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# Sprint 3 Calibrated Techniques: Ways to Improve Fraud Detection Systems

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# Credit Card Fraud

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- Fraud committed using a credit card or any similar form of payment mechanism
- The purpose is to obtain unauthorized funds from the credit cardholder's account

## Philippine Outlook Global Outlook

- 25% of complaints received were related to credit cards
- March -May 2020
  - ◆ 98.4% of criminal incidents reported were cyber or online in nature
  - ◆ Losses equivalent to 60.6 M or 54.5% of all total bank losses

Source: Merchant Savy UK, 2020

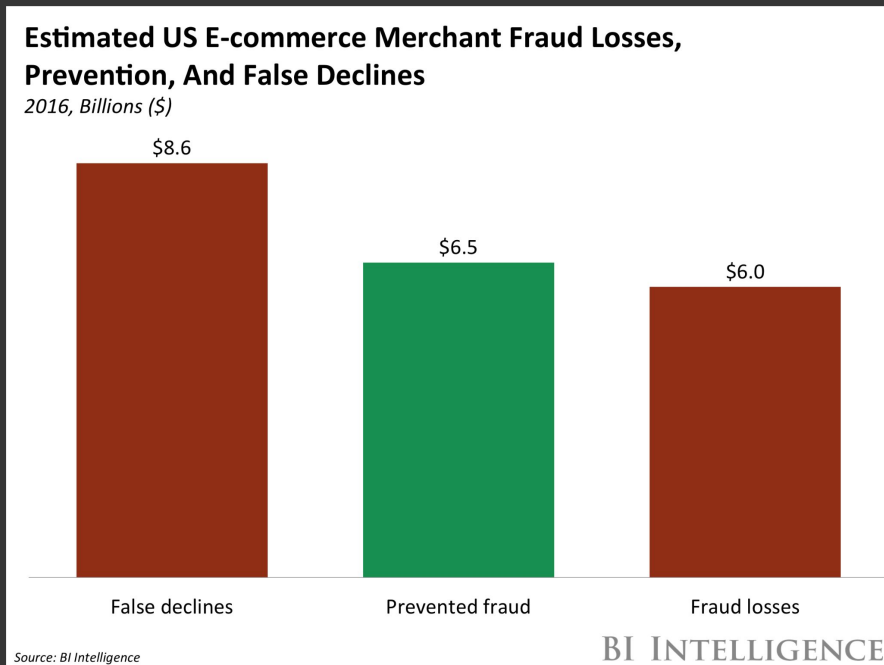
# Problem Overview

- Fraud Detection System
  - Tags fraudulent transactions
  - Automatic process
- Case study:
  - CEO's card was blocked
  - CEO was on travel



# The Case of False Positives

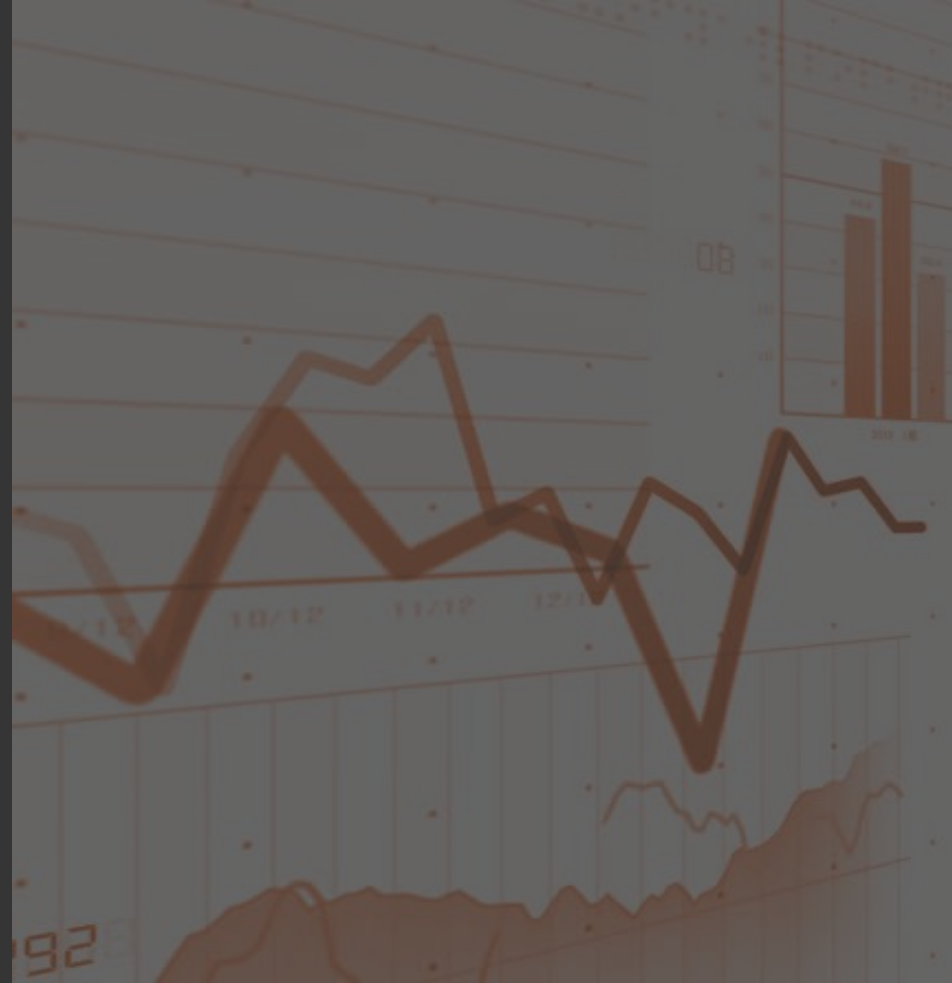
- Occurs when merchants or financial institutions decline legitimate orders



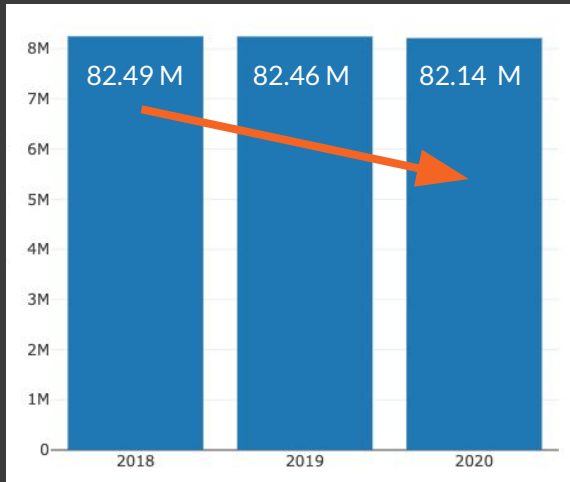
# Objectives

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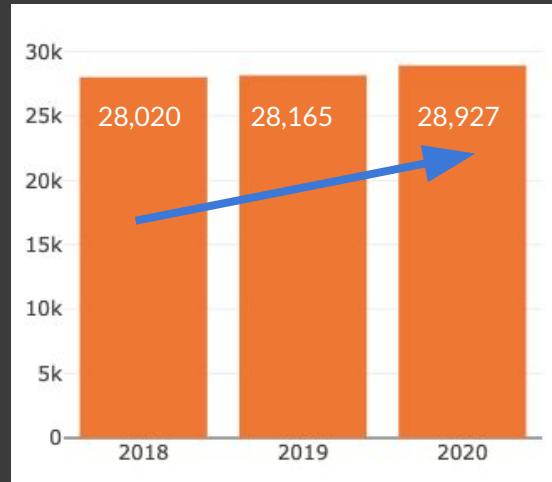
1. Review current fraud detection system
2. Recommend ways to make the system better



# Overview of Fraudulent Transactions



Total credit card transactions  
(2018-2020)

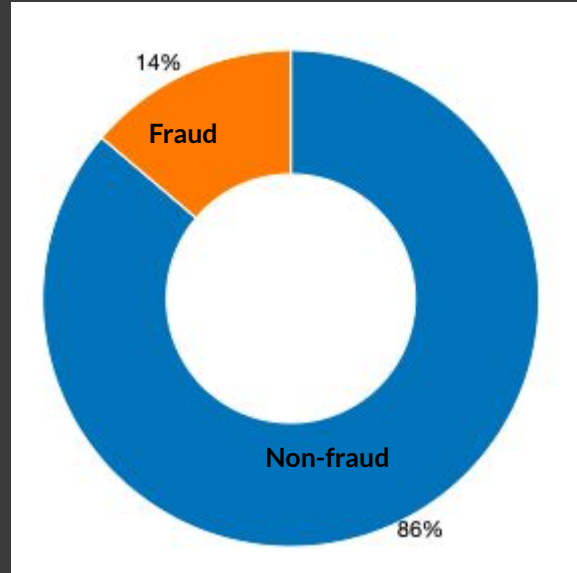
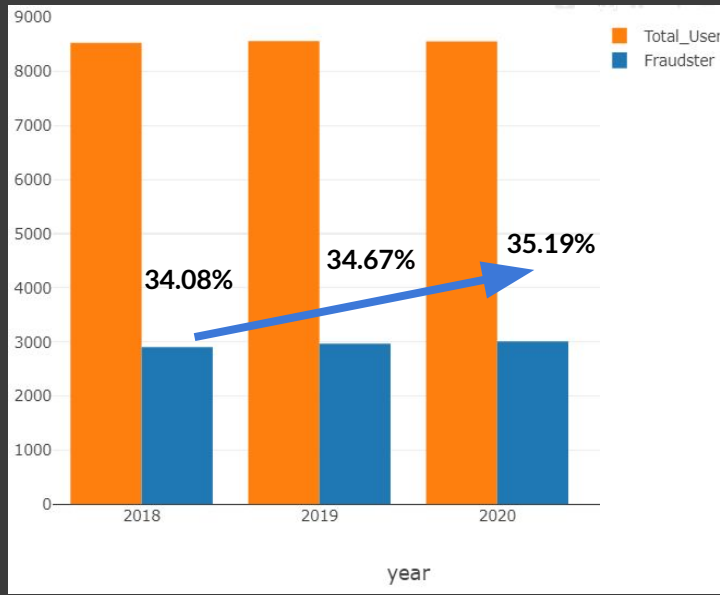


Fraudulent transactions  
(2018-2020)

For the last 3 years:

- gradual decrease in total credit card transactions
- gradual increase in fraudulent transactions

# Overview of Fraudulent Transactions



For the last 3 years, ~35% of total users experience fraud annually

~14% of the most recent user transactions are fraudulent

## Client Profile data

ssn | credit card number |  
account number | name |  
sex | address | profession |  
birthdate

## Spending Behavior data

transaction number |  
transaction date and time |  
product category | amount |  
merchant | merchant location



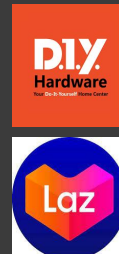
Amount



Geospatial  
Occurrence



Merchants



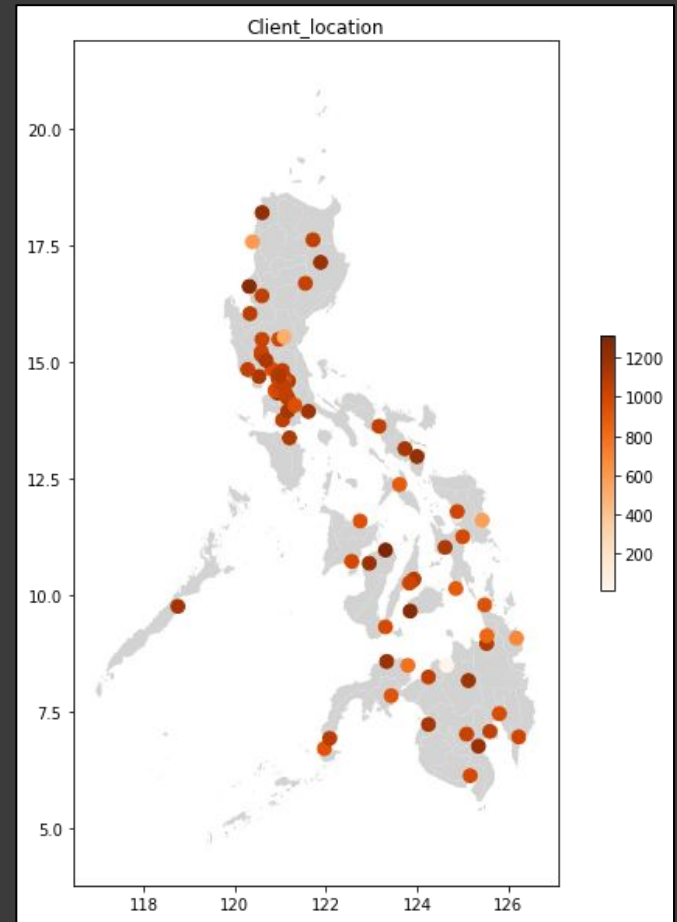
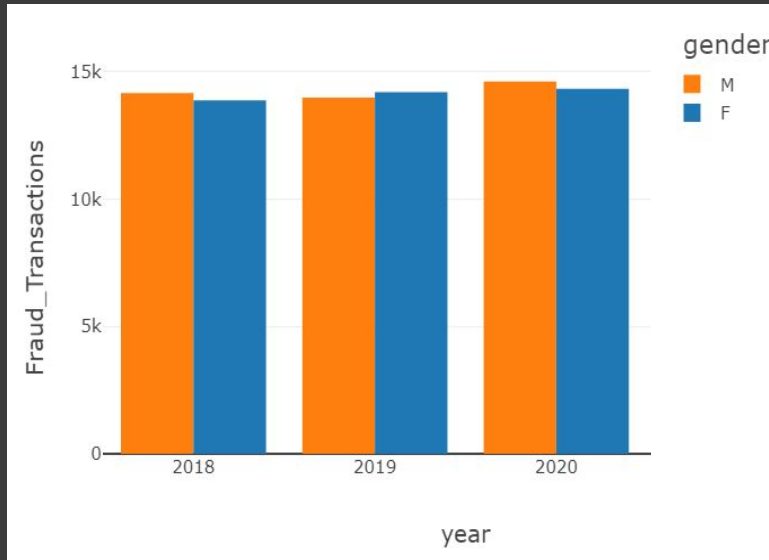
Product Category



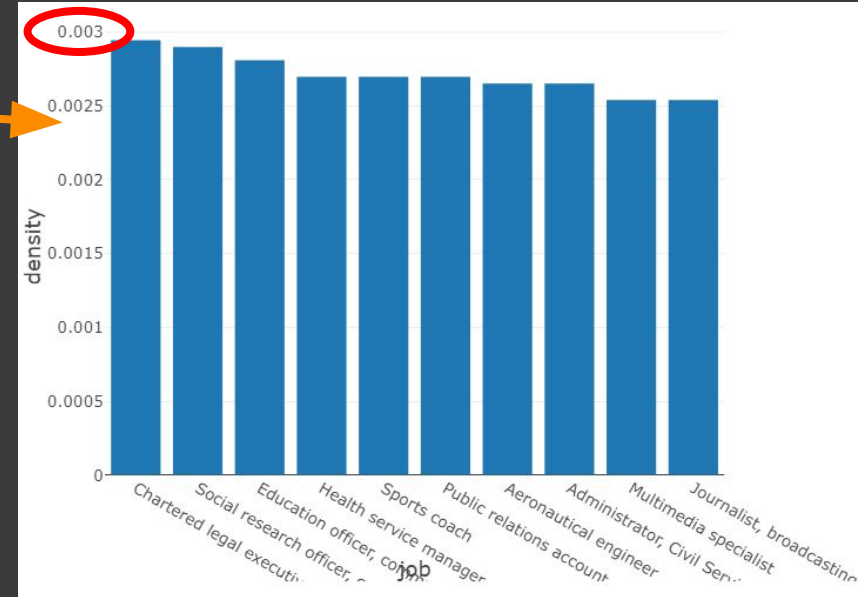
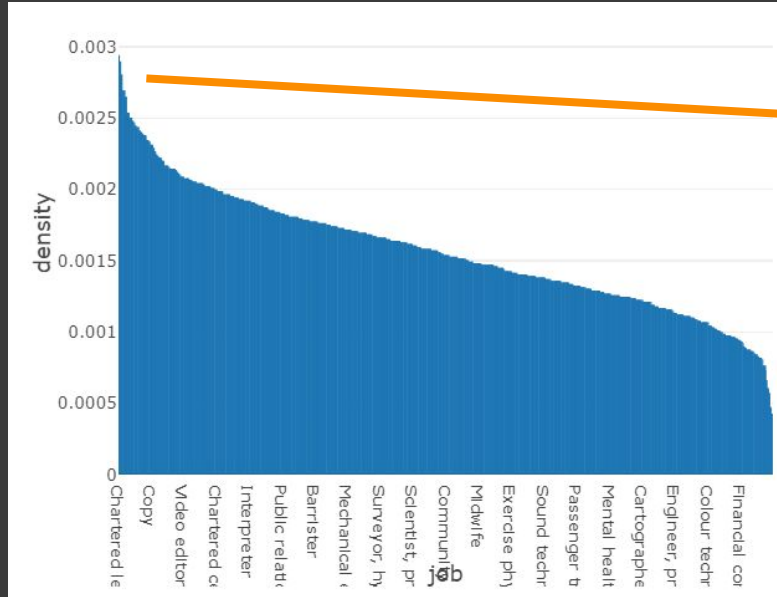
Time Period



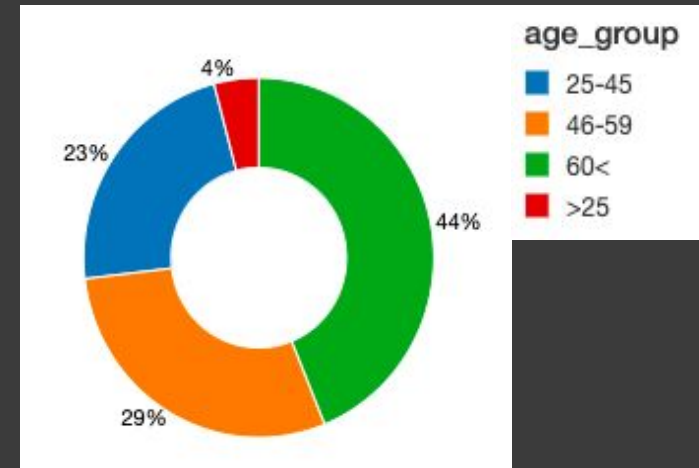
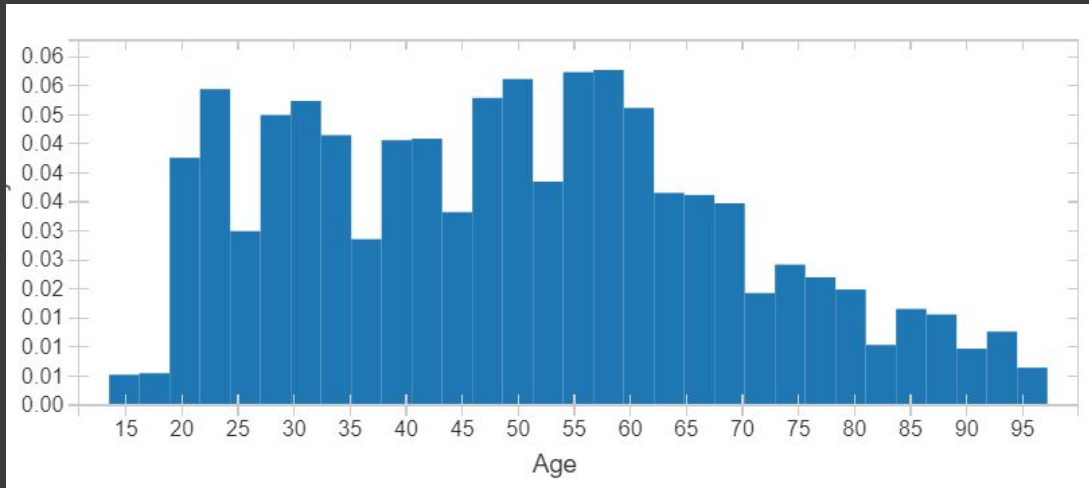
# Fraudulent Transactions: Client Profile (Sex, Address)



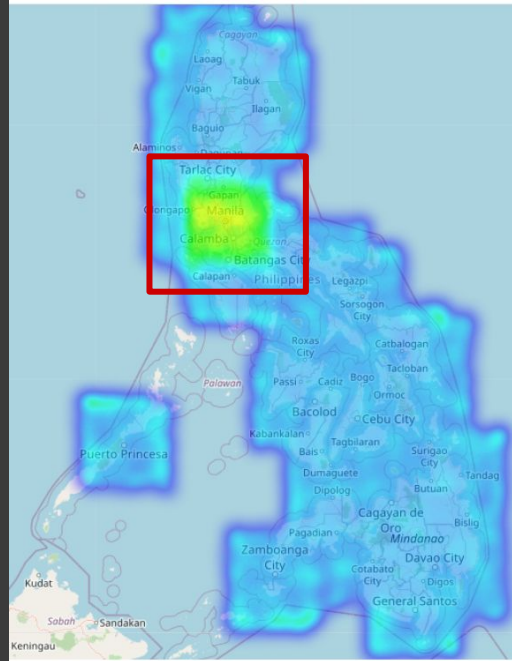
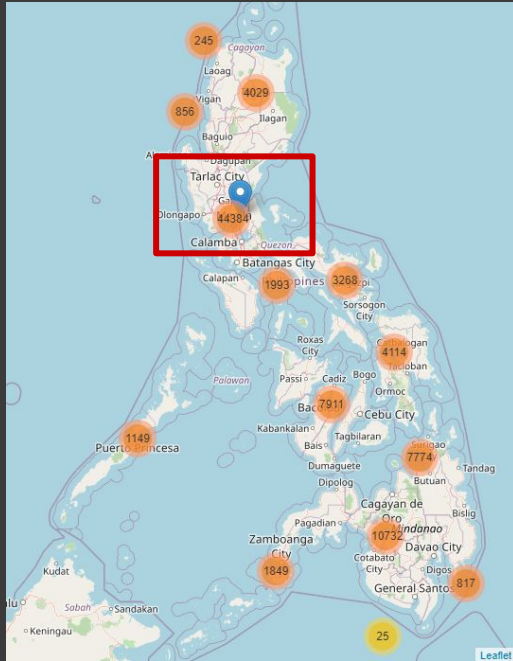
# Fraudulent Transactions: Client Profile (Job)



# Fraudulent Transactions: Client Profile (Age)

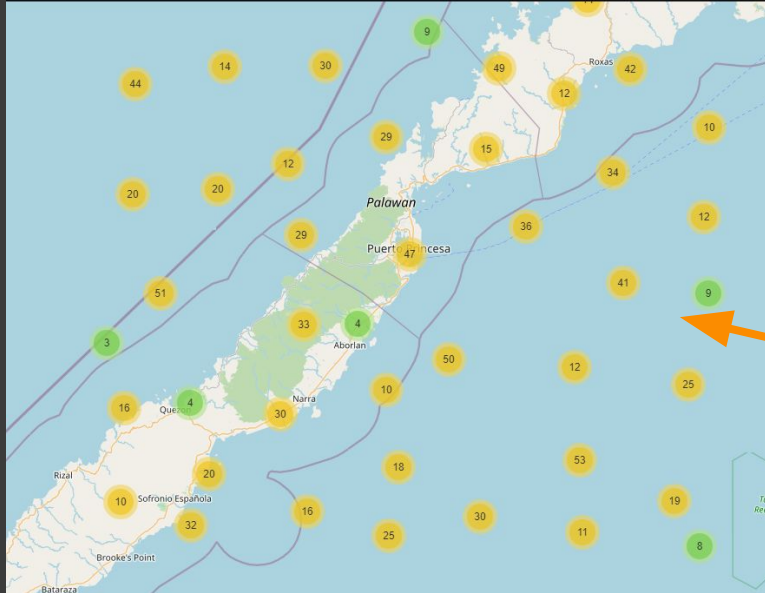


# Fraudulent Transactions: Geospatial Occurrence



Fraud transactions  
mostly occurs on **NCR**  
**Area** and nearby  
provinces

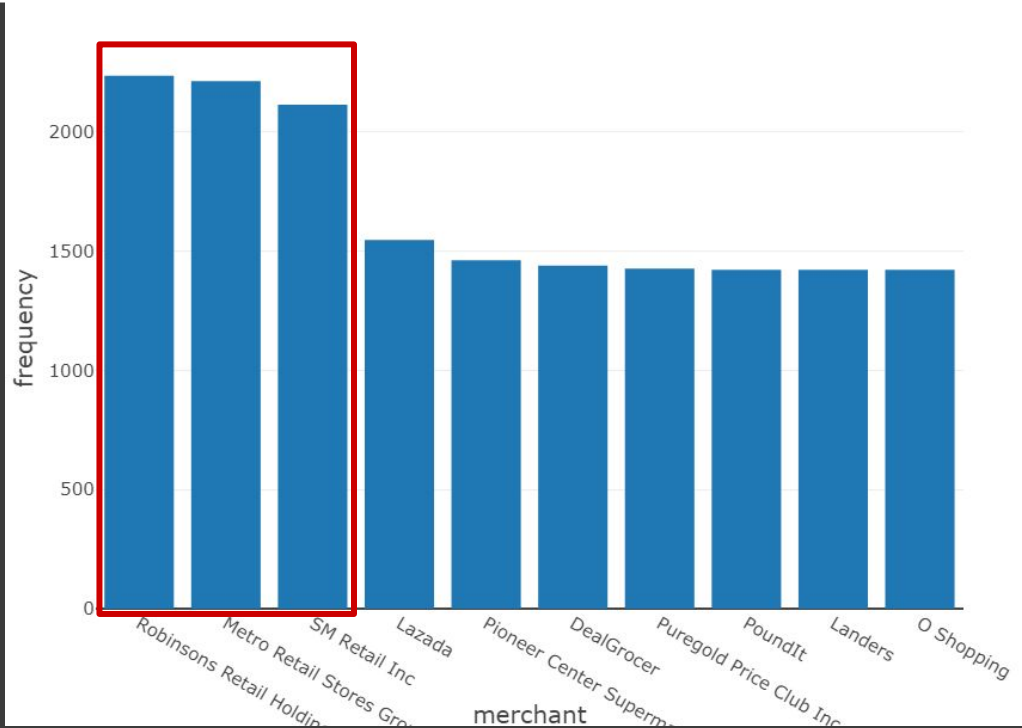
# Fraudulent Transactions: Geospatial Occurrence



Fraud transactions mostly occurs on **NCR Area and nearby provinces**

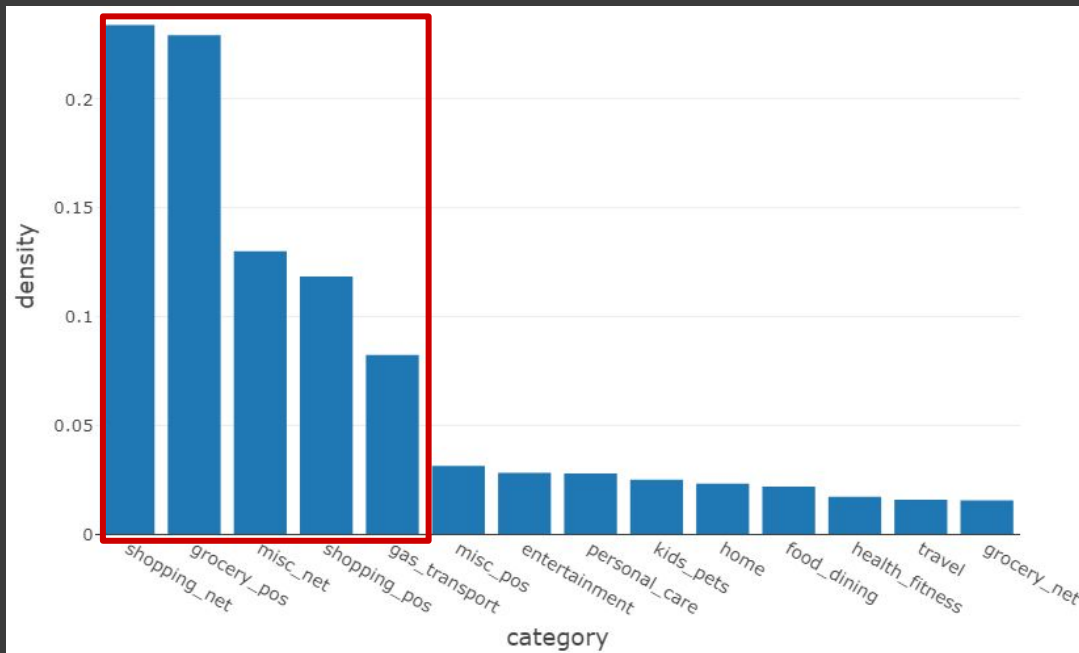
However, geospatial points are inaccurate. Many locations are outside land areas

# Fraudulent Transactions: Most Common Merchants



**Robinsons, Metro Retail Stores Groceries, and SM Retail Inc.** are merchants with the highest occurrence of fraud

# Fraudulent Transactions: Product Category

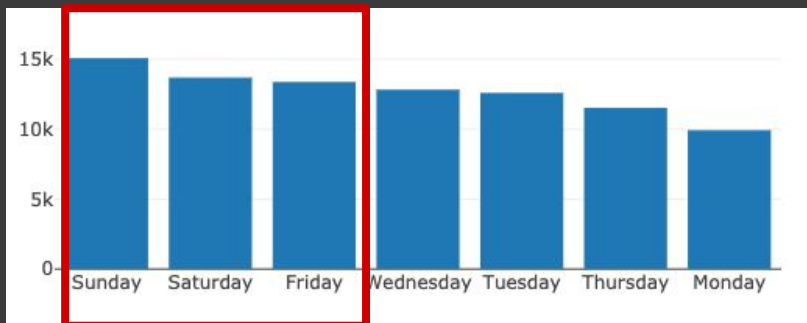


**~80%** of total fraud transactions came from the following categories

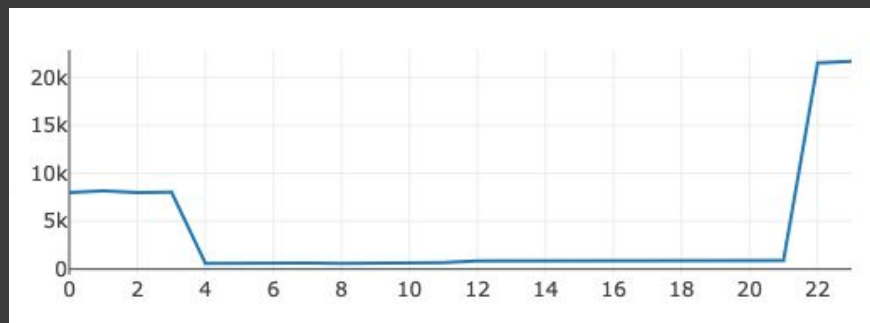
- **Online Shopping (23.4%)**
- **Groceries (22.9%)**
- **Misc. Online Transactions (13%)**
- **Shopping (11.8%)**
- **Gas and Transport (8.2%)**

# Fraudulent Transactions: Time Period of Occurrence

- Fraudulent transactions occur most often during the weekend (Friday-Sun) and at 10PM - 3AM



Total number of fraudulent transactions per day of the week

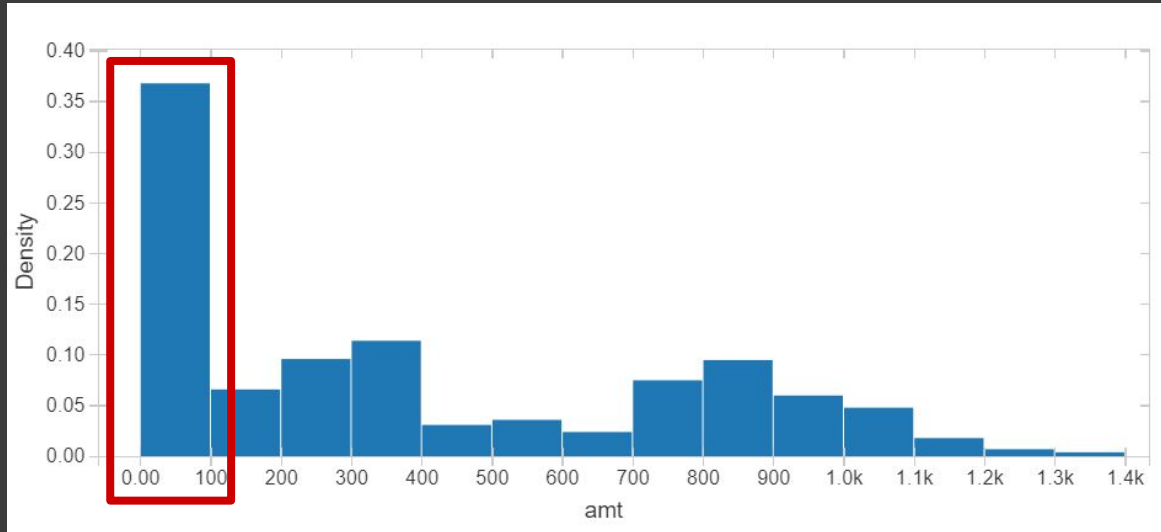


Total number of fraudulent transactions per hour



# Fraudulent Transactions: Most Common Amount

- Majority of fraudulent transactions costs PHP 100 or less



# Common Features of Fraudulent Transactions

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## Time Occurrence

10PM-3AM

## Day Occurrence

Friday to Sunday

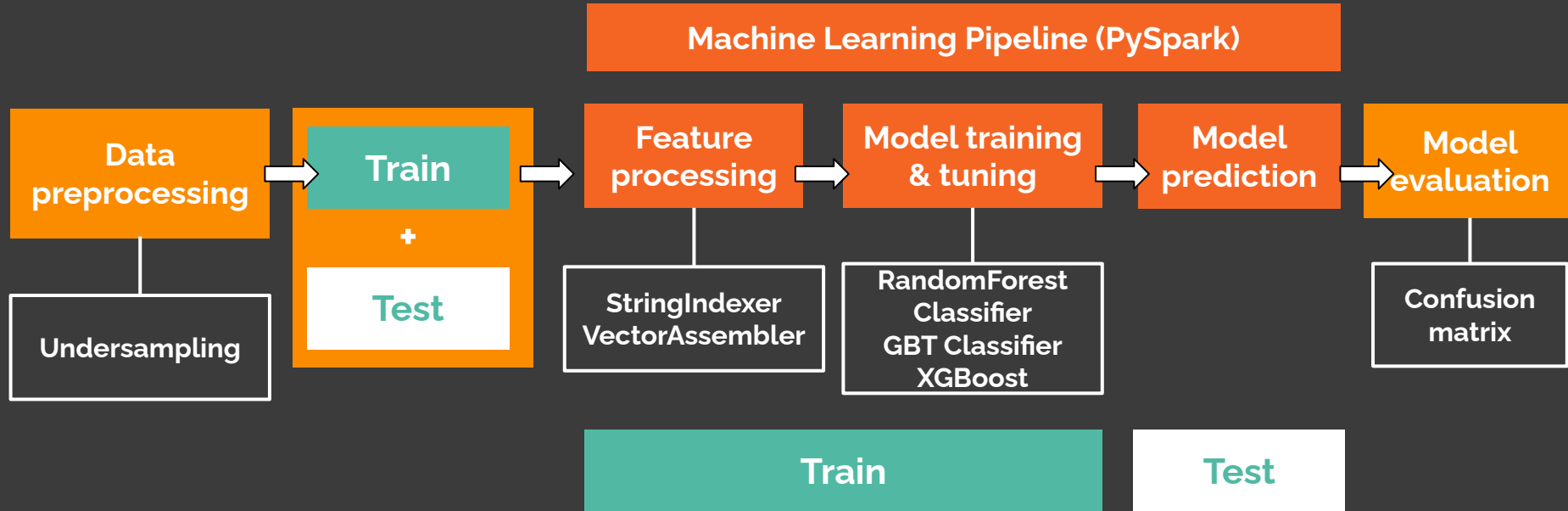
## Transaction Amount

PHP 100.00 and below

## Product Category

Online Shopping, Groceries,  
Online Transactions, Shopping,  
Gas and Transport

# Fraud Detection System Version 1.0



# Fraud Detection System Version 1.0

## Performance

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### Accuracy:

How many Fraud and Legitimate Transactions were predicted accurately out of total transactions

### Precision:

How many of those predicted as Legitimate are actually Legitimate

\*single class metric

### Recall:

How many Fraud cases are accurately identified as Fraud

\*single class metric

# Fraud Detection System Version 1.0

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## GBTClassifier: XGBoost

|           | Precision | Recall |
|-----------|-----------|--------|
| Non-fraud | 97%       | 97%    |
| Fraud     | 97%       | 97%    |

## Random Forest Classifier

|           | Precision | Recall |
|-----------|-----------|--------|
| Non-fraud | 94%       | 97%    |
| Fraud     | 96%       | 94%    |

# Fraud Detection System Version 1.0

## GBTClassifier: XGBoost

```
gbt = GBTClassifier(labelCol='label', featuresCol="features", maxBins=250)
```

### Confusion Matrix

|           |           |
|-----------|-----------|
| TP: 17284 | FP: 474   |
| FN: 470   | TN: 17368 |

### Feature Importance

|          |        |                   |        |
|----------|--------|-------------------|--------|
| Amount   | 0.6518 | Age               | 0.0039 |
| Time     | 0.1489 | Gender            | 0.0019 |
| Merchant | 0.1192 | Merchant Distance | 0.0    |
| Category | 0.0742 | Day of the Week   | 0.0    |

# Fraud Detection System Version 2.0

## Conclusion

- False positives must be reduced in order for fraud detection mechanisms to be cost effective
- Issues with false-positives can be summarized into 3 categories:
  1. Identity-related
  2. Technical
  3. Structural
- Consumer spending behavior VARY GREATLY
- Feature engineering is (almost) everything
- Need for a better model that can provide a deeper analysis of spending behavior

# Fraud Detection System Version 2.0

## Recommendations

- Identity-related (historical data + transaction data)
  - biometrics, IP address, conflicting billing + shipping information, updated card information...
- Technical (bank)
  - local domains, smart routing
- Structural (Version 2.0):
  - Increase processing power for further hyperparameter tuning
  - Extract better features
  - Increase number of features
  - Consistent updating and review