ETHEREUM FRAUD DETECTION

Problem Statement

- To predict weather the transaction is fraudulent or not-fraudulent using the transaction data.

Dataset Description

- The dataset folder contains the following files:
  transaction_dataset.csv : (9841, 51)

Columns Provided in the Dataset

- Index: the index number of a row
- Address: the address of the ethereum account
- FLAG: whether the transaction is fraud or not
- Avg min between sent tnx: Average time between sent transactions for account in minutes
- Avgminbetweenreceivedtnx: Average time between received transactions for account in minutes
- TimeDiffbetweenfirstand_last(Mins): Time difference between the first and last transaction
- Sent_tnx: Total number of sent normal transactions
- Received_tnx: Total number of received normal transactions
- NumberofCreated_Contracts: Total Number of created contract transactions
- UniqueReceivedFrom_Addresses: Total Unique addresses from which account received transactions
- UniqueSentTo_Addresses20: Total Unique addresses from which account sent transactions
- MinValueReceived: Minimum value in Ether ever received
- MaxValueReceived: Maximum value in Ether ever received
- AvgValueReceived5Average value in Ether ever received
- MinValSent: Minimum value of Ether ever sent
- MaxValSent: Maximum value of Ether ever sent
- AvgValSent: Average value of Ether ever sent
- MinValueSentToContract: Minimum value of Ether sent to a contract
- MaxValueSentToContract: Maximum value of Ether sent to a contract
- AvgValueSentToContract: Average value of Ether sent to contracts
- TotalTransactions(IncludingTnxtoCreate_Contract): Total number of transactions
- TotalEtherSent:Total Ether sent for account address
- TotalEtherReceived: Total Ether received for account address
- TotalEtherSent_Contracts: Total Ether sent to Contract addresses
- TotalEtherBalance: Total Ether Balance following enacted transactions
- TotalERC20Tnxs: Total number of ERC20 token transfer transactions
- ERC20TotalEther_Received: Total ERC20 token received transactions in Ether
- ERC20TotalEther_Sent: Total ERC20token sent transactions in Ether
- ERC20TotalEtherSentContract: Total ERC20 token transfer to other contracts in Ether
- ERC20UniqSent_Addr: Number of ERC20 token transactions sent to Unique account addresses
- ERC20UniqRec_Addr: Number of ERC20 token transactions received from Unique addresses
- ERC20UniqRecContractAddr: Number of ERC20token transactions received from Unique contract addresses
- ERC20AvgTimeBetweenSent_Tnx: Average time between ERC20 token sent transactions in minutes
- ERC20AvgTimeBetweenRec_Tnx: Average time between ERC20 token received transactions in minutes
- ERC20AvgTimeBetweenContract_Tnx: Average time ERC20 token between sent token transactions
- ERC20MinVal_Rec: Minimum value in Ether received from ERC20 token transactions for account
- ERC20MaxVal_Rec: Maximum value in Ether received from ERC20 token transactions for account
- ERC20AvgVal_Rec: Average value in Ether received from ERC20 token transactions for account
- ERC20MinVal_Sent: Minimum value in Ether sent from ERC20 token transactions for account
- ERC20MaxVal_Sent: Maximum value in Ether sent from ERC20 token transactions for account
- ERC20AvgVal_Sent: Average value in Ether sent from ERC20 token transactions for account
- ERC20UniqSentTokenName: Number of Unique ERC20 tokens transferred
- ERC20UniqRecTokenName: Number of Unique ERC20 tokens received
- ERC20MostSentTokenType: Most sent token for account via ERC20 transaction
- ERC20MostRecTokenType: Most received token for account via ERC20 transactions

In [1]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

In [2]:
```
# Importing Necessary Libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
pd.set_option('display.max_columns', None)
```

In [3]:
```
# Read csv file using pandas
path = '/content/drive/MyDrive/Projects/Ethereum Fraud Detection/transaction_dataset.csv'
df = pd.read_csv(path)
```

Basic EDA

In [4]:
```
#check shape of the dataset
df.shape
```

Out[4]:
```
(9841, 51)
```

In [5]:
```python
# check columns of dataset
df.columns
```

Out[5]:
```
Index(['Unnamed: 0', 'Index', 'Address', 'FLAG', 'Avg min between sent tnx',
       'Avg min between received tnx',
       'Time Diff between first and last (Mins)', 'Sent tnx', 'Received Tnx',
       'Number of Created Contracts', 'Unique Received From Addresses',
       'Unique Sent To Addresses', 'min value received', 'max value received ',
       'avg val received', 'min val sent', 'max val sent', 'avg val sent',
       'min value sent to contract', 'max val sent to contract',
       'avg value sent to contract',
       'total transactions (including tnx to create contract',
       'total Ether sent', 'total ether received',
       'total ether sent contracts', 'total ether balance',
       ' Total ERC20 tnxs', ' ERC20 total Ether received',
       ' ERC20 total ether sent', ' ERC20 total Ether sent contract',
       ' ERC20 uniq sent addr', ' ERC20 uniq rec addr',
       ' ERC20 uniq sent addr.1', ' ERC20 uniq rec contract addr',
       ' ERC20 avg time between sent tnx', ' ERC20 avg time between rec tnx',
       ' ERC20 avg time between rec 2 tnx',
       ' ERC20 avg time between contract tnx', ' ERC20 min val rec',
       ' ERC20 max val rec', ' ERC20 avg val rec', ' ERC20 min val sent',
       ' ERC20 max val sent', ' ERC20 avg val sent',
       ' ERC20 min val sent contract', ' ERC20 max val sent contract',
       ' ERC20 avg val sent contract', ' ERC20 uniq sent token name',
       ' ERC20 uniq rec token name', ' ERC20 most sent token type',
       ' ERC20_most_rec_token_type'],
      dtype='object')
```

In [6]:
```python
#drop Unnamed: 0, Address, Index from dataset
df.drop(columns = ['Unnamed: 0', 'Address', 'Index'], inplace = True)
```

In [7]:
```python
# Check which columns are having categorical, numerical or boolean values
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9841 entries, 0 to 9840
Data columns (total 48 columns):
 #   Column                                                Non-Null Count  Dtype  
---  ------                                                --------------  -----  
 0   FLAG                                                  9841 non-null   int64  
 1   Avg min between sent tnx                              9841 non-null   float64
 2   Avg min between received tnx                          9841 non-null   float64
 3   Time Diff between first and last (Mins)               9841 non-null   float64
 4   Sent tnx                                              9841 non-null   int64  
 5   Received Tnx                                          9841 non-null   int64  
 6   Number of Created Contracts                           9841 non-null   int64  
 7   Unique Received From Addresses                        9841 non-null   int64  
 8   Unique Sent To Addresses                              9841 non-null   int64  
 9   min value received                                    9841 non-null   float64
 10  max value received                                    9841 non-null   float64
 11  avg val received                                      9841 non-null   float64
 12  min val sent                                          9841 non-null   float64
 13  max val sent                                          9841 non-null   float64
 14  avg val sent                                          9841 non-null   float64
 15  min value sent to contract                            9841 non-null   float64
 16  max val sent to contract                              9841 non-null   float64
 17  avg value sent to contract                            9841 non-null   float64
 18  total transactions (including tnx to create contract  9841 non-null   int64  
 19  total Ether sent                                      9841 non-null   float64
 20  total ether received                                  9841 non-null   float64
 21  total ether sent contracts                            9841 non-null   float64
 22  total ether balance                                   9841 non-null   float64
 23   Total ERC20 tnxs                                     9012 non-null   float64
 24   ERC20 total Ether received                           9012 non-null   float64
 25   ERC20 total ether sent                               9012 non-null   float64
 26   ERC20 total Ether sent contract                      9012 non-null   float64
 27   ERC20 uniq sent addr                                 9012 non-null   float64
 28   ERC20 uniq rec addr                                  9012 non-null   float64
 29   ERC20 uniq sent addr.1                               9012 non-null   float64
 30   ERC20 uniq rec contract addr                         9012 non-null   float64
 31   ERC20 avg time between sent tnx                      9012 non-null   float64
 32   ERC20 avg time between rec tnx                       9012 non-null   float64
 33   ERC20 avg time between rec 2 tnx                     9012 non-null   float64
 34   ERC20 avg time between contract tnx                  9012 non-null   float64
 35   ERC20 min val rec                                    9012 non-null   float64
 36   ERC20 max val rec                                    9012 non-null   float64
 37   ERC20 avg val rec                                    9012 non-null   float64
 38   ERC20 min val sent                                   9012 non-null   float64
 39   ERC20 max val sent                                   9012 non-null   float64
 40   ERC20 avg val sent                                   9012 non-null   float64
 41   ERC20 min val sent contract                          9012 non-null   float64
 42   ERC20 max val sent contract                          9012 non-null   float64
 43   ERC20 avg val sent contract                          9012 non-null   float64
 44   ERC20 uniq sent token name                           9012 non-null   float64
 45   ERC20 uniq rec token name                            9012 non-null   float64
 46   ERC20 most sent token type                           9000 non-null   object 
 47   ERC20_most_rec_token_type                            8990 non-null   object 
dtypes: float64(39), int64(7), object(2)
memory usage: 3.6+ MB
```

In [8]:
```python
# For more information on the dataset like the total count in all the columns of train data
# min, max values and more information of the respective columns
df.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
FLAG	9841.0	2.214206e-01	4.152241e-01	0.00	0.000000	0.000000e+00	0.000000	1.000000e+00
Avg min between sent tnx	9841.0	5.086879e+03	2.148655e+04	0.00	0.000000	1.734000e+01	565.470000	4.302877e+05
Avg min between received tnx	9841.0	8.004851e+03	2.308171e+04	0.00	0.000000	5.097700e+02	5480.390000	4.821755e+05
Time Diff between first and last (Mins)	9841.0	2.183333e+05	3.229379e+05	0.00	316.930000	4.663703e+04	304070.980000	1.954861e+06
Sent tnx	9841.0	1.159317e+02	7.572264e+02	0.00	1.000000	3.000000e+00	11.000000	1.000000e+04
Received Tnx	9841.0	1.637009e+02	9.408366e+02	0.00	1.000000	4.000000e+00	27.000000	1.000000e+04
Number of Created Contracts	9841.0	3.729702e+00	1.414456e+02	0.00	0.000000	0.000000e+00	0.000000	9.995000e+03
Unique Received From Addresses	9841.0	3.036094e+01	2.986211e+02	0.00	1.000000	2.000000e+00	5.000000	9.999000e+03
Unique Sent To Addresses	9841.0	2.584016e+01	2.638204e+02	0.00	1.000000	2.000000e+00	3.000000	9.287000e+03
min value received	9841.0	4.384515e+01	3.259291e+02	0.00	0.001000	9.585600e-02	2.000000	1.000000e+04
max value received	9841.0	5.231525e+02	1.300882e+04	0.00	1.000000	6.000000e+00	67.067040	8.000000e+05
avg val received	9841.0	1.007117e+02	2.885002e+03	0.00	0.426905	1.729730e+00	22.000000	2.836188e+05
min val sent	9841.0	4.800090e+00	1.386097e+02	0.00	0.000000	4.912600e-02	0.998800	1.200000e+04
max val sent	9841.0	3.146173e+02	6.629213e+03	0.00	0.164577	4.999380e+00	61.520653	5.200000e+05
avg val sent	9841.0	4.475573e+01	2.390802e+02	0.00	0.086184	1.606000e+00	21.999380	1.200000e+04
min value sent to contract	9841.0	3.048471e-06	2.253968e-04	0.00	0.000000	0.000000e+00	0.000000	2.000000e-02
max val sent to contract	9841.0	7.725739e-06	5.158151e-04	0.00	0.000000	0.000000e+00	0.000000	4.602900e-02
avg value sent to contract	9841.0	5.387054e-06	3.234341e-04	0.00	0.000000	0.000000e+00	0.000000	2.301400e-02
total transactions (including tnx to create contract	9841.0	2.833624e+02	1.352404e+03	0.00	4.000000	8.000000e+00	54.000000	1.999500e+04
total Ether sent	9841.0	1.016092e+04	3.583227e+05	0.00	0.226206	1.248680e+01	100.998974	2.858096e+07
total ether received	9841.0	1.163832e+04	3.642048e+05	0.00	2.670424	3.052963e+01	101.000000	2.858159e+07
total ether sent contracts	9841.0	7.725710e-06	5.158125e-04	0.00	0.000000	0.000000e+00	0.000000	4.602871e-02
total ether balance	9841.0	1.477395e+03	2.424254e+05	-15605352.04	0.000621	1.722000e-03	0.044520	1.428864e+07
Total ERC20 tnxs	9012.0	3.625566e+01	4.475289e+02	0.00	0.000000	1.000000e+00	3.000000	1.000100e+04
ERC20 total Ether received	9012.0	1.296207e+08	1.053858e+10	0.00	0.000000	1.000000e-12	100.337000	1.000020e+12
ERC20 total ether sent	9012.0	1.386849e+07	1.180390e+09	0.00	0.000000	0.000000e+00	0.000000	1.120000e+11
ERC20 total Ether sent contract	9012.0	1.109392e+02	6.128635e+03	0.00	0.000000	0.000000e+00	0.000000	4.160000e+05
ERC20 uniq sent addr	9012.0	5.638038e+00	1.052525e+02	0.00	0.000000	0.000000e+00	0.000000	6.582000e+03
ERC20 uniq rec addr	9012.0	7.598535e+00	8.181847e+01	0.00	0.000000	1.000000e+00	2.000000	4.293000e+03
ERC20 uniq sent addr.1	9012.0	3.439858e-03	6.569787e-02	0.00	0.000000	0.000000e+00	0.000000	3.000000e+00
ERC20 uniq rec contract addr	9012.0	4.901909e+00	1.724658e+01	0.00	0.000000	1.000000e+00	2.000000	7.820000e+02
ERC20 avg time between sent tnx	9012.0	0.000000e+00	0.000000e+00	0.00	0.000000	0.000000e+00	0.000000	0.000000e+00
ERC20 avg time between rec tnx	9012.0	0.000000e+00	0.000000e+00	0.00	0.000000	0.000000e+00	0.000000	0.000000e+00
ERC20 avg time between rec 2 tnx	9012.0	0.000000e+00	0.000000e+00	0.00	0.000000	0.000000e+00	0.000000	0.000000e+00
ERC20 avg time between contract tnx	9012.0	0.000000e+00	0.000000e+00	0.00	0.000000	0.000000e+00	0.000000	0.000000e+00
ERC20 min val rec	9012.0	4.856147e+02	1.688328e+04	0.00	0.000000	0.000000e+00	0.001523	9.900000e+05
ERC20 max val rec	9012.0	1.252524e+08	1.053741e+10	0.00	0.000000	0.000000e+00	99.000000	1.000000e+12
ERC20 avg val rec	9012.0	4.346203e+06	2.141192e+08	0.00	0.000000	0.000000e+00	29.464673	1.724181e+10
ERC20 min val sent	9012.0	1.174126e+04	1.053567e+06	0.00	0.000000	0.000000e+00	0.000000	1.000000e+08
ERC20 max val sent	9012.0	1.303594e+07	1.179905e+09	0.00	0.000000	0.000000e+00	0.000000	1.120000e+11
ERC20 avg val sent	9012.0	6.318389e+06	5.914764e+08	0.00	0.000000	0.000000e+00	0.000000	5.614756e+10
ERC20 min val sent contract	9012.0	0.000000e+00	0.000000e+00	0.00	0.000000	0.000000e+00	0.000000	0.000000e+00
ERC20 max val sent contract	9012.0	0.000000e+00	0.000000e+00	0.00	0.000000	0.000000e+00	0.000000	0.000000e+00
ERC20 avg val sent contract	9012.0	0.000000e+00	0.000000e+00	0.00	0.000000	0.000000e+00	0.000000	0.000000e+00
ERC20 uniq sent token name	9012.0	1.384931e+00	6.735121e+00	0.00	0.000000	0.000000e+00	0.000000	2.130000e+02
ERC20 uniq rec token name	9012.0	4.826676e+00	1.667861e+01	0.00	0.000000	1.000000e+00	2.000000	7.370000e+02

In [9]:
```python
# check length of dataset
print(f" dataset length : {len(df)}")
```

```
dataset length : 9841
```

In [10]:
```
# loop through datatset to find count of unique values of each column
for col in df.columns:
  print(f" {col} : {len(df[col].value_counts())}")
```

```
 FLAG : 2
 Avg min between sent tnx : 5013
 Avg min between received tnx : 6223
 Time Diff between first and last (Mins) : 7810
 Sent tnx : 641
 Received Tnx : 727
 Number of Created Contracts : 20
 Unique Received From Addresses : 256
 Unique Sent To Addresses : 258
 min value received : 4589
 max value received  : 6302
 avg val received : 6767
 min val sent : 4719
 max val sent : 6647
 avg val sent : 5854
 min value sent to contract : 3
 max val sent to contract : 4
 avg value sent to contract : 4
 total transactions (including tnx to create contract : 897
 total Ether sent : 5868
 total ether received : 6728
 total ether sent contracts : 4
 total ether balance : 5717
  Total ERC20 tnxs : 300
  ERC20 total Ether received : 3460
  ERC20 total ether sent : 1415
  ERC20 total Ether sent contract : 29
  ERC20 uniq sent addr : 107
  ERC20 uniq rec addr : 147
  ERC20 uniq sent addr.1 : 4
  ERC20 uniq rec contract addr : 123
  ERC20 avg time between sent tnx : 1
  ERC20 avg time between rec tnx : 1
  ERC20 avg time between rec 2 tnx : 1
  ERC20 avg time between contract tnx : 1
  ERC20 min val rec : 1276
  ERC20 max val rec : 2647
  ERC20 avg val rec : 3380
  ERC20 min val sent : 476
  ERC20 max val sent : 1130
  ERC20 avg val sent : 1309
  ERC20 min val sent contract : 1
  ERC20 max val sent contract : 1
  ERC20 avg val sent contract : 1
  ERC20 uniq sent token name : 70
  ERC20 uniq rec token name : 121
  ERC20 most sent token type : 305
  ERC20_most_rec_token_type : 467
```

In [11]:
```
# Check for missing values in all the columnns of the dataset
df.isnull().sum()
```

Out[11]:
```
FLAG                                                     0
Avg min between sent tnx                                 0
Avg min between received tnx                             0
Time Diff between first and last (Mins)                  0
Sent tnx                                                 0
Received Tnx                                             0
Number of Created Contracts                              0
Unique Received From Addresses                           0
Unique Sent To Addresses                                 0
min value received                                       0
max value received                                       0
avg val received                                         0
min val sent                                             0
max val sent                                             0
avg val sent                                             0
min value sent to contract                               0
max val sent to contract                                 0
avg value sent to contract                               0
total transactions (including tnx to create contract     0
total Ether sent                                         0
total ether received                                     0
total ether sent contracts                               0
total ether balance                                      0
 Total ERC20 tnxs                                      829
 ERC20 total Ether received                            829
 ERC20 total ether sent                                829
 ERC20 total Ether sent contract                       829
 ERC20 uniq sent addr                                  829
 ERC20 uniq rec addr                                   829
 ERC20 uniq sent addr.1                                829
 ERC20 uniq rec contract addr                          829
 ERC20 avg time between sent tnx                       829
 ERC20 avg time between rec tnx                        829
 ERC20 avg time between rec 2 tnx                      829
 ERC20 avg time between contract tnx                   829
 ERC20 min val rec                                     829
 ERC20 max val rec                                     829
 ERC20 avg val rec                                     829
 ERC20 min val sent                                    829
 ERC20 max val sent                                    829
 ERC20 avg val sent                                    829
 ERC20 min val sent contract                           829
 ERC20 max val sent contract                           829
 ERC20 avg val sent contract                           829
 ERC20 uniq sent token name                            829
 ERC20 uniq rec token name                             829
 ERC20 most sent token type                            841
 ERC20_most_rec_token_type                             851
dtype: int64
```

Correlation Matrix

Why?

- A correlation matrix is a table showing correlation coefficients between variables

There are three broad reasons for computing a correlation matrix:

1. To summarize a large amount of data where the goal is to see patterns. In our example above, the observable pattern is that all the variables highly correlate with each other.
2. To input into other analyses. For example, people commonly use correlation matrixes as inputs for exploratory factor analysis, confirmatory factor analysis, structural equation models, and linear regression when excluding missing values pairwise.
3. As a diagnostic when checking other analyses. For example, with linear regression, a high amount of correlations suggests that the linear regression estimates will be unreliable.

In [12]:
```
# Using pandas
df.corr().style.background_gradient(cmap='coolwarm')
```

```
/usr/local/lib/python3.8/dist-packages/pandas/io/formats/style.py:2813: RuntimeWarning: All-NaN slice encountered
  smin = np.nanmin(gmap) if vmin is None else vmin
/usr/local/lib/python3.8/dist-packages/pandas/io/formats/style.py:2814: RuntimeWarning: All-NaN slice encountered
  smax = np.nanmax(gmap) if vmax is None else vmax
```

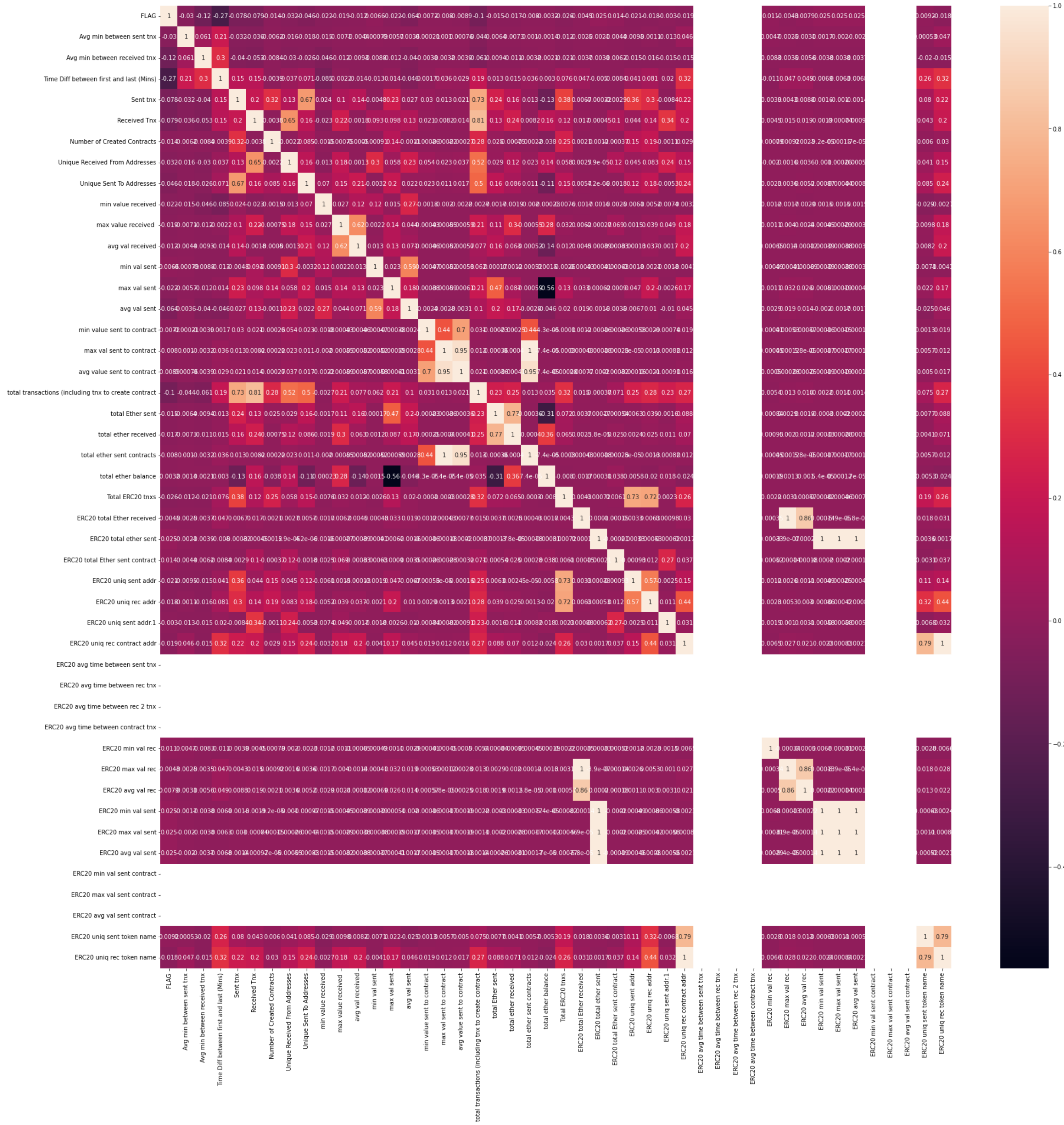
Out[12]:

	FLAG	Avg min between sent tnx	Avg min between received tnx	Time Diff between first and last (Mins)	Sent tnx	Received Tnx	Number of Created Contracts	Unique Received From Addresses	Unique Sent To Addresses	min value received	max value received	avg val received	min val sent	max val sent	avg val sent	min value sent to contract	max val sent to contract	avg value sent to contract	total transactions (including tnx to create contract
FLAG	1.000000	-0.029754	-0.118533	-0.269354	-0.078006	-0.079316	-0.013711	-0.031941	-0.045584	-0.021641	-0.019259	-0.011881	0.006626	-0.022437	-0.063556	-0.007213	-0.007988	-0.008883	-0.100289
Avg min between sent tnx	-0.029754	1.000000	0.060979	0.214722	-0.032289	-0.035735	-0.006186	-0.015912	-0.017688	-0.014886	-0.007104	-0.004382	-0.000789	-0.005716	0.003597	-0.000210	0.001044	0.000759	-0.043586
Avg min between received tnx	-0.118533	0.060979	1.000000	0.303897	-0.040419	-0.053478	-0.008378	-0.029571	-0.025747	-0.045753	-0.011575	-0.009313	-0.008761	-0.012176	-0.040011	-0.003916	-0.003230	-0.003940	-0.060711
Time Diff between first and last (Mins)	-0.269354	0.214722	0.303897	1.000000	0.154480	0.148376	-0.003881	0.037043	0.071140	-0.084996	-0.002240	-0.014002	-0.013107	0.014194	-0.046039	0.001734	0.036162	0.029440	0.189311
Sent tnx	-0.078006	-0.032289	-0.040419	0.154480	1.000000	0.198455	0.320603	0.130064	0.670014	0.024015	0.102109	0.140677	-0.004846	0.225356	0.027468	0.029529	0.013263	0.020865	0.731503
Received Tnx	-0.079316	-0.035735	-0.053478	0.148376	0.198455	1.000000	-0.003838	0.648655	0.164112	-0.022936	0.224805	-0.001786	0.093448	0.097769	0.125075	0.020645	0.008243	0.013767	0.806393
Number of Created Contracts	-0.013711	-0.006186	-0.008378	-0.003881	0.320603	-0.003838	1.000000	-0.002211	0.084598	-0.001542	-0.000752	-0.000498	-0.000913	0.141919	-0.001083	-0.000261	-0.000225	-0.000270	0.281428
Unique Received From Addresses	-0.031941	-0.015912	-0.029571	0.037043	0.130064	0.648655	-0.002211	1.000000	0.159829	-0.012939	0.175860	-0.001324	0.296240	0.058060	0.226712	0.053946	0.023258	0.037343	0.523848
Unique Sent To Addresses	-0.045584	-0.017688	-0.025747	0.071140	0.670014	0.164112	0.084598	0.159829	1.000000	0.070145	0.148182	0.207410	-0.003166	0.196573	0.022143	0.023183	0.010926	0.016790	0.498165
min value received	-0.021641	-0.014886	-0.045753	-0.084996	0.024015	-0.022936	-0.001542	-0.012939	0.070145	1.000000	0.026710	0.122911	0.117682	0.015061	0.267280	-0.001820	-0.002015	-0.002241	-0.002671
max value received	-0.019259	-0.007104	-0.011575	-0.002240	0.102109	0.224805	-0.000752	0.175860	0.148182	0.026710	1.000000	0.622959	0.002239	0.135937	0.043989	-0.000427	-0.000550	-0.000588	0.213485
avg val received	-0.011881	-0.004382	-0.009313	-0.014002	0.140677	-0.001786	-0.000498	-0.001324	0.207410	0.122911	0.622959	1.000000	0.012988	0.134113	0.070700	-0.000457	-0.000516	-0.000571	0.077472
min val sent	0.006626	-0.000789	-0.008761	-0.013107	-0.004846	0.093448	-0.000913	0.296240	-0.003166	0.117682	0.002239	0.012988	1.000000	0.022662	0.594868	-0.000468	-0.000519	-0.000577	0.062200
max val sent	-0.022437	-0.005716	-0.012176	0.014194	0.225356	0.097769	0.141919	0.058060	0.196573	0.015061	0.135937	0.134113	0.022662	1.000000	0.184962	-0.000378	-0.000594	-0.000605	0.209038
avg val sent	-0.063556	0.003597	-0.040011	-0.046039	0.027468	0.125075	-0.001083	0.226712	0.022143	0.267280	0.043989	0.070700	0.594868	0.184962	1.000000	-0.002445	-0.002764	-0.003056	0.102278
min value sent to contract	-0.007213	-0.000210	-0.003916	0.001734	0.029529	0.020645	-0.000261	0.053946	0.023183	-0.001820	-0.000427	-0.000457	-0.000468	-0.000378	-0.002445	1.000000	0.436849	0.696789	0.030868
max val sent to contract	-0.007988	0.001044	-0.003230	0.036162	0.013263	0.008243	-0.000225	0.023258	0.010926	-0.002015	-0.000550	-0.000516	-0.000519	-0.000594	-0.002764	0.436849	1.000000	0.949607	0.013137
avg value sent to contract	-0.008883	0.000759	-0.003940	0.029440	0.020865	0.013767	-0.000270	0.037343	0.016790	-0.002241	-0.000588	-0.000571	-0.000577	-0.000605	-0.003056	0.696789	0.949607	1.000000	0.021232
total transactions (including tnx to create contract	-0.100289	-0.043586	-0.060711	0.189311	0.731503	0.806393	0.281428	0.523848	0.498165	-0.002671	0.213485	0.077472	0.062200	0.209038	0.102278	0.030868	0.013137	0.021232	1.000000
total Ether sent	-0.014993	-0.006440	-0.009442	0.012999	0.244434	0.132150	0.024877	0.028881	0.164535	-0.001748	0.112739	0.155433	0.000166	0.470139	0.198750	-0.000226	-0.000356	-0.000363	0.231397
total ether received	-0.016900	-0.007285	-0.010720	0.014756	0.155811	0.235282	-0.000753	0.124897	0.086376	-0.001874	0.296173	0.062609	0.001171	0.086551	0.165232	-0.000252	-0.000400	-0.000406	0.250842
total ether sent contracts	-0.007988	0.001044	-0.003230	0.036162	0.013263	0.008243	-0.000225	0.023258	0.010926	-0.002015	-0.000550	-0.000516	-0.000519	-0.000594	-0.002764	0.436852	1.000000	0.949608	0.013137
total ether balance	-0.003229	-0.001425	-0.002149	0.002955	-0.127211	0.158146	-0.037902	0.144949	-0.113428	-0.000233	0.278315	-0.135682	0.001514	-0.564872	-0.045534	-0.000043	-0.000074	-0.000074	0.034828
Total ERC20 tnxs	-0.025697	-0.012307	-0.020578	0.075922	0.381311	0.116203	0.249500	0.057718	0.148071	-0.007648	0.032261	0.012264	-0.002574	0.130834	0.020393	-0.000103	-0.000304	-0.000279	0.320750
ERC20 total Ether received	-0.004475	-0.002542	-0.003656	0.046788	0.006683	0.016501	0.002072	0.002742	0.005709	-0.001727	0.006230	0.004474	-0.000425	0.032880	0.019350	0.001242	0.000426	0.000773	0.015447
ERC20 total ether sent	0.024762	-0.002105	-0.003876	-0.005014	-0.000315	-0.000452	0.001166	0.000059	0.000004	-0.001627	-0.000266	-0.000390	-0.000407	0.000615	-0.001598	-0.000157	-0.000180	-0.000198	-0.000369
ERC20 total Ether sent contract	0.013514	-0.004409	-0.006160	-0.008389	-0.002897	0.104870	-0.000374	0.116672	-0.001848	-0.002546	0.068704	-0.000330	-0.000628	-0.000896	-0.003523	-0.000256	-0.000283	-0.000315	0.071317
ERC20 uniq sent addr	-0.020554	-0.009477	-0.014776	0.040686	0.356065	0.044187	0.154788	0.045200	0.121789	-0.006072	0.001475	-0.000135	-0.001857	0.046650	-0.006726	-0.000578	0.000050	-0.000162	0.246555
ERC20 uniq rec addr	-0.017539	-0.001133	-0.016037	0.080709	0.300461	0.136485	0.190646	0.083026	0.176988	-0.005190	0.039185	0.037338	-0.002092	0.198918	0.010298	0.002891	0.001310	0.002052	0.283377
ERC20 uniq sent addr.1	-0.003047	-0.012754	-0.014698	0.019961	-0.008379	0.337727	-0.001083	0.241494	-0.005345	-0.007365	0.048690	-0.001739	-0.001817	-0.002590	-0.010191	-0.000740	-0.000820	-0.000911	0.230217
ERC20 uniq rec contract addr	-0.018527	0.045615	-0.014932	0.319176	0.219665	0.201686	0.028986	0.147741	0.237351	-0.003216	0.181375	0.202583	-0.004108	0.165755	0.045245	0.018657	0.012053	0.016112	0.266519
ERC20 avg time between sent tnx	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
ERC20 avg time between rec tnx	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
ERC20 avg time between rec 2 tnx	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
ERC20 avg time between contract tnx	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
ERC20 min val rec	0.011163	0.004673	-0.008319	-0.010543	-0.003868	-0.004464	-0.000788	-0.001999	-0.002333	-0.001154	-0.001076	-0.000648	-0.000490	-0.001124	-0.002931	-0.000406	-0.000450	-0.000500	-0.005357
ERC20 max val rec	-0.004313	-0.002456	-0.003544	0.046512	0.004291	0.015379	0.000920	0.001603	0.003598	-0.001670	0.003993	0.001357	-0.000411	0.031620	0.018990	0.000526	0.000117	0.000277	0.013204
ERC20 avg val rec	0.007881	-0.003149	-0.005606	0.049020	0.008843	0.019126	0.002052	0.003592	0.005246	-0.002852	0.002440	-0.000120	-0.000694	0.026005	0.014155	0.000573	0.000058	0.000246	0.018482
ERC20 min val sent	0.025364	-0.001687	-0.003758	-0.006852	-0.001557	-0.001899	-0.000092	-0.001044	-0.000967	-0.001498	-0.000448	-0.000386	-0.000387	-0.000514	-0.001974	-0.000157	-0.000174	-0.000194	-0.002204

	FLAG	Avg min between sent tnx	Avg min between received tnx	Time Diff between first and last (Mins)	Sent tnx	Received Tnx	Number of Created Contracts	Unique Received From Addresses	Unique Sent To Addresses	min value received	max value received	avg val received	min val sent	max val sent	avg val sent	min value sent to contract	max val sent to contract	avg value sent to contract	total transactions (including tnx to create contract
ERC20 max val sent	0.025038	-0.002020	-0.003780	-0.006268	-0.001019	-0.000744	0.000149	-0.000261	-0.000439	-0.001529	-0.000293	-0.000380	-0.000383	-0.000194	-0.001682	-0.000148	-0.000169	-0.000186	-0.001073
ERC20 avg val sent	0.025044	-0.001965	-0.003727	-0.006802	-0.001415	-0.000918	-0.000070	-0.000546	-0.000827	-0.001477	-0.000315	-0.000377	-0.000370	-0.000413	-0.001667	-0.000147	-0.000165	-0.000183	-0.001439
ERC20 min val sent contract	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
ERC20 max val sent contract	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
ERC20 avg val sent contract	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan	nan
ERC20 uniq sent token name	0.009249	0.000529	-0.019896	0.263939	0.079728	0.042681	0.006033	0.040674	0.084897	-0.028810	0.009788	0.008208	-0.007117	0.022046	-0.024549	0.001291	0.005651	0.004956	0.075024
ERC20 uniq rec token name	-0.018047	0.047202	-0.014966	0.324288	0.220614	0.202747	0.030089	0.148851	0.237520	-0.002695	0.179039	0.200168	-0.004092	0.165062	0.045800	0.019074	0.012411	0.016543	0.267906

In [13]:
```python
#Using seaborn
plt.figure(figsize = (30,30))
sns.heatmap(df.corr(), annot = True)
```

Out[13]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f80640f4cd0>
```



CHECKING IF DATASET IS SKEWED OR NOT

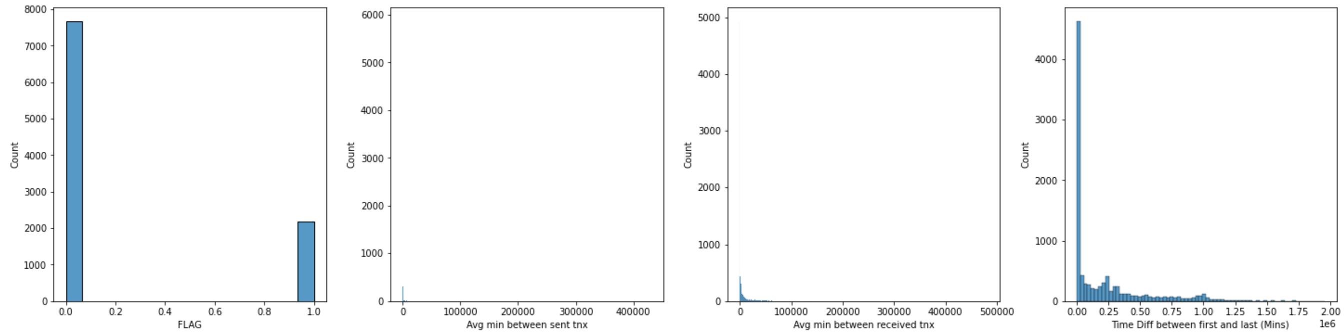
Histogram

1. A histogram is an approximate representation of the distribution of numerical data.
2. To construct a histogram, the first step is to "bin" (or "bucket") the range of values—that is, divide the entire range of values into a series of intervals—and then count how many values fall into each interval.
3. The words used to describe the patterns in a histogram are: "symmetric", "skewed left" or "right", "unimodal", "bimodal" or "multimodal".

In [14]:
```python
df.columns[:6]
```

Out[14]:
```
Index(['FLAG', 'Avg min between sent tnx', 'Avg min between received tnx',
       'Time Diff between first and last (Mins)', 'Sent tnx', 'Received Tnx'],
      dtype='object')
```

In [15]:
```python
# Histogram using pandas
fig, ax = plt.subplots(ncols=4, nrows=1, figsize=(20,5))
index = 0
ax = ax.flatten()
for col, value in df.iloc[ : , : 4].items():
  if df[col].dtypes != 'O':
    sns.histplot(value, ax=ax[index])
    index += 1
plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```



Skewness

- The skew method returns a scalar value representing the skewness of the distribution. A positive value indicates a positive skew (i.e., the tail on the right side of the distribution is longer), a negative value indicates a negative skew (i.e., the tail on the left side of the distribution is longer), and a value of 0 indicates that the distribution is symmetrical

In [16]:
```python
# check skewness of dataset
df.skew(axis = 0, skipna = True)
```

```
<ipython-input-16-77a6948006c4>:2: FutureWarning: Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is deprecated; in a future version this will ra
ise TypeError.  Select only valid columns before calling the reduction.
  df.skew(axis = 0, skipna = True)
```

Out[16]:
```
FLAG                                                     1.342100
Avg min between sent tnx                                 8.420000
Avg min between received tnx                             6.745298
Time Diff between first and last (Mins)                  1.809977
Sent tnx                                                10.484544
Received Tnx                                             8.821383
Number of Created Contracts                             51.720220
Unique Received From Addresses                          18.116107
Unique Sent To Addresses                                18.354325
min value received                                      23.295883
max value received                                      46.423682
avg val received                                        96.513680
min val sent                                            73.426748
max val sent                                            59.833713
avg val sent                                            25.531087
min value sent to contract                              79.849427
max val sent to contract                                78.848894
avg value sent to contract                              63.607723
total transactions (including tnx to create contract     6.849046
total Ether sent                                        62.363237
total ether received                                    58.795284
total ether sent contracts                              78.848737
total ether balance                                     -1.205262
 Total ERC20 tnxs                                       19.930233
 ERC20 total Ether received                             94.806604
 ERC20 total ether sent                                 94.786924
 ERC20 total Ether sent contract                        59.280265
 ERC20 uniq sent addr                                   40.648025
 ERC20 uniq rec addr                                    37.586021
 ERC20 uniq sent addr.1                                 23.720828
 ERC20 uniq rec contract addr                           16.330917
 ERC20 avg time between sent tnx                         0.000000
 ERC20 avg time between rec tnx                          0.000000
 ERC20 avg time between rec 2 tnx                        0.000000
 ERC20 avg time between contract tnx                     0.000000
 ERC20 min val rec                                      50.535806
 ERC20 max val rec                                      94.833841
 ERC20 avg val rec                                      71.026899
 ERC20 min val sent                                     94.882248
 ERC20 max val sent                                     94.904137
 ERC20 avg val sent                                     94.919941
 ERC20 min val sent contract                             0.000000
 ERC20 max val sent contract                             0.000000
 ERC20 avg val sent contract                             0.000000
 ERC20 uniq sent token name                             12.305550
 ERC20 uniq rec token name                              15.538524
dtype: float64
```

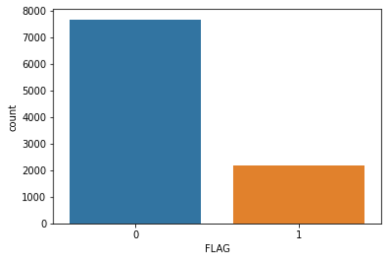
After checking skewness of dataset and from histogram we can see that the dataset is heavily skewed, with most of the weight being on the left tail.

CHECKING IF DATASET IS BALANCED OR NOT

In [17]:
```
# count plot of flag column
sns.countplot(df['FLAG'])
```

```
/usr/local/lib/python3.8/dist-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional ar
gument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7f805b270580>



In [18]:
```
# check total number of fraudulent and non-fraudulent instances
df['FLAG'].value_counts()
```

Out[18]:
```
0    7662
1    2179
Name: FLAG, dtype: int64
```

In [19]:
```
# find Percentage of non-fraudulent instances
print(f"% of fraudulent instances : {round(df['FLAG'].value_counts(normalize = True)[0]*100,0)}%")
```

```
% of fraudulent instances : 78.0%
```

In [20]:
```
# find Percentage of fraudulent instances
print(f"% of fraudulent instances : {round(df['FLAG'].value_counts(normalize = True)[1]*100,0)}%")
```

```
% of fraudulent instances : 22.0%
```

- The dataset is heavily imbalanced with only 22% of fraudulent instance.

Understanding more about dataset

In [21]:
```
# display unique values in categorical columns
for col in df.columns:
  if df[col].dtypes == 'O':
    print(df[col].unique)
```

```
<bound method Series.unique of 0            Cofoundit
1       Livepeer Token
2                 None
3               Raiden
4        StatusNetwork
             ...
9836
9837
9838
9839               NaN
9840
Name:  ERC20 most sent token type, Length: 9841, dtype: object>
<bound method Series.unique of 0                              Numeraire
1                         Livepeer Token
2                                  XENON
3                                  XENON
4                                    EOS
                       ...
9836                          GSENetwork
9837               Blockwell say NOTSAFU
9838    Free BOB Tokens - BobsRepair.com
9839                                 NaN
9840                          INS Promo1
Name:  ERC20_most_rec_token_type, Length: 9841, dtype: object>
```

In [22]:
```
# drop categorical columns
for col in df.columns:
  if df[col].dtypes == 'O':
    df.drop(columns = [col], inplace = True)
```

- Most of the tockens occur only once so they are irrelevant in fraud detection. So droped them.

In [23]:
```
# Replace missings of numerical variables with median
for col in df.columns:
  df[col] = df[col].fillna(df[col].median())
```

In [24]:
```
# Filtering the features with 0 variance
variance = df.var()

# Select only the features with a non-zero variance
df_filtered = df[variance[variance > 0].index]
# Drop features with 0 variance --- these features will not help in the performance of the model
df = df.drop(columns = df[variance[variance == 0].index].columns, axis =1)
```

In [25]:
```
df_copied = df.copy()
```

In [26]:
```
# drop columns that holds only zeros and highly correlated features
df.drop(columns = ['min value sent to contract', 'max val sent to contract','avg value sent to contract',' ERC20 uniq sent addr.1'], axis = 1, inplace = True)
upper_tri = df.corr().where(np.triu(np.ones(df.corr().shape),k=1).astype(np.bool))
to_drop = [column for column in upper_tri.columns if any(upper_tri[column] > 0.5)]
df = df.drop(columns = to_drop, axis=1)
```

```
<ipython-input-26-967f9e24f774>:3: DeprecationWarning: `np.bool` is a deprecated alias for the builtin `bool`. To silence this warning, use `bool` by itself. Doing this will not modify any behavior and is safe. If you specifically wanted the numpy scalar type, use `np.bool_` here.
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  upper_tri = df.corr().where(np.triu(np.ones(df.corr().shape),k=1).astype(np.bool))
```

In [27]:
```
# Check which columns are having categorical, numerical or boolean values  ERC20 uniq sent addr.1 'avg value sent to contract'
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9841 entries, 0 to 9840
Data columns (total 20 columns):
 #   Column                                Non-Null Count  Dtype  
---  ------                                --------------  -----  
 0   FLAG                                  9841 non-null   int64  
 1   Avg min between sent tnx              9841 non-null   float64
 2   Avg min between received tnx          9841 non-null   float64
 3   Time Diff between first and last (Mins)  9841 non-null   float64
 4   Sent tnx                              9841 non-null   int64  
 5   Received Tnx                          9841 non-null   int64  
 6   Number of Created Contracts           9841 non-null   int64  
 7   min value received                    9841 non-null   float64
 8   max value received                    9841 non-null   float64
 9   min val sent                          9841 non-null   float64
 10  max val sent                          9841 non-null   float64
 11  total Ether sent                      9841 non-null   float64
 12  total ether sent contracts            9841 non-null   float64
 13  total ether balance                   9841 non-null   float64
 14   Total ERC20 tnxs                     9841 non-null   float64
 15   ERC20 total Ether received           9841 non-null   float64
 16   ERC20 total ether sent               9841 non-null   float64
 17   ERC20 total Ether sent contract      9841 non-null   float64
 18   ERC20 uniq rec contract addr         9841 non-null   float64
 19   ERC20 min val rec                    9841 non-null   float64
dtypes: float64(16), int64(4)
memory usage: 1.5 MB
```

In [28]:
```
#recheck the correlation matrix
df.corr()
```

Out[28]:

	FLAG	Avg min between sent tnx	Avg min between received tnx	Time Diff between first and last (Mins)	Sent tnx	Received Tnx	Number of Created Contracts	min value received	max value received	min val sent
FLAG	1.000000	-0.029754	-0.118533	-0.269354	-0.078006	-0.079316	-0.013711	-0.021641	-0.019259	0.006626
Avg min between sent tnx	-0.029754	1.000000	0.060979	0.214722	-0.032289	-0.035735	-0.006186	-0.014886	-0.007104	-0.000789
Avg min between received tnx	-0.118533	0.060979	1.000000	0.303897	-0.040419	-0.053478	-0.008378	-0.045753	-0.011575	-0.008761
Time Diff between first and last (Mins)	-0.269354	0.214722	0.303897	1.000000	0.154480	0.148376	-0.003881	-0.084996	-0.002240	-0.013107
Sent tnx	-0.078006	-0.032289	-0.040419	0.154480	1.000000	0.198455	0.320603	0.024015	0.102109	-0.004846
Received Tnx	-0.079316	-0.035735	-0.053478	0.148376	0.198455	1.000000	-0.003838	-0.022936	0.224805	0.093448
Number of Created Contracts	-0.013711	-0.006186	-0.008378	-0.003881	0.320603	-0.003838	1.000000	-0.001542	-0.000752	-0.000913
min value received	-0.021641	-0.014886	-0.045753	-0.084996	0.024015	-0.022936	-0.001542	1.000000	0.026710	0.117682
max value received	-0.019259	-0.007104	-0.011575	-0.002240	0.102109	0.224805	-0.000752	0.026710	1.000000	0.002239
min val sent	0.006626	-0.000789	-0.008761	-0.013107	-0.004846	0.093448	-0.000913	0.117682	0.002239	1.000000
max val sent	-0.022437	-0.005716	-0.012176	0.014194	0.225356	0.097769	0.141919	0.015061	0.135937	0.022662
total Ether sent	-0.014993	-0.006440	-0.009442	0.012999	0.244434	0.132150	0.024877	-0.001748	0.112739	0.000166
total ether sent contracts	-0.007988	0.001044	-0.003230	0.036162	0.013263	0.008243	-0.000225	-0.002015	-0.000550	-0.000519
total ether balance	-0.003229	-0.001425	-0.002149	0.002955	-0.127211	0.158146	-0.037902	-0.000233	0.278315	0.001514
Total ERC20 tnxs	-0.034132	-0.011061	-0.019177	0.078482	0.381859	0.117093	0.249601	-0.006751	0.032524	-0.002451
ERC20 total Ether received	-0.005711	-0.002339	-0.003430	0.046570	0.006840	0.016648	0.002099	-0.001580	0.006272	-0.000406
ERC20 total ether sent	0.018428	-0.001916	-0.003653	-0.004338	-0.000158	-0.000283	0.001192	-0.001488	-0.000225	-0.000389
ERC20 total Ether sent contract	0.008127	-0.004101	-0.005813	-0.007337	-0.002652	0.104939	-0.000334	-0.002331	0.068761	-0.000600
ERC20 uniq rec contract addr	-0.052473	0.047946	-0.011693	0.324088	0.221971	0.204128	0.029421	-0.000881	0.181755	-0.003749
ERC20 min val rec	0.004434	0.004998	-0.007794	-0.008921	-0.003480	-0.004043	-0.000724	-0.000847	-0.000976	-0.000446

	max val sent	total Ether sent	total ether sent contracts	total ether balance	Total ERC20 tnxs	ERC20 total Ether received	ERC20 total ether sent	ERC20 total Ether sent contract	ERC20 uniq rec contract addr	ERC2 min v re
FLAG	-0.022437	-0.014993	-0.007988	-0.003229	-0.034132	-0.005711	0.018428	0.008127	-0.052473	0.0044
Avg min between sent tnx	-0.005716	-0.006440	0.001044	-0.001425	-0.011061	-0.002339	-0.001916	-0.004101	0.047946	0.0049
Avg min between received tnx	-0.012176	-0.009442	-0.003230	-0.002149	-0.019177	-0.003430	-0.003653	-0.005813	-0.011693	-0.0077
Time Diff between first and last (Mins)	0.014194	0.012999	0.036162	0.002955	0.078482	0.046570	-0.004338	-0.007337	0.324088	-0.0089
Sent tnx	0.225356	0.244434	0.013263	-0.127211	0.381859	0.006840	-0.000158	-0.002652	0.221971	-0.0034
Received Tnx	0.097769	0.132150	0.008243	0.158146	0.117093	0.016648	-0.000283	0.104939	0.204128	-0.0040
Number of Created Contracts	0.141919	0.024877	-0.000225	-0.037902	0.249601	0.002099	0.001192	-0.000334	0.029421	-0.0007
min value received	0.015061	-0.001748	-0.002015	-0.000233	-0.006751	-0.001580	-0.001488	-0.002331	-0.000881	-0.0008
max value received	0.135937	0.112739	-0.000550	0.278315	0.032524	0.006272	-0.000225	0.068761	0.181755	-0.0009
min val sent	0.022662	0.000166	-0.000519	0.001514	-0.002451	-0.000406	-0.000389	-0.000600	-0.003749	-0.0004
max val sent	1.000000	0.470139	-0.000594	-0.564872	0.131102	0.032925	0.000663	-0.000822	0.166292	-0.0010
total Ether sent	0.470139	1.000000	-0.000356	-0.313816	0.072154	0.003749	0.000199	-0.000491	0.088149	-0.0007
total ether sent contracts	-0.000594	-0.000356	1.000000	-0.000074	-0.000201	0.000442	-0.000165	-0.000259	0.012325	-0.0004
total ether balance	-0.564872	-0.313816	-0.000074	1.000000	-0.007995	-0.001737	-0.000301	0.037944	-0.023787	-0.0001
Total ERC20 tnxs	0.131102	0.072154	-0.000201	-0.007995	1.000000	0.004378	0.000802	0.006198	0.264907	-0.0019
ERC20 total Ether received	0.032925	0.003749	0.000442	-0.001737	0.004378	1.000000	0.000113	-0.000132	0.030039	-0.0003
ERC20 total ether sent	0.000663	0.000199	-0.000165	-0.000301	0.000802	0.000113	1.000000	-0.000195	0.001920	-0.0002
ERC20 total Ether sent contract	-0.000822	-0.000491	-0.000259	0.037944	0.006198	-0.000132	-0.000195	1.000000	0.037021	-0.0004
ERC20 uniq rec contract addr	0.166292	0.088149	0.012325	-0.023787	0.264907	0.030039	0.001920	0.037021	1.000000	-0.0059
ERC20 min val rec	-0.001008	-0.000766	-0.000412	-0.000170	-0.001969	-0.000322	-0.000297	-0.000477	-0.005930	1.0000

In [29]:
```
# check columns of dataset
df.columns
```

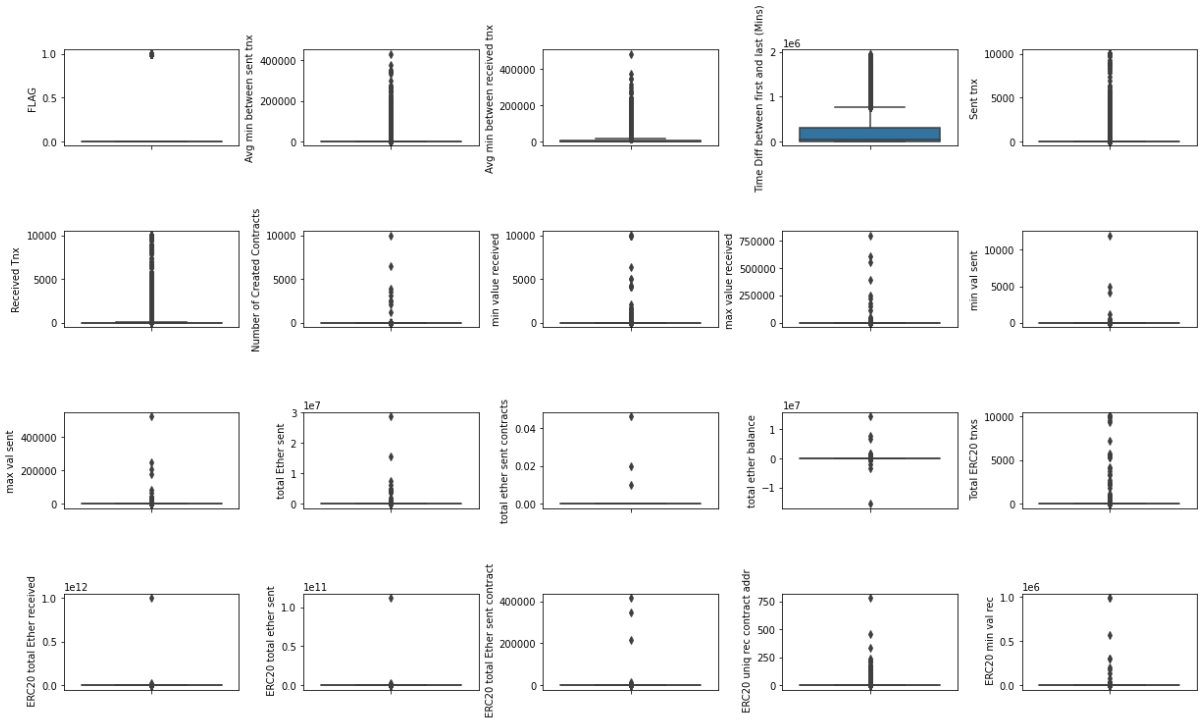
Out[29]:
```
Index(['FLAG', 'Avg min between sent tnx', 'Avg min between received tnx',
       'Time Diff between first and last (Mins)', 'Sent tnx', 'Received Tnx',
       'Number of Created Contracts', 'min value received',
       'max value received ', 'min val sent', 'max val sent',
       'total Ether sent', 'total ether sent contracts', 'total ether balance',
       ' Total ERC20 tnxs', ' ERC20 total Ether received',
       ' ERC20 total ether sent', ' ERC20 total Ether sent contract',
       ' ERC20 uniq rec contract addr', ' ERC20 min val rec'],
      dtype='object')
```

Box plot

- A boxplot is a standardized way of displaying the dataset based on a five-number summary:

1. Minimum (Q0 or 0th percentile): the lowest data point excluding any outliers.
2. Maximum (Q4 or 100th percentile): the largest data point excluding any outliers.
3. Median (Q2 or 50th percentile): the middle value of the dataset.
4. First quartile (Q1 or 25th percentile): also known as the lower quartile qn(0.25), is the median of the lower half of the dataset.
5. Third quartile (Q3 or 75th percentile): also known as the upper quartile qn(0.75), is the median of the upper half of the dataset

```
In [30]: # box plot using pandas
         # box plot for Avg min between sent tnx column
         fig, ax = plt.subplots(ncols = 5, nrows = 4, figsize=(17,10))
         index = 0
         ax = ax.flatten()
         for col, value in df.items():
           sns.boxplot(y = col, data = df, ax=ax[index])
           index += 1
         plt.tight_layout(pad=0.5, w_pad=0.7, h_pad=5.0)
```

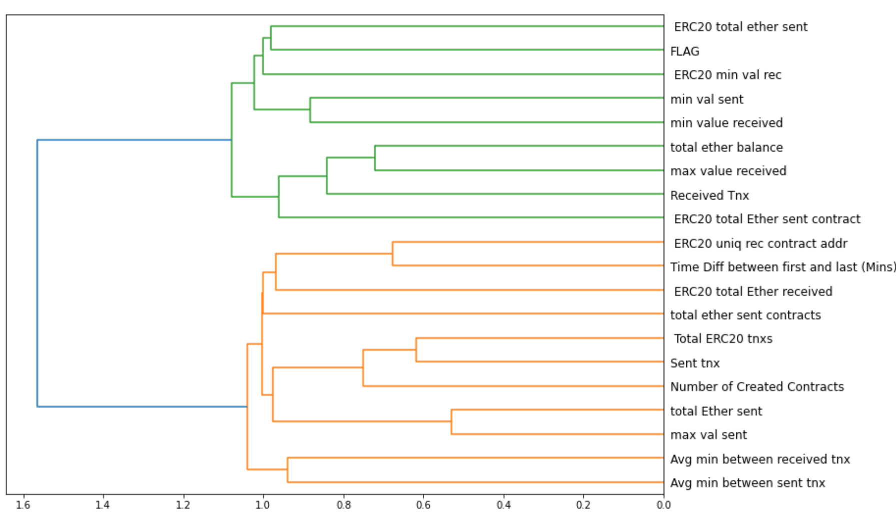


- From all boxen plot we can see that the dataset is heavily skewed

DENDROGRAM

```
In [31]: # Plot a Dendrogram on the columns of the dataset
         # from collections import defaultdict
         from scipy.spatial.distance import pdist, squareform
         from scipy.cluster.hierarchy import linkage, dendrogram
         %pylab inline
         from pylab import rcParams
         rcParams['figure.figsize'] = 12, 9
         clustdf_t = df.transpose()
         c_dist = pdist(clustdf_t) # computing the distance
         c_link = linkage(clustdf_t,  metric='correlation', method='complete')# computing the linkage
         B=dendrogram(c_link,labels=list(df.columns),orientation='left')
         # droping the NaN values
```

```
Populating the interactive namespace from numpy and matplotlib
```



DATA PREPROCESSING

In [32]:
```
## Split the labels and the target
X = df.iloc[ : , 1: ]
y = df.iloc[ : , :1 ]

#check the shape
print(X.shape)
print(y.shape)
```

```
(9841, 19)
(9841, 1)
```

In [33]:
```
# import train test split
from sklearn.model_selection import train_test_split
```

In [34]:
```
# Split into training (80%) and testing set (20%)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=1)
# check the shape of train and test
print(X_train.shape)
print(X_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(7872, 19)
(1969, 19)
(7872, 1)
(1969, 1)
```

HANDLING SKEWNESS

In [35]:
```
# import pipeline
#import standaer scalar
# import simple imputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
```

In [36]:
```
# create pipeline
# 1.simple imputer
# 2. standard scalar
pipe = Pipeline([
    ('imputer', SimpleImputer(strategy='mean')),
    ('scaler', StandardScaler())
])
```

In [37]:
```
# fit the pipline on train data
X_train = pipe.fit_transform(X_train)
X_test = pipe.transform(X_test)
```

HANDLING IMBALANCE

SMOTE stands for Synthetic Minority Oversampling Technique. This is a statistical technique for increasing the number of cases in your dataset in a balanced way. The module works by generating new instances from existing minority cases that you supply as input.

SMOTE - https://www.geeksforgeeks.org/ml-handling-imbalanced-data-with-smote-and-near-miss-algorithm-in-python/ (https://www.geeksforgeeks.org/ml-handling-imbalanced-data-with-smote-and-near-miss-algorithm-in-python/)

In [38]:
```
from imblearn.over_sampling import SMOTE

# Instantiate the SMOTE class
sm = SMOTE(sampling_strategy='minority')

# Fit and transform the training data using SMOTE
X_train, y_train = sm.fit_resample(X_train, y_train)

# Print the shape of X_train after oversampling
print("Shape of X_train after oversampling:", X_train.shape)

# Print the shape of y_train after oversampling
print("Shape of y_train after oversampling:", y_train.shape)
```

```
Shape of X_train after oversampling: (12222, 19)
Shape of y_train after oversampling: (12222, 1)
```

MODELING

In [39]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.ensemble import VotingClassifier
from sklearn.tree import DecisionTreeClassifier
from xgboost import XGBClassifier
from lightgbm import LGBMClassifier
from imblearn.under_sampling import RandomUnderSampler
from imblearn.pipeline import Pipeline
from sklearn.linear_model import SGDClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import RandomizedSearchCV
# Evaluation Metrics
from sklearn.metrics import accuracy_score,roc_auc_score, classification_report, precision_score, recall_score, f1_score, confusion_matrix, roc_curve
# Plots
from sklearn import tree
```

In [40]:
```python
# Function for calculating all the relevant metrics
"""Function to calculate all evaluation metrics"""
def evaluation(y_test,y_pred):
    Accuracy = accuracy_score(y_test, y_pred)
    conf_mat = confusion_matrix(y_test, y_pred)
    true_positive = conf_mat[0][0]
    false_positive = conf_mat[0][1]
    false_negative = conf_mat[1][0]
    true_negative = conf_mat[1][1]
    Precision = true_positive /(true_positive + false_positive)
    Recall = true_positive/(true_positive + false_negative)
    F1_Score = 2*(Recall * Precision) / (Recall + Precision)
    AUC = roc_auc_score(y_test, y_pred)
    return Accuracy,Precision,Recall,F1_Score,AUC
```

Model Creation

Hyper parameter tunning

- A hyperparameter is a parameter whose value is set before the learning process begins
- Hyperparameters tuning is crucial as they control the overall behavior of a machine learning model
- Every machine learning models will have different hyperparameters that can be set

Note: Directly hpyerparametr tuning has been done to get the best accuracy based on the experience. Beginner should always build basic model first then go for hyper parameter tuning

In [41]:
```python
'''Hyperparameters of Logistics Regression'''
LR_parameters = {
    'C': np.random.uniform(0.001,1,5),
    'tol':np.random.uniform(0.0001,0.1,5)
    }

'''Hyperparameters of SGD Classifier With Hinge Loss'''
SGD_parameters = {
    'penalty': ['l1','l2'],
    'alpha':np.random.uniform(0.0001,0.1,9)
    }

'''Hyperparameters of Naive Bayes'''
NB_parameters = {
    'var_smoothing': np.random.uniform(1e-16,1e-14,100)
    }

'''Hyperparameters of Decision Tree Classifier'''
DTC_parameters = {
    'max_depth': np.random.randint(10,25,5)
    }

'''Hyperparameters of Random Forest Classifer'''
RF_parameters = {
    'n_estimators': [300,500,600,650,700],
    'max_depth': [80,110,125,135]
    }

'''Hyperparameters of Gradient Boosted Decision Trees'''
GBDT_parameters = {
    'n_estimators':[100, 250,350,500],
    'max_depth': [4,6,10,15],
    'learning_rate':[0.001,0.01,0.1,1,10]
    }

'''Hyperparameters of AdaBoost Classifier'''
AB_parameters = {
    'n_estimators':[ 400 , 600 , 650 , 700 , 750 , 800 ]
    }

'''All Models'''
models = {
1 : RandomizedSearchCV(estimator = LogisticRegression(), param_distributions = LR_parameters, scoring= 'f1',verbose=2, n_jobs = -1, cv=5),
2 : RandomizedSearchCV(estimator = SGDClassifier(), param_distributions = SGD_parameters, scoring= 'f1',verbose=2, n_jobs = -1, cv=5),
3 : RandomizedSearchCV(estimator = GaussianNB(), param_distributions = NB_parameters, scoring= 'f1',verbose=2, n_jobs = -1, cv=5),
4 : RandomizedSearchCV(estimator = DecisionTreeClassifier(), param_distributions = DTC_parameters, scoring= 'f1',verbose=2, n_jobs = -1, cv=5),
5 : RandomizedSearchCV(estimator = RandomForestClassifier(), param_distributions = RF_parameters, scoring= 'f1',verbose=2, n_jobs = -1, cv=5),
6 : RandomizedSearchCV(estimator = GradientBoostingClassifier(), param_distributions = GBDT_parameters, scoring= 'f1',verbose=2, n_jobs = -1, cv=5),
7 : RandomizedSearchCV(estimator = AdaBoostClassifier(), param_distributions = AB_parameters, scoring= 'f1',verbose=2, n_jobs = -1, cv=5)

}

map_keys = list(models.keys())
```

In [42]:
```python
# Get model name using id from linear_model_collection
def get_model_building_technique_name(num):
  if num == 1:
    return 'LogisticRegression_Tuned'
  if num == 2:
    return 'SGDClassifier_Hinge_Loss_Tuned'
  if num == 3:
    return 'NaiveBayes_Tune'
  if num == 4:
    return 'DecisionTreeClassifier_Tuned'
  if num == 5:
    return 'RandomForestClassifier_Tuned'
  if num == 6:
    return 'GradientBoostingClassifier_Tuned'
  if num == 7:
    return 'AdaBoostClassifier_Tuned'
  return ''
```

In [43]:
```
results = [];
for key_index in range(len(map_keys)):
  key = map_keys[key_index]
  try:
    # if key in [3,4,5,6,7,8]:
    model = models[key]
    print(key)
    model.fit(X_train, y_train)


    y_pred_train = model.predict(X_train)
    y_pred_test = model.predict(X_test)

    '''Test Accuracy'''
    Accuracy_Test, Precision_Test, Recall_Test, F1_Score_Test, AUC_Test =  evaluation(y_test, y_pred_test)

    '''Train Accuracy'''
    y_pred_train = model.predict(X_train)

    Accuracy_Train, Precision_Train, Recall_Train, F1_Score_Train, AUC_Train =  evaluation(y_train, y_pred_train)

    results.append({
        'Model Name' : get_model_building_technique_name(key),
        'Trained Model' : model,
        'Accuracy_Test' : Accuracy_Test,
        'Precision_Test' : Precision_Test,
        'Recall_Test' : Recall_Test,
        'F1_Macro_Score_Test' : F1_Score_Test,
        'AUC_Test' : AUC_Test,
        'Accuracy_Train' : Accuracy_Train,
        'Precision_Train' : Precision_Train,
        'Recall_Train' : Recall_Train,
        'F1_Macro_Score_Train' : F1_Score_Train,
        'AUC_Train' : AUC_Train
        })

  except Exception as e:
    print(e)
```

```
1
Fitting 5 folds for each of 10 candidates, totalling 50 fits

/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:993: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)

2
Fitting 5 folds for each of 10 candidates, totalling 50 fits

/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:993: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)

3
Fitting 5 folds for each of 10 candidates, totalling 50 fits

/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:993: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
/usr/local/lib/python3.8/dist-packages/sklearn/model_selection/_search.py:292: UserWarning: The total space of parameters 5 is smaller than n_iter=10. Running 5 iterations. For
exhaustive searches, use GridSearchCV.
  warnings.warn(

4
Fitting 5 folds for each of 5 candidates, totalling 25 fits
5
Fitting 5 folds for each of 10 candidates, totalling 50 fits

/usr/local/lib/python3.8/dist-packages/sklearn/model_selection/_search.py:926: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change th
e shape of y to (n_samples,), for example using ravel().
  self.best_estimator_.fit(X, y, **fit_params)

6
Fitting 5 folds for each of 10 candidates, totalling 50 fits

/usr/local/lib/python3.8/dist-packages/sklearn/ensemble/_gb.py:494: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape of
y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)

7
Fitting 5 folds for each of 6 candidates, totalling 30 fits

/usr/local/lib/python3.8/dist-packages/sklearn/model_selection/_search.py:292: UserWarning: The total space of parameters 6 is smaller than n_iter=10. Running 6 iterations. For
exhaustive searches, use GridSearchCV.
  warnings.warn(
/usr/local/lib/python3.8/dist-packages/sklearn/utils/validation.py:993: DataConversionWarning: A column-vector y was passed when a 1d array was expected. Please change the shape
of y to (n_samples, ), for example using ravel().
  y = column_or_1d(y, warn=True)
```

In [44]:
```
result_df = pd.DataFrame(results)
result_df
# result_df_test = result_df.iloc[: , [0,2,3,4,5,6]]
# result_df_test
# result_df_train = result_df.iloc[: , [0,7,8,9,10,11]]
# result_df_train
```

Out[44]:

	Model Name	Trained Model	Accuracy_Test	Precision_Test	Recall_Test	F1_Macro_Score_Test	AUC_Test	Accuracy_Train	Precision_Train	Recall_Train	F1_Macro_Score_Train	AUC_Train
0	LogisticRegression_Tuned	RandomizedSearchCV(cv=5, estimator=LogisticReg...	0.604368	0.535783	0.933708	0.680868	0.697318	0.707822	0.552610	0.801376	0.654140	0.707822
1	SGDClassifier_Hinge_Loss_Tuned	RandomizedSearchCV(cv=5, estimator=SGDClassifi...	0.601828	0.534494	0.930415	0.678952	0.693084	0.705367	0.552774	0.795572	0.652312	0.705367
2	NaiveBayes_Tune	RandomizedSearchCV(cv=5, estimator=GaussianNB(...	0.311326	0.128304	0.980296	0.226910	0.559367	0.566519	0.150057	0.898139	0.257151	0.566519
3	DecisionTreeClassifier_Tuned	RandomizedSearchCV(cv=5, estimator=DecisionTre...	0.960386	0.974855	0.974855	0.974855	0.940777	1.000000	1.000000	1.000000	1.000000	1.000000
4	RandomForestClassifier_Tuned	RandomizedSearchCV(cv=5, estimator=RandomFores...	0.974606	0.984526	0.983258	0.983892	0.961163	1.000000	1.000000	1.000000	1.000000	1.000000
5	GradientBoostingClassifier_Tuned	RandomizedSearchCV(cv=5, estimator=GradientBoo...	0.974099	0.982592	0.984496	0.983543	0.962588	1.000000	1.000000	1.000000	1.000000	1.000000
6	AdaBoostClassifier_Tuned	RandomizedSearchCV(cv=5, estimator=AdaBoostCla...	0.965465	0.970342	0.985593	0.977908	0.958855	0.984045	0.982163	0.985874	0.984015	0.984045

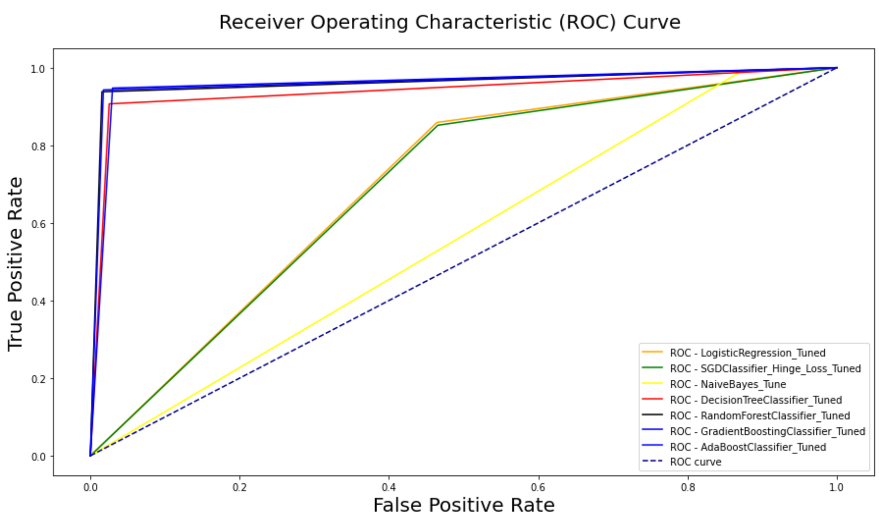
ROC Curve

- The overall performance of a classifier, summarized over all possible thresholds, is given by the Receiver Operating Characteristics (ROC) curve. The name “ROC” is historical and comes from communications theory. ROC Curves are used to see how well your classifier can separate positive and negative examples and to identify the best threshold for separating them.
- To be able to use the ROC curve, your classifier should be able to rank examples such that the ones with higher rank are more likely to be positive (fraudulent)
- ROC Curves summarize the trade-off between the true positive rate and false positive rate for a predictive model using different probability thresholds.

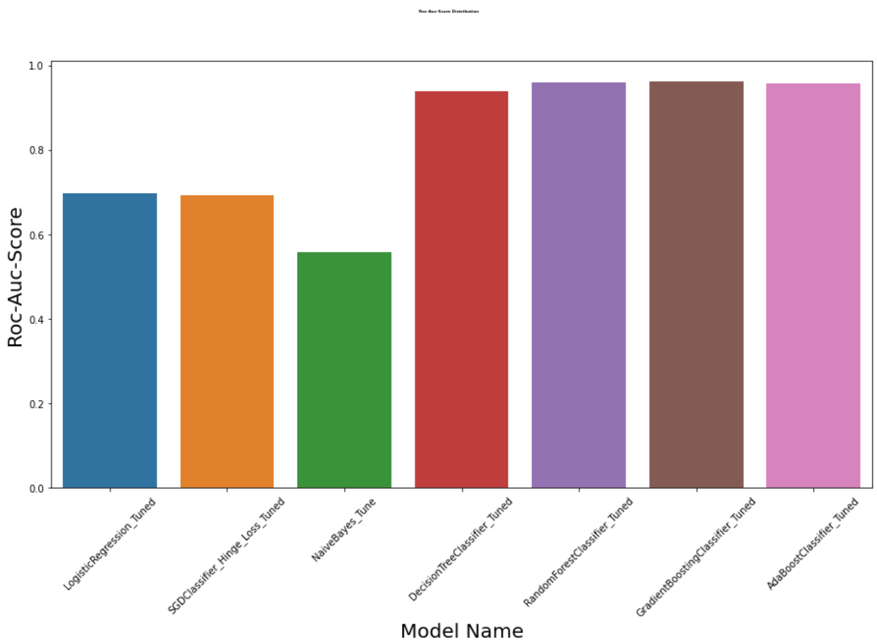
AUC (Area Under the Curve)

- The model performance is determined by looking at the area under the ROC curve (or AUC). An excellent model has AUC near to the 1.0, which means it has a good measure of separability

In [54]:
```
fpr_dict = {}
tpr_dict = {}
for i in range(len(map_keys)):

    model_pred = result_df['Trained Model'][i].predict(X_test)
    fpr, tpr, thresholds = roc_curve(y_test, model_pred)
    fpr_dict[i] = fpr
    tpr_dict[i] = tpr

plt.figure(figsize=(15,8))
plt.suptitle('\nReceiver Operating Characteristic (ROC) Curve', fontsize=20)
plt.plot(fpr_dict[0], tpr_dict[0], color='orange', label=f"ROC - {result_df['Model Name'][0]}")
plt.plot(fpr_dict[1], tpr_dict[1], color='green', label=f"ROC - {result_df['Model Name'][1]}")
plt.plot(fpr_dict[2], tpr_dict[2], color='yellow', label=f"ROC - {result_df['Model Name'][2]}")
plt.plot(fpr_dict[3], tpr_dict[3], color='red', label=f"ROC - {result_df['Model Name'][3]}")
plt.plot(fpr_dict[4], tpr_dict[4], color='black', label=f"ROC - {result_df['Model Name'][4]}")
plt.plot(fpr_dict[5], tpr_dict[5], color='blue', label=f"ROC - {result_df['Model Name'][5]}")
plt.plot(fpr_dict[6], tpr_dict[6], color='blue', label=f"ROC - {result_df['Model Name'][6]}")

plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--',label='ROC curve')
plt.xlabel('False Positive Rate',fontdict={'fontsize': 20})
plt.ylabel('True Positive Rate',fontdict={'fontsize': 20})
plt.legend()
plt.show()
```



In [55]:
```
plt.figure(figsize=(15,8))
plt.suptitle('\nRoc-Auc-Score Distribution\n\n', fontsize=4, fontweight='bold')
sns.barplot(data=result_df, x='Model Name', y='AUC_Test')
plt.xlabel('Model Name',fontdict={'fontsize': 20})
plt.ylabel('Roc-Auc-Score',fontdict={'fontsize': 20})
plt.xticks(rotation=45)
plt.show()
```



In [56]:
```
Best_Model_Name = result_df['Trained Model'][result_df[result_df['AUC_Test'] == max(result_df['AUC_Test'])]['Trained Model'].index[0]]
Best_Model_Index = result_df['Trained Model'][result_df[result_df['AUC_Test'] == max(result_df['AUC_Test'])]['Trained Model'].index].index[0]
Best_Model_Name
```

Out[56]:
```
RandomizedSearchCV(cv=5, estimator=GradientBoostingClassifier(), n_jobs=-1,
                   param_distributions={'learning_rate': [0.001, 0.01, 0.1, 1,
                                                          10],
                                        'max_depth': [4, 6, 10, 15],
                                        'n_estimators': [100, 250, 350, 500]},
                   scoring='f1', verbose=2)
```

In [57]:
```
import pickle
with open('ETHEREUM_Fraud_Detection.sav', 'wb') as best_model_pickle:
 pickle.dump(Best_Model_Name, best_model_pickle)
```

Conclusion

- We did training and prediction using all the above models and selected Gradient Boosting Classifier as final model as it performed well compard to other models with acurracy of 98%
- We have performed EDA, preprocessing, build different models, visualized feature importance, hyper parameter tunning and did prediction
- We also perform necessary operations to handle imbalanced and skewed nature of data

THE END