```
import numpy as np
import pandas as pd
```

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
sns.set_style('darkgrid')

data_test = pd.read_csv('https://cloudstor.aarnet.edu.au/plus/s/umT99TnxvbpkkoE/download?path
data_train = pd.read_csv('https://cloudstor.aarnet.edu.au/plus/s/umT99TnxvbpkkoE/download?pat

data_train.head()

	pkSeqID	proto	saddr	sport	daddr	dport	seq	stddev	N_IN_Cor
0	3142762	udp	192.168.100.150	6551	192.168.100.3	80	251984	1.900363	_
1	2432264	tcp	192.168.100.150	5532	192.168.100.3	80	256724	0.078003	
2	1976315	tcp	192.168.100.147	27165	192.168.100.3	80	62921	0.268666	
3	1240757	udp	192.168.100.150	48719	192.168.100.3	80	99168	1.823185	
4	3257991	udp	192.168.100.147	22461	192.168.100.3	80	105063	0.822418	

data_train.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2934817 entries, 0 to 2934816

Data columns (total 19 columns):

#	Column	Dtype
0	pkSeqID	int64
1	proto	object
2	saddr	object
3	sport	object
4	daddr	object
5	dport	object
6	seq	int64
7	stddev	float64
8	N_IN_Conn_P_SrcIP	int64
9	min	float64
10	state_number	int64
11	mean	float64
12	N_IN_Conn_P_DstIP	int64
13	drate	float64
14	srate	float64
15	max	float64
16	attack	int64
17	category	object

```
18 subcategory object dtypes: float64(6), int64(6), object(7) memory usage: 425.4+ MB
```

Data Preprocessing

```
data train.dtypes[data train.dtypes=='object']
    proto
                   object
                   object
    saddr
                   object
    sport
    daddr
                   object
    dport
                   object
    category
                   object
    subcategory
                    object
    dtype: object
data_train['category'].value_counts()
    DDoS
                       1541315
    DoS
                       1320148
                       72919
    Reconnaissance
    Normal
                           370
    Theft
                            65
    Name: category, dtype: int64
data_train.groupby(['category','subcategory']).count()
```

pkSeqID proto saddr sport daddr dport sec

data_train.groupby(['category'])['subcategory'].value_counts()

category	subcategory	
DDoS	TCP	782228
	UDP	758301
	HTTP	786
DoS	UDP	826349
	TCP	492615
	HTTP	1184
Normal	Normal	370
Reconnaissance	Service_Scan	58626
	OS_Fingerprint	14293
Theft	Keylogging	59
	Data_Exfiltration	6

Name: subcategory, dtype: int64

#Merging category and subcategory into one column
data_train['target'] = data_train['category'] + "_" + data_train['subcategory']
data_train.head()

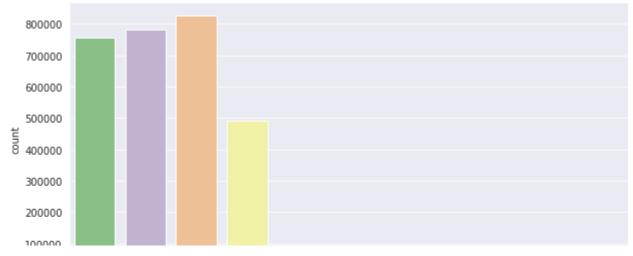
	pkSeqID	proto	saddr	sport	daddr	dport	seq	stddev	N_IN_Cor
0	3142762	udp	192.168.100.150	6551	192.168.100.3	80	251984	1.900363	
1	2432264	tcp	192.168.100.150	5532	192.168.100.3	80	256724	0.078003	
2	1976315	tcp	192.168.100.147	27165	192.168.100.3	80	62921	0.268666	
3	1240757	udp	192.168.100.150	48719	192.168.100.3	80	99168	1.823185	
4	3257991	udp	192.168.100.147	22461	192.168.100.3	80	105063	0.822418	

```
plt.figure(figsize=(10,5))
```

plt.xticks(rotation=90)

sns.countplot(data_train['target'],palette='Accent')

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the FutureWarning contains at 0x7fe9ed086950>



#Merging category and subcategory into one column
data_test['target'] = data_test['category'] + "_" + data_test['subcategory']
data_test.head()

	pkSeqID	proto	saddr	sport	daddr	dport	seq	stddev	N_IN_Cor
0	792371	udp	192.168.100.150	48516	192.168.100.3	80	175094	0.226784	
1	2056418	tcp	192.168.100.148	22267	192.168.100.3	80	143024	0.451998	
2	2795650	udp	192.168.100.149	28629	192.168.100.3	80	167033	1.931553	
3	2118009	tcp	192.168.100.148	42142	192.168.100.3	80	204615	0.428798	
4	303688	tcp	192.168.100.149	1645	192.168.100.5	80	40058	2.058381	

```
#Dropping Theft since it has very low values
indexNames = data_train[data_train['category']=='Theft'].index
data_train.drop(indexNames , inplace=True)
```

```
indexNames = data_test[data_test['category']=='Theft'].index
data_test.drop(indexNames , inplace=True)
```

```
data_train.drop(["pkSeqID","seq"], axis=1, inplace=True)
data_test.drop(["pkSeqID","seq"], axis=1, inplace=True)
```

```
data_train[data_train['category']=='Normal']
```

		proto	saddr	sport	daddr	dport	stddev	N_IN_Conn_I	
	3377	tcp	192.168.100.5	0	192.168.100.3	0	0.235357		
	7683	udp	192.168.100.150	46295	192.168.217.2	53	0.000000		
	8844	tcp	192.168.100.3	80	192.168.100.55	8080	0.228494		
	10110	udp	192.168.100.147	38275	192.168.217.2	53	0.000000		
	16479	udp	192.168.100.150	56155	255.255.255.255	3289	0.000000		

	2896922	udp	192.168.100.3	60946	192.31.80.30	53	0.000000		
	2907572	ipv6- icmp	fe80::250:56ff:febe:c038	133	ff02::2	0	0.000000		
	2912220	udp	192.168.100.4	60001	192.168.100.1	53	0.323125		
	2917520	udp	192.168.100.148	41735	8.8.8.8	53	0.000000		
data_	train['sp	ort'].v	ralue_counts()						
	0x0303 7156 80 3220 1822 878 60541 869 1216 868 39364 31 18992 30 39305 30 0x000d 10 0x0011 8 Name: sport, Length: 65541, dtype: int64								
<pre># converting Hexadecimal value to decimal in port number check='0x' s_res = set([i for i in data_train['sport'] if i.startswith(check)]) s_res {'0x0008', '0x000d', '0x0011', '0x0303'}</pre>									
<pre>data_train['sport']=data_train['sport'].replace(['0x0303'],'771') data_train['sport']=data_train['sport'].replace(['0x0011'],'17') data_train['sport']=data_train['sport'].replace(['0x000d'],'13') data_train['sport']=data_train['sport'].replace(['0x00008'],'8')</pre>									
<pre>data_test['sport']=data_test['sport'].replace(['0x0303'],'771') data_test['sport']=data_test['sport'].replace(['0x0011'],'17') data_test['sport']=data_test['sport'].replace(['0x000d'],'13')</pre>									

data_test['sport']=data_test['sport'].replace(['0x0008'],'8')

```
data train["sport"] = data train["sport"].astype(str).astype(int)
data test["sport"] = data test["sport"].astype(str).astype(int)
check='0x'
d res = set([i for i in data train['dport'] if i.startswith(check)])
print(len(d_res))
     1062
data\_train["dport"] = data\_train["dport"].apply(lambda x: int(x,16) if len(x)>1 and x[1]=="x"]
data_test["dport"] = data_test["dport"].apply(lambda x: int(x,16) if len(x)>1 and x[1]=="x" e
data train['dport'].value counts()
      80
               2858794
      1
                  5379
                  3757
      3306
      53
                   275
                   163
     -1
      13445
                     1
      6636
                     1
      29153
                     1
      29152
                     1
      8863
     Name: dport, Length: 6778, dtype: int64
# checking for negative port numbers
len(data train[data train['dport']<0]['dport'])</pre>
     163
data_train[data_train['dport']==-1]['target'].value_counts()
     Normal_Normal
                                       38
     Reconnaissance Service Scan
                                       34
     Reconnaissance OS Fingerprint
                                       26
     DoS UDP
                                       18
     DoS_TCP
                                       17
     DDoS TCP
                                       15
     DDoS UDP
                                       10
     DoS HTTP
                                        5
     Name: target, dtype: int64
#Since dport can't be negative, we are dropping it
indexNames = data_train[data_train['dport'] == -1].index
data train.drop(indexNames, inplace=True)
```

```
data_test[data_test['dport']==-1]['target'].value_counts()
     Reconnaissance Service Scan
                                       12
     Normal Normal
                                        9
     DDoS UDP
                                        6
     Reconnaissance OS Fingerprint
                                        6
     DoS UDP
                                        6
     DDoS TCP
                                        3
                                        2
     DoS TCP
     DDoS_HTTP
                                        1
                                        1
     DoS HTTP
     Name: target, dtype: int64
indexNames = data test[data test['dport']==-1].index
data test.drop(indexNames , inplace=True)
data_train.groupby(['category'])['subcategory'].value_counts()
     category
                     subcategory
     DDoS
                     TCP
                                        782213
                     UDP
                                        758291
                     HTTP
                                           786
     DoS
                     UDP
                                        826331
                     TCP
                                        492598
                     HTTP
                                          1179
     Normal
                     Normal
                                           332
     Reconnaissance Service Scan
                                         58592
                     OS Fingerprint
                                         14267
     Name: subcategory, dtype: int64
data_train['target'].value_counts()
     DoS UDP
                                       826331
     DDoS TCP
                                       782213
     DDoS UDP
                                       758291
     DoS TCP
                                       492598
     Reconnaissance Service Scan
                                        58592
     Reconnaissance_OS_Fingerprint
                                        14267
     DoS HTTP
                                         1179
     DDoS HTTP
                                          786
     Normal_Normal
                                          332
     Name: target, dtype: int64
data train.dtypes[data train.dtypes=='object']
                    object
     proto
     saddr
                    object
     daddr
                    object
     category
                    object
     subcategory
                    object
     target
                    object
     dtype: object
```

data_train.drop(["category","subcategory"], axis=1, inplace=True)
data_test.drop(["category","subcategory"], axis=1, inplace=True)

[] 🖟 5 cells hidden

Scaling

[] 🖟 8 cells hidder

Sampling

[] L 5 cells hidden

Light GBM

[] L 12 cells hidden

Hyper parameter tuning

[] L 8 cells hidden

Results

[] 1, 3 cells hidden

Base Model

[] L, 3 cells hidden

Tuned Model

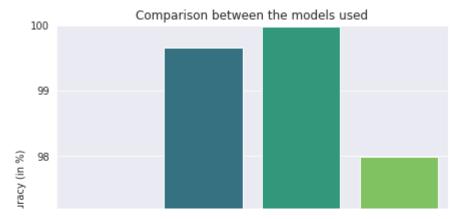
```
ytest.value counts()
     5
         206620
     1
         195149
     2
         189948
     4
         123183
     8
         14530
     7
           3615
     3
            300
     0
            202
     6
             98
     Name: target_enc, dtype: int64
#Test Model: 4
multilabel confusion matrix(ytest,pred 10)
     array([[[733397,
                       46],
                      85]],
            [ 117,
           [[537961, 535],
            [ 4092, 191057]],
           [[543697, 0],
            [ 7954, 181994]],
           [[733338,
                       7],
            [ 120, 180]],
           [[607019, 3443],
            [ 562, 122621]],
           [[519074, 7951],
            [ 4, 206616]],
           [[733544, 5],
1. 97]],
           [[730030,
            [ 1808, 1807]],
           [[716323, 2792],
            [ 119, 14411]])
conf = confusion_matrix(ytest,pred_10)
label = ['DDoS_HTTP','DDoS_TCP','DDoS_UDP','DoS_HTTP','DoS_TCP','DoS_UDP',
          'Normal Normal', 'OS Fingerprint', 'Service Scan']
cm = pd.DataFrame(conf,index=label,columns=label)
cm
```

	DDoS_HTTP	DDoS_TCP	DDoS_UDP	DoS_HTTP	DoS_TCP	DoS_UDP	Normal_Normal
DDoS_HTTP	85	111	0	0	0	0	С
DDoS_TCP	19	191057	0	1	3313	0	C
DDoS_UDP	0	4	181994	0	0	7950	C
DoS_HTTP	26	59	0	180	4	0	C
DoS_TCP	0	276	0	5	122621	0	C
DoS_UDP	0	1	0	0	0	206616	3
Normal Normal	0	Ο	0	0	Ω	Ω	97

print(classification_report(ytest,pred_10))

	precision	recall	f1-score	support
	0.65	0.40	0 54	200
0	0.65	0.42	0.51	202
1	1.00	0.98	0.99	195149
2	1.00	0.96	0.98	189948
3	0.96	0.60	0.74	300
4	0.97	1.00	0.98	123183
5	0.96	1.00	0.98	206620
6	0.97	0.99	0.98	98
7	1.00	0.50	0.67	3615
8	0.84	0.99	0.91	14530
accuracy			0.98	733645
macro avg	0.93	0.83	0.86	733645
weighted avg	0.98	0.98	0.98	733645

```
plt.figure(figsize=(7,6))
results = [96.99, 99.65, 99.98, 97.98]
model_names = ['Logistic Regression', 'SVM', 'XGBoost', 'Random Forest']
sns.barplot(x = model_names, y=results, palette='viridis')
plt.xlabel('Models')
plt.ylabel('Accuracy (in %)')
plt.ylim([95, 100])
plt.title('Comparison between the models used')
plt.show()
```



Therefore, we can see that XGBoost gives the best accuracy of 99.98%.

