# Adaboost for Fraud Detection

See jupyter notebook on github
This Slide Link

## Machine Learning Project 2
## IndonesiaAI ML Batch 7


2025 02 28

Andyp

# Introduction

- **Project Goal:** Develop a model to detect fraudulent transactions.
- **Dataset:** 'fraudTrain.csv' containing transaction data.
- **Approach:** Data analysis, preprocessing, modeling, and evaluation.

# Background

As more and more people rely on digital payments, fraud is getting smarter, sneakier, and harder to catch. Traditional systems? They just can't keep up anymore.

What if we could use machine learning to *really* understand the patterns behind these transactions and spot the shady ones before they do damage?

That's where this project comes in. I took the `fraudTrain.csv` dataset — real transaction data — and started digging. The goal? Build a model that doesn't just guess, but learns how fraud behaves, and catches it with speed and precision.

# Libraries and Tools

- **Data Handling:** pandas, numpy
- **Data Splitting:** train_test_split (sklearn)
- **Imbalanced Data Handling:** SMOTE (imblearn)
- **Modeling:** AdaBoostClassifier (sklearn)
- **Evaluation:** classification_report, confusion_matrix, roc_auc_score (sklearn)
- **Visualization:** matplotlib, seaborn
- **Model Serialization:** pickle

# Data Overview

- **Total Columns:** 22
- **Key Columns:**
    a. Transaction Details: `trans_date_trans_time`, `amt`
    b. User Details: `cc_num`, `first`, `last`, `gender`, `dob`
    c. Merchant Details: `merchant`, `category`
    d. Geographical Info: `street`, `city`, `state`, `zip`, `lat`, `long`
    e. Target Variable: `is_fraud`

# Data Preparation

- **Sampling:** Used 1000 rows initially for quick analysis
- **EDA:**
  - Generated a PDF report (`eda_report__df_train.pdf`)
  - Non-null counts, missing values, distinct values
  - Numerical & categorical summaries
- **Creating New Features:**

# Data Preparation

```
1  df_train.info()
```

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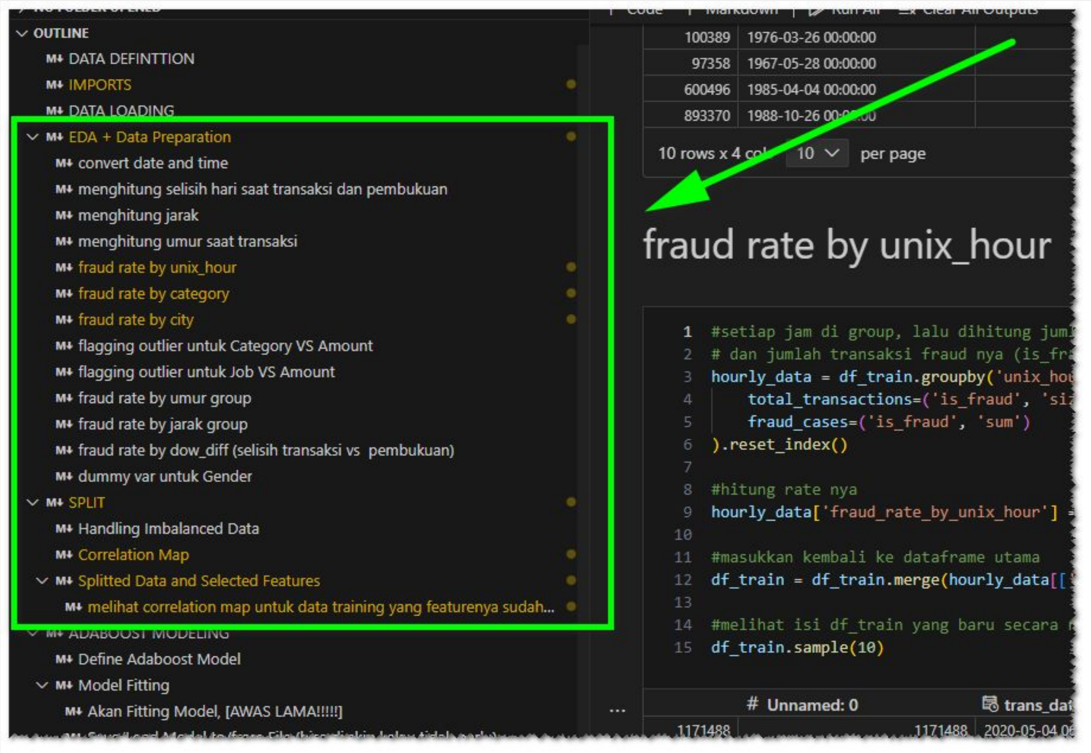
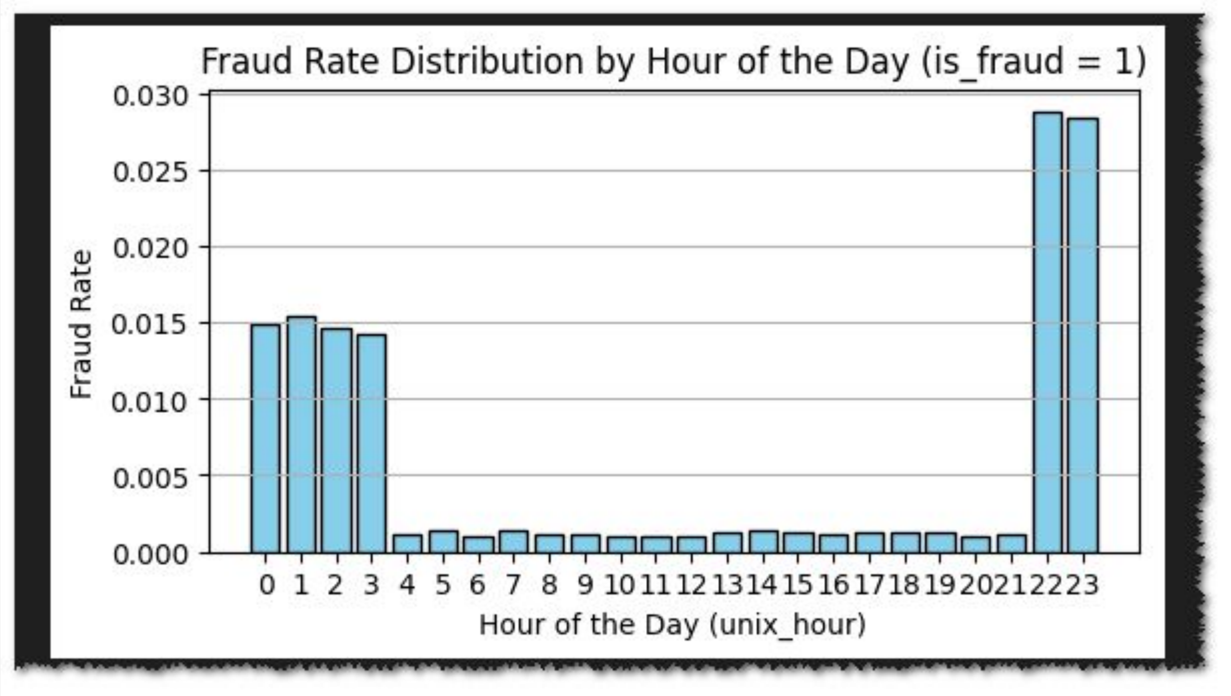
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1296675 entries, 0 to 1296674
Data columns (total 23 columns):
 #   Column                 Non-Null Count    Dtype
---  ------                 --------------    -----
 0   Unnamed: 0             1296675 non-null  int64
 1   trans_date_trans_time  1296675 non-null  object
 2   cc_num                 1296675 non-null  int64
 3   merchant               1296675 non-null  object
 4   category               1296675 non-null  object
 5   amt                    1296675 non-null  float64
 6   first                  1296675 non-null  object
 7   last                   1296675 non-null  object
 8   gender                 1296675 non-null  object
 9   street                 1296675 non-null  object
 10  city                   1296675 non-null  object
 11  state                  1296675 non-null  object
 12  zip                    1296675 non-null  int64
 13  lat                    1296675 non-null  float64
 14  long                   1296675 non-null  float64
 15  city_pop               1296675 non-null  int64
 16  job                    1296675 non-null  object
 17  dob                    1296675 non-null  object
 18  trans_num              1296675 non-null  object
 19  unix_time              1296675 non-null  int64
...
 21  merch_long             1296675 non-null  float64
 22  is_fraud               1296675 non-null  int64
dtypes: float64(5), int64(6), object(12)
memory usage: 227.5+ MB
```

*Output is truncated. View as a scrollable element or open in a text editor. Adjust cell output settings...*

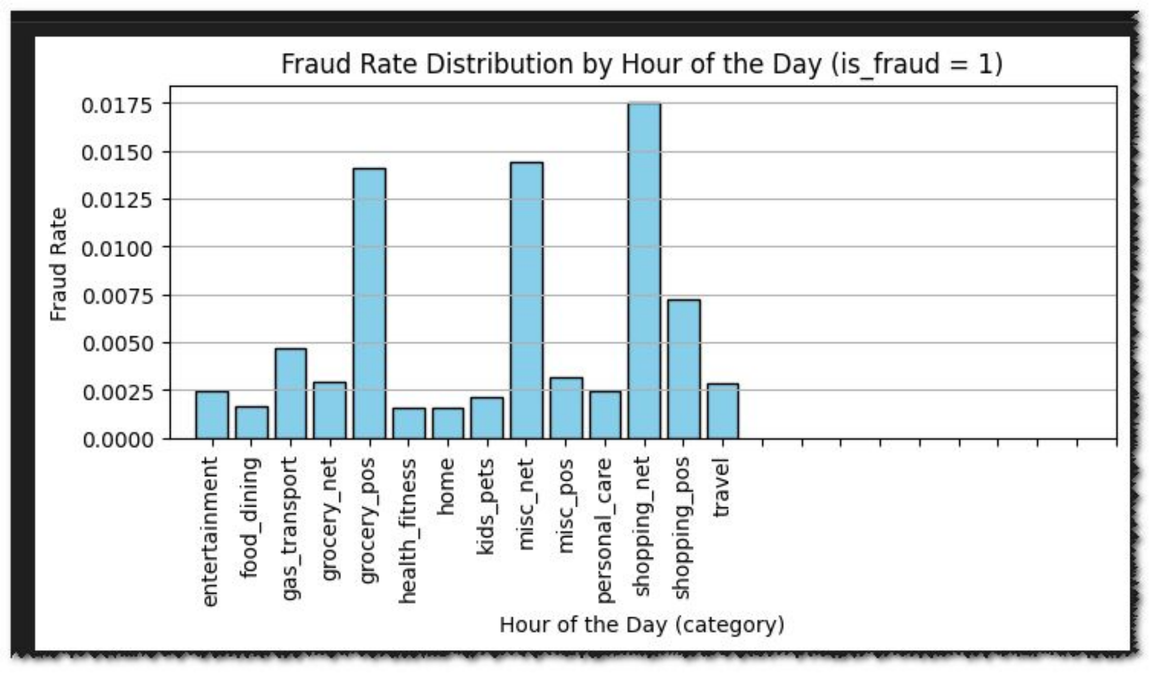
# Data Preparation



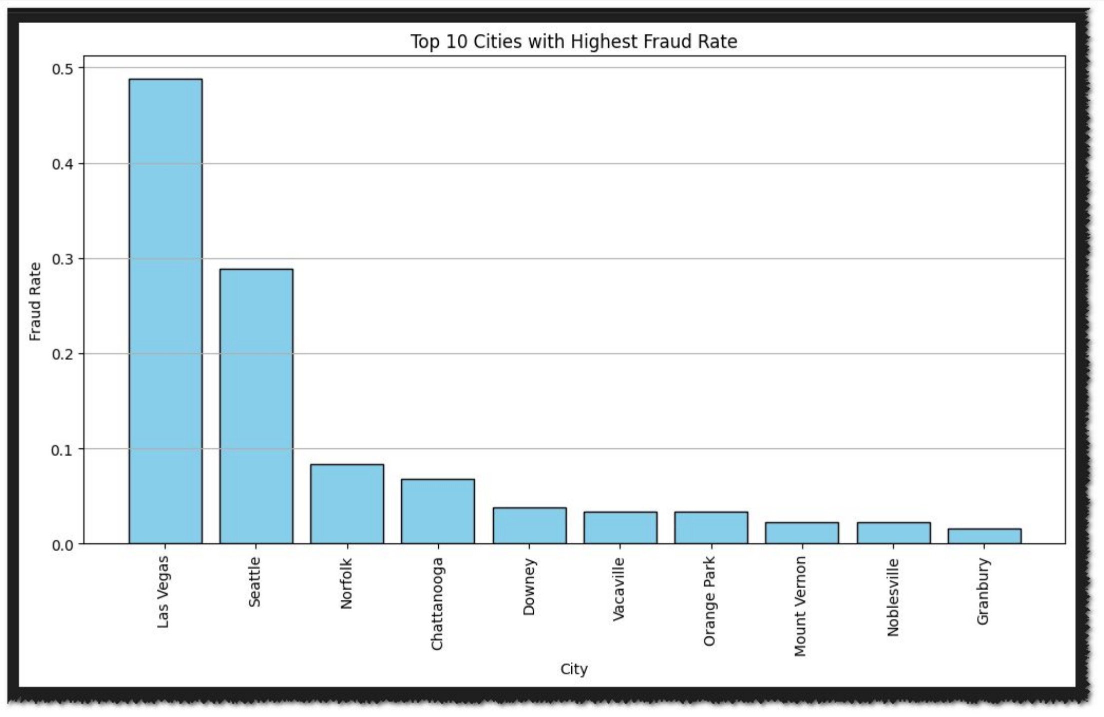

# Data Preparation



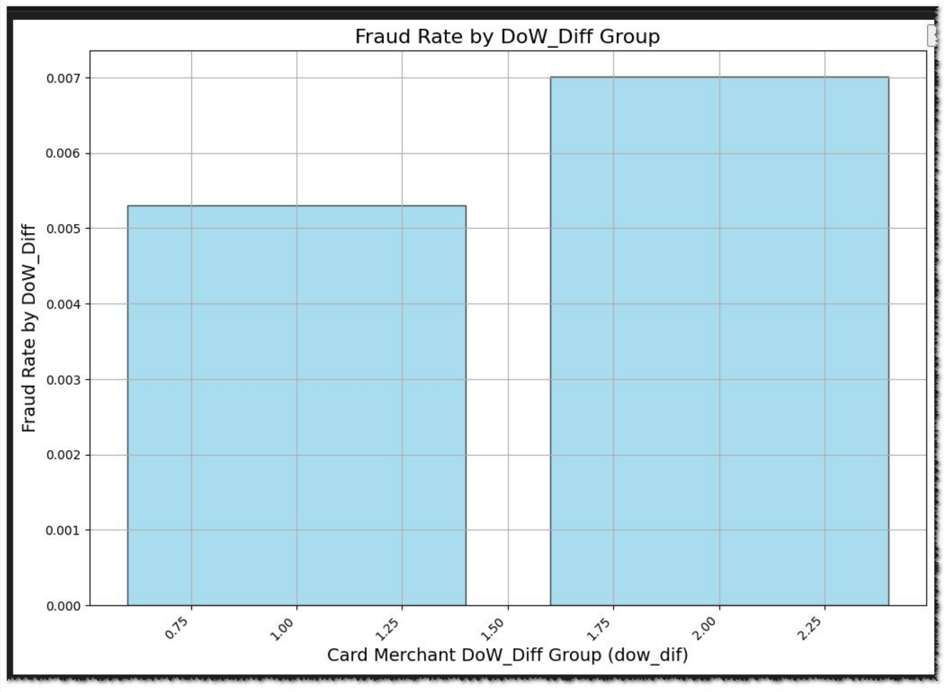

# Data Preparation



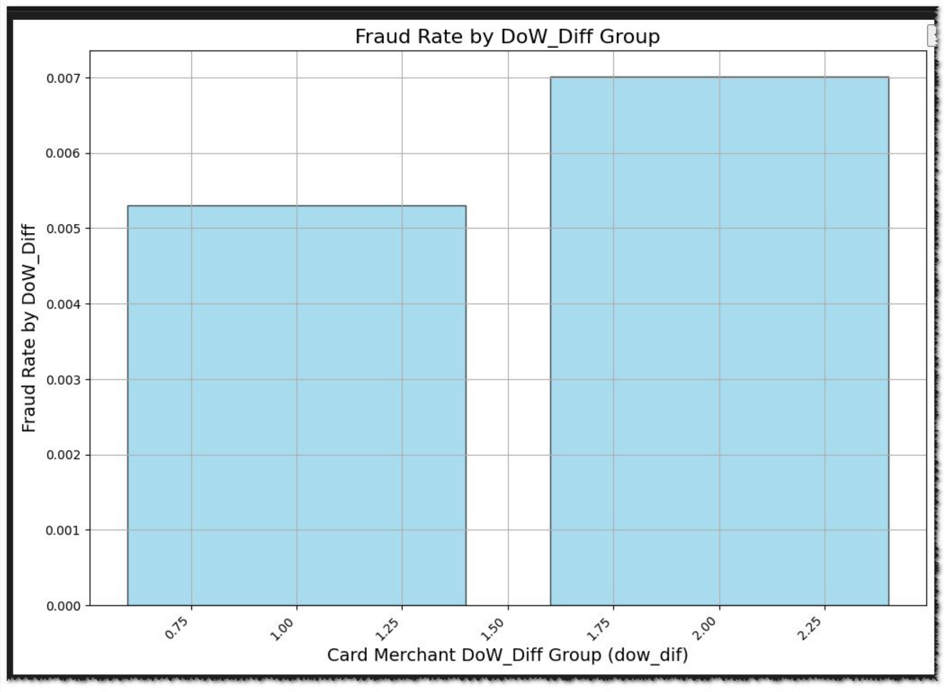

# Data Preparation



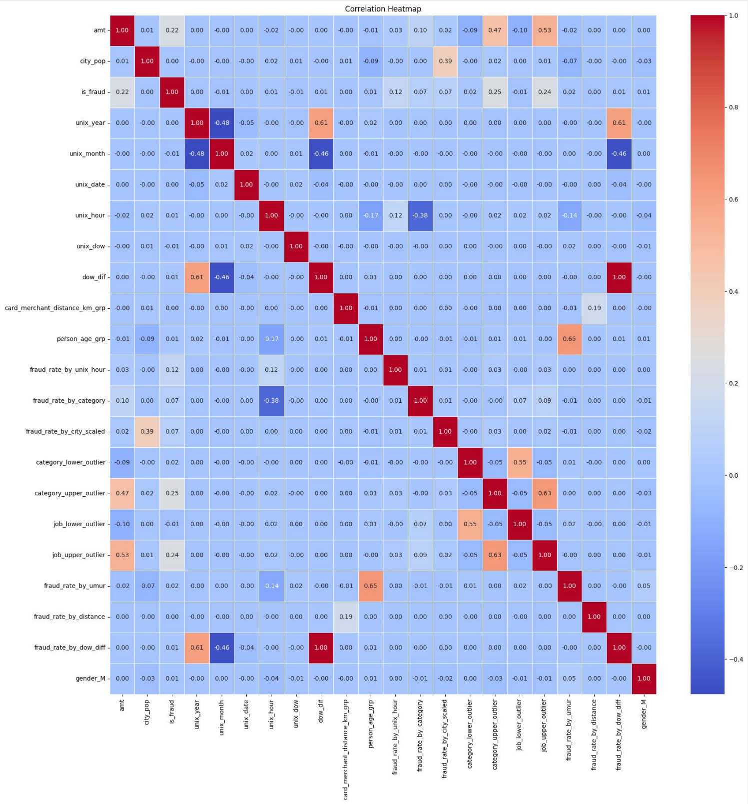

# Data Preparation




# Data Preparation




# Data Preparation




# Modeling

- **Models Used:**
  a. `AdaBoostClassifier`
- **Handling Imbalanced Data:** SMOTE
- **Model Evaluation Metrics:**
  a. Classification report
  b. Confusion matrix
  c. ROC AUC score
- **Feature Importance**
- **Run Model with Important Feature Only**

# Modeling

## Define Adaboost Model

```
#
base_estimator = RandomForestClassifier() # tidak ada parameter di set , saya ambil default saja semua

# Initialize AdaBoost with base estimator and n_estimators (number of trees)
model = AdaBoostClassifier(
        estimator=base_estimator,
        n_estimators=100,
        random_state=42)

```

## Model Fitting

### Akan Fitting Model, [AWAS LAMA!!!!!]

skip saja kalau udah pernah , langsung load saja di bawah

```
X = df_train_balanced_smote.drop('is_fraud', axis=1)
y = df_train_balanced_smote['is_fraud']
```

# Modeling

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+ Code + Markdown

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```
feature_importance_df
```

| | Feature | Importance |
|---|---|---|
| 10 | fraud_rate_by_unix_hour | 0.3050826510215114 |
| 0 | amt | 0.22111923750812024 |
| 14 | category_upper_outlier | 0.11910041584439623 |
| 11 | fraud_rate_by_category | 0.08741715006619467 |
| 16 | job_upper_outlier | 0.08566922496922108 |
| 5 | unix_hour | 0.04470641657439381 |
| 19 | fraud_rate_by_dow_diff | 0.017820550076904564 |
| 12 | fraud_rate_by_city_scaled | 0.017639410602988962 |
| 17 | fraud_rate_by_umur | 0.015927352302554394 |
| 1 | city_pop | 0.012412966599913604 |
| 13 | category_lower_outlier | 0.010854914583336766 |
| 6 | unix_dow | 0.010032869604976059 |
| 9 | person_age_grp | 0.008114118126266324 |
| 7 | dow_dif | 0.007207350363013228 |
| 20 | gender_M | 0.007009923678833331 |
| 18 | fraud_rate_by_distance | 0.006704709253933432 |
| 8 | card_merchant_distance_km_grp | 0.00595865717346875 |
| 3 | unix_month | 0.005759184413537581 |
| 4 | unix_date | 0.004428203334890267 |
| 15 | job_lower_outlier | 0.0037194998192841638 |
| 2 | unix_year | 0.003315194082261369 |

21 rows x 2 cols 50 per page Page 1 of 1

# Modeling

## ADABOOST MODELING (LAGI)

(kali ini akan dicoba menggunakan feature yang kontribusinya lebih dari 1% saja berdasar feature importance)

### Feature Selection based on Feature Importance

```
#memilih feature2 yang kontribusinya >= 1% saja
list_of_selected_field2 = feature_importance_df[feature_importance_df['Importance']>=0.01]
list_of_selected_field2
```

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| | Feature | Importance |
|---|---|---|
| 10 | fraud_rate_by_unix_hour | 0.3050826510215114 |
| 0 | amt | 0.22111923750812024 |
| 14 | category_upper_outlier | 0.11910041584439623 |
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| 17 | fraud_rate_by_umur | 0.015927352302554394 |
| 1 | city_pop | 0.012412966599913604 |

12 rows x 2 cols 10 per page Page 1 of 2

# Results

- **Key Metrics:**
  - Precision, Recall, F1-Score
  - ROC AUC

# Results

```
Classification Report untuk Test Data menggunakan model dengan feature pilihan manual
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    257815
           1       0.94      0.77      0.85      1520

    accuracy                           1.00    259335
   macro avg       0.97      0.89      0.92    259335
weighted avg       1.00      1.00      1.00    259335
-------------------------------------------------------
Classification Report untuk Test Data menggunakan model dengan important feature saja
              precision    recall  f1-score   support

           0       1.00      1.00      1.00    257815
           1       0.91      0.80      0.85      1520

    accuracy                           1.00    259335
   macro avg       0.95      0.90      0.92    259335
weighted avg       1.00      1.00      1.00    259335
-------------------------------------------------------
```

# Conclusion

- **Model Performance:** Second Try with Important Feature only has similar result with faster processing (fewer feature being use)
- **Next Steps can be done:**
  a. Improve feature engineering
  b. Hyperparameter tuning
  c. Implement in a real-time fraud detection system

# Thank You