

# Subject: **Online Payment Fraud Detection using Machine Learning (ML)**

## Agenda:

1. Dataset **insights**
2. Machine learning **model performance** (supervised classification)

Data: **Financial dataset** from Kaggle

Target audience: **Financial Institutions and Banks**

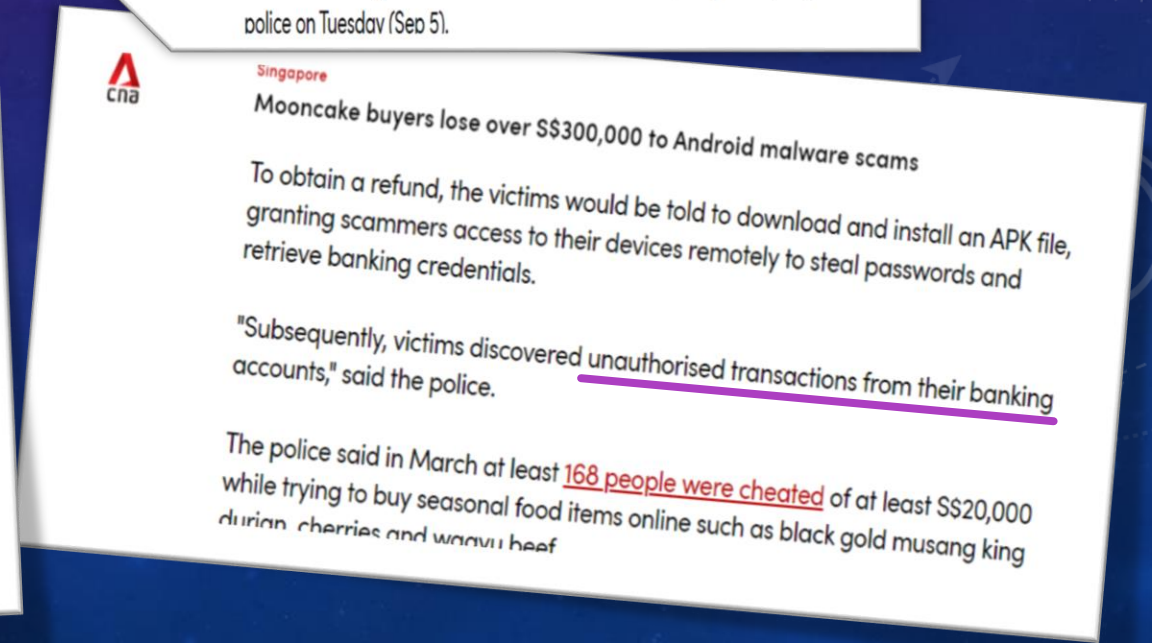
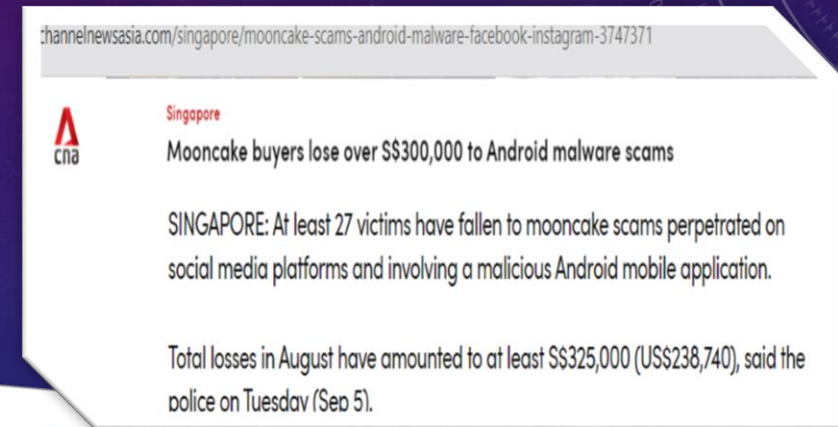
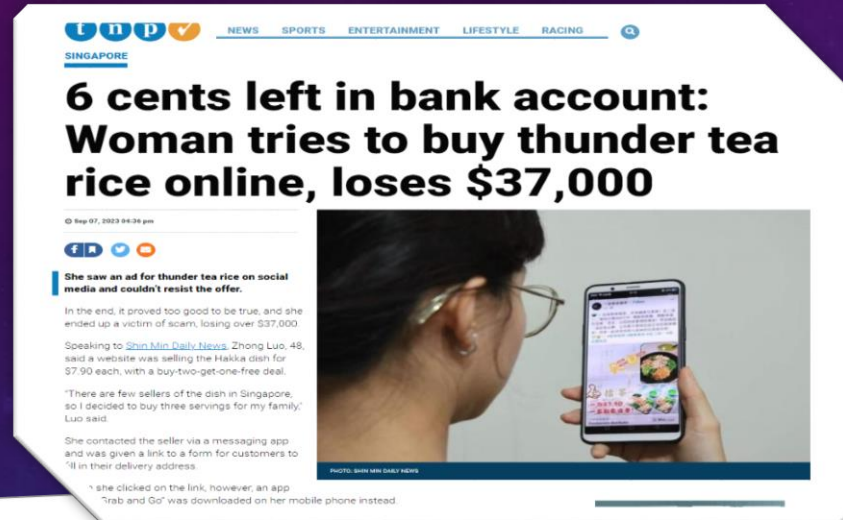
Conclusion: ML model is capable to **identify fraudulent transactions** with **99% recall**.

## Future work:

1. Overfitting of training data – revisiting feature engineering; e.g. **feature selection** & obtain **domain-specific knowledge**.
2. Improve data generalization – **collect more latest data** and **retrain** the model **regularly** to **capture latest fraud pattern**
3. Anomaly detection using clustering (DBSCAN, K-means) - extract relevant features during data pre-processing & identify previously unknown or evolving fraud patterns.

# FRAUD DETECTION USING MACHINE LEARNING

- While incidences of major crimes in Singapore had been decreasing in the last ten years, commercial crimes such as **frauds and scams** have been on the rise. The increase in such cases has pushed the **crime rate** in Singapore to a **ten-year high**. Source: [Statista\(2022\)](#)





## FRAUD DETECTION USING MACHINE LEARNING– CONT.

- Crucial for banking institution to **enhance** its **fraud prevention** strategy, **protect customers**, and **minimize financial losses**.
- Need for more **proactive** and **adaptive detection methods** in response to the increasing sophistication of fraudsters
- Enabling banks to identify and **prevent fraudulent** activities with **greater accuracy** and **speed**.



Singapore

**S\$661 million lost to scams in 2022, with young adults most likely to fall victim: SPF**

The total number of scam and cybercrime cases rose by more than a quarter to 33,669 in 2022, compared to 26,886 the year before. Scams accounted for 94.2 per cent of these cases.

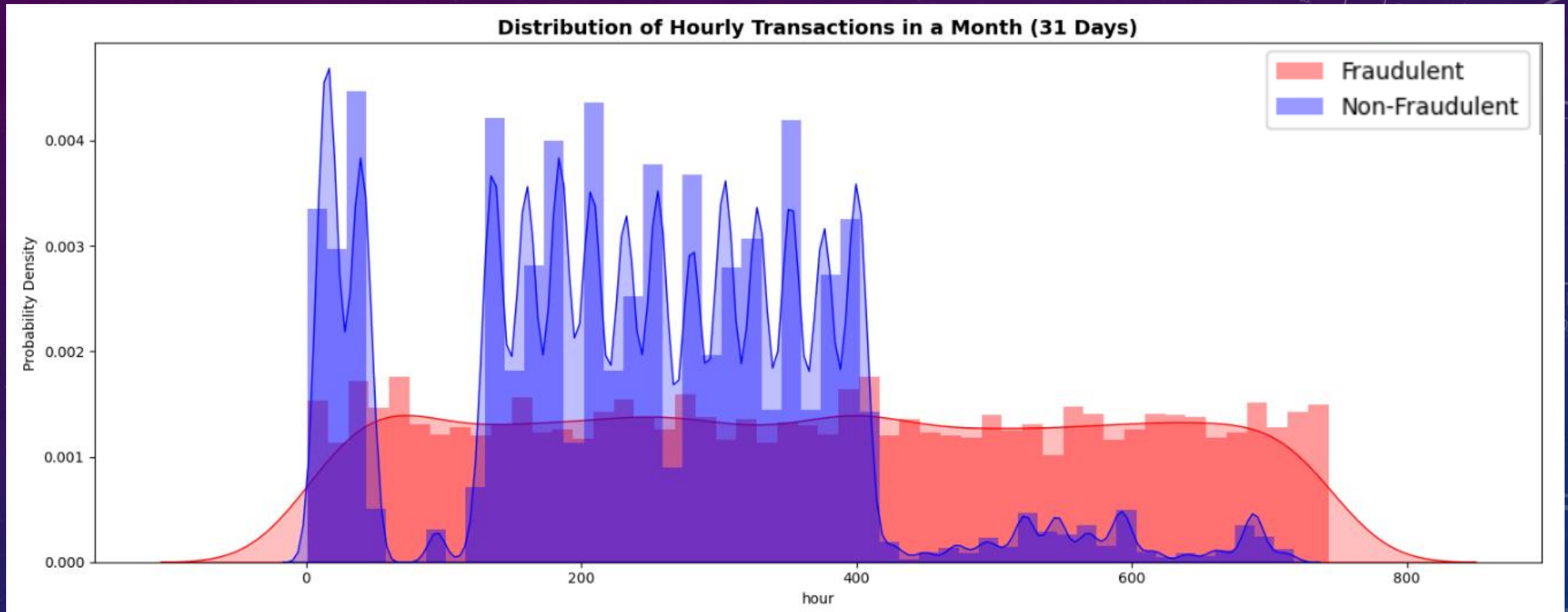
The top five scam types were phishing scams, job scams, e-commerce scams, investment scams and fake friend call scams. They made up more than 80 per cent of the top 10 scam types in Singapore.

The number of cases of each of these scam types rose across the board.

Number of cases of top five scam types

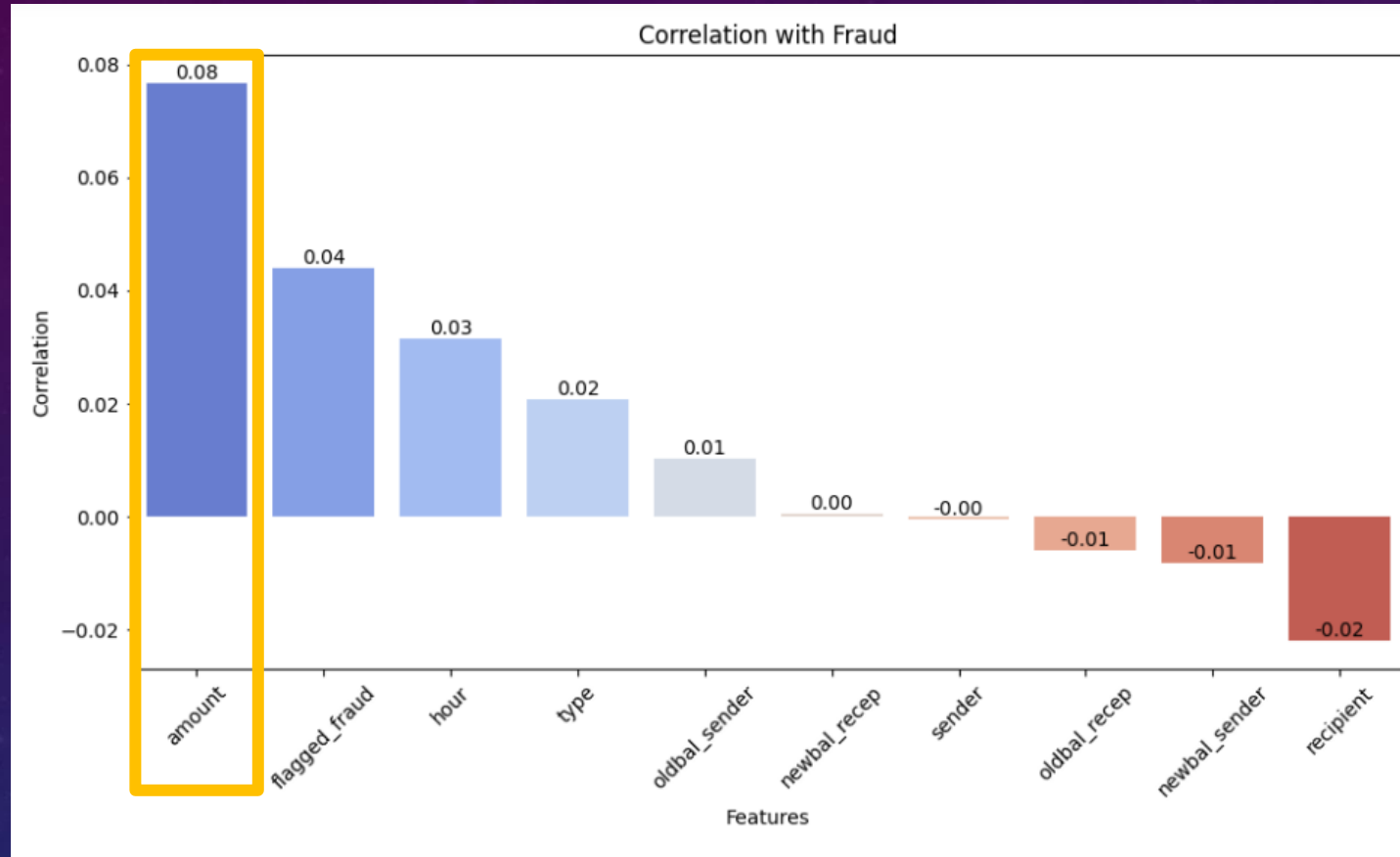
	2021	2022	Percentage change
Phishing scams	5,023	7,097	+41.3%
Job scams	4,550	6,492	+42.7%
E-commerce scams	2,729	4,762	+74.5%

## Insights:



- Fraud transaction occur evenly throughout the month.
- Genuine transaction peaks at start and mid of the month.

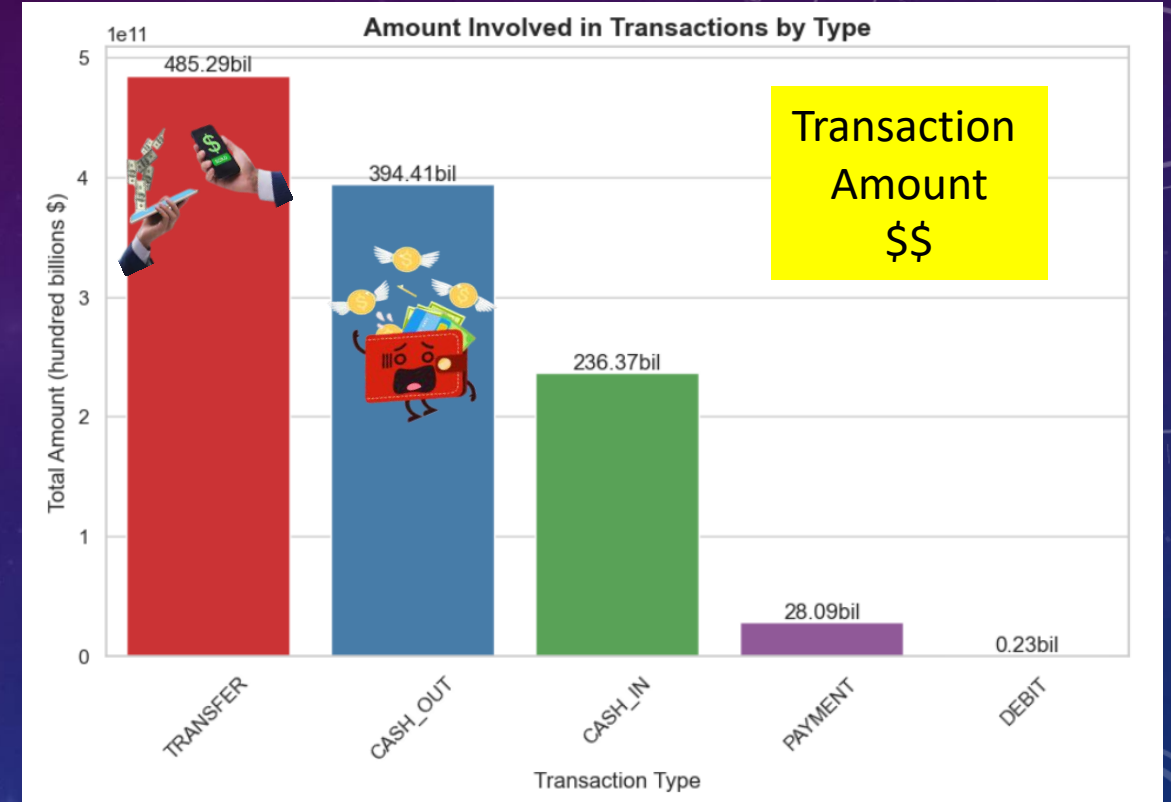
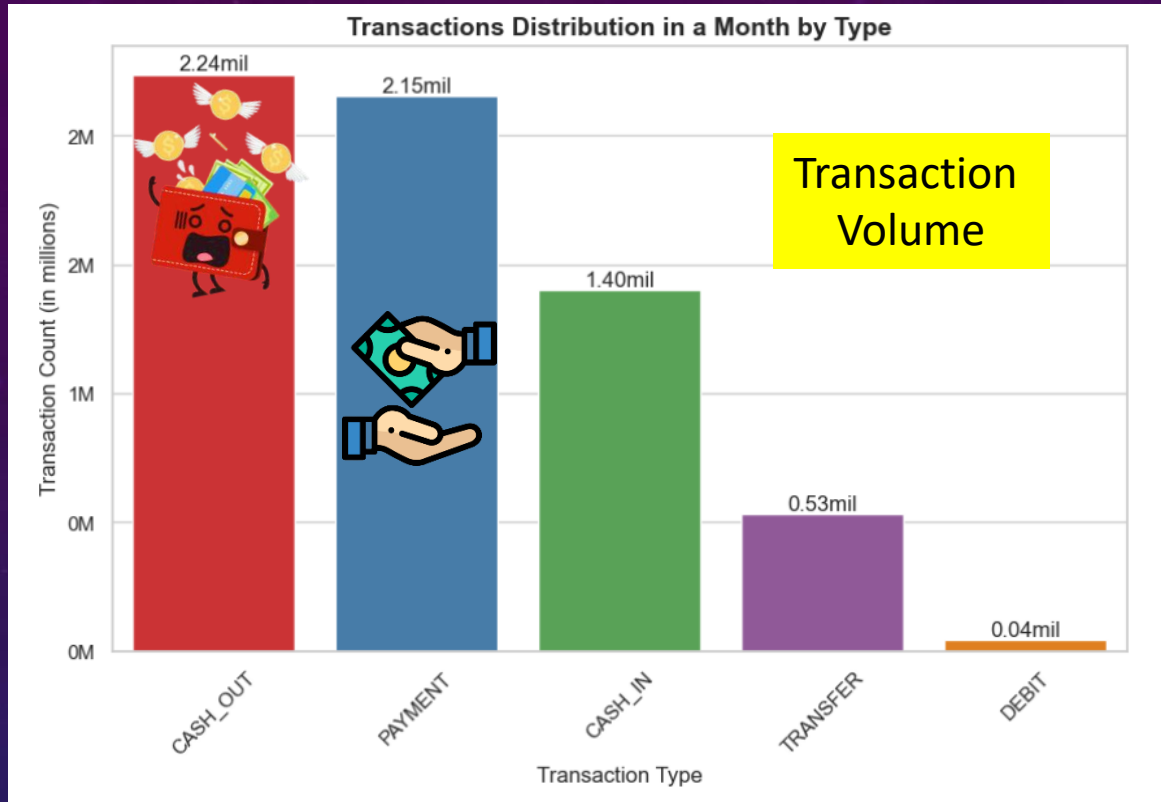
## Insights:



- Overall, data on hand shows **weak correlation** to fraudulent transaction.
- **Transaction amount** which have the highest correlation score is only **8% correlated** statistically.

# FRAUD DETECTION USING MACHINE LEARNING– CONT.

## Insights:



- Top transaction volume:
  1. Cash Out (~2.2 mill counts = 35%)

2. Payment



- Top \$\$ involved (~\$880 bil = 77% of \$1.1tril):

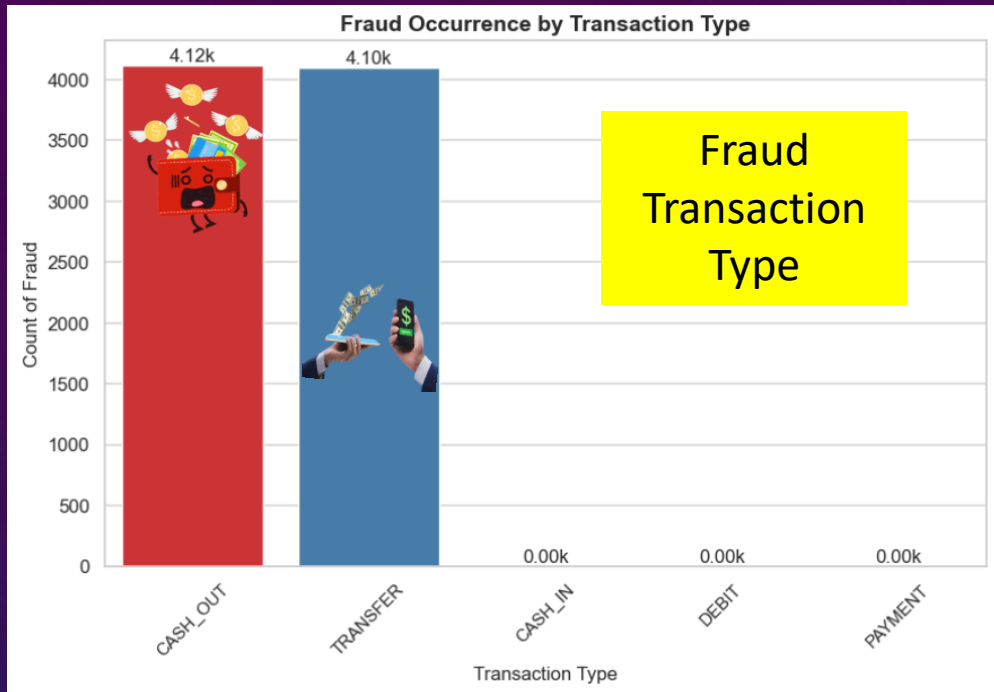
1. Transfer

2. Cash out



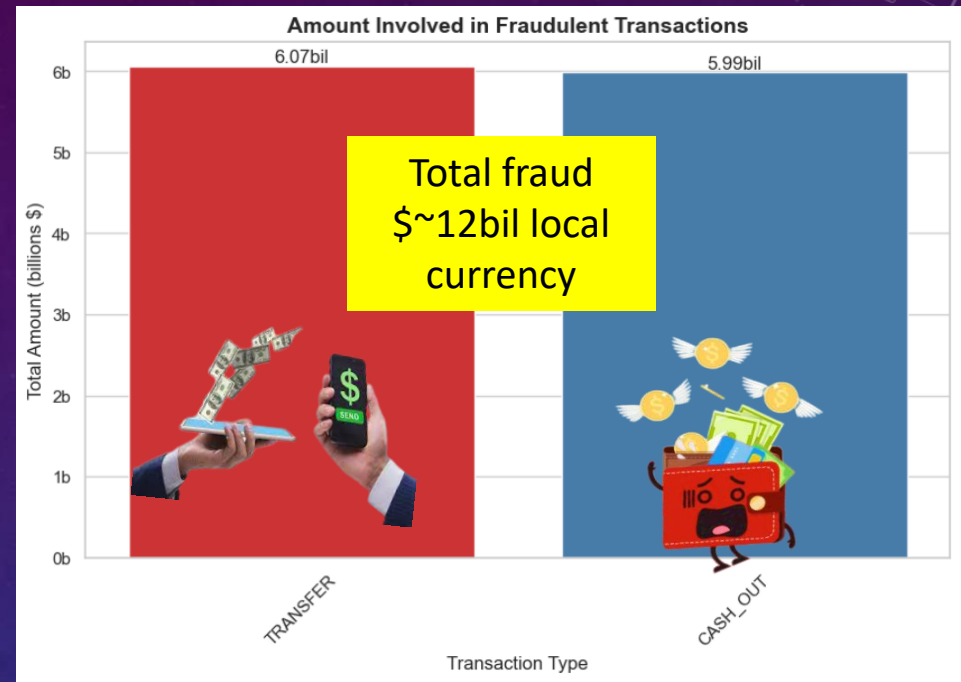


# FRAUD DETECTION USING MACHINE LEARNING– CONT.



Highest fraud transaction type (total 8000 counts):

1. Cash Out
2. Transfer



High fraud amount involved (total \$12 billions) :

1. Transfer
2. Cash Out

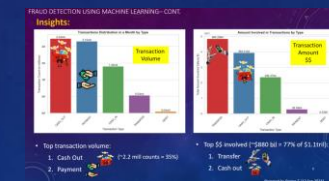
## Actionable Insights:

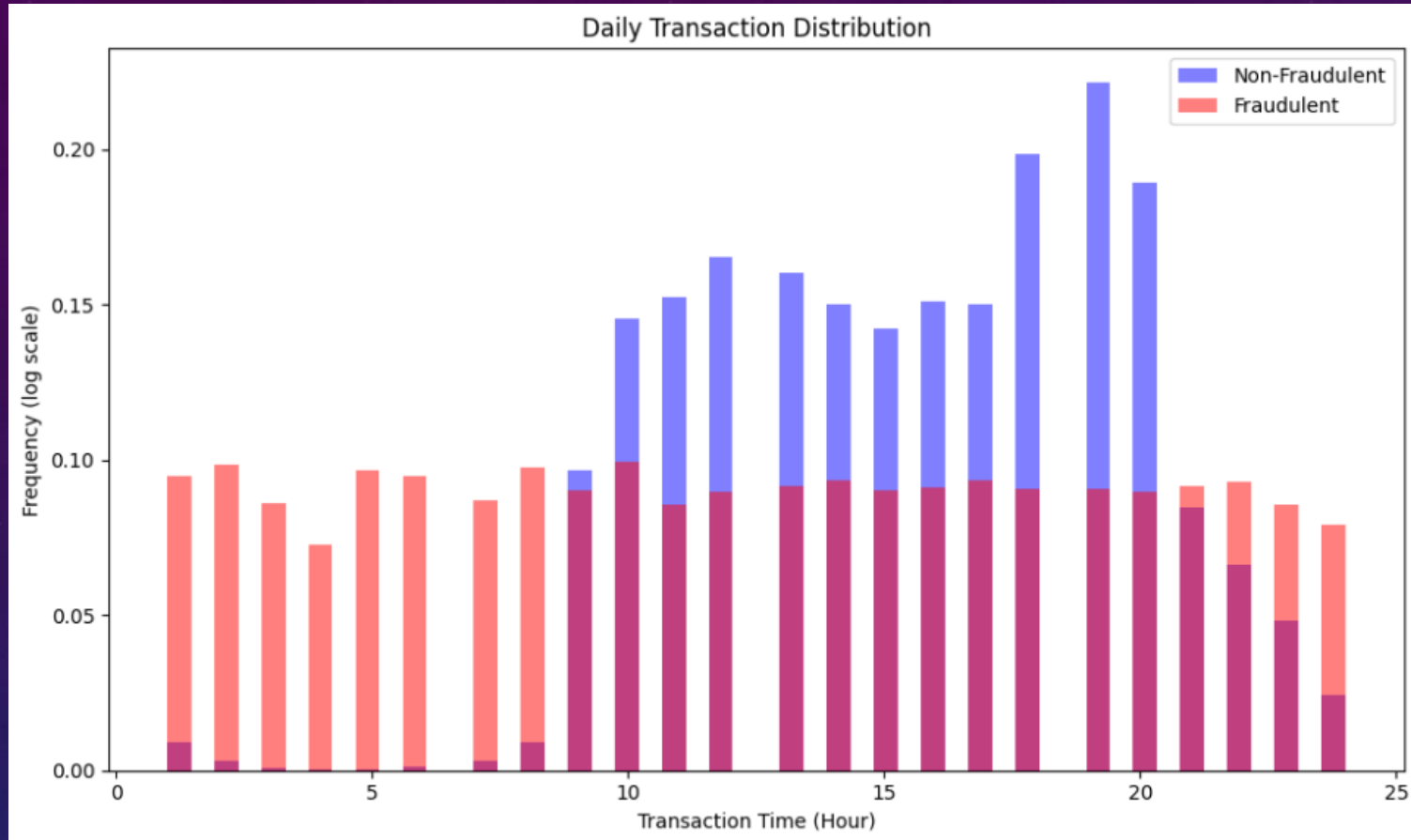
Fraudsters tend to **favour cash out** and **transfer**.  
Crucial to control fraud (high volume & high amount transacted).  
To mitigate risk, we can **enhance** our **verification process** for customers for customer using cash out and transfer.

Remember?

Cash Out + Transfer = 2.7mill counts (43%)

Cash Out + Transfer = \$880 bil (~77%)





Assumption: 1<sup>st</sup> hour in dataset starts at 0000hrs.

### Actionable Insights:

The probability of genuine transaction is higher during office hour while the probability of fraudulent transaction is higher during non-office hour, peak around pre-dawn.

Implementation of real-time monitoring between 11PM to 8AM is highly recommended and potentially restrict high-value transactions during this time frame.



## CURRENT SYSTEM

### Transaction Monitoring:

Rule-based systems that flag transactions based on predefined rules (e.g. exceed limits on transaction amounts, frequency, or locations).

+

### Manual Review:

Suspicious transactions flagged. Human analysts investigate the flagged transactions to determine if they are fraudulent.

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### Customer Verification:

Contacting the customer directly to verify the legitimacy of a transaction, especially for high-risk or unusual transactions.

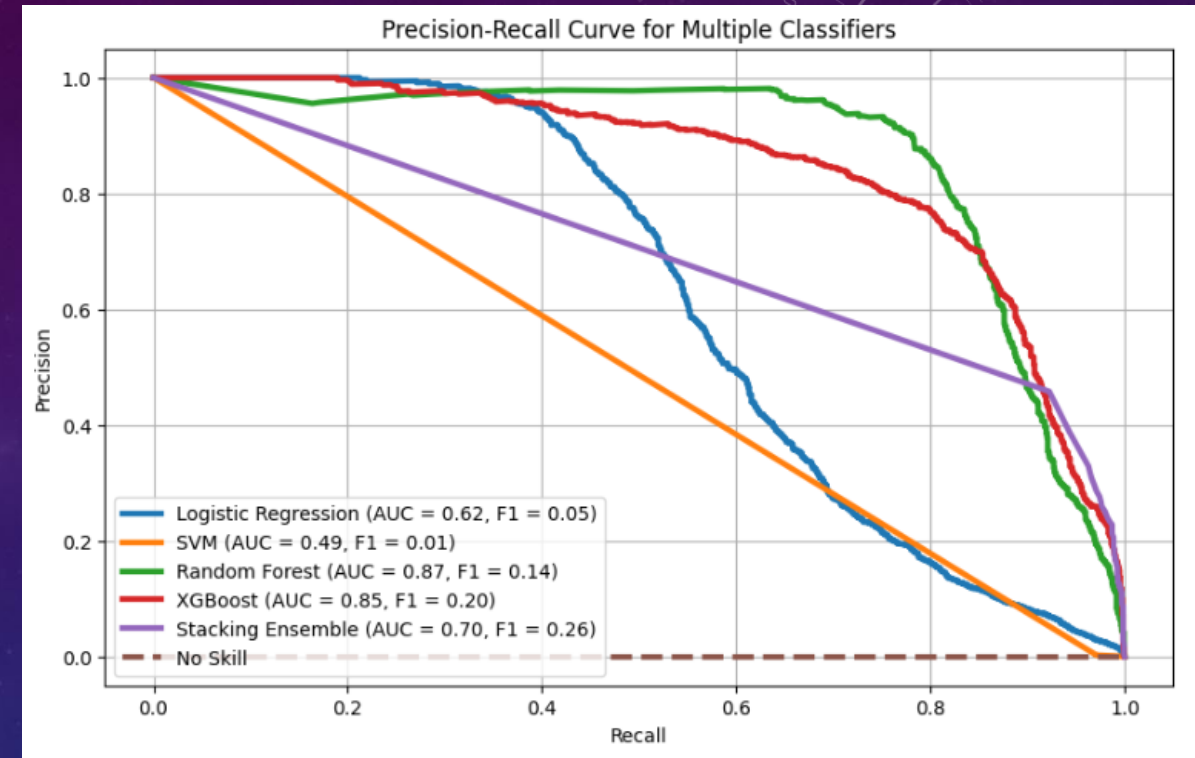
“ADVANCE SYSTEM”

### Adoption of Machine Learning and AI:

- Leverage ML and AI algorithms
- Analyze vast amounts of data and identify complex patterns & anomalies indicative of fraud in real-time.
- These systems can adapt and improve accuracy over time.

## MACHINE LEARNING RESULT

- Dataset is **severely imbalance**.
  - 6mill unique entry. **Fraudulent 1%**
  - Challenge: All models trained have **high False Positive** (actually genuine but predicted fraudulent) = low Precision score for fraudulent
- Model is trained using **4 algorithms (classifiers)**.
  - Logistic Regression
  - Support Vector Machine (SVM)
  - Random Forest
  - XGBoost (Gradient Boosting).
  - Stacking Ensemble (combining prediction from 4 base models - often improve overall performance as it leverages the strengths of different models)
- Model performance visualisation using **Precision-Recall Plot**.
  - More informative** and give an **accurate prediction** of future classification performance.
  - The plot **evaluate** the fraction of true positives (**fraudulent**) among positive predictions (**predicted fraudulent**).



### Precision-Recall Curve Interpretation Guideline:

- Ideal Precision-Recall curve** is one that starts at (0, 1) and goes to (1, 1), meaning perfect precision and recall, a curve that is as close to the top-right corner as possible.
- Precision:** "Out of all the cases the model predicted as positive, how many were truly positive?"
- Recall (Sensitivity):** "Out of all the actual positive cases, how many did the model correctly identify?" (actual positive)

## WHICH MODEL TO USE?

Classifier	Precision	Recall	F1-Score	AUC
Logistic Regression	0.0086	0.9937	0.0488	0.6199
SVM	0.2521	0.7355	0.0072	0.4874
Random Forest	0.0577	0.9924	0.1403	0.8693
XGBoosting	0.0127	0.9981	0.198	0.8468
Stacking Ensemble	0.0775	0.9955	0.2559	0.6968

1. If **minimizing false positives** (precision) is crucial due to the cost of investigating non-fraudulent transactions, the "**Random Forest**" model may be preferred. **Random Forest (F1 = 0.1403, AUC = 0.8693)**
2. If **maximizing the detection of fraud cases** is paramount, even at the **risk** of **some false alarms**, the "**XGBoosting**" model stands out. **XGBoosting (F1 = 0.198, AUC = 0.8468)**
3. For a **balanced approach** where both precision and recall matter, the "**Stacking Ensemble**" model offers a competitive F1-Score. **Stacking Ensemble (F1 = 0.2559, AUC = 0.6968)**

Ultimately, the choice of the best model depends on the specific goals and constraints of the fraud detection task, including the tolerance for false alarms and the consequences of missing actual fraud cases.