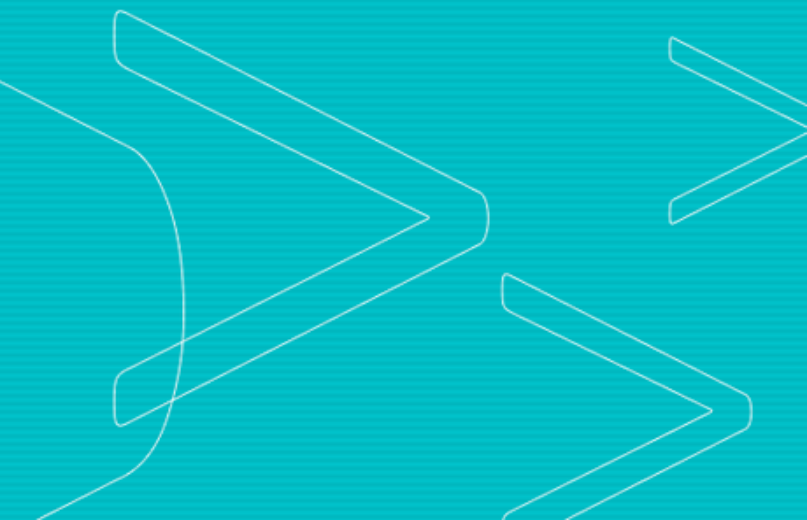


Meteorite Group Report

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Inter-Uni Datathon 2024

Member: Tong Zhu (Judy), Kevin Shen, Kevin
Xu, Shubhanker Rawat



Introduction & Aim

- Skyline Financial Services (SFS) faced an unexpected dip in monthly revenue.
- Internal investigations revealed fraud slipping past current detection systems
- Our task is to analyze transaction data and detect potential fraudulent activities

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Data Understanding & Exploration

Data Overview:

train.csv: contains transactions with the IsFraud label.

test.csv: contains similar transactions but without IsFraud label for predictions.

sample_submission.csv: provides the format for submitting fraud predictions

Preprocessing Method

Methods

For preprocessing, we utilized multiple different data preprocessing methods, which includes:

- Text Processing(extracting domains from email and removing \$ symbols)
- Currency Exchange(from AED or GBP to AUD)
- Data Clipping(transform outliers into -1 for age)
- Grouping(gender, transaction location and device type)
- Label encoding(occupation, education level, marital status ...)
- ...

Preprocessing Method Data Example

Clipping age outliers

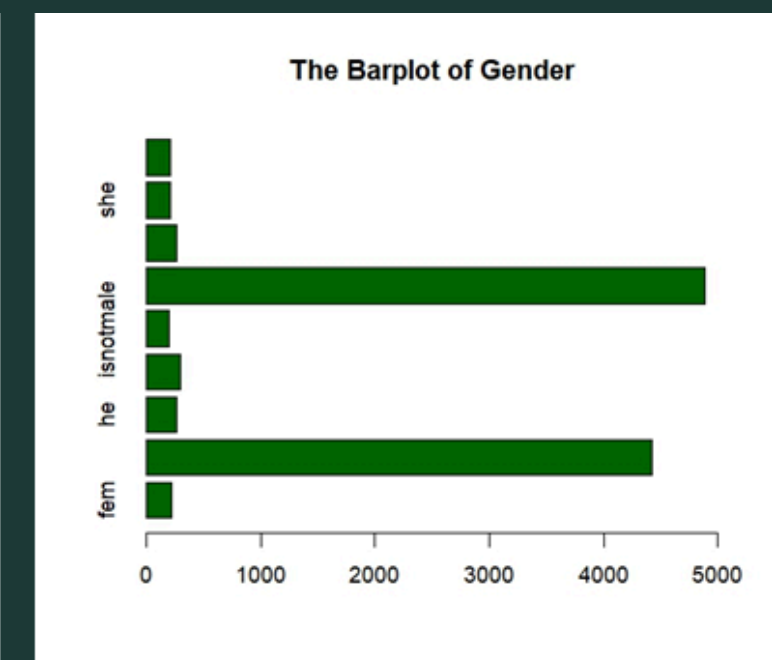
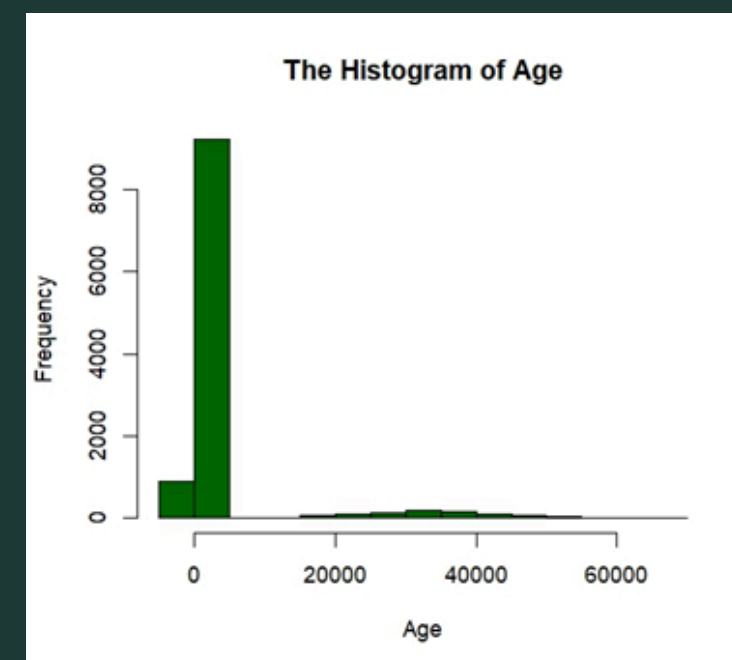
- Improve accuracy(consider ages above 100 or below 0 as misinput)

Transforming different monetary units into AUD(income, expenditure, gift)

-1 AED = 0.4 AUD

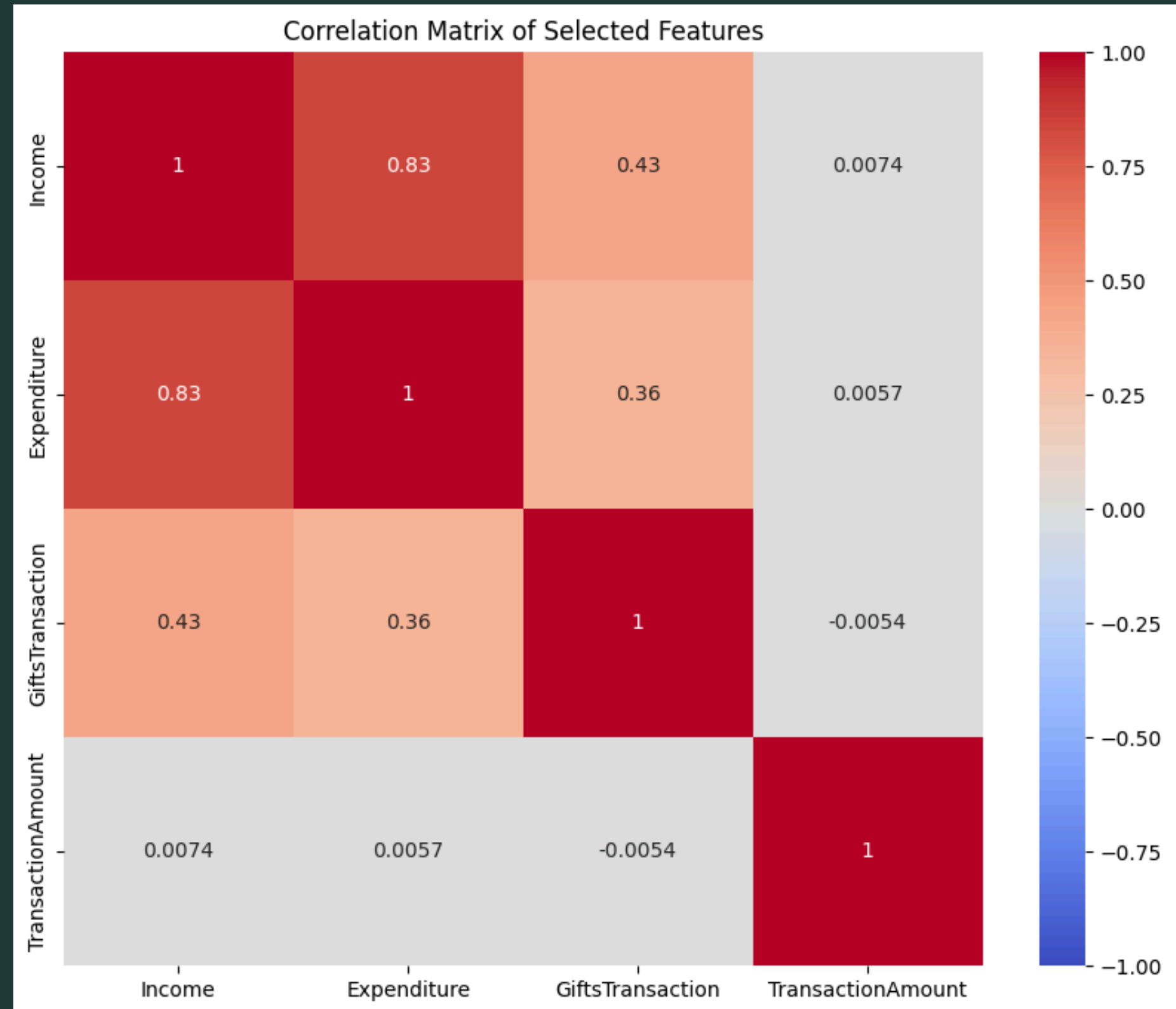
-1 GBP = 2.0 AUD

- Grouping iphone 15 as Mobile for device type



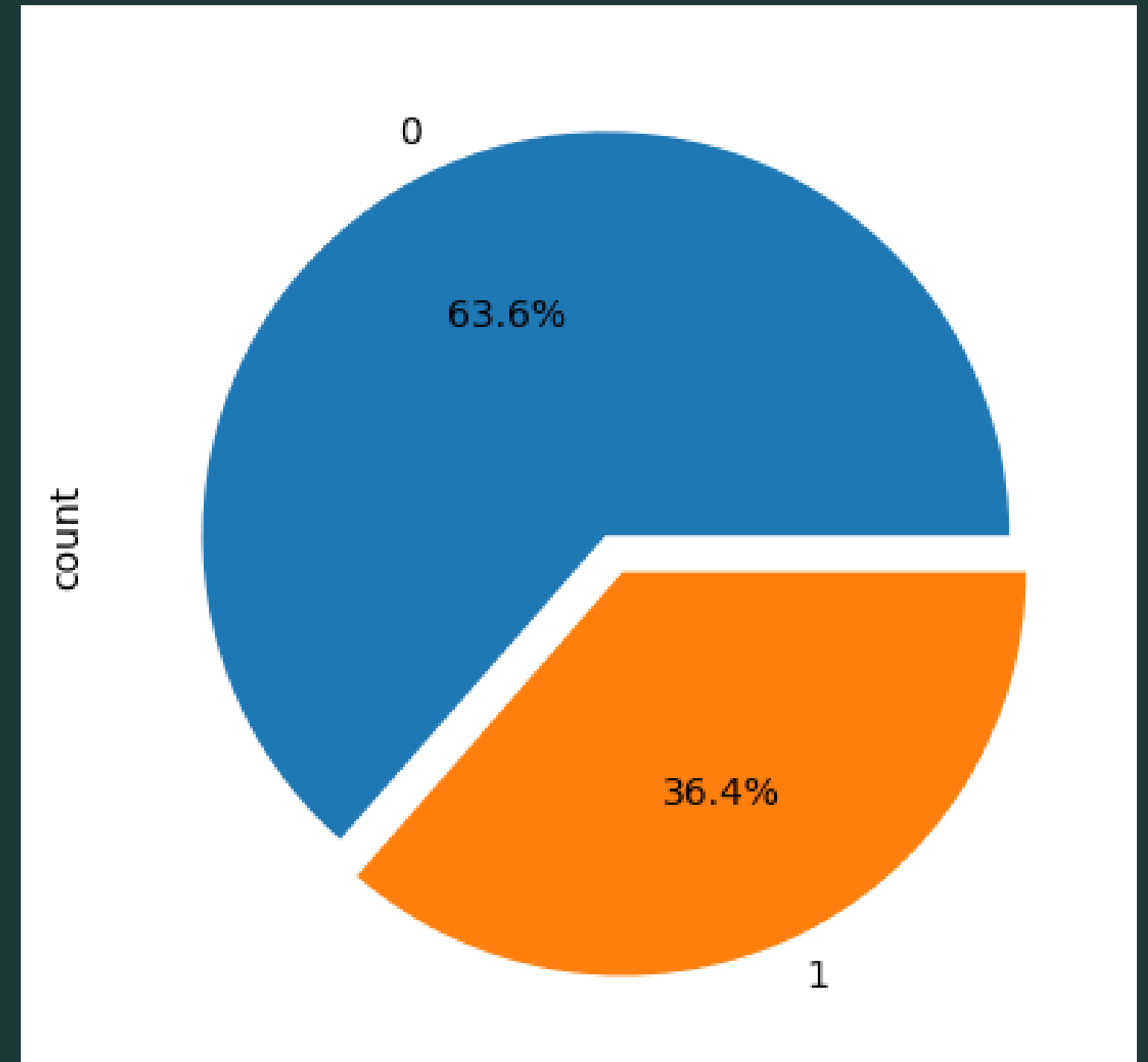
Data Analysis - Correlations

The correlations among all numeric variables are relatively low.



Data Analysis - Label Distribution

There are 36.4% Fraud and 63.6% not Fraud in the train dataset.



Data Analysis - Label Encoding

Before Label Encoding ->

| Gender | Occupation | EducationLevel | MaritalStatus | NumDependents | Income | Expenditure | ... | MerchantID | TransactionType | TransactionLocation | DeviceType |
|--------|--------------|----------------|---------------|---------------|------------------|------------------|-----|------------|-----------------|---------------------|------------|
| Female | Professional | Bachelor | Widowed | 3 | 28884.43 AUD | 14610.61 AUD | ... | M006 | Withdrawal | Adelaide | Mobile |
| Male | Student | High School | Married | 4 | AU\$ 54919.07 | 39169.49 AUD | ... | M002 | Withdrawal | Canberra | Mobile |
| Male | Unemployed | Master | Married | 2 | AU\$ 74728.57 | 55873.76 AUD | ... | M008 | Purchase | Brisbane | Mobile |
| Male | Professional | High School | Married | 3 | AU\$ 55712.62 | AED 89649.04 | ... | M001 | Purchase | Darwin | iphone 15 |
| Male | Professional | High School | Single | 4 | 53004.7 AUD | AED 43601.02 | ... | M001 | Withdrawal | MLB | Tablet |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| Male | Unemployed | High School | Single | 3 | 64488.68 AUD | AU\$ 21813.53 | ... | M007 | Purchase | Canberra | Mobile |
| Female | Professional | High School | Married | 2 | 80403.31 AUD | AU\$ 63429.08 | ... | M003 | Purchase | Hobart | iphone 15 |

After Label Encoding ->

| Gender | Occupation | EducationLevel | MaritalStatus | NumDependents | Income | Expenditure | GiftsTransaction | TransactionAmount | TransactionType | TransactionLocation |
|--------|------------|----------------|---------------|---------------|----------|-------------|------------------|-------------------|-----------------|---------------------|
| 0 | 2 | 1 | 3 | 3 | 28884.43 | 14610.610 | 2100.02 | 258.140 | 3 | 0 |
| 1 | 0 | 0 | 1 | 4 | 54919.07 | 39169.490 | 9939.42 | 34.940 | 3 | 2 |
| 1 | 1 | 2 | 1 | 2 | 74728.57 | 55873.760 | 2299.70 | 323.820 | 1 | 1 |
| 1 | 2 | 0 | 1 | 3 | 55712.62 | 35859.616 | 4335.70 | 12.996 | 1 | 3 |
| 1 | 2 | 0 | 0 | 4 | 53004.70 | 17440.408 | 4763.48 | 456.300 | 3 | 5 |
| ... | ... | ... | ... | ... | ... | ... | ... | ... | ... | ... |
| 1 | 1 | 0 | 0 | 3 | 64488.68 | 21813.530 | 5489.06 | 182.510 | 1 | 2 |
| 0 | 2 | 0 | 1 | 2 | 80403.31 | 63429.080 | 382.42 | 137.500 | 1 | 4 |

We use label encoding method to transfer categorical to numerical type.

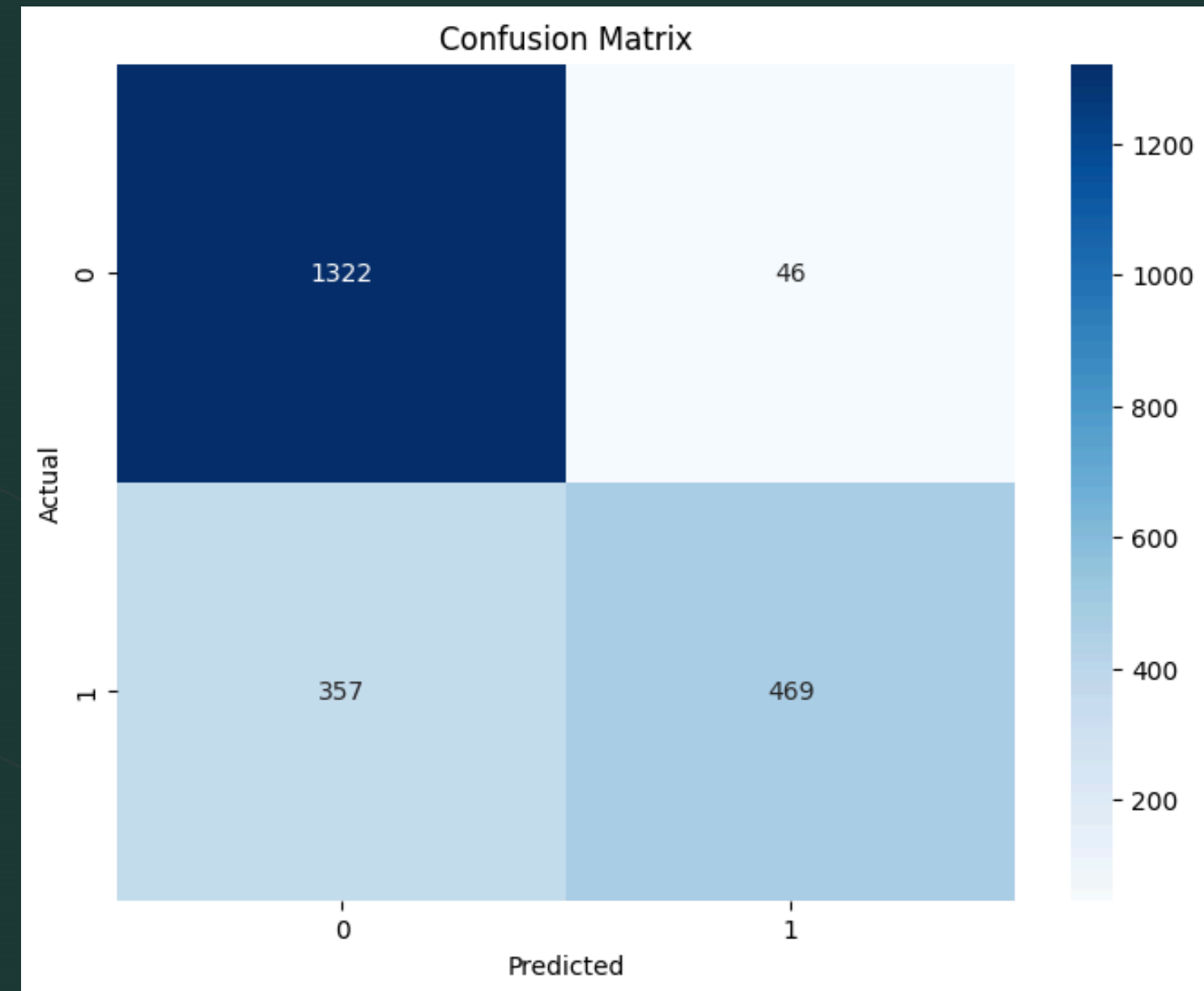
Model Evaluation & Testing

For Machine Learning, we utilized multiple different machine learning methods, which includes:

- **Random Forest Classifier**
- **Linear Regression**
- **Logistic Regression**
- **XGBoost**

Random Forest Classifier

- **Classification**
 - Dividing dataset into a single train set (80%) and a test set (20%)
- **Accuracy** : Around 82%.
- **AUC-ROC**: Around 87%.
- **Confusion Matrix**



XGBoost

- **Classification**

- Dividing dataset into a single train set (70%) and a test set (30%)
- Accuracy : Around 85%.
- AUC-ROC: Around 83%.

```
AUC-ROC Score: 0.8346641490258302
              precision    recall  f1-score   support

         0         0.79      0.94      0.86       2091
         1         0.85      0.58      0.69       1199

 accuracy          0.81       3290
 macro avg         0.82       0.76      0.77       3290
weighted avg         0.81       0.81      0.80       3290
```

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Linear Regression & Logistic Regression

- Linear Regression
 - Low R squared score

Mean Squared Error: 0.1863773827213508
R² Score: 0.20603691515753342

- Logistic Regression
 - Low accuracy

| Classification Report: | | | | |
|------------------------|-----------|--------|----------|---------|
| | precision | recall | f1-score | support |
| 0 | 0.63 | 0.97 | 0.77 | 1368 |
| 1 | 0.57 | 0.07 | 0.12 | 826 |
| accuracy | | | 0.63 | 2194 |
| macro avg | 0.60 | 0.52 | 0.44 | 2194 |
| weighted avg | 0.61 | 0.63 | 0.52 | 2194 |

Regression is not suitable.

Results & Analysis

- Although the model's accuracy is high, there is room for improvement in handling fraudulent transactions. The confusion matrix reveals a noticeable number of false negatives (357 fraud cases classified as non-fraud).
- The AUC-ROC score shows strong overall classification capability, but further optimization is needed, especially for fraud detection, where recall and false negatives are critical.

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Thank You!