### **Data Processing**

#### **Imports**

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from matplotlib import pyplot as plt
import seaborn as sns

c:\Users\Hunter\anaconda3\Lib\site-packages\pandas\core\arrays\masked.py:60: UserWarn
ing: Pandas requires version '1.3.6' or newer of 'bottleneck' (version '1.3.5' curren
tly installed).
    from pandas.core import (

Read the project_data.csv file
```

Out[]:

•		Flow ID	Source IP	Source Port	Destination IP	Destination Port	Protocol	Timestamp	Flow Duration
	0	192.168.10.5- 104.16.207.165- 54865-443-6	104.16.207.165	443	192.168.10.5	54865	6	7/7/2017 3:30	3
	1	192.168.10.5- 104.16.28.216- 55054-80-6	104.16.28.216	80	192.168.10.5	55054	6	7/7/2017 3:30	109
	2	192.168.10.5- 104.16.28.216- 55055-80-6	104.16.28.216	80	192.168.10.5	55055	6	7/7/2017 3:30	52
	3	192.168.10.16- 104.17.241.25- 46236-443-6	104.17.241.25	443	192.168.10.16	46236	6	7/7/2017 3:30	34
	4	192.168.10.5- 104.19.196.102- 54863-443-6	104.19.196.102	443	192.168.10.5	54863	6	7/7/2017 3:30	3

5 rows × 85 columns

- 1. Remove the column with majority NaN values
- 2. Use isnull() to figure out the number of NaN values per column

```
In [ ]: df.columns = df.columns.str.strip()
    df.dropna(axis=0, inplace=True)
    df.isnull().sum().sum()
    #df.isna()
```

Out[]:

1. Dropping unnecessary columns

```
In []: df.drop(columns=['Source IP'], inplace=True)
    df.drop(columns=['Destination IP'], inplace=True)
    df.drop(columns=['Source Port'], inplace=True)
    df.drop(columns=['Destination Port'], inplace=True)
    df.drop(columns=['Flow ID'], inplace=True)
    df.drop(columns=['Timestamp'], inplace=True)
```

1. Convert labels from 'benign' and 'ddos' to 0 and 1

```
In [ ]: df['Label_encoded'] = df['Label'].map({'BENIGN': 0, 'DDoS': 1})
    df.drop(columns=['Label'], inplace=True)
    df.head()
```

Out[]:

	Protocol	Flow Duration	Total Fwd Packets	Total Backward Packets		Total Length of Bwd Packets			Fwd Packet Length Mean	Fwd Packet Length Std	•••	miı
0	6	3	2	0	12	0	6	6	6.0	0.0		
1	6	109	1	1	6	6	6	6	6.0	0.0		
2	6	52	1	1	6	6	6	6	6.0	0.0		
3	6	34	1	1	6	6	6	6	6.0	0.0		
4	6	3	2	0	12	0	6	6	6.0	0.0		

5 rows × 79 columns

```
In []: #print tail of the data df.tail()
```

Out[ ]:		Protocol	Flow Duration	Total Fwd Packets	Total Backward Packets	Total Length of Fwd Packets	Total Length of Bwd Packets			Fwd Packet Length Mean	Fwd Packet Length Std	•
	225740	6	61	1	1	6	6	6	6	6.0	0.0	
	225741	6	72	1	1	6	6	6	6	6.0	0.0	
	225742	6	75	1	1	6	6	6	6	6.0	0.0	
	225743	6	48	2	0	12	0	6	6	6.0	0.0	
	225744	6	68	1	1	6	6	6	6	6.0	0.0	•

5 rows × 79 columns

1. Converted the column 'Protocol' to dummy variable using pandas get\_dummies

```
In []: cols = ['Protocol']
    df_dummies = pd.get_dummies(df, columns=cols , prefix=cols,prefix_sep='_')
#show the head
    df_dummies.head()
```

Out[ ]:		Flow Duration	Total Fwd Packets	Total Backward Packets		Total Length of Bwd Packets			Fwd Packet Length Mean			•••	Activ Ma
	0	3	2	0	12	0	6	6	6.0	0.0	0		
	1	109	1	1	6	6	6	6	6.0	0.0	6		
	2	52	1	1	6	6	6	6	6.0	0.0	6		
	3	34	1	1	6	6	6	6	6.0	0.0	6		
	4	3	2	0	12	0	6	6	6.0	0.0	0		

5 rows × 81 columns

### Data preparation for Logistic Regression

• Correlation heatmap

```
top_corr = df_dummies[top_features].corr()

plt.figure(figsize=(12, 8))
sns.heatmap(top_corr, annot=True, cmap='YlOrRd')
plt.title("Correlation Matrix of Top Features")
plt.show()
```

Correlation Matrix of Top Features													1.00				
Label_encoded -	1	0.6	0.6	0.58	0.58	0.47	-0.47	-0.46	0.45	0.45	0.44	-0.43	0.41	0.41	-0.41		1.00
Bwd Packet Length Mean -	0.6	1	1	0.96	0.96	0.29	-0.29	-0.32	0.87	0.87	0.86	-0.37	0.83	0.78	-0.24		- 0.75
Avg Bwd Segment Size -	0.6	1	1	0.96	0.96	0.29	-0.29	-0.32	0.87	0.87	0.86	-0.37	0.83	0.78	-0.24		0.75
Bwd Packet Length Max -	0.58	0.96	0.96	1	0.99	0.29	-0.29	-0.3	0.83	0.83	0.89	-0.37	0.88	0.85	-0.23		- 0.50
Bwd Packet Length Std -	0.58	0.96	0.96	0.99	1	0.29	-0.29	-0.29	0.82	0.82	0.89	-0.36	0.87	0.87	-0.23		
Protocol_6 -	0.47	0.29	0.29	0.29	0.29	1	-1	0.17	0.33	0.32	0.34	-0.89	0.34	0.28	-0.47		- 0.25
Protocol_17 -	-0.47	-0.29	-0.29	-0.29	-0.29	-1	1	-0.17	-0.33	-0.32	-0.34	0.89	-0.34	-0.28	0.47		
URG Flag Count -	-0.46	-0.32	-0.32	-0.3	-0.29	0.17	-0.17	1	-0.19	-0.2	-0.15	-0.12	-0.11	-0.15	-0.057		- 0.00
Packet Length Mean -	0.45	0.87	0.87	0.83	0.82	0.33	-0.33	-0.19	1	1	0.95	-0.42	0.9	0.84	-0.27		
Average Packet Size -	0.45	0.87	0.87	0.83	0.82	0.32	-0.32	-0.2	1	1	0.95	-0.4	0.9	0.85	-0.27		0.25
Packet Length Std -	0.44	0.86	0.86	0.89	0.89	0.34	-0.34	-0.15	0.95	0.95	1	-0.42	0.98	0.95	-0.27		
Min Packet Length -	-0.43	-0.37	-0.37	-0.37	-0.36	-0.89	0.89	-0.12	-0.42	-0.4	-0.42	1	-0.42	-0.35	0.4		0.50
Max Packet Length -	0.41	0.83	0.83	0.88	0.87	0.34	-0.34	-0.11	0.9	0.9	0.98	-0.42	1	0.93	-0.27		
Packet Length Variance -	0.41	0.78	0.78	0.85	0.87	0.28	-0.28	-0.15	0.84	0.85	0.95	-0.35	0.93	1	-0.24		0.75
min_seg_size_forward -	-0.41	-0.24	-0.24	-0.23	-0.23	-0.47	0.47	-0.057	-0.27	-0.27	-0.27	0.4	-0.27	-0.24	1		
	Label_encoded -	Bwd Packet Length Mean -	Avg Bwd Segment Size -	Bwd Packet Length Max -	Bwd Packet Length Std -	Protocol_6 -	Protocol_17 -	URG Flag Count -	Packet Length Mean -	Average Packet Size -	Packet Length Std -	Min Packet Length -	Max Packet Length -	Packet Length Variance -	min_seg_size_forward -		

```
In [ ]: sns.histplot(data = df_dummies , x = 'Bwd Packet Length Mean',y = 'Label_encoded')
    #sns.histplot(data = df , x = 'Bwd Packet Length Std',y = 'Label_encoded')
    #sns.histplot(data = df , x = 'Bwd Packet Length Max',y = 'Label_encoded')
    #sns.histplot(data = df , x = 'Avg Bwd Segment Size',y = 'Label_encoded')
```

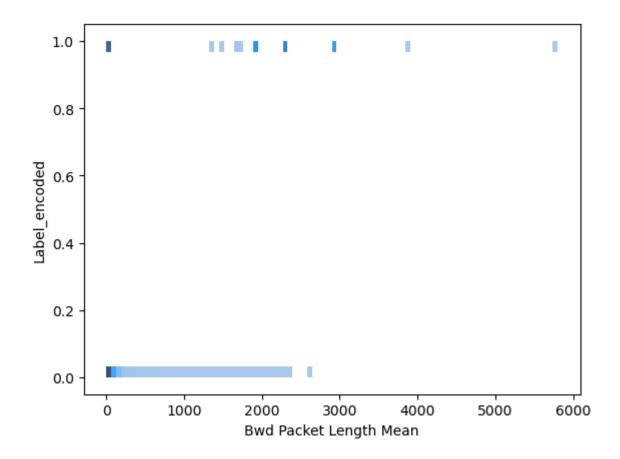
C:\Users\tobyu\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119: FutureWarning: u se\_inf\_as\_na option is deprecated and will be removed in a future version. Convert in f values to NaN before operating instead.

with pd.option\_context('mode.use\_inf\_as\_na', True):

C:\Users\tobyu\anaconda3\Lib\site-packages\seaborn\\_oldcore.py:1119: FutureWarning: u se\_inf\_as\_na option is deprecated and will be removed in a future version. Convert in f values to NaN before operating instead.

with pd.option\_context('mode.use\_inf\_as\_na', True):

+「 ]. <Axes: xlabel='Bwd Packet Length Mean', ylabel='Label\_encoded'>



1. Split the data into features (X) and target (y):

```
In [ ]: X = df.drop(['Label_encoded'], axis=1)
y = df['Label_encoded']
```

1. Handle categorical variables based on highest correlation

```
In [ ]: X = df_dummies[['Bwd Packet Length Mean', 'Avg Bwd Segment Size']]
```

1. Use StandardScaler from sklearn to transform the x dataframe.

```
In [ ]: from sklearn.preprocessing import StandardScaler
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
```

1. Split dataset into train and test data use train\_test\_split with test\_size = 0.2 and random\_state = 42

```
In [ ]: from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size=0.2, random
```

## Classification Model 1: Logistic Regression

- 1. Create a logistic regression model using sklearn
- 2. Fit the model with the train data
- 3. Get the score from the model using test data
- 4. Plot confusion matrix using [ConfusionMatrixDisplay]

```
In []: from sklearn.metrics import ConfusionMatrixDisplay
import matplotlib.pyplot as plt

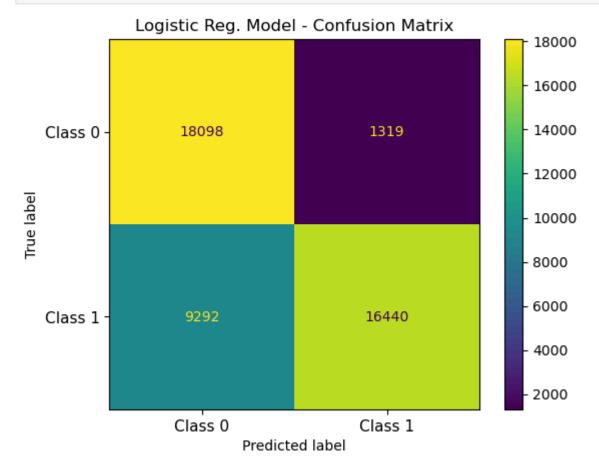
# Create a logistic regression model using sklearn library
clf=LogisticRegression()
clf.fit(X_train,y_train)

#print score for test data
print(clf.score(X_test,y_test))
```

#### 0.7649781833484685

```
In [ ]: from sklearn.metrics import ConfusionMatrixDisplay

cm = ConfusionMatrixDisplay.from_estimator(clf,X_test, y_test)
#plt.figure()
#plot_confusion_matrix(cm, figsize=(12,8), hide_ticks=True, cmap=plt.cm.Blues)
plt.title("Logistic Reg. Model - Confusion Matrix")
plt.xticks(range(2), ["Class 0", "Class 1"], fontsize=11)
plt.yticks(range(2), ["Class 0", "Class 1"], fontsize=11)
plt.show()
```



```
In [ ]: y_pred = clf.predict(X_test)

from sklearn.metrics import accuracy_score
accuracy = accuracy_score(y_test, y_pred)
print(f'Accuracy: {accuracy:.2f}')
```

Accuracy: 0.76

# Classification Model 2: K Nearest Neighbor Classifier

- 1. Create a KNN model using sklearn library, and initialize n\_neighbors
- 2. Fit the model with the train data
- 3. Predict the values from test data
- 4. Print out the score from training and test data
- 5. Repeat Step 1.- 4. for a range of n\_neighbors values (k in kNN) from 1 to 30.

```
In []: from sklearn.neighbors import KNeighborsClassifier

# Define KNN model
for k in range(1,30):

knn = KNeighborsClassifier(n_neighbors=k)

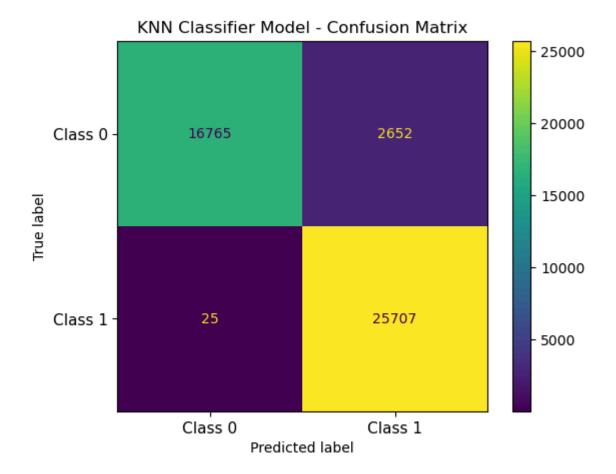
#Fit KNN model on xtrain, ytrain from above
knn.fit(X_train, y_train)

#predict y values from xtest
y_pred=knn.predict(X_test)

#print score for test data
print("K: ",k,"Train Score: ",knn.score(X_train,y_train), "Test Score: ",knn.score
```

```
1 Train Score: 0.9414315141313016 Test Score:
                                                  0.9407295842654322
   2 Train Score: 0.9414204394436076 Test Score: 0.9407295842654322
Κ:
Κ:
   3 Train Score: 0.9413816780366794 Test Score: 0.9407074353806286
K: 4 Train Score: 0.793213431381235 Test Score: 0.7941039668652683
K: 5 Train Score: 0.9413706033489856 Test Score: 0.9407074353806286
Κ:
  6 Train Score: 0.9413706033489856 Test Score: 0.9407074353806286
Κ:
  7 Train Score: 0.9413373792859041 Test Score: 0.9406631376110213
Κ:
  8 Train Score: 0.9413373792859041 Test Score: 0.9406631376110213
Κ:
   9 Train Score: 0.9413373792859041 Test Score: 0.9406631376110213
Κ:
  10 Train Score: 0.9413373792859041 Test Score: 0.9406631376110213
K: 11 Train Score: 0.9413041552228227 Test Score: 0.9406409887262176
K:
  12 Train Score: 0.9413041552228227 Test Score:
                                                   0.9406409887262176
K: 13 Train Score: 0.9412709311597413 Test Score: 0.940618839841414
K: 14 Train Score: 0.9412709311597413 Test Score: 0.940618839841414
K: 15 Train Score: 0.9412432444405068 Test Score:
                                                   0.940618839841414
K: 16 Train Score: 0.9412432444405068 Test Score: 0.940618839841414
K: 17 Train Score: 0.9412377070966599 Test Score: 0.9405966909566104
K: 18 Train Score: 0.9412377070966599 Test Score: 0.9405966909566104
K: 19 Train Score: 0.9411989456897315 Test Score: 0.940552393187003
K: 20 Train Score: 0.9411989456897315 Test Score: 0.940552393187003
K: 21 Train Score: 0.9411823336581908 Test Score: 0.940552393187003
K: 22 Train Score: 0.9411823336581908 Test Score:
                                                   0.940552393187003
K: 23 Train Score: 0.9411657216266501 Test Score: 0.9405080954173958
K: 24 Train Score: 0.9411657216266501 Test Score: 0.9405080954173958
K: 25 Train Score: 0.9411380349074157 Test Score:
                                                  0.9404859465325921
K: 26 Train Score: 0.9411380349074157 Test Score: 0.9404859465325921
K: 27 Train Score: 0.9411214228758749 Test Score: 0.9404637976477884
Κ:
   28 Train Score: 0.9411214228758749 Test Score:
                                                  0.9404637976477884
   29 Train Score: 0.9410937361566404 Test Score: 0.9404637976477884
```

- 1. Create a KNN Classifier model using the best value of k found from previous question.
- 2. Train the model using xtrain, ytrain values.
- 3. Plot confusion matrix for the xtest and ytest,



```
In [ ]: print ("Accuracy is ",knn_best.score(X_test,y_test))
```

Accuracy is 0.9407074353806286

```
In [ ]: from sklearn.model_selection import cross_val_score
    for k in range(1,30):
        knn_crossval = KNeighborsClassifier(n_neighbors=k)

# Use sklearn for 5 fold cross validation
        scores_cv=cross_val_score(knn_crossval,X_train,y_train,cv=5)

# print the scores from different folds
    print(scores_cv)
```

```
[0.7926576  0.94124976  0.94149731  0.94091589  0.94257711]
        [0.79290678 0.94124976 0.94149731 0.94094357 0.94257711]
        [0.79290678 0.94124976 0.94149731 0.9408882 0.94257711]
        [0.79290678 0.94124976 0.94149731 0.9408882 0.94257711]
        [0.79290678 0.94122207 0.94144194 0.94086051 0.94249405]
        [0.79290678 0.94122207 0.94144194 0.94086051 0.94249405]
        [0.79290678 0.94119439 0.94141425 0.94086051 0.94249405]
        [0.79290678 0.94119439 0.94141425 0.94086051 0.94249405]
        [0.79290678 0.9411667 0.94135888 0.94083283 0.94243867]
        [0.79290678 0.9411667 0.94135888 0.94083283 0.94243867]
        [0.9405576  0.94111133  0.94133119  0.94083283  0.94241099]
        [0.9405576 0.94111133 0.94133119 0.94083283 0.94241099]
        [0.94050223 0.94111133 0.94130351 0.94077745 0.94241099]
        [0.94050223 0.94111133 0.94130351 0.94083283 0.94241099]
        [0.94047454 0.94111133 0.94122044 0.94069439 0.94241099]
        [0.94047454 0.94111133 0.94122044 0.94069439 0.94241099]
        [0.94044686 0.94108364 0.94116507 0.9406667 0.94241099]
        [0.94044686 0.94108364 0.94116507 0.9406667 0.94241099]
        [0.94044686 0.94102827 0.94113738 0.94063902 0.94235561]
        [0.94044686 0.94102827 0.94113738 0.94063902 0.94235561]
        [0.94044686 0.9409729 0.94105432 0.94058364 0.94232793]
        [0.94044686 0.9409729 0.94105432 0.94058364 0.94232793]
        [0.94044686 0.9409729 0.94099895 0.94058364 0.94227255]
        [0.79276835 0.9409729 0.94099895 0.94058364 0.94227255]
        [0.94041917 0.94094521 0.94097126 0.94052827 0.94221718]
        [0.79274066 0.94094521 0.94097126 0.94052827 0.94221718]
        [0.79271298 0.94094521 0.94091589 0.94052827 0.94218949]
        [0.79271298 0.94094521 0.94091589 0.94052827 0.94218949]
        [0.79271298 0.94094521 0.94086051 0.94044521 0.94218949]
In [ ]:
```

#### Classification Model 3: Decision Tree Classifier

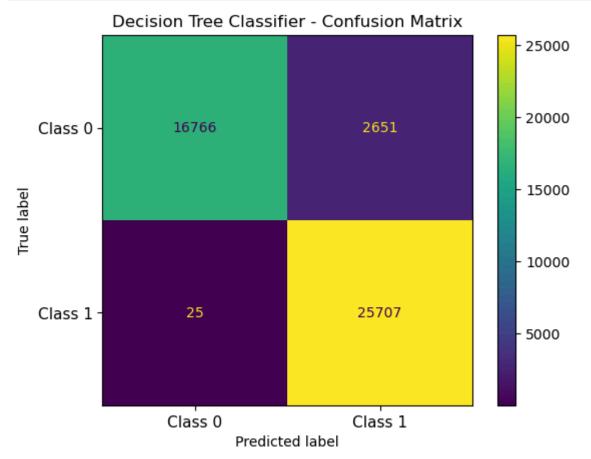
- 1. Create a DecisionTreeClassifier model
- 2. Fit the model with train data
- 3. Predict the test data using the trained model
- 4. Calculate the Mean Squared Error (MSE) of the model's prediction
- 5. Print the precison recall curve for the test data with minimum MSE value from the trained model
- 6. Plot Confusion Matrix
- 7. Display accuracy of prediction

```
#Predict
y_1 = clf_1.predict(X_test)

#Calculate mean_squared_error
print(mean_squared_error(y_test, y_1))
```

0.05927041573456777

```
In [ ]: cm = ConfusionMatrixDisplay.from_estimator(clf_1, X_test, y_test)
    plt.title("Decision Tree Classifier - Confusion Matrix")
    plt.xticks(range(2), ["Class 0","Class 1"], fontsize=11)
    plt.yticks(range(2), ["Class 0","Class 1"], fontsize=11)
    plt.show()
```



```
In [ ]: accuracy = accuracy_score(y_test, y_1)
    print(f'Accuracy: {accuracy:.2f}')
    Accuracy: 0.94
In [ ]:
```