K-Means Clustering in Python

K-Means Clustering is a concept that falls under *Unsupervised* Learning. This algorithm can be used to find groups within *unlabeled* data. To demonstrate this concept, I’ll review a simple example of K-Means Clustering in Python.

**K-means Clustering in Python**

K-means clustering is a clustering algorithm that aims to partition nn observations into kk clusters.

There are 3 steps:

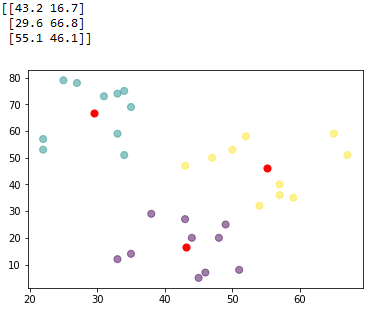
* Initialisation – K initial “means” (centroids) are generated at random
* Assignment – K clusters are created by associating each observation with the nearest centroid
* Update – The centroid of the clusters becomes the new mean

Assignment and Update are repeated iteratively until convergence

The end result is that the sum of squared errors is minimised between points and their respective centroids

Topics to be covered:

* Creating the DataFrame for two-dimensional data-set
* Finding the centroids for 3 clusters, and then for 4 clusters
* Adding a graphical user interface (GUI) to display the results



Note that the center of each cluster (in red) represents the mean of all the observations that belong to that cluster.

As you may also see, the observations that belong to a given cluster are closer to the center of that cluster, in comparison to the centers of other clusters.

Let’s view it in action using k=3:

In [1]:

## Initialisation

**import** **pandas** **as** **pd**

**import** **numpy** **as** **np**

**import** **matplotlib.pyplot** **as** **plt**

%**matplotlib** inline

df = pd.DataFrame({

'x': [12, 20, 28, 18, 29, 33, 24, 45, 45, 52, 51, 52, 55, 53, 55, 61, 64, 69, 72],

'y': [39, 36, 30, 52, 54, 46, 55, 59, 63, 70, 66, 63, 58, 23, 14, 8, 19, 7, 24]

})

np.random.seed(200)

k = 3

# centroids[i] = [x, y]

centroids = {

i+1: [np.random.randint(0, 80), np.random.randint(0, 80)]

**for** i **in** range(k)

}

fig = plt.figure(figsize=(5, 5))

plt.scatter(df['x'], df['y'], color='k')

colmap = {1: 'r', 2: 'g', 3: 'b'}

**for** i **in** centroids.keys():

plt.scatter(\*centroids[i], color=colmap[i])

plt.xlim(0, 80)

plt.ylim(0, 80)

plt.show()

In [2]:

## Assignment Stage

**def** assignment(df, centroids):

**for** i **in** centroids.keys():

# sqrt((x1 - x2)^2 - (y1 - y2)^2)

df['distance\_from\_{}'.format(i)] = (

np.sqrt(

(df['x'] - centroids[i][0]) \*\* 2

+ (df['y'] - centroids[i][1]) \*\* 2

)

)

centroid\_distance\_cols = ['distance\_from\_{}'.format(i) **for** i **in** centroids.keys()]

df['closest'] = df.loc[:, centroid\_distance\_cols].idxmin(axis=1)

df['closest'] = df['closest'].map(**lambda** x: int(x.lstrip('distance\_from\_')))

df['color'] = df['closest'].map(**lambda** x: colmap[x])

**return** df

df = assignment(df, centroids)

**print**(df.head())

fig = plt.figure(figsize=(5, 5))

plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')

**for** i **in** centroids.keys():

plt.scatter(\*centroids[i], color=colmap[i])

plt.xlim(0, 80)

plt.ylim(0, 80)

plt.show()

x y distance\_from\_1 distance\_from\_2 distance\_from\_3 closest color

0 12 39 26.925824 56.080300 56.727418 1 r

1 20 36 20.880613 48.373546 53.150729 1 r

2 28 30 14.142136 41.761226 53.338541 1 r

3 18 52 36.878178 50.990195 44.102154 1 r

4 29 54 38.118237 40.804412 34.058773 3 b

In [3]:

## Update Stage

**import** **copy**

old\_centroids = copy.deepcopy(centroids)

**def** update(k):

**for** i **in** centroids.keys():

centroids[i][0] = np.mean(df[df['closest'] == i]['x'])

centroids[i][1] = np.mean(df[df['closest'] == i]['y'])

**return** k

centroids = update(centroids)

fig = plt.figure(figsize=(5, 5))

ax = plt.axes()

plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')

**for** i **in** centroids.keys():

plt.scatter(\*centroids[i], color=colmap[i])

plt.xlim(0, 80)

plt.ylim(0, 80)

**for** i **in** old\_centroids.keys():

old\_x = old\_centroids[i][0]

old\_y = old\_centroids[i][1]

dx = (centroids[i][0] - old\_centroids[i][0]) \* 0.75

dy = (centroids[i][1] - old\_centroids[i][1]) \* 0.75

ax.arrow(old\_x, old\_y, dx, dy, head\_width=2, head\_length=3, fc=colmap[i], ec=colmap[i])

plt.show()

In [4]:

## Repeat Assigment Stage

df = assignment(df, centroids)

# Plot results

fig = plt.figure(figsize=(5, 5))

plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')

**for** i **in** centroids.keys():

plt.scatter(\*centroids[i], color=colmap[i])

plt.xlim(0, 80)

plt.ylim(0, 80)

plt.show()

Note that one of the reds is now green and one of the blues is now red.

We are getting closer.

We now repeat until there are no changes to any of the clusters.

In [5]:

# Continue until all assigned categories don't change any more

**while** True:

closest\_centroids = df['closest'].copy(deep=True)

centroids = update(centroids)

df = assignment(df, centroids)

**if** closest\_centroids.equals(df['closest']):

**break**

fig = plt.figure(figsize=(5, 5))

plt.scatter(df['x'], df['y'], color=df['color'], alpha=0.5, edgecolor='k')

**for** i **in** centroids.keys():

plt.scatter(\*centroids[i], color=colmap[i])

plt.xlim(0, 80)

plt.ylim(0, 80)

plt.show()

So we have 3 clear clusters with 3 means at the centre of these clusters.

We will now repeat the above using scikit-learn, we first fit to our data

In [6]:

df = pd.DataFrame({

'x': [12, 20, 28, 18, 29, 33, 24, 45, 45, 52, 51, 52, 55, 53, 55, 61, 64, 69, 72],

'y': [39, 36, 30, 52, 54, 46, 55, 59, 63, 70, 66, 63, 58, 23, 14, 8, 19, 7, 24]

})

**from** **sklearn.cluster** **import** KMeans

kmeans = KMeans(n\_clusters=3)

kmeans.fit(df)

Out[6]:

KMeans(algorithm='auto', copy\_x=True, init='k-means++', max\_iter=300,

n\_clusters=3, n\_init=10, n\_jobs=1, precompute\_distances='auto',

random\_state=None, tol=0.0001, verbose=0)

Then we learn the labels

In [7]:

labels = kmeans.predict(df)

centroids = kmeans.cluster\_centers\_

In [8]:

fig = plt.figure(figsize=(5, 5))

colors = map(**lambda** x: colmap[x+1], labels)

plt.scatter(df['x'], df['y'], color=colors, alpha=0.5, edgecolor='k')

**for** idx, centroid **in** enumerate(centroids):

plt.scatter(\*centroid, color=colmap[idx+1])

plt.xlim(0, 80)

plt.ylim(0, 80)

plt.show()

We get the exact same result, albeit with the colours in a different order.

Some things to take note of though:

* k-means clustering is very sensitive to scale due to its reliance on Euclidean distance so be sure to normalize data if there are likely to be scaling problems.
* If there are some symmetries in your data, some of the labels may be mis-labelled
* It is recommended to do the same k-means with different initial centroids and take the most common label.