



# Risk Scores Suggestion

Identify the risk scores for least no.of fraudulent chargeback



# TOC

Problem Statement

Feature Engineering & Target Creation

ML Methods & Models

Performance Results

Results & Conclusion

# Problem Statement

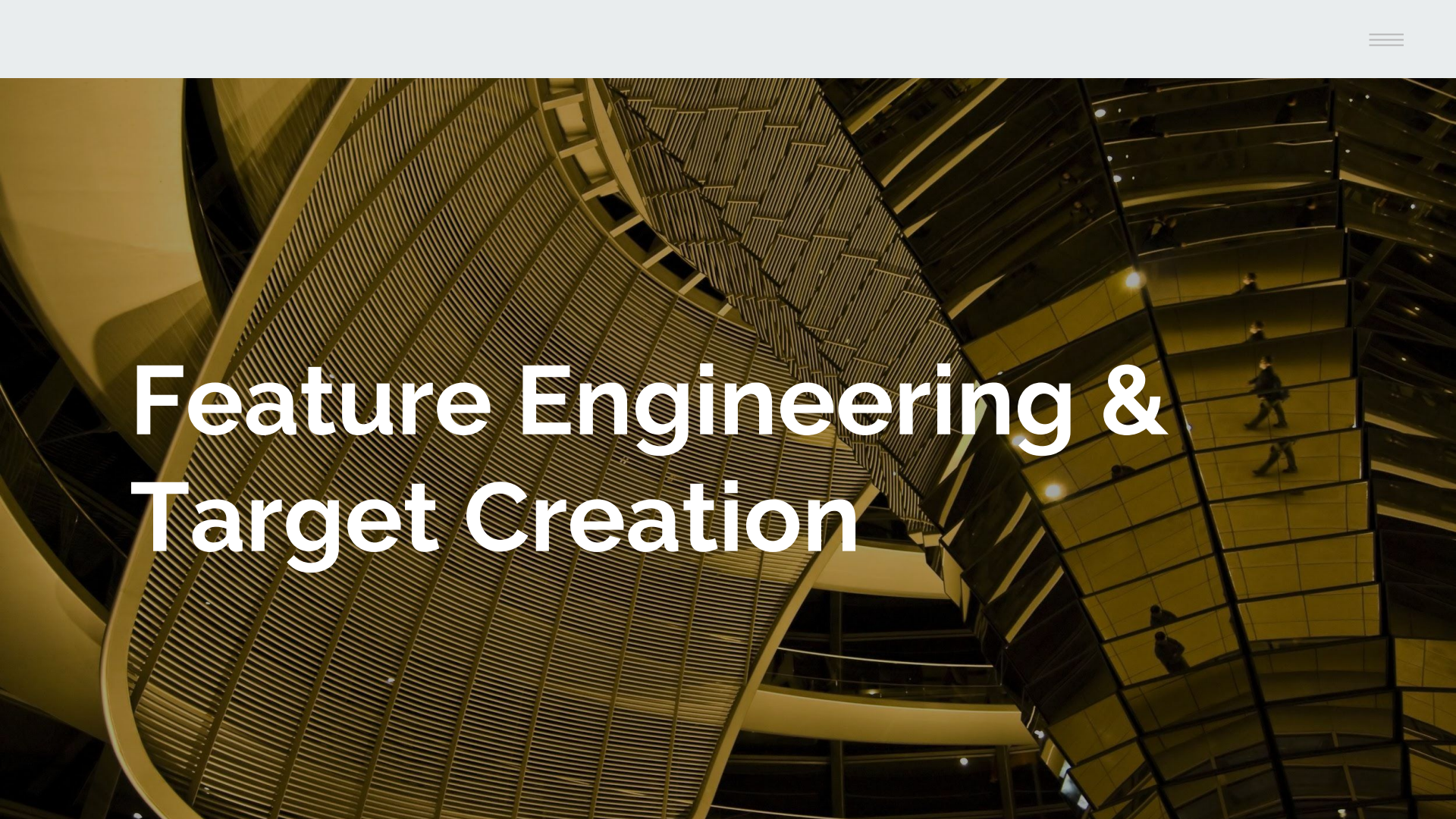
Adyen is looking to help a large Food ordering merchant optimize its risk settings. Adyen has a Rule Based Risk Engine with 78 different rules. A merchant can assign a score to each of the rules, if the combined score of the rules passes a threshold of 100, Adyen's risk engine will automatically block the transaction. The merchant has asked us if we could determine the optimal risk score for them.

- Fraudulent chargebacks should be less than 1 pc (or as low as possible)



Fig : POS Sales





# Feature Engineering & Target Creation

# Feature Engineering & Target Creation



## Target :

Classification Problem : ( Fraud = 1, Not Fraud = 0 )

1. Highly Imbalanced dataset.

## Features :

1. Rules from 1-78 are only considered.
2. More features can be created too .  
Eg (recency, amount of transaction , rating of the bank for fraud usage, origin country etc) . However since we want to assign weights to the rules, not considering other features.

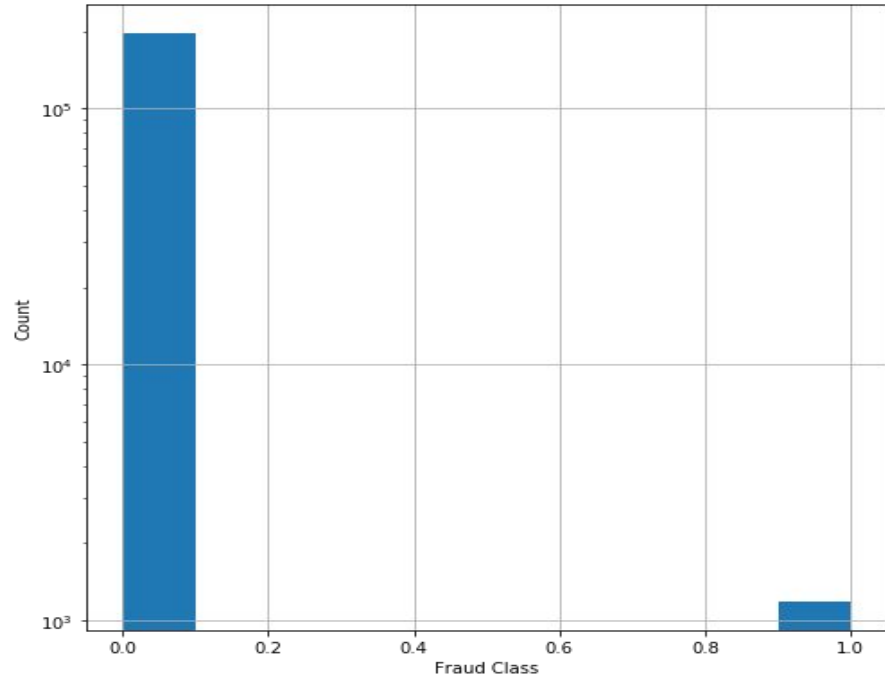


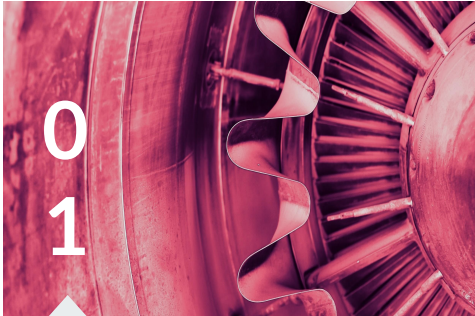
Fig : Fraud Histogram (Log Transformed)





# Experiment Design

# Experiment Design



## Data Cleaning Target & Feature Creation

In this step, we read the data, create targets and features.



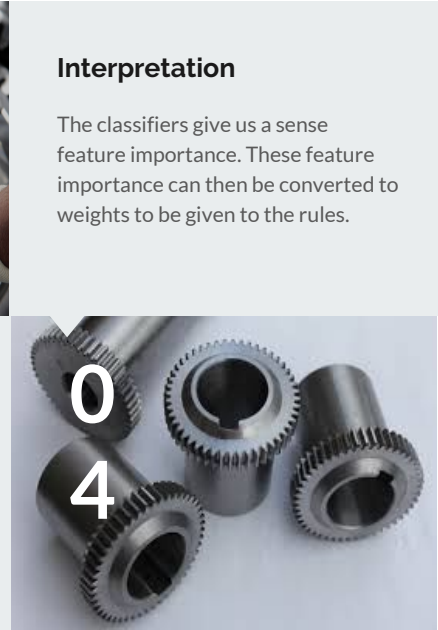
## Handle Data Imbalance

Since we are dealing with highly imbalanced datasets, we try various sampling techniques.



## Classification

On the sampled datasets, we try multiple classification techniques namely ( Logistic Regression, Bagging and Boosting Trees ). We use scoring metrics like AUC, Precision & Recall, Cohen-Kappa.



## Interpretation

The classifiers give us a sense of feature importance. These feature importance values can then be converted to weights to be given to the rules.



# Getting Ready- Common Settings



## Training & Testing datasets

01

Test data ratio : 0.3

## Model Evaluation

02

High Precision on Majority Class - 0/High Recall on Minority Class - 1.

AUC

Cohen-Kappa Score





# Imbalanced Class



- **Modify class weights**

01

Assign weights to class

- **Sampling Techniques**

02

Random Under & Over Sampling

NearMiss

SMOTE

- **Ensemble Methods**

03

Bagging Classifier

SMOTE+EEN



# Classification

## Decision Tree

O1

Though Decision tree classifiers suffer from the disadvantages such as growing complex and still unable to generalise the data well.

It is simple to understand and trees can be visualised .

Test AUC / Cohen-Kappa score : 0.73/ 0.049

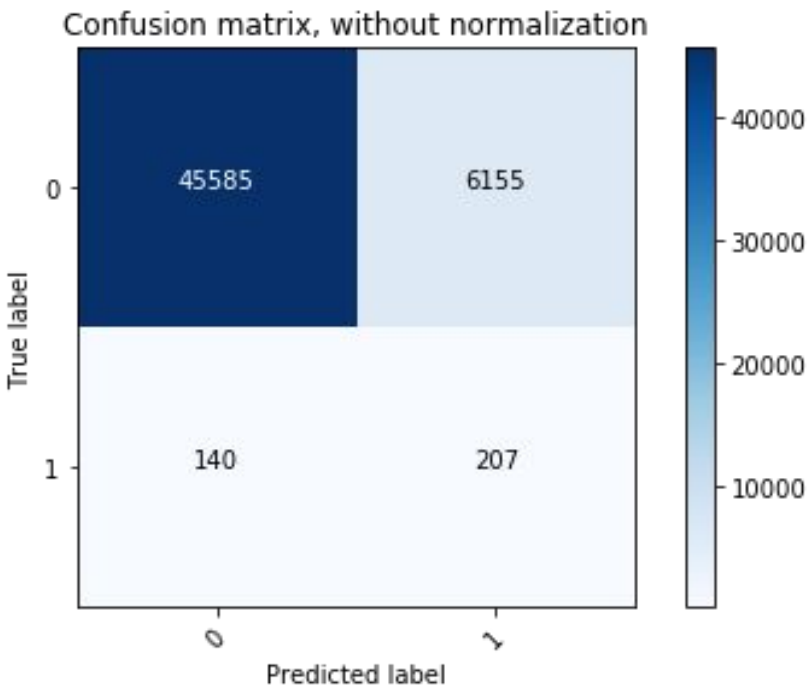


Fig : Classification Report

# Classification

## Random Forest & Extra Trees Classifier

02

One of the most robust set of classifiers, inherently reduces overfitting.

Provides a list of feature importance, which can help in identifying entity attributes.

Random Forest :  
AUC / Cohen-Kappa : 0.72/0.049

Extra Trees Classifier :  
AUC / Cohen-Kappa : 0.73/0.05

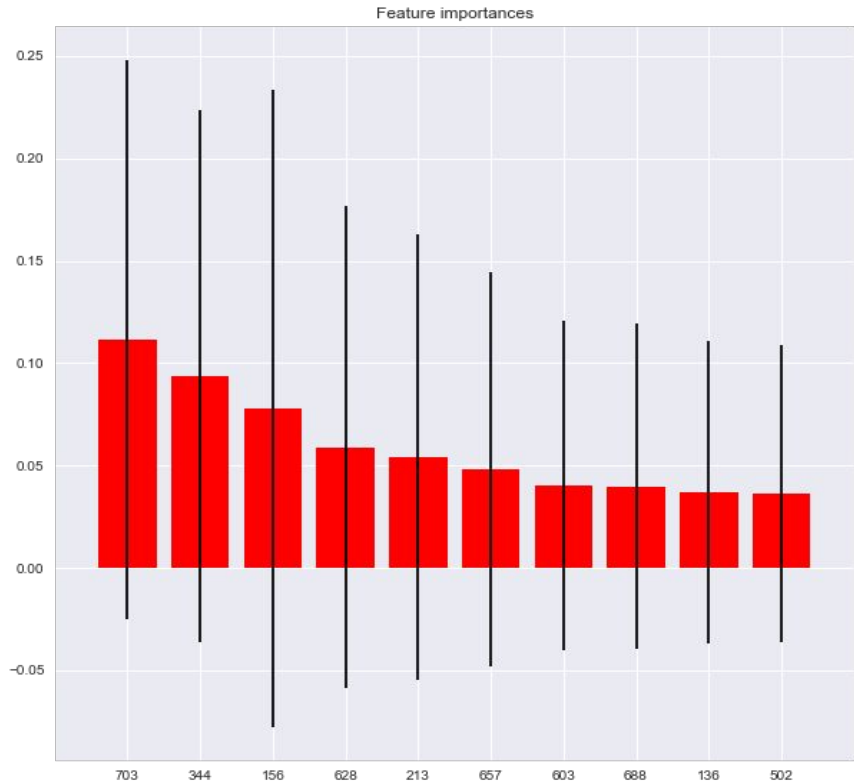


Fig : Extra Trees Classifier Feature Importance



# Results



# Performance Analysis



A run is considered good enough for usage if :

- Train & Test ROC-AUC is  $\geq 0.72$
- Training AUC and Testing AUC  $\leq 5$  percentage points
- Cohen - Kappa is  $\geq 0.04$
- Recall on class 1  $\geq 0.6$

Sampling Technique	Class Weights					
ML Algorithm	LR	DT	RF	ET	GBT	ABT
Metrics (Test Set)						
Precision on 0 class	1	1	1	1	0.99	0.99
Recall on 1 class	0.61	0.62	0.58	0.62	0.02	0.01
F1 Score	0.06	0.07	0.06	0.07	0.03	0.03
AUC	0.73	0.74	0.73	0.73	0.52	0.52
Cohen-Kappa score	0.04	0.04	0.05	0.05	0.02	0.02



# Most Important Rules

Rule No	Importance(%)
Rule 49	19
Rule 55	8
Rule 63	14
Rule 74	11





# Future Work

- **Better Features & Grid Search**

01

Create more features that can detect fraudulent transactions .

Grid search for hyper parameter tuning .

SMOTE with KBest features

- **Anomaly Detection**

02

Treat fraud cases as anomaly .

- **Modify Threshold**

03

Modify default threshold probability of 0.5 .

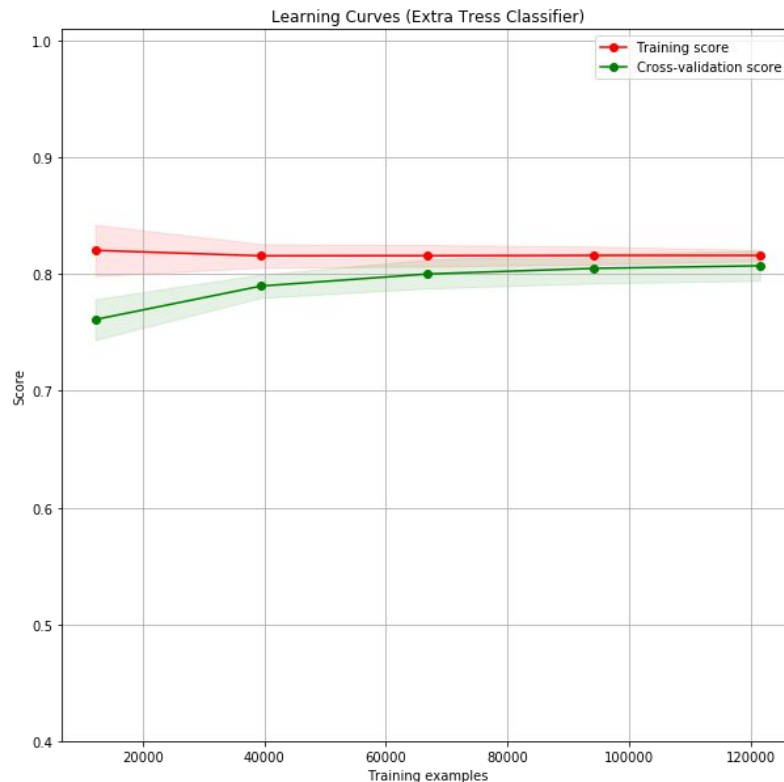


Fig : Extra Trees Classifier Learning Curve



# Thank you.

