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CS306: DATA ANALYSIS AND VISUALIZATION
         LAB 8: K-Means Clustering
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In [1]: import numpy as np
         import matplotlib.pyplot as plt
         import pandas as pd
         import random
         %matplotlib inline
          from sklearn.preprocessing import StandardScaler,RobustScaler
         import seaborn as sns
         from sklearn.metrics import mean_squared_error as mse
         from sklearn.cluster import KMeans
         from sklearn.datasets import load_digits
         import warnings
         warnings.filterwarnings('ignore')
In [2]: def find_centroids(k,n):
             random.seed(5)
             idx=[]
             for i in range(k):
                 idx.append(random.randint(0,n-1))
             return idx
In [3]: def find_clusters(df,c,k,n):
             dist=[[] for _ in range(k)]
             for i in range(n):
                  temp=[]
                  for j in range(k):
                      dist_temp = np.sum((df[i]-c[j])**2)
                      temp.append(dist_temp)
                 location=temp.index(min(temp))
                  dist[location].append(i)
             return dist
In [4]: def find_new_centroids(df, dist, c, k, m):
             for i in range(k):
                  temp_mean=[0 for _ in range(m)]
                  for j in range(len(dist[i])):
                      id=dist[i][j]
                      temp=0
                      for kk in range(m):
                          temp_mean[kk]+=df[id][kk]/len(dist[i])
                  for j in range(m):
                      c[i][j]=temp_mean[j]
             return c
In [5]: def plot_2D(dist,df,c,k):
             plt.figure(figsize=[10,6])
             distx=[[] for i in range(k)]
             disty=[[] for i in range(k)]
             for i in range(k):
                 for j in range(len(dist[i])):
                      id=dist[i][j]
                      distx[i].append(df[id][0])
                      disty[i].append(df[id][1])
             cx=[];cy=[]
             for i in range(k):
                 cx.append(c[i][0])
                 cy.append(c[i][1])
                 sns.scatterplot(distx[i], disty[i], markers='o', s=200)#, c=next(clr))
             sns.scatterplot(cx,cy,color='.2',marker='*',s=200)
             plt.grid()
             plt.xlabel('X', fontsize=15)
             plt.ylabel('Y', fontsize=15)
In [6]: def k_means(df,k,plot):
             n=df.shape[0]
             m=df.shape[1]
             #indices of centroid
             idx=find_centroids(k,n)
             #to store the centroids kxm
             c=[[] for _ in range(k)]
             cprev=[[] for _ in range(k)]
             for i in range(k):
                  for j in range(m):
                      c[i].append(df[idx[i]][j])
                      cprev[i].append(df[idx[i]][j])
             #to get the points in a given cluster kxdim
             #just store the indices in the original array
             dist=[[] for _ in range(k)]
             itr=0
             flag=False
             while flag==False and itr!=150:
                  #k clusters with elements in the cluster
                  dist=find_clusters(df,c,k,n)
                  #store previous centroids
                 cprev=np.copy(c)
                 #finding the new centroids
                 c=find_new_centroids(df, dist, c, k, m)
                  count=0
                  for i in range(k):
                      for j in range(len(c[0])):
                          if c[i][j]==cprev[i][j]:
                              count+=1
                 if count==k*len(c[0]):
                     break
                 itr+=1
             #to plot if plot=True
             if plot==True:
                  plot_2D(dist,df,c,k)
             return c, dist
In [7]: def find_inertia(c,d,df):
             ans=0
             for i in range(len(c)):
                  indices=d[i]
                  for kk in range(len(indices)):
                      for j in range(len(c[0])):
                          ans+=(c[i][j]-df[indices[kk]][j])**2
             return ans
         Q1
 In [8]: x = [10, 14, 8, 12, 15, 12, 15, 17, 5, 18, 22, 25, 35, 21, 39, 27, 25, 33, 30, 36]
         y = [8, 25, 10, 30, 35, 12, 14, 15, 22, 32, 2, 21, 35, 7, 15, 29, 33, 23, 17, 11]
In [9]: df=[]
         df.append(x)
         df.append(y)
         df=np.array(df).transpose()
         scaler = StandardScaler()
         df_scaled = scaler.fit_transform(df)
In [10]: SSE_q1=[]
         n=20
          for i in range(1,n):
             c_q1, dist_q1=k_means(df, i, False)
             SSE_q1.append(find_inertia(c_q1, dist_q1, df))
In [11]: x_axis=np.arange(1,20)
          plt.figure(figsize=[10,6])
          plt.plot(x_axis, SSE_q1, 'k-o')
         plt.grid()
         plt.ylabel('SSE', fontsize=15)
         plt.xlabel('K(number of clusters)', fontsize=15)
         plt.title('Elbow Curve', fontsize=15)
Out[11]: Text(0.5, 1.0, 'Elbow Curve')
                                             Elbow Curve
             4000 -
             3500
             3000
             2500
          2000
2000
            1500
            1000
             500
                        2.5
                                5.0
                                                 10.0
                                                          12.5
                                                                   15.0
                                                                           17.5
                                         K(number of clusters)
In [12]: diff_x=np.arange(2,20)
         diff_sse_q1 = [SSE_q1[i-1]-SSE_q1[i] for i in range(1,len(SSE_q1))]
         plt.figure(figsize=[10,6])
         plt.plot(diff_x, diff_sse_q1, 'k-o')
         plt.grid()
         plt.ylabel('SSE[i-1] - SSE[i]', fontsize=15)
         plt.xlabel('i', fontsize=15)
         plt.title('Optimal cluster size', fontsize=15)
Out[12]: Text(0.5, 1.0, 'Optimal cluster size')
                                          Optimal cluster size
            1400
            1200
            1000
          SSE[i-1] -
             600
             200
                                                         12.5
                                                                           17.5
                    2.5
                              5.0
                                       7.5
                                                10.0
                                                                  15.0
         We can see that at i=6 we get almost zero difference and after that we get such a case for
         i>10 for which the computation time increases significantly hence, K=6 is a good choice for
         number of clusters.
In [13]: c_q1, dist_q1=k_means(df, 6, True)
             35
             30
             25
            15
             10
                                               30
                                   15
                                             20
                                                Χ
         Q2
In [14]: | data_digits=load_digits().data
         data_digits.shape
Out[14]: (1797, 64)
In [15]: | scaler = StandardScaler()
         data_scaled = scaler.fit_transform(data_digits)
          kmeans.fit(data_scaled)
         SSE_kmeans=kmeans.inertia_
         print('SSE using inbuilt function:',SSE_kmeans)
         SSE using inbuilt function: 69408.34813425265
         SSE_q2_myfunc = find_inertia(c_q2, dist_q2, data_scaled)
         print('SSE using my function(k_means):', SSE_q2_myfunc)
         SSE using my function(k_means): 69476.70340699745
```

My function for digits dataset

In [19]: SSE_q2=[]

for i in range(1, n):

n=11

kmeans.fit(data_scaled)

SSE_inbuilt.append(kmeans.inertia_)

c_q2, dist_q2=k_means(data_scaled, i, False)

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In [20]: x_axis=[i for i in range(1,11)]
    plt.figure(figsize=[10,6])
    plt.plot(x_axis,SSE_q2,'k-o',label='My Function')
    plt.plot(x_axis,SSE_inbuilt,'r-o',label='Inbuilt')
    plt.grid()
    plt.ylabel('SSE',fontsize=15)
```

plt.xlabel('K(number of clusters)', fontsize=15)
plt.title('Elbow Curve', fontsize=15)
plt.legend(fontsize=12)

Out[20]: <matplotlib.legend.Legend at 0x7f4c5ddc7a10>

Elbow Curve

110000

My Function
Inbuilt

