Fraud Detection Analysis

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Using Data Mining Techniques

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01 - Introduction

- Financial fraud costs billions annually.
- Fraud detection is critical for both financial institutions and consumers.
- In 2016, global losses from fraudulent transactions exceeded $16 billion.

Our goal: To classify transactions as legitimate or fraudulent

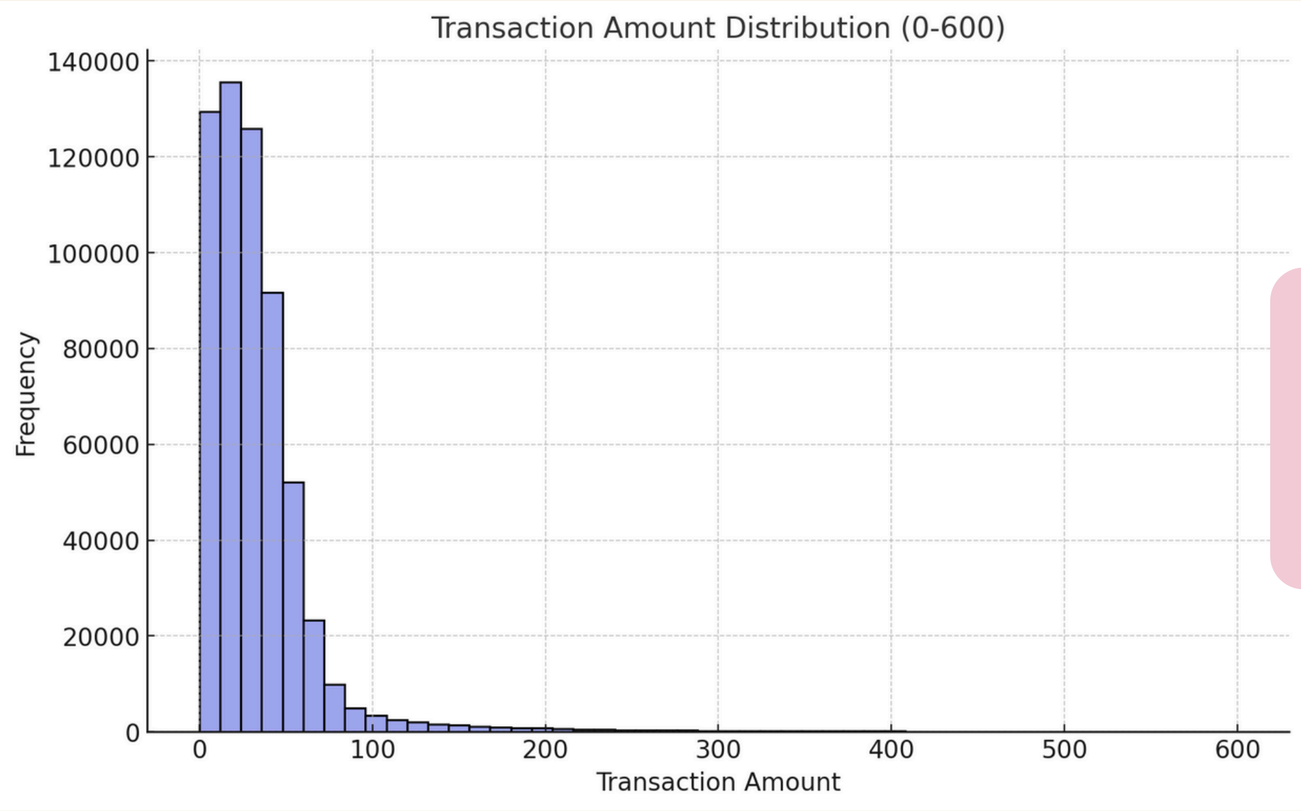
Dataset Overview

The dataset consists of 594,643 transactions with various attributes such as:

- Customer information (age, gender)
- Merchant information (ZIP code, merchant category)
- Transaction details (amount, time step)

The target variable: Fraudulent (1) or Legitimate (0)

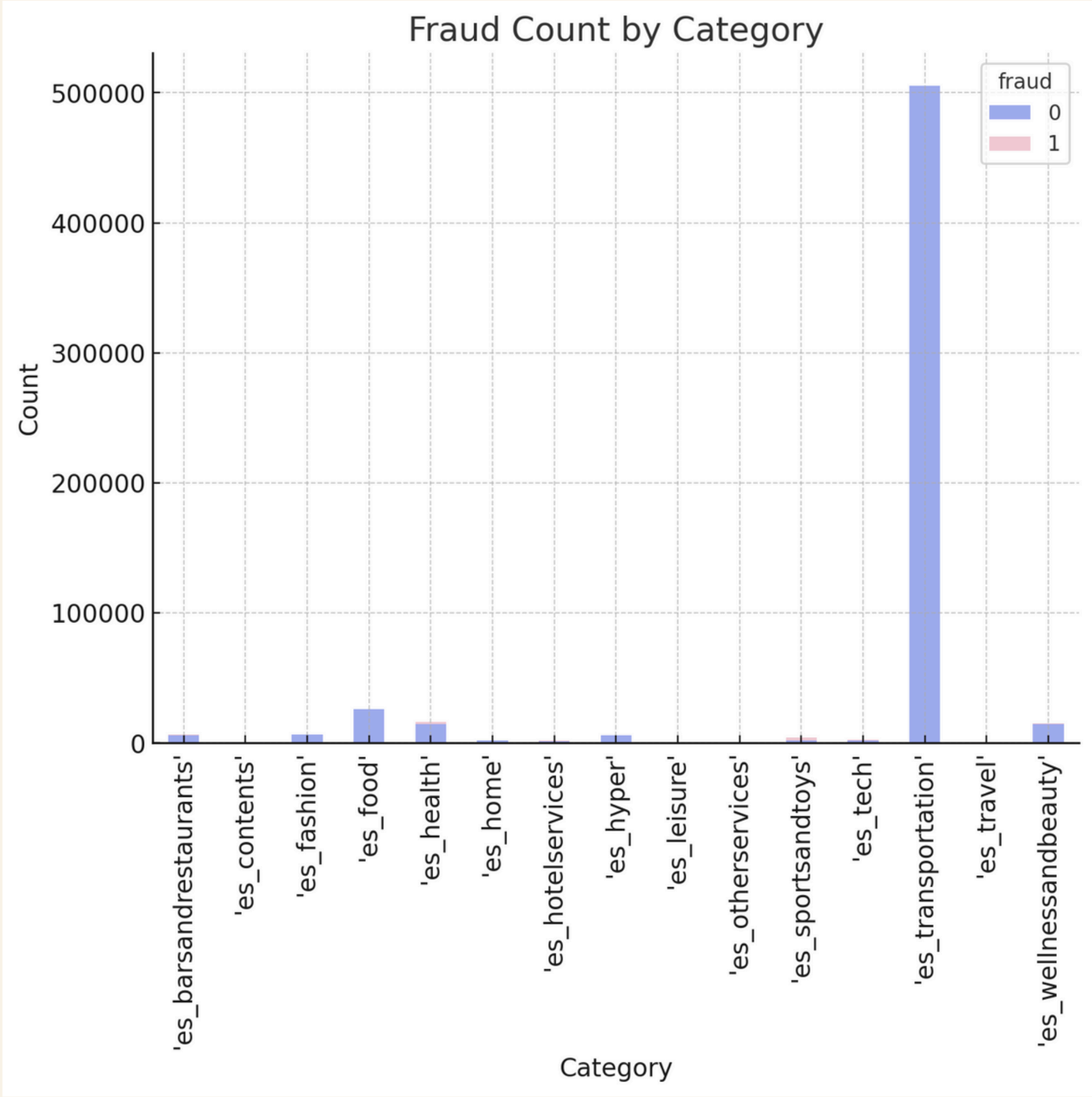
02 - Data Visualization



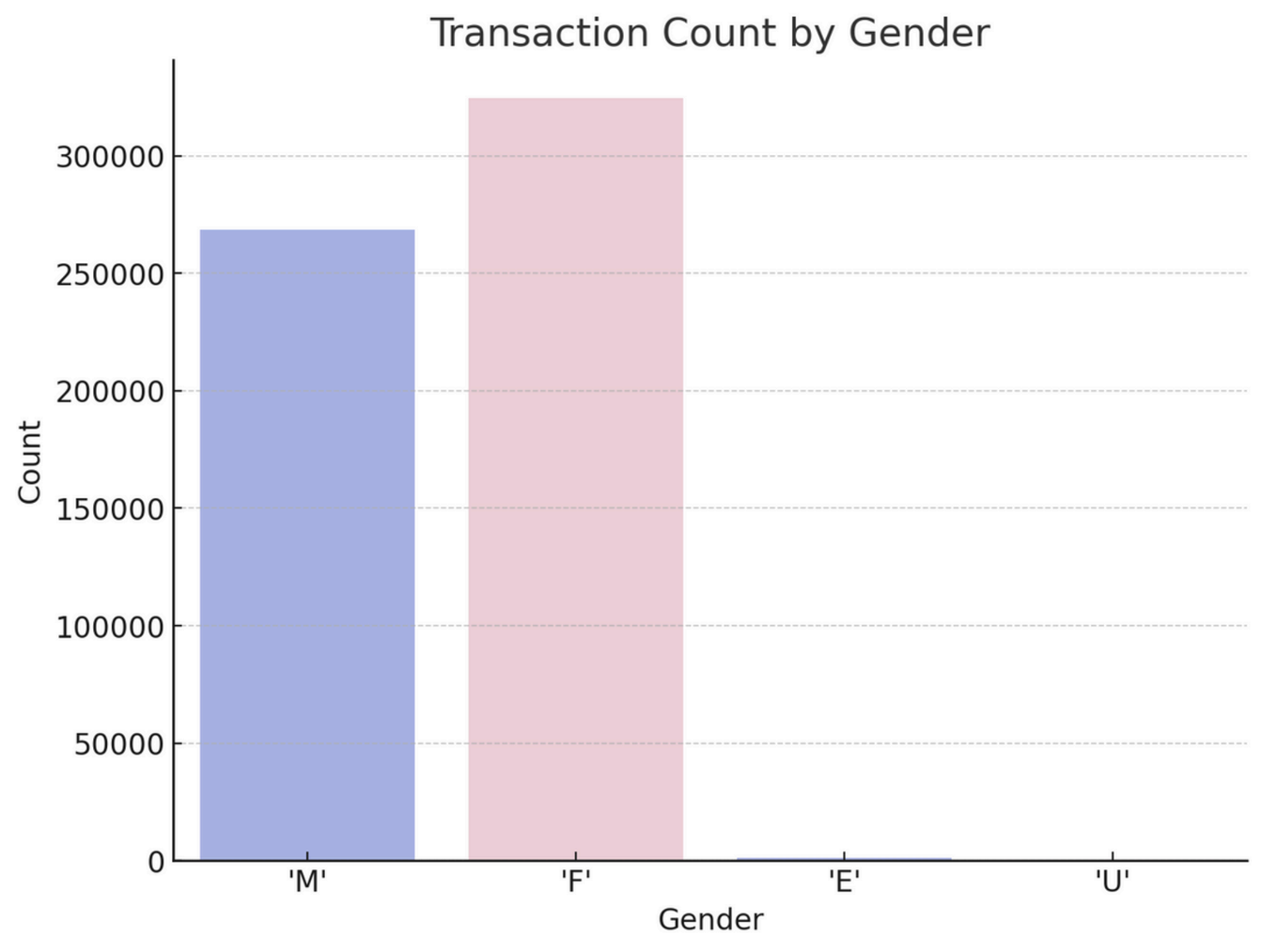
Distribution of Transaction Amounts

Fraud Distribution by Category

Visualizes the count of fraudulent and non-fraudulent transactions by merchant category.



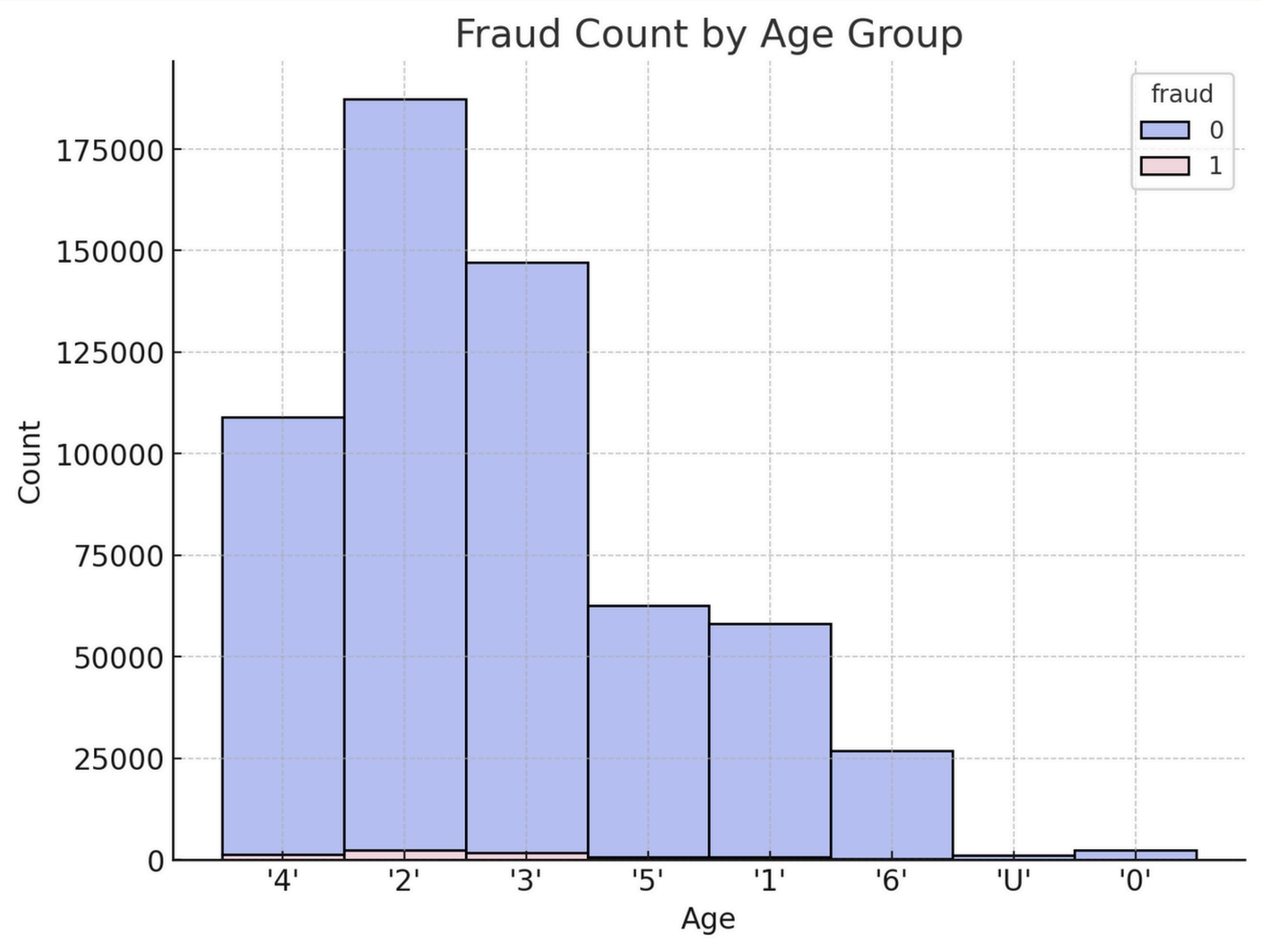
Transaction Amount by Gender



Fraud Distribution by Transaction Amount

Boxplot showing how transaction amounts differ between fraudulent and non-fraudulent transactions.

Fraud Count by Age Group



Count plot depicting fraud distribution across different age groups.

03 - Models

Models Used for Fraud Detection

a. Naive Bayes

b. Logistic Regression

c. Neural Networks

d. Decision Trees

e. Random Forest

Data Preprocessing

Data Cleaning:

- Removed special characters from categorical columns
- Categorical variables were encoded using one-hot encoding

Standardization:

- Standardized numerical features to improve model performance

Handling Imbalance:

- Used SMOTE to address class imbalance (very few fraudulent transactions)

Evaluation Metrics

- **Precision**: How many predicted fraud cases were correct?
  (High precision = fewer false positives)
- **Recall**: How many actual fraud cases were correctly identified?
  (High recall = fewer false negatives)

- **False Positives (FP)**: Legitimate transactions classified as fraudulent.
- **False Negatives (FN)**: Fraudulent transactions classified as legitimate.

Evaluation

Model	Precision	Recall	FP	FN
Naive Bayes	0.1957	0.9993	2	11695
Logistic Regression	0.8887	0.7236	796	261
Neural Network	0.8721	0.7624	684	322
Decision Tree	0.9027	0.7212	803	224
Random Forest	0.8845	0.7462	1096	421

Model Performance Comparison

Key Insights

- **Naive Bayes**: High recall but impractically low precision. Good at identifying fraud but too many false positives.
- **Logistic Regression**: Balanced performance but slightly lower recall.
- **Neural Networks**: Excellent balance between precision and recall, making it reliable for reducing both FP and FN.
- **Decision Tree**: High precision, useful for identifying fraud accurately, but slightly lower recall.
- **Random Forest**: Robust model with balanced performance, fewer false negatives than decision trees.

04 - Conclusions

How to Use These Findings in Business

Fraud Detection Automation:

- Implement the chosen machine learning models (e.g., Neural Networks, Random Forest) into real-time transaction monitoring systems.
- Automate fraud detection, flagging suspicious transactions for further review before they are processed.

Customer Trust & Experience:

- Reduce false positives to avoid unnecessary transaction holds or customer service calls.
- Improve customer satisfaction by minimizing fraud-related disruptions.

How to Use These Findings in Business

Cost Savings:

- By minimizing both false positives and negatives, reduce losses from fraudulent activities.
- Decrease manual transaction review costs by utilizing high-precision models to reduce the volume of false alerts.

Risk Mitigation:

- Leverage the model insights to enhance fraud prevention strategies, identify high-risk customers or transactions, and adjust security measures proactively.

Thanks