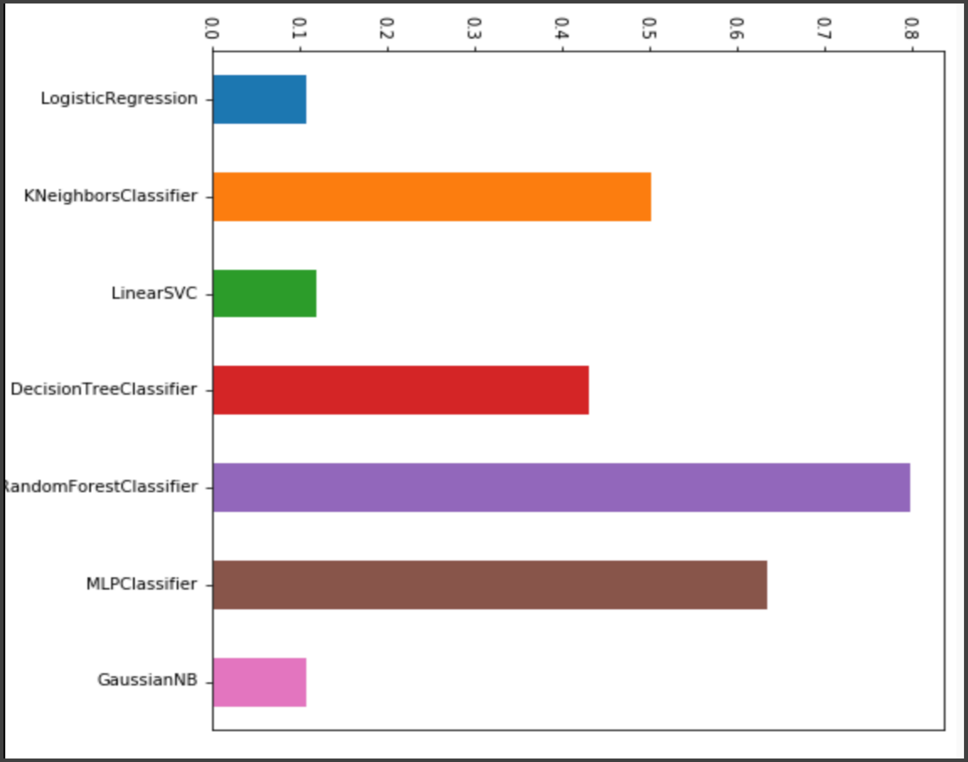
F1 SCORES:

Random Forest (Tuned): 0. 827025
CNN: 0.745591
CNN 2: 0.79167 (w/o CV)

CNN work:

Increase in precision, by about 10%.. Recall not quite there yet with respect to Random Forest

Further tuning may balance results



F1 score of baseline models. Tree based / NN are best, RF in particular.

What's left to do…

- Further tuning of CNN models to give insight to what could be achieved (i.e the window size, batch size, optimizer function etc).
- Experiment with the GAN work
- Finalize results and draw evaluations, using methods discussed previously