



Detecting Anomalous Financial Transactions

Using big data to help FinCEN fight financial fraud and money laundering

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Agenda

1

BUSINESS UNDERSTANDING

The high cost of money
laundering

2

DATA UNDERSTANDING

A model is only as good
as the data

3

THE MODELS

Can we reliably spot
anomalous transactions?

4

ANALYSIS & INFERENCES

What have we learned?

5

CONCLUSION & RECOMMENDATIONS

What are the takeaways?





Business Understanding

"THE ESTIMATED AMOUNT OF MONEY LAUNDERED GLOBALLY IN ONE YEAR IS 2% - 5% OF GLOBAL GDP, OR \$800 BILLION - \$2 TRILLION USD" – UNITED NATIONS OFFICE ON DRUGS AND CRIME



THEFT AND MAJOR CRIMES

- From stolen pandemic aid to drug dealing and racketeering - criminals go to great lengths to hide the source of their cash



SANCTIONS DIVERSION

- Sanctioned organizations and nation-states will attempt to skirt restrictions through clandestine operations



TERRORIST FINANCING

- Terrorist organizations require capital to carry out their activities



HARMS INDUSTRY AND CONSUMERS

- Banks can suffer reputational damage and face regulatory scrutiny, and costs often pass on to consumers

Data Understanding

A collaboration between NIST and the NSF

Transactions dataframe

```
-----  
root  
|-- MessageId: string  
|-- Timestamp: timestamp  
|-- UETR: string  
|-- Sender: string  
|-- Receiver: string  
|-- TransactionReference: string  
|-- OrderingAccount: string  
|-- OrderingName: string  
|-- OrderingStreet: string  
|-- OrderingCountryCityZip: string  
|-- BeneficiaryAccount: string  
|-- BeneficiaryName: string  
|-- BeneficiaryStreet: string  
|-- BeneficiaryCountryCityZip: string  
|-- SettlementDate: integer  
|-- SettlementCurrency: string  
|-- SettlementAmount: double  
|-- InstructedCurrency: string  
|-- InstructedAmount: double  
|-- Label: integer
```

Target class distribution

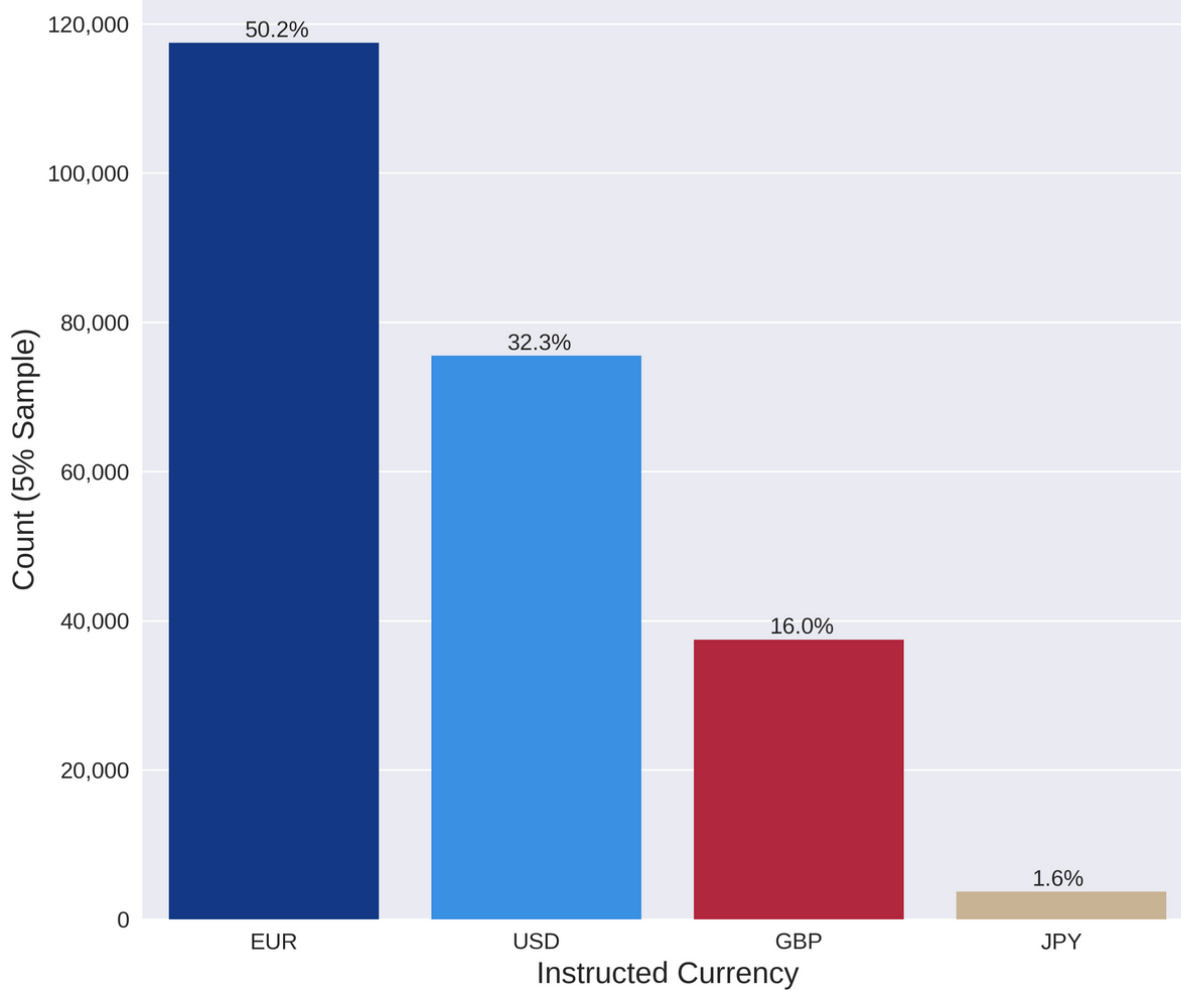
```
-----  
+-----+-----+-----+  
|Label          |count    |percent   |  
+-----+-----+-----+  
|Anomalous (1)  |4,900    |0.104%   |  
|Non-anomalous (0) |4,686,825 |99.895%  |  
+-----+-----+-----+
```

5.5M Transactions
530k Matching Accounts
91 Features

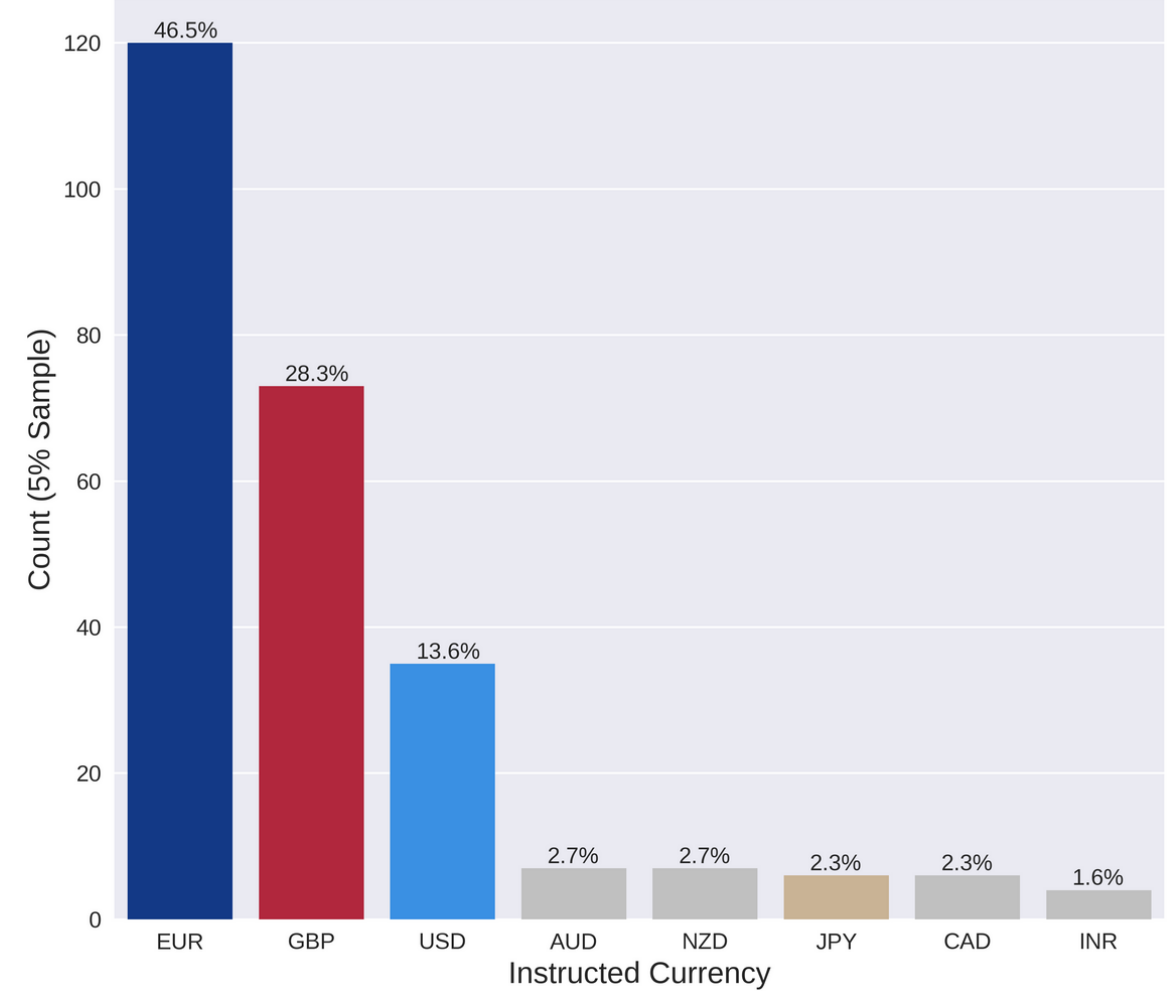
Bank accounts dataframe

```
-----  
root  
|-- Bank: string  
|-- Account: string  
|-- Name: string  
|-- Street: string  
|-- CountryCityZip: string  
|-- Flags: integer
```

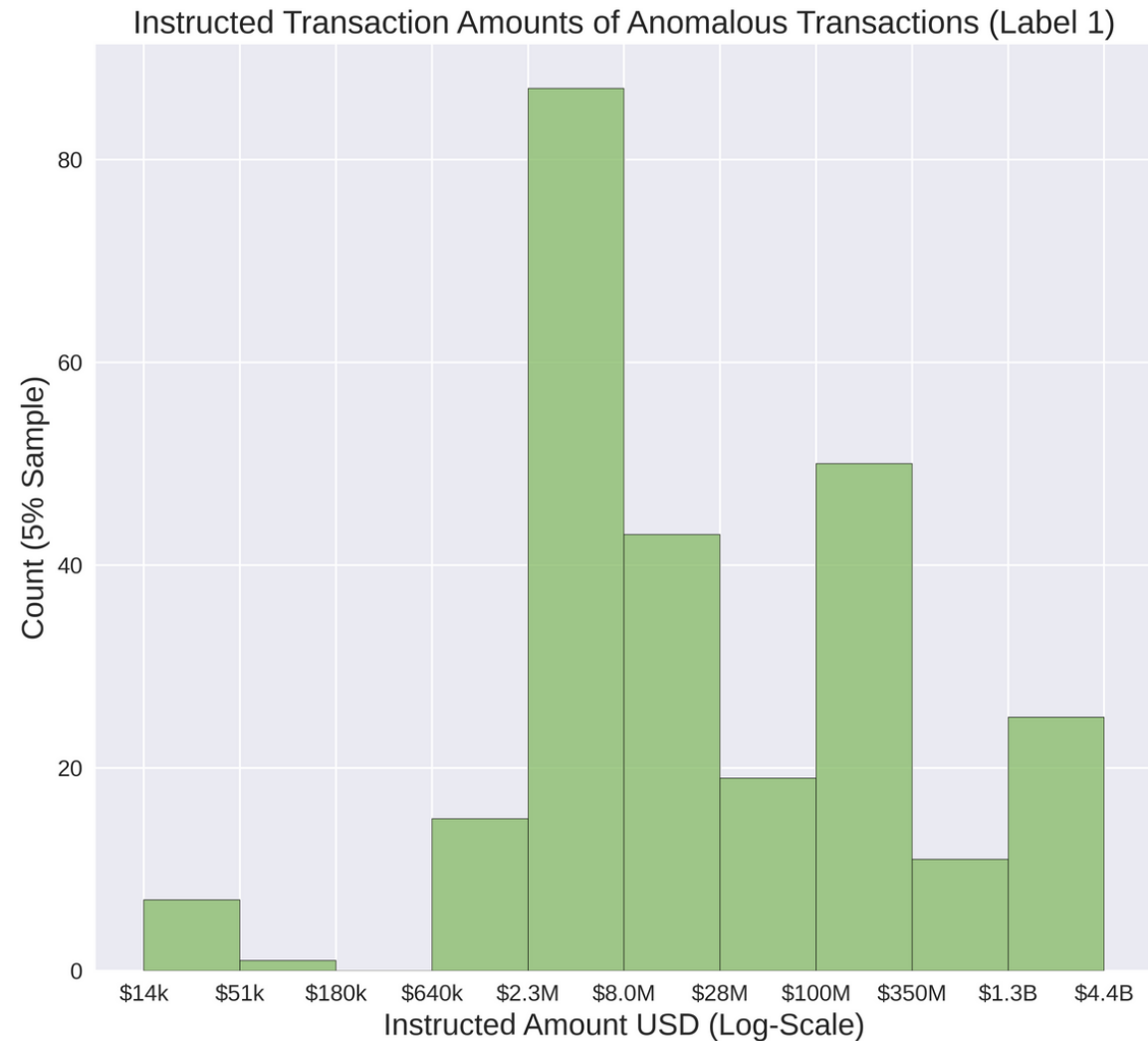
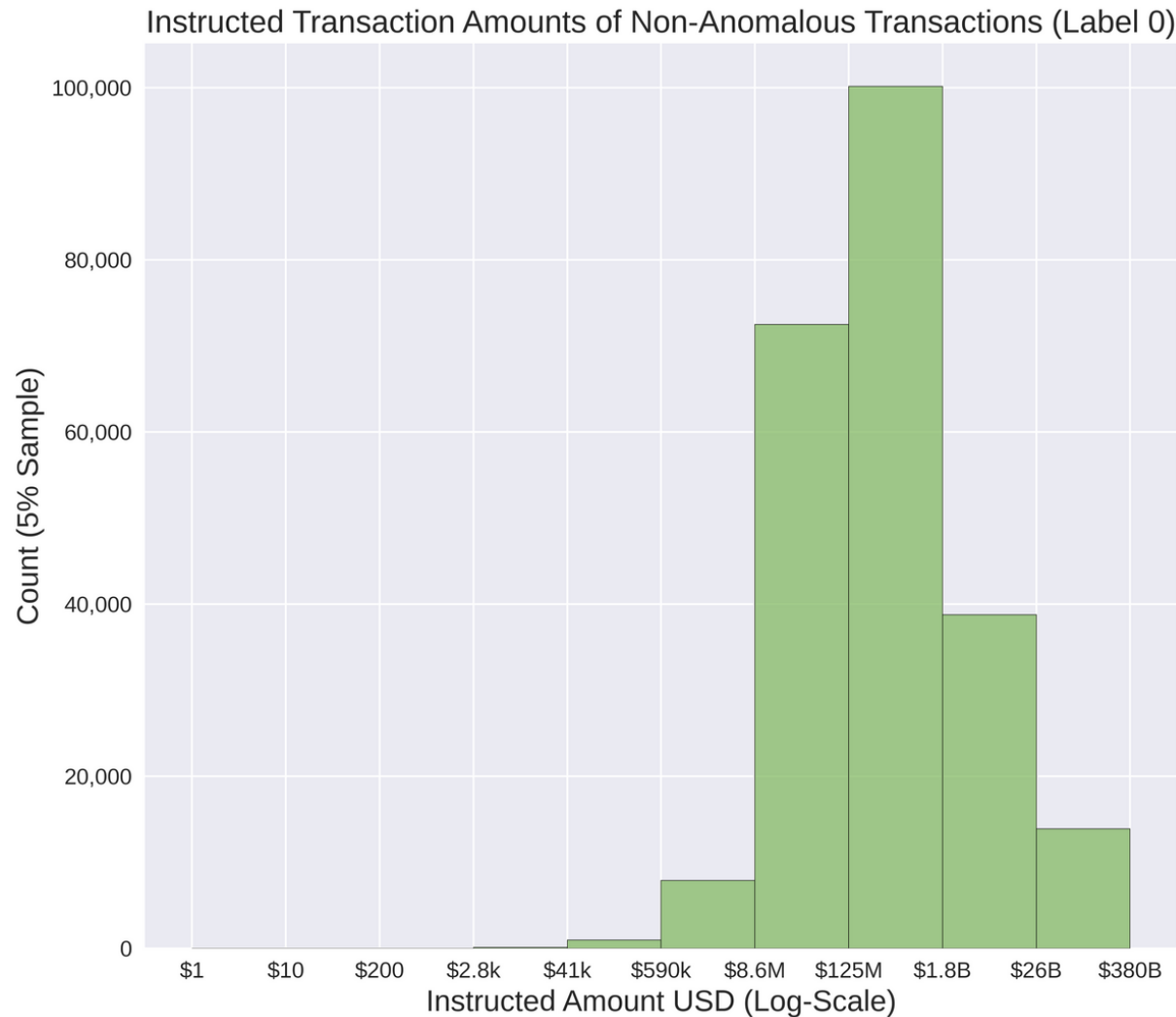
Instructed Currencies of Non-Anomalous Transactions (Label 0)



Instructed Currencies of Anomalous Transactions (Label 1)

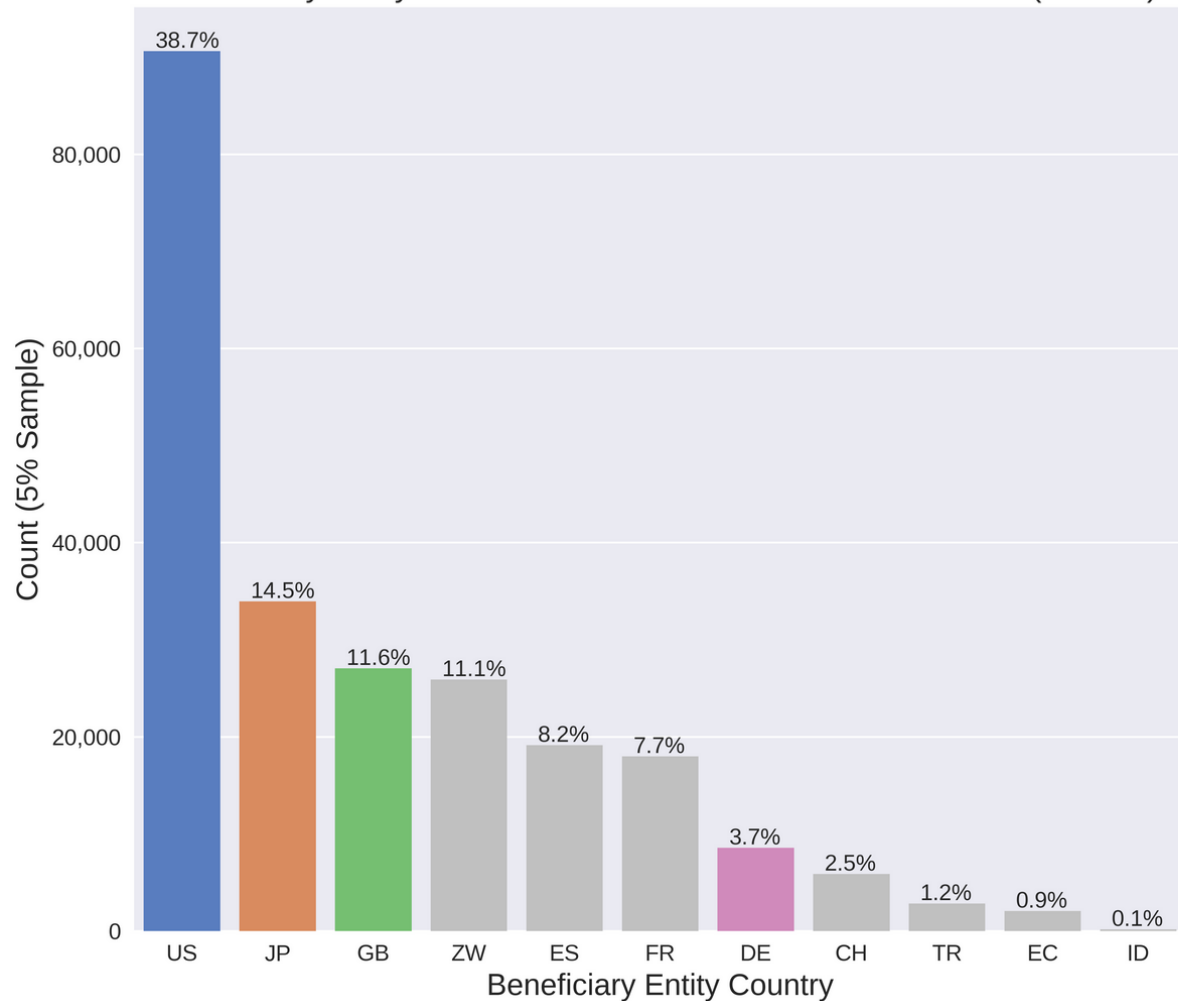


INSTRUCTED TRANSACTION CURRENCIES

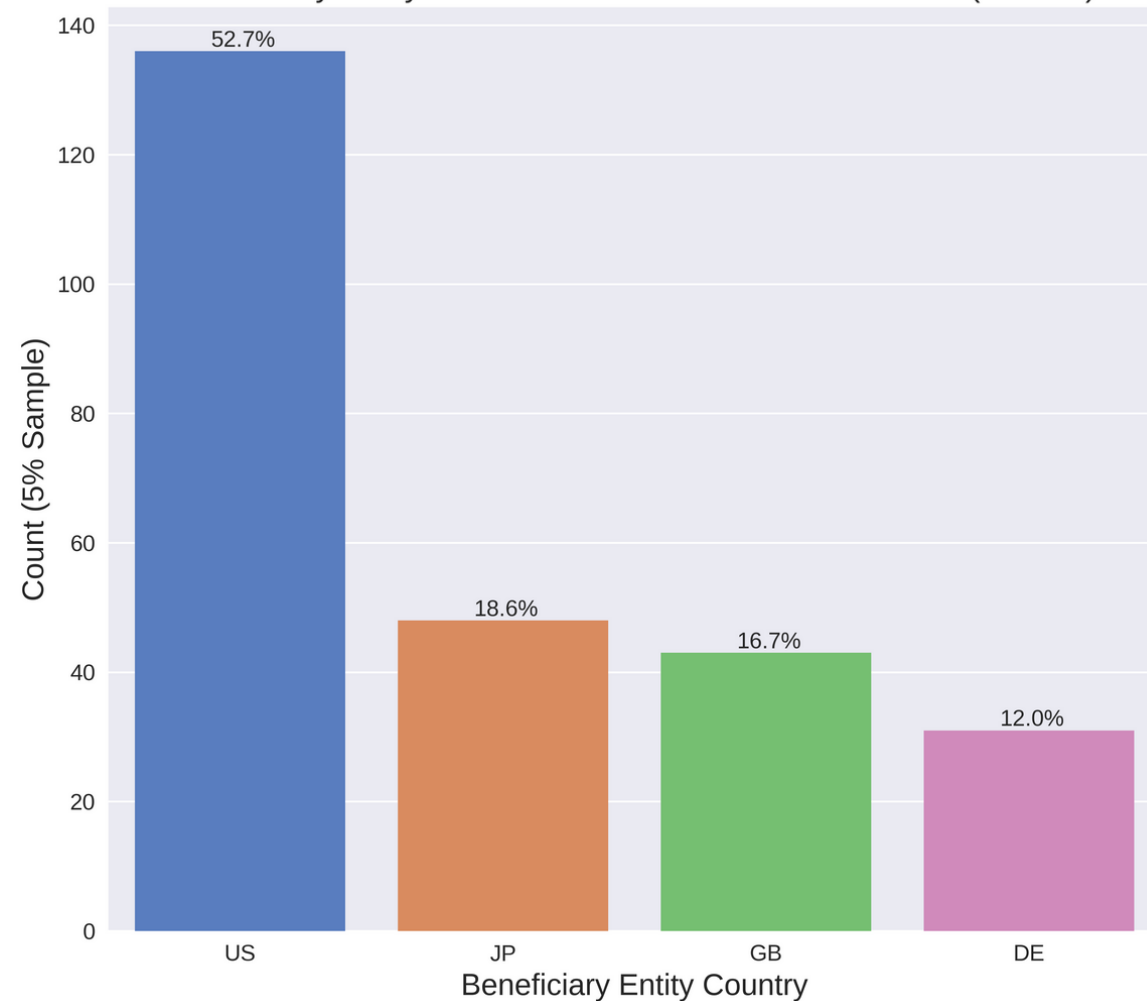


INSTRUCTED TRANSACTION AMOUNTS (LOG-SCALE USD)

Beneficiary Entity Countries of Non-Anomalous Transactions (Label 0)



Beneficiary Entity Countries of Anomalous Transactions (Label 1)



BENEFICIARY ENTITY COUNTRIES

Modeling Results

As measured by test data F1 scores

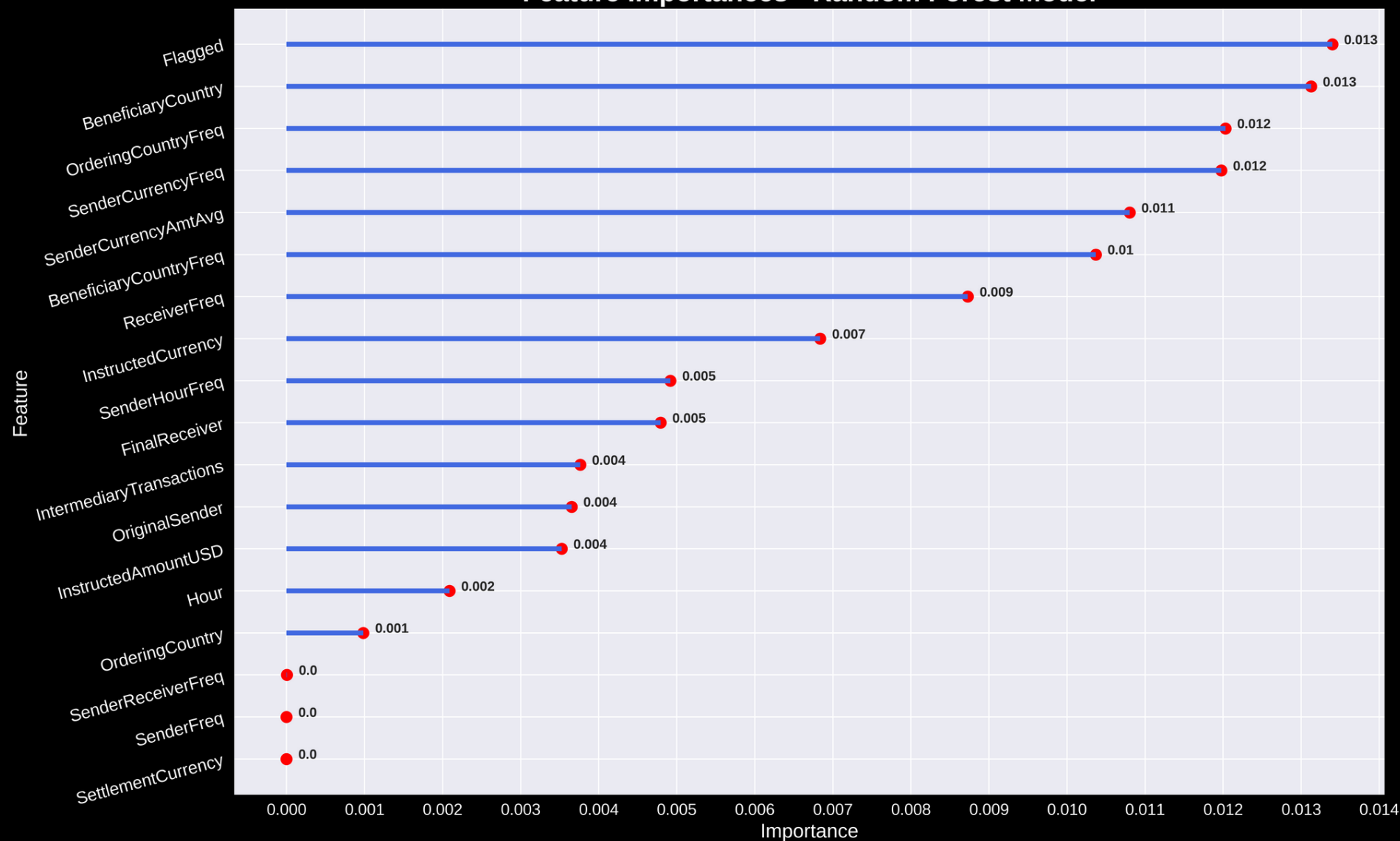


CONFUSION MATRIX

TRUE \ PREDICTED	0	1
0	704K	22
1	451	310

Analysis

Feature Importances - Random Forest Model

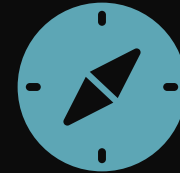


Conclusion & Recommendations



IT'S A TRADE OFF

Catching more anomalous transactions = more false positives



USE MODEL TO FOCUS RESOURCES

Knowing where to look is half the battle



OBTAIN MORE POSITIVE CLASS OBSERVATIONS

Models could be improved with more data

Thank you

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