Synthetic Financial Datasets For Fraud Detection

University of Colorado Boulder

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1. Problem Statement

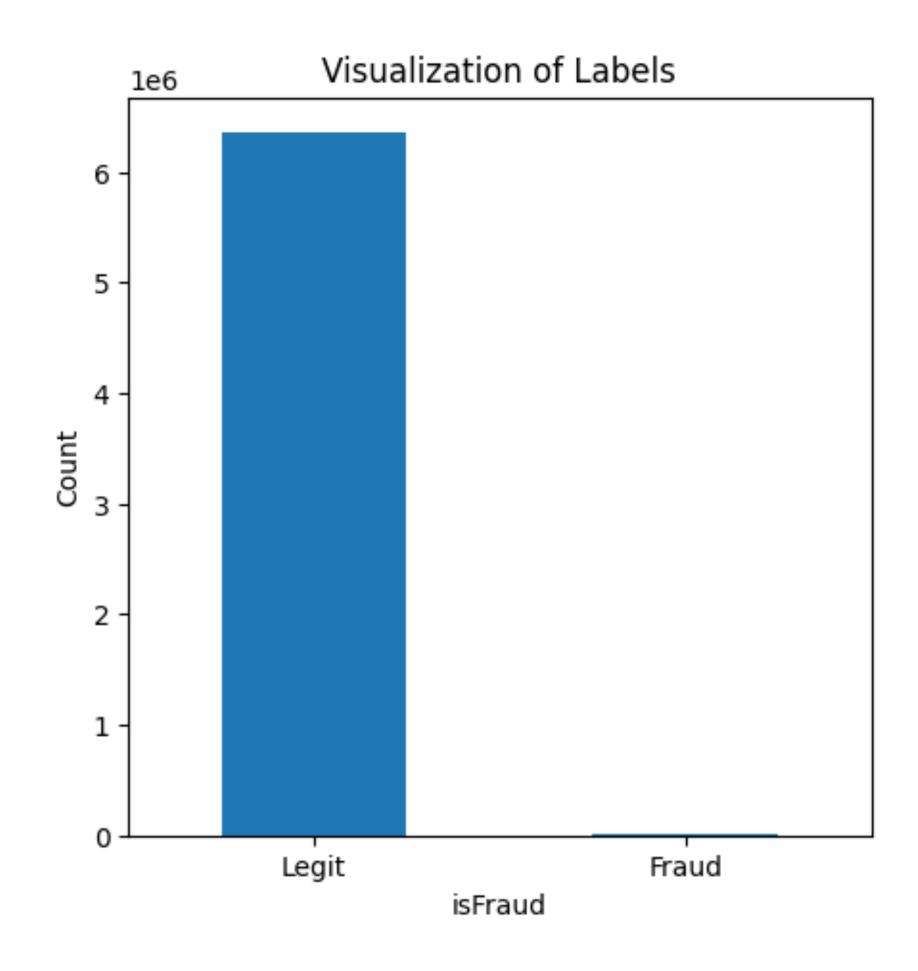
- Digital Fraud
- The dilemma making financial datasets publicly available
- How Synthetic data can help overcome these barriers

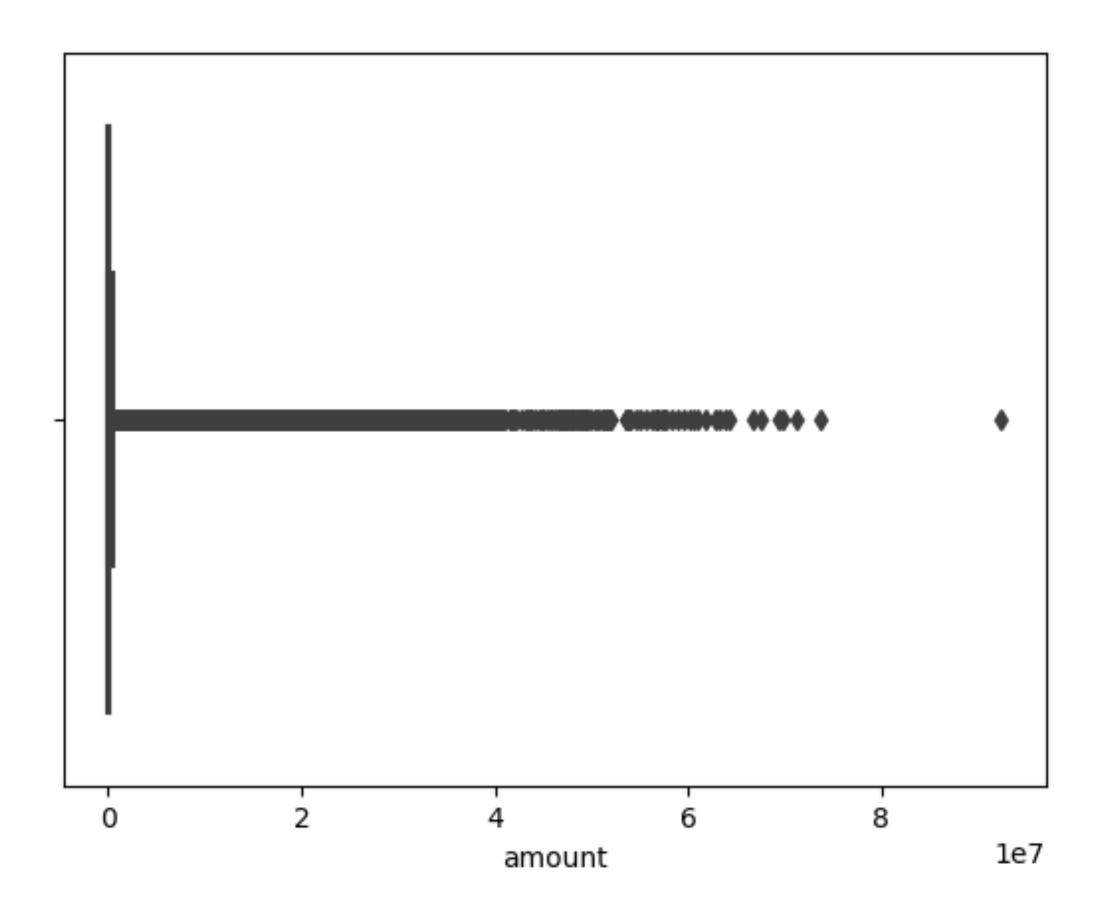
2. Related Work

- Synthetic Logs Generator for Fraud Detection in Mobile Transfer Services
- PaySim: A Financial Mobile Money Simulator For Fraud Detection
- Analysis of fraud controls using the PaySim financial simulator
- Advantages of the PaySim Simulator for Improving Financial Fraud Controls
- Fraud Detection in Mobile Payment Utilizing Process Behaviour Analysis

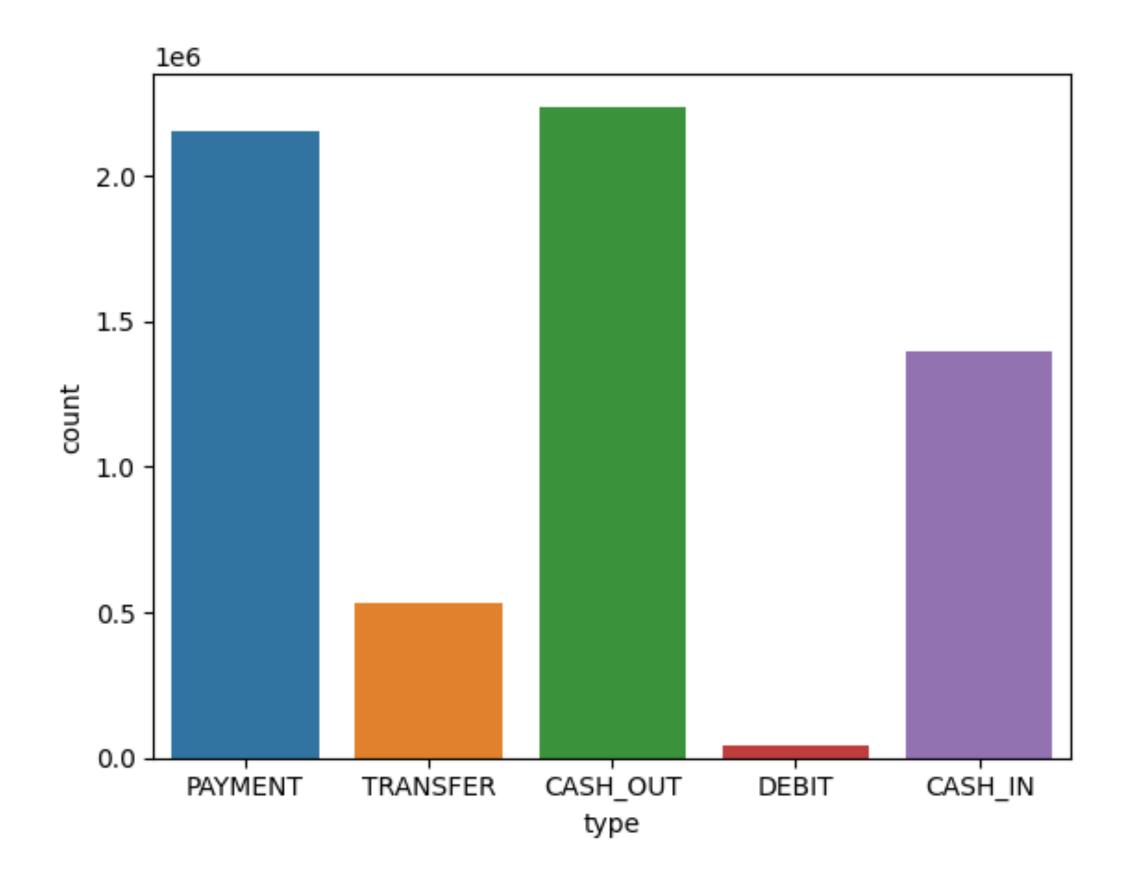
- Analysis of the Synthetic Financial Dataset for Fraud Detection
- Data Splitting
- Data Modeling

4.1 Analysis of the Synthetic Financial Dataset for Fraud Detection



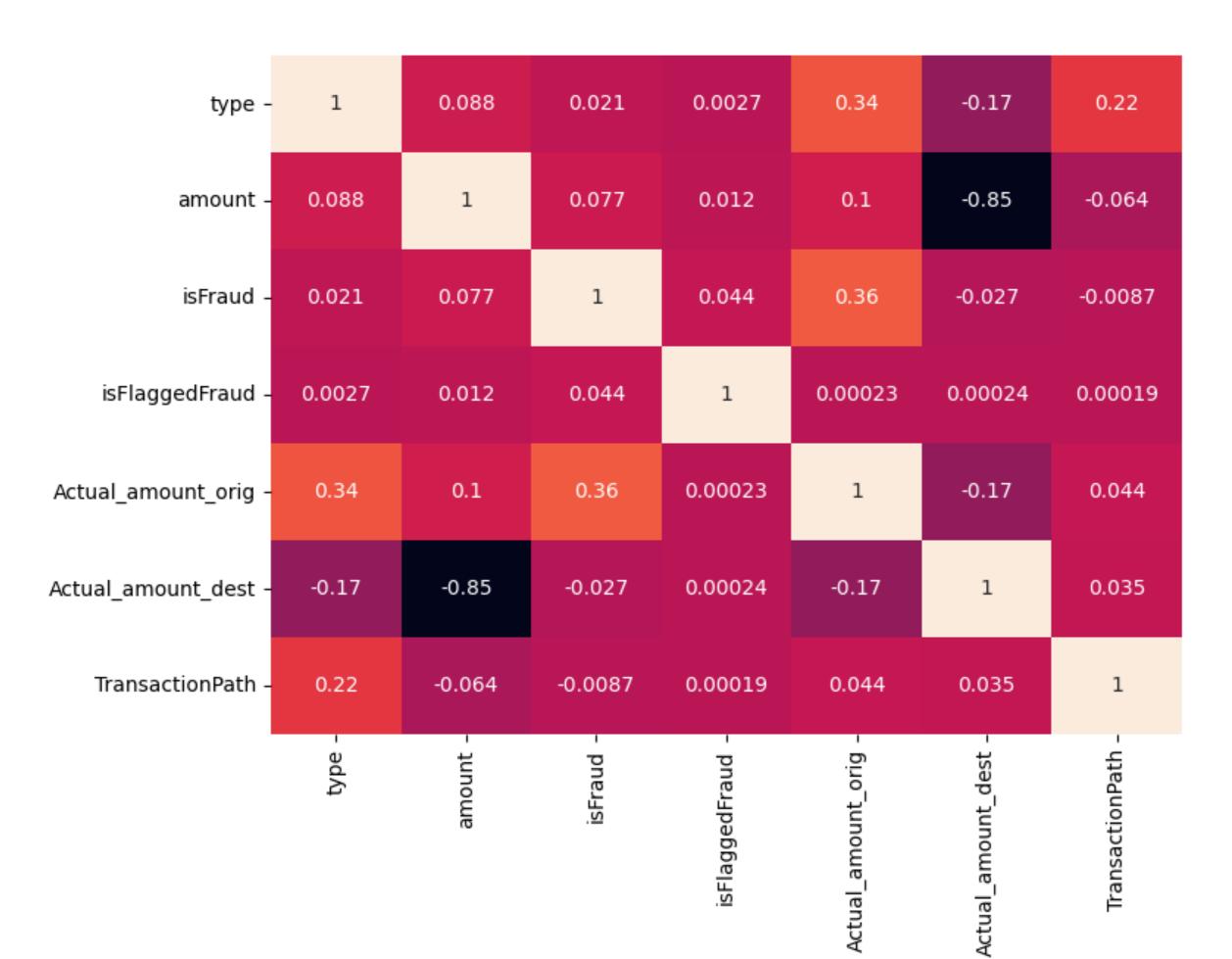


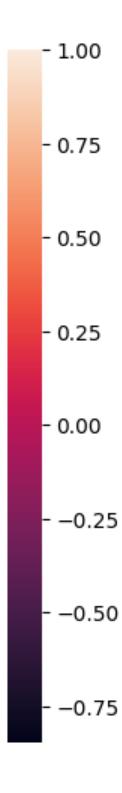
4.1 Analysis of the Synthetic Financial Dataset for Fraud Detection



4.1 Analysis of the Synthetic Financial Dataset for Fraud Detection

| | variables | VIF |
|---|--------------------|----------|
| 0 | type | 2.687803 |
| 1 | amount | 3.818902 |
| 2 | isFraud | 1.184479 |
| 3 | isFlaggedFraud | 1.002546 |
| 4 | Actual_amount_orig | 1.307910 |
| 5 | Actual_amount_dest | 3.754335 |
| 6 | TransactionPath | 2.677167 |





4.2 Data Splitting

```
Shape of X_train: (4453834, 6)
  Shape of X_test: (1908786, 6)
B) Counts before oversampling minority class:
      4448056
         5778
 Name: isFraud, dtype: int64
C) Counts after oversampling:
  0
       4448056
       4448056
  Name: isFraud, dtype: int64
```

4.3 Data Modeling

```
# LOGISTIC REGRESSOR
y_train = upsampled.isFraud
X_train = upsampled.drop('isFraud', axis=1)

logistic_regressor = LogisticRegression(solver='liblinear', random_state=0)
logistic_regressor.fit(X_train, y_train)

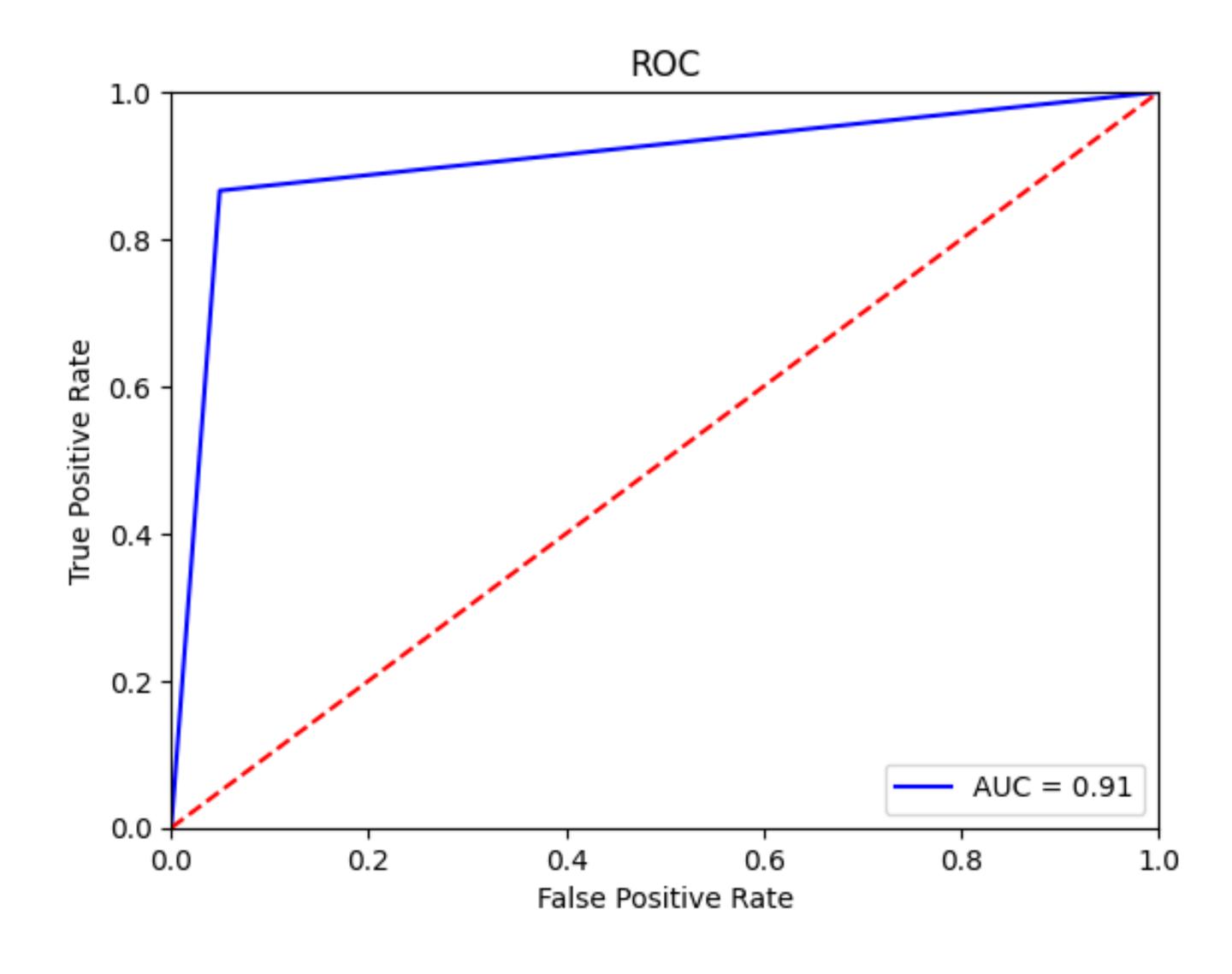
y_pred_lr = logistic_regressor.predict(X_test)
logistic_regressor_score = logistic_regressor.score(X_test, y_test) * 100
```

5. Evaluation

| Classification Report | | precision | recall | f1-score | support | | | |
|-----------------------|------|--------------|--------|-----------------|---------|----------------------|-------|--------|
| 0 1 | 1.00 | 0.95 0.87 | 0.97 | 1906351 2435 | | | | |
| | | | | | | Confusion Matrix 1e6 | | 1e6 |
| accuracy | | | 0.95 | 1908786 | | | | - 1.75 |
| macro avg | | 0.91 | 0.51 | 1908786 | | | | |
| weighted avg | 1.00 | 0.95 | 0.97 | 1908786 | | | | - 1.50 |
| | | | | | 0 - | 1.8e+06 | 93758 | |
| | | | | | | | | - 1.25 |
| | | | | | label | | | - 1.00 |
| | | | | | True | | | - 0.75 |
| | | | | | 1 - | 326 | 2109 | - 0.50 |
| | | | | | | | | - 0.25 |
| | | | | | | 0 | i | |

Predicted label

5. Evaluation



6. Conclusion

- Digital Fraud Threats
- Synthetic Data Alternatives
- Modelling and Results
- Opportunities
- Further Research