Network Traffic Classification

CICIDS2017 Intrusion Detection Evaluation Dataset

CICIDS2017 dataset contains benign and the most up-to-date common attacks, which resembles the true real-world data (PCAPs). It also includes the results of the network traffic analysis using CICFlowMeter with labeled flows based on the time stamp, source, and destination IPs, source and destination ports, protocols and attack.

The data capturing period started at 9 a.m., Monday, July 3, 2017, and ended at 5 p.m. on Friday, July 7, 2017, for a total of 5 days. Monday is the normal day and only includes benign traffic. 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.

The intent of this analysis is to train and test a classification method to identify if a capture network traffic register is benign or malign considering the Friday DDoS dataset. For more information about DDoS atacks see here.

Initial exploration of the dataset

This analysis start importing the tools required for ploting, preprocessing, data processing and direcories reading.

In [1]:

```
from mpl_toolkits.mplot3d import Axes3D
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split, validation_curve
from sklearn.tree import DecisionTreeClassifier
from sklearn.datasets import load_digits
from sklearn.svm import SVC
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import os
```

There are 8 files in this dataset but we will use only one: `Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv` .

In [2]:

```
for dirname, _, filenames in os.walk('data'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
data/Thursday-WorkingHours-Afternoon-Infilteration.pcap_ISCX.csv
data/Monday-WorkingHours.pcap_ISCX.csv
data/Friday-WorkingHours-Morning.pcap_ISCX.csv
data/Friday-WorkingHours-Afternoon-PortScan.pcap_ISCX.csv
```

```
data/Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv
data/Tuesday-WorkingHours.pcap_ISCX.csv
data/Wednesday-workingHours.pcap_ISCX.csv
```

The three methods below were built with the intention to facilitate the generation of distribution, correlation, and scatter plots visualizations. They provide analysis over each field and correlation combination possible.

I am not responsible for the creation of these methods, the original work was made by this very helpful Kaggle user.

In [3]:

```
# Distribution graphs (histogram/bar graph) of column data
def plotPerColumnDistribution(df, nGraphShown, nGraphPerRow):
    nunique = df.nunique()
    df = df[[col for col in df if nunique[col] > 1 and nunique[col] < 20]] #
    nRow, nCol = df.shape
    columnNames = list(df)
    nGraphRow = (nCol + nGraphPerRow - 1) / nGraphPerRow
    plt.figure(num = None, figsize = (6 * nGraphPerRow, 8 * nGraphRow), dpi =
    for i in range(min(nCol, nGraphShown)):
        plt.subplot(nGraphRow, nGraphPerRow, i + 1)
        columnDf = df.iloc[:, i]
        if (not np.issubdtype(type(columnDf.iloc[0]), np.number)):
            valueCounts = columnDf.value_counts()
            valueCounts.plot.bar()
        else:
            columnDf.hist()
        plt.ylabel('counts')
        plt.xticks(rotation = 90)
        plt.title(f'{columnNames[i]} (column {i})')
    plt.tight_layout(pad = 1.0, w_pad = 1.0, h_pad = 1.0)
    plt.show()
```

In [4]:

```
# Correlation matrix
def plotCorrelationMatrix(df, graphWidth):
    #filename = df.dataframeName
    df = df.dropna('columns') # drop columns with NaN
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns wher
    if df.shape[1] < 2:
        print(f'No correlation plots shown: The number of non-NaN or constant
        return
    corr = df.corr()
    plt.figure(num=None, figsize=(graphWidth, graphWidth), dpi=80, facecolor=
    corrMat = plt.matshow(corr, fignum = 1)
    plt.xticks(range(len(corr.columns)), corr.columns, rotation=90)
    plt.yticks(range(len(corr.columns)), corr.columns)
    plt.gca().xaxis.tick_bottom()
    plt.colorbar(corrMat)
    plt.title(f'Correlation Matrix', fontsize=15)
    plt.show()
```

In [5]:
```
# Scatter and density plots
def plotScatterMatrix(df, plotSize, textSize):
    df = df.select_dtypes(include =[np.number]) # keep only numerical columns
    # Remove rows and columns that would lead to df being singular
    df = df.dropna('columns')
    df = df[[col for col in df if df[col].nunique() > 1]] # keep columns wher
    columnNames = list(df)
    if len(columnNames) > 10: # reduce the number of columns for matrix inver
        columnNames = columnNames[:10]
    df = df[columnNames]
    ax = pd.plotting.scatter_matrix(df, alpha=0.75, figsize=[plotSize, plotSi
    corrs = df.corr().values
    for i, j in zip(*plt.np.triu_indices_from(ax, k = 1)):
        ax[i, j].annotate('Corr. coef = %.3f' % corrs[i, j], (0.8, 0.2), xyco
    plt.suptitle('Scatter and Density Plot')
    plt.show()
```

Friday DDoS dataset analysis

In [6]:
```
rows = None # numbers of lines to read. None = all
ddos = pd.read_csv('data/Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv', d
ddos.dataframeName = 'Friday-WorkingHours-Afternoon-DDos.pcap_ISCX.csv'
nRow, nCol = ddos.shape
print(f'There are {nRow} rows and {nCol} columns')
```

```
There are 225745 rows and 79 columns
```

Peaking at the rows we can see there is a `Label` field we can use to build a classification method.

In [7]:
```
ddos.head()
```

Out[7]:

	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	Fw Pack Leng S
0	54865	3	2	0	12	0	6	6	6.0	0
1	55054	109	1	1	6	6	6	6	6.0	0
2	55055	52	1	1	6	6	6	6	6.0	0
3	46236	34	1	1	6	6	6	6	6.0	0
4	54863	3	2	0	12	0	6	6	6.0	0

5 rows × 79 columns

Count the unique values from all columns.

In [8]:
```
a = ddos.nunique()
with pd.option_context('display.max_rows', None, 'display.max_columns', None)
    print(a.sort_values(ascending=True))
```

```
 Fwd Avg Packets/Bulk              1
 Bwd Avg Bytes/Bulk                1
 Bwd Avg Packets/Bulk              1
Bwd Avg Bulk Rate                  1
 CWE Flag Count                    1
 Fwd Avg Bulk Rate                 1
Fwd Avg Bytes/Bulk                 1
 Bwd PSH Flags                     1
 Fwd URG Flags                     1
 Bwd URG Flags                     1
 RST Flag Count                    2
FIN Flag Count                     2
 ACK Flag Count                    2
 URG Flag Count                    2
Fwd PSH Flags                      2
 ECE Flag Count                    2
 SYN Flag Count                    2
 PSH Flag Count                    2
 Label                             2
 Down/Up Ratio                     8
 min_seg_size_forward              8
 Min Packet Length               109
 Fwd Packet Length Min           151
 act_data_pkt_fwd                234
Subflow Fwd Packets              297
 Total Fwd Packets               297
 Bwd Packet Length Min           343
 Subflow Bwd Packets             367
 Total Backward Packets          367
 Fwd Header Length.1             714
 Fwd Header Length               714
 Bwd Header Length               806
Init_Win_bytes_forward          1804
 Fwd Packet Length Max          1891
 Init_Win_bytes_backward        1922
Bwd Packet Length Max           1945
 Max Packet Length              2352
 Bwd IAT Min                    3787
Total Length of Fwd Packets     3831
 Subflow Fwd Bytes              3831
 Active Std                     5669
 Idle Std                       5857
 Total Length of Bwd Packets    6760
 Subflow Bwd Bytes              6760
 Fwd Packet Length Mean         7401
 Avg Fwd Segment Size           7401
 Bwd Packet Length Mean         8655
 Avg Bwd Segment Size           8655
 Fwd IAT Min                    8820
 Fwd Packet Length Std          9555
 Bwd Packet Length Std          9650
 Flow IAT Min                  11093
 Average Packet Size           11270
 Packet Length Mean            11680
 Packet Length Std             13502
 Packet Length Variance        13502
 Destination Port              23950
 Idle Max                      33002
Idle Mean                      35285
 Active Min                    38393
```

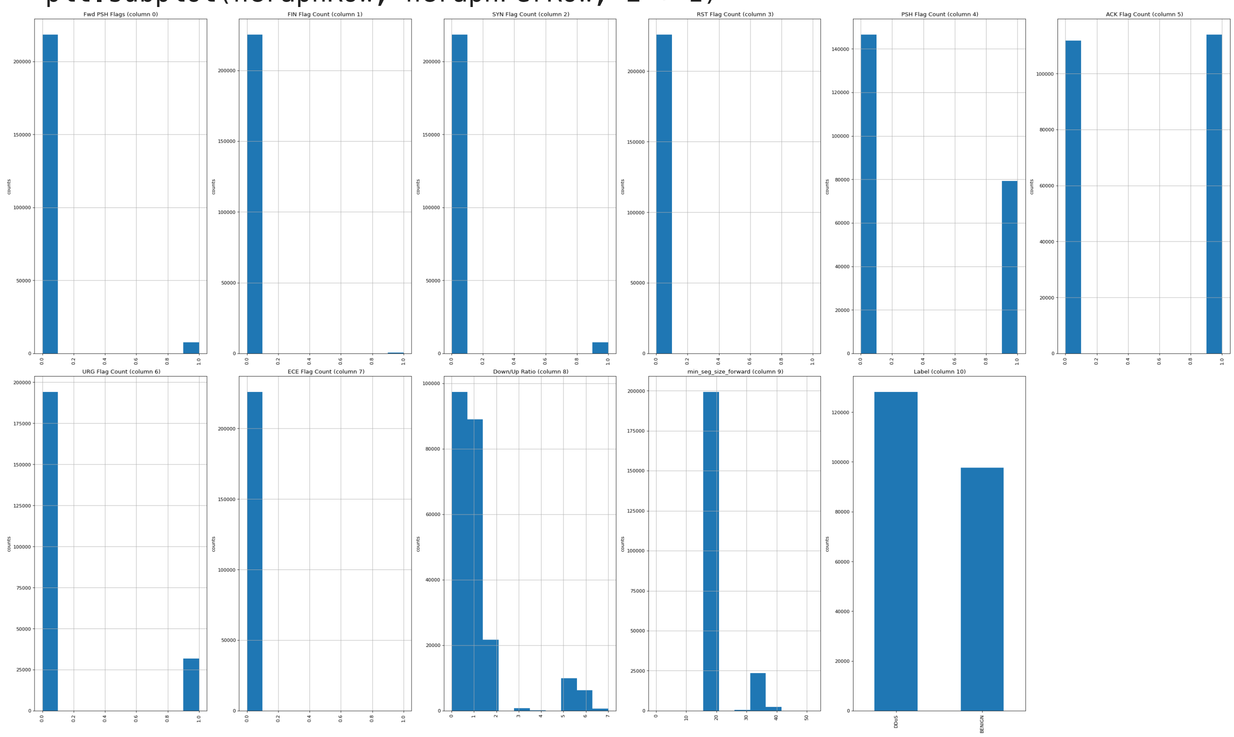
```
 Active Max                     40313
Active Mean                     40409
 Idle Min                       48018
 Fwd IAT Max                    77978
Fwd IAT Total                   78049
 Fwd IAT Std                    91184
 Fwd IAT Mean                   95095
 Bwd IAT Max                   101379
Bwd IAT Total                  101942
 Bwd IAT Std                   113859
 Bwd IAT Mean                  117311
 Flow IAT Max                  139745
 Bwd Packets/s                 144444
 Flow IAT Std                  159622
 Flow Duration                 187752
Fwd Packets/s                  192230
 Flow IAT Mean                 193666
 Flow Packets/s                194094
Flow Bytes/s                   202293
dtype: int64
```

Doesn't make sense get unique values from columns that have counts an gauges so we need to get the distribution graphs only from columns that have from 2 to 20 unique values.

In [9]:

```python
plotPerColumnDistribution(ddos, 12, 6)
```

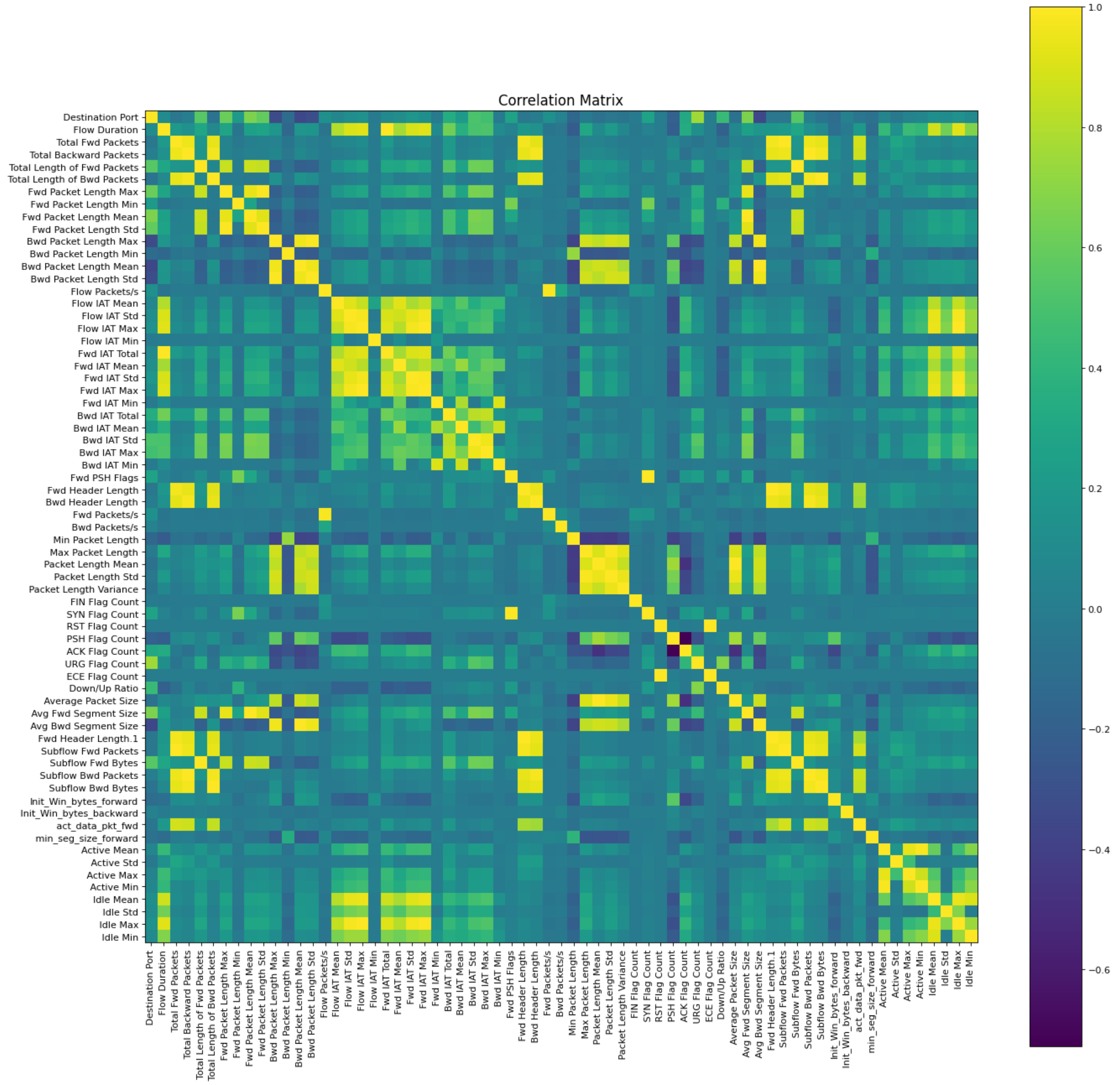
```
<ipython-input-3-3767a2c45b2f>:10: MatplotlibDeprecationWarning: Passing non-integers as three-element position specification is deprecated since 3.3 and will be removed two minor releases later.
  plt.subplot(nGraphRow, nGraphPerRow, i + 1)
```



Below we have a very nice implementation of one correlation matrix.
Note the column `Label` is not there. Categorical features (not numerical) are ignored during this process due to their nature of not being continuous. It makes no sense to say if

categorical_var1 is increased by one, categorical_var2 also increases by X (X's value

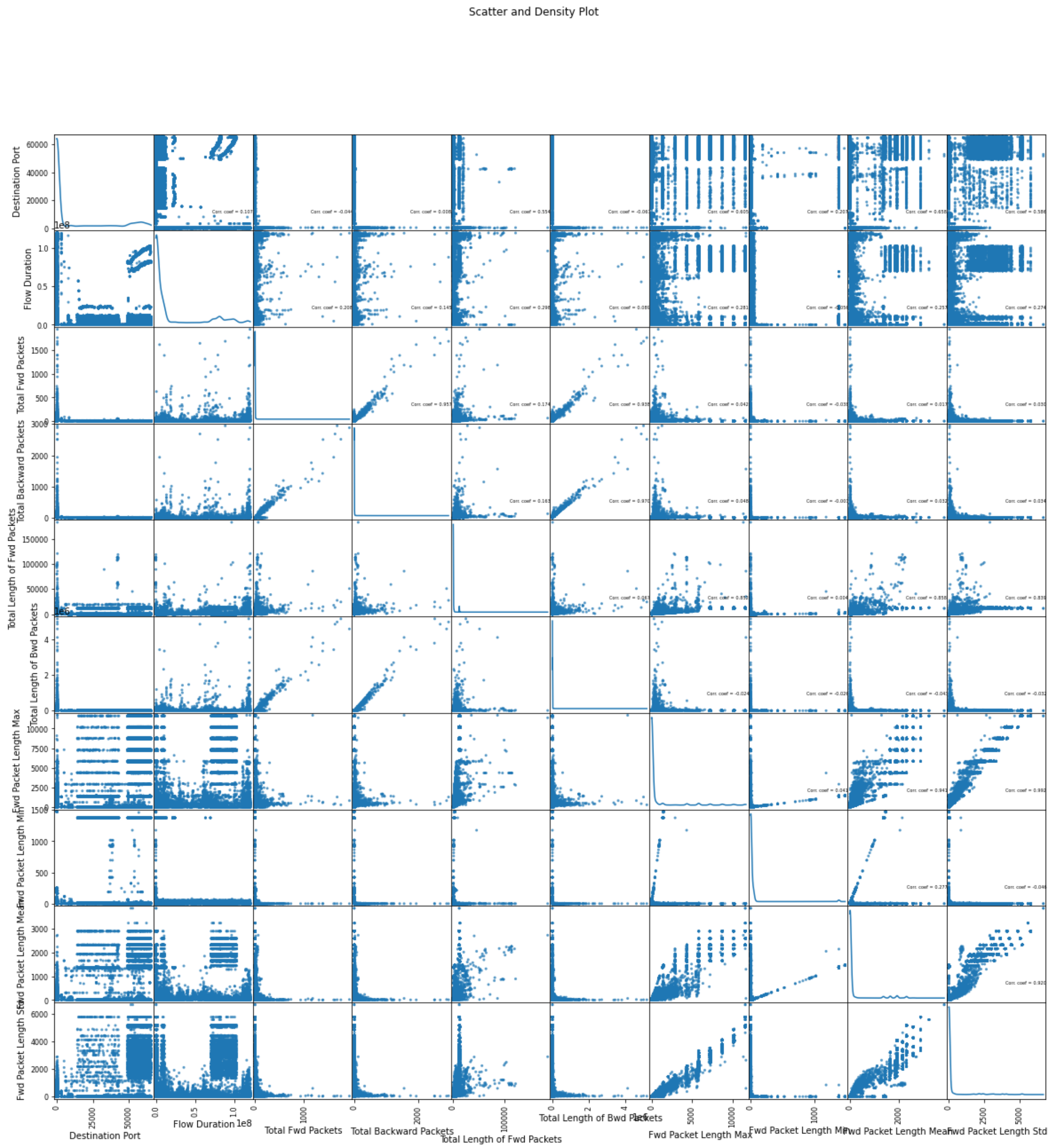
In [10]:
```
plotCorrelationMatrix(ddos, 20)
```



Now for the Scatter and density analisys.

If you are running this notebook be careful, if you are using the whole dataset this can take several minutes. Note we are selecting only the first 10 columns on the function.

In [11]:
```
plotScatterMatrix(ddos, 20, 5)
```



Research Question

- Can we predict whether the analyzed network traffic is a malignant DDoS attack through a simplistic classification method?

Methods

Data cleaning

First, we need to choose do some cleaning on the dataset.

In [12]:
```
ddos.shape
```

Out[12]:
```
(225745, 79)
```

Some column names start with space so to keep consistency we need to make some cleaning on them.

In [13]:
```
ddos.columns
```

Out[13]:
```
Index([' 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.1', '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'],
      dtype='object')
```

In [14]:
```
ddos.columns = ddos.columns.str.replace(' ','') # remove spaces from column n
ddos.columns
```

Out[14]:
```
Index(['DestinationPort', 'FlowDuration', 'TotalFwdPackets',
       'TotalBackwardPackets', 'TotalLengthofFwdPackets',
       'TotalLengthofBwdPackets', 'FwdPacketLengthMax', 'FwdPacketLengthMin',
       'FwdPacketLengthMean', 'FwdPacketLengthStd', 'BwdPacketLengthMax',
       'BwdPacketLengthMin', 'BwdPacketLengthMean', 'BwdPacketLengthStd',
       'FlowBytes/s', 'FlowPackets/s', 'FlowIATMean', 'FlowIATStd',
       'FlowIATMax', 'FlowIATMin', 'FwdIATTotal', 'FwdIATMean', 'FwdIATStd',
       'FwdIATMax', 'FwdIATMin', 'BwdIATTotal', 'BwdIATMean', 'BwdIATStd',
       'BwdIATMax', 'BwdIATMin', 'FwdPSHFlags', 'BwdPSHFlags', 'FwdURGFlags',
       'BwdURGFlags', 'FwdHeaderLength', 'BwdHeaderLength', 'FwdPackets/s',
       'BwdPackets/s', 'MinPacketLength', 'MaxPacketLength',
       'PacketLengthMean', 'PacketLengthStd', 'PacketLengthVariance',
       'FINFlagCount', 'SYNFlagCount', 'RSTFlagCount', 'PSHFlagCount',
```

```
       'ACKFlagCount', 'URGFlagCount', 'CWEFlagCount', 'ECEFlagCount',
       'Down/UpRatio', 'AveragePacketSize', 'AvgFwdSegmentSize',
       'AvgBwdSegmentSize', 'FwdHeaderLength.1', 'FwdAvgBytes/Bulk',
       'FwdAvgPackets/Bulk', 'FwdAvgBulkRate', 'BwdAvgBytes/Bulk',
       'BwdAvgPackets/Bulk', 'BwdAvgBulkRate', 'SubflowFwdPackets',
       'SubflowFwdBytes', 'SubflowBwdPackets', 'SubflowBwdBytes',
       'Init_Win_bytes_forward', 'Init_Win_bytes_backward', 'act_data_pkt_fwd
',
       'min_seg_size_forward', 'ActiveMean', 'ActiveStd', 'ActiveMax',
       'ActiveMin', 'IdleMean', 'IdleStd', 'IdleMax', 'IdleMin', 'Label'],
```

To make sure we also check if the dataset have any null value.

In [15]:
```
ddos.isnull().sum().sum()
```

Out[15]: 4

In [16]:
```
ddos.shape
```

Out[16]: (225745, 79)

In [17]:
```
ddos = ddos.dropna()
ddos.shape
```

Out[17]: (225741, 79)

Binarize the Label to 0 or 1

In [18]:
```
ddos['BinayLabel'] = (ddos['Label'] == 'DDoS')
print(ddos['BinayLabel'])
```

```
0         False
1         False
2         False
3         False
4         False
          ...
225740    False
225741    False
225742    False
225743    False
225744    False
Name: BinayLabel, Length: 225741, dtype: bool
```

The target result of `Label` is stored in `y`

In [19]:
```
y=ddos[['BinayLabel']].copy()
y.head()
```

Out[19]:

	BinayLabel
0	False

	BinayLabel
1	False
2	False
3	False

Column selection

The feature columns were chosen based on the previous exploration of the dataset correlations and some empiric knowledge about network.

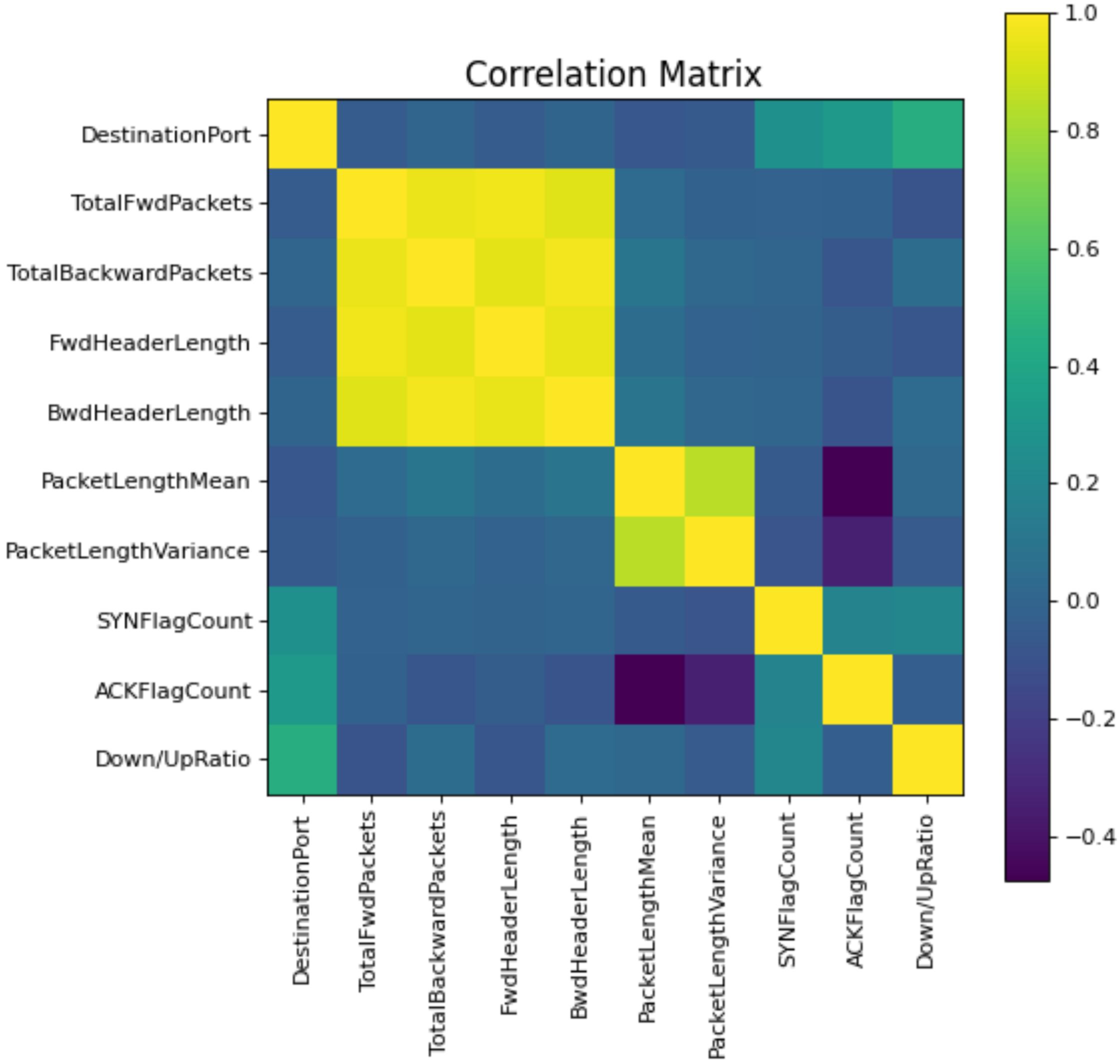
In [20]:
```
features = ['DestinationPort','TotalFwdPackets','TotalBackwardPackets','FwdHe
            'PacketLengthMean','PacketLengthVariance','SYNFlagCount','ACKFlag
```

In [21]:
```
x = ddos[features].copy()
x.columns
```

Out[21]:
```
Index(['DestinationPort', 'TotalFwdPackets', 'TotalBackwardPackets',
       'FwdHeaderLength', 'BwdHeaderLength', 'PacketLengthMean',
       'PacketLengthVariance', 'SYNFlagCount', 'ACKFlagCount', 'Down/UpRatio
'],
      dtype='object')
```

Correlation Matrix for `x`.

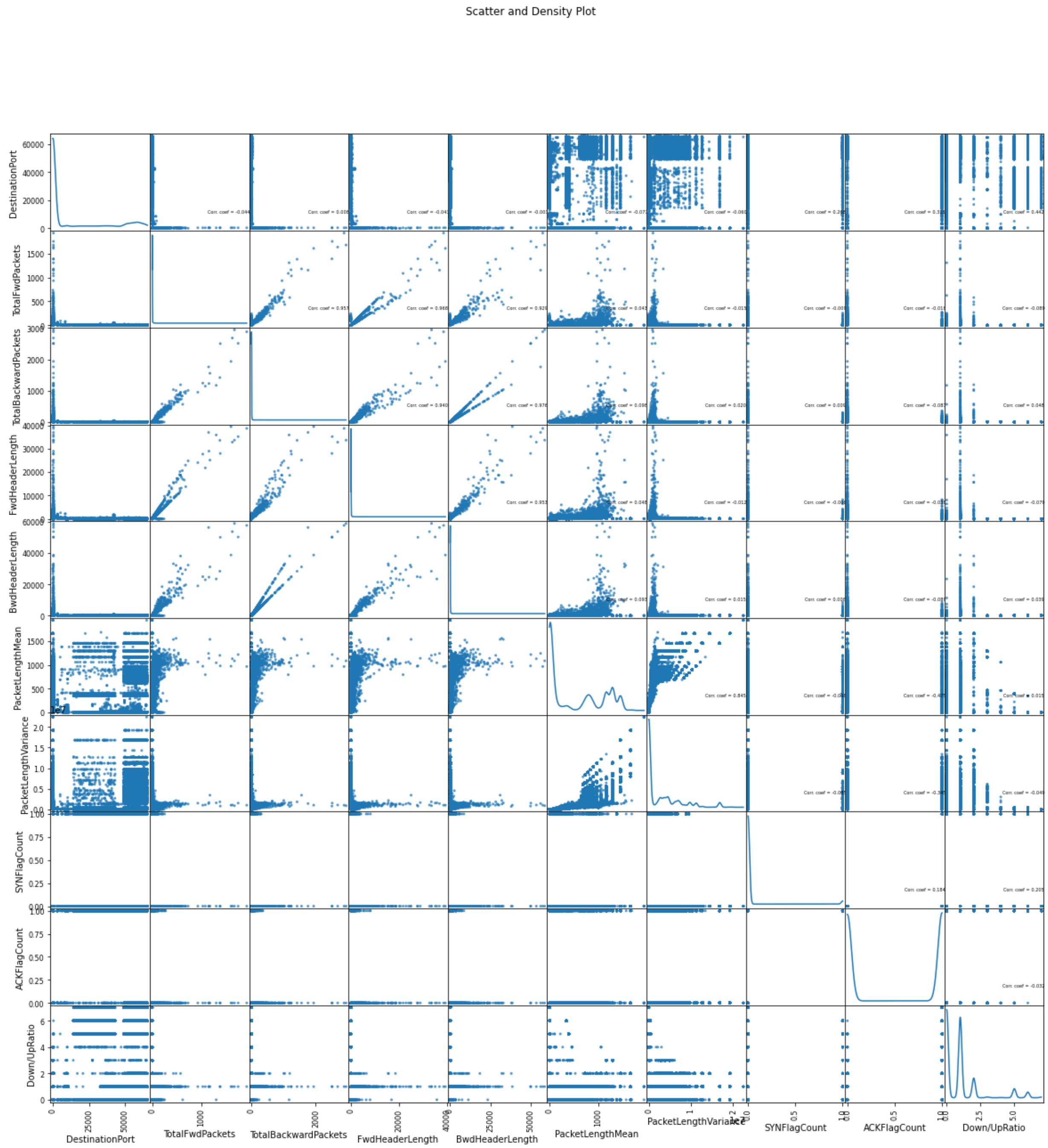
In [22]:
```
plotCorrelationMatrix(x, 7)
```



Scatter and density Plot of `x`.

In [23]:

```
# This can take several minutes
plotScatterMatrix(x, 20, 5)
```



Training Phase

In this phase the learning algorithm uses the training data to adjust the model's parameters to minimize errors.

In [24]:

```
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.33, ran
```

In [25]:

```
# type(x_train)
# type(x_test)
# type(y_train)
# type(y_test)
x_train.head()
#y_train.describe()
```

Out[25]:

	DestinationPort	TotalFwdPackets	TotalBackwardPackets	FwdHeaderLength	BwdHead
82052	80	7	4	152	
58912	80	3	5	72	
117927	80	3	6	72	
169641	80	8	4	172	
141781	80	8	4	172	

Getting the trained model.

In [26]:

```
classifier = DecisionTreeClassifier(max_leaf_nodes=10, random_state=0)
classifier.fit(x_train, y_train)
```

Out[26]:

```
DecisionTreeClassifier(max_leaf_nodes=10, random_state=0)
```

In [27]:

```
type(classifier)
```

Out[27]:

```
sklearn.tree._classes.DecisionTreeClassifier
```

Testing phase

In this the trained model is applied to test data. Test data is separate from the training data, and is previously unseen by the model. The model is then evaluated on how it performs on the test data.

In [28]:

```
predictions = classifier.predict(x_test)
```

In [29]:

```
predictions[:10]
```

Out[29]:

```
array([ True, False, False, False,  True,  True,  True, False,  True,
        True])
```

In [30]:

```
y_test['BinayLabel'][:10]
```

Out[30]:

```
154017     True
59280     False
1570      False
219132    False
172751     True
122145     True
132950     True
166177    False
178301     True
44114      True
Name: BinayLabel, dtype: bool
```

Measure Accuracy

The goal in building a classifier model is to have the model perform well on training as well as test data.

In [31]:
```
accuracy_score(y_true = y_test, y_pred = predictions)
```

Out[31]: 0.99479159675145598

Conclusion

99% of accuracy? Seems something is not right, but I don't know what exactly went wrong. I do trust that my method is correct though.

Some hypotheses to be answered on future works:

- Evaluate if the traffic generated have variation enough.
  Since the traffic analyzed on this dataset was generated by a simulation maybe the requests created are too specific making things easy for the classifier. From Kaggle:

  > Generating realistic background traffic was our top priority in building this dataset. We have used our proposed B-Profile system (Sharafaldin, et al. 2016) to profile the abstract behavior of human interactions and generates naturalistic benign background traffic. For this dataset, we built the abstract behavior of 25 users based on the HTTP, HTTPS, FTP, SSH, and email protocols.

  Maybe the traffic isn't realistic as expected.

- Same for the DDoS attacks created.
  Maybe the attacks are too specific, which is not the real nature of them. This will lead to training the method only to one specific attack type.

- Get some real traffic flow dataset and add DDoS variance.
  There are not many DDoS public datasets available so maybe build one or add new types for the dataset used on this work may be a good option.

- Simply find my error.
  I wasn't able to find if there is something wrong with my training and test methods.

In [ ]:
```
```