

# Global Black Money Transactions: Unmasking Financial Crime

Analyzing suspicious transactions across countries and industries.

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# Dataset Overview

14 months: December 2012 to February 2014

## Time Period

1

Source (Illegal, Legal), 10 countries, amount (USD), and industry

## Key Variables

3

## Scale

10,000 instances, 14 attributes

# World Country GDP Dataset

Key variables: GDP\_USD & GDP Per Capita

Dimensionality: 16492 instances by 5 variables

Combined with previous dataset joined by year and country (inner join)

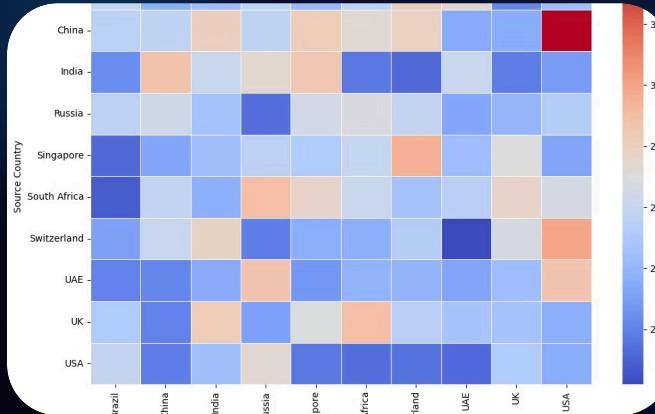
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# Money Flow



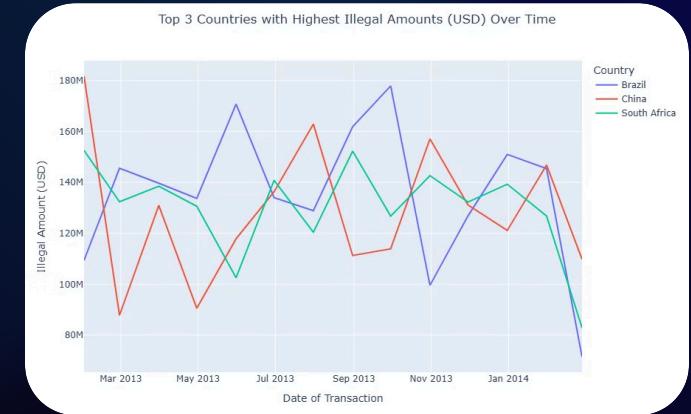
## Global Transactions

Illustrating the movement of funds across countries.



## Currency Exchange

Highlighting the exchange of funds between different currencies. China has the highest exchange with the USA



## Financial Networks

Showing the top 3 highest income (USD) countries in our Dataset

# Research Questions

**Main Question:** What factors are key indicators in determining fraudulent activities?

1

## Suspicious Activity Origins

Identify countries with highest fraudulent transactions

2

## Amount of Money Moved

Locate primary destinations for laundered funds

3

## High-Risk Industries

Pinpoint sectors with elevated money laundering rates

# Trying to Answer These Questions

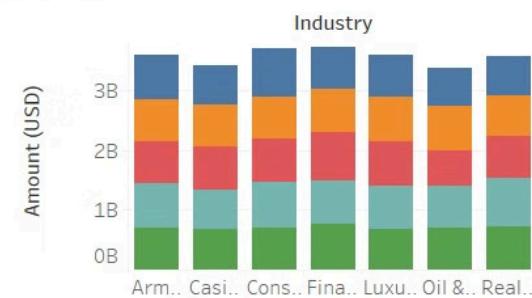
Average Money Laundering Risk Score per Country



Average Amount in each Transaction per Country



Amount Transferred by each Industry



Transaction Type

Cash Withd..	Offshore Tr..	Stocks Tran..
Cryptocurre..	Property Pu..	

Average Risk Score and Amount Transferred



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# Choropleth of Illegal Money Count

 Google Docs

Recording 2024-12-03 184248.mp4



Choropleth Map by month of the  
Illegal transactions happening

Brazil and South Africa have the  
highest count of illegal  
transactions.

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# Bar Graph of Illegal Money vs. GDP

Google Docs

Recording 2024-12-03 233418.mp4

This bar graph visually compares the amount of illegal money transactions with the GDP of different countries. Noticeably, South Africa and Brazil show a disproportionately high volume of illegal transactions relative to their GDP.

# Classification Model Overview

Random Forest

Accuracy: 0.6975

AdaBoost

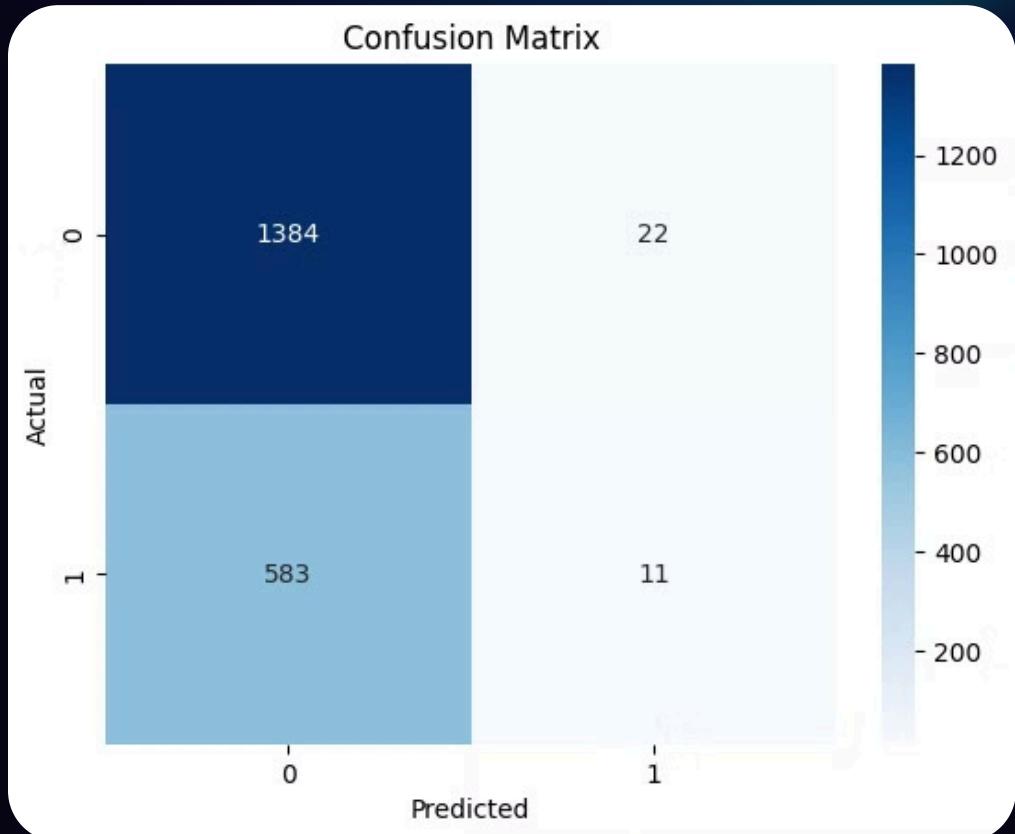
Accuracy 0.703

Gradient Boost

Accuracy 0.701

Support Vector

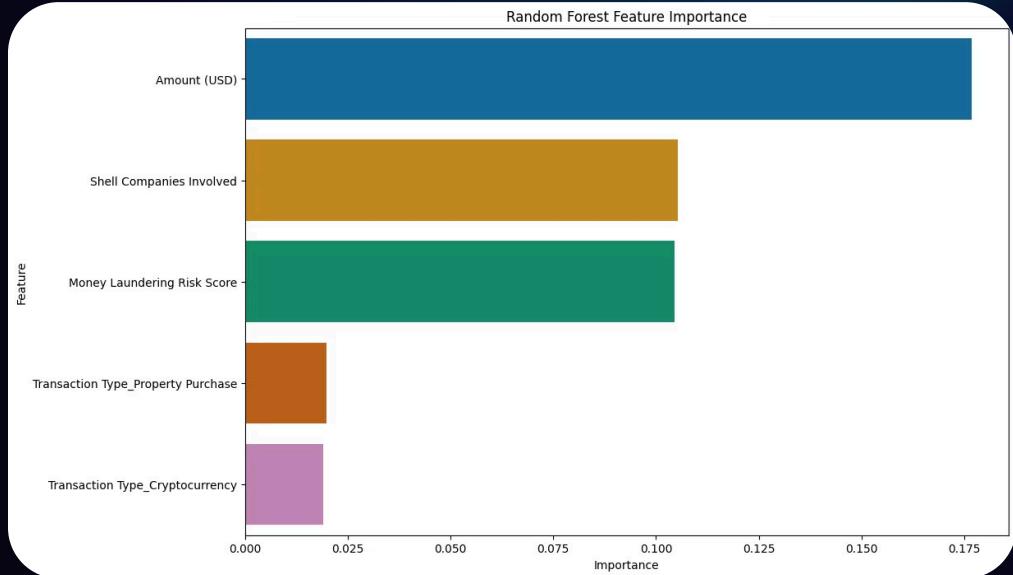
Accuracy 0.703



# How did the model do?

Predicts the illegal transactions well but completely misclassifies the legal transactions.

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# Key Findings

When doing a feature importance on the model the top 3 characteristics for prediction are Amount of Money, Number of Shell companies used, and the Risk score of the money laundering

# References

Hendriyetty, N. and Grewal, B.S. (2017), "Macroeconomics of money laundering: effects and measurements", Journal of Financial Crime, Vol. 24 No. 1, pp. 65-81. [\*\*https://doi.org/10.1108/JFC-01-2016-0004\*\*](https://doi.org/10.1108/JFC-01-2016-0004)

Tertychnyi, P., Godgildieva, M., Dumas, M., & Ollikainen, M. (2022). Time-aware and interpretable predictive monitoring system for Anti-Money Laundering. Machine Learning with Applications, 8, 100306.

[\*\*https://doi.org/10.1016/j.mlwa.2022.100306\*\*](https://doi.org/10.1016/j.mlwa.2022.100306)