



CREDIT CARD FRAUD DETECTION

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Agenda

- Objective
- Background
- Key Insights
- Cost Benefit Analysis
- Appendix:
- Data Attributes
- Data Methodology
- Attached Files

Objective

- Getting in place a credit card fraud detection system to save on incurred costs incurred.
- Huge costs are being incurred due to frauds and a manual detection system

Background

- A machine learning model has been built to detect frauds early and avoid risk of losses.
- A cost benefit analysis has been done for the deployment of the same.

Key Insights

- Transaction amount, category and gender are the most important variables
- Gas and transport, grocery and shopping are the top three categories

Current Incurred Losses

- 77,183 credit card transactions per month
- 402 fraudulent transactions per month
- \$ 530.66 amount per fraud transaction
- Total costs incurred from fraud transactions is
\$ 213,392.22

After New Model Deployment

- 1720 fraudulent transactions detected by the model
- \$ 1.5 cost to provide customer support to these transactions that is \$ 2,580.38 in total
- 68 fraudulent transactions not detected by model which amounts to \$ 35,908.09 loss
- Total cost incurred after new model deployment is \$ 38,488.46
- Final savings after new model deployment is \$174,903.76 that is reduction in losses by ~82%

Appendix: Data Attribute

- Snapshot of data

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1852394 entries, 0 to 1852393
Data columns (total 22 columns):
#   Column          Dtype
---  -
0   cc_num          int64
1   merchant        object
2   category        object
3   amt             float64
4   gender          object
5   street          object
6   city            object
7   state           object
8   zip             int64
9   lat             float64
10  long            float64
11  city_pop        int64
12  job             object
13  trans_num       object
14  unix_time       int64
15  merch_lat       float64
16  merch_long      float64
17  is_fraud        int64
18  trans_hour      int64
19  trans_day_of_week object
20  trans_year_month period[M]
21  age             float64
```


Appendix: Data Methodology

- A random forest classifier built on top a Kaggle simulated dataset
- Smote sampling method
- Manual hyperparameter tuning done due to extensive computational times when using Grid Search Cross Validation

Attached Files

- Cost Benefit Analysis:
 - Cost Benefit Analysis
- Random Forest Classifier Model1:
 - CC FRAUD DETECTION