Music Genre Classification using K Means

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#importing useful modules of python
          import numpy as np
          import pandas as pd
          import scipy as sp
          import seaborn as sns
          import matplotlib.pyplot as plt
          from sklearn.cluster import KMeans
          from sklearn.metrics import confusion_matrix
In [3]:
          #loading the data from .csv file
          dataframe=pd.read_csv('Genre_data.csv')
          print("Coloumns of the data file....\n")
          for col in dataframe.columns:
              print(col)
         Coloumns of the data file....
         filename
         length
         {\tt chroma\_stft\_mean}
         chroma_stft_var
         rms_mean
         rms_var
         spectral_centroid_mean
         spectral_centroid_var
         spectral_bandwidth_mean
         spectral_bandwidth_var
         rolloff_mean
         rolloff_var
         zero_crossing_rate_mean
         zero_crossing_rate_var
         harmony_mean
         harmony_var
         perceptr_mean
         perceptr_var
         tempo
         mfcc1_mean
         mfcc1_var
         mfcc2_mean
         mfcc2_var
         mfcc3_mean
         mfcc3_var
         mfcc4_mean
         mfcc4_var
         mfcc5_mean
         mfcc5_var
         mfcc6_mean
         mfcc6_var
         mfcc7_mean
         mfcc7_var
         mfcc8_mean
         mfcc8_var
         mfcc9_mean
         mfcc9_var
         mfcc10_mean
         mfcc10_var
         mfcc11_mean
         mfcc11_var
         mfcc12_mean
         mfcc12_var
         mfcc13_mean
         mfcc13_var
         mfcc14_mean
         mfcc14_var
         mfcc15_mean
         mfcc15_var
         mfcc16_mean
         mfcc16_var
         mfcc17_mean
         mfcc17_var
         mfcc18_mean
         mfcc18_var
         mfcc19_mean
         mfcc19_var
         mfcc20_mean
         mfcc20_var
         label
In [4]:
          #dictionary which maps lable name to a positive integer
          genre_to_number= {
              'blues':0,
              'classical':1,
              'country':2,
              'disco':3,
              'hiphop':4,
              'jazz':5,
              'metal':6,
              'pop':7,
              'reggae':8,
              'rock':9,
In [5]:
          #removing unnecessary columns
          dataframe.label=[genre_to_number[item] for item in dataframe.label]
          labels=dataframe['label']
          dataframe=dataframe.drop(['filename', 'length', 'label'], axis = 1)
 In [6]:
          #Converting into numpy array
          X=dataframe.to_numpy()
          y=labels.to_numpy()
In [7]:
          #Verifying the shape
          print(X.shape)
          print(y.shape)
         (9990, 57)
         (9990,)
 In [8]:
          print("Number of datapoints: ", X.shape[0])
          print("Number of features: ", X.shape[1])
         Number of datapoints: 9990
         Number of features: 57
In [9]:
          #Performing the K-means clustering
          km = KMeans(
              n_clusters=10, init='random',
              n_init=200, max_iter=500,
              tol=1e-04, random_state=0
          y_pred = km.fit_predict(X)
In [11]:
          #Calculating the density of each cluster
          freq_denominator=np.zeros(10)
          for i in range(9990):
              freq_denominator[y_pred[i]]+=1
          print("ith element represents the number of data points belonging to cluster i")
          print(freq_denominator)
         ith element represents the number of data points belonging to cluster i
         [ 269. 2343. 1674. 498. 71. 1255. 2538. 821. 186. 335.]
         Observation: Here we can see that each cluster contains different amount of data points. So K-means is not able to form appropriate clusters.
In [13]:
          #giving proper lables
          m=y_pred.shape[0]
          cluster_to_label=np.zeros(10)
          freq=np.zeros([10,10])
          for i in range(m):
              freq[y_pred[i]][y[i]]+=1
          for i in range(10):
              cluster_to_label[i]=np.argmax(freq[i])
          for i in range(m):
              y_pred[i]=cluster_to_label[y_pred[i]]
In [14]:
          print("(i,j) element represents the number of datapoints belonging to cluster i and having j as original label: ")
          print(freq)
          print("ith element represents which cluster represents which label: ")
          print(cluster_to_label)
         (i,j) element represents the number of datapoints belonging to cluster i and having j as original label:
         [[ 2. 0. 11. 13. 59. 1. 2. 113. 53. 15.]
          [349. 77. 277. 289. 203. 318. 339. 105. 93. 293.]
          [116. 21. 255. 282. 183. 177. 101. 175. 140. 224.]
           [ 44.
                  6. 43. 39. 71. 15.
                                           2.
                                               99. 148. 31.]
                                           0. 17. 19. 14.]
            Θ.
                  1.
                      Θ.
                           4. 14.
                                      2.
          [ 89. 13. 168. 197. 174. 95. 16. 199. 172. 132.]
          [304. 869. 136. 64. 81. 312. 532. 21. 45. 174.]
                  9. 85.
                           80.
                                98. 66.
                                           7. 139. 183. 84.]
                     3.
                           9. 50.
                                      6.
                                           0. 41. 55. 13.]
          [ 19.
                  0. 19. 22. 65.
                                      8.
                                           1. 91. 92. 18.]]
         ith element represents which cluster represents which label:
         [7. 0. 3. 8. 8. 7. 1. 8. 8. 8.]
In [15]:
          #plotting confusion matrix
          print("Confusion matrix is visualized below. Where X axis has ground truth and Y axis has predicted values.\n\n\n")
          plt.figure(figsize=(15,15))
          sns.heatmap(confusion_matrix(y,y_pred),annot=True)
          plt.show()
         Confusion matrix is visualized below. Where X axis has ground truth and Y axis has predicted values.
```

3.5e+02 3e+02 1.2e+02 91 1.4e+02 - 800 8.7e+02 21 13 18 - 700 2.8e+02 1.4e+02 0 2.6e+02 0 1.8e+02 1.5e+02 0 - 600

2.9e+02 2.8e+02 2.1e+02 1.5e+02 500 1.8e+02 2e+02 3e+02 - 400 3.1e+02 1.8e+02 3.2e+02 18 10 3.4e+02 le+02 - 300 1.0e+02 21 1.8e+02 3.1e+02 3.9e+02 0 - 200 5e+02 45 1.4e+02 2.2e+02 0 - 100 2.2e+02 1.5e+02 1.6e+02 0

Observation: On a final note K-means is not sufficient to classify the music genre and we need to come up with another ML model.