

▼ Importing relevant libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import sklearn
from sklearn.metrics import r2_score, mean_squared_error, mean_absolute_error, accuracy_score
import math
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import time
from sklearn.metrics import precision_score, recall_score, confusion_matrix, class_report

from google.colab import drive
drive.mount('/content/drive')
```

🔗 Drive already mounted at /content/drive; to attempt to forcibly remount, call

▼ Setting headers (as given in pdf)

```
headers = """duration,
protocol_type,
service,
flag,
src_bytes,
dst_bytes,
land,
wrong_fragment,
urgent,
hot,
num_failed_logins,
logged_in,
num_compromised,
root_shell,
su_attempted,
num_root,
num_file_creations,
num_shells,
num_access_files,
num_outbound_cmds,
is_host_login,
is_guest_login,
count,
srv_count,
error_rate
```

```
error_rate,  
srv_error_rate,  
rerror_rate,  
srv_rerror_rate,  
same_srv_rate,  
diff_srv_rate,  
srv_diff_host_rate,  
dst_host_count,  
dst_host_srv_count,  
dst_host_same_srv_rate,  
dst_host_diff_srv_rate,  
dst_host_same_src_port_rate,  
dst_host_srv_diff_host_rate,  
dst_host_serror_rate,  
dst_host_srv_serror_rate,  
dst_host_rerror_rate,  
dst_host_srv_rerror_rate""  
  
columns =headers.split(",")  
for i in range(len(columns)):  
    columns[i]=columns[i].strip("\n")
```

▼ Loading training data

```
columns.append('target')  
print("number of features present in dataset",len(columns))  
training_df = pd.read_csv("/content/drive/My Drive/full.csv",names=columns)  
training_df
```

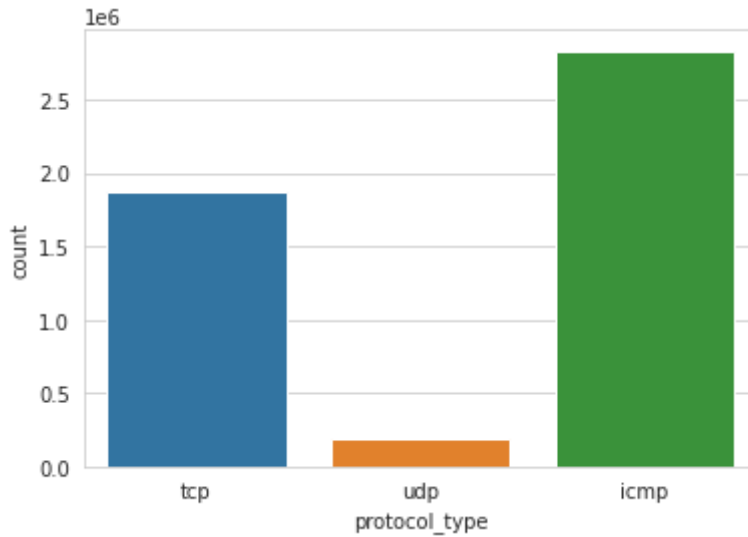
number of features present in dataset 42

duration protocol_type service flag src_bytes dst_bytes land wr

▼ Plotting data count of protocols in training data

```
sns.set_style('whitegrid')
sns.countplot(x='protocol_type', data=training_df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f4127e4d810>



▼ Loading testing data

```
testing_df = pd.read_csv("/content/drive/My Drive/test.csv", names=columns[:-1])
testing_df
```

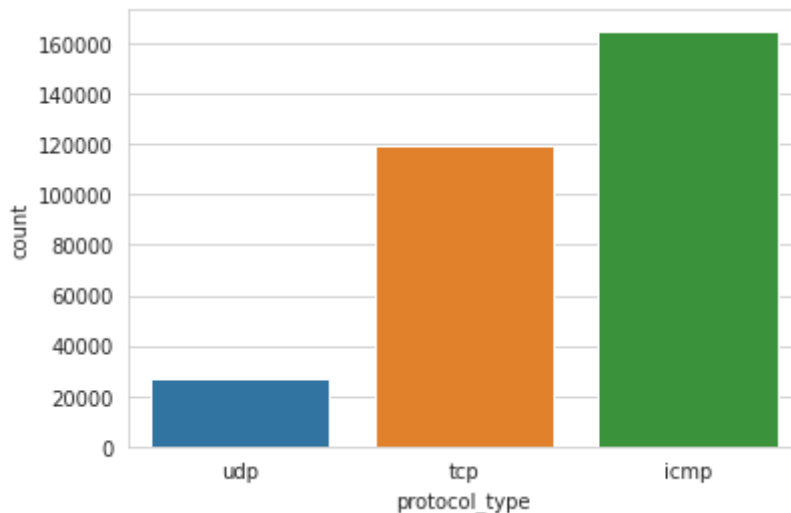
```
/usr/local/lib/python3.7/dist-packages/IPython/core/interactiveshell.py:2718:
interactivity=interactivity, compiler=compiler, result=result)
```

```
duration protocol_type service flag src_bytes dst_bytes land wr
```

▼ Plotting data counts of each protocol in testing data

```
sns.set_style('whitegrid')
sns.countplot(x='protocol_type', data=testing_df)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f41112b09d0>



▼ Dropping index

```
training_df.reset_index(drop=True,inplace=True)
testing_df.reset_index(drop=True,inplace=True)
```

▼ Printing the unique values of our target column

```
unique_target = training_df["target"].unique()
print("Unique values in target column (" + len(unique_target) + " classes) :\n")
for val in unique_target:
    print(val)
```

Unique values in target column (23 classes) :

```
normal.
buffer_overflow.
loadmodule.
perl.
neptune.
smurf.
guess_passwd.
pod.
teardrop.
portsweep.
ipsweep.
```

```

land.
ftp_write.
back.
imap.
satan.
phf.
nmap.
multihop.
warezmaster.
warezclient.
spy.
rootkit.

```

▼ Describing training data in details

```
training_df.describe()
```

	duration	src_bytes	dst_bytes	land	wrong_fragment	
count	4.898431e+06	4.898431e+06	4.898431e+06	4.898431e+06	4.898431e+06	4.898431e+06
mean	4.834243e+01	1.834621e+03	1.093623e+03	5.716116e-06	6.487792e-04	7.961116e-06
std	7.233298e+02	9.414311e+05	6.450123e+05	2.390833e-03	4.285434e-02	7.215116e-06
min	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
25%	0.000000e+00	4.500000e+01	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
50%	0.000000e+00	5.200000e+02	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
75%	0.000000e+00	1.032000e+03	0.000000e+00	0.000000e+00	0.000000e+00	0.000000e+00
max	5.832900e+04	1.379964e+09	1.309937e+09	1.000000e+00	3.000000e+00	1.400000e+00

▼ Checking for missing values in the dataset

```
training_df.isnull().sum()
```

```

duration          0
protocol_type     0
service           0
flag              0
src_bytes         0
dst_bytes         0
land              0
wrong_fragment    0
urgent            0
hot               0
num_failed_logins 0
logged_in         0
num_compromised   0
root_shell        0
su_attempted      0

```

```

num_root          0
num_file_creations 0
num_shells        0
num_access_files  0
num_outbound_cmds 0
is_host_login     0
is_guest_login    0
count            0
srv_count        0
serror_rate      0
srv_serror_rate  0
rerror_rate      0
srv_rerror_rate  0
same_srv_rate    0
diff_srv_rate    0
srv_diff_host_rate 0
dst_host_count   0
dst_host_srv_count 0
dst_host_same_srv_rate 0
dst_host_diff_srv_rate 0
dst_host_same_src_port_rate 0
dst_host_srv_diff_host_rate 0
dst_host_serror_rate 0
dst_host_srv_serror_rate 0
dst_host_rerror_rate 0
dst_host_srv_rerror_rate 0
target          0
dtype: int64

```

▼ Describing test data in details

```
testing_df.describe()
```

	duration	src_bytes	dst_bytes	land	wrong_fragment	
count	311029.000000	3.110290e+05	3.110290e+05	311029.000000	311029.000000	311029.000000
mean	17.902736	1.731702e+03	7.479937e+02	0.000029	0.000763	
std	407.644400	1.276567e+05	1.612018e+04	0.005382	0.040369	
min	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	
25%	0.000000	1.050000e+02	0.000000e+00	0.000000	0.000000	
50%	0.000000	5.200000e+02	0.000000e+00	0.000000	0.000000	
75%	0.000000	1.032000e+03	0.000000e+00	0.000000	0.000000	
max	57715.000000	6.282565e+07	5.203179e+06	1.000000	3.000000	

▼ Getting numeric data from training dataset

```

num_cols = training_df._get_numeric_data().columns
print("numeric data containing columns are (", len(num_cols), " columns ) :\n")

```

```
print(list(num_cols))
```

numeric data containing columns are (38 columns) :

```
['duration', 'src_bytes', 'dst_bytes', 'land', 'wrong_fragment', 'urgent', 'h
```

▼ Getting categorical data from training data

```
category_cols=list(set(training_df.columns)-set(num_cols))
print("categorical data containing columns are (", len(category_cols)," columns )
print(category_cols)
```

categorical data containing columns are (4 columns) :

```
['protocol_type', 'target', 'service', 'flag']
```

▼ Dropping columns from training and testing data where value is NaN

```
training_df.dropna('columns',inplace=True)
testing_df.dropna('columns',inplace=True)
```

▼ Getting columns with more than one value

```
cols=[col for col in training_df if training_df[col].nunique() > 1]
cols
```

```
['duration',
 'protocol_type',
 'service',
 'flag',
 'src_bytes',
 'dst_bytes',
 'land',
 'wrong_fragment',
 'urgent',
 'hot',
 'num_failed_logins',
 'logged_in',
 'num_compromised',
 'root_shell',
 'su_attempted',
 'num_root',
 'num_file_creations',
 'num_shells',
 'num_access_files',
 'is_host_login',
 'is_guest_login',
 'count',
 'srv_count',
 'serror_rate',
```

```
'srv_serror_rate',
'rerror_rate',
'srv_rerror_rate',
'same_srv_rate',
'diff_srv_rate',
'srv_diff_host_rate',
'dst_host_count',
'dst_host_srv_count',
'dst_host_same_srv_rate',
'dst_host_diff_srv_rate',
'dst_host_same_src_port_rate',
'dst_host_srv_diff_host_rate',
'dst_host_serror_rate',
'dst_host_srv_serror_rate',
'dst_host_rerror_rate',
'dst_host_srv_rerror_rate',
'target']
```

▼ Dropping columns with only single value

```
list(set(training_df.columns)-set(cols))
training_df.drop('num_outbound_cmds', axis = 1, inplace = True)
testing_df.drop('num_outbound_cmds', axis = 1, inplace = True)
```

▼ Displaying reduced number of features

```
len(training_df.columns)
```

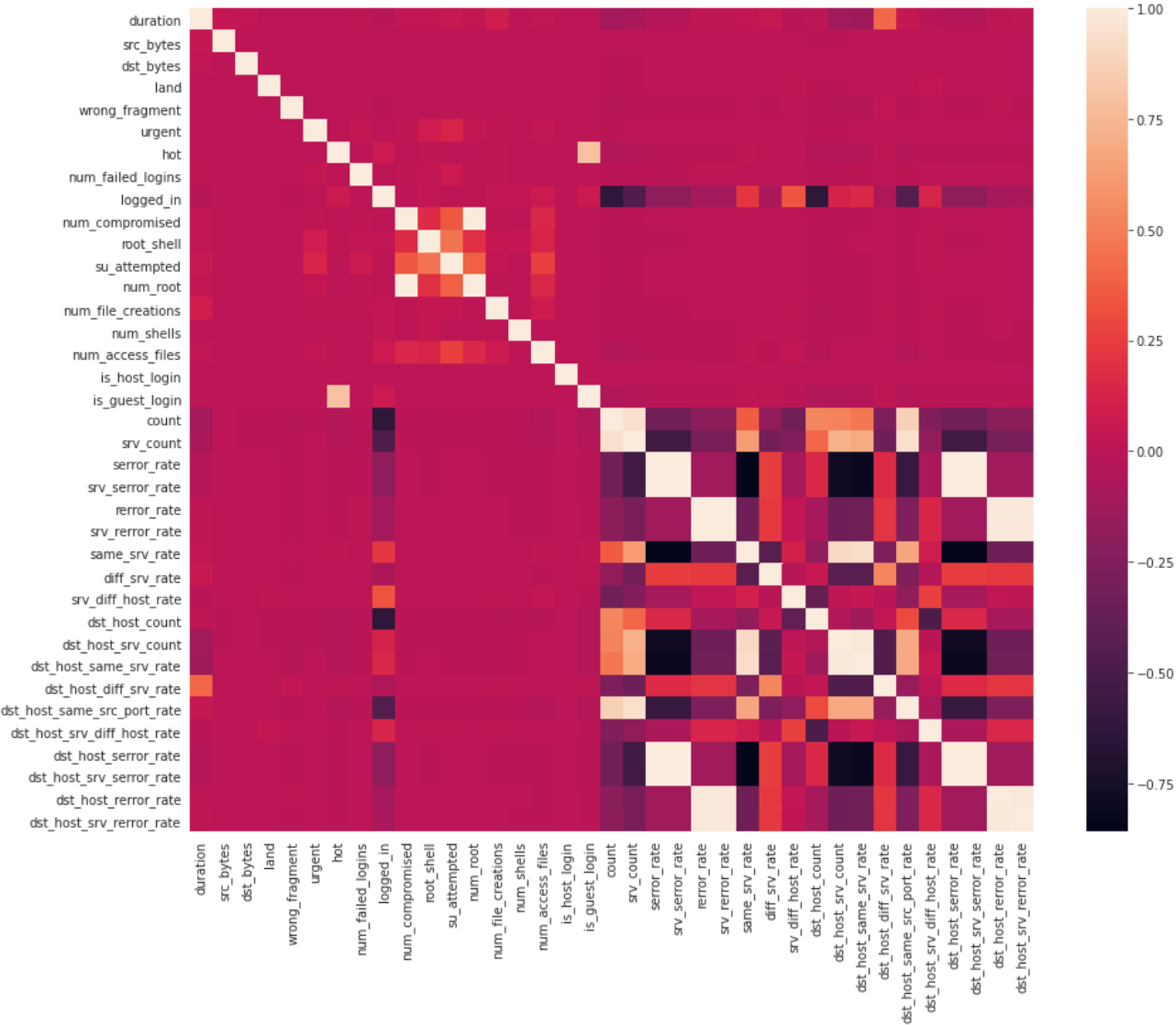
```
41
```

▼ Getting correlation matrix and plotting heatmap

```
correaltion_marix=training_df.corr()
plt.figure(figsize =(15, 12))

sns.heatmap(correaltion_marix)

plt.show()
```

▼ Printing correlation matrix

```
correaltion_marix
```

num_access_files	0.023524	-2.223002e-05	0.000352	-0.000069	-0.000000
is_host_login	-0.000021	-1.084695e-06	0.000004	-0.000002	-0.000000
is_guest_login	0.002389	-3.608617e-05	0.000035	-0.000069	-0.000000
count	-0.105074	-1.662632e-03	-0.002646	-0.003735	-0.000000
srv_count	-0.079863	-1.150591e-03	-0.001998	-0.002852	-0.000000
serror_rate	-0.031098	-5.858538e-04	-0.000774	0.004997	-0.000000
srv_serror_rate	-0.031110	-6.321879e-04	-0.000773	0.005141	-0.000000
rerror_rate	0.016549	3.209510e-03	0.002463	-0.000347	-0.000000
srv_rerror_rate	0.016836	3.287307e-03	0.002467	-0.000593	-0.000000
same_srv_rate	0.021719	6.696333e-04	0.000910	0.000926	0.000000
diff_srv_rate	0.050286	3.294335e-04	-0.000393	0.000503	-0.000000
srv_diff_host_rate	-0.012754	-1.422368e-04	0.000311	0.013491	0.000000
dst_host_count	0.010914	-2.415847e-03	-0.001534	-0.008610	-0.000000
dst_host_srv_count	-0.117309	-1.715221e-03	-0.001067	-0.004174	-0.000000
dst_host_same_srv_rate	-0.119105	-1.548066e-03	-0.000968	0.000865	-0.000000
dst_host_diff_srv_rate	0.409009	7.188089e-04	0.003307	-0.000236	0.000000
dst_host_same_src_port_rate	0.042774	-7.931844e-04	-0.000558	0.001479	-0.000000
dst_host_srv_diff_host_rate	-0.008582	4.755028e-06	0.000346	0.033193	0.000000
dst_host_serror_rate	-0.030546	-8.206068e-04	-0.000765	0.004648	-0.000000
dst_host_srv_serror_rate	-0.030570	-6.346845e-04	-0.000763	0.003096	-0.000000
dst_host_rerror_rate	0.010569	-1.542303e-04	0.002502	-0.000552	0.000000
dst_host_srv_rerror_rate	0.016034	2.927064e-03	0.002512	-0.000597	-0.000000

▼ Dropping following highly correlated features from dataset:

- num_root
- srv_serror_rate
- srv_rerror_rate
- dst_host_srv_serror_rate
- dst_host_serror_rate
- dst_host_rerror_rate
- dst_host_srv_rerror_rate
- dst_host_same_srv_rate

```
training_df.drop('num_root', axis = 1, inplace = True)
training_df.drop('srv_serror_rate', axis = 1, inplace = True)
training_df.drop('srv_rerror_rate', axis = 1, inplace = True)
training_df.drop('dst_host_srv_serror_rate', axis = 1, inplace = True)
training_df.drop('dst_host_serror_rate', axis = 1, inplace = True)
training_df.drop('dst_host_rerror_rate', axis = 1, inplace = True)
training_df.drop('dst_host_srv_rerror_rate', axis = 1, inplace = True)
training_df.drop('dst_host_same_srv_rate', axis = 1, inplace = True)
```

```
testing_df.drop('num_root', axis = 1, inplace = True)
testing_df.drop('srv_serror_rate', axis = 1, inplace = True)
testing_df.drop('srv_rerror_rate', axis = 1, inplace = True)
testing_df.drop('dst_host_srv_serror_rate', axis = 1, inplace = True)
testing_df.drop('dst_host_serror_rate', axis = 1, inplace = True)
testing_df.drop('dst_host_rerror_rate', axis = 1, inplace = True)
testing_df.drop('dst_host_srv_rerror_rate', axis = 1, inplace = True)
testing_df.drop('dst_host_same_srv_rate', axis = 1, inplace = True)
```

▼ Printing length of current features after dropping

```
len(training_df.columns)
```

```
33
```

```
len(testing_df.columns)
```

```
32
```

▼ Handling categorical data:

- protocol type feature mapping
- flag feature mapping

```
cat_map = {'protocol_map': {'icmp':0, 'tcp':1, 'udp':2}, 'flag_feature_map': {'SF'
training_df['protocol_type'] = training_df['protocol_type'].map(cat_map['protocol_ma
testing_df['protocol_type'] = testing_df['protocol_type'].map(cat_map['protocol_ma
training_df['flag'] = training_df['flag'].map(cat_map['flag_feature_map'])
testing_df['flag'] = testing_df['flag'].map(cat_map['flag_feature_map'])
```

```
training_df.drop('service', axis = 1, inplace = True)
testing_df.drop('service', axis = 1, inplace = True)
```

▼ Extracting X_train, X_test and y_train

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
```

```
y=training_df["target"]
training_df.drop(['target', ], axis = 1,inplace=True)
```

```
testing_df=testing_df[1:]
```

▼ Feature scaling

```
sc = MinMaxScaler()
X = sc.fit_transform(training_df)
X_test=sc.fit_transform(testing_df)
```

```
X_actual=np.copy(X)
y_actual=np.copy(y)
X_temp=np.copy(X)
y_temp=np.copy(y)
```

```
print(X_actual.shape)
print(y_actual.shape)

(4898431, 31)
(4898431,)
```

▼ Training on Gaussian Naive Bayes

```
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score

clfg = GaussianNB()
start_time = time.time()
clfg.fit(X, y.values.ravel())
end_time = time.time()
print("Training time: ", end_time-start_time, "seconds")
```

Training time: 14.985315084457397 seconds

▼ Printing accuracy, recall, precision, f1 score and other comparison parameters

```
y_train_pred_gauss = clfg.predict(X)
print('Accuracy:\n', accuracy_score(y, y_train_pred_gauss))
print('F1 score:\n', f1_score(y, y_train_pred_gauss, average= None))
print('Recall:\n', recall_score(y, y_train_pred_gauss, average= None))
print('Precision:\n', precision_score(y, y_train_pred_gauss, average= None))
```

```
Accuracy:
0.8695747679205852
F1 score:
[0.03341816 0.0028463 0.00108807 0.01206217 0.01022305 0.02992326
0.85714286 0.01515152 0.03883495 0.9977684 0.02267832 0.53536328
1. 1. 0.02895372 0.94211711 0.00115902 0.69589041
0.99941702 0.8 0.37632135 0.00370588 0.0031343 ]
Recall:
[0.98955969 0.7 1. 0.98113208 0.91666667 0.06810352
1. 0.66666667 0.28571429 0.99555231 0.72970639 0.36616361
1. 1. 1. 0.9448766 0.5 0.95098163
0.99883471 1. 1. 0.41372549 1. ]
Precision:
[1.69960628e-02 1.42604916e-03 5.44328775e-04 6.06838604e-03
5.14018692e-03 1.91739415e-02 7.50000000e-01 7.66283525e-03
2.08333333e-02 9.99994378e-01 1.15181462e-02 9.95261153e-01
1.00000000e+00 1.00000000e+00 1.46895170e-02 9.39373687e-01]
```

5.80181016e-04 5.48705660e-01 1.00000000e+00 6.66666667e-01

2 217708222 01 1 061277402 02 1 560612212 021

```
print('\n clasifcation report:\n', classification_report(y, y_train_pred_gauss))
```

```
print('\n confussion matrix:\n',confusion_matrix(y, y_train_pred_gauss))
```

```

-      -      -      -      -      -      -      -      -
      0      0      0      0      0      0      0      0      0
      0      0      0      0      1]
[      0      0      0      0      11      0      0      0      0
      0      0      0      0      0      0      0      0      0
      0      0      0      0      1]
[      0      0      15      13      0      850      0      2      0
      0      3319      6      0      0      8248      27      0      0
      0      0      0      1      0]
[      0      0      0      0      0      0      21      0      0
      0      0      0      0      0      0      0      0      0
      0      0      0      0      0]
[      0      1      0      0      0      0      0      6      1
      0      0      0      0      0      0      0      0      0
      0      0      0      0      1]
[      0      0      0      0      1      0      0      0      2
      0      0      0      0      0      0      0      0      0
      0      0      0      0      4]
[      0      0      0      0      22      0      0      0      0
1067249      2524      13      0      0      0      208      0      2001
      0      0      0      0      0]
[      0      0      0      0      0      0      0      0      0
      0      1690      0      0      0      587      9      29      1
      0      0      0      0      0]
[126085      14425      14515      8496      2099      43463      7      769      91
      6      137195      356197      0      0      8573      318      8545      9942
      0      1      3187      226294      12573]
[      0      0      0      0      0      0      0      0      0
      0      0      0      3      0      0      0      0      0
      0      0      0      0      0]
[      0      0      0      0      0      0      0      0      0
      0      0      0      0      4      0      0      0      0
      0      0      0      0      0]
[      0      0      0      0      0      0      0      0      0
      0      0      0      0      0      264      0      0      0
      0      0      0      0      0]
[      0      0      0      0      1      18      0      0      0
      0      52      9      0      0      6      9839      0      486
      0      0      0      2      0]
[      0      1      0      0      0      0      0      0      0
      0      2      0      0      0      0      0      5      0
      0      0      0      0      2]
[      0      0      1      0      0      0      0      4      0
      0      561      25      0      0      36      73      7      15113
      0      0      58      6      8]
[      0      0      0      0      0      0      0      0      0
      0      1382      1632      0      0      258      0      0      0
2804614      0      0      0      0]
[      0      0      0      0      0      0      0      0      0
      0      0      0      0      0      0      0      0      0
      0      2      0      0      0]
[      0      0      0      0      0      0      0      0      0
      0      0      0      0      0      0      0      0      0
      0      0      979      0      0]
[      0      277      157      1      0      0      0      2      0
      0      0      3      0      0      0      0      31      0
      0      0      0      422      127]
-      -      -      -      -      -      -      -      -

```

```
[
    0      0      0      0      0      0      0      0      0      0
    0      0      0      0      0      0      0      0      0      0
    0      0      0      0      0      20]]
```

▼ Training on Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
```

```
clfd = DecisionTreeClassifier(criterion ="entropy", max_depth = 4)
start_time = time.time()
clfd.fit(X, y.values.ravel())
end_time = time.time()
print("Training time: ", end_time-start_time)
```

```
Training time: 16.418840646743774
```

```
y_train_pred_dt = clfd.predict(X)
```

▼ Printing accuracy, recall, precision, f1 score and other comparison parameters

```
print('Accuracy:', accuracy_score(y, y_train_pred_dt))
print('F1 score:', f1_score(y, y_train_pred_dt, average= None))
print('Recall:', recall_score(y, y_train_pred_dt, average= None))
print('Precision:', precision_score(y, y_train_pred_dt, average= None))
print('\n clasifcation report:\n', classification_report(y, y_train_pred_dt))
print('\n confussion matrix:\n',confusion_matrix(y, y_train_pred_gauss))
```

```

      0      0      0      0      0      0      0      0      0
      0      0      0      0      1]
[      0      0      0      0      11      0      0      0      0
      0      0      0      0      0      0      0      0      0
      0      0      0      0      1]
[      0      0      15      13      0      850      0      2      0
      0      3319      6      0      0      8248      27      0      0
      0      0      0      1      0]
[      0      0      0      0      0      0      21      0      0
      0      0      0      0      0      0      0      0      0
      0      0      0      0      0]
[      0      1      0      0      0      0      0      6      1
      0      0      0      0      0      0      0      0      0
      0      0      0      0      1]
[      0      0      0      0      1      0      0      0      2
      0      0      0      0      0      0      0      0      0
      0      0      0      0      4]
[      0      0      0      0      22      0      0      0      0
1067249      2524      13      0      0      0      208      0      2001
      0      0      0      0      0]
[      0      0      0      0      0      0      0      0      0
      0      1690      0      0      0      587      9      29      1
      0      0      0      0      0]
[126085      14425      14515      8496      2099      43463      7      769      91
      6      137105      356107      0      0      8573      318      8515      0017
```

https://colab.research.google.com/drive/1pXzCmwFMslv0uZcB_dYIs7C9yNagpGkQ#scrollTo=...


```

print('F1 score:', f1_score(y, y_train_pred_rf, average= None))
print('Recall:', recall_score(y, y_train_pred_rf, average= None))
print('Precision:', precision_score(y, y_train_pred_rf, average= None))
print('\n clasifcation report:\n', classification_report(y, y_train_pred_rf))
print('\n confussion matrix:\n',confusion_matrix(y, y_train_pred_rf))

```

```

[ 0 0 0 53 0 0 0 0 0
 0 0 0 0 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 12 0 0 0 0
 0 0 0 0 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 12411 0 0 0
 0 2 68 0 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 21 0 0
 0 0 0 0 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 9 0
 0 0 0 0 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 6
 0 0 1 0 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 1072017 0 0 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 20 0 0 0
 0 2242 54 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 4 5 0 0
 0 0 972760 0 0 1 1 0 0
 0 0 0 10 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 0 3 0 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 0 0 4 0 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 262 0 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 3 0 0 0 10410 0 0
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 3 0 0 0 0 7 0
 0 0 0 0 0]
[ 0 0 0 0 0 2 0 0 0
 0 0 35 0 0 0 0 0 15855
 0 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 1 0 0 0 0 0 0
 2807885 0 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0
 0 2 0 0 0]
[ 0 0 0 0 0 0 0 0 0
 0 0 0 0 0 0 0 0 0
 0 0 979 0 0]
[ 0 0 0 0 0 0 0 0 0

```

	0	0	1	0	0	0	0	0	0
	0	0	0	1019	0]				
[0	0	0	0	0	0	0	0	0

Printing accuracy, recall, precision, f1 score and other comparison parameters

From above, we saw that the best performance on training data was given by

- ▼ tree based models. Selecting random forest as our model, we perform the following:

- predict label of test data
- store them in a csv file

```
start_time = time.time()
y_test_pred = clfr.predict(X_test)
end_time = time.time()
print("Execution time:", end_time - start_time, " seconds")
print(y_test_pred)
print(y_test_pred.shape)
print(type(y_test_pred))
df_ans = pd.DataFrame(y_test_pred, columns = ['target'])
print(df_ans)
df_ans.to_csv('testLabel.csv', header="True", index= "False")
```