Data Science Bootcamp

Project 2
Transaction Fraud Detection

Marwa Salah

Project Overview

Identify potential fraudulant activity (transactions) using ML based on existing card transaction data

Anonymized credit card transactions labeled as fraudulent or genuine
Transformed using PCA
2 Features were not transformed using PCA which are Time & Amount

k
source

Due to nature classes are highly unbalanced.

0.17% vs 99.8%
Class Balance

Transaction Fraud Detection WHY?

1B+

Transactions per Day

11K+

Transactions per Second
~19 Fradulant/sec

$2-3

Cost of each dollar lost to fraud

$ 29B

Fraud Losses 2019

$ 35B

Expected Fraud Losses 2022

Impacts

Individuals | Businesses | Financial Instituations

https://fortunly.com/statistics/cash-versus-credit-card-spending-statistics/#gref
https://www.ncr.com/blogs/payments/credit-card-fraud-detection

Objectives

Identify potentially fraudulent activity

Detecting fraudulent activity before those transactions are even completed

Primary

↓↓ Minimize Accepted Fraudulant Transactions

FN

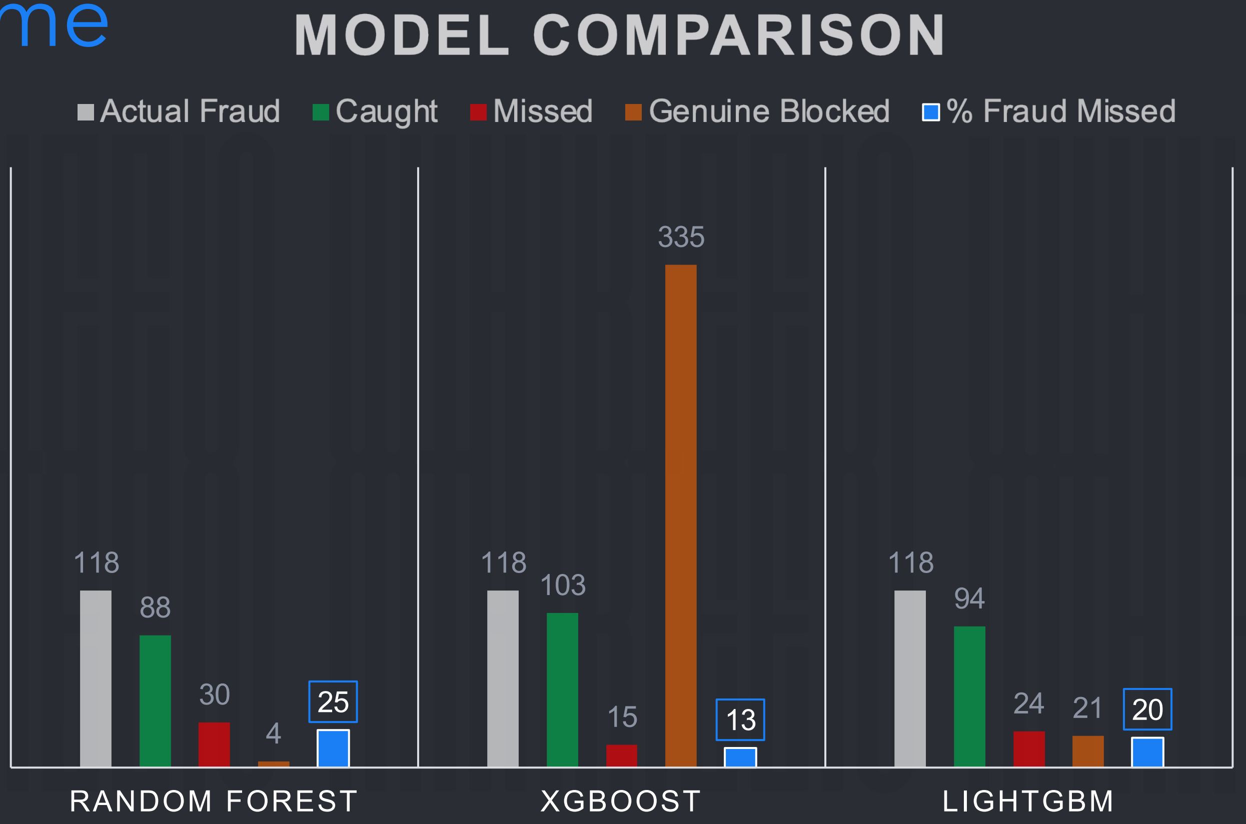
Secondary

↓ Avoid Declining Genuine Transactions

FP

Outcome

~71k
#Transactions Tested



Conclusion & Next Step

Full Dataset

Fraud: $ 60K
Genuine: $ 25M

@87% Detection Rate →

Fraud: $ 9K
Genuine: $ 25M (-Genuine Blocked if not validated)

Example based cost-sensitive learning & Cost–dependant Classification

	Actual Fraud $y_{true} = 1$	Actual Legitimate $y_{true} = 0$
Predicted Fraud $y_{pred} = 1$	*True Positive* $cost_{TP}$ = Admin	*False Positive* $cost_{FP}$ = Admin
Predicted Legitimate $y_{pred} = 0$	*False Negative* $cost_{FN}$ = Transaction	*True Negative* $cost_{TN}$ = $0

https://towardsdatascience.com/fraud-detection-with-cost-sensitive-machine-learning-24b8760d35d9

Challenges

- Annomyzation of Data
- Diversity of Data

- Time
- Compute Resources

Technical Project Details

Project Description

- In this project we were initially tasked with selecting a couple of datasets for analysis that meet the following rules:
  - Available to use
  - Suitable for use in a professional environment
  - Does not contain any personal information
  - Not used for any assignment, lecture or task from this environment

- My Proposed Sets: Credit Card Transaction Data & Financial Sales Data. Former was approved.

- So far, the project covers the following progress:
  - Data Cleaning & EDA
  - Evaluating & Tuning 3 Different Models (RandomForest, XGBoost, LightGBM)
  - Testing Impact of example-based cost sensitive learning
  - Model performance comparison

Data Description

Anonymized credit card transactions labeled as fraudulent or genuine
Transformed using PCA
Contains transactions made by European credit card holders in Sep 2013
2 Features were not transformed using PCA which are Time & Amount

Data source is kaggle.

Due to nature classes are highly unbalanced.

Data Shape is:
- 28 Components, 2 Features & 1 Label
- 284807 Rows (Observations)

Data Types:
All features are
Integers of type int64

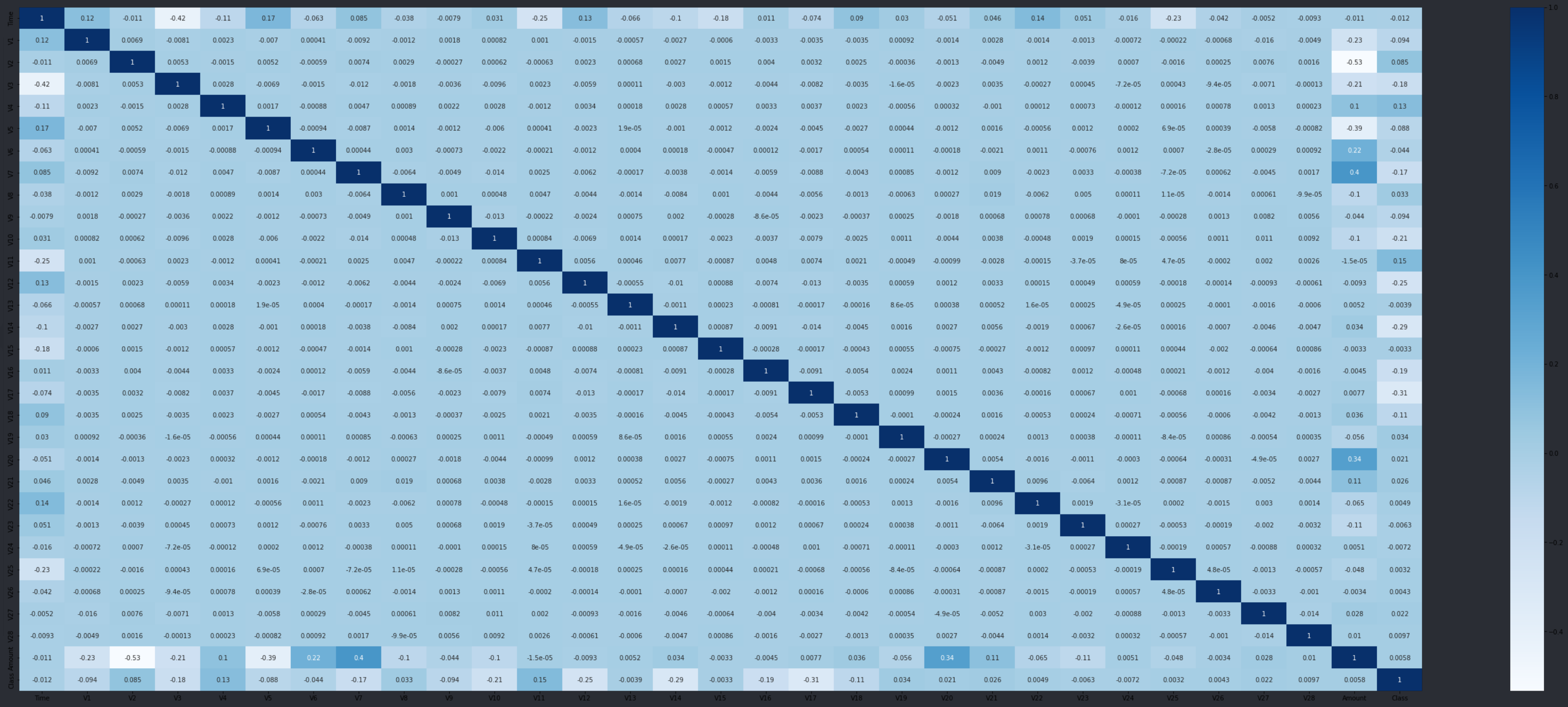
ML Problem Type is:
Classification

Classification Target:
Feature 'Class' is the response variable, and it takes value 1 in case of fraud and 0 otherwise.

Data Cleaning

- Due to PCA preprocessing Data Cleaning needed was very limited.
- No Nulls found
- No Data Type Inconcistencies
- No Categorical Inconsistencies would exist
- No Illogical Values
- A Number of Duplicates were there (~1000 rows) which were dropped

Visuals



Time
V1
V2
V3
V4
V5
V6
V7
V8
V9
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V20
V21
V22
V23
V24
V25
V26
V27
V28
Amount
Class
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Model Tunning – Parameters Used

Random Forest

```
max_depth: None
max_features: 'auto'
```

XGBoost

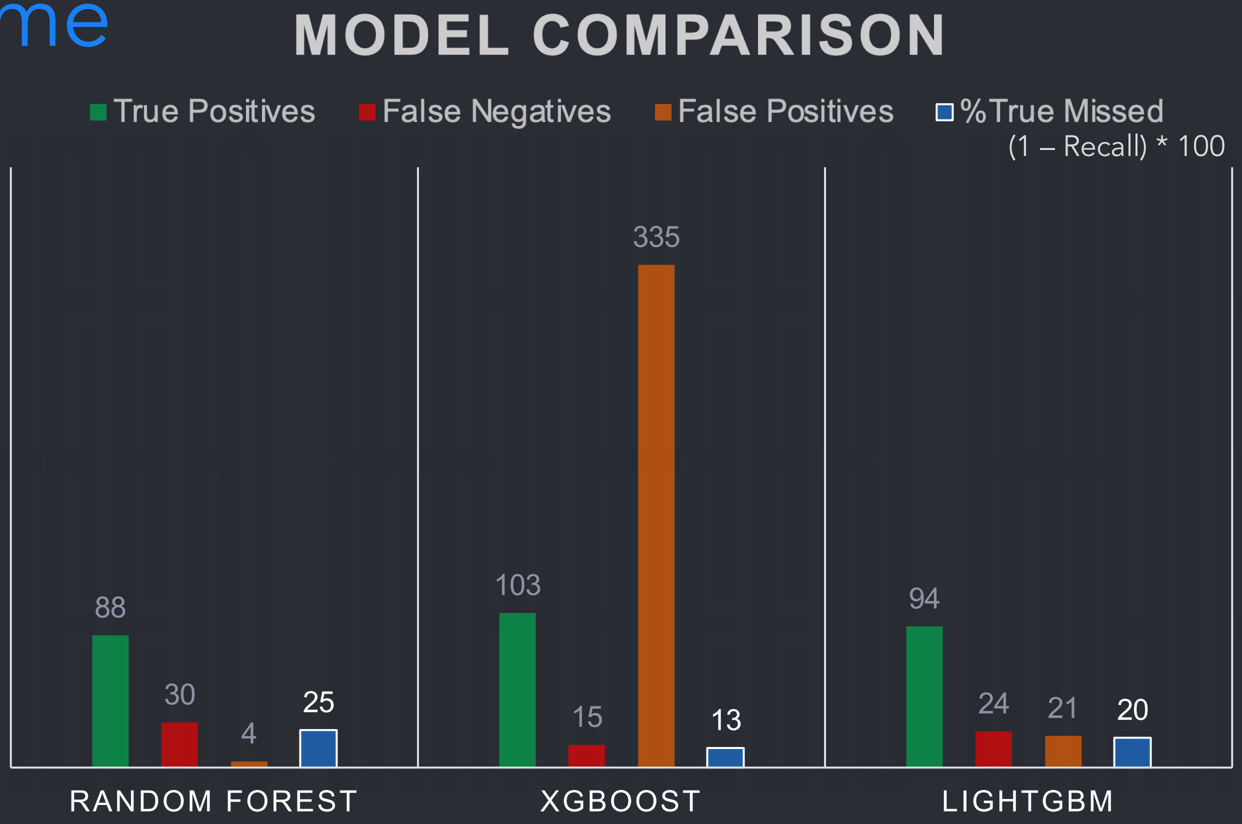
```
learning_rate: 0.35
max_depth: 6
tree_method: 'auto'
use_rmm: 'true'
```

LightGBM

```
eval_metric: 'auc'
learning_rate: 0.08
max_depth: 13
tree_method: 'gpu_hist'
```

Outcome

~71k
#Transactions Tested



Technical Outcome Summary

Outcome Summary

	Model	precision	recall	f1-score
0 Genuine	Random Forest	1	1	1
	XGBoost	1	0.99	1
	LightGBM	1	1	1
1 Fraud	Random Forest	0.96	0.74	0.83
	XGBoost	0.21	0.86	0.33
	LightGBM	0.83	0.80	0.81

Outcome Summary (without Time)

	Model	precision	recall	f1-score
0 Genuine	Random Forest	1	1	1
	XGBoost	1	1	1
	LightGBM	1	1	1
1 Fraud	Random Forest	0.96	0.75	0.84
	XGBoost	0.24	0.87	0.37
	LightGBM	0.82	0.80	0.81

Confusion Matrix

All features

74% Recall

96% Precision

True Label		0 Genuine (Predicted)	1 Fraud (Predicted)
	0 Genuine	70809	5
	1 Fraud	31	87

Predicted Label

Time Excluded

75% Recall

96% Precision

True Label		0 Genuine (Predicted)	1 Fraud (Predicted)
	0 Genuine	70810	4
	1 Fraud	30	88

Predicted Label

Random Forest

Confusion Matrix

All features

86% Recall

21% Precision

True Label		Predicted 0 Genuine	Predicted 1 Fraud
	0 Genuine	70424	390
	1 Fraud	16	102

Time Excluded

87% Recall

24% Precision

True Label		Predicted 0 Genuine	Predicted 1 Fraud
	0 Genuine	70479	335
	1 Fraud	15	103

XGBoost

Confusion Matrix

All features

80%
Recall

83%
Precision

True Label		Predicted Label: 0 Genuine	Predicted Label: 1 Fraud
	0 Genuine	70795	19
	1 Fraud	24	94

Time Excluded

80%
Recall

82%
Precision

True Label		Predicted Label: 0 Genuine	Predicted Label: 1 Fraud
	0 Genuine	70793	21
	1 Fraud	24	94

LightGBM