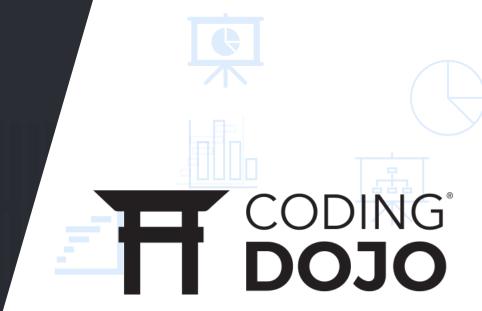
Data Science Bootcamp

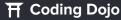
Project 2
Transaction Fraud Detection

Marwa Salah











Project Overview



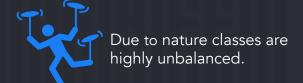
Identify potential fraudulant activity (transactions) using ML based on existing card transaction data



Anonymized credit card transactions labeled as fraudulent or genuine Transformed using PCA

<u>2 Features were not transformed using PCA</u> which are Time & Amount





0.17% vs 99.8% Class Balance



Transaction Fraud Detection WHY?



\$2-3

Cost of each dollar lost to fraud



Impacts
Individuals | Businesses |
Financial Instituations

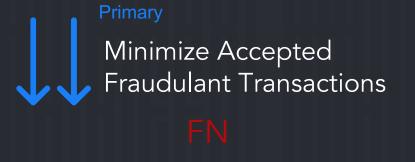
https://fortunly.com/statistics/cash-versus-credit-card-spending-statistics/#grefhttps://www.ncr.com/blogs/payments/credit-card-fraud-detection



Objectives

Identify potentially fraudulent activity

Detecting fraudulent activity before those transactions are even completed





Secondary

Avoid Declining
Genuine Transactions

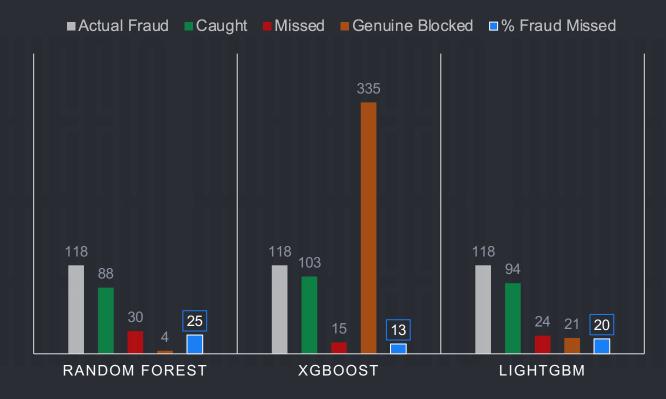
FP



Outcome

MODEL COMPARISON









Conclusion & Next Step

Full Dataset

Fraud: \$ 60K Genuine: \$ 25M @87% Detection Rate

Fraud: \$ 9K

Genuine: \$25M (-Genuine Blocked if not validated)

Example based costsensitive 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					

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

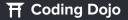


Challenges

- 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
 - O Does not contain any personal information
 - O 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

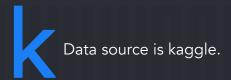


Data Description



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





Due to nature classes are highly unbalanced.

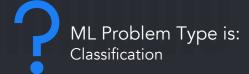


Data Shape is:

- 28 Components, 2 Features & 1 Label 284807 Rows (Observations)



Data Types: All features are Integers of type int64





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



1	0.12	-0.011	-0.42	-0.11	0.17	-0.063	0.085	-0.038	-0.0079	0.031	-0.25	0.13	-0.066	-0.1	-0.18	0.011	-0.074	0.09	0.03	-0.051	0.046	0.14	0.051	-0.016	-0.23	-0.042	-0.0052	-0.0093	-0.011	-0.012
0.12	1	0.0069	-0.0081	0.0023	-0.007	0.00041	-0.0092	-0.0012	0.0018	0.00082	0.001	-0.0015	-0.00057	-0.0027	-0.0006	-0.0033	-0.0035	-0.0035	0.00092	-0.0014	0.0028	-0.0014	-0.0013	-0.00072	-0.00022	-0.00068	-0.016	-0.0049	-0.23	-0.094
-0.011	0.0069	1	0.0053	-0.0015	0.0052	-0.00059	0.0074	0.0029	-0.00027	0.00062	-0.00063	0.0023	0.00068	0.0027	0.0015	0.004	0.0032	0.0025	-0.00036	-0.0013	-0.0049	0.0012	-0.0039	0.0007	-0.0016	0.00025	0.0076	0.0016	-0.53	0.085
-0.42	-0.0081	0.0053	1	0.0028	-0.0069	-0.0015	-0.012	-0.0018	-0.0036	-0.0096	0.0023	-0.0059	0.00011	-0.003	-0.0012	-0.0044	-0.0082	-0.0035	-1.6e-05	-0.0023	0.0035	-0.00027	0.00045	-7.2e-05	0.00043	-9.4e-05	-0.0071	-0.00013	-0.21	-0.18
0.11	0.0023	-0.0015	0.0028	1	0.0017	-0.00088	0.0047	0.00089	0.0022	0.0028	-0.0012	0.0034	0.00018	0.0028	0.00057	0.0033	0.0037	0.0023	-0.00056	0.00032	-0.001	0.00012	0.00073	-0.00012	0.00016	0.00078	0.0013	0.00023	0.1	0.13
0.17	-0.007	0.0052	-0.0069	0.0017	1	-0.00094	-0.0087	0.0014	-0.0012	-0.006	0.00041	-0.0023	1.9e-05	-0.001	-0.0012	-0.0024	-0.0045	-0.0027	0.00044	-0.0012	0.0016	-0.00056	0.0012	0.0002	6.9e-05	0.00039	-0.0058	-0.00082	-0.39	-0.088
-0.063	0.00041	-0.00059	-0.0015	-0.00088	-0.00094	1	0.00044	0.003	-0.00073	-0.0022	-0.00021	-0.0012	0.0004	0.00018	-0.00047	0.00012	-0.0017	0.00054	0.00011	-0.00018	-0.0021	0.0011	-0.00076	0.0012	0.0007	-2.8e-05	0.00029	0.00092	0.22	-0.044
0.085	-0.0092	0.0074	-0.012	0.0047	-0.0087	0.00044	1	-0.0064	-0.0049	-0.014	0.0025	-0.0062	-0.00017	-0.0038	-0.0014	-0.0059	-0.0088	-0.0043	0.00085	-0.0012	0.009	-0.0023	0.0033	-0.00038	-7.2e-05	0.00062	-0.0045	0.0017	0.4	-0.17
-0.038	-0.0012	0.0029	-0.0018	0.00089	0.0014	0.003	-0.0064	1	0.001	0.00048	0.0047	-0.0044	-0.0014	-0.0084	0.001	-0.0044	-0.0056	-0.0013	-0.00063	0.00027	0.019	-0.0062	0.005	0.00011	1.1e-05	-0.0014	0.00061	-9.9e-05	-0.1	0.033
-0.0079	0.0018	-0.00027	-0.0036	0.0022	-0.0012	-0.00073	-0.0049	0.001	1	-0.013	-0.00022	-0.0024	0.00075	0.002	-0.00028	-8.6e-05	-0.0023	-0.00037	0.00025	-0.0018	0.00068	0.00078	0.00068	-0.0001	-0.00028	0.0013	0.0082	0.0056	-0.044	-0.094
0.031	0.00082	0.00062	-0.0096	0.0028	-0.006	-0.0022	-0.014	0.00048	-0.013	1	0.00084	-0.0069	0.0014	0.00017	-0.0023	-0.0037	-0.0079	-0.0025	0.0011	-0.0044	0.0038	-0.00048	0.0019	0.00015	-0.00056	0.0011	0.011	0.0092	-0.1	-0.21
-0.25	0.001	-0.00063	0.0023	-0.0012	0.00041	-0.00021	0.0025	0.0047	-0.00022	0.00084	1	0.0056	0.00046	0.0077	-0.00087	0.0048	0.0074	0.0021	-0.00049	-0.00099	-0.0028	-0.00015	-3.7e-05	8e-05	4.7e-05	-0.0002	0.002	0.0026	-1.5e-05	0.15
0.13	-0.0015	0.0023	-0.0059	0.0034	-0.0023	-0.0012	-0.0062	-0.0044	-0.0024	-0.0069	0.0056	1	-0.00055	-0.01	0.00088	-0.0074	-0.013	-0.0035	0.00059	0.0012	0.0033	0.00015	0.00049	0.00059	-0.00018	-0.00014	-0.00093	-0.00061	-0.0093	-0.25
-0.066	0.00057	0.00068	0.00011	0.00018	1.9e-05	0.0004	-0.00017	-0.0014	0.00075	0.0014	0.00046	-0.00055	1	-0.0011	0.00023	-0.00081	-0.00017	-0.00016	8.6e-05	0.00038	0.00052	1.6e-05	0.00025	-4.9e-05	0.00025	-0.0001	-0.0016	-0.0006	0.0052	-0.0039
-0.1	-0.0027	0.0027	-0.003	0.0028	-0.001	0.00018	-0.0038	-0.0084	0.002	0.00017	0.0077	-0.01	-0.0011	1	0.00087	-0.0091	-0.014	-0.0045	0.0016	0.0027	0.0056	-0.0019	0.00067	-2.6e-05	0.00016	-0.0007	-0.0046	-0.0047	0.034	-0.29
-0.18	-0.0006	0.0015	-0.0012	0.00057	-0.0012	-0.00047	-0.0014	0.001	-0.00028	-0.0023	-0.00087	0.00088	0.00023	0.00087	1	-0.00028	-0.00017	-0.00043	0.00055	-0.00075	-0.00027	-0.0012	0.00097	0.00011	0.00044	-0.002	-0.00064	0.00086	-0.0033	-0.0033
	-0.0033	0.004	-0.0044	0.0033	-0.0024	0.00012	-0.0059	-0.0044	-8.6e-05	-0.0037	0.0048	-0.0074	-0.00081		-0.00028	1	-0.0091		0.0024	0.0011	0.0043	-0.00082	0.0012	-0.00048	0.00021	-0.0012	-0.004	-0.0016	-0.0045	-0.19
		0.0032	-0.0082	0.0037	-0.0045	-0.0017	-0.0088	-0.0056	-0.0023	-0.0079	0.0074	-0.013	-0.00017	-0.014		-0.0091	1		0.00099	0.0015	0.0036	-0.00016	0.00067	0.001	-0.00068	0.00016	-0.0034	-0.0027	0.0077	-0.31
		0.0025				0.00054	-0.0043	-0.0013	-0.00037		0.0021	-0.0035		-0.0045	-0.00043		-0.0053	1		-0.00024		-0.00053			-0.00056	-0.0006	-0.0042	-0.0013	0.036	-0.11
			-1.6e-05			0.00011		-0.00063		0.0011	-0.00049	0.00059	8.6e-05	0.0016	0.00055	0.0024	0.00099	-0.0001	1		0.00024	0.0013	0.00038		-8.4e-05	0.00086	-0.00054		-0.056	
		-0.0013				-0.00018	-0.0012	0.00027	-0.0018	-0.0044	-0.00099	0.0012	0.00038	0.0027	-0.00075	0.0011	0.0015		-0.00027	1	0.0054		-0.0011		-0.00064	-0.00031			0.34	0.021
		-0.0049		-0.001	0.0016	-0.0021	0.009	0.019	0.00068	0.0038	-0.0028	0.0033		0.0056	-0.00027	0.0043	0.0036	0.0016	0.00024	0.0054	1	0.0096	-0.0064		-0.00087		-0.0052	-0.0044	0.11	0.026
	-0.0014 -0.0013				-0.00056	0.0011	0.0023	0.0062	0.00078	0.00048	-0.00015 -3.7e-05	0.00015	1.6e-05 0.00025	0.0019	0.0012	-0.00082	0.00016	0.00053	0.0013	-0.0016	-0.0096	0.0019	0.0019	-3.1e-05	0.0002	-0.0015	0.003	-0.0014	-0.065	0.0049
			-7.2e-05					0.00011	-0.0001		3.7e-05	0.00049		-2 6e-05	0.00097		0.00067		-0.00011	-0.0011	0.0012		0.00027	0.00027		0.00019		0.00032	0.0051	.0.0063
				0.00012	6.96.05	0.0012	-7.2e-05	11e.05	-0.00028		4.7e-05	-0.00018	0.00025	0.00016	0.00011	0.00021	-0.00068	-0.00071	-8.4e-05	0.0003	-0.00087	0.0002		-0.00019	1	4.8e-05	-0.0003	-0.00057	.0.048	0.0072
					0.00039	-2 Re-05	0.00062	.0 0014	0.00026	0.00056	u.7e-05	.0.00016	.0.00025	.0.00016	.0.00044	J. 0012	0.00068	-0.00056 -0.0006	0.00086	.0.00064 .0.00031	.0.00087	-0.0015	-0.00053		4.8e-05	4.8e-U5	-0.0013		JO 0034	
			-0.0071					0.00061	0.0013	0.011	0.002	-0.00014		-0.0046	-0.00064	-0.0012	-0.0034		-0.00054		-0.0052	0.003	-0.00019		-0.0013		1	-0.014	0.028	0.0043
			-0.00013				0.0017	-9.9e-05	0.0056	0.0092	0.0026	-0.00061	-0.0006	-0.0047	0.00086	-0.0016	-0.0027	-0.0013	0.00035	0.0027	-0.0044	0.0014	-0.0032	0.00032	-0.00057	-0.001	-0.014	1	0.01	0.0097
-0.011	-0.23	-0.53	-0.21	0.1	-0.39	0.22	0.4	-0.1	-0.044	-0.1	-1.5e-05	-0.0093	0.0052	0.034	-0.0033	-0.0045	0.0077	0.036	-0.056	0.34	0.11	-0.065	-0.11	0.0051	-0.048	-0.0034	0.028	0.01		0.0058
	0.094	0.085	-0.18	0.13	-0.088	-0.044	0.17	0.033	-0.094	-0.21	0.15	-0.25	-0.0039	-0.29	-0.0033	-0.19	-0.31	0.030	0.034	0.021	0.026	0.0049	-0.0063	-0.0072	0.0032	0.0034	0.020	0.0097	0.0058	1



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'
```

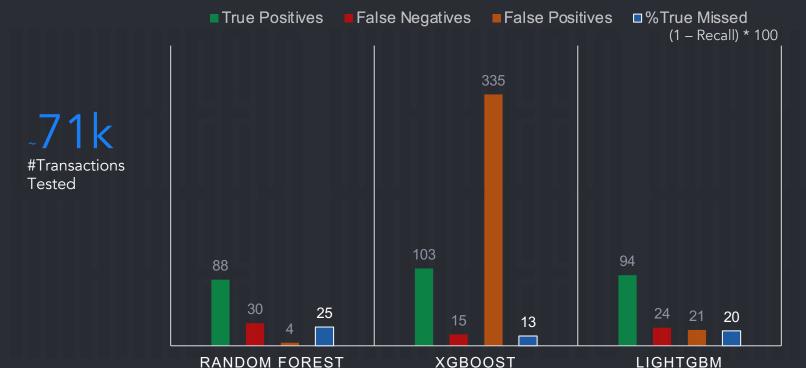
<u>LightGBM</u>

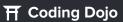
```
eval_metric: 'auc'
learning_rate: 0.08
max_depth: 13
tree_method: 'gpu_hist'
```



Outcome

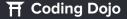
MODEL COMPARISON







Technical Outcome Summary





Outcome Summary

	Model	precision	recall	f1-score				
	Random Forest	1	1	1				
O Genuine	XGBoost	1	0.99	1				
	LightGBM	1	1					
1 Fraud	Random Forest	0.96	<u>0.74</u>	0.83				
	XGBoost	0.21	0.86	0.33				
	LightGBM	0.83	0.80	0.81				

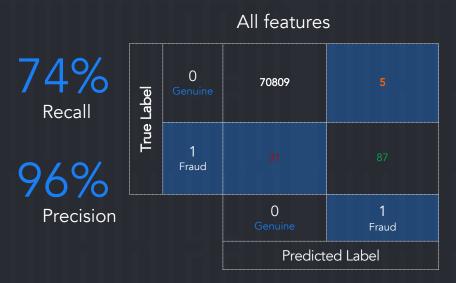


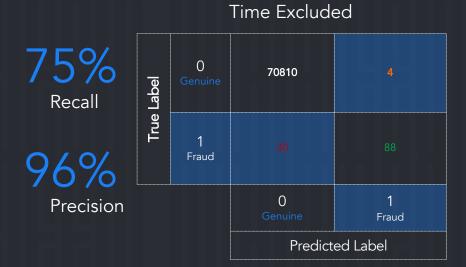
Outcome Summary (without Time)

	Model	precision	recall	f1-score
	Random Forest	1	1	1
O Genuine	XGBoost	1	1	1
	LightGBM	1	1	1
	Random Forest	0.96	<u>0.75</u>	0.84
1 Fraud	XGBoost	0.24	0.87	0.37
	LightGBM	0.82	0.80	0.81



Confusion Matrix

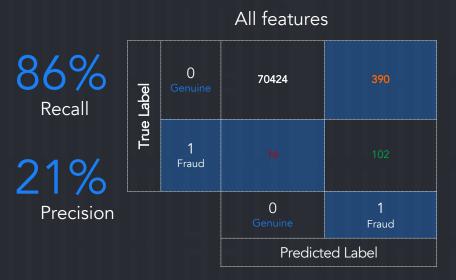


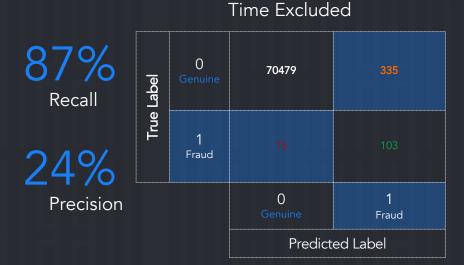


Random Forest



Confusion Matrix

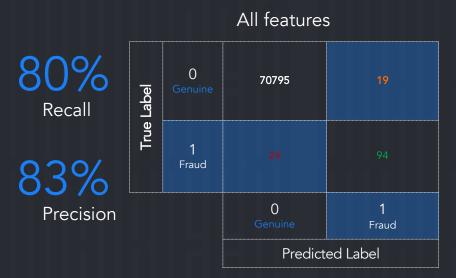




XGBoost



Confusion Matrix



Time Excluded

80%
Recall

1
Fraud

0
Genuine

1
Fraud

0
Genuine

1
Fraud

Predicted Label

LightGBM