

Optimizing Online Fraud Transaction Detection

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Motivation

- According to TD Bank’s recent survey, the **risk of payment fraud is the number one concern** for 44% of financial industry
- According to Juniper Research, **losses due to online and mobile payment frauds** is estimated to be **\$22 billion this year**—and could go as high as \$48 billion by 2023
- **“Prevention is better than Cure”** — The costs associated with being wrong are very expensive !

Dataset & Approach

- Dataset sourced from Vesta's **real-world** e-commerce transactions
- Re-classifying all categorical variables using **One hot encoding**
- Replacing all **NA’s** with the **column means** of the dataset
- **Class Balancing** after splitting into **Training** and **Test** data-sets
- Model trained on **30000+** observations and tested with **170000+** observations across **242** variables

Model Creation & Prediction



Confusion Matrix Weights				Confusion Matrix Counts			
		Predicted Fraud				Predicted Fraud	
		0	1			0	1
Actual	Fraud	0	\$ - \$ 20.00	Actual	Fraud	0	167755 1240
		1	\$ 50.00 \$ -			1	35432 46062

- The Average loss due to misclassification amounted to ~ \$ 70 from the dataset. This is used as the weightage for false-positives and false-negatives with weightage for false-positives being more
- The model was compared against Logistics Regression and was found to give a better optimized classification with better AUC
- Lastly, running solver on the model suggested a threshold value of 0.83 with a minimized 0.4 % loss of ~ \$ 200,,000 for an overall \$ 79.83 M transaction amount

Metric for Loss

Actual

Predicted

0

1

TP

FP

FN

TN

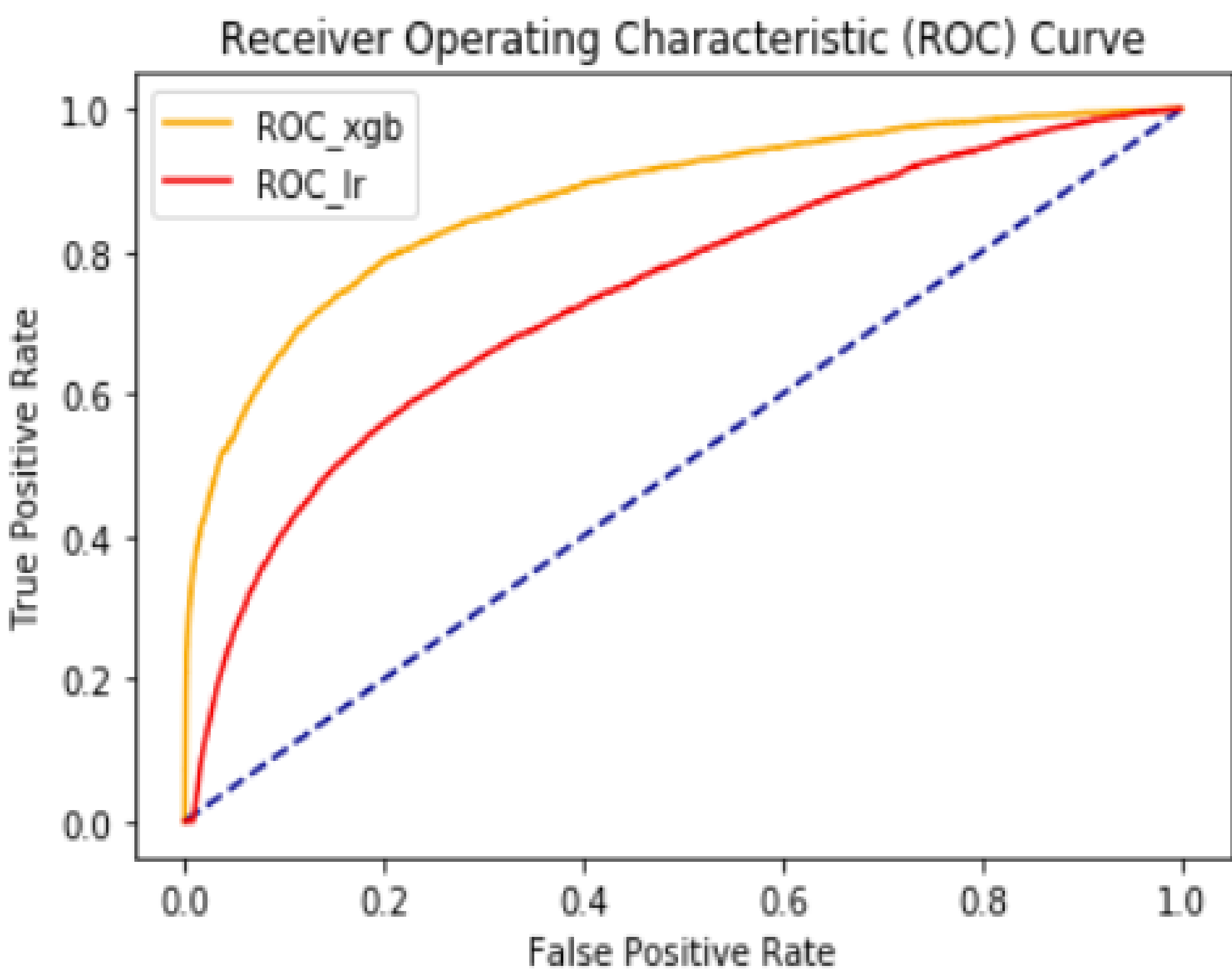
Expected Loss = $\sum p(o_i).v(o_i)$

Class priors => $p(p) = (TP+FN)/Total$
 $p(n) = (FP+TN)/Total$

$tp\ rate = TP/(TP+FN)$ $fp\ rate = FP/(FP+TN)$
 $fn\ rate = FN/(TP+FN)$ $tn\ rate = TN/(FP+TN)$

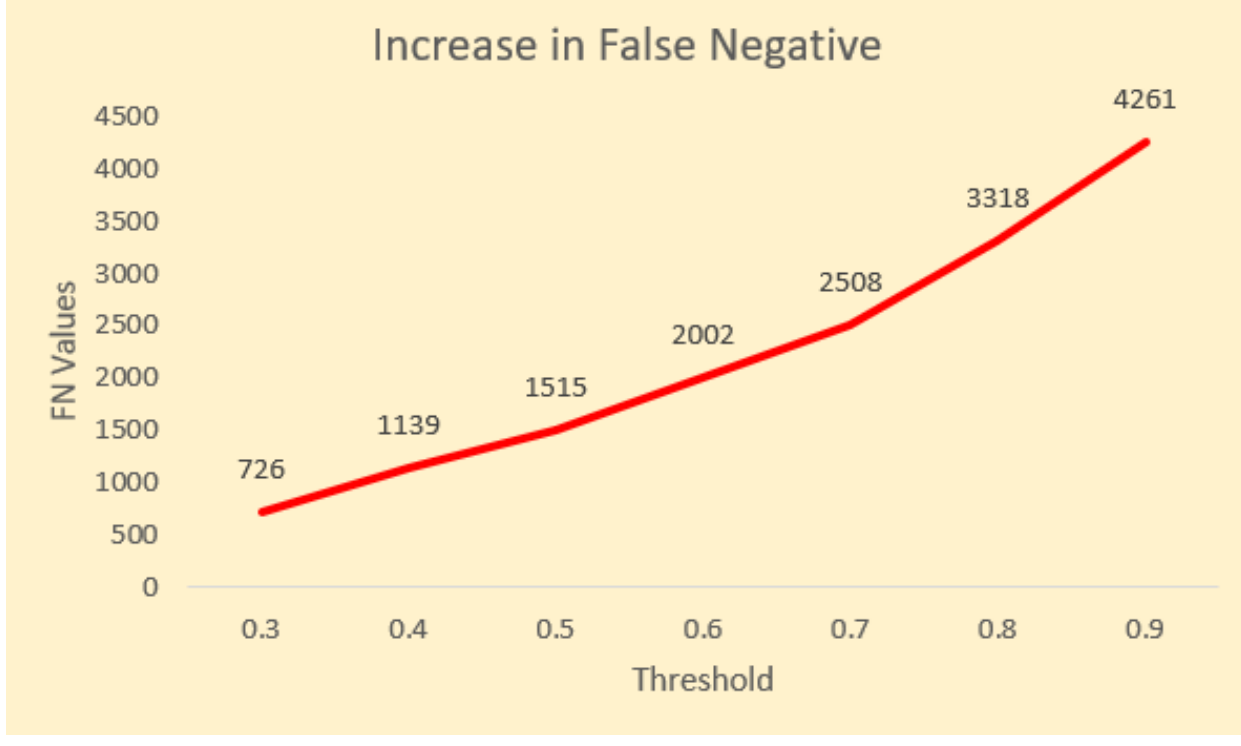
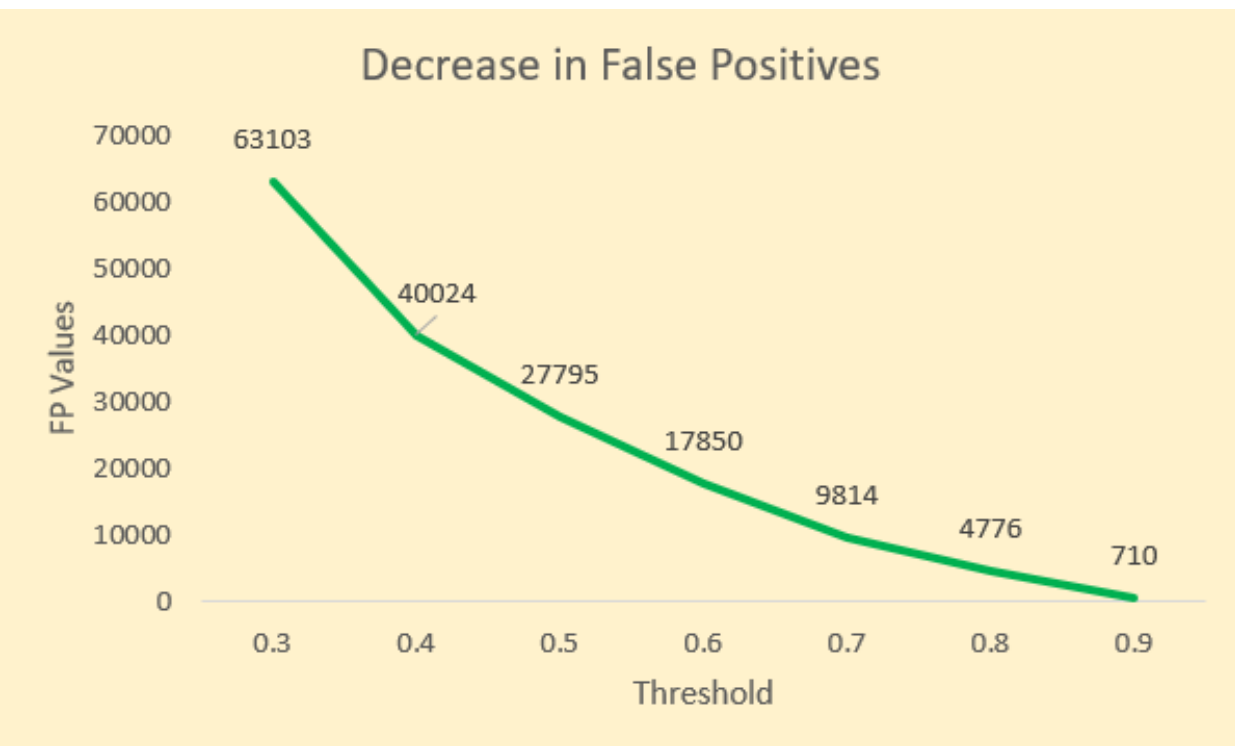
Metric for Loss = $p(p) . [tp\ rate.(TP\ cost) + fn\ rate.(FN\ cost)] +$
 $p(n) . [tn\ rate.(TN\ cost) + fp\ rate.(FP\ cost)]$

XGB & LR ROC



Sensitivity Analysis

Threshold	True Positive	True Negative	Fasle Positive	False Negative
0.3	107934	5399	63103	726
0.4	131013	4986	40024	1139
0.5	143242	4610	27795	1515
0.6	153187	4123	17850	2002
0.7	161223	3617	9814	2508
0.8	166261	2807	4776	3318
0.9	170327	1864	710	4261



Confusion Matrix

- Varying the threshold of prediction probability for XGBoost model to create a sensitivity analysis on false positives and false negatives
- Large decrease is observed in the false positive values which are predicted frauds but not actually fraudulent transactions
- There is a slight increase in the number of false negatives which are the transactions which cannot be certainly be classified as fraudulent

Future Scope

- Combining various model outputs and evaluate the confusion matrix to get better classification and improved accuracy.
- Perform time-series analysis and make use of variables such as transaction timing and deltas to classify fraudulent transactions
- Use techniques such as k-fold cross validation to get the aggregate of classifications and analyze the attributes of the resultant confusion matrix