## **Network Traffic Classification**

## 1. using K-Means Clustering:

```
#Import all required libraries
```

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import LabelEncoder, StandardScaler
# Load the dataset
dataset = pd.read_csv('/content/drive/MyDrive/DMML/nw2.csv')
dataset.head()
features = ["Time","Length"]
#Encode the data
label_encoders = {}
for col in ["Source", "Destination", "Protocol"]:
    le = LabelEncoder()
    dataset[col] = le.fit_transform(dataset[col])
    label_encoders[col] = le
X = dataset[features]
```

```
→
                   Time Length
               0.000000
               0.784682
               1.169060
               2.167949
                             60
               3.170095
                             60
                            . . .
    394131 1255.897236
                             98
    394132 1255.897921
                             98
    394133 1255.993209
                             74
    394134 1256.921232
                             98
    394135 1256.922008
                             98
    [394136 rows x 2 columns]
```

print(X)

```
# Standardize the data
```

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print(X_scaled)
```

```
[[-2.96506256 -1.06712294]
[-2.9620858 -1.06712294]
[-2.96062763 -1.10533781]
...
[ 1.79965264 -1.0886188 ]
[ 1.80317318 -1.05995765]
[ 1.80317612 -1.05995765]]
```

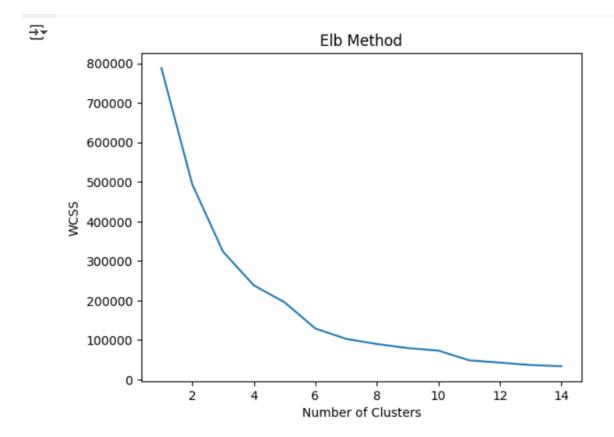
## #Compute within-cluster sum of squares (WCSS) for different cluster sizes

from sklearn.cluster import KMeans

```
wcss=[]
for i in range(1,15):
    kmeans=KMeans(n_clusters=i,init='k-means++',random_state=42)
    kmeans.fit(X_scaled)
    wcss.append(kmeans.inertia_)
```

#### **#Plot the elbow method**

```
plt.plot(range(1,15),wcss)
plt.title("Elb Method")
plt.xlabel("Number of Clusters")
plt.ylabel("WCSS")
plt.show()
```



### **#K-Means clustering and visualize the model.**

kmeans = KMeans(n clusters=8, random state=42, n init=10)

y\_kmeans = kmeans.fit\_predict(X\_scaled)

print(np.unique(y\_kmeans))

 $plt.scatter(X\_scaled[y\_kmeans==0,0], X\_scaled[y\_kmeans==0,1], s=10, c='red', label='C1')$ 

 $plt.scatter(X\_scaled[y\_kmeans==1,0], X\_scaled[y\_kmeans==1,1], s=10, c='blue', label='C2')$ 

 $plt.scatter(X\_scaled[y\_kmeans==2,0], X\_scaled[y\_kmeans==2,1], s=10, c='green', label='C3')$ 

 $plt.scatter(X\_scaled[y\_kmeans==3,0], X\_scaled[y\_kmeans==3,1], s=10, c='cyan', label='C4')$ 

 $plt.scatter(X\_scaled[y\_kmeans==4,0], X\_scaled[y\_kmeans==4,1], s=10, c='mage nta', label='C5')$ 

 $plt.scatter(X\_scaled[y\_kmeans==5,0], X\_scaled[y\_kmeans==5,1], s=10, c='orange', label='C6')$ 

```
plt.scatter(X_scaled[y_kmeans==6,0],X_scaled[y_kmeans==6,1],s=10,c='brow n',label='C7')

plt.scatter(X_scaled[y_kmeans==7,0],X_scaled[y_kmeans==7,1],s=10,c='black',label='C8')

#

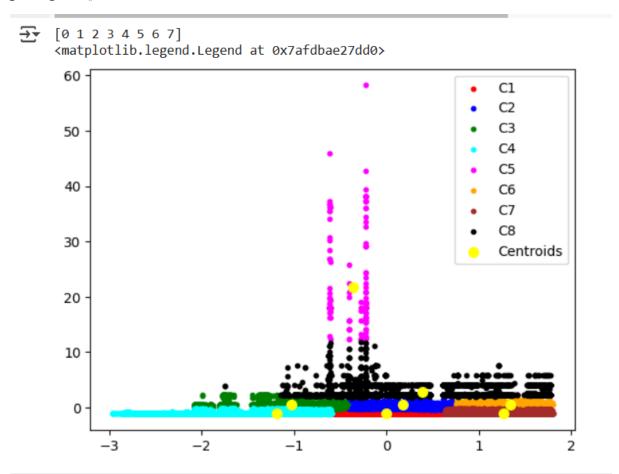
plt.scatter(X[y_kmeans==3]['Protocol'],X[y_kmeans==3]['Length'],s=100,c='cy an',label='C4')

#

plt.scatter(X[y_kmeans==4]['Protocol'],X[y_kmeans==4]['Length'],s=100,c='m agenta',label='C5')

plt.scatter(kmeans.cluster_centers_[:,0], kmeans.cluster_centers_[:,1],s=50,c='yellow',label='Centroids')

plt.legend()
```



# 2. using Hierarchical Clustering:

**#Import all required libraries** 

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import LabelEncoder, StandardScaler
import scipy.cluster.hierarchy as sch
#Loading and sampling of the dataset
dataset = pd.read csv('/content/drive/MyDrive/DMML/nw2.csv')
dataset sample = dataset.sample(n=1000, random state=42)
dataset sample.head()
features = ["Time","Length"]
#Perform label encoding
label encoders = {}
for col in ["Source", "Destination", "Protocol"]:
  le = LabelEncoder()
  dataset[col] = le.fit transform(dataset[col])
  label encoders[col] = le
X = dataset sample[features]
print(X)
                        Time
                              Length
      351660 1159.739058
                                   54
      147074
                684.013951
                                  580
      141496 653.704734
                                 1514
      224466 814,918402
                                  405
      381701 1233.302231
                                 1514
      . . .
                         . . .
                                  . . .
      372835 1223.674828
                                 1514
      297389 988.107413
                                   60
      279611
                 941.512538
                                 1462
      104787
                 571.123548
                                   54
      508
                 103.362516
                                   98
      [1000 rows x 2 columns]
```

```
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
print(X_scaled)
plt.figure(figsize=(12, 6))
dendrogram = sch.dendrogram(sch.linkage(X_scaled, method = 'ward'))
plt.title('Dendrogram')
plt.xlabel('Time')
plt.ylabel('Length')
plt.show()
```

```
[[ 1.46000345 -1.24068847]
[-0.36628354 -0.53400222]
[-0.48263925 0.7208361 ]
...
[ 0.62224179 0.65097358]
[-0.79966465 -1.24068847]
[-2.59537792 -1.18157403]]
```

