Task 1:

Malicious Ethereum Addresses Detection

Case Study for BMW Interview

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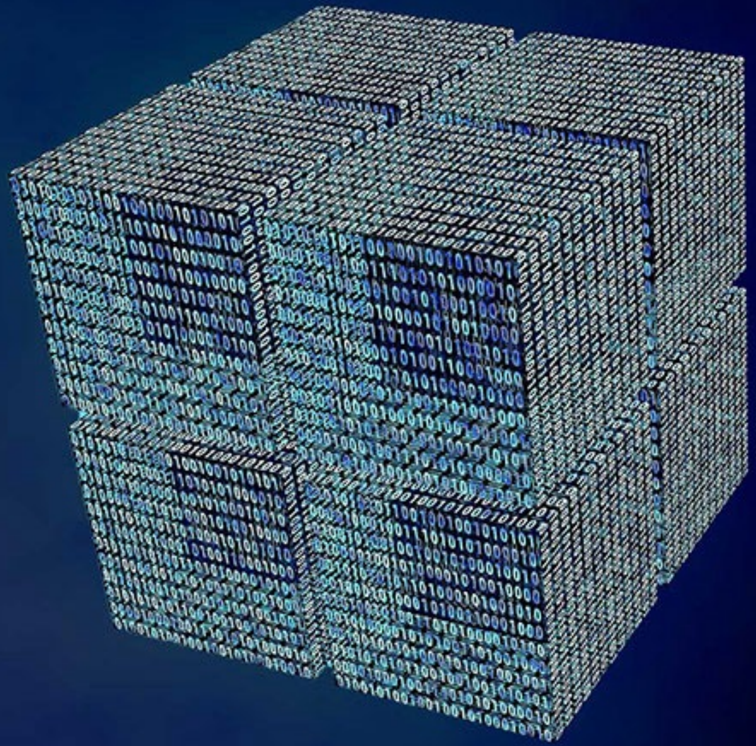
21st Jun 2022

Content



01 Problem

Malicious Ethereum addresses Detection

02 Feature Engineering

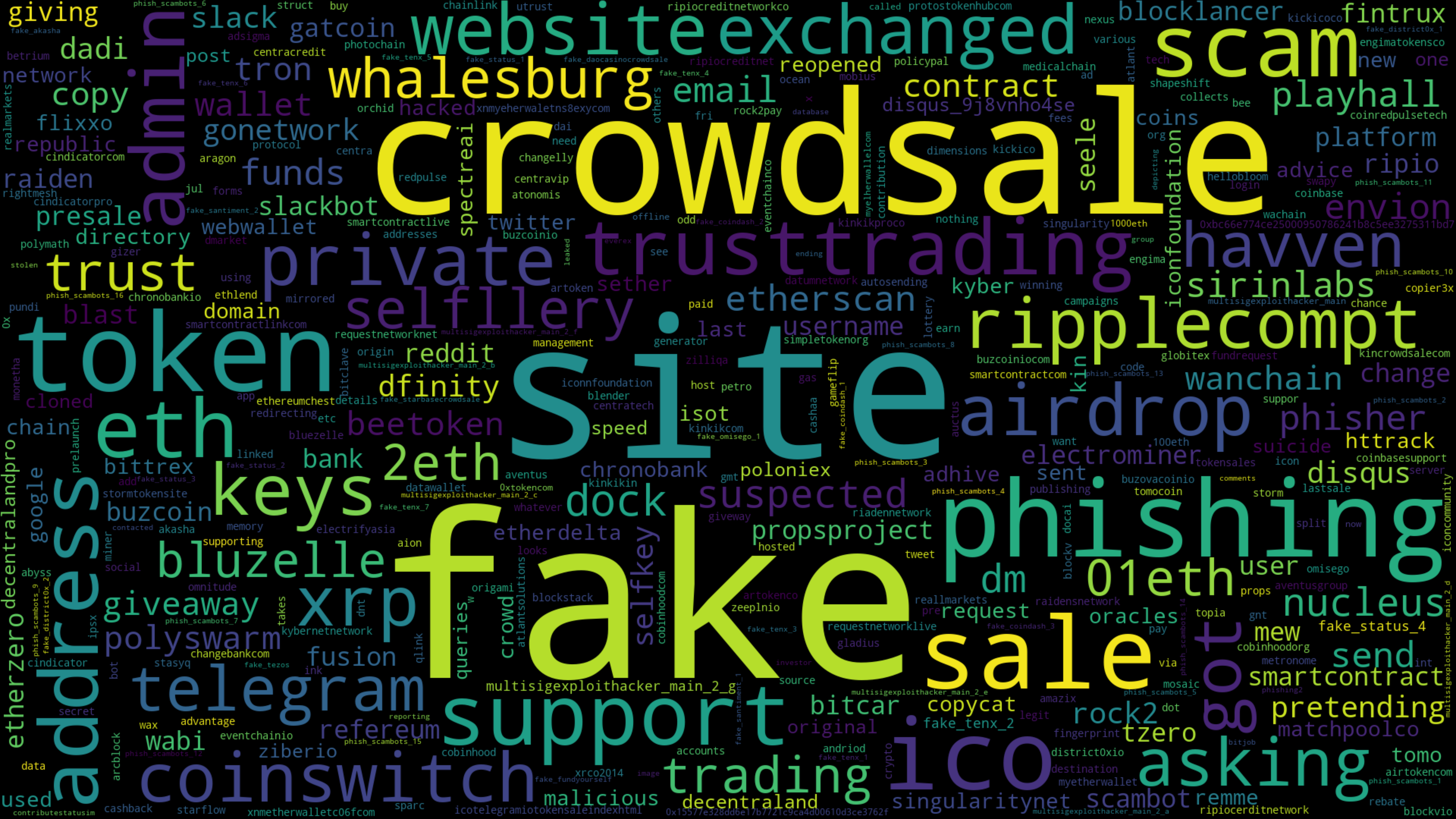
Data Preprocessing, Feature Engineering, Exploratory Data Analysis

03 Modelling

Standard Machine Learning Models, Hyperparameter Optimization, Feature Importance

04 Solution & Discussion

Business Suggestions, Limitation


fake
site
crowdsale
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token
address
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trusttrading
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airdrop
ripplecompt
havven
asking
coinswitch
telegram
trading
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2eth
nucleus
dock
dm
suspected
phisher
playhall
envion
sirinlabs
etherscan
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polyswarm
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raiden
presale
slackbot
directory
webwallet
twitter
beetoken
dfinity
reddit
domain
bank
bittrex
buzcoin
chain
etherzero
decentralandpro
google
wabi
refereum
fusion
ziberio
malicious
decentraland
singularitynet
scambot
remme
smartcontract
pretending
send
disqus
httrack
wanchain
change
ripio
platform
advice
coins
fintrux
blocklancer
new
one
chronobank
electrominer
poloniex
propsproject
etherdelta
selfkey
crowd
queries
request
oracles
mew
rock2
tzero
copycat
bitcar
original
matchpoolco
tomo
user
adhive
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suicide
kyber
sether
username
last
isot
speed
iconfoundation
seele
spectreai
reopened
hacked
disqus_9j8vnho4se
blast
cloned
used
giving
network
post
kin
fake_status_4
fake_tenx_2
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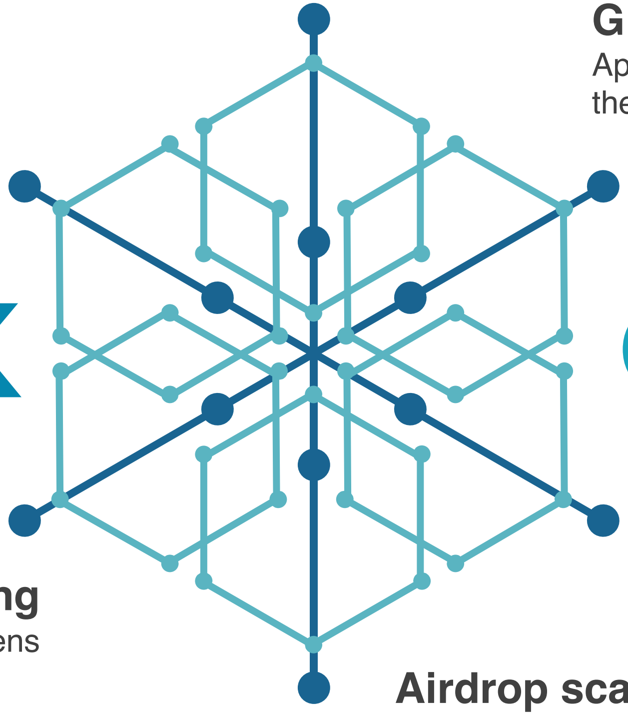
Malicious Activities

Phishing scam
Redirect users to imitation websites, ask them to reset their password or sent ETH.

Giveaway scam
Appear in many forms to ask users to send ETH to the provided wallet address, e.g., support giveaway..

Fake (crowdsale) website
Included in phishing scam and many other scams.

BLOCK



CHAIN

Social media hacks
Organizations and celebrities get hacked to post a cryptocurrency giveaway.

Fake Initial Coin Offering
Fake admin in ICOs, fake tokens

Airdrop scam
Airdrop an asset into your wallet and sending a scam website to claim the airdropped asset.

Case Study Dataset

Malicious Addresses with Comments	Malicious Transactions	Normal Transactions
663 Addresses 268 Comments From 2017-07-18 to 2020-11-17	551 Addresses 21961 Transactions From 2017-05-20 to 2022-05-05	87 Addresses 30000 Transactions From 2016-05-26 to 2022-06-08

Task: To detect malicious addresses

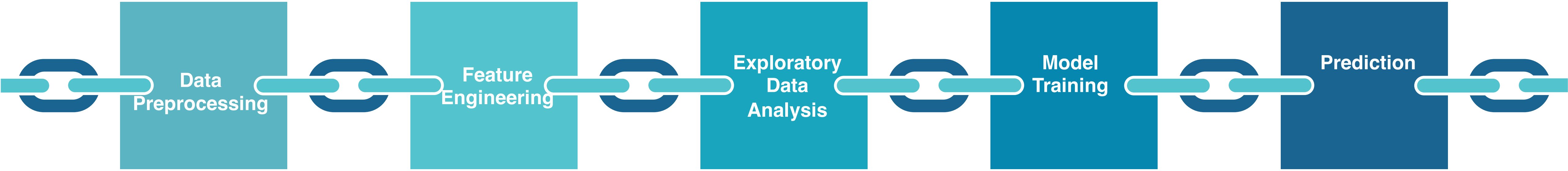
Role: member of a Crypto startup

Transactions with features:

address
from address, to address, contractAddress
input
timestamp
value
gas, gasPrice, cumulativeGasUsed
isError, txreceipt_status
blockNumber, hash, nounce, blockHash, transactionIndex
transactionIndex, confirmations

-> ML Objective: Prediction of maliciousness
(Binary classification)

Machine learning Pipeline



Data Formatting, Transformation

Data types,
Lowercase addresses,
Timestamp to time,
Gas Price from Gwei to Ethr.

Select features, Create New Features

Group and aggregate features

Plots

Distributions,
Correlations

Standard machine Leaning models

Training, Evaluation Metrics,
Hyperparameter Optimization of selected models.

Test Dataset

Feature importance

Feature Engineering

Smart Contract
Address types and Transaction Types.

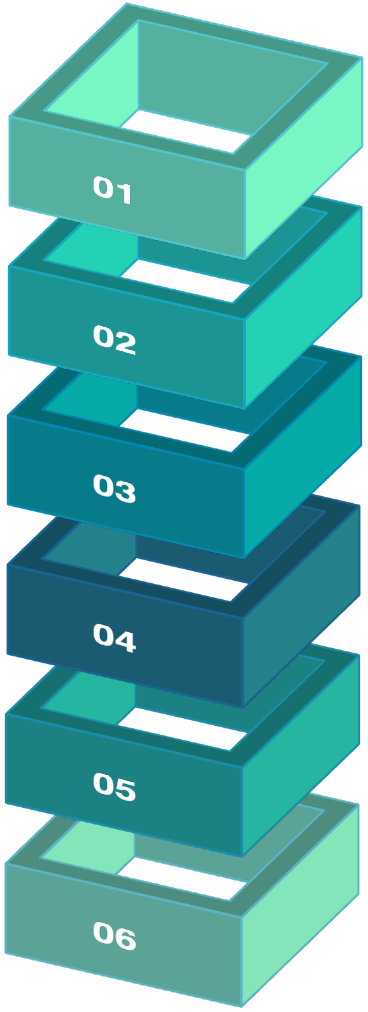
Transactions Sent and Received
Bi-directional graph.

Time
Temporal aspect.

Value
Amount of Ether in the transactions.

Gas Used and Price

Failed and Error Transactions

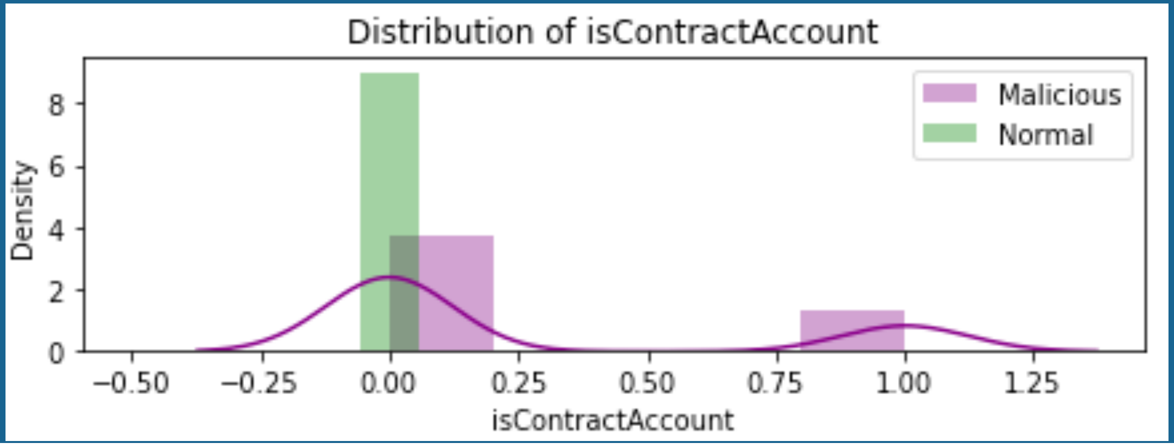


Exploratory Data Analysis

Account

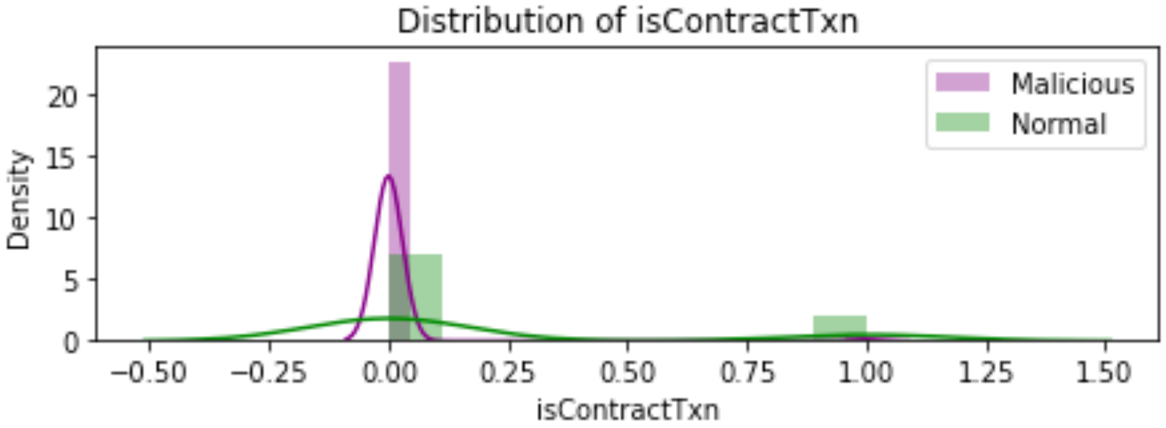
Smart Contract (SC)

Externally Owned (EOA)



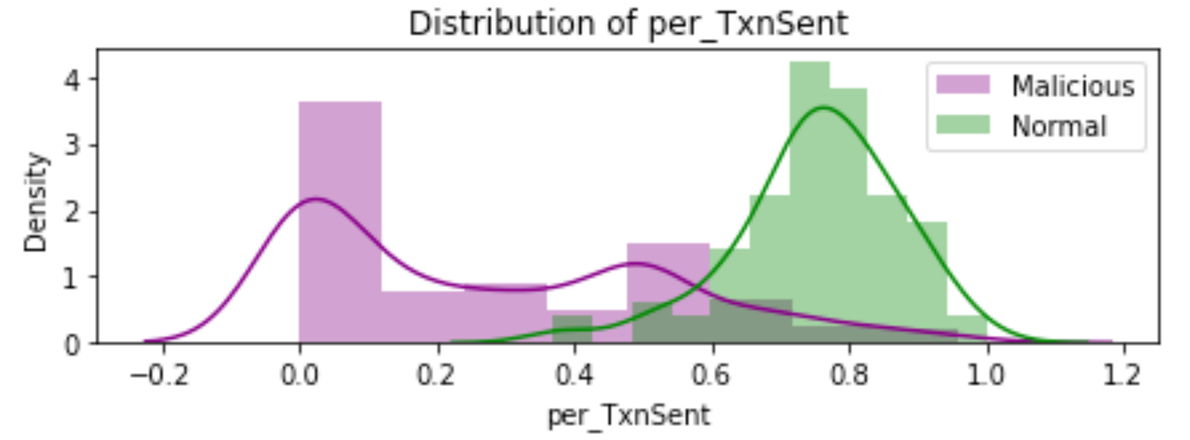
Many of malicious addresses are not SC accounts, SC accounts can be malicious.

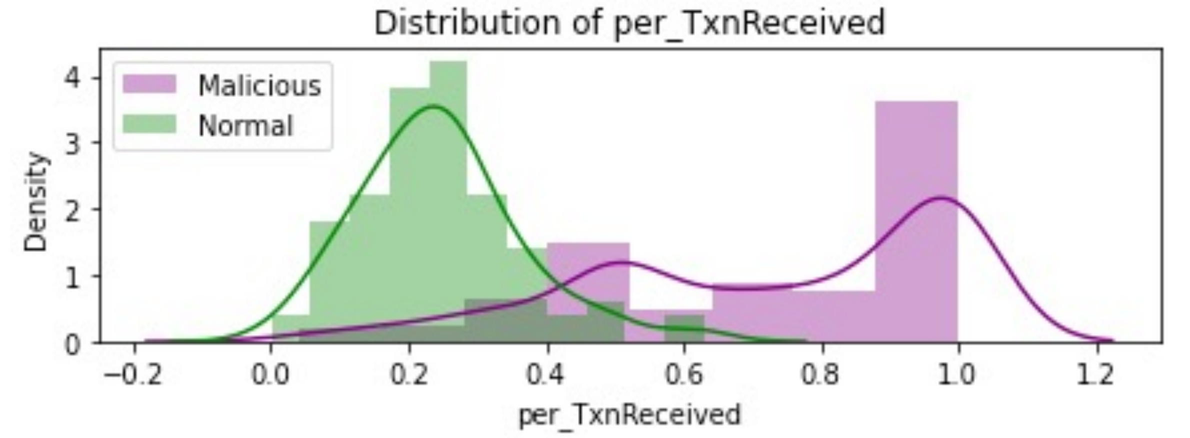
Malicious EOA accounts tend not to run on smart contract.



Exploratory Data Analysis

Transactions
Sent
Received

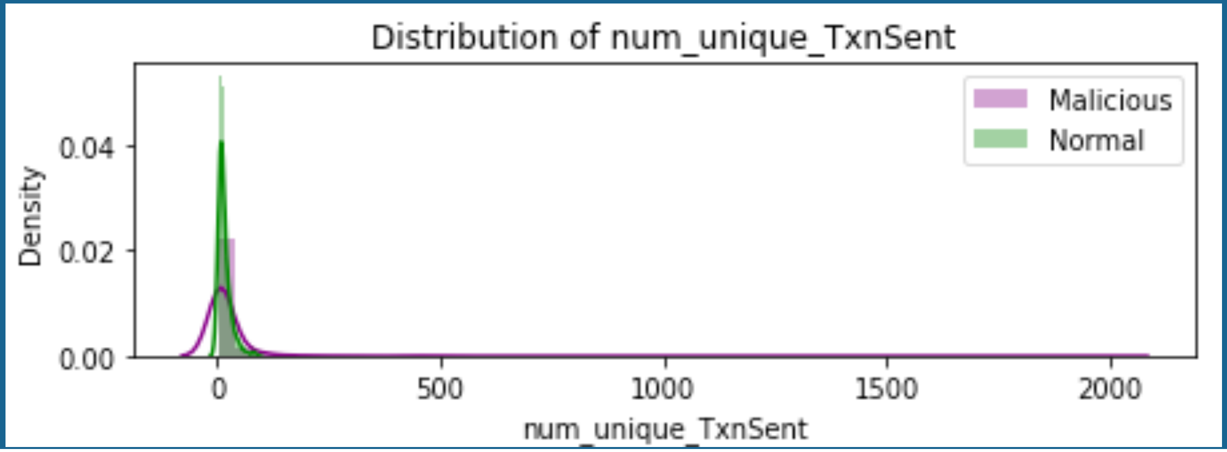


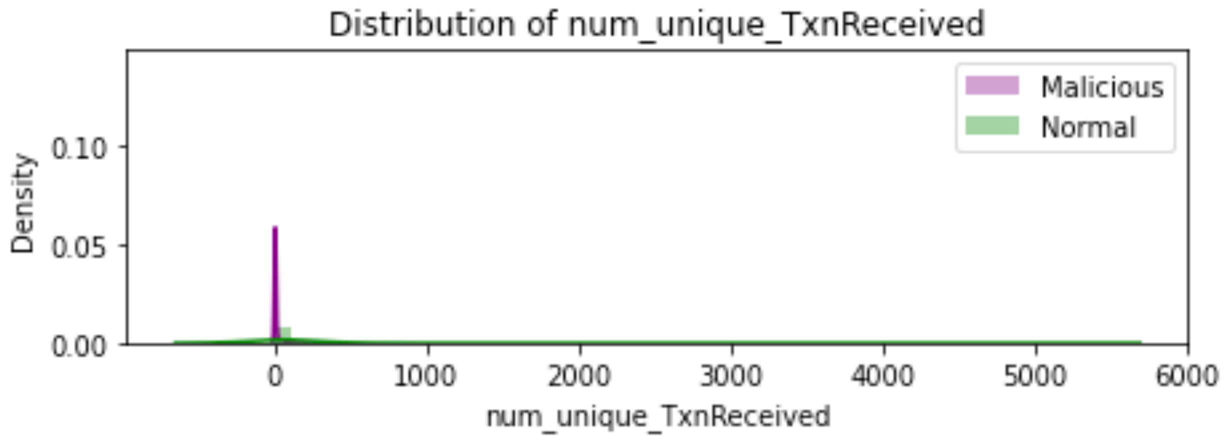


Malicious addresses have much more transactions received than sent, compared to normal addresses.

Exploratory Data Analysis

Unique Transactions
Sent
Received

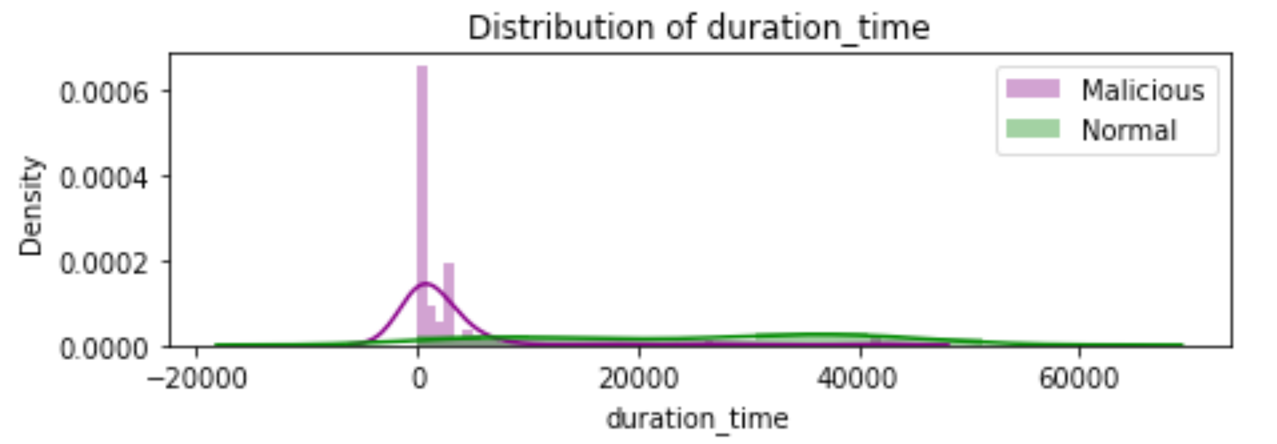




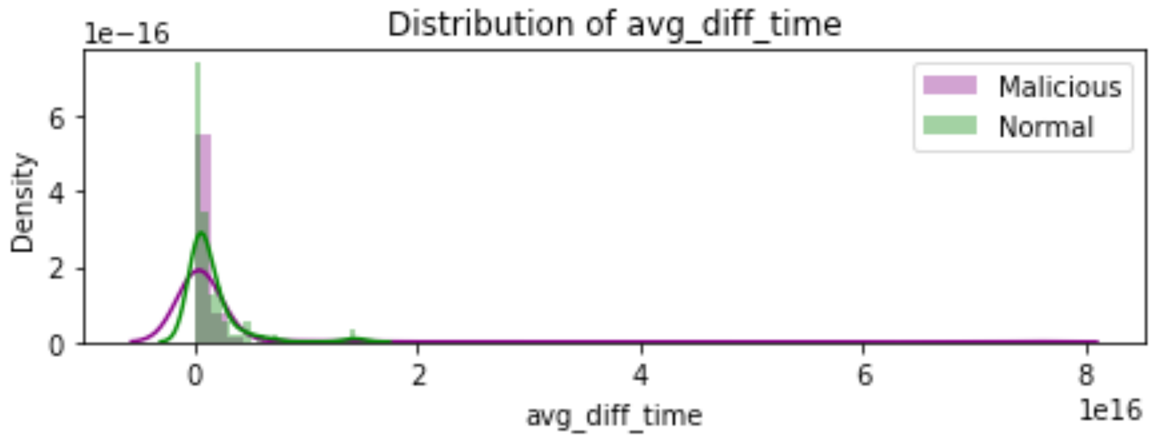
Malicious addresses tend to send transactions to less unique addresses, but receive transactions from more unique addresses.

Exploratory Data Analysis

Time
Duration
Difference

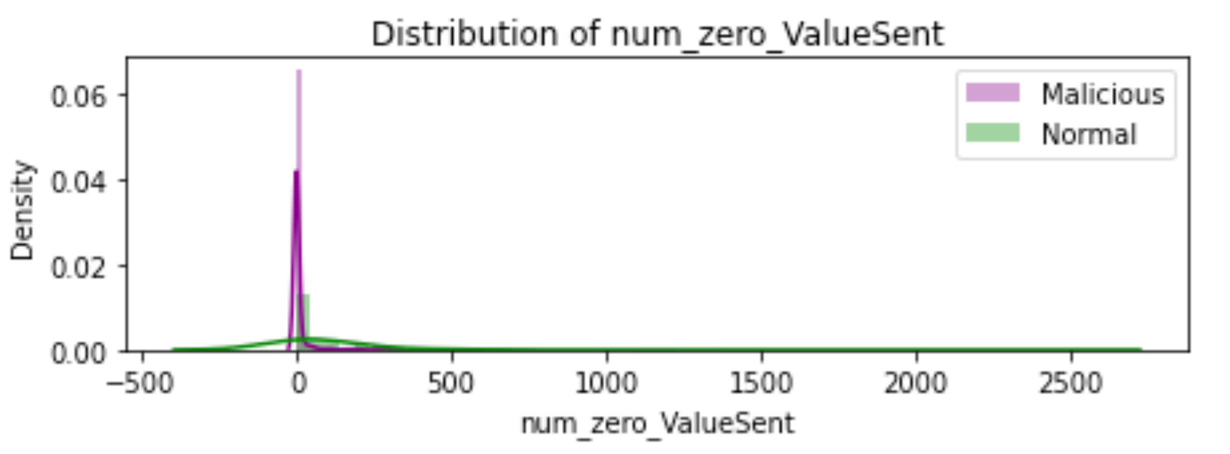


Malicious activities last shorter and with short intervals.

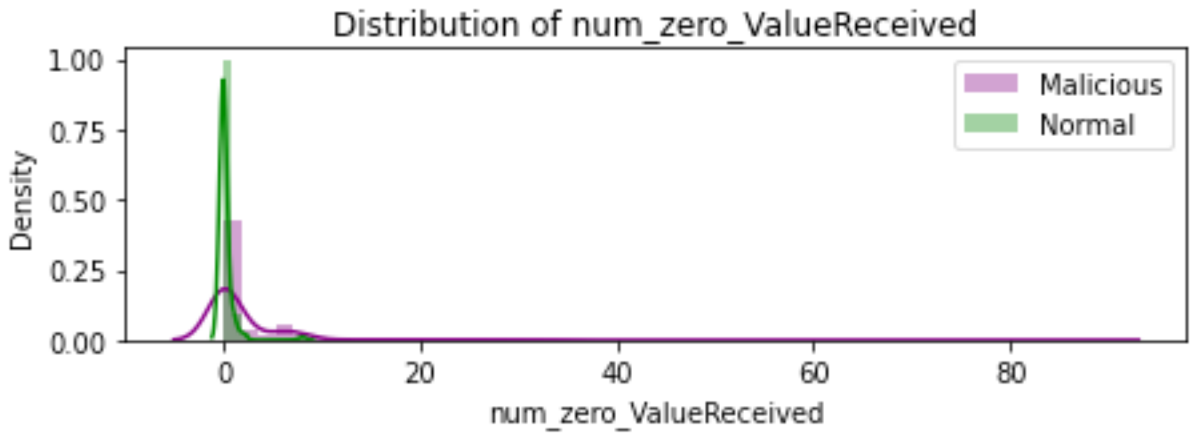


Exploratory Data Analysis

Value
Sent
Received

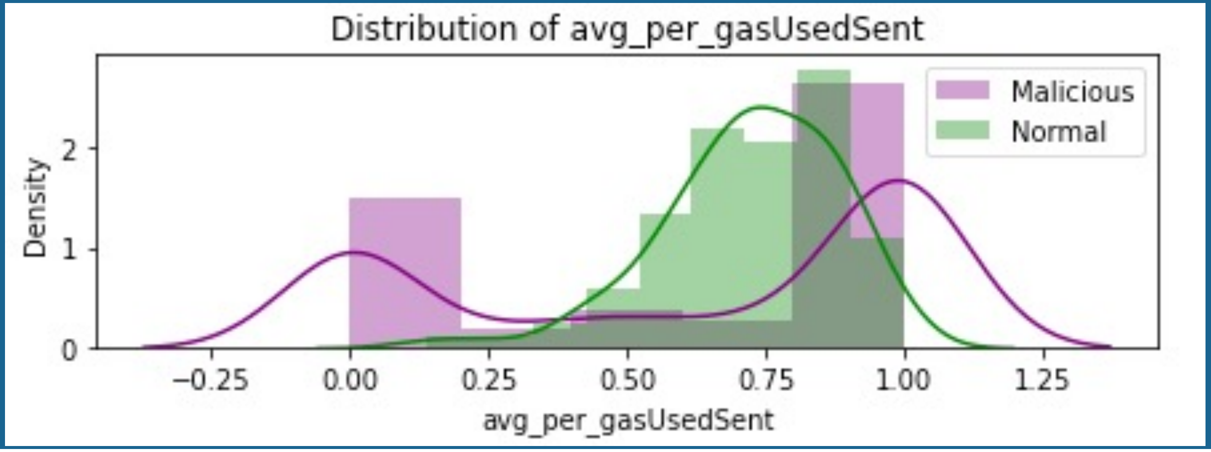


Malicious addresses send more zero value transactions, normal addresses receive more.

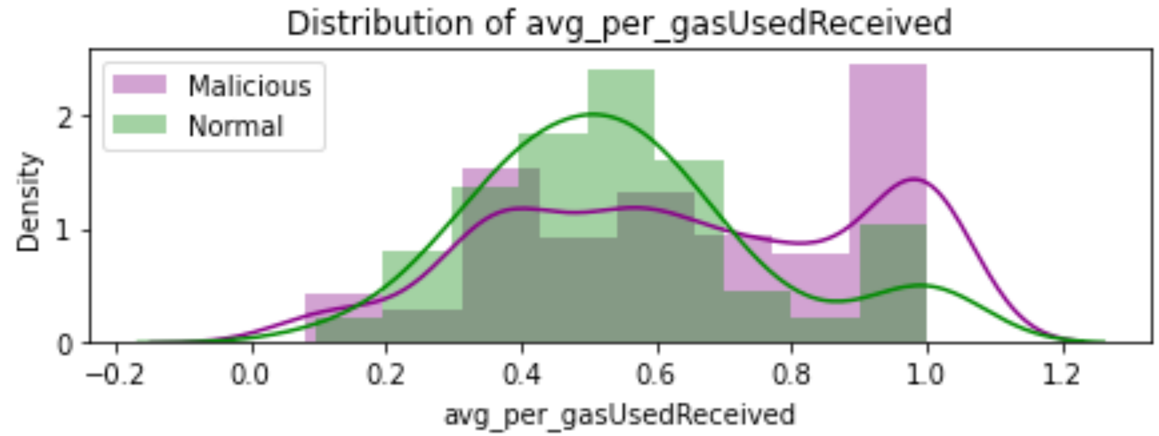


Exploratory Data Analysis

Average Percentage Gas
Sent
Received

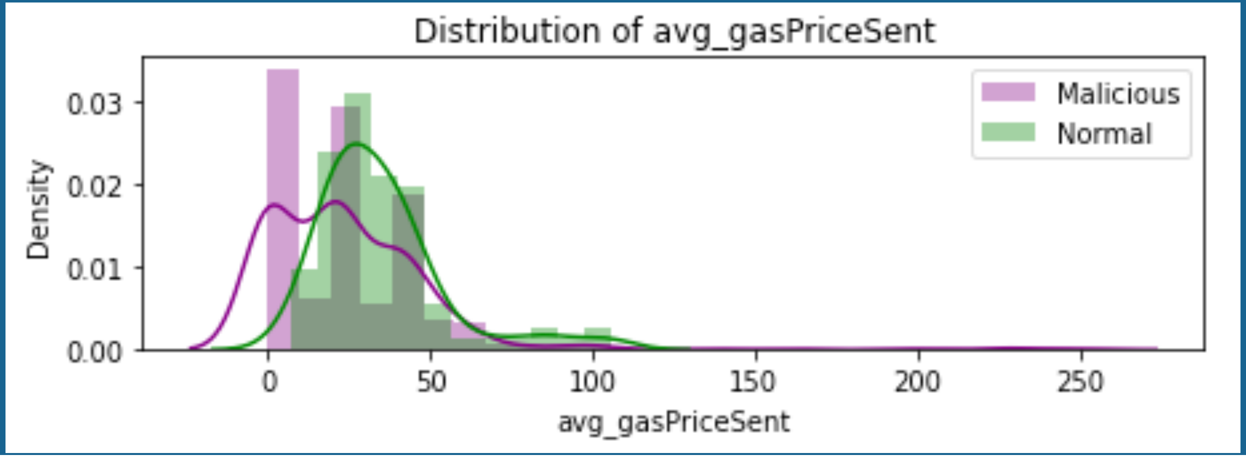


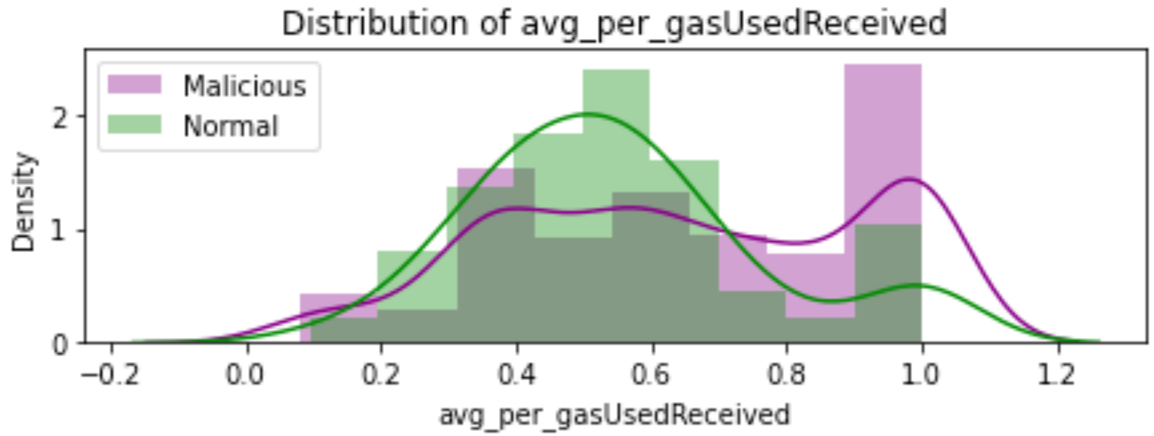
Malicious addresses tend to use the upper limit of the gas.



Exploratory Data Analysis

Average Gas Price
Sent
Received

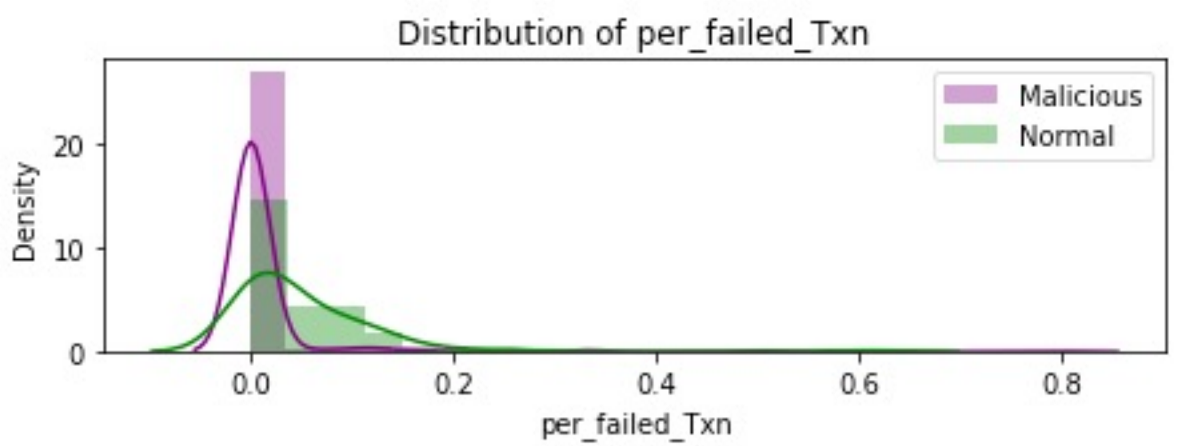


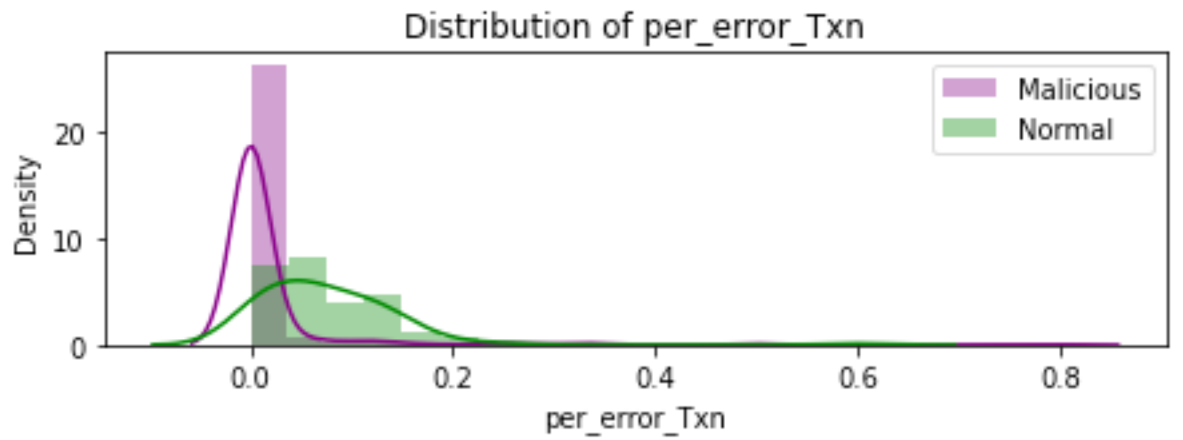


Malicious addresses set the gas price to be lower when sending the transactions, but when they receive transactions, it's much higher.

Exploratory Data Analysis

Transactions
Failure
Error





Malicious transactions are less likely to have error or fail.

Modelling

01 Dataset

Combine malicious and normal addresses,
Split into training and test dataset (80%),

02 Models

Standard classification models

03 Training

10 fold cross validation on the 80% training dataset.

04 Evaluation

Accuracy,
Precision,
Recall,
F1-score

05 Optimization

Hyperparameter tuning for Random Forest and XGboost

06 Prediction

With the 20% dataset.

Performance

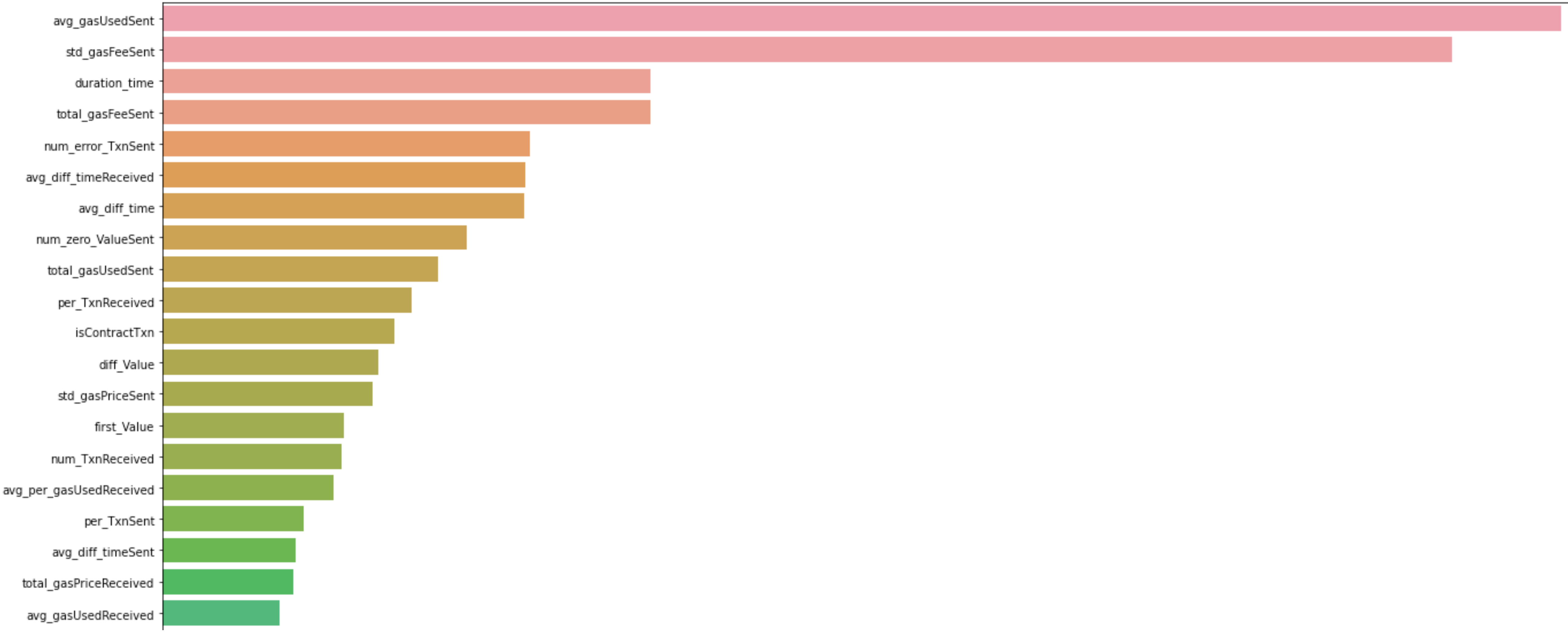
	val_ accuracy	val_ precision	val_ recall	val_ f1	test_ accuracy	test_ precision	test_ recall	test_ f1
Logistic Regression	0.858824	0.955820	0.880354	**0.914815**	0.875000	0.942857	0.908257	**0.925234**
SVM	0.872549	0.873333	0.997727	**0.931354**	0.851562	0.851562	1.000000	**0.919831**
KNN	0.888235	0.923547	0.950253	**0.936462**	0.859375	0.902655	0.935780	**0.918919**
Random Forest	0.968627	0.975648	0.988737	**0.982070**	0.945312	0.955357	0.981651	**0.968326**
XGBoost	0.966667	0.973478	0.988687	**0.980974**	0.945312	0.963636	0.972477	**0.968037**

Random Forrest and XGBoost outperform other models.

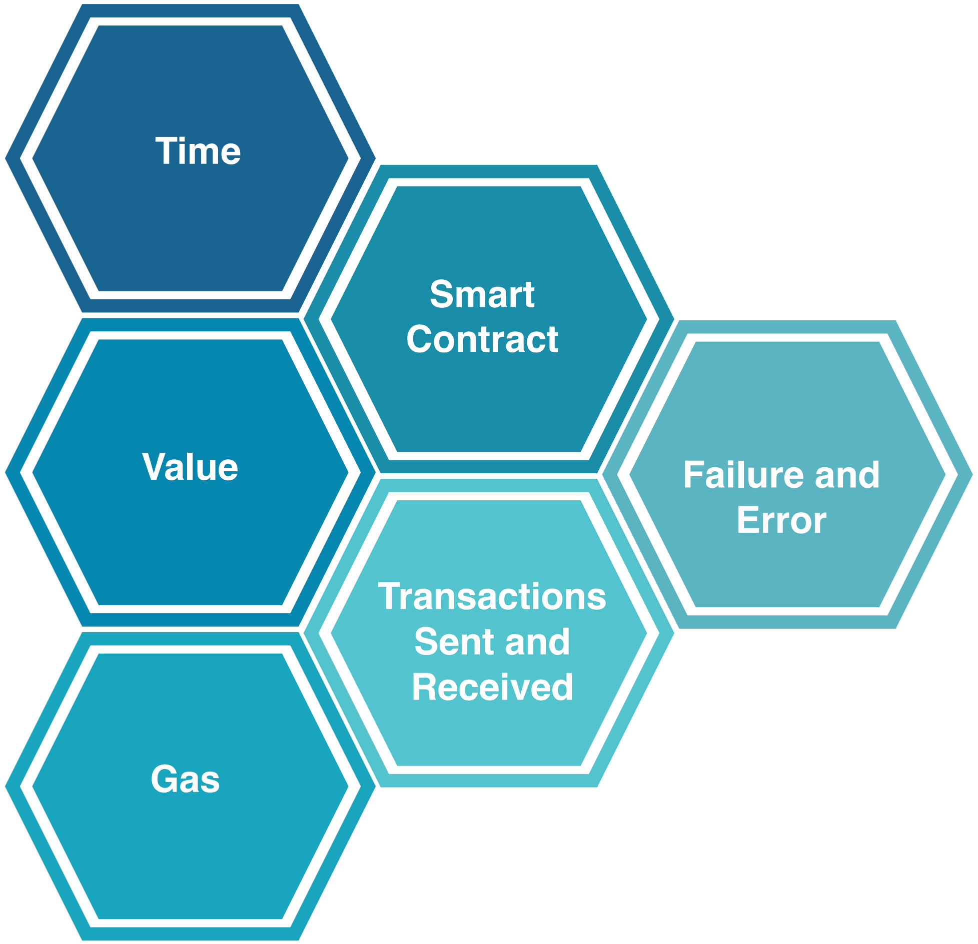
-> Hyperparameter tuning

-> Confusion Matrix: TP=107, TN=15, FP=4, FN=2

Feature Importance



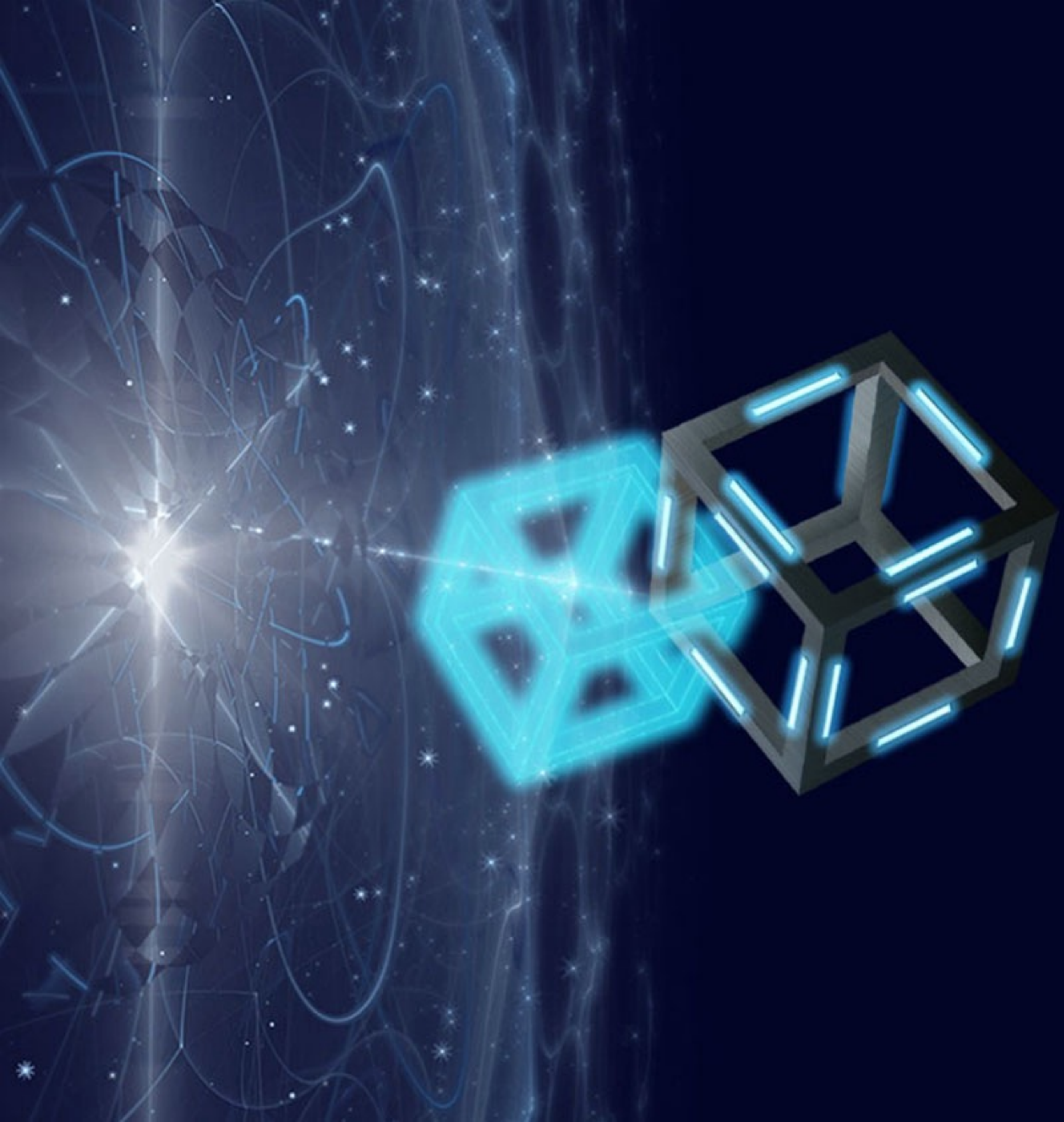
Solution & Discussion



Vulnerabilities of Smart Contract

Phishing Scams

Detection of Abnormal Value



Task 2

Bad Suppliers Detection

Bad Suppliers Detection

Supply Chain for a Food Company

Reliability

Time
Amount
Quantity

Anomaly Detection

Construct features of good suppliers, manifest larger errors for bad suppliers.

Historical Data

Supplier
Location
Time
Item
Amount of items
Item Price
Returned amount

Limitation

Class imbalance, majority of suppliers are good, abnormal behaviors are unpredictable.

External Effects

Weather, Transport, Global Pandemic…


THANK YOU