Machine Learning for the Detection of Network Attacks

Part II Computer Science, Univeristy of Cambridge

I will perform, and analyse the following 5 machine learning algorithms on the CICIDS 2017 Dataset (https://www.unb.ca/cic/datasets/ids-2017.html):

- Support Vector Machine (SVM)
- Decision Tree
- Naive Bayes
- K Means Clustering
- K Nearest Neighbours

First, I will prepare the dataset, making sure it is the right shape and there are no null values. Next I will perform feature selection, using a filter approach. Lastly, I will then train and test the different models.

[1]: Iman Sharafaldin, Arash Habibi Lashkari, and Ali A. Ghorbani, “Toward Generating a New Intrusion Detection Dataset and Intrusion Traffic Characterization”, 4th International Conference on Information Systems Security and Privacy (ICISSP), Portugal, January 2018

Imports

In [1]:

```
# import required libraries
import glob
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import seaborn
import time

from numpy import array

from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import MinMaxScaler
from sklearn.preprocessing import RobustScaler

from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import LinearSVC
from sklearn.naive_bayes import MultinomialNB
from sklearn.neighbors import NearestNeighbors
from sklearn.neighbors import KNeighborsClassifier
from sklearn.cluster import KMeans
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import RandomForestClassifier

from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2
from sklearn.feature_selection import mutual_info_classif

from sklearn import metrics
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_recall_fscore_support as score
from sklearn.metrics import completeness_score, homogeneity_score, v_measure_score

from sklearn.model_selection import train_test_split
```

Reading in Data

The implemented attacks include Brute Force FTP, Brute Force SSH, DoS, Heartbleed, Web Attack, Infiltration, Botnet and DDoS. They have been executed both morning and afternoon on Tuesday, Wednesday, Thursday and Friday.

Day, Date, Description, Size (GB)

- Monday, Normal Activity, 11.0G
- Tuesday, attacks + Normal Activity, 11G
- Wednesday, attacks + Normal Activity, 13G
- Thursday, attacks + Normal Activity, 7.8G
- Friday, attacks + Normal Activity, 8.3G

They have split the csv into 8 different files (for the different days), so need to combine these.

In [4]:

```
# path to where ML files are stored
path = 'ids/MachineLearningCVE'
all_files = glob.glob(path + "/*.csv")

# concatenate the 8 files into 1
dataset = pd.concat((pd.read_csv(f) for f in all_files))
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: DtypeWarnin
g: Columns (14,15) have mixed types. Specify dtype option on import or set l
ow_memory=False.
  This is separate from the ipykernel package so we can avoid doing imports
until
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: DtypeWarnin
g: Columns (14) have mixed types. Specify dtype option on import or set low_
memory=False.
  This is separate from the ipykernel package so we can avoid doing imports
until
```

Column names from the dataset

In [5]:

```
col_names = ["Destination_Port",
             "Flow_Duration",
             "Total_Fwd_Packets",
             "Total_Backward_Packets",
             "Total_Length_of_Fwd_Packets",
             "Total_Length_of_Bwd_Packets",
             "Fwd_Packet_Length_Max",
             "Fwd_Packet_Length_Min",
             "Fwd_Packet_Length_Mean",
             "Fwd_Packet_Length_Std",
             "Bwd_Packet_Length_Max",
             "Bwd_Packet_Length_Min",
             "Bwd_Packet_Length_Mean",
             "Bwd_Packet_Length_Std",
             "Flow_Bytes_s",
             "Flow_Packets_s",
             "Flow_IAT_Mean",
             "Flow_IAT_Std",
             "Flow_IAT_Max",
             "Flow_IAT_Min",
             "Fwd_IAT_Total",
             "Fwd_IAT_Mean",
             "Fwd_IAT_Std",
             "Fwd_IAT_Max",
             "Fwd_IAT_Min",
             "Bwd_IAT_Total",
             "Bwd_IAT_Mean",
             "Bwd_IAT_Std",
             "Bwd_IAT_Max",
             "Bwd_IAT_Min",
             "Fwd_PSH_Flags",
             "Bwd_PSH_Flags",
             "Fwd_URG_Flags",
             "Bwd_URG_Flags",
             "Fwd_Header_Length",
             "Bwd_Header_Length",
             "Fwd_Packets_s",
             "Bwd_Packets_s",
             "Min_Packet_Length",
             "Max_Packet_Length",
             "Packet_Length_Mean",
             "Packet_Length_Std",
             "Packet_Length_Variance",
             "FIN_Flag_Count",
             "SYN_Flag_Count",
             "RST_Flag_Count",
             "PSH_Flag_Count",
             "ACK_Flag_Count",
             "URG_Flag_Count",
             "CWE_Flag_Count",
             "ECE_Flag_Count",
             "Down_Up_Ratio",
             "Average_Packet_Size",
             "Avg_Fwd_Segment_Size",
             "Avg_Bwd_Segment_Size",
             "Fwd_Header_Length",
             "Fwd_Avg_Bytes_Bulk",
             "Fwd_Avg_Packets_Bulk",
             "Fwd_Avg_Bulk_Rate",
```

```
             "Bwd_Avg_Bytes_Bulk",
             "Bwd_Avg_Packets_Bulk",
             "Bwd_Avg_Bulk_Rate",
             "Subflow_Fwd_Packets",
             "Subflow_Fwd_Bytes",
             "Subflow_Bwd_Packets",
             "Subflow_Bwd_Bytes",
             "Init_Win_bytes_forward",
             "Init_Win_bytes_backward",
             "act_data_pkt_fwd",
             "min_seg_size_forward",
             "Active_Mean",
             "Active_Std",
             "Active_Max",
             "Active_Min",
             "Idle_Mean",
             "Idle_Std",
             "Idle_Max",
             "Idle_Min",
             "Label"
            ]
```

Inspect the Dataset

In [6]:

```
# Assign the column names
dataset.columns = col_names
# Peak at first 5 records in the dataset
dataset.head(5)
```

Out[6]:

	Destination_Port	Flow_Duration	Total_Fwd_Packets	Total_Backward_Packets	Total_Length_o
0	80	38308	1	1	
1	389	479	11	5	
2	88	1095	10	6	
3	389	15206	17	12	
4	88	1092	9	6	

5 rows × 79 columns

In [7]:

```
# get statistics about each feature
dataset.describe().transpose()
```

Out[7]:

	count	mean	std	min	25
Destination_Port	2830743.0	8.071483e+03	1.828363e+04	0.000000e+00	53.00000
Flow_Duration	2830743.0	1.478566e+07	3.365374e+07	-1.300000e+01	155.00000
Total_Fwd_Packets	2830743.0	9.361160e+00	7.496728e+02	1.000000e+00	2.00000
Total_Backward_Packets	2830743.0	1.039377e+01	9.973883e+02	0.000000e+00	1.00000
Total_Length_of_Fwd_Packets	2830743.0	5.493024e+02	9.993589e+03	0.000000e+00	12.00000
Total_Length_of_Bwd_Packets	2830743.0	1.616264e+04	2.263088e+06	0.000000e+00	0.00000
Fwd_Packet_Length_Max	2830743.0	2.075999e+02	7.171848e+02	0.000000e+00	6.00000
Fwd_Packet_Length_Min	2830743.0	1.871366e+01	6.033935e+01	0.000000e+00	0.00000
Fwd_Packet_Length_Mean	2830743.0	5.820194e+01	1.860912e+02	0.000000e+00	6.00000
Fwd_Packet_Length_Std	2830743.0	6.891013e+01	2.811871e+02	0.000000e+00	0.00000
Bwd_Packet_Length_Max	2830743.0	8.708495e+02	1.946367e+03	0.000000e+00	0.00000
Bwd_Packet_Length_Min	2830743.0	4.104958e+01	6.886260e+01	0.000000e+00	0.00000
Bwd_Packet_Length_Mean	2830743.0	3.059493e+02	6.052568e+02	0.000000e+00	0.00000
Bwd_Packet_Length_Std	2830743.0	3.353257e+02	8.396932e+02	0.000000e+00	0.00000
Flow_IAT_Mean	2830743.0	1.298449e+06	4.507944e+06	-1.300000e+01	63.66666
Flow_IAT_Std	2830743.0	2.919271e+06	8.045870e+06	0.000000e+00	0.00000
Flow_IAT_Max	2830743.0	9.182475e+06	2.445954e+07	-1.300000e+01	123.00000
Flow_IAT_Min	2830743.0	1.623796e+05	2.950282e+06	-1.400000e+01	3.00000
Fwd_IAT_Total	2830743.0	1.448296e+07	3.357581e+07	0.000000e+00	0.00000
Fwd_IAT_Mean	2830743.0	2.610193e+06	9.525722e+06	0.000000e+00	0.00000
Fwd_IAT_Std	2830743.0	3.266957e+06	9.639055e+06	0.000000e+00	0.00000
Fwd_IAT_Max	2830743.0	9.042939e+06	2.452916e+07	0.000000e+00	0.00000
Fwd_IAT_Min	2830743.0	1.021893e+06	8.591436e+06	-1.200000e+01	0.00000
Bwd_IAT_Total	2830743.0	9.893830e+06	2.873661e+07	0.000000e+00	0.00000
Bwd_IAT_Mean	2830743.0	1.805784e+06	8.887197e+06	0.000000e+00	0.00000
Bwd_IAT_Std	2830743.0	1.485973e+06	6.278469e+06	0.000000e+00	0.00000
Bwd_IAT_Max	2830743.0	4.684692e+06	1.716095e+07	0.000000e+00	0.00000
Bwd_IAT_Min	2830743.0	9.672614e+05	8.308983e+06	0.000000e+00	0.00000
Fwd_PSH_Flags	2830743.0	4.644646e-02	2.104500e-01	0.000000e+00	0.00000
Bwd_PSH_Flags	2830743.0	0.000000e+00	0.000000e+00	0.000000e+00	0.00000
...	...	...	...	...	.
URG_Flag_Count	2830743.0	9.482316e-02	2.929706e-01	0.000000e+00	0.00000
CWE_Flag_Count	2830743.0	1.112782e-04	1.054826e-02	0.000000e+00	0.00000
ECE_Flag_Count	2830743.0	2.433990e-04	1.559935e-02	0.000000e+00	0.00000

	count	mean	std	min	25'
Down_Up_Ratio	2830743.0	6.835004e-01	6.804920e-01	0.000000e+00	0.00000
Average_Packet_Size	2830743.0	1.919837e+02	3.318603e+02	0.000000e+00	7.50000
Avg_Fwd_Segment_Size	2830743.0	5.820194e+01	1.860912e+02	0.000000e+00	6.00000
Avg_Bwd_Segment_Size	2830743.0	3.059493e+02	6.052568e+02	0.000000e+00	0.00000
Fwd_Header_Length	2830743.0	-2.599739e+04	2.105286e+07	-3.221223e+10	40.00000
Fwd_Avg_Bytes_Bulk	2830743.0	0.000000e+00	0.000000e+00	0.000000e+00	0.00000
Fwd_Avg_Packets_Bulk	2830743.0	0.000000e+00	0.000000e+00	0.000000e+00	0.00000
Fwd_Avg_Bulk_Rate	2830743.0	0.000000e+00	0.000000e+00	0.000000e+00	0.00000
Bwd_Avg_Bytes_Bulk	2830743.0	0.000000e+00	0.000000e+00	0.000000e+00	0.00000
Bwd_Avg_Packets_Bulk	2830743.0	0.000000e+00	0.000000e+00	0.000000e+00	0.00000
Bwd_Avg_Bulk_Rate	2830743.0	0.000000e+00	0.000000e+00	0.000000e+00	0.00000
Subflow_Fwd_Packets	2830743.0	9.361160e+00	7.496728e+02	1.000000e+00	2.00000
Subflow_Fwd_Bytes	2830743.0	5.492919e+02	9.980070e+03	0.000000e+00	12.00000
Subflow_Bwd_Packets	2830743.0	1.039377e+01	9.973883e+02	0.000000e+00	1.00000
Subflow_Bwd_Bytes	2830743.0	1.616230e+04	2.263057e+06	0.000000e+00	0.00000
Init_Win_bytes_forward	2830743.0	6.989837e+03	1.433873e+04	-1.000000e+00	-1.00000
Init_Win_bytes_backward	2830743.0	1.989433e+03	8.456883e+03	-1.000000e+00	-1.00000
act_data_pkt_fwd	2830743.0	5.418218e+00	6.364257e+02	0.000000e+00	0.00000
min_seg_size_forward	2830743.0	-2.741688e+03	1.084989e+06	-5.368707e+08	20.00000
Active_Mean	2830743.0	8.155132e+04	6.485999e+05	0.000000e+00	0.00000
Active_Std	2830743.0	4.113412e+04	3.933815e+05	0.000000e+00	0.00000
Active_Max	2830743.0	1.531825e+05	1.025825e+06	0.000000e+00	0.00000
Active_Min	2830743.0	5.829582e+04	5.770923e+05	0.000000e+00	0.00000
Idle_Mean	2830743.0	8.316037e+06	2.363008e+07	0.000000e+00	0.00000
Idle_Std	2830743.0	5.038439e+05	4.602984e+06	0.000000e+00	0.00000
Idle_Max	2830743.0	8.695752e+06	2.436689e+07	0.000000e+00	0.00000
Idle_Min	2830743.0	7.920031e+06	2.336342e+07	0.000000e+00	0.00000

76 rows × 8 columns

In [9]:

```
# check all the values are numerical
# if not, would have to encode
dataset.dtypes
```

Out[9]:

```
Destination_Port                 int64
Flow_Duration                    int64
Total_Fwd_Packets                int64
Total_Backward_Packets           int64
Total_Length_of_Fwd_Packets      int64
Total_Length_of_Bwd_Packets      int64
Fwd_Packet_Length_Max            int64
Fwd_Packet_Length_Min            int64
Fwd_Packet_Length_Mean         float64
Fwd_Packet_Length_Std          float64
Bwd_Packet_Length_Max            int64
Bwd_Packet_Length_Min            int64
Bwd_Packet_Length_Mean         float64
Bwd_Packet_Length_Std          float64
Flow_Bytes_s                    object
Flow_Packets_s                  object
Flow_IAT_Mean                  float64
Flow_IAT_Std                   float64
Flow_IAT_Max                     int64
Flow_IAT_Min                     int64
Fwd_IAT_Total                    int64
Fwd_IAT_Mean                   float64
Fwd_IAT_Std                    float64
Fwd_IAT_Max                      int64
Fwd_IAT_Min                      int64
Bwd_IAT_Total                    int64
Bwd_IAT_Mean                   float64
Bwd_IAT_Std                    float64
Bwd_IAT_Max                      int64
Bwd_IAT_Min                      int64
                                ...
CWE_Flag_Count                   int64
ECE_Flag_Count                   int64
Down_Up_Ratio                    int64
Average_Packet_Size            float64
Avg_Fwd_Segment_Size           float64
Avg_Bwd_Segment_Size           float64
Fwd_Header_Length                int64
Fwd_Avg_Bytes_Bulk               int64
Fwd_Avg_Packets_Bulk             int64
Fwd_Avg_Bulk_Rate                int64
Bwd_Avg_Bytes_Bulk               int64
Bwd_Avg_Packets_Bulk             int64
Bwd_Avg_Bulk_Rate                int64
Subflow_Fwd_Packets              int64
Subflow_Fwd_Bytes                int64
Subflow_Bwd_Packets              int64
Subflow_Bwd_Bytes                int64
Init_Win_bytes_forward           int64
Init_Win_bytes_backward          int64
act_data_pkt_fwd                 int64
min_seg_size_forward             int64
Active_Mean                    float64
```

```
Active_Std                    float64
Active_Max                      int64
Active_Min                      int64
Idle_Mean                     float64
Idle_Std                      float64
Idle_Max                        int64
Idle_Min                        int64
Label                          object
Length: 79, dtype: object
```

Flow_Bytes_s, Flow_Packets_s are of type object, the rest apart from attack are numeric. However, the data inside these are numeric so will convert them. Also, they have Fwd_Header_Length twice so drop the second occurence.

In [10]:

```
dataset['Flow_Bytes_s'] = dataset['Flow_Bytes_s'].astype('float64')
dataset['Flow_Packets_s'] = dataset['Flow_Packets_s'].astype('float64')
dataset = dataset.loc[:, ~dataset.columns.duplicated()]
```

Remove NaN/Null/Inf Values

In [11]:

```
# check if there are any Null values
dataset.isnull().any().any()
```

Out[11]:

```
True
```

In [12]:

```
# Replace Inf values with NaN
dataset = dataset.replace([np.inf, -np.inf], np.nan)
# Drop all occurences of NaN
dataset = dataset.dropna()
# Double check these are all gone
dataset.isnull().any().any()
```

Out[12]:

```
False
```

Explore Attacks in Dataset

In [13]:

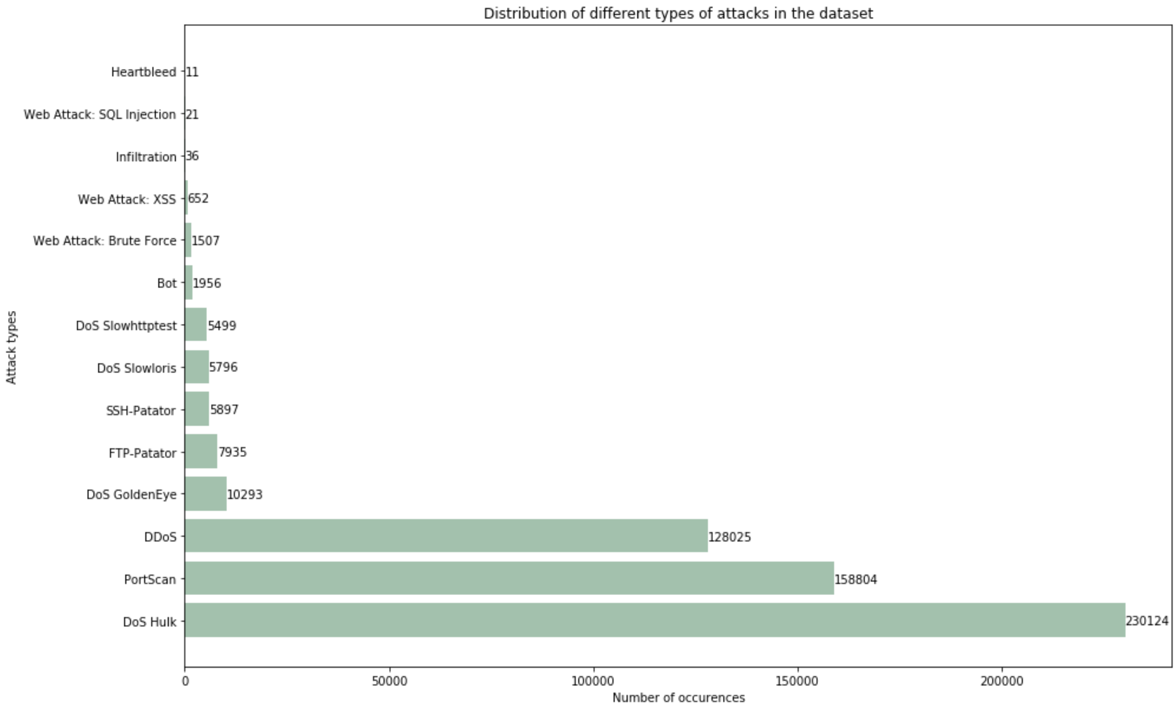
```
# Distribution of Dataset
dataset['Label'].value_counts()
```

Out[13]:

```
BENIGN                        2271320
DoS Hulk                       230124
PortScan                       158804
DDoS                           128025
DoS GoldenEye                   10293
FTP-Patator                      7935
SSH-Patator                      5897
DoS slowloris                    5796
DoS Slowhttptest                 5499
Bot                              1956
Web Attack � Brute Force         1507
Web Attack � XSS                  652
Infiltration                       36
Web Attack � Sql Injection         21
Heartbleed                         11
Name: Label, dtype: int64
```

In [14]:

```
plt.figure(figsize=(15,10))

attack = ('DoS Hulk', 'PortScan', 'DDoS', 'DoS GoldenEye', 'FTP-Patator', 'SSH-Patator', 'D
          'DoS Slowhttptest', 'Bot', 'Web Attack: Brute Force', 'Web Attack: XSS', 'Infiltr
y_pos = np.arange(len(attack))
amount = dataset['Label'].value_counts()[1:]
plt.barh(y_pos, amount, align='center', color='#a3c1ad' )
plt.yticks(y_pos, attack)
plt.title('Distribution of different types of attacks in the dataset')
plt.xlabel('Number of occurences')
plt.ylabel('Attack types')
for i, v in enumerate(amount):
    plt.text(v + 3, i-0.1 , str(v))

plt.show()
```



There are only 11, 21, and 36 instances of Heartbleed, SQL injection and infiltration respectively. So, we will drop these since there will not be sufficient trianing data. In addition, rename the web attacks to remove the unicode ?

In [15]:

```
dataset = dataset.replace(['Heartbleed', 'Web Attack � Sql Injection', 'Infiltration'], np
dataset = dataset.dropna()
dataset['Label'].value_counts()
```

Out[15]:

```
BENIGN                      2271320
DoS Hulk                     230124
PortScan                     158804
DDoS                         128025
DoS GoldenEye                 10293
FTP-Patator                    7935
SSH-Patator                    5897
DoS slowloris                  5796
DoS Slowhttptest               5499
Bot                            1956
Web Attack � Brute Force       1507
Web Attack � XSS                652
Name: Label, dtype: int64
```

In [16]:

```
dataset.loc[dataset.Label == 'Web Attack � Brute Force', ['Label']] = 'Brute Force'
dataset.loc[dataset.Label == 'Web Attack � XSS', ['Label']] = 'XSS'
```

We will add a binary attack column - indicating a 0 if benign, or 1 if there was an attack.

Furthermore, since there are several types of attacks, I propose a grouping of attacks, which should lead to a better accuracy and generalisation.

In [17]:

```
# Create attack column, containing binary labels
dataset['Attack'] = np.where(dataset['Label'] == 'BENIGN', 0, 1)
```

In [18]:

```
# Proposed Groupings
attack_group = {'BENIGN': 'benign',
                'DoS Hulk': 'dos',
                'PortScan': 'probe',
                'DDoS': 'ddos',
                'DoS GoldenEye': 'dos',
                'FTP-Patator': 'brute_force',
                'SSH-Patator': 'brute_force',
                'DoS slowloris': 'dos',
                'DoS Slowhttptest': 'dos',
                'Bot': 'botnet',
                'Brute Force': 'web_attack',
                'XSS': 'web_attack'}
# Create grouped label column
dataset['Label_Category'] = dataset['Label'].map(lambda x: attack_group[x])
dataset['Label_Category'].value_counts()
```

Out[18]:

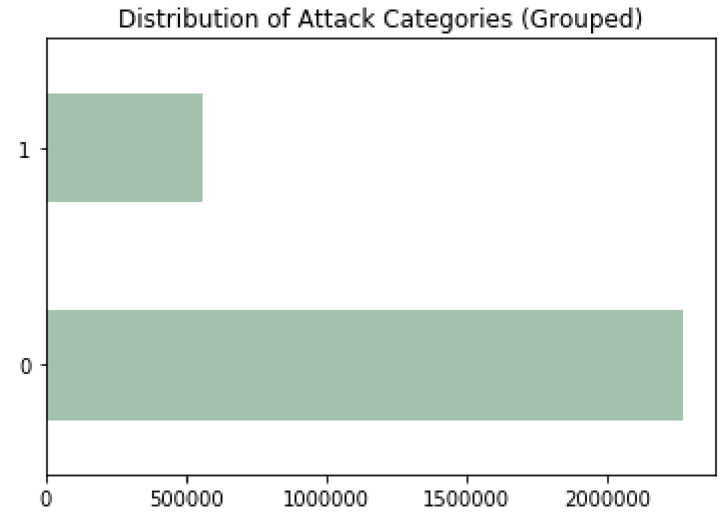
```
benign         2271320
dos             251712
probe           158804
ddos            128025
brute_force      13832
web_attack        2159
botnet            1956
Name: Label_Category, dtype: int64
```

In [19]:

```
train_attacks = dataset['Attack'].value_counts()
train_attacks.plot(kind='barh', color='#a3c1ad')
plt.title('Distribution of Attack Categories (Grouped)')
```

Out[19]:

```
Text(0.5, 1.0, 'Distribution of Attack Categories (Grouped)')
```

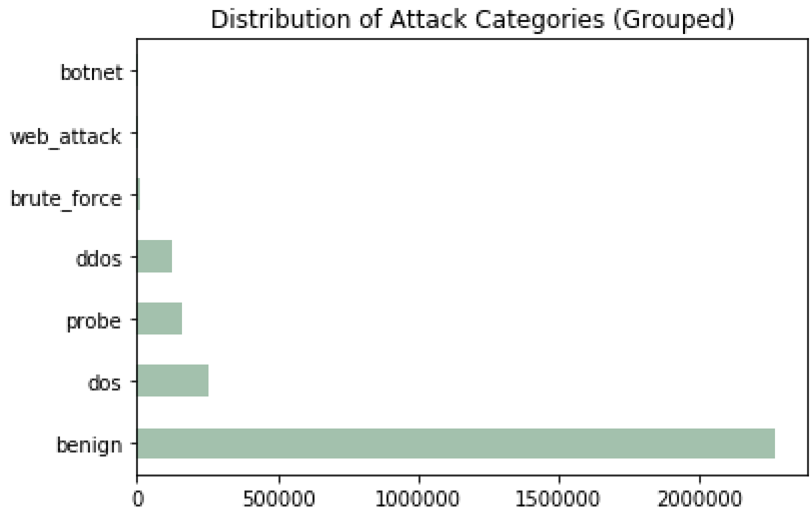


In [20]:

```
train_attacks = dataset['Label_Category'].value_counts()
train_attacks.plot(kind='barh', color='#a3c1ad')
plt.title('Distribution of Attack Categories (Grouped)')
```

Out[20]:

```
Text(0.5, 1.0, 'Distribution of Attack Categories (Grouped)')
```

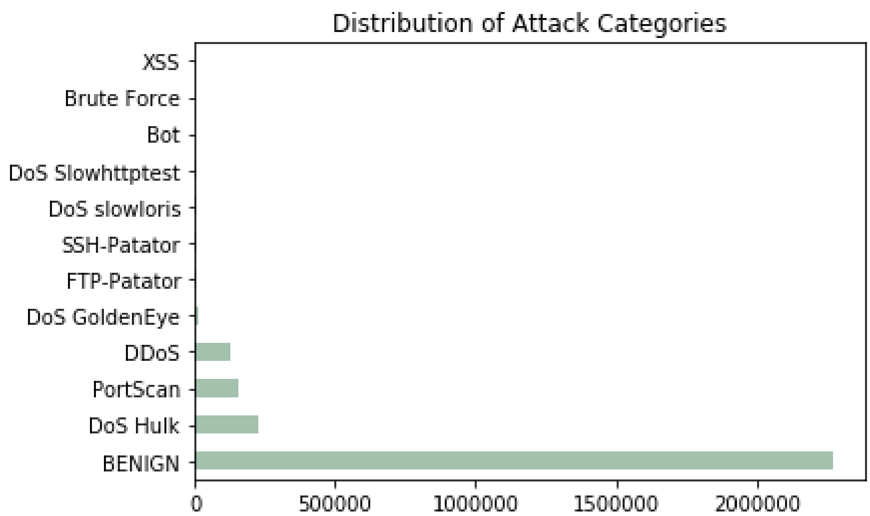


In [21]:

```
train_attacks = dataset['Label'].value_counts()
train_attacks.plot(kind='barh', color='#a3c1ad')
plt.title('Distribution of Attack Categories')
```

Out[21]:

```
Text(0.5, 1.0, 'Distribution of Attack Categories')
```



Split Data

Split data using 60:20:20 ratio, for training, test and validation dataset. We stratify such that the proportions of attacks remain the same throughout the 3 sets.

In [22]:

```
# 3 Different labeling options
attacks = ['Label', 'Label_Category', 'Attack']

# xs=feature vectors, ys=labels
xs = dataset.drop(attacks, axis=1)
ys = dataset[attacks]

# split dataset - stratified
x_train, x_temp, y_train, y_temp = train_test_split(xs, ys, test_size=0.4, random_state=0,
x_test, x_validate, y_test, y_validate = train_test_split(x_temp, y_temp, test_size=0.5, ra
```

In [23]:

```
column_names = np.array(list(x_train))
to_drop = []
for x in column_names:
    size = x_train.groupby([x]).size()
    # check for columns that only take one value
    if (len(size.unique()) == 1):
        to_drop.append(x)
to_drop
```

Out[23]:

```
['Bwd_PSH_Flags',
 'Bwd_URG_Flags',
 'Fwd_Avg_Bytes_Bulk',
 'Fwd_Avg_Packets_Bulk',
 'Fwd_Avg_Bulk_Rate',
 'Bwd_Avg_Bytes_Bulk',
 'Bwd_Avg_Packets_Bulk',
 'Bwd_Avg_Bulk_Rate']
```

Drop these because they only contain one value, and so are redundant as columns

In [24]:

```
x_train = x_train.drop(to_drop, axis=1)
x_validate = x_validate.drop(to_drop, axis=1)
x_test = x_test.drop(to_drop, axis=1)
dataset_copy = dataset.drop(to_drop, axis=1)
```

Apply Normalisation

Using minmax normalisation

In [25]:

```
# Normalise
min_max_scaler = MinMaxScaler().fit(x_train)

# Apply normalisation to dataset
x_train = min_max_scaler.transform(x_train)
x_validate = min_max_scaler.transform(x_validate)
x_test = min_max_scaler.transform(x_test)

# All values between 0 and 1
pd.Series(x_train.flatten()).describe()
```

```
/usr/lib/python3/dist-packages/sklearn/preprocessing/data.py:334: DataConver
sionWarning: Data with input dtype int64, float64 were all converted to floa
t64 by MinMaxScaler.
  return self.partial_fit(X, y)
```

Out[25]:

```
count    1.170712e+08
mean     8.823915e-02
std      2.515841e-01
min      0.000000e+00
25%      0.000000e+00
50%      8.235825e-07
75%      6.410256e-03
max      1.000000e+00
dtype: float64
```

Feature Selection

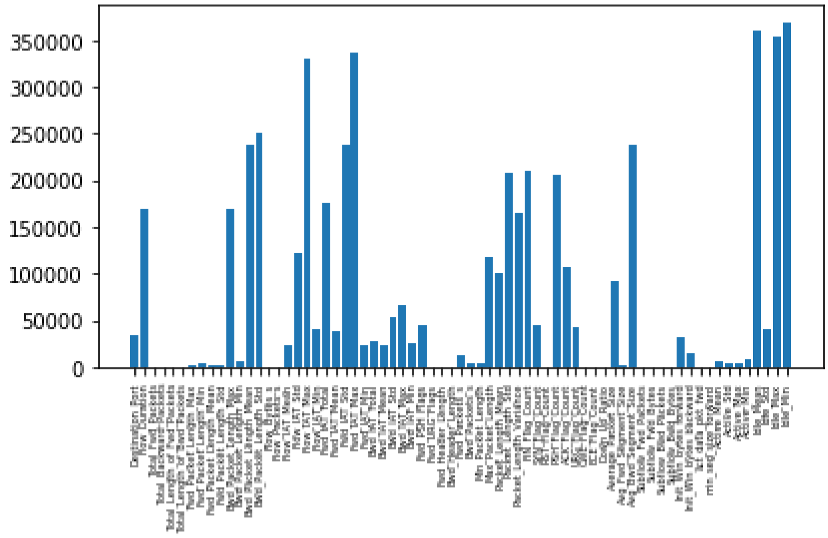
Use chi2 select k best First, score all the features

In [26]:

```
features = SelectKBest(score_func=chi2, k=x_train.shape[1])

#fit features to the training dataset
fit = features.fit(x_train, y_train.Label)
```

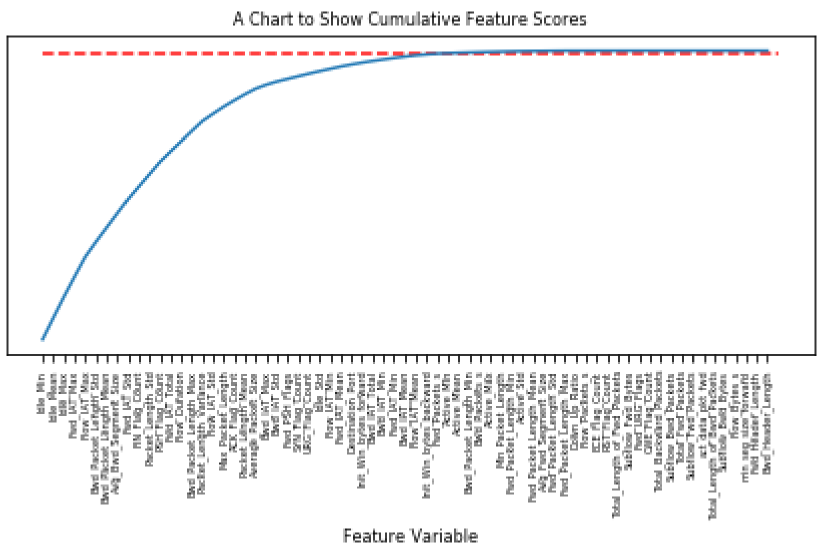
In [27]:

```
# plot the score associated with each feature
plt.bar([i for i in range(len(features.scores_))], features.scores_)
plt.xticks([i for i in range(len(features.scores_))], dataset_copy.columns)
plt.xticks(rotation=90, fontsize=5)
plt.tight_layout()
plt.savefig('features.png', dpi=300)
```



In [28]:

```
# sort the features by importance score
feature_importances = zip(dataset_copy.columns, features.scores_)
feature_importances = sorted(feature_importances, key = lambda x: x[1], reverse = True)
sorted_importances = [importance[1] for importance in feature_importances]
sorted_features = [importance[0] for importance in feature_importances]

x_values = list(range(len(feature_importances)))

# plot the cumulative scores
cumulative_importances = np.cumsum(sorted_importances)
plt.plot(x_values, cumulative_importances)

# Draw line at 99% of importance retained
value99 = cumulative_importances[-1]*0.99

plt.hlines(y = value99, xmin=0, xmax=len(sorted_importances), color = 'r', linestyles = 'da
plt.xticks(x_values, sorted_features, rotation = 'vertical', fontsize=5)
plt.yticks([], [])
plt.xlabel('Feature Variable', fontsize=8)
plt.title('A Chart to Show Cumulative Feature Scores', fontsize=8)
#plt.figure(figsize=(500,200))
plt.tight_layout()
plt.savefig('cum_features.png', dpi=300)
```



We select 40 features. 99% of the information is contained in the first 40, so this is the cut off point

In [29]:

```
# perform selectkbest with k=40
features = SelectKBest(score_func=chi2, k=40)
fit = features.fit(x_train, y_train.Label)
x_train = fit.transform(x_train)
x_test = fit.transform(x_test)
x_validate = fit.transform(x_validate)
```

Need to find out what are the new features that we need to collect

In [30]:

```
new_features = dataset_copy.columns[features.get_support(indices=True)]
```

In [31]:

```
new_features
```

Out[31]:

```
Index(['Destination_Port', 'Flow_Duration', 'Bwd_Packet_Length_Max',
       'Bwd_Packet_Length_Mean', 'Bwd_Packet_Length_Std', 'Flow_IAT_Mean',
       'Flow_IAT_Std', 'Flow_IAT_Max', 'Flow_IAT_Min', 'Fwd_IAT_Total',
       'Fwd_IAT_Mean', 'Fwd_IAT_Std', 'Fwd_IAT_Max', 'Fwd_IAT_Min',
       'Bwd_IAT_Total', 'Bwd_IAT_Mean', 'Bwd_IAT_Std', 'Bwd_IAT_Max',
       'Bwd_IAT_Min', 'Fwd_PSH_Flags', 'Fwd_Packets_s', 'Max_Packet_Length',
       'Packet_Length_Mean', 'Packet_Length_Std', 'Packet_Length_Variance',
       'FIN_Flag_Count', 'SYN_Flag_Count', 'PSH_Flag_Count', 'ACK_Flag_Coun
t',
       'URG_Flag_Count', 'Average_Packet_Size', 'Avg_Bwd_Segment_Size',
       'Init_Win_bytes_forward', 'Init_Win_bytes_backward', 'Active_Mean',
       'Active_Min', 'Idle_Mean', 'Idle_Std', 'Idle_Max', 'Idle_Min'],
      dtype='object')
```

In [32]:

```
attack = np.array(['BENIGN', 'Bot', 'Brute Force', 'DDoS', 'DoS GoldenEye', 'DoS Hulk', 'Do
                   'DoS slowloris', 'FTP-Patator', 'PortScan', 'SSH-Patator', 'XSS'])
attack_groups = np.array(['benign', 'botnet', 'brute_force', 'ddos', 'dos', 'probe', 'web_a
```

1. SVM

Try our first algorithm - a support vector machine 1. On all labels 2. On grouped labels 3. On binary labels

In [31]:

```
classifier = LinearSVC()
```

All labels

In [127]:

```
# fit the model
start = time.time()
classifier.fit(x_train, y_train.Label)
end = time.time()
training_time = end - start

# predict validation
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_svm_1 = pd.crosstab(y_validate.Label, y_predicted)
confusion_svm_1
```

```
453.01398611068726 0.19631695747375488
```

Out[127]:

col_0	BENIGN	Bot	Brute Force	DDoS	DoS GoldenEye	DoS Hulk	DoS Slowhttptest	DoS slowloris	FTP-Patator
Label									
BENIGN	440755	19	1	56	124	1469	211	8	0
Bot	291	0	0	0	0	0	0	0	0
Brute Force	301	0	0	0	0	0	0	0	0
DDoS	4178	0	0	20934	1	487	0	0	0
DoS GoldenEye	685	0	0	0	1369	0	1	2	0
DoS Hulk	8817	14	0	222	108	36849	2	12	0
DoS Slowhttptest	308	0	0	18	0	0	751	23	0
DoS slowloris	586	0	0	0	0	10	13	547	0
FTP-Patator	797	0	0	0	0	0	0	0	790
PortScan	506	0	0	0	4	19	0	6	0
SSH-Patator	1179	0	0	0	0	0	0	0	0
XSS	130	0	0	0	0	0	0	0	0

In [128]:

```
precision, recall, fscore, support = score(y_validate.Label, y_predicted)

d = {'attack': attack, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-package
s/sklearn/metrics/classification.py:1437: UndefinedMetricWarning: Precision
and F-score are ill-defined and being set to 0.0 in labels with no predicted
samples.
  'precision', 'predicted', average, warn_for)
```

Out[128]:

	attack	precision	recall	fscore
0	BENIGN	0.961229	0.970260	0.965723
1	Bot	0.000000	0.000000	0.000000
2	Brute Force	0.000000	0.000000	0.000000
3	DDoS	0.986057	0.817575	0.893947
4	DoS GoldenEye	0.852428	0.665209	0.747271
5	DoS Hulk	0.948885	0.800630	0.868476
6	DoS Slowhttptest	0.767894	0.682727	0.722810
7	DoS slowloris	0.914716	0.471959	0.622652
8	FTP-Patator	1.000000	0.497795	0.664703
9	PortScan	0.726947	0.983155	0.835858
10	SSH-Patator	0.000000	0.000000	0.000000
11	XSS	0.000000	0.000000	0.000000

In [129]:

```
precision_svm_1, recall_svm_1, fscore_svm_1, support = score(y_validate.Label, y_predicted,
accuracy_svm_1 = accuracy_score(y_validate.Label, y_predicted)
```

Grouped labels

In [130]:

```
# fit the model
start = time.time()
classifier.fit(x_train, y_train.Label_Category)
end = time.time()
training_time = end - start

# predict validation
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_svm_2 = pd.crosstab(y_validate.Label_Category, y_predicted)
confusion_svm_2
```

343.225998878479 0.09940409660339355

Out[130]:

col_0	benign	botnet	brute_force	ddos	dos	probe	web_attack
Label_Category							
benign	440552	24	0	54	2010	11619	6
botnet	291	0	0	0	0	100	0
brute_force	1957	0	794	0	15	1	0
ddos	4175	0	0	20571	854	5	0
dos	10455	40	0	294	39549	4	0
probe	505	0	0	0	24	31232	0
web_attack	431	0	0	0	0	0	0

In [131]:

```
precision, recall, fscore, support = score(y_validate.Label_Category, y_predicted)

d = {'attack': attack_groups, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[131]:

	attack	precision	recall	fscore
0	benign	0.961136	0.969813	0.965455
1	botnet	0.000000	0.000000	0.000000
2	brute_force	1.000000	0.286953	0.445942
3	ddos	0.983364	0.803398	0.884318
4	dos	0.931617	0.785606	0.852404
5	probe	0.726985	0.983344	0.835952
6	web_attack	0.000000	0.000000	0.000000

In [132]:

```
precision_svm_2, recall_svm_2, fscore_svm_2, n = score(y_validate.Label_Category, y_predict
accuracy_svm_2 = accuracy_score(y_validate.Label_Category, y_predicted)
```

Binary Labels

In [133]:

```
# fit the model
start = time.time()
classifier.fit(x_train, y_train.Attack)
end = time.time()
training_time = end - start

# predict validation
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)
confusion_svm_3 = pd.crosstab(y_validate.Attack, y_predicted)
confusion_svm_3
```

121.44809889793396 0.03398299217224121

Out[133]:

col_0	0	1
Attack		
0	437550	16715
1	24741	86556

In [134]:

```
precision, recall, fscore, support = score(y_validate.Attack, y_predicted)
d = {'attack': [0,1], 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[134]:

	attack	precision	recall	fscore
0	0	0.946482	0.963204	0.954770
1	1	0.838144	0.777703	0.806793

In [135]:

```
precision_svm_3, recall_svm_3, fscore_svm_3, n = score(y_validate.Attack, y_predicted, aver
accuracy_svm_3 = accuracy_score(y_validate.Attack, y_predicted)
```

Results for SVM:

In [136]:

```
print('Support Vector Machine: Precision / Recall / Fscore / Accuracy')
print('All Labels:', precision_svm_1, recall_svm_1, fscore_svm_1,  accuracy_svm_1)
print('Groupued Labels:', precision_svm_2, recall_svm_2, fscore_svm_2, accuracy_svm_2)
print('Binary Labels:', precision_svm_3, recall_svm_3, fscore_svm_3, accuracy_svm_3)
```

```
Support Vector Machine: Precision / Recall / Fscore / Accuracy
All Labels: 0.5965129640062673 0.4907757713834196 0.5267867496144032 0.94281
61722322221
Groupued Labels: 0.6575860130297377 0.5470163903531152 0.569152989098072 0.9
418914283491465
Binary Labels: 0.8923130307182863 0.8704536000472447 0.8807814983275402 0.92
66994600061532
```

2. Decision Tree

In [231]:

```
classifier = DecisionTreeClassifier(random_state = 0)
```

All labels

In [232]:

```
# fit the model
start = time.time()
classifier.fit(x_train, y_train.Label)
end = time.time()
training_time = end - start

# predict validation
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_dt_1 = pd.crosstab(y_validate.Label, y_predicted)
confusion_dt_1
```

```
105.93187499046326 0.7262368202209473
```

Out[232]:

col_0	BENIGN	Bot	Brute Force	DDoS	DoS GoldenEye	DoS Hulk	DoS Slowhttptest	DoS slowloris	FTP-Patator
Label									
BENIGN	453896	73	2	11	4	79	10	8	0
Bot	71	320	0	0	0	0	0	0	0
Brute Force	2	0	224	0	0	0	0	1	0
DDoS	7	0	0	25596	0	1	1	0	0
DoS GoldenEye	5	0	0	0	2044	7	0	2	0
DoS Hulk	60	0	1	0	1	45960	0	0	0
DoS Slowhttptest	7	0	0	0	2	0	1083	8	0
DoS slowloris	1	0	0	0	0	0	9	1148	0
FTP-Patator	1	0	0	0	0	0	0	0	1586
PortScan	220	0	0	0	0	5	0	0	0
SSH-Patator	0	0	0	0	0	0	0	0	1
XSS	1	0	76	0	0	0	0	1	0

In [235]:

```
precision, recall, fscore, support = score(y_validate.Label, y_predicted)
d = {'attack': attack, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[235]:

	attack	precision	recall	fscore
0	BENIGN	0.999175	0.999188	0.999181
1	Bot	0.814249	0.818414	0.816327
2	Brute Force	0.739274	0.744186	0.741722
3	DDoS	0.999570	0.999649	0.999609
4	DoS GoldenEye	0.996587	0.993197	0.994889
5	DoS Hulk	0.998002	0.998588	0.998295
6	DoS Slowhttptest	0.981868	0.984545	0.983205
7	DoS slowloris	0.982877	0.990509	0.986678
8	FTP-Patator	0.999370	0.999370	0.999370
9	PortScan	0.994136	0.992853	0.993494
10	SSH-Patator	0.999153	0.999153	0.999153
11	XSS	0.393701	0.384615	0.389105

In [236]:

```
precision_dt_1, recall_dt_1, fscore_dt_1, n = score(y_validate.Label, y_predicted, average
accuracy_dt_1 = accuracy_score(y_validate.Label, y_predicted)
```

Grouped Labels

In [237]:

```
# fit the model
start = time.time()
classifier.fit(x_train, y_train.Label_Category)
end = time.time()
training_time = end - start

# predict validation
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_dt_2 = pd.crosstab(y_validate.Label_Category, y_predicted)
confusion_dt_2
```

```
100.00708293914795 0.22777891159057617
```

Out[237]:

col_0	benign	botnet	brute_force	ddos	dos	probe	web_attack
Label_Category							
benign	453899	71	1	14	95	175	10
botnet	65	326	0	0	0	0	0
brute_force	1	0	2766	0	0	0	0
ddos	9	0	0	25596	0	0	0
dos	69	0	0	0	50267	5	1
probe	221	0	0	0	5	31533	2
web_attack	3	0	0	0	1	0	427

In [238]:

```
precision, recall, fscore, support = score(y_validate.Label_Category, y_predicted)

d = {'attack': attack_groups, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[238]:

	attack	precision	recall	fscore
0	benign	0.999190	0.999194	0.999192
1	botnet	0.821159	0.833760	0.827411
2	brute_force	0.999639	0.999639	0.999639
3	ddos	0.999453	0.999649	0.999551
4	dos	0.997995	0.998510	0.998252
5	probe	0.994324	0.992821	0.993572
6	web_attack	0.970455	0.990719	0.980482

In [239]:

```
precision_dt_2, recall_dt_2, fscore_dt_2, n = score(y_validate.Label_Category, y_predicted,
accuracy_dt_2 = accuracy_score(y_validate.Label_Category, y_predicted)
```

Binary Labels

In [240]:

```
# fit the model
start = time.time()
classifier.fit(x_train, y_train.Attack)
end = time.time()
training_time = end - start

# predict validation
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_dt_3 = pd.crosstab(y_validate.Attack, y_predicted)
confusion_dt_3
```

92.32936334609985 0.16121602058410645

Out[240]:

col_0	0	1
Attack		
0	453916	349
1	369	110928

In [241]:

```
precision, recall, fscore, support = score(y_validate.Attack, y_predicted)
d = {'attack': [0,1], 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[241]:

	attack	precision	recall	fscore
0	0	0.999188	0.999232	0.999210
1	1	0.996864	0.996685	0.996774

In [242]:

```
precision_dt_3, recall_dt_3, fscore_dt_3, n = score(y_validate.Attack, y_predicted, average
accuracy_dt_3 = accuracy_score(y_validate.Attack, y_predicted)
```

Decision tree results

In [243]:

```
print('Decision Tree: Precision / Recall / Fscore / Accuracy')
print('All Labels:', precision_dt_1, recall_dt_1, fscore_dt_1, accuracy_dt_1)
print('Groupued Labels:', precision_dt_2, recall_dt_2, fscore_dt_2, accuracy_dt_2)
print('Binary Labels:', precision_dt_3, recall_dt_3, fscore_dt_3, accuracy_dt_3)
```

```
Decision Tree: Precision / Recall / Fscore / Accuracy
All Labels: 0.9081634383001905 0.9086888973262549 0.9084189640790116 0.99833
44001188199
Groupued Labels: 0.9688877040659636 0.9734702614491766 0.9711570807064333 0.
9986774217504005
Binary Labels: 0.9980257085469522 0.9979581363641041 0.9979919181892469 0.99
87304663326037
```

3. Naive Bayes

In [148]:

```
classifier = MultinomialNB()
```

Original labels

In [149]:

```
# fit model
start = time.time()
classifier.fit(x_train, y_train.Label)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_nb_1 = pd.crosstab(y_validate.Label, y_predicted)
confusion_nb_1
```

```
11.465129137039185 0.12616705894470215
```

Out[149]:

col_0	BENIGN	DDoS	DoS GoldenEye	DoS Hulk	DoS Slowhttptest	DoS slowloris	PortScan
Label							
BENIGN	447618	226	14	1390	59	4655	303
Bot	388	3	0	0	0	0	0
Brute Force	301	0	0	0	0	0	0
DDoS	9471	12706	0	3428	0	0	0
DoS GoldenEye	1217	669	106	0	0	66	0
DoS Hulk	15354	2558	0	28113	0	0	0
DoS Slowhttptest	906	0	0	0	194	0	0
DoS slowloris	926	0	0	0	35	198	0
FTP-Patator	1587	0	0	0	0	0	0
PortScan	31722	13	0	0	0	17	9
SSH-Patator	1180	0	0	0	0	0	0
XSS	130	0	0	0	0	0	0

In [150]:

```
precision, recall, fscore, support = score(y_validate.Label, y_predicted)
d = {'attack': attack, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-package
s/sklearn/metrics/classification.py:1437: UndefinedMetricWarning: Precision
and F-score are ill-defined and being set to 0.0 in labels with no predicted
samples.
  'precision', 'predicted', average, warn_for)
```

Out[150]:

	attack	precision	recall	fscore
0	BENIGN	0.876308	0.985368	0.927643
1	Bot	0.000000	0.000000	0.000000
2	Brute Force	0.000000	0.000000	0.000000
3	DDoS	0.785533	0.496231	0.608234
4	DoS GoldenEye	0.883333	0.051506	0.097337
5	DoS Hulk	0.853694	0.610820	0.712118
6	DoS Slowhttptest	0.673611	0.176364	0.279539
7	DoS slowloris	0.040113	0.170837	0.064971
8	FTP-Patator	0.000000	0.000000	0.000000
9	PortScan	0.028846	0.000283	0.000561
10	SSH-Patator	0.000000	0.000000	0.000000
11	XSS	0.000000	0.000000	0.000000

In [151]:

```
precision_nb_1, recall_nb_1, fscore_nb_1, n = score(y_validate.Label, y_predicted, average
accuracy_nb_1 = accuracy_score(y_validate.Label, y_predicted)
```

Grouped labels

In [152]:

```
# fit model
start = time.time()
classifier.fit(x_train, y_train.Label_Category)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_nb_2 = pd.crosstab(y_validate.Label_Category, y_predicted)
confusion_nb_2
```

```
7.065007209777832 0.11336398124694824
```

Out[152]:

col_0	benign	ddos	dos	probe
Label_Category				
benign	448265	226	5471	303
botnet	388	3	0	0
brute_force	2767	0	0	0
ddos	9471	12623	3511	0
dos	18513	3226	28603	0
probe	31739	13	0	9
web_attack	431	0	0	0

In [153]:

```
precision, recall, fscore, support = score(y_validate.Label_Category, y_predicted)
d = {'attack': attack_groups, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-package
s/sklearn/metrics/classification.py:1437: UndefinedMetricWarning: Precision
and F-score are ill-defined and being set to 0.0 in labels with no predicted
samples.
  'precision', 'predicted', average, warn_for)
```

Out[153]:

	attack	precision	recall	fscore
0	benign	0.876247	0.986792	0.928240
1	botnet	0.000000	0.000000	0.000000
2	brute_force	0.000000	0.000000	0.000000
3	ddos	0.784476	0.492990	0.605478
4	dos	0.761022	0.568174	0.650608
5	probe	0.028846	0.000283	0.000561
6	web_attack	0.000000	0.000000	0.000000

In [154]:

```
precision_nb_2, recall_nb_2, fscore_nb_2, n = score(y_validate.Label_Category, y_predicted,
accuracy_nb_2 = accuracy_score(y_validate.Label_Category, y_predicted)
```

Binary Labels

In [155]:

```
# fit model
start = time.time()
classifier.fit(x_train, y_train.Attack)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_nb_3 = pd.crosstab(y_validate.Attack, y_predicted)
confusion_nb_3
```

0.5996789932250977 0.05989408493041992

Out[155]:

col_0	0	1
Attack		
0	443615	10650
1	62736	48561

In [156]:

```
precision, recall, fscore, support = score(y_validate.Attack, y_predicted)
d = {'attack': [0,1], 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[156]:

	attack	precision	recall	fscore
0	0	0.876102	0.976556	0.923605
1	1	0.820135	0.436319	0.569604

In [157]:

```
precision_nb_3, recall_nb_3, fscore_nb_3, n = score(y_validate.Attack, y_predicted, average
accuracy_nb_3 = accuracy_score(y_validate.Attack, y_predicted)
```

Naive Bayes Results

In [158]:

```
print('Naive Bayes: Precision / Recall / Fscore / Accuracy')
print('All labels:', precision_nb_1, recall_nb_1, fscore_nb_1, accuracy_nb_1)
print('Grouped labels:', precision_nb_2, recall_nb_2, fscore_nb_2, accuracy_nb_2)
print('Binary labels:', precision_nb_3, recall_nb_3, fscore_nb_3, accuracy_nb_3)
```

```
Naive Bayes: Precision / Recall / Fscore / Accuracy
All labels: 0.34511992674625697 0.20761743591662676 0.22420028175606552 0.86
45276733585354
Grouped labels: 0.3500843249521696 0.29260550848150363 0.31212663524995427
0.8655107662820345
Binary labels: 0.8481182638783868 0.7064372865069797 0.7466045211044006 0.87
02423430145589
```

4. K Nearest Neighbours

Find what the value of K is best

In [ ]:

```
p_list = []
r_list = []
f_list = []

# for odd values of k, 1-50 (note: takes a long time to run)
k_range = range(1, 51, 2)

for k in k_range:
    classifier = KNeighborsClassifier(n_neighbors = k)
    # fit model
    classifier.fit(x_train, y_train.Label)
    # predict validation
    y_predicted = classifier.predict(x_validate)
    # calculate metrics
    precision, recall, fscore, n = score(y_validate.Label, y_predicted, average = 'macro')
    # append to the list
    p_list.append(precision)
    r_list.append(recall)
    f_list.append(fscore)
```

In [ ]:

```
# plot results
plt.plot(k_range, p_list, label='Precision')
plt.plot(k_range, r_list, label='Recall')

plt.plot(k_range, f1_list, label='F1 Score')
plt.legend(loc='best')
plt.xlabel('K Value')
plt.ylabel('%')
plt.title('A chart to show Precision, Recall, and F1 Score for different K Values')
plt.savefig('knn_k_values.png')
```

All labels with k=7

In [72]:

```
# fit model
classifier = KNeighborsClassifier(n_neighbors = 7)
start = time.time()
classifier.fit(x_train, y_train.Label)
end = time.time()
training_time = end - start

#predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

#calculate metrics
precision_knn_1, recall_knn_1, fscore_knn_1, n = score(y_validate.Label, y_predicted, avera
accuracy_knn_1=  accuracy_score(y_validate.Label, y_predicted)

confusion_knn_1 = pd.crosstab(y_validate.Label, y_predicted)
confusion_knn_1
```

```
2306.966103076935 1963.9200639724731
```

Out[72]:

col_0	BENIGN	Bot	Brute Force	DDoS	DoS GoldenEye	DoS Hulk	DoS Slowhttptest	DoS slowloris	FTP-Patator
Label									
BENIGN	451806	88	2	34	15	150	27	4	5
Bot	126	265	0	0	0	0	0	0	0
Brute Force	2	0	246	0	0	0	0	0	0
DDoS	12	0	0	25466	4	123	0	0	0
DoS GoldenEye	16	0	0	2	2034	4	2	0	0
DoS Hulk	90	0	1	32	6	45894	0	0	0
DoS Slowhttptest	6	0	0	0	0	0	1092	2	0
DoS slowloris	12	0	0	0	0	0	4	1142	1
FTP-Patator	3	0	0	0	0	0	0	2	1581
PortScan	1203	0	2	0	0	8	0	0	0
SSH-Patator	11	0	0	0	0	2	0	0	2
XSS	2	0	89	0	0	0	0	0	0

In [66]:

```
precision, recall, fscore, support = score(y_validate.Label, y_predicted)
d = {'attack': attack, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[66]:

	attack	precision	recall	fscore
0	BENIGN	0.996728	0.994587	0.995656
1	Bot	0.750708	0.677749	0.712366
2	Brute Force	0.723529	0.817276	0.767551
3	DDoS	0.997337	0.994571	0.995952
4	DoS GoldenEye	0.987858	0.988338	0.988098
5	DoS Hulk	0.993785	0.997154	0.995467
6	DoS Slowhttptest	0.970667	0.992727	0.981573
7	DoS slowloris	0.993043	0.985332	0.989173
8	FTP-Patator	0.994965	0.996219	0.995592
9	PortScan	0.934990	0.961809	0.948210
10	SSH-Patator	0.988964	0.987288	0.988126
11	XSS	0.423913	0.300000	0.351351

grouped labels, k=7

In [67]:

```
# fit model
classifier = KNeighborsClassifier(n_neighbors = 7)
start = time.time()
classifier.fit(x_train, y_train.Label_Category)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

# metrics
precision_knn_2, recall_knn_2, fscore_knn_2, n = score(y_validate.Label_Category, y_predict
accuracy_knn_2 =  accuracy_score(y_validate.Label_Category, y_predicted)

confusion_knn_2 = pd.crosstab(y_validate.Label_Category, y_predicted)
confusion_knn_2
```

```
2507.444155931473 2064.9058079719543
```

Out[67]:

col_0	benign	botnet	brute_force	ddos	dos	probe	web_attack
Label_Category							
benign	451800	88	17	34	202	2122	2
botnet	126	265	0	0	0	0	0
brute_force	14	0	2749	0	4	0	0
ddos	12	0	0	25466	127	0	0
dos	120	0	1	34	50184	2	1
probe	1203	0	0	0	8	30548	2
web_attack	4	0	0	0	0	0	427

In [68]:

```
precision, recall, fscore, support = score(y_validate.Label_Category, y_predicted)
d = {'attack': attack_groups, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[68]:

	attack	precision	recall	fscore
0	benign	0.996737	0.994574	0.995654
1	botnet	0.750708	0.677749	0.712366
2	brute_force	0.993495	0.993495	0.993495
3	ddos	0.997337	0.994571	0.995952
4	dos	0.993251	0.996861	0.995053
5	probe	0.934990	0.961809	0.948210
6	web_attack	0.988426	0.990719	0.989571

binary labels, k=7

In [69]:

```
# fit model
classifier = KNeighborsClassifier(n_neighbors = 7)
start = time.time()
classifier.fit(x_train, y_train.Attack)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

# metrics
precision_knn_3, recall_knn_3, fscore_knn_3, n = score(y_validate.Attack, y_predicted, aver
accuracy_knn_3 =  accuracy_score(y_validate.Attack, y_predicted)

confusion_knn_3 = pd.crosstab(y_validate.Attack, y_predicted)
confusion_knn_3
```

```
2457.469139814377 2008.6706459522247
```

Out[69]:

col_0	0	1
Attack		
0	451794	2471
1	1478	109819

In [70]:

```
precision, recall, fscore, support = score(y_validate.Attack, y_predicted)
d = {'attack': [0,1], 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[70]:

	attack	precision	recall	fscore
0	0	0.996739	0.99456	0.995649
1	1	0.977994	0.98672	0.982338

KNN Results

In [73]:

```
print('KNN: Precision / Recall / Fscore / Accuracy')
print('All Labels:', precision_knn_1, recall_knn_1, fscore_knn_1, accuracy_knn_1)
print('Grouped Labels:', precision_knn_2, recall_knn_2, fscore_knn_2, accuracy_knn_2)
print('Binary Labels:', precision_knn_3, recall_knn_3, fscore_knn_3, accuracy_knn_3)
```

```
KNN: Precision / Recall / Fscore / Accuracy
All Labels: 0.8963741251470352 0.8910875528672011 0.8924261821796824 0.99242
52336613846
Grouped Labels: 0.9507062807952753 0.9442540539135168 0.9471858125286714 0.
9927099062525417
Binary Labels: 0.9873668716531467 0.9906403304353256 0.9889933168036794 0.99
30175648293202
```

5. K Means Cluster

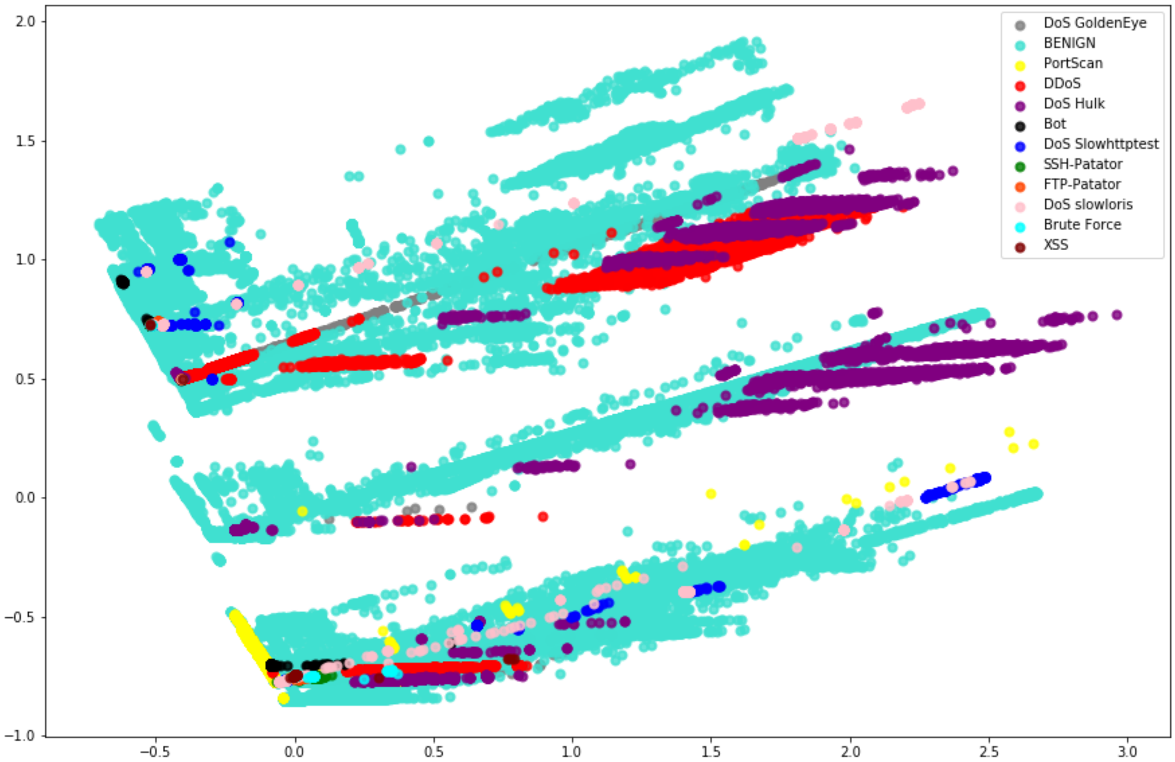
In [159]:

```
colors = ['gray', 'turquoise', 'yellow', 'red',
          'purple', 'black', 'blue', 'green',
         'orangered', 'pink', 'cyan', 'maroon']
```

All labels

In [163]:

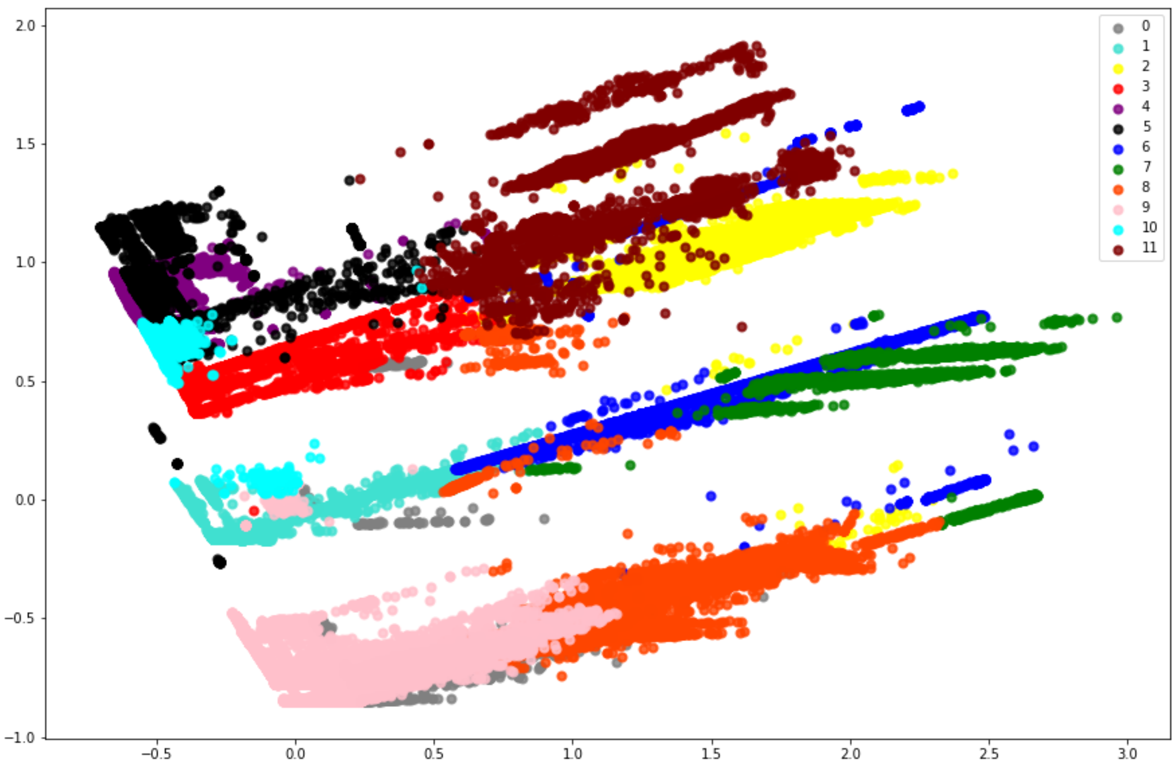
```
#Use PCA to remove dimensionality so we can visualise dataset in 2D
pca = PCA(n_components=40)
x_validate_pca_cont = pca.fit_transform(x_validate)

plt.figure(figsize=(15,10))
for color, l in zip(colors, y_validate.Label.unique()):
    plt.scatter(x_validate_pca_cont[y_validate.Label == l, 0],
                x_validate_pca_cont[y_validate.Label == l, 1],
               color = color, alpha=0.8, lw=2, label = l)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.show()
```



In [164]:

```
#fit
start = time.time()
kmeans = KMeans(n_clusters = 12, random_state = 17).fit(x_train)
y_kmeans = kmeans.labels_
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = kmeans.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

# plot pca graph
x_validate_pca_cont = pca.fit_transform(x_validate)

plt.figure(figsize=(15,10))
for color, l in zip(colors, np.unique(y_predicted)):
    plt.scatter(x_validate_pca_cont[y_predicted == l, 0],
                x_validate_pca_cont[y_predicted == l, 1],
               color = color, alpha=0.8, lw=2, label = l)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.show()

# cross tabulate to show actual groupings & clusters predicted
cluster_df = pd.DataFrame({'Predicted': y_predicted, 'Actual': y_validate.Label})
pd.crosstab(cluster_df.Actual, cluster_df.Predicted)
```

```
84.50838494300842 0.2103137969970703
```



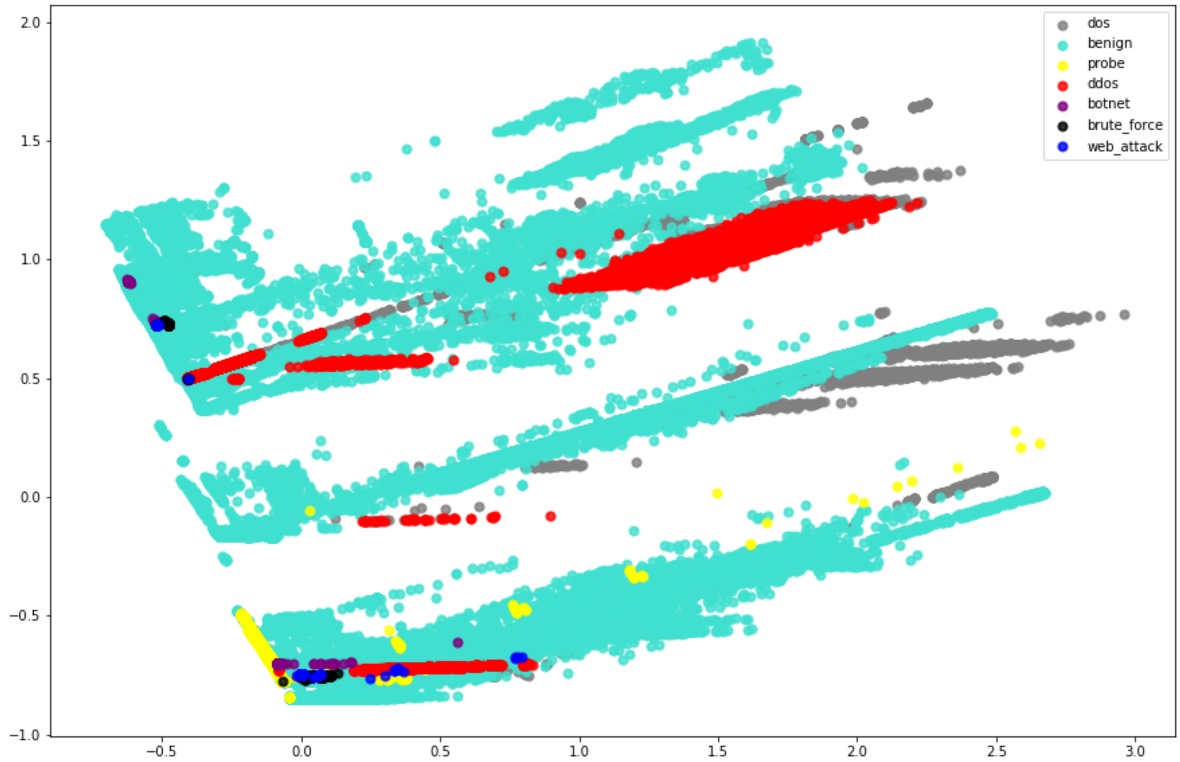
Out[164]:

Predicted	0	1	2	3	4	5	6	7	8	9	10
Actual											
BENIGN	2939	200212	131	28099	48945	22094	6314	151	34010	81328	24970
Bot	3	0	0	3	151	0	0	0	1	233	0
Brute Force	1	0	0	0	28	0	0	0	0	272	0
DDoS	11784	0	4216	9601	0	0	0	0	0	4	0
DoS GoldenEye	1010	0	61	340	13	0	151	0	7	476	0
DoS Hulk	2796	1652	17937	13399	39	0	10	10148	0	38	0
DoS Slowhttptest	0	0	0	18	56	191	194	0	46	595	0
DoS slowloris	0	0	0	1	14	160	214	0	363	400	0
FTP-Patator	0	0	0	4	2	791	0	0	0	790	0
PortScan	20	1	0	10	2	0	21	0	0	31707	0
SSH-Patator	0	0	0	2	598	4	0	0	0	576	0
XSS	1	0	0	1	2	0	0	0	4	122	0

Labled Grouped:

In [167]:

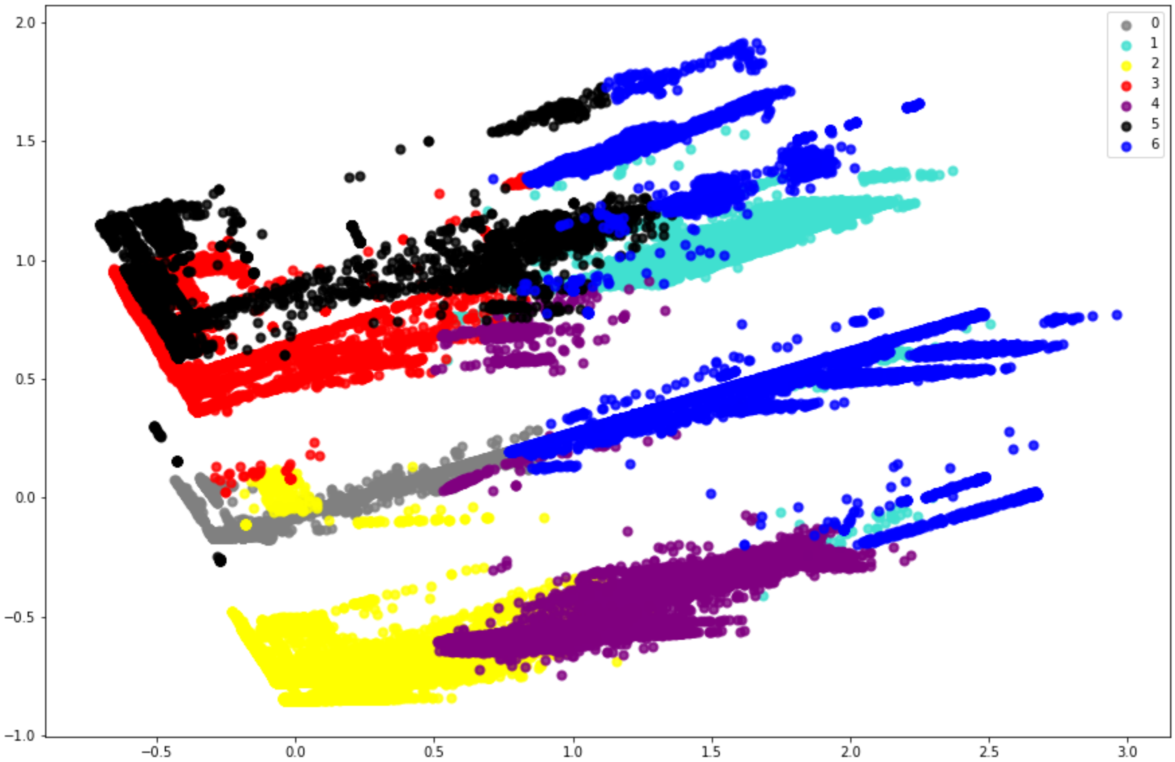
```
#Use PCA to remove dimensionality so we can visualise dataset in 2D
pca = PCA(n_components=40)
x_validate_pca_cont = pca.fit_transform(x_validate)

plt.figure(figsize=(15,10))
for color, l in zip(colors, y_validate.Label_Category.unique()):
    plt.scatter(x_validate_pca_cont[y_validate.Label_Category == l, 0],
                x_validate_pca_cont[y_validate.Label_Category == l, 1],
               color = color, alpha=0.8, lw=2, label = l)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.show()
```



In [168]:

```
# fit model
start = time.time()
kmeans = KMeans(n_clusters = 7, random_state = 17).fit(x_train)
y_kmeans = kmeans.labels_
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = kmeans.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

# apply pca to see the clustering visually
x_validate_pca_cont = pca.fit_transform(x_validate)

plt.figure(figsize=(15,10))
for color, l in zip(colors, np.unique(y_predicted)):
    plt.scatter(x_validate_pca_cont[y_predicted == l, 0],
                x_validate_pca_cont[y_predicted == l, 1],
               color = color, alpha=0.8, lw=2, label = l)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.show()

# crosstabulate
cluster_df = pd.DataFrame({'Predicted': y_predicted, 'Actual': y_validate.Label_Category})
pd.crosstab(cluster_df.Actual, cluster_df.Predicted)
```

```
47.64226818084717 0.1977989673614502
```



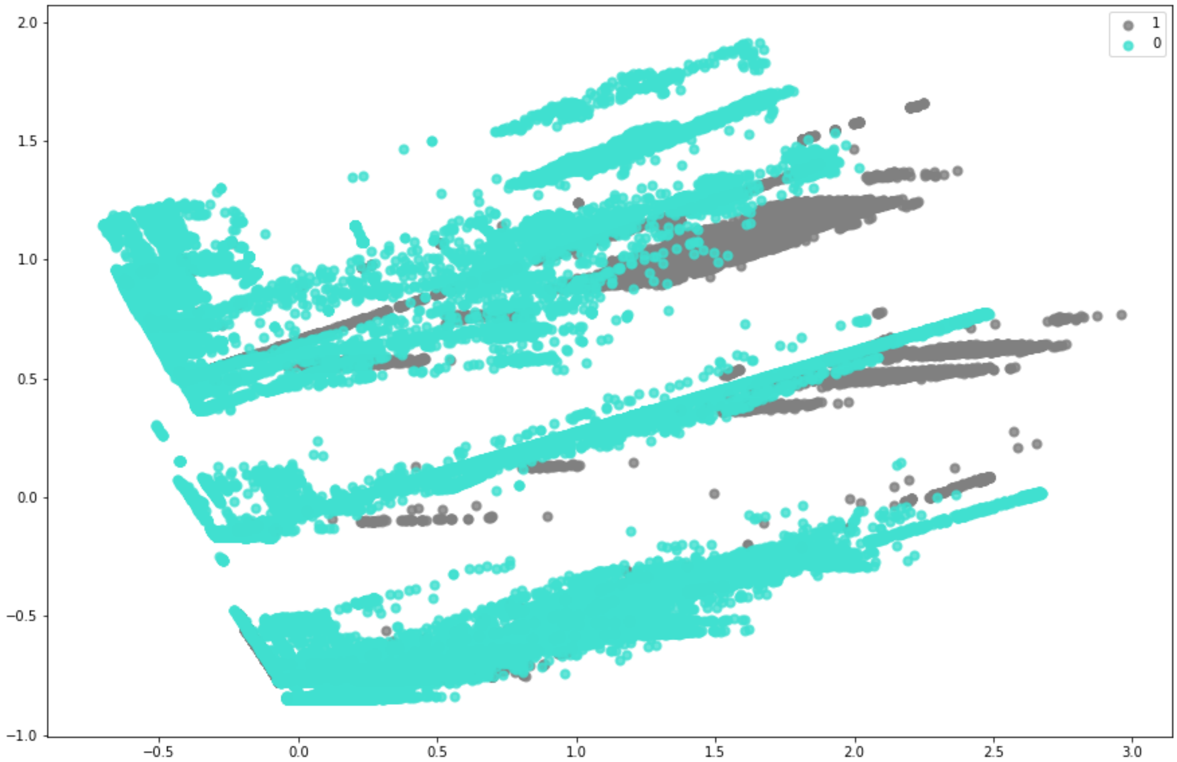
Out[168]:

Predicted	0	1	2	3	4	5	6
Actual							
benign	200622	153	84357	101962	34051	24325	8795
botnet	0	0	236	154	1	0	0
brute_force	0	0	1366	606	0	795	0
ddos	0	4218	11675	9712	0	0	0
dos	1656	18399	5309	13839	407	358	10374
probe	1	0	31727	12	9	0	12
web_attack	0	0	396	31	4	0	0

Binary Labels

In [169]:

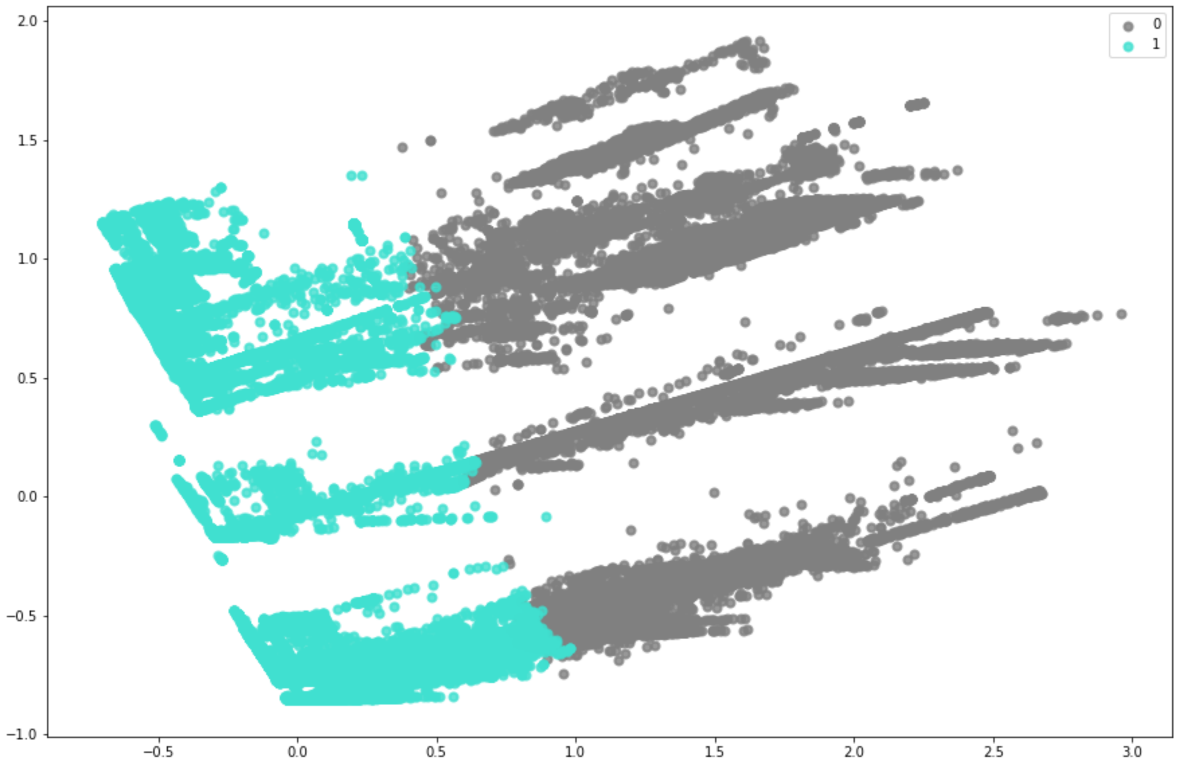
```
#Use PCA to remove dimensionality so we can visualise dataset in 2D
pca = PCA(n_components=40)
x_validate_pca_cont = pca.fit_transform(x_validate)

plt.figure(figsize=(15,10))
for color, l in zip(colors, y_validate.Attack.unique()):
    plt.scatter(x_validate_pca_cont[y_validate.Attack == l, 0],
                x_validate_pca_cont[y_validate.Attack == l, 1],
               color = color, alpha=0.8, lw=2, label = l)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.show()
```



In [170]:

```
# fit
start = time.time()
kmeans = KMeans(n_clusters = 2, random_state = 17).fit(x_train)
y_kmeans = kmeans.labels_
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = kmeans.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

# plot pca
x_validate_pca_cont = pca.fit_transform(x_validate)

plt.figure(figsize=(15,10))
for color, l in zip(colors, np.unique(y_predicted)):
    plt.scatter(x_validate_pca_cont[y_predicted == l, 0],
                 x_validate_pca_cont[y_predicted == l, 1],
                color = color, alpha=0.8, lw=2, label = l)
plt.legend(loc='best', shadow=False, scatterpoints=1)
plt.show()

# cross tab
cluster_df = pd.DataFrame({'Predicted': y_predicted, 'Actual': y_validate.Attack})
pd.crosstab(cluster_df.Actual, cluster_df.Predicted)
```

```
25.979379177093506 0.1752021312713623
```



Out[170]:

Predicted	0	1

Predicted	0	1
Actual		
0	38857	415408
1	33468	77829

6. Random Forest

Due to the success of decision tree, try ensemble method - random forest

In [244]:

```
classifier =  RandomForestClassifier()
```

All labels

In [245]:

```
#fit
start = time.time()
classifier.fit(x_train, y_train.Label)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_rf_1 = pd.crosstab(y_validate.Label, y_predicted)
confusion_rf_1
```

```
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-package
s/sklearn/ensemble/forest.py:245: FutureWarning: The default value of n_esti
mators will change from 10 in version 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)

77.36000728607178 0.9905002117156982
```

Out[245]:

col_0	BENIGN	Bot	Brute Force	DDoS	DoS GoldenEye	DoS Hulk	DoS Slowhttptest	DoS slowloris	FTP-Patator
Label									
BENIGN	453761	50	0	0	2	274	3	0	1
Bot	77	314	0	0	0	0	0	0	0
Brute Force	2	0	230	0	0	0	0	0	0
DDoS	10	0	0	25595	0	0	0	0	0
DoS GoldenEye	8	0	0	0	2042	6	2	0	0
DoS Hulk	21	0	1	2	1	45999	0	0	0
DoS Slowhttptest	7	0	0	0	0	0	1091	2	0
DoS slowloris	3	0	1	0	0	0	6	1149	0
FTP-Patator	3	0	0	0	0	0	0	0	1584
PortScan	1	0	3	0	0	4	0	0	0
SSH-Patator	6	0	0	0	0	0	0	0	0
XSS	4	0	89	0	0	0	0	0	0

In [246]:

```
precision, recall, fscore, support = score(y_validate.Label, y_predicted)
d = {'attack': attack, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[246]:

	attack	precision	recall	fscore
0	BENIGN	0.999687	0.998891	0.999289
1	Bot	0.862637	0.803069	0.831788
2	Brute Force	0.709877	0.764120	0.736000
3	DDoS	0.999922	0.999609	0.999766
4	DoS GoldenEye	0.998533	0.992225	0.995369
5	DoS Hulk	0.993864	0.999435	0.996642
6	DoS Slowhttptest	0.990018	0.991818	0.990917
7	DoS slowloris	0.998262	0.991372	0.994805
8	FTP-Patator	0.999369	0.998110	0.998739
9	PortScan	0.994519	0.999717	0.997111
10	SSH-Patator	1.000000	0.994915	0.997451
11	XSS	0.345794	0.284615	0.312236

In [247]:

```
precision_rf_1, recall_rf_1, fscore_rf_1, n = score(y_validate.Label, y_predicted, average
accuracy_rf_1 = accuracy_score(y_validate.Label, y_predicted)
```

Grouped Labels

In [248]:

```
# fit
start = time.time()
classifier.fit(x_train, y_train.Label_Category)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_rf_2 = pd.crosstab(y_validate.Label_Category, y_predicted)
confusion_rf_2
```

78.26494002342224 0.8967947959899902

Out[248]:

col_0	benign	botnet	brute_force	ddos	dos	probe	web_attack
Label_Category							
benign	453905	41	0	0	144	175	0
botnet	86	305	0	0	0	0	0
brute_force	3	0	2764	0	0	0	0
ddos	11	0	0	25594	0	0	0
dos	30	0	0	0	50309	2	1
probe	3	0	0	2	5	31749	2
web_attack	7	0	0	0	0	0	424

In [249]:

```
precision, recall, fscore, support = score(y_validate.Label_Category, y_predicted)
d = {'attack': attack_groups, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[249]:

	attack	precision	recall	fscore
0	benign	0.999692	0.999208	0.999450
1	botnet	0.881503	0.780051	0.827680
2	brute_force	1.000000	0.998916	0.999458
3	ddos	0.999922	0.999570	0.999746
4	dos	0.997047	0.999344	0.998194
5	probe	0.994456	0.999622	0.997032
6	web_attack	0.992974	0.983759	0.988345

In [250]:

```
precision_rf_2, recall_rf_2, fscore_rf_2, n = score(y_validate.Label_Category, y_predicted,
accuracy_rf_2 = accuracy_score(y_validate.Label_Category, y_predicted)
```

Binary Labels

In [251]:

```
# fit
start = time.time()
classifier.fit(x_train, y_train.Attack)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_rf_3 = pd.crosstab(y_validate.Attack, y_predicted)
confusion_rf_3
```

```
70.18696808815002 0.6450691223144531
```

Out[251]:

col_0	0	1
Attack		
0	453890	375
1	249	111048

In [252]:

```
precision, recall, fscore, support = score(y_validate.Attack, y_predicted)
d = {'attack': [0,1], 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[252]:

	attack	precision	recall	fscore
0	0	0.999452	0.999174	0.999313
1	1	0.996634	0.997763	0.997198

In [253]:

```
precision_rf_3, recall_rf_3, fscore_rf_3, n = score(y_validate.Attack, y_predicted, average
accuracy_rf_3 = accuracy_score(y_validate.Attack, y_predicted)
```

Random forest results

In [254]:

```
print('Random Forrest: Precision / Recall / FScore / Accuracy')
print('All labels:', precision_rf_1, recall_rf_1, fscore_rf_1, accuracy_rf_1)
print('Grouped labels:', precision_rf_2, recall_rf_2, fscore_rf_2, accuracy_rf_2)
print('Binary labels:', precision_rf_3, recall_rf_3, fscore_rf_3,accuracy_rf_3)
```

```
Random Forrest: Precision / Recall / FScore / Accuracy
All labels: 0.9077068772911527 0.9014913450347017 0.9041760974675533 0.99852
53606147514
Grouped labels: 0.9807990901037212 0.9657814591692369 0.9728435436488378 0.9
990947057970656
Binary labels: 0.9980430784129006 0.998468616795907 0.9982556784130228 0.998
8966726901737
```

Final Label Grouping:

In [33]:

```
# proposed final grouping of labels
attack_group = {'BENIGN': 'Benign',
                'DoS Hulk': 'DoS',
                'PortScan': 'Probe',
                'DDoS': 'DDoS',
                'DoS GoldenEye': 'DoS',
                'FTP-Patator': 'FTP-Patator',
                'SSH-Patator': 'SSH-Patator',
                'DoS slowloris': 'DoS',
                'DoS Slowhttptest': 'DoS',
                'Bot': 'Botnet',
                'Brute Force': 'Web Attack',
                'XSS': 'Web Attack'}

attacks = np.array(['Benign', 'Botnet', 'DDoS', 'DoS', 'FTP-Patator', 'Probe', 'SSH-Patator

# add new column to y of the mapping of labels
y_train['New_Label'] = y_train.Label.map(lambda x: attack_group[x])
y_test['New_Label'] = y_test.Label.map(lambda x: attack_group[x])
y_validate['New_Label'] = y_validate.Label.map(lambda x: attack_group[x])
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:14: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:15: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
  from ipykernel import kernelapp as app
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:16: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/s
table/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pand
as-docs/stable/indexing.html#indexing-view-versus-copy)
  app.launch_new_instance()
```

Optimising

Find the number of estimators value we should use

In [34]:

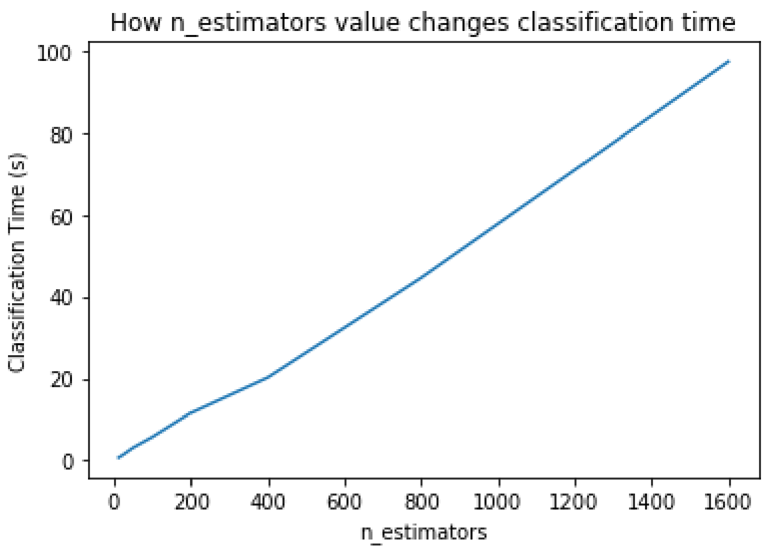
```
# n estimators is the number of decision trees we consider in the ensemble
n_estimators = [12, 25, 50, 100, 200, 400, 800, 1600]
results = []
time_results = []
```

In [ ]:

```
# note: takes a long time
for estimator in n_estimators:
    # fit model with n_estimators parameter
    classifier =  RandomForestClassifier(n_estimators=estimator)
    classifier.fit(x_train, y_train.New_Label)

    # predict validation
    start = time.time()
    y_pred = classifier.predict(x_validate)
    end = time.time()

    # calculate metrics
    p, r, f1, n = score(y_validate.New_Label, y_pred, average = 'macro')

    # append f1 and time to results array
    results.append(f1)
    time_results.append(end-start)
```

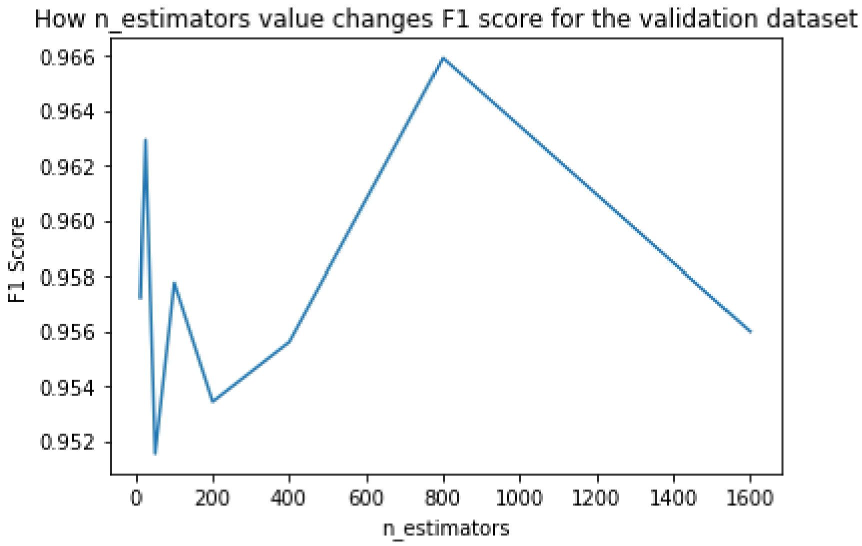
In [49]:

```
# plot classification time for n_estimators
plt.plot(n_estimators, time_results)
plt.xlabel('n_estimators')
plt.ylabel('Classification Time (s)')
plt.title('How n_estimators value changes classification time')
plt.savefig('n_estimators-time.png')
```



In [50]:

```
# plot f1 score for n estimators
plt.plot(n_estimators, results)
plt.xlabel('n_estimators')
plt.ylabel('F1 Score')
plt.title('How n_estimators value changes F1 score for the validation dataset')
plt.savefig('n_estimators.png')
```



Although n_estimators=800 was highest, that many number of estimators is not realistic in terms of classificaiton times. We go with the second peak - n_estimators = 25

In [52]:

```
from sklearn.model_selection import RandomizedSearchCV

max_features = [int(x) for x in np.linspace(2, 40, num = 20)] # from 2 to 40 (max number) o
max_features.append('auto')
max_depth = [int(x) for x in np.linspace(10, 200, num = 10)] # 10 values for max depth from
max_depth.append(None) # also have option for no max depth
min_samples_split = [2, 5, 10]
min_samples_leaf = [1, 2, 4]
bootstrap = [True, False]

random_grid = {'n_estimators': [25], # chosen n_estimator
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
```

In [53]:

```
# Use the random grid to search for best hyperparameters

rf = RandomForestClassifier()

rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter =
rf_random.fit(x_train, y_train['New_Label'])
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:  6.7min
[Parallel(n_jobs=-1)]: Done 130 tasks      | elapsed: 116.5min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed: 272.7min finished
```

Out[53]:

```
RandomizedSearchCV(cv=3, error_score='raise-deprecating',
          estimator=RandomForestClassifier(bootstrap=True, class_weight=Non
e, criterion='gini',
            max_depth=None, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators='warn', n_jobs=None,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False),
          fit_params=None, iid='warn', n_iter=100, n_jobs=-1,
          param_distributions={'n_estimators': [25], 'max_features': [2, 4,
6, 8, 10, 12, 14, 16, 18, 20, 22, 24, 26, 28, 30, 32, 34, 36, 38, 40, 'aut
o'], 'max_depth': [10, 31, 52, 73, 94, 115, 136, 157, 178, 200, None], 'min_
samples_split': [2, 5, 10], 'min_samples_leaf': [1, 2, 4], 'bootstrap': [Tru
e, False]},
          pre_dispatch='2*n_jobs', random_state=42, refit=True,
          return_train_score='warn', scoring=None, verbose=2)
```

In [54]:

```
rf_random.best_params_
```

Out[54]:

```
{'n_estimators': 25,
 'min_samples_split': 5,
 'min_samples_leaf': 1,
 'max_features': 20,
 'max_depth': 200,
 'bootstrap': True}
```

Test our validation dataset, on the new labels, with these parameters

In [55]:

```
classifier =  RandomForestClassifier(n_estimators=25,
                                     max_depth=200,
                                     min_samples_split=5,
                                     min_samples_leaf=1,
                                     max_features=20,
                                     bootstrap=True
)
# fit
start = time.time()
classifier.fit(x_train, y_train.New_Label)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_validate)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

confusion_rf = pd.crosstab(y_validate.New_Label, y_predicted)
confusion_rf
```

```
262.80538630485535 1.2185838222503662
```

Out[55]:

col_0	Benign	Botnet	DDoS	DoS	FTP-Patator	Probe	SSH-Patator	Web Attack
New_Label								
Benign	453915	46	7	86	0	211	0	0
Botnet	77	314	0	0	0	0	0	0
DDoS	6	0	25599	0	0	0	0	0
DoS	18	0	0	50321	0	2	0	1
FTP-Patator	1	0	0	0	1586	0	0	0
Probe	1	0	0	5	0	31753	0	2
SSH-Patator	2	0	0	0	0	0	1178	0
Web Attack	5	0	0	0	0	0	0	426

In [56]:

```
precision, recall, fscore, support = score(y_validate.New_Label, y_predicted)
d = {'attack': attacks, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[56]:

	attack	precision	recall	fscore
0	Benign	0.999758	0.999230	0.999494
1	Botnet	0.872222	0.803069	0.836218
2	DDoS	0.999727	0.999766	0.999746
3	DoS	0.998195	0.999583	0.998888
4	FTP-Patator	1.000000	0.999370	0.999685
5	Probe	0.993337	0.999748	0.996532
6	SSH-Patator	1.000000	0.998305	0.999152
7	Web Attack	0.993007	0.988399	0.990698

In [57]:

```
precision, recall, fscore, n = score(y_validate.New_Label, y_predicted, average = 'macro')
accuracy = accuracy_score(y_validate.New_Label, y_predicted)
precision, recall, fscore, accuracy
```

Out[57]:

```
(0.9820306386052342,
 0.9734336572608587,
 0.9775516100271164,
 0.9991689682121501)
```

Very good results. Fingers crossed this works just as well on the hold out dataset...

Final

Peform random forest, using the new attack groupings and parameters, on the dataset held out for testing

In [66]:

```
# chosen hyperparameters
classifier =  RandomForestClassifier(n_estimators=25,
                                     max_depth=200,
                                     min_samples_split=5,
                                     min_samples_leaf=1,
                                     max_features=20,
                                     bootstrap=True
)
```

In [61]:

```
# fit
start = time.time()
classifier.fit(x_train, y_train.New_Label)
end = time.time()
training_time = end - start

# predict
start = time.time()
y_predicted = classifier.predict(x_test)
end = time.time()
predict_time = end  - start
print(training_time, predict_time)

# metrics
confusion = pd.crosstab(y_test.New_Label, y_predicted)
precision, recall, fscore, n = score(y_test.New_Label, y_predicted, average = 'macro')
accuracy = accuracy_score(y_test.New_Label, y_predicted)
```

```
285.71641540527344 1.2713243961334229
```

In [62]:

```
confusion
```

Out[62]:

col_0 New_Label	Benign	Botnet	DDoS	DoS	FTP-Patator	Probe	SSH-Patator	Web Attack
Benign	453877	68	0	116	1	202	0	0
Botnet	67	324	0	0	0	0	0	0
DDoS	8	0	25597	0	0	0	0	0
DoS	24	0	1	50317	0	0	0	0
FTP-Patator	2	0	0	0	1585	0	0	0
Probe	4	0	0	3	0	31753	0	1
SSH-Patator	2	0	0	0	0	0	1177	0
Web Attack	7	0	0	1	0	2	0	423

In [63]:

```
precision, recall, fscore, accuracy
```

Out[63]:

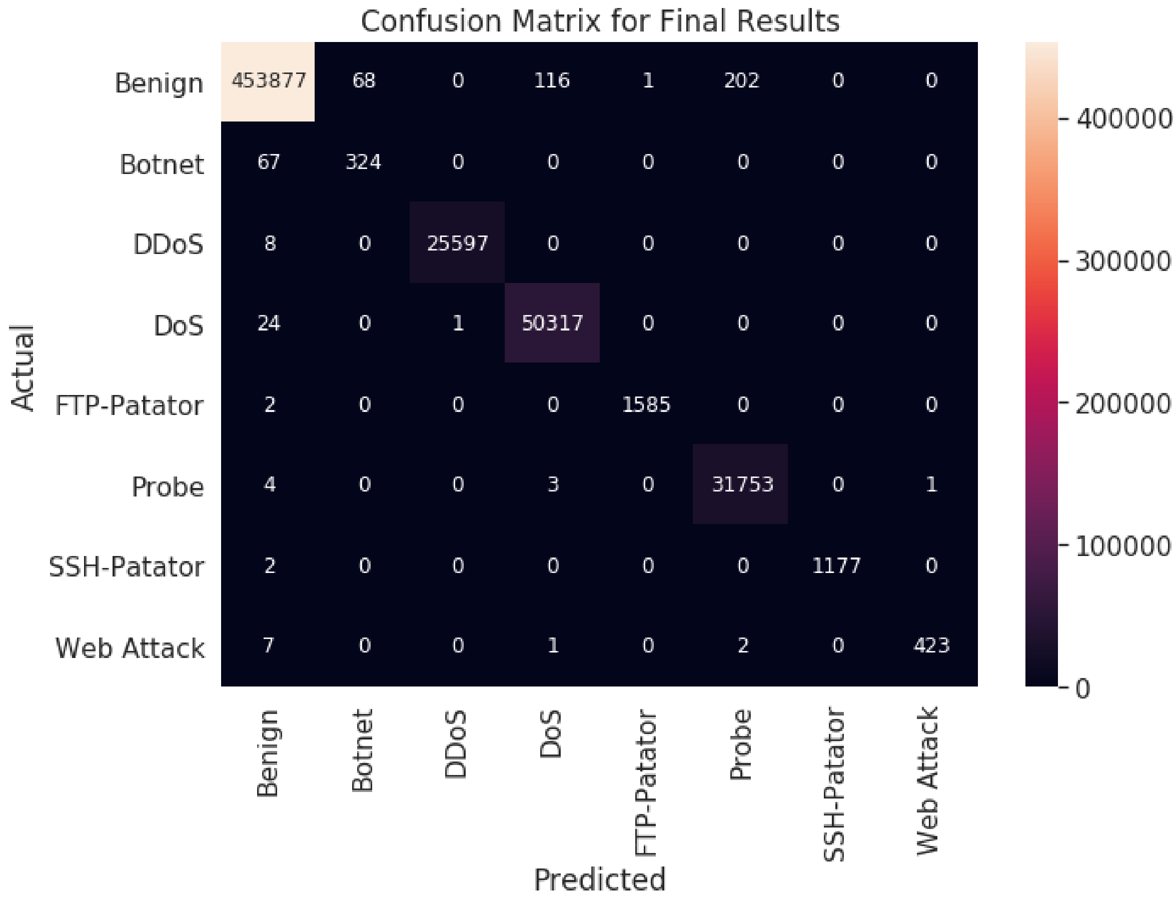
```
(0.976811081141097, 0.9750850462260028, 0.9759328787689289, 0.99910001025528
59)
```

In [68]:

```
# plot heat map confusion matrix
plt.figure(figsize = (10,7))
seaborn.set(font_scale=1.4)
ax = seaborn.heatmap(confusion, annot=True, annot_kws={"size": 12}, fmt='g')
bottom, top = ax.get_ylim()
#ax.set_ylim(bottom + 0.5, top - 0.5)
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix for Final Results')
```

Out[68]:

```
Text(0.5, 1.0, 'Confusion Matrix for Final Results')
```



In [65]:

```
precision, recall, fscore, support = score(y_test.New_Label, y_predicted)
d = {'attack': attacks, 'precision': precision, 'recall' : recall, 'fscore': fscore}
results = pd.DataFrame(data=d)
results
```

Out[65]:

	attack	precision	recall	fscore
0	Benign	0.999749	0.999148	0.999448
1	Botnet	0.826531	0.828645	0.827586
2	DDoS	0.999961	0.999688	0.999824
3	DoS	0.997621	0.999503	0.998561
4	FTP-Patator	0.999369	0.998740	0.999055
5	Probe	0.993616	0.999748	0.996673
6	SSH-Patator	1.000000	0.998304	0.999151
7	Web Attack	0.997642	0.976905	0.987165

% of the training dataset each label took

In [64]:

```
y_train['New_Label'].value_counts()/len(y_train)*100
```

Out[64]:

```
Benign         80.320849
DoS             8.901363
Probe           5.615778
DDoS            4.527360
FTP-Patator     0.280606
SSH-Patator     0.208524
Web Attack      0.076325
Botnet          0.069194
Name: New_Label, dtype: float64
```

In [ ]:

```
```