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ICP 7

Due Date: 10/12/2020

My explanation

The n_cluster variable value was changed six times to observe how it was affecting the overall clustering groups. From the table below we can see that the number of clusters changes with the change of n_cluster variable value. Some of the cluster groups increased or decreased depending on the closet center, which is the basic concept of K-means, which is partitioning k cluster means to represent k cluster and assigning objects to the closet center, where k is given(class PowerPoint definition). There are some limitations since the algorithm is highly sensitive to outliers for objects with extremely high value and therefore distort the distribution of the data. For n_cluster = 5, 6, and 7, one thing is noticeable right away, that is cluster 4 decreases then increases for n_cluster 7. This could be due to the centroid position and the distance calculated for each data point. Overall, based on n_cluster = 10 the group seems to proportional to each other based on the centroid position.

For n_cluster = 5 group 4 decreases but increased for n_cluster (7).

N_cluster = 5	N_cluster = 6
4 298 2 289 3 245 1 241 0 177	0 291 5 213 2 213 1 206 4 172 3 155
N_cluster = 7	**N_cluster = 8**
4 231 5 223 0 187 3 184 1 158 2 137 6 130	5 229 7 201 1 167 0 152 2 150 3 123 4 120 6 108
N_cluster = 9	**N_cluster = 10**
3 214 1 185 2 144 7 124 8 123 0 122 5 119 6 114 4 105	2 188 3 164 9 163 0 162 1 129 4 122 6 107 5 87 7 73 8 55

a. What you learned in the ICP

One of the main components I learned from this ICP was that K – Means clustering can be useful for features where the labels are unknown. This can be useful in finding structure in the unlabeled data. Also, discover groups, and pattern of objects, and can be useful for explorative analysis. Lastly, how the algorithm is implemented. First the parameters are initialized to some random values(theta). Then, the probability is computed for each of the value z, given theta. Next, the computed values of z are computed again to obtain a better estimate for the parameter's theta. The last two steps are repeated until convergence.

b. ICP description what was the task you were performing.

- First imported the required libraries and creating dataset using make_blobs.
- Standardizing the data by passing in my variable called 'data'.
- Data was then scaled.
- Created k-means object with initialization as 'k-means++'
- Then, fitting the k means algorithm on scaled data.
- Used kmeans.inertia_ on the fitted data.
- Used kmean.n_iter_ to find the number of iterations needed to converge.
- Finally, fitting the multiple k – means algorithm and sotring the values in an empty list.
- Used elbow curve method to determine the n_cluster number. For this case I decided to use KneeLocator to find the elbow
- Using kmeans for cluster ranging from 5 – 10, and plotted the results.

c. Challenges that you faced

One of the challenges I faced during this ICP was how to construct a scatter plot and generate my own data. But I was able to figure that out. The most difficult part was making sense of my scatter plots and giving a logical explanation why some clusters increased or decreased.

d. Screen shots that shows the successful execution of each required step of your code

Importing and downloading the required libraries

```
[154] from sklearn.cluster import DBSCAN
      import sklearn.metrics as metrics
```

```
[128] import pandas as pd
      import numpy as np
      import matplotlib.pyplot as plt
      %matplotlib inline
      from sklearn.cluster import KMeans
```

```
[ ] #!pip install mglearn
```

```
[ ] #import mglearn
    #mglearn.plots.plot_kmeans_algorithm()
```

```
[155] from sklearn.datasets import make_blobs
```

Generating my own dataset to be used for clustering

```
[130] centers = [[1, 1], [-1, -1], [1, -1]]
      num_classes = len(centers)
      data, labels_true = make_blobs(n_samples=1250, centers=centers, n_features=num_classes,cluster_std=1, random_state=5)
      #data,labels_true = make_blobs(n_samples=1500, centers=5, n_features=2, cluster_std=1.3, random_state=75)
```

```
[156] data[:10] #looking at the first 10 elements
```

```
array([[ 1.37339557,  1.30040454],
       [ 0.15862724, -1.918858  ],
       [ 0.88509514, -0.21319462],
       [ 0.16951588, -1.3832473 ],
       [-1.71954053, -1.32462002],
       [-0.75611468,  0.17360364],
       [ 2.13213132, -1.47912148],
       [-0.84965117, -0.65054655],
       [ 0.80724405, -2.12318622],
       [-2.00592736, -1.73879533]])
```

```
# standardizing the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data)

# statistics of scaled data
data_s=pd.DataFrame(data_scaled).describe()
data_s
```

	0	1
count	1.250000e+03	1.250000e+03
mean	-2.753353e-18	1.062261e-16
std	1.000400e+00	1.000400e+00
min	-3.112247e+00	-3.041999e+00
25%	-6.626224e-01	-7.410919e-01
50%	5.686005e-02	-9.143744e-02
75%	7.131647e-01	7.060237e-01
max	2.830986e+00	3.132684e+00

```
# defining the kmeans function with initialization as k-means++
kmeans = KMeans(n_clusters=num_classes, init='k-means++')

# fitting the k means algorithm on scaled data
kmeans.fit(data_scaled)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=3, n_init=10, n_jobs=None, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

```
[159] # inertia on the fitted data
      kmeans.inertia_ #lowest SSE value
```

```
961.753015538184
```

```
[160] kmeans.cluster_centers_ #finding the centroid locations
```

```
array([[ 0.56283502, -0.68757025],
       [ 0.5317137 ,  1.10252672],
       [-1.10087992, -0.43255342]])
```

```
[161] kmeans.n_iter_ # number of iterations needed to converge
```

```
8
```

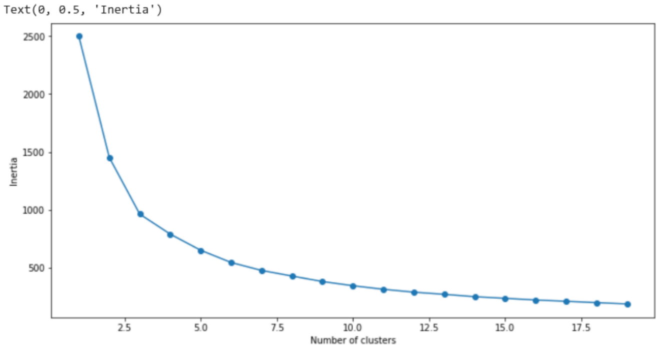
```
kmeans.labels_ #this stores the cluster assignments as 1D NumPy array in kmeans.lables_
```

```
array([1, 0, 0, ..., 2, 2, 1], dtype=int32)
```

```
[163] # fitting multiple k-means algorithms and storing the values in an empty list
      SSE = []
      for cluster in range(1,20):
          kmeans = KMeans(n_jobs = -1, n_clusters = cluster, init='k-means++')
          kmeans.fit(data_scaled)
          SSE.append(kmeans.inertia_)

      # converting the results into a dataframe and plotting them
      frame = pd.DataFrame({'Cluster':range(1,20), 'SSE':SSE})
      plt.figure(figsize=(12,6))
      plt.plot(frame['Cluster'], frame['SSE'], marker='o')
      plt.xlabel('Number of clusters')
      plt.ylabel('Inertia')
```

```
Text(0, 0.5, 'Inertia')
```



This is used to determine the elbow point in the SSE curve. I used python package kneed to determine the elbow point

```
[98] ! pip install kneed #need to install the package first
```

```
Requirement already satisfied: kneed in /usr/local/lib/python3.6/dist-packages (0.7.0)
Requirement already satisfied: numpy>=1.14.2 in /usr/local/lib/python3.6/dist-packages (from kneed) (1.18.5)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.6/dist-packages (from kneed) (3.2.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.6/dist-packages (from kneed) (1.4.1)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->kneed) (2.8.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->kneed) (2.4.7)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.6/dist-packages (from matplotlib->kneed) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.6/dist-packages (from matplotlib->kneed) (0.10.0)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packages (from python-dateutil>=2.1->matplotlib->kneed) (1.15.0)
```

```
[164] from kneed import DataGenerator, KneeLocator #import the libaray
```

```
[165] k_1 = KneeLocator(range(1, 20), SSE, curve="convex", direction="decreasing")
      k_1.elbow
```

```
5
```

n_cluster = 5

n_cluster = 5

```
kmeans = KMeans(n_jobs = -1, n_clusters = 5, init='k-means++')
kmeans.fit(data_scaled)
pred = kmeans.predict(data_scaled)
print(kmeans)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=5, n_init=10, n_jobs=-1, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
```

[167]
```
frame = pd.DataFrame(data_scaled)
frame['cluster'] = pred
frame['cluster'].value_counts()
```

```
2    302
0    279
1    243
3    235
4    191
Name: cluster, dtype: int64
```

```
frame
```

	0	1	cluster
0	0.783778	1.182565	0
1	-0.110193	-1.159079	1
2	0.424428	0.081595	2
3	-0.102179	-0.769483	1
4	-1.492371	-0.726839	4
...	...	...	...
1245	0.528027	0.149718	2
1246	-0.394260	-0.973137	1
1247	-0.303324	-0.340086	1
1248	-0.746488	-0.774706	1
1249	-0.203586	1.474952	0

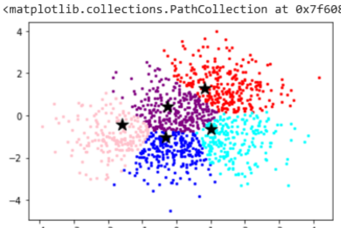
1250 rows × 3 columns

[169]
```
centers = np.array(kmeans.cluster_centers_)
```

```
plt.scatter(data[pred==0,0], data[pred==0,1], s=5, c='red')
plt.scatter(data[pred==1,0], data[pred==1,1], s=5, c='blue')
plt.scatter(data[pred==2,0], data[pred==2,1], s=5, c='purple')
plt.scatter(data[pred==3,0], data[pred==3,1], s=5, c='cyan')
plt.scatter(data[pred==4,0], data[pred==4,1], s=5, c='pink')

plt.scatter(centers[:,0], centers[:,1],s=200, c='black', marker='*')
```

```
<matplotlib.collections.PathCollection at 0x7f60894968d0>
```



[171]
```
pd.crosstab(pred,kmeans.labels_,  dropna=False)
```

n_clusters = 6

[172]
```python
# k means using 6 clusters and k-means++ initialization
kmeans = KMeans(n_jobs = -1, n_clusters = 6, init='k-means++')
kmeans.fit(data_scaled)
pred = kmeans.predict(data_scaled)

print(kmeans)
print(pred)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=6, n_init=10, n_jobs=-1, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
[3 5 4 ... 4 5 1]
```

[173]
```python
frame = pd.DataFrame(data_scaled)
frame['cluster'] = pred
frame['cluster'].value_counts()
```

```
4    292
5    213
0    213
3    205
2    172
1    155
Name: cluster, dtype: int64
```

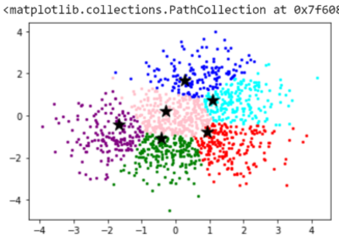
[174]
```python
centers = np.array(kmeans.cluster_centers_)
```

[175]
```python
plt.scatter(data[pred==0,0], data[pred==0,1], s=5, c='red')
plt.scatter(data[pred==1,0], data[pred==1,1], s=5, c='blue')
plt.scatter(data[pred==2,0], data[pred==2,1], s=5, c='purple')
plt.scatter(data[pred==3,0], data[pred==3,1], s=5, c='cyan')
plt.scatter(data[pred==4,0], data[pred==4,1], s=5, c='pink')
plt.scatter(data[pred==5,0], data[pred==5,1], s=5, c='green')



plt.scatter(centers[:,0], centers[:,1],s=200, c='black', marker='*')
```

```
<matplotlib.collections.PathCollection at 0x7f608940ea20>
```



n_clusters = 7

```python
# k means using 7 clusters and k-means++ initialization
kmeans = KMeans(n_jobs = -1, n_clusters = 7, init='k-means++')
kmeans.fit(data_scaled)
pred = kmeans.predict(data_scaled)

print(kmeans)
print(pred)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=7, n_init=10, n_jobs=-1, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
[0 2 6 ... 6 2 4]
```

[177]
```python
frame = pd.DataFrame(data_scaled)
frame['cluster'] = pred
frame['cluster'].value_counts()
```

```
6    222
2    213
5    184
3    172
0    172
4    157
1    130
Name: cluster, dtype: int64
```

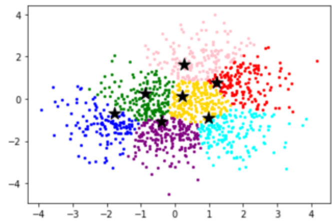
[178]
```python
centers = np.array(kmeans.cluster_centers_)
```

```
plt.scatter(data[pred==0,0], data[pred==0,1], s=5, c='red')
plt.scatter(data[pred==1,0], data[pred==1,1], s=5, c='blue')
plt.scatter(data[pred==2,0], data[pred==2,1], s=5, c='purple')
plt.scatter(data[pred==3,0], data[pred==3,1], s=5, c='cyan')
plt.scatter(data[pred==4,0], data[pred==4,1], s=5, c='pink')
plt.scatter(data[pred==5,0], data[pred==5,1], s=5, c='green')
plt.scatter(data[pred==6,0], data[pred==6,1], s=5, c='gold')



plt.scatter(centers[:,0], centers[:,1],s=200, c='black', marker='*')
```

```
<matplotlib.collections.PathCollection at 0x7f608938b978>
```



n_cluster = 8

```
# k means using 8 clusters and k-means++ initialization
kmeans = KMeans(n_jobs = -1, n_clusters = 8, init='k-means++')
kmeans.fit(data_scaled)
pred = kmeans.predict(data_scaled)

print(kmeans)
print(pred)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=8, n_init=10, n_jobs=-1, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
[3 6 0 ... 7 7 4]
```

```
[181] frame = pd.DataFrame(data_scaled)
      frame['cluster'] = pred
      frame['cluster'].value_counts()
```

```
0    207
7    200
2    192
6    146
3    138
4    133
1    122
5    112
Name: cluster, dtype: int64
```

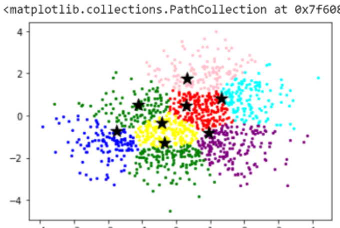
```
[182] centers = np.array(kmeans.cluster_centers_)
```

```
plt.scatter(data[pred==0,0], data[pred==0,1], s=5, c='red')
plt.scatter(data[pred==1,0], data[pred==1,1], s=5, c='blue')
plt.scatter(data[pred==2,0], data[pred==2,1], s=5, c='purple')
plt.scatter(data[pred==3,0], data[pred==3,1], s=5, c='cyan')
plt.scatter(data[pred==4,0], data[pred==4,1], s=5, c='pink')
plt.scatter(data[pred==5,0], data[pred==5,1], s=5, c='green')
plt.scatter(data[pred==6,0], data[pred==6,1], s=5, c='green')
plt.scatter(data[pred==7,0], data[pred==7,1], s=5, c='yellow')



plt.scatter(centers[:,0], centers[:,1],s=200, c='black', marker='*')
```

```
<matplotlib.collections.PathCollection at 0x7f6089306be0>
```



n_cluster = 9

```
# k means using 9clusters and k-means++ initialization
kmeans = KMeans(n_jobs = -1, n_clusters = 9, init='k-means++')
kmeans.fit(data_scaled)
pred = kmeans.predict(data_scaled)

print(kmeans)
print(pred)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=9, n_init=10, n_jobs=-1, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
[0 1 8 ... 2 2 6]
```

```
[185] frame = pd.DataFrame(data_scaled)
      frame['cluster'] = pred
      frame['cluster'].value_counts()
```

```
2    206
8    203
3    162
1    126
7    124
0    114
4    112
6    102
5    101
Name: cluster, dtype: int64
```

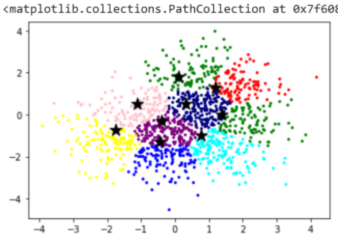
```
[186] centers = np.array(kmeans.cluster_centers_)
```

```
plt.scatter(data[pred==0,0], data[pred==0,1], s=5, c='red')
plt.scatter(data[pred==1,0], data[pred==1,1], s=5, c='blue')
plt.scatter(data[pred==2,0], data[pred==2,1], s=5, c='purple')
plt.scatter(data[pred==3,0], data[pred==3,1], s=5, c='cyan')
plt.scatter(data[pred==4,0], data[pred==4,1], s=5, c='pink')
plt.scatter(data[pred==5,0], data[pred==5,1], s=5, c='green')
plt.scatter(data[pred==6,0], data[pred==6,1], s=5, c='green')
plt.scatter(data[pred==7,0], data[pred==7,1], s=5, c='yellow')
plt.scatter(data[pred==8,0], data[pred==8,1], s=5, c='navy')




plt.scatter(centers[:,0], centers[:,1],s=200, c='black', marker='*')
```

```
<matplotlib.collections.PathCollection at 0x7f608928f048>
```



n_cluster = 10

```
# k means using 10 clusters and k-means++ initialization
kmeans = KMeans(n_jobs = -1, n_clusters = 10, init='k-means++')
kmeans.fit(data_scaled)
pred = kmeans.predict(data_scaled)

print(kmeans)
print(pred)
```

```
KMeans(algorithm='auto', copy_x=True, init='k-means++', max_iter=300,
       n_clusters=10, n_init=10, n_jobs=-1, precompute_distances='auto',
       random_state=None, tol=0.0001, verbose=0)
[9 0 2 ... 3 0 1]
```

```
[124] frame = pd.DataFrame(data_scaled)
      frame['cluster'] = pred
      frame['cluster'].value_counts()
```

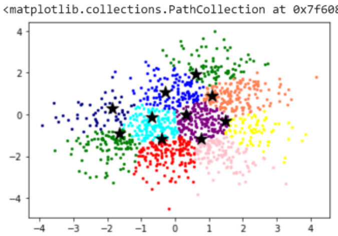
```
2    188
3    164
9    163
0    162
1    129
4    122
6    107
5     87
7     73
8     55
Name: cluster, dtype: int64
```

```
[125] centers = np.array(kmeans.cluster_centers_)
```

```
plt.scatter(data[pred==0,0], data[pred==0,1], s=5, c='red')
plt.scatter(data[pred==1,0], data[pred==1,1], s=5, c='blue')
plt.scatter(data[pred==2,0], data[pred==2,1], s=5, c='purple')
plt.scatter(data[pred==3,0], data[pred==3,1], s=5, c='cyan')
plt.scatter(data[pred==4,0], data[pred==4,1], s=5, c='pink')
plt.scatter(data[pred==5,0], data[pred==5,1], s=5, c='green')
plt.scatter(data[pred==6,0], data[pred==6,1], s=5, c='green')
plt.scatter(data[pred==7,0], data[pred==7,1], s=5, c='yellow')
plt.scatter(data[pred==8,0], data[pred==8,1], s=5, c='navy')
plt.scatter(data[pred==9,0], data[pred==9,1], s=5, c='coral')


plt.scatter(centers[:,0], centers[:,1],s=200, c='black', marker='*')
```

```
<matplotlib.collections.PathCollection at 0x7f60896e6128>
```



e. Output file link if applicable

https://github.com/UMKC-APL-BigDataAnalytics/icp7-irfancheemaa

f. Video link (YouTube or any other publicly available video platform)

https://umkc.hosted.panopto.com/Panopto/Pages/Viewer.aspx?id=4bdd4976-a970-4f23-8548-ac520164f0bc

g. Any inside about the data or the ICP in general

This was good introduction to K-Means and enjoyed working on the topic to gain better understanding. Would like to see more details on how the clusters are affected with changing the n_cluster value.