FRAUD DETECTION USING MACHINE LEARNING

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BUSINESS PROBLEM : LOSS DUE TO CREDIT CARD FRAUD

AGENDA

A brief look at what we will discuss going further

- Background
- Business Question Vs Data Question
- The Pipeline
- EDA and Feature Engineering
- Modelling
- Summary and Insights
- Cost Benefit Analysis

BACKGROUND

Credit card fraud is the fraudulent use of a credit card done so through the theft of the cardholder’s personal details. Thanks to the invention of the internet and the endless supply of eCommerce sites that came with it, credit card scammers now have an easier time than ever pinching your details

Data from the Australian Payments Network showed that card fraud cost $447.2 million in the 2019/20 financial year. Most of this happened online through card-not-present (CNP) fraud, which made up the bulk of card fraud (87.7%)

TYPES OF CREDIT CARD FRAUD

Card-not-present (CNP) fraud

Counterfeit and skimming fraud

Lost and stolen card fraud

Card-never arrived-fraud

False application fraud

Business Question

How to detect the fraudulent transactions out of the non-fraudulent ones?

Data Question

Which model can predict fraud transactions more accurately?

The Pipeline

01

Identify the Business Question

How to detect and minimise fraud?

02

Transform to Data Question

- How to build a model which can predict fraud?
- What data we require?
- What are the important features?
- Which model can predict fraud accurately?

03

EDA and Feature Engineering

Explore the Data. Find and create the right features in order to predict fraud.

04

Design the Model

Try various algorithms and compare.

05

Validation Testing

Select the best model that can predict fraud accurately

If classified as fraud, investigate further

If classified non fraud, good to go.

How Frauds are detected?

- **Regional Statistics** : When purchases are made from different locations.
- **Transaction Statistics** : If a customer deviates from the regular buying pattern or time.
- **Time Based Number Of Transactions Statistics** : When large number of transactions are made from a card in short span of time.
- **Time Based Amount Statistics** : When suddenly costly items are purchased.

THE DATASET

This is a simulated credit card transaction dataset from Kaggle containing legitimate and fraud transactions from the duration 1st Jan 2019 - 30th June 2020. It covers credit cards of 1000 customers doing transactions with a pool of 800 merchants.

Number of rows = 1,852,394

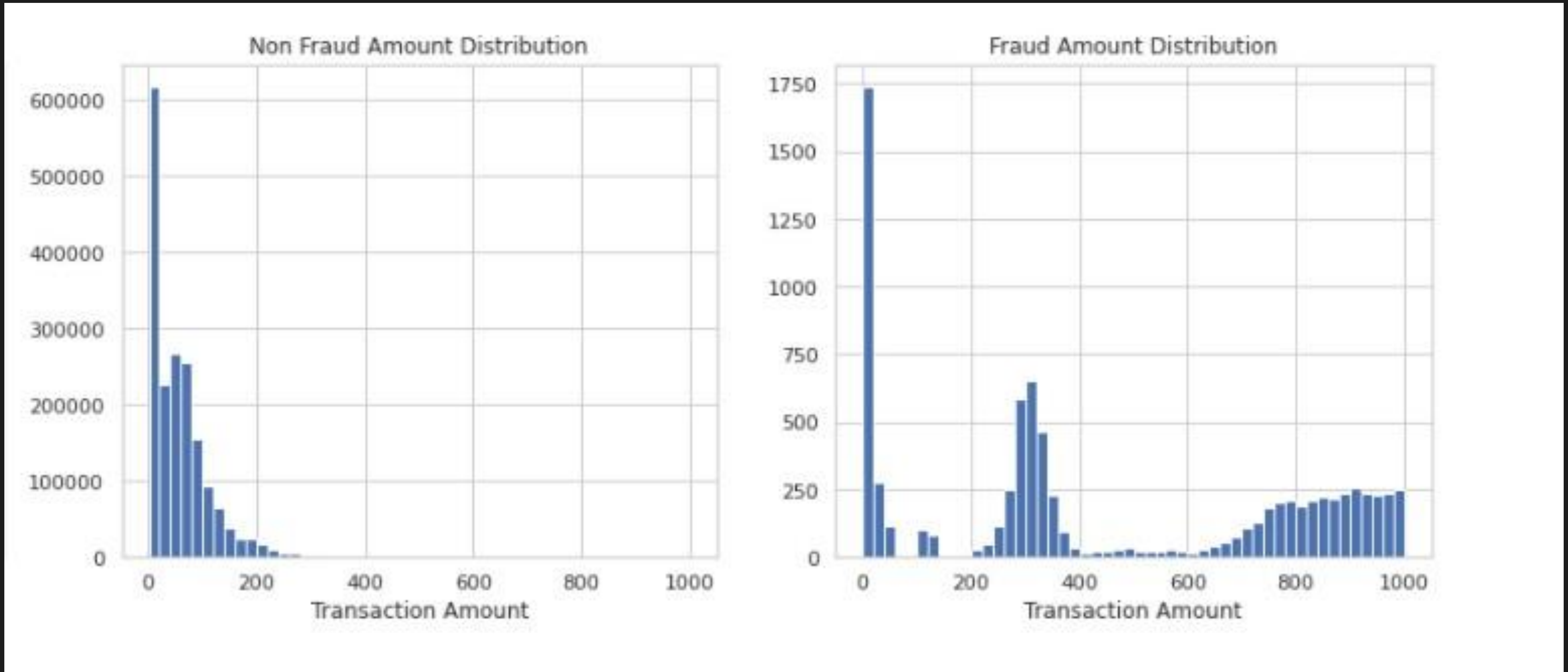
Number of columns = 22

	is_fraud	count	percentage
0	0	1842743	99.478999
1	1	9651	0.521001

trans_date_trans_time	datetime64[ns]
cc_num	int64
merchant	object
category	object
amt	float64
first	object
last	object
gender	object
street	object
city	object
state	object
zip	int64
lat	float64
long	float64
city_pop	int64
job	object
dob	object
trans_num	object
unix_time	int64
merch_lat	float64
merch_long	float64
is_fraud	int64
trans_hour	int64
day_of_week	object
year_month	period[M]
hourEnc	int64

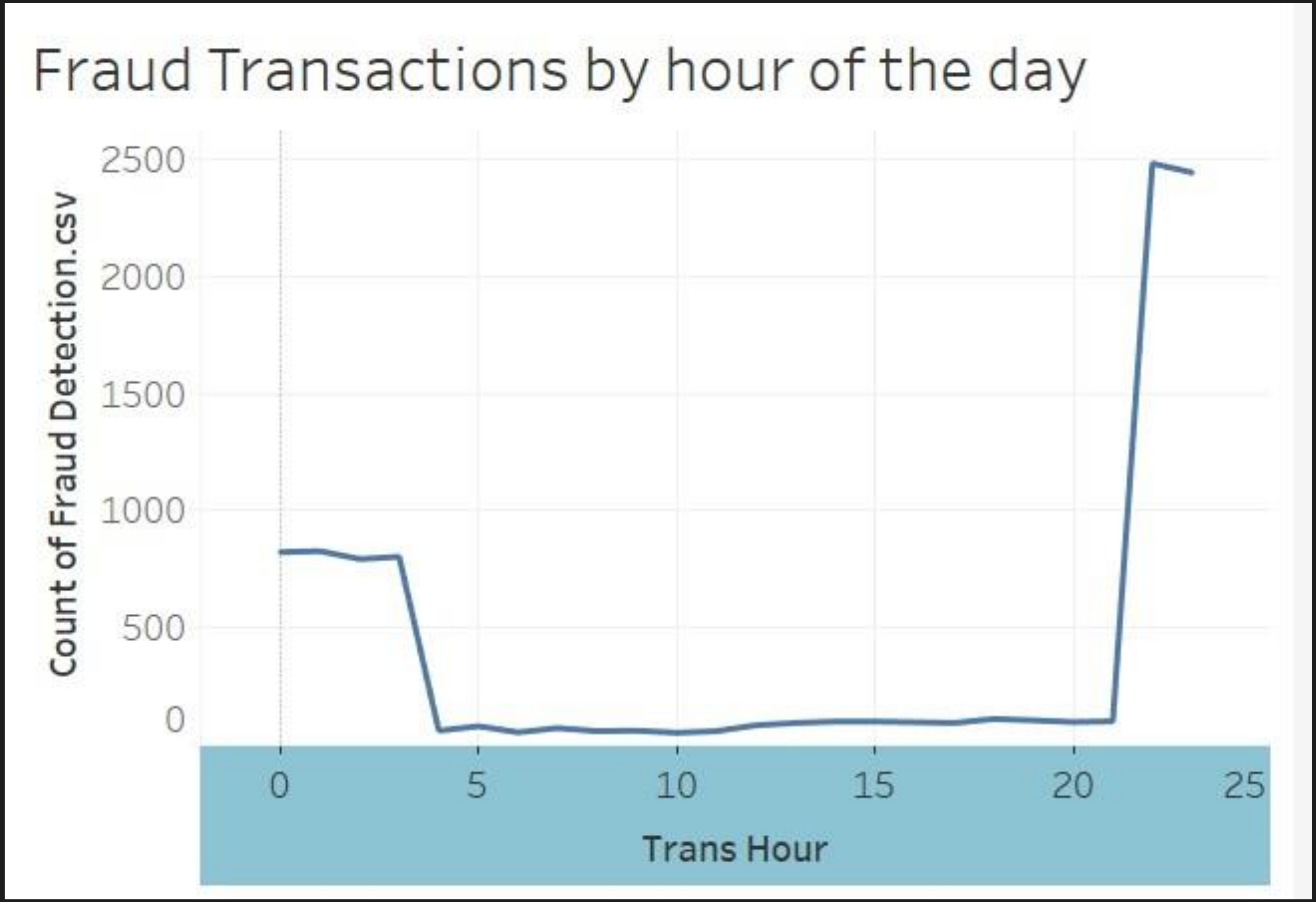
dtype: object

Exploratory Data Analysis



Mean of Fraudulent Transactions = 530

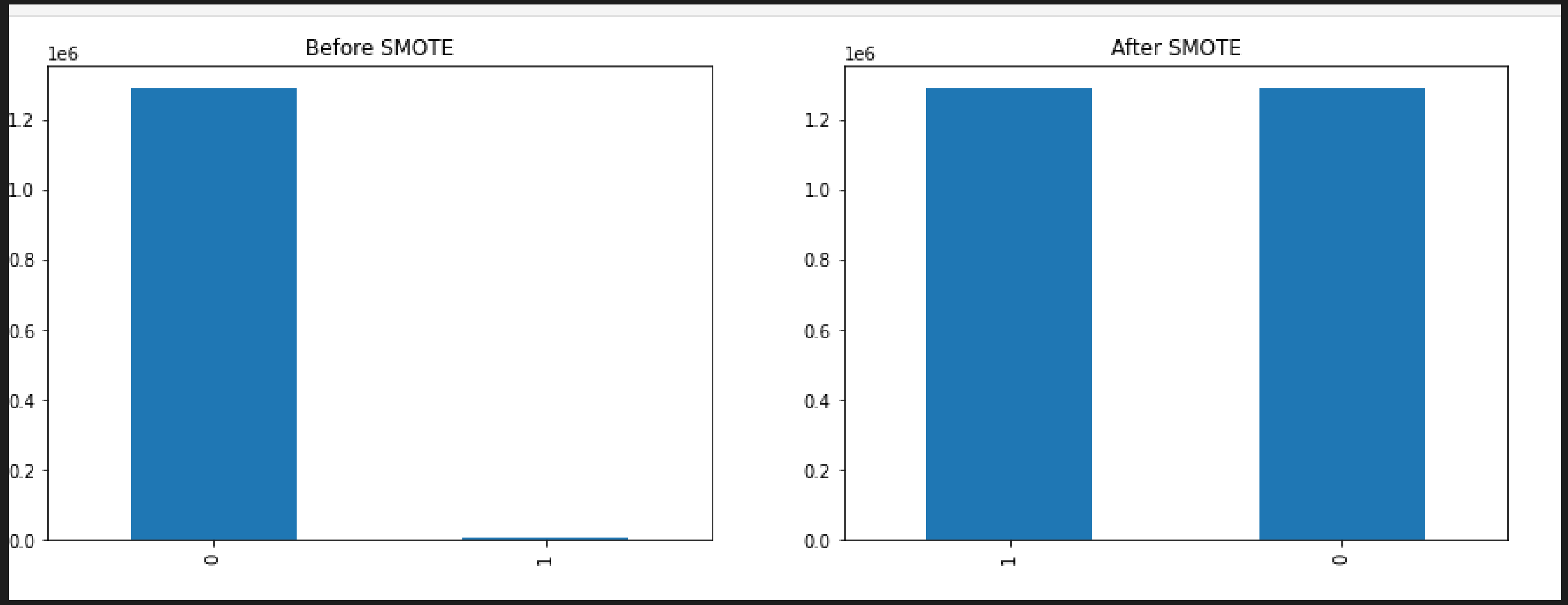
Mean of Non Fraud Transactions = 67



Clearly we can see, most of the fraud transactions are done in the abnormal hours

Feature Engineering

This Data was highly imbalanced so we have done oversampling with SMOTE to balance the data.



Extracted trans_hour, transday_of_week and transmonth_year from "trans_date_trans_time" column

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Created new features which are as follows:

- Hourenc {Encoded transactions done in normal hours 0500-2100 as normal (0) and transactions done in abnormal hours 2100-0500 as abnormal (1)}
- Derive age of the Customer (Transaction date – DOB)
- Calculated the distance between the Customer and the merchant from Latitude and longitude features.
- Extracted frequencies of transactions and Total Avg spend in last 60 days by customer
- Extracted frequencies of transactions in last 1 day by customer
- Extracted frequencies of fraud transactions in last 1 day by customer

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Encoded the Categorical features

Feature Selection

```
is_fraud                     1.000000
hist_fraud_trans_24h         0.772578
amt                          0.209307
hourEnc                      0.095764
hist_trans_avg_amt_60d       0.084064
hist_trans_60d               0.047788
category_shopping_net        0.042452
category_grocery_pos         0.033483
category_misc_net            0.024667
category_home                0.016623
category_kids_pets           0.014307
category_food_dining         0.013939
category_health_fitness      0.013681
unix_time                    0.013330
trans_hour                   0.013196
category_personal_care       0.011378
age                          0.010686
category_misc_pos            0.008514
week_Monday                  0.008270
category_grocery_net         0.006649
category_travel              0.006286
gender_M                     0.005844
week_Thursday                0.005712
category_gas_transport       0.005155
category_shopping_pos        0.004948
week_Wednesday               0.004183
week_Sunday                  0.003870
week_Tuesday                 0.003026
lat                          0.002903
merch_lat                    0.002777
week_Saturday                0.002612
zip                          0.002190
cc_num                       0.001125
long                         0.001021
merch_long                   0.000999
hist_trans_24h               0.000486
distance                     0.000359
city_pop                     0.000325
val_for_agg                       NaN
Name: is_fraud, dtype: float64
```

MODELLING

MODEL	PRECISION	RECALL	AUC
Logistic Regression	0.54	0.90	0.94
Gaussian Naive Bayes	0.49	0.86	0.92
Random Forest	0.90	0.90	0.95
Decision Tree with Bagging	0.87	0.89	0.94
Decision Tree with Adaptive Boosting	0.49	0.93	0.96
XG Boost	**0.66**	**0.94**	**0.97**

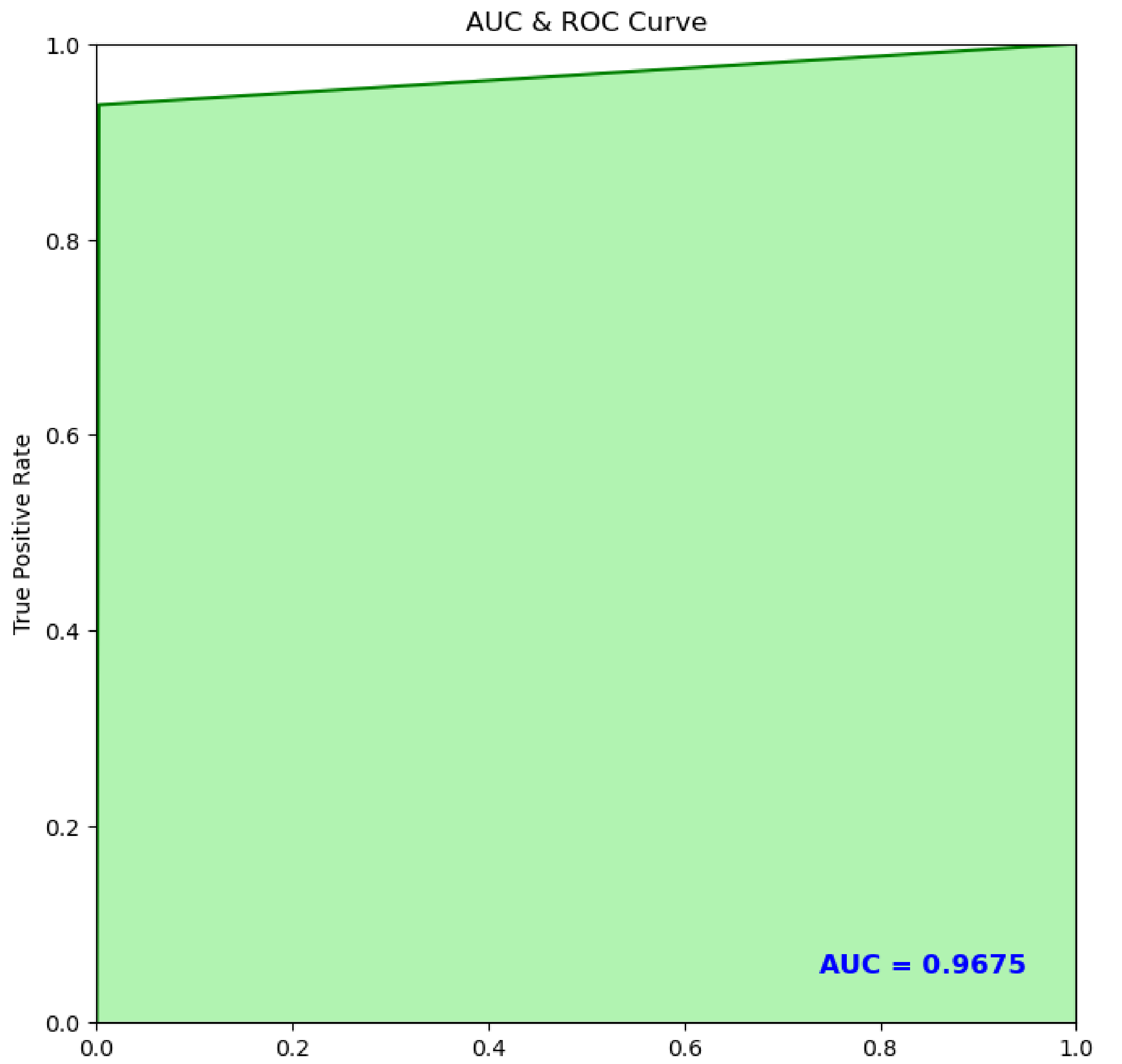
SUMMARY AND INSIGHTS

The cost of False Negatives is much higher than the cost of False Positives. By looking at the problem among all the metrics, we need to focus on getting high recall and at the same time, can evaluate the model performance by looking at precision, and AUC score.

XGBoost Model can predict fraud with 94% accuracy.

```
[[551457   1380]
 [   182   2726]]
```

	precision	recall	f1-score	support
0	1.00	1.00	1.00	552837
1	0.66	0.94	0.78	2908
accuracy			1.00	555745
macro avg	0.83	0.97	0.89	555745
weighted avg	1.00	1.00	1.00	555745



Limitations

- This is a simulated dataset and may not be comparable to the real life problem.

COST BENEFIT ANALYSIS

Average number of transactions per month : 77,183

Average number of fraudulent transaction per month : 402

Average amount per fraud transaction: 530

Annual Loss from Fraud : $2,556,720

Even if we detect 94% of fraud, we can save $2,403,316.

Thank you for listening