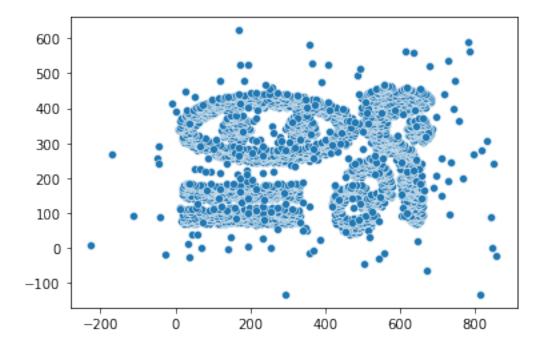
Task4 ALI

December 6, 2022

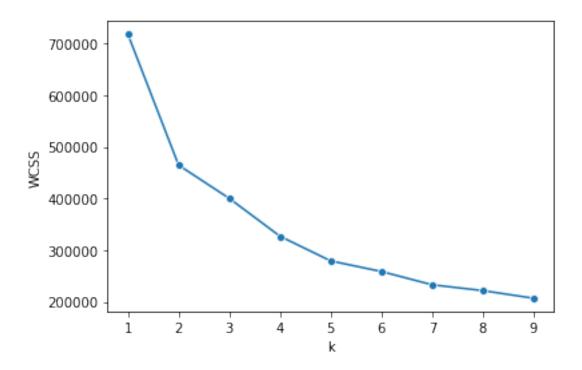
```
[2]: import pandas as pd
      import numpy as np
      from sklearn import metrics
      from sklearn.cluster import KMeans
      import seaborn as sns
      import warnings
      warnings.filterwarnings('ignore')
      import matplotlib.pyplot as plt
      import scipy.stats as stats
      import sklearn
      from sklearn.cluster import DBSCAN
      from sklearn.neighbors import NearestNeighbors
      from collections import Counter
      from sklearn.preprocessing import StandardScaler
 [3]: df2 = pd.read_csv("Shuttle22.csv", header= None)
      df = pd.read_csv("complex9_gn8.txt", header = None,sep=',')
[18]: def purity_score(y_true, y_pred,outliers):
          # compute contingency matrix (also called confusion matrix)
          contingency_matrix = metrics.cluster.contingency_matrix(y_true, y_pred)
          # return purity
          return np.sum(np.amax(contingency_matrix, axis=0)) / np.
       →sum(contingency_matrix)
[87]: X=df[[0,1]]
      X=X.values
      sns.scatterplot(X[:,0], X[:, 1])
      data = df[[0,1]]
      plt.show()
      data,X
```



```
[87]: (
                    0
                       304.2250
              660.976
              636.213 306.1740
        1
        2
              662.753
                       307.5650
        3
              657.487
                       307.7400
        4
              635.273
                       308.1570
              728.899
                       535.6270
        3268
        3269
              504.528
                       -46.2297
        3270
              373.256
                       409.0260
        3271
              850.838
                       242.7110
        3272
              641.676
                       347.5440
        [3273 rows x 2 columns],
        array([[660.976, 304.225],
               [636.213, 306.174],
               [662.753, 307.565],
               [373.256, 409.026],
               [850.838, 242.711],
               [641.676, 347.544]]))
[102]: def calculate_cost(X, centroids, cluster):
           sum = 0
           for i, val in enumerate(X):
```

```
return sum
      def kmeans(X, k):
          diff = 1
          cluster = np.zeros(X.shape[0])
          centroids = data.sample(n=k).values
          while diff:
          # for each observation
              for i, row in enumerate(X):
                  mn_dist = float('inf')
                  # dist of the point from all centroids
                  for idx, centroid in enumerate(centroids):
                      d = np.sqrt((centroid[0]-row[0])**2 + (centroid[1]-row[1])**2)
                      # store closest centroid
                      if mn dist > d:
                          mn dist = d
                          cluster[i] = idx
              new_centroids = pd.DataFrame(X).groupby(by=cluster).mean().values
           # if centroids are same then leave
              if np.count nonzero(centroids-new centroids) == 0:
                  diff = 0
              else:
                  centroids = new_centroids
          return centroids, cluster
      cost_list = []
      for k in range(1, 10):
          centroids, cluster = kmeans(X, k)
          # WCSS (Within cluster sum of square)
          cost = calculate_cost(X, centroids, cluster)
          cost_list.append(cost)
[104]: sns.lineplot(x=range(1,10), y=cost_list, marker='o')
      plt.xlabel('k')
      plt.ylabel('WCSS')
      plt.show()
```

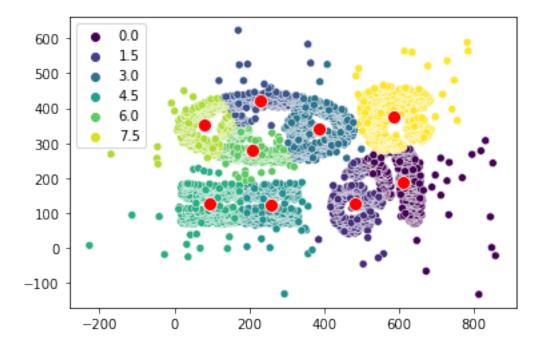
sum += np.sqrt((centroids[int(cluster[i]), 0]-val[0])**2_



```
[143]: palette=sns.color_palette("viridis", as_cmap=True)

k = 9
centroids, cluster = kmeans(X, k)

sns.scatterplot(X[:,0], X[:, 1], hue=cluster,palette=palette)
sns.scatterplot(centroids[:,0], centroids[:, 1], s=100, color='r')
plt.show()
```

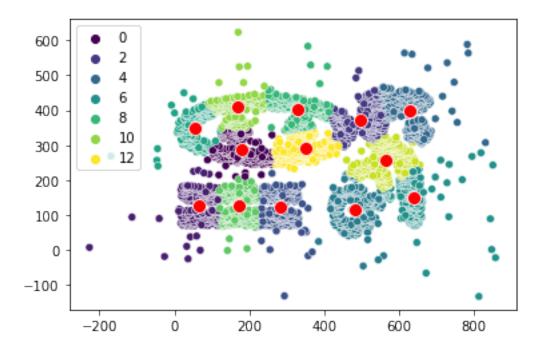


```
[154]: true = df[2]
    purity_score(true,cluster)

[154]: 0.7100519401161014

[155]: k = 13
    centroids, cluster = kmeans(X, k)

    sns.scatterplot(X[:,0], X[:, 1], hue=cluster,palette=palette)
    sns.scatterplot(centroids[:,0], centroids[:, 1], s=100, color='r')
    plt.show()
    purity_score(true,cluster)
```

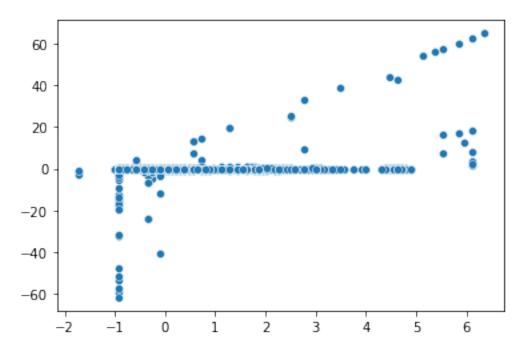


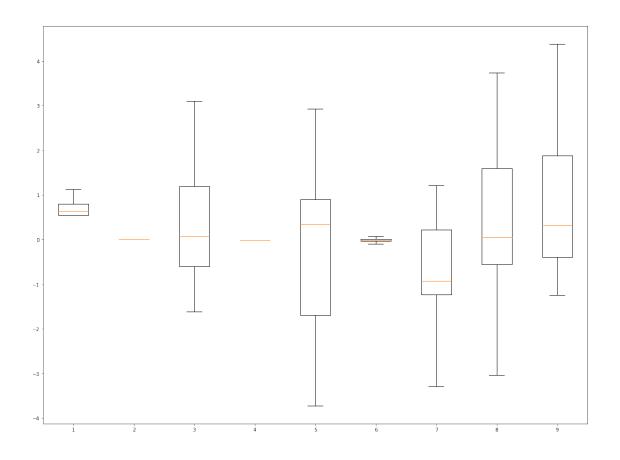
[155]: 0.6804155209288115

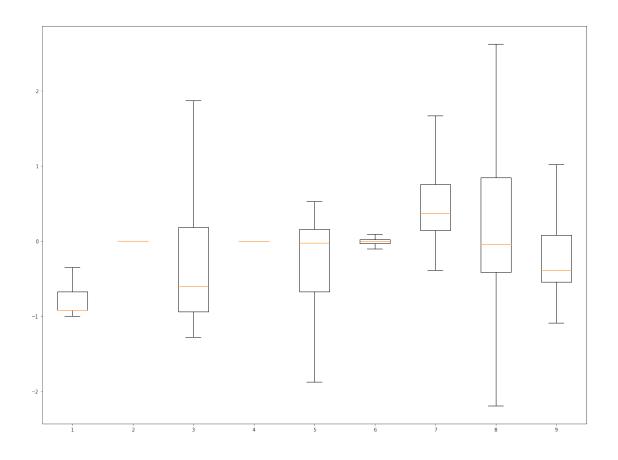
```
[4]: z = df2[[0,1,2,3,4,5,6,7,8]]
ZSHUT=z.apply(stats.zscore)
ZSHUT[9] = df2[9]

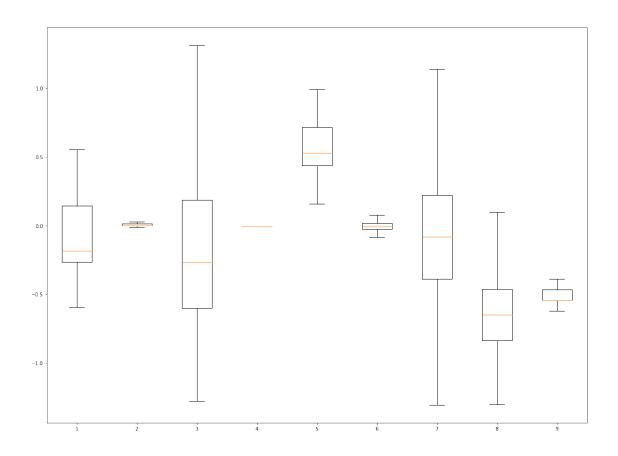
zdata = ZSHUT[[0,1,2,3,4,5,6,7,8]]
zdata= zdata.values
zdata
#z
```

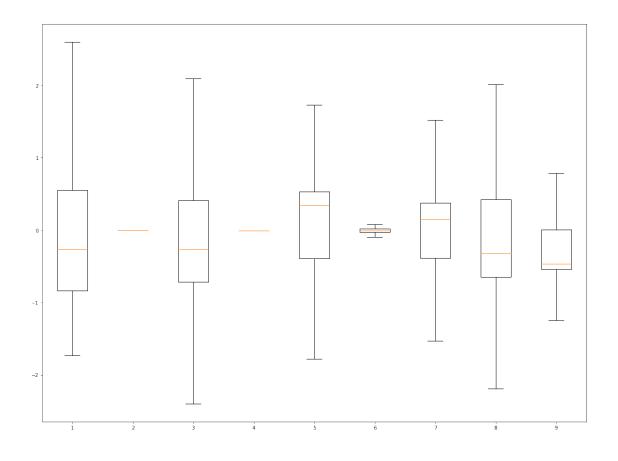
```
[5]: data =ZSHUT[[0,1,2,3,4,5,6,7,8]]
       data
  [5]:
                               1
                                          2
                                                   3
                                                             4
                                                                        5
       0
              0.143954   0.269627   -0.937820   -0.00711   -0.302395   -0.007391   -0.769741
              0.552518 0.000249 0.747064 -0.00711 -1.595103 0.112097 -0.083311
       1
       2
              0.389093 \quad 0.000249 \quad -0.376192 \quad -0.00711 \quad 0.805641 \quad -0.030369 \quad -0.617201
             -0.918313 0.000249 -1.050145 -0.00711 -0.302395 0.075331 0.221769
       3
       4
             -0.918313 0.000249 -0.713169 -0.00711 -0.025386 -0.126878 0.450579
       57995 2.595340 0.000249 -0.151541 -0.00711 -3.257157 -0.140665 -2.523951
       57996 0.552518 0.000249 -0.488517 -0.00711 -2.518466 0.107501 -0.846011
       57997 0.552518 0.000249 -0.937820 -0.00711 -1.041086 -0.108496 -1.151091
       57998 -0.918313 0.000249 1.982645 -0.00711 -0.764077 -0.080922 2.204789
       57999 0.634231 0.025905 1.421017 -0.00711 0.805641 -0.002795 0.374309
                    7
             -0.13468 0.314970
       0
       1
              1.91968 1.642380
       2
             -0.97510 -0.465859
       3
             -0.13468 -0.231610
       4
             -0.22806 -0.465859
       57995 3.22700 3.984867
       57996 2.38658 2.423209
       57997 0.65905 1.095800
       57998 1.59285 0.236887
       57999 -0.22806 -0.387776
       [58000 rows x 9 columns]
[353]: k = 3
       centroids, cluster = kmeans(zdata, k)
       true2 = ZSHUT[9]
       purity_score(true2,cluster)
       #cluster
[353]: 0.868948275862069
[340]: sns.scatterplot(zdata[:,0], zdata[:, 1])
       plt.show()
```











```
[64]: def dbscan(dataset, epsilon, minsamples):
          dbscan_data = dataset[[0,1,2,3,4,5,6,7,8,9]]
          model1 = DBSCAN(eps=epsilon, min_samples=minsamples, metric='euclidean').\
          fit(dbscan_data)
          outliers_df = dataset[model1.labels_ == -1]
          num_clusters = len(set(model1.labels_))
          clusters_df = [dataset[model1.labels_ == n] for n in range(num_clusters)]
          colors = model1.labels_
          color_clusters = colors[colors != -1]
          color_outliers = 'white'
          clusters1 = Counter(model1.labels_)
          return clusters_df
      def dbscanplot(dataset, epsilon, minsamples):
          dbscan_data = dataset[[0,1,2,3,4,5,6,7,8,9]]
          \#return\ dbscan\_data
          model1 = DBSCAN(eps=epsilon, min_samples=minsamples, metric='euclidean').\
```

```
fit(dbscan_data)
          #return model1
          outliers_df = dataset[model1.labels_ == -1]
          clusters_df = dataset[model1.labels_ != -1]
          return model1.labels_
          '''colors = model1.labels_
          color_clusters = colors[colors != -1]
          color_outliers = 'white'
          clusters1 = Counter(model1.labels )
          print(clusters_df)
          print(clusters1)
          #print(dataset[model1.labels_ == -1].head())
          print('number of clusters: {}'.format(len(clusters1)-1))
          #dbscan_plot(clusters_df,color_clusters)'''
      def dbscan_plot(cluster,cluster_colors):
          fig = plt.figure()
          ax = fig.add_axes([.2, .2, 2, 2])
          ax.scatter(ZSHUT[[0,1,2,3,4,5,6,7,8]],
          c = cluster_colors, edgecolors = 'black', s = 70)
          ax.set_xlabel('Latitude', fontsize=10)
          ax.set_ylabel('Longitude', fontsize=10)
          plt.title('title',fontsize=12)
          plt.grid(which='major',color='#cccccc', alpha=0.45)
          plt.show()
 [8]: dbscandata= ZSHUT[[0,1,2,3,4,5,6,7,8]]
      dbscanplot(dbscandata, .26,100)
 [8]: array([-1, 0, 1, ..., 3, 5, 1], dtype=int64)
 [9]: clusterlist =dbscan(dbscandata, .26,100)
[11]: q = dbscanplot(dbscandata, .26,100)
[36]: n=np.delete(q, np.where(q == -1))
      ZSHUT[9].max
[36]: <bound method NDFrame._add_numeric_operations.<locals>.max of 0
                                                                               2
      1
               4
      2
               1
      3
               1
      4
               1
              . .
      57995
               5
      57996
               4
      57997
               4
      57998
               1
```

```
Name: 9, Length: 58000, dtype: int64>
[40]: clusterlist[1]
[40]:
                                     2
                                              3
            0.389093 \quad 0.000249 \quad -0.376192 \quad -0.007110 \quad 0.805641 \quad -0.030369 \quad -0.617201
     2
     3
           -0.918313 0.000249 -1.050145 -0.007110 -0.302395 0.075331
                                                                    0.221769
     4
           0.450579
            0.552518 -0.012578 1.084041 -0.089254 0.897977 -0.025773
                                                                    0.221769
     10
           0.374309
     57990 -0.836600 0.025905 -0.713169 -0.007110 0.159287 0.075331 0.374309
     57992 -0.754887 -0.025406 -0.600843 -0.116636 0.159287 -0.007391
                                                                    0.298039
     57993 -0.428036 0.000249 -0.488517 0.020271 0.343959 -0.048752 -0.007041
     57994 0.062241 0.000249 0.185436 -0.007110 0.528632 -0.062539
                                                                    0.069229
     57999 0.634231 0.025905 1.421017 -0.007110 0.805641 -0.002795
                                                                    0.374309
                 7
                           8
           -0.97510 -0.465859
     2
     3
           -0.13468 -0.231610
           -0.22806 -0.465859
     7
           -0.46151 -0.465859
     10
           0.65905 0.393053
     57990 -0.46151 -0.543942
     57992 -0.46151 -0.543942
     57993 -0.55489 -0.465859
     57994 -0.46151 -0.465859
     57999 -0.22806 -0.387776
     [42135 rows x 9 columns]
[51]: ze = ZSHUT
     ze[10]=q
     ze2 = ze[ze[10] != -1]
     truer = ze2[9]
     mine = ze2[10]
     purity_score(truer,mine)
[51]: 0.9325662054264966
[4]: def dbscanplot1(dataset, epsilon, minsamples):
         dbscan_data = dataset[[0,1,2,3,4,5,6,7,8]]
         #return dbscan_data
```

57999

```
fit(dbscan_data)
           #return model1
           outliers_df = dataset[model1.labels_ == -1]
           clusters_df = dataset[model1.labels_ != -1]
           colors = model1.labels_
           color_clusters = colors[colors != -1]
           color_outliers = 'white'
           clusters1 = Counter(model1.labels )
           #return model1.labels
           #print(clusters df)
           print(clusters1)
           #print(dataset[model1.labels_ == -1].head())
           print('number of clusters: {}'.format(len(clusters1)-1))
           #dbscan_plot(clusters_df,color_clusters)
       def dbscanplot2(dataset, epsilon, minsamples):
           dbscan_data = dataset[[0,1,2,3,4,5,6,7,8]]
           #return dbscan data
           model1 = DBSCAN(eps=epsilon, min_samples=minsamples, metric='euclidean').\
           fit(dbscan data)
           #return model1
           outliers df = dataset[model1.labels == -1]
           clusters_df = dataset[model1.labels_ != -1]
           colors = model1.labels
           color_clusters = colors[colors != -1]
           color_outliers = 'white'
           clusters1 = Counter(model1.labels_)
           return model1.labels_
[178]: yo =dbscanplot1(ZSHUT, .66, 100)
      Counter({0: 54416, 1: 2334, 2: 887, -1: 363})
      number of clusters: 3
[167]: ssa =dbscanplot1(ZSHUT, .46,10)
      Counter({0: 54398, 1: 2324, 2: 885, -1: 332, 4: 19, 3: 17, 5: 15, 6: 10})
      number of clusters: 7
[164]: \#(Counter(yo[0]) + Counter(yo[1]) + Counter(yo[2]) + Counter(yo[3]) + Counter(yo[-1]))
       Counter(yo1)
[164]: Counter({0: 54470, 1: 2353, -1: 252, 2: 887, 3: 38})
```

model1 = DBSCAN(eps=epsilon, min_samples=minsamples, metric='euclidean').\

```
[180]: 252/5800
[180]: 0.043448275862068966
[174]: yo1 =dbscanplot2(ZSHUT, .66,10)
[175]: clusters11 = Counter(yo1)
       clusters11
[175]: Counter({0: 54470, 1: 2353, -1: 252, 2: 887, 3: 38})
[176]: ze1 = ZSHUT
       ze1[10] = yo1
       ze22 = ze1[ze1[10] != -1]
       truer = ze22[9]
       mine = ze22[10]
       purity_score(truer,mine)
       #np.sum(1/55348)
[176]: 0.8432153494493316
[120]: contingency_matrix = metrics.cluster.contingency_matrix(truer, mine)
           #return np.sum(np.amax(contingency_matrix, axis=0)) / np.
        ⇒sum(contingency_matrix)
       np.sum(np.amax(contingency_matrix, axis=0)/np.sum(contingency_matrix))
[120]: 0.9325662054264966
  []: ###start of search procedure###
       yo =dbscanplot1(ZSHUT, .66,10) #gets the number of clusters and outlier_
        ⇔percentage
       yo1 =dbscanplot2(ZSHUT, .66,10) #qets the cluster_df which holds labels for the
        \hookrightarrow clusters
       ze1 = ZSHUT #initilize the ZSHUT dataset
       ze1[10]=yo1 #add the clusters_df to our zshut dataset
       ze22 = ze1[ze1[10] != -1] #wherever the cluster is labeled -1 aka an outlier we_1
       ⇔will remove from the dataset
       truer = ze22[9] #set original cluster labels as y_true
       mine = ze22[10] #set the new labels we obtained as y_pred
       purity_score(truer,mine) #run our purity score function to get the purity score_
        ⇔of our sclustering
  [6]: shuttle = df2[[0,1,2,3,4,5,6,7,8]]
       shuttle
```

```
[6]:
             0
                       2 3 4
                                  5
                                      6
                                           7
                                                8
                 1
     0
             50
                 21
                      77 0
                             28
                                  0
                                     27
                                          48
                                               22
      1
                      92 0
                                 26
             55
                  0
                              0
                                     36
                                          92
                                               56
      2
             53
                  0
                      82 0 52
                                 -5
                                     29
                                                2
                                          30
      3
             37
                  0
                      76 0
                             28
                                 18
                                     40
                                          48
                                                8
                      79 0
                             34 -26
                                                2
             37
                  0
                                     43
                                          46
                                 . .
      57995
            80
                  0
                      84 0 -36 -29
                                      4
                                         120
                                              116
      57996 55
                  0
                      81 0 -20
                                25
                                     26
                                         102
                                               76
      57997
            55
                  0
                      77
                          0
                             12 -22
                                     22
                                          65
                                               42
                                               20
      57998 37
                  0
                     103 0 18 -16
                                     66
                                          85
      57999 56
                  2
                                  1 42
                                                4
                      98 0 52
                                          46
      [58000 rows x 9 columns]
 []: ###start of search procedure###
      yo =dbscanplot1(shuttle, .66,10) #gets the number of clusters and outlier
       →percentage
      yo1 =dbscanplot2(shuttle, .66,10) #qets the cluster_df which holds labels for_
       ⇔the clusters
      ze1 = shuttle #initilize the ZSHUT dataset
      ze1[10]=yo1 #add the clusters_df to our zshut dataset
      ze22 = ze1[ze1[10] != -1] #wherever the cluster is labeled -1 aka an outlier we_
       ⇔will remove from the dataset
      truer = ze22[9] #set original cluster labels as y_true
      mine = ze22[10] #set the new labels we obtained as y pred
      purity_score(truer,mine) #run our purity score function to get the purity score_
       ⇔of our sclustering
[10]: yo =dbscanplot1(shuttle,10,10) #gets the number of clusters and outlier_
       \rightarrowpercentage
     Counter({0: 54172, 1: 2295, 2: 882, -1: 615, 3: 24, 4: 12})
     number of clusters: 5
[11]: yo1 =dbscanplot2(shuttle,10,10) #qets the cluster of which holds labels for the
       \hookrightarrow clusters
[19]: ze1 = df2 #initilize the ZSHUT dataset
      ze1[10]=yo1 #add the clusters df to our zshut dataset
      ze22 = ze1[ze1[10] != -1] #wherever the cluster is labeled -1 aka an outlier we_
       ⇔will remove from the dataset
      truer = ze22[9] #set original cluster labels as y_true
      mine = ze22[10] #set the new labels we obtained as y_pred
```

purity_score(truer,mine) #run our purity score function to get the purity score \downarrow of our sclustering

[19]: 0.84522087653568