Project

December 3, 2023

0.1 Project

0.1.1 Problem definition

1) Ethereum is a decentralized blockchain platform that establishes a peer-to-peer network that securely executes and verifies application code, called smart contracts. A transaction once done can't be undone in blockchain network. So it is very important to identify any illegal transactions in the network and prevent them from corrupting the entire blockchain network.

2) The goal of this project is to build a machine learning model which classifies a given transaction as fraud or valid transaction.

3) We will use F1 score and Area under ROC curve as the metrics.

0.1.2 Data

1. Download the data from this link https://www.kaggle.com/datasets/vagifa/ethereum-frauddetection-dataset/data. Copy the transaction_dataset.csv in the download folder to data/

[1]:
```python
import numpy as np
import pandas as pd
import warnings
warnings.filterwarnings('ignore', category=Warning)
```

[2]:
```python
# Load the transactions data
df = pd.read_csv('data/transaction_dataset.csv')

# Sample transactions
df.head()
```

[2]:
```
   Unnamed: 0  Index                                     Address  FLAG  \
0           0      1  0x00009277775ac7d0d59eaad8fee3d10ac6c805e8     0
1           1      2  0x0002b44ddb1476db43c868bd494422ee4c136fed     0
2           2      3  0x0002bda54cb772d040f779e88eb453cac0daa244     0
3           3      4  0x00038e6ba2fd5c09aedb96697c8d7b8fa6632e5e     0
4           4      5  0x00062d1dd1afb6fb02540ddad9cdebfe568e0d89     0

   Avg min between sent tnx  Avg min between received tnx  \
0                    844.26                       1093.71
```

```
1               12709.07                       2958.44
2              246194.54                       2434.02
3               10219.60                      15785.09
4                  36.61                      10707.77

   Time Diff between first and last (Mins)  Sent tnx  Received Tnx  \
0                                704785.63       721            89
1                               1218216.73        94             8
2                                516729.30         2            10
3                                397555.90        25             9
4                                382472.42      4598            20

   Number of Created Contracts  …   ERC20 min val sent   ERC20 max val sent  \
0                            0  …             0.000000         1.683100e+07
1                            0  …             2.260809         2.260809e+00
2                            0  …             0.000000         0.000000e+00
3                            0  …           100.000000         9.029231e+03
4                            1  …             0.000000         4.500000e+04

    ERC20 avg val sent   ERC20 min val sent contract  \
0        271779.920000                           0.0
1             2.260809                           0.0
2             0.000000                           0.0
3          3804.076893                           0.0
4         13726.659220                           0.0

    ERC20 max val sent contract   ERC20 avg val sent contract  \
0                           0.0                           0.0
1                           0.0                           0.0
2                           0.0                           0.0
3                           0.0                           0.0
4                           0.0                           0.0

    ERC20 uniq sent token name   ERC20 uniq rec token name  \
0                         39.0                        57.0
1                          1.0                         7.0
2                          0.0                         8.0
3                          1.0                        11.0
4                          6.0                        27.0

    ERC20 most sent token type   ERC20_most_rec_token_type
0                    Cofoundit                   Numeraire
1               Livepeer Token              Livepeer Token
2                         None                       XENON
3                       Raiden                       XENON
4                 StatusNetwork                        EOS
```

```
[5 rows x 51 columns]
```

[3]:
```
df.shape
```

[3]:
```
(9841, 51)
```

0.1.3 Preprocessing

[4]:
```
# Stats of the features
df.describe()
```

[4]:
```
         Unnamed: 0        Index         FLAG  Avg min between sent tnx  \
count  9841.000000  9841.000000  9841.000000               9841.000000
mean   4920.000000  1815.049893     0.221421               5086.878721
std    2840.996333  1222.621830     0.415224              21486.549974
min       0.000000     1.000000     0.000000                  0.000000
25%    2460.000000   821.000000     0.000000                  0.000000
50%    4920.000000  1641.000000     0.000000                 17.340000
75%    7380.000000  2601.000000     0.000000                565.470000
max    9840.000000  4729.000000     1.000000             430287.670000

       Avg min between received tnx  Time Diff between first and last (Mins)  \
count                   9841.000000                             9.841000e+03
mean                    8004.851184                             2.183333e+05
std                    23081.714801                             3.229379e+05
min                        0.000000                             0.000000e+00
25%                        0.000000                             3.169300e+02
50%                      509.770000                             4.663703e+04
75%                     5480.390000                             3.040710e+05
max                   482175.490000                             1.954861e+06

         Sent tnx  Received Tnx  Number of Created Contracts  \
count   9841.000000   9841.000000                  9841.000000
mean     115.931714    163.700945                     3.729702
std      757.226361    940.836550                   141.445583
min        0.000000      0.000000                     0.000000
25%        1.000000      1.000000                     0.000000
50%        3.000000      4.000000                     0.000000
75%       11.000000     27.000000                     0.000000
max    10000.000000  10000.000000                  9995.000000

       Unique Received From Addresses  …   ERC20 max val rec  \
count                     9841.000000  …        9.012000e+03
mean                        30.360939  …        1.252524e+08
std                        298.621112  …        1.053741e+10
min                          0.000000  …        0.000000e+00
25%                          1.000000  …        0.000000e+00
```

50%	2.000000	…	0.000000e+00
75%	5.000000	…	9.900000e+01
max	9999.000000	…	1.000000e+12

	ERC20 avg val rec	ERC20 min val sent	ERC20 max val sent	\
count	9.012000e+03	9.012000e+03	9.012000e+03	
mean	4.346203e+06	1.174126e+04	1.303594e+07	
std	2.141192e+08	1.053567e+06	1.179905e+09	
min	0.000000e+00	0.000000e+00	0.000000e+00	
25%	0.000000e+00	0.000000e+00	0.000000e+00	
50%	0.000000e+00	0.000000e+00	0.000000e+00	
75%	2.946467e+01	0.000000e+00	0.000000e+00	
max	1.724181e+10	1.000000e+08	1.120000e+11	

	ERC20 avg val sent	ERC20 min val sent contract	\
count	9.012000e+03	9012.0	
mean	6.318389e+06	0.0	
std	5.914764e+08	0.0	
min	0.000000e+00	0.0	
25%	0.000000e+00	0.0	
50%	0.000000e+00	0.0	
75%	0.000000e+00	0.0	
max	5.614756e+10	0.0	

	ERC20 max val sent contract	ERC20 avg val sent contract	\
count	9012.0	9012.0	
mean	0.0	0.0	
std	0.0	0.0	
min	0.0	0.0	
25%	0.0	0.0	
50%	0.0	0.0	
75%	0.0	0.0	
max	0.0	0.0	

	ERC20 uniq sent token name	ERC20 uniq rec token name
count	9012.000000	9012.000000
mean	1.384931	4.826676
std	6.735121	16.678607
min	0.000000	0.000000
25%	0.000000	0.000000
50%	0.000000	1.000000
75%	0.000000	2.000000
max	213.000000	737.000000

[8 rows x 48 columns]

[5]:
```
# NaNs in each features
df.isna().sum()
```

[5]:
```
Unnamed: 0                                               0
Index                                                    0
Address                                                  0
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
```

[6]:
```
# number of distinct values in each features
df.nunique()
```

[6]:
```
Unnamed: 0                                               9841
Index                                                    4729
Address                                                  9816
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
dtype: int64
```

0.1.4 Removing irrelevent features and records

1. The features 'Index', 'Unnamed: 0' are just row numbers, they are not relavent to our problem.
2. The feature 'Address' is a random number given to the each node in the blockchain network. It's a value used to identify the node in the network. So feature 'Address' doesn't have any influence of on the transaction type and is not relavent to our problem.
3. From the number of distinct values in each features above we can see that there are 7 features with only one value. Keeping these in the model data is not relevent (since all transactions have same value) in predicting the type of transaction.
4. The features ' ERC20 most sent token type' and ' ERC20_most_rec_token_type' have garbage data, so removing.
5. Removing the records which have NaN values beacuse we cannot fill them with random values or mean values becuase each transaction is different and filling them may add bias to the data.
6. Dropping the duplicates

[7]:
```
df = df.drop(['Index'], axis = 1)
df = df.drop(['Unnamed: 0'], axis = 1)
df = df.drop(['Address'], axis = 1)
df = df.drop([' ERC20 most sent token type'], axis = 1)
df = df.drop([' ERC20_most_rec_token_type'], axis = 1)
df = df.drop([' ERC20 avg time between sent tnx'], axis = 1)
df = df.drop([' ERC20 avg time between rec tnx'], axis = 1)
df = df.drop([' ERC20 avg time between rec 2 tnx'], axis = 1)
df = df.drop([' ERC20 avg time between contract tnx'], axis = 1)
df = df.drop([' ERC20 min val sent contract'], axis = 1)
df = df.drop([' ERC20 max val sent contract'], axis = 1)
df = df.drop([' ERC20 avg val sent contract'], axis = 1)
df = df.dropna()
df = df.drop_duplicates()
```

0.1.5 Balancing dataset

[8]:
```
print("Number of invalid transaction in data = " +str(np.sum(np.
↪where(df['FLAG']==1,1,0))))
print("Number of valid transaction in data = " +str(np.sum(np.
↪where(df['FLAG']==0,1,0))))
```

```
Number of invalid transaction in data = 1107
Number of valid transaction in data = 7632
```

[9]:
```
Y = df['FLAG']
X = df.drop(['FLAG'], axis = 1)
```

[10]:
```
# Balancing data
from imblearn.over_sampling import RandomOverSampler
ros = RandomOverSampler(random_state=42)
X, Y = ros.fit_resample(X, Y)
print("X dimensions = "+str(X.shape))
print("Y dimensions = "+str(Y.shape))
```

```
X dimensions = (15264, 38)
Y dimensions = (15264,)
```

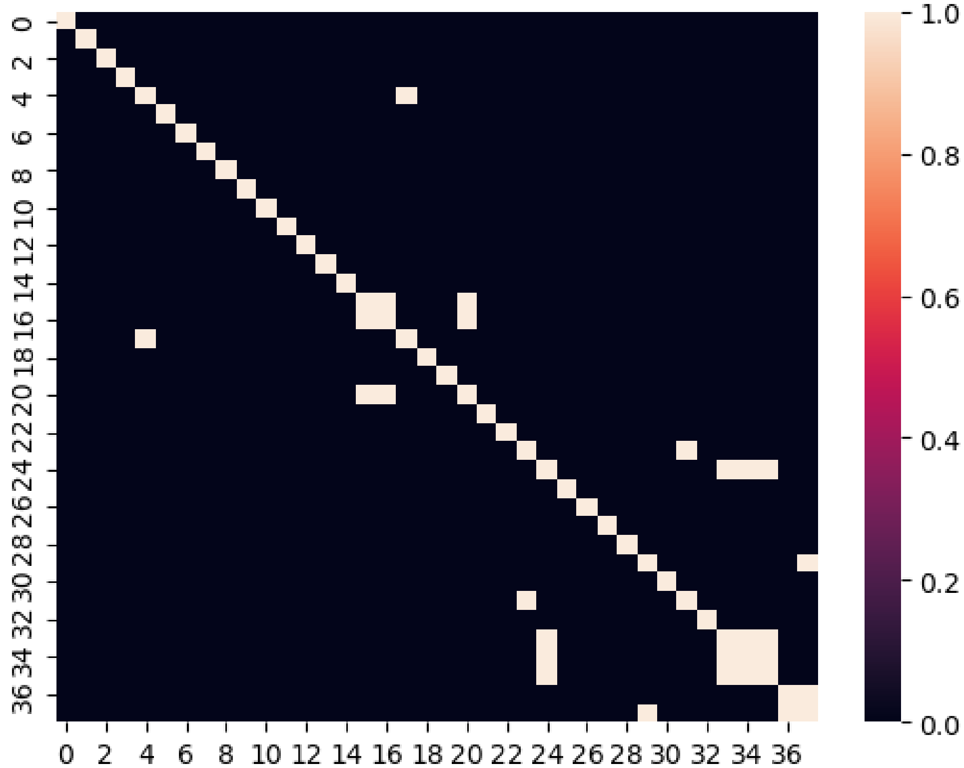
[11]:
```
print("Number of invalid transaction in data after balancing = " +str(np.sum(np.
↪where(Y==1,1,0))))
print("Number of valid transaction in data after balancing = " +str(np.sum(np.
↪where(Y==0,1,0))))
```

```
Number of invalid transaction in data after balancing = 7632
Number of valid transaction in data after balancing = 7632
```

0.1.6 Data reduction

[12]:
```
# Correlation of data
import seaborn as sns
import matplotlib.pyplot as plt

correlation = X.corr()
correlation_count = (np.sum(np.where(np.abs(correlation)>0.8,1,0)) -␣
↪correlation.shape[0])/2
print("Number of pairs of feaures which have correlation coefficient > 0.8 = "␣
↪+ str(correlation_count))

print("Correlation plot:")
sns.heatmap(np.where(np.abs(correlation)>0.8,1,0));
```

```
Number of pairs of feaures which have correlation coefficient > 0.8 = 13.0
Correlation plot:
```



Perform PCA and reduce the number of features from 38 to 25. (Removing one of the feature from each 13 pair highly correlated featured)

[13]:
```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler

X_scaled = StandardScaler().fit_transform(X)
X_pca = PCA(n_components=25).fit_transform(X_scaled)
```

0.1.7 Data split

Data is divided randomly into train, validation and test data with 60% in train, 20% in validation and 20% in test

[14]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X_pca, Y, test_size=0.2,␣
 ↪random_state=42)
X_train, X_val, Y_train, Y_val = train_test_split(X_train, Y_train, test_size=0.
 ↪25, random_state=42) # 0.25 x 0.8 = 0.2
```

[15]:
```
print("Train data shape = "+str(X_train.shape))
print("Validation data shape = "+str(X_val.shape))
```

```
print("Test data shape = "+str(X_test.shape))
```

```
Train data shape = (9158, 25)
Validation data shape = (3053, 25)
Test data shape = (3053, 25)
```

0.1.8 Models

```
1) Logistic regression
2) Decision tree
3) AdaBoostClassifier (ensemble method with Decision tree as base estimator)
4) Support Vector Machines (with 'linear', 'poly', 'rbf', 'sigmoid' kernels)
5) Neural Network (MLPClassifier)
```

[16]:
```
from sklearn.metrics import roc_auc_score, roc_curve, auc
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix, precision_score, recall_score,␣
 ↪f1_score
```

0.1.9 Logistic Regression

1. Used the default parameters of the model. So, L2 regularization with regularization strength(C) = 1.0

[17]:
```
## Logistic regression
from sklearn.linear_model import LogisticRegression
LR_model = LogisticRegression(random_state=42).fit(X_train, Y_train)

Y_train_pred = LR_model.predict_proba(X_train)[:, 1]
Y_val_pred = LR_model.predict_proba(X_val)[:, 1]
Y_test_pred = LR_model.predict_proba(X_test)[:, 1]

f1score_train = f1_score(Y_train, Y_train_pred>0.5)
f1score_val = f1_score(Y_val, Y_val_pred>0.5)
f1score_test = f1_score(Y_test, Y_test_pred>0.5)

print("Train F1 score = "+str(f1score_train))
print("Validation F1 score = "+str(f1score_val))
print("Test F1 score = "+str(f1score_test))

auc_train = roc_auc_score(Y_train, Y_train_pred)
auc_val = roc_auc_score(Y_val, Y_val_pred)
auc_test = roc_auc_score(Y_test, Y_test_pred)

print("\nTrain AUC = "+str(auc_train))
print("Validation AUC = "+str(auc_val))
print("Test AUC = "+str(auc_test))
```

```
Train F1 score = 0.7419354838709677
```

```
Validation F1 score = 0.7468926553672317
Test F1 score = 0.7357452966714907

Train AUC = 0.8211310862666497
Validation AUC = 0.8350363133551925
Test AUC = 0.8171074190771364
```

Comment on logistic regresion model:

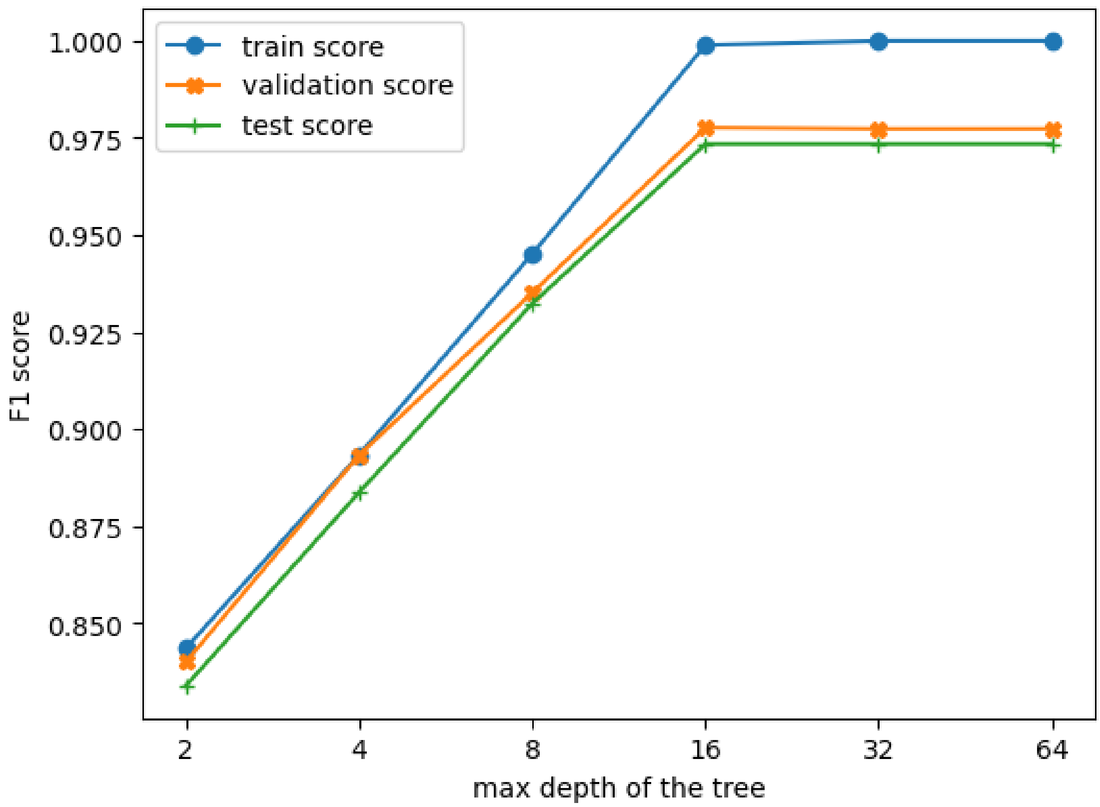
1. From the F1 score we can see that this model is not doing a good job.
2. F1 score of train, validation & test data is in the range of 0.73 - 0.75

0.1.10 Decision Tree

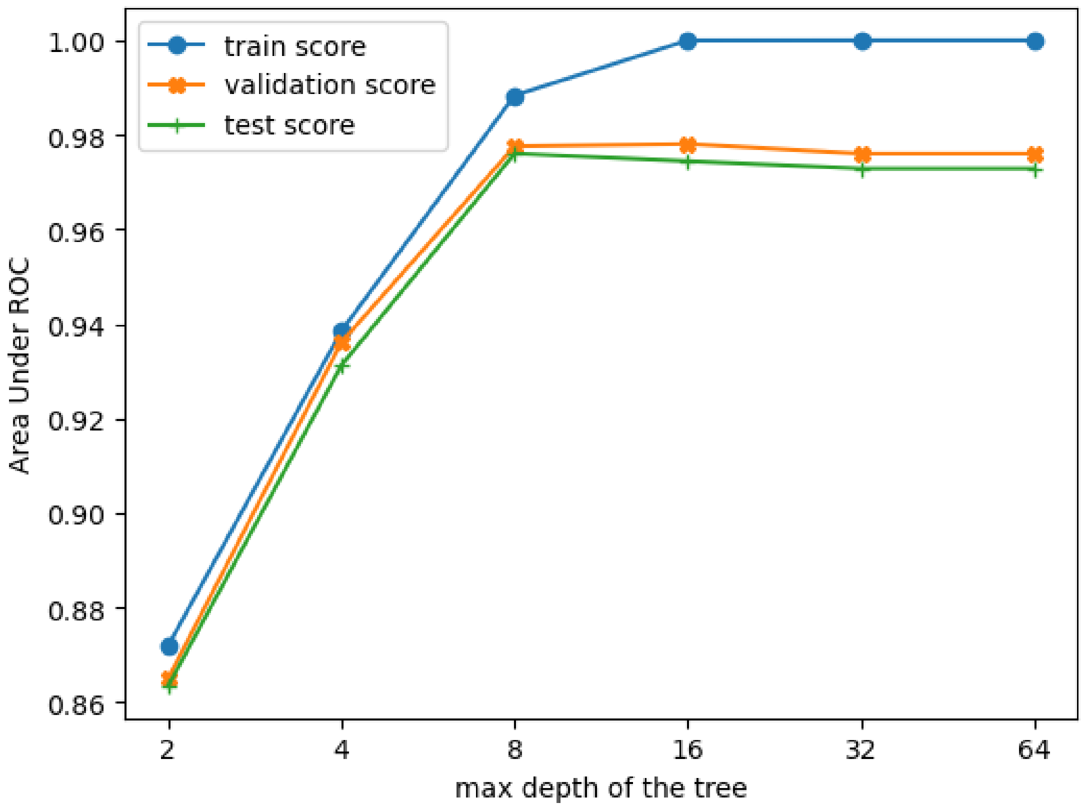
1. Used Entropy as the impurity measure

[18]:
```
## Decision Tree
from sklearn.tree import DecisionTreeClassifier

max_depths = [2,4,8,16,32,64]
DT_train_f1score = []
DT_val_f1score = []
DT_test_f1score = []

DT_train_aucscore = []
DT_val_aucscore = []
DT_test_aucscore = []

for depth in max_depths:
    DT_model = DecisionTreeClassifier(criterion='entropy', max_depth=depth,␣
 ↪random_state=42).fit(X_train, Y_train)

    Y_train_pred = DT_model.predict_proba(X_train)[:, 1]
    Y_val_pred = DT_model.predict_proba(X_val)[:, 1]
    Y_test_pred = DT_model.predict_proba(X_test)[:, 1]

    f1score_train = f1_score(Y_train, Y_train_pred>0.5)
    f1score_val = f1_score(Y_val, Y_val_pred>0.5)
    f1score_test = f1_score(Y_test, Y_test_pred>0.5)

    DT_train_f1score.append(f1score_train)
    DT_val_f1score.append(f1score_val)
    DT_test_f1score.append(f1score_test)

    auc_train = roc_auc_score(Y_train, Y_train_pred)
    auc_val = roc_auc_score(Y_val, Y_val_pred)
    auc_test = roc_auc_score(Y_test, Y_test_pred)
```

```
    DT_train_aucscore.append(auc_train)
    DT_val_aucscore.append(auc_val)
    DT_test_aucscore.append(auc_test)


plt.plot([str(i) for i in max_depths], DT_train_f1score, 'o-', label = "train␣
 ↪score")
plt.plot([str(i) for i in max_depths], DT_val_f1score, 'X-', label =␣
 ↪"validation score")
plt.plot([str(i) for i in max_depths], DT_test_f1score, '+-', label = "test␣
 ↪score")
plt.xlabel("max depth of the tree")
plt.ylabel("F1 score")
plt.legend()
plt.show()

plt.plot([str(i) for i in max_depths], DT_train_aucscore, 'o-', label = "train␣
 ↪score")
plt.plot([str(i) for i in max_depths], DT_val_aucscore, 'X-', label =␣
 ↪"validation score")
plt.plot([str(i) for i in max_depths], DT_test_aucscore, '+-', label = "test␣
 ↪score")
plt.xlabel("max depth of the tree")
plt.ylabel("Area Under ROC")
plt.legend()
plt.show()
```



train score
validation score
test score
1.000
0.975
0.950
0.925
0.900
0.875
0.850
F1 score
2
4
8
16
32
64
max depth of the tree



Comments on Desicion tree

1. Desicion tree with max_depths = [2,4,8,16,32,64] are build on this data
2. Even with the max_depth = 2, the F1 score of desicion tree model is more then logistic regression model. But the F1 score is still less for desicion tree with max_depth = 2 (~0.83)
3. As the max_depth of the desicion tree increases we can see the increase in the F1 score (from max_depth = 2 to max_depth = 16)
4. But when the max_depth still increases(>16) we can see overfitting. The F1 score of train data increases but the validation and test F1 scores are slightly decreases or remains almost same.
5. At max_depth=16 the F1 score of train, validation & test data is in the range of 0.96 - 0.98. Which is far better than logistic regression model and is good enough.
6. We will use ensemble method AdaBoost to improve the F1 scores.

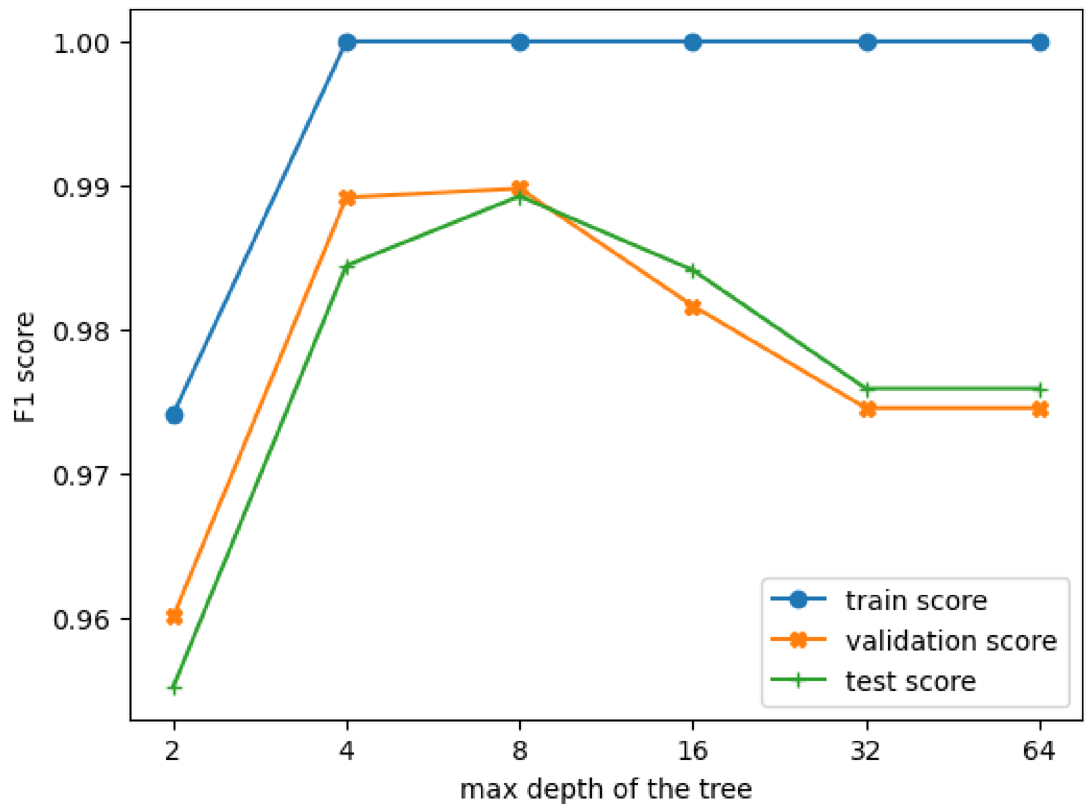
0.1.11 Decision Tree with AdaBoostClassifier

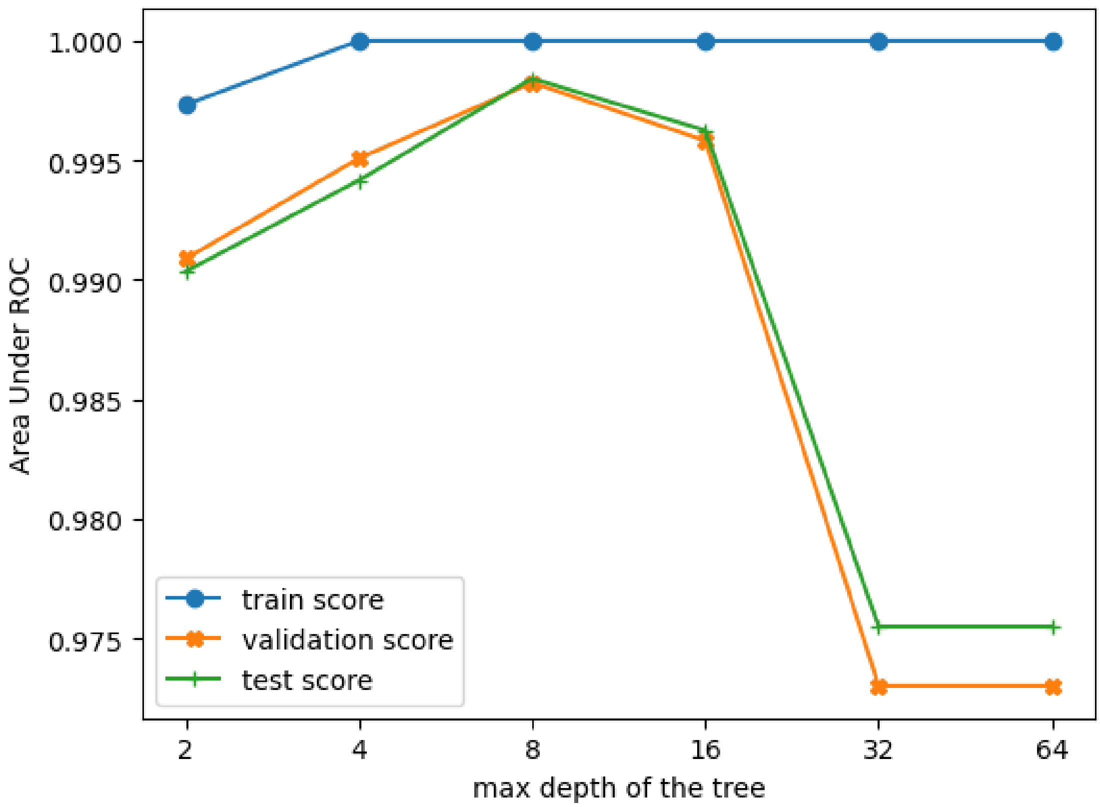
Adaptive boosting with DecisionTreeClassifier with criterion='entropy' as base estimator

[19]:
```
## Decision Tree with ADA
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import AdaBoostClassifier
```

```
max_depths = [2,4,8,16,32,64]
ABC_train_f1score = []
ABC_val_f1score = []
ABC_test_f1score = []

ABC_train_aucscore = []
ABC_val_aucscore = []
ABC_test_aucscore = []

for depth in max_depths:
    entropy_tree = DecisionTreeClassifier(criterion='entropy', max_depth=depth, random_state=42)
    ABC_model = AdaBoostClassifier(base_estimator=entropy_tree,random_state=42).fit(X_train, Y_train)

    Y_train_pred = ABC_model.predict_proba(X_train)[:, 1]
    Y_val_pred = ABC_model.predict_proba(X_val)[:, 1]
    Y_test_pred = ABC_model.predict_proba(X_test)[:, 1]

    f1score_train = f1_score(Y_train, Y_train_pred>0.5)
    f1score_val = f1_score(Y_val, Y_val_pred>0.5)
    f1score_test = f1_score(Y_test, Y_test_pred>0.5)

    ABC_train_f1score.append(f1score_train)
    ABC_val_f1score.append(f1score_val)
    ABC_test_f1score.append(f1score_test)

    auc_train = roc_auc_score(Y_train, Y_train_pred)
    auc_val = roc_auc_score(Y_val, Y_val_pred)
    auc_test = roc_auc_score(Y_test, Y_test_pred)

    ABC_train_aucscore.append(auc_train)
    ABC_val_aucscore.append(auc_val)
    ABC_test_aucscore.append(auc_test)

plt.plot([str(i) for i in max_depths], ABC_train_f1score, 'o-', label = "train score")
plt.plot([str(i) for i in max_depths], ABC_val_f1score, 'X-', label = "validation score")
plt.plot([str(i) for i in max_depths], ABC_test_f1score, '+-', label = "test score")
plt.xlabel("max depth of the tree")
plt.ylabel("F1 score")
plt.legend()
plt.show()
```

```
plt.plot([str(i) for i in max_depths], ABC_train_aucscore, 'o-', label = "train␣
  ↪score")
plt.plot([str(i) for i in max_depths], ABC_val_aucscore, 'X-', label =␣
  ↪"validation score")
plt.plot([str(i) for i in max_depths], ABC_test_aucscore, '+-', label = "test␣
  ↪score")
plt.xlabel("max depth of the tree")
plt.ylabel("Area Under ROC")
plt.legend()
plt.show()
```





Comments on using AdaBoost ensemble method

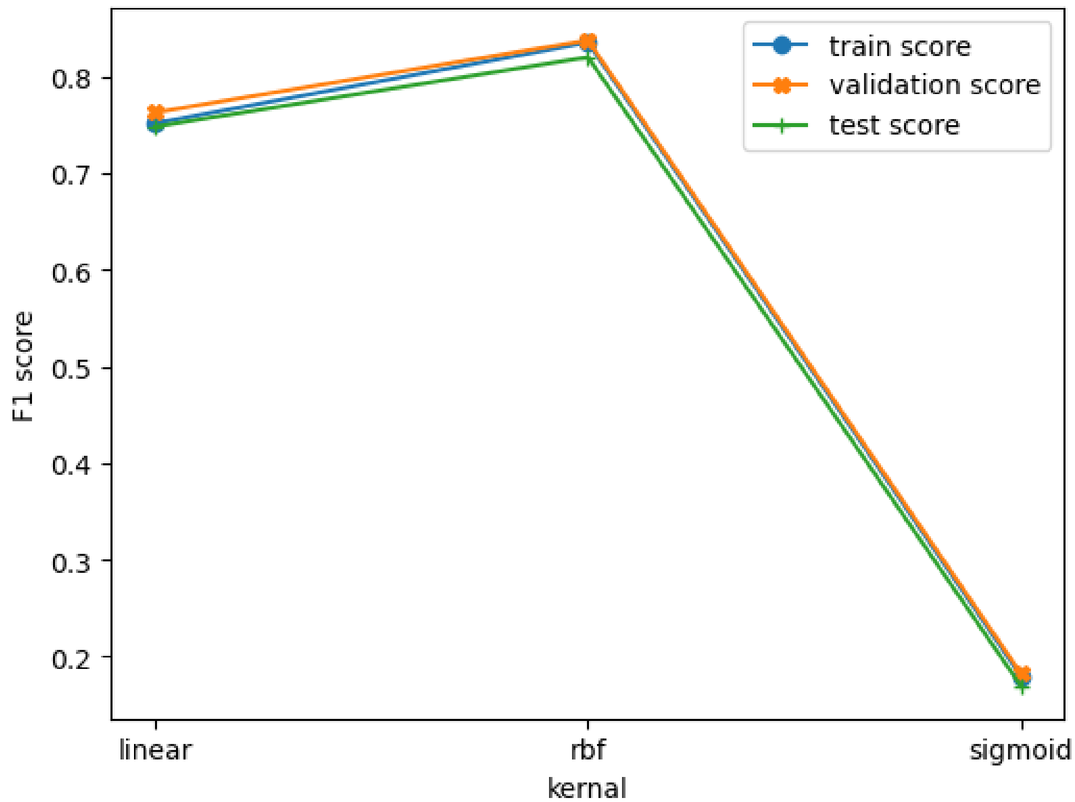
1. Desicion tree with AdaBoost ensemble method for max_depths = [2,4,8,16,32,64] are build on this data
2. Even at max_depth = 2 the F1 score of AdaBoostClassifier is more that F1 score of desicion tree model and logistic regression model.
3. As the max_depth of the AdaBoostClassifier increases we can see the increase in the F1 score (from max_depth = 2 to max_depth = 8)
4. But when the max_depth still increases(>8) we can see overfitting. The F1 score of train data is already 1.0 but the validation and test F1 scores decreases.
5. For AdaBoostClassifier for max_depth=8 the F1 score of train is 1.0 and F1 score of validation & test data is in the range of 0.99 which is a very good model.
6. So AdaBoostClassifier outperforms DecisionTreeClassifier and logistic regression model and is a very good model for the probelm we are trying to solve.

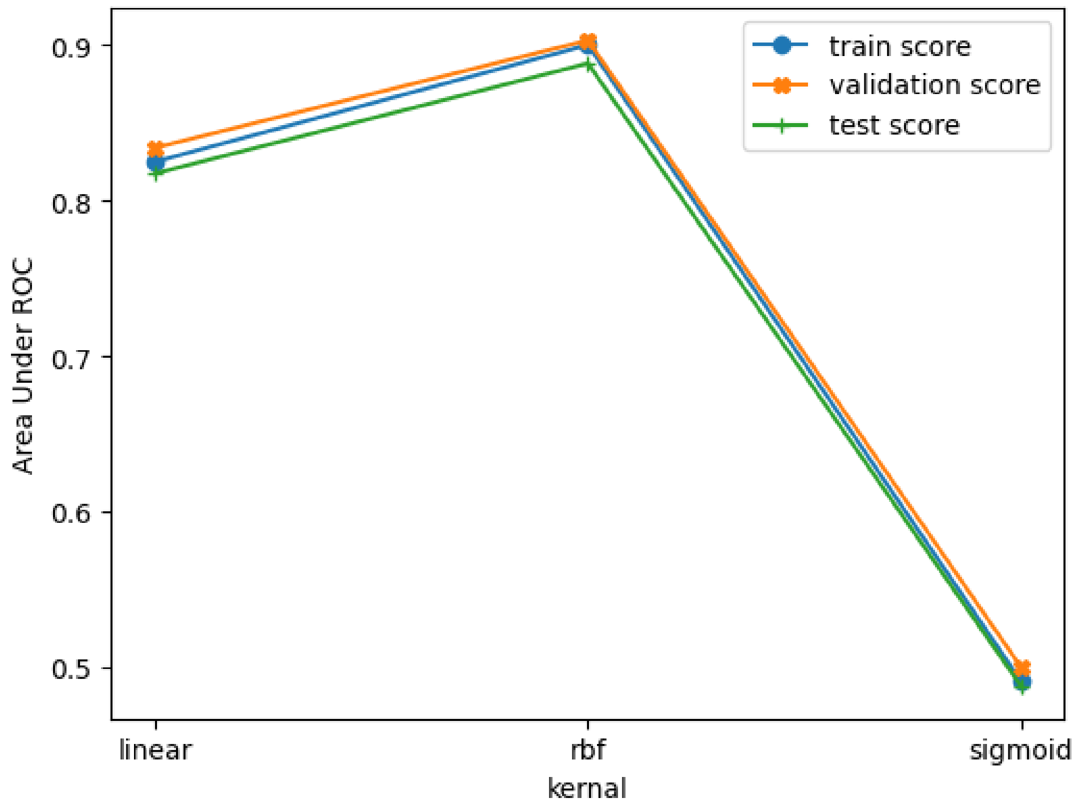
0.1.12 Support Vector Machines

Three kernals ‘linear’, ‘rbf’, ‘sigmoid’ are used

[20]:
```
from sklearn.svm import SVC
kernals = ['linear', 'rbf', 'sigmoid']
SVM_train_f1score = []
```

```python
SVM_val_f1score = []
SVM_test_f1score = []

SVM_train_aucscore = []
SVM_val_aucscore = []
SVM_test_aucscore = []

for kernal in kernals:
    SVM_model = SVC(kernel=kernal, probability=True, random_state=42).
 ↪fit(X_train, Y_train)

    Y_train_pred = SVM_model.predict_proba(X_train)[:, 1]
    Y_val_pred = SVM_model.predict_proba(X_val)[:, 1]
    Y_test_pred = SVM_model.predict_proba(X_test)[:, 1]

    f1score_train = f1_score(Y_train, Y_train_pred>0.5)
    f1score_val = f1_score(Y_val, Y_val_pred>0.5)
    f1score_test = f1_score(Y_test, Y_test_pred>0.5)

    SVM_train_f1score.append(f1score_train)
    SVM_val_f1score.append(f1score_val)
    SVM_test_f1score.append(f1score_test)

    auc_train = roc_auc_score(Y_train, Y_train_pred)
    auc_val = roc_auc_score(Y_val, Y_val_pred)
    auc_test = roc_auc_score(Y_test, Y_test_pred)

    SVM_train_aucscore.append(auc_train)
    SVM_val_aucscore.append(auc_val)
    SVM_test_aucscore.append(auc_test)


plt.plot(kernals, SVM_train_f1score, 'o-', label = "train score")
plt.plot(kernals, SVM_val_f1score, 'X-', label = "validation score")
plt.plot(kernals, SVM_test_f1score, '+-', label = "test score")
plt.xlabel("kernal")
plt.ylabel("F1 score")
plt.legend()
plt.show()

plt.plot(kernals, SVM_train_aucscore, 'o-', label = "train score")
plt.plot(kernals, SVM_val_aucscore, 'X-', label = "validation score")
plt.plot(kernals, SVM_test_aucscore, '+-', label = "test score")
plt.xlabel("kernal")
plt.ylabel("Area Under ROC")
plt.legend()
plt.show()
```


train score
validation score
test score
0.8
0.7
0.6
0.5
0.4
0.3
0.2
F1 score
linear
rbf
sigmoid
kernal



Comments on SVM with different kernals

1. SVM with each of the 3 kernals 'linear', 'rbf', 'sigmoid' performs poorly than AdaBoostClassifier and DecisionTreeClassifier.
2. Performance of SVM and logistic regression models is approximately same.
3. F1 score is very low for all the 3 kernals. So, SVM is not a good model for the probelm we are trying to solve.

0.1.13 Neural Network

Neural Network with 5 hidden layers with each layer having (20,13,10,5,3) nodes with activation='relu' (default)

[21]:
```
## MLP
from sklearn.neural_network import MLPClassifier
NN_model = MLPClassifier(hidden_layer_sizes = (20,13,10,5,3,), random_state=42)
NN_model.fit(X_train, Y_train)
NN_train_score = NN_model.score(X_train, Y_train)
NN_val_score = NN_model.score(X_val, Y_val)
NN_test_score = NN_model.score(X_test, Y_test)
# print(NN_train_score)
# print(NN_val_score)
```

```python
# print(NN_test_score)

Y_train_pred = NN_model.predict_proba(X_train)[:, 1]
Y_val_pred = NN_model.predict_proba(X_val)[:, 1]
Y_test_pred = NN_model.predict_proba(X_test)[:, 1]

f1score_train = f1_score(Y_train, Y_train_pred>0.5)
f1score_val = f1_score(Y_val, Y_val_pred>0.5)
f1score_test = f1_score(Y_test, Y_test_pred>0.5)

print("Train F1 score = "+str(f1score_train))
print("Validation F1 score = "+str(f1score_val))
print("Test F1 score = "+str(f1score_test))

auc_train = roc_auc_score(Y_train, Y_train_pred)
auc_val = roc_auc_score(Y_val, Y_val_pred)
auc_test = roc_auc_score(Y_test, Y_test_pred)

print("\nTrain AUC = "+str(auc_train))
print("Validation AUC = "+str(auc_val))
print("Test AUC = "+str(auc_test))
```

```
Train F1 score = 0.9725576289791438
Validation F1 score = 0.9646302250803859
Test F1 score = 0.9652686762778506

Train AUC = 0.9964439345568347
Validation AUC = 0.9916619659781768
Test AUC = 0.9919289566222724
```

Comments on Neural Network

1. F1 score of train, validation & test data is in the range of 0.96 - 0.98 which is a pretty good model for the probelm we are trying to solve.
2. This Neural Network outperforms logistic regression and Support Vector Machine (SVM).
3. Performance of this Neural Network, DecisionTreeClassifier(for width=16) is approximately same.
4. But AdaBoostClassifier(for width=8) outperforms this Neural Network model.

0.1.14 Conclusion

1. AdaBoostClassifier performs better for the problem we are trying to solve.
2. F1 scores are in the range 0.99, which is reasanable score for a very good model.