ETE LAB EXAMINATION

Machine Learning

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Year - 3rd / 5th sem

TOPIC : **Write a program to demonstrate the working of the K-means Clustering. Use an appropriate data set for the implementation.**

What is k- means clustering ?

***k*-means clustering** is a method of vector quantization, originally from signal processing, that aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid), serving as a prototype of the cluster.

K Means Algorithm

K means algorithm is an iterative algorithm that tries to partition the dataset into *K*pre-defined distinct non-overlapping subgroups (clusters)

where each data point belongs to **only one group**. It tries to make the intra-cluster data points as similar as possible while also keeping the clusters as different (far) as possible.

The way k means algorithm works is as follows:

1. Specify number of clusters *K*.
2. Initialize centroids by first shuffling the dataset and then randomly selecting *K* data points for the centroids without replacement.(here k =3)
3. Keep iterating until there is no change to the centroids. i.e assignment of data points to clusters isn't changing.
4. Compute the sum of the squared distance between data points and all centroids.
5. Assign each data point to the closest cluster (centroid).
6. Compute the centroids for the clusters by taking the average of all data points that belong to each cluster.

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.

Let’s view it in action using k=3:

PROGRAM

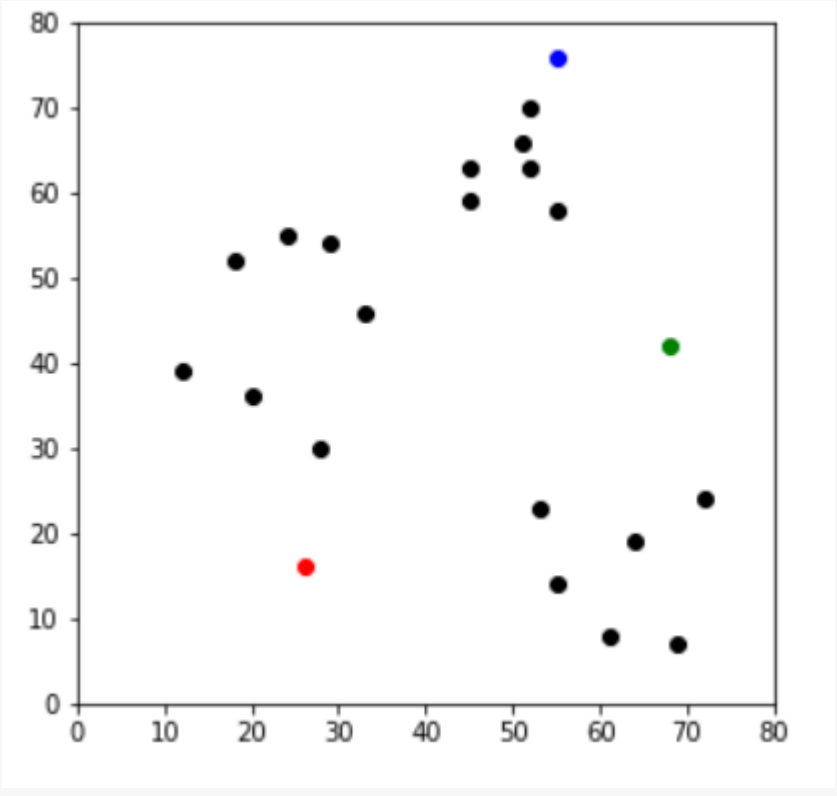
Step 1 :

```
## 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()
```



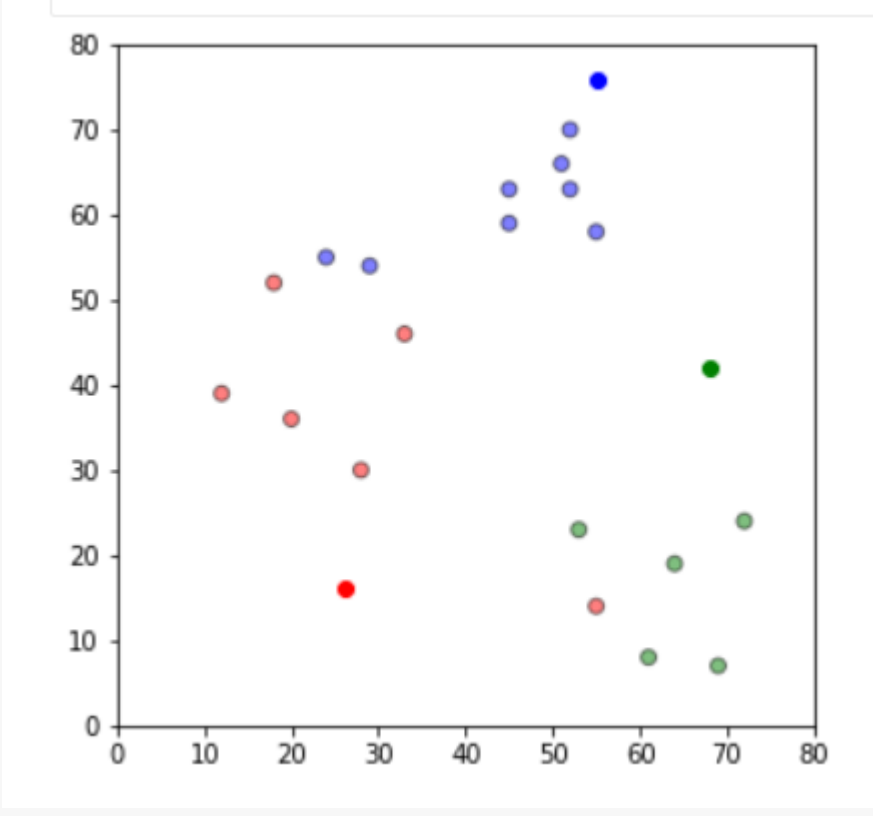
Step 2:

```
## 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

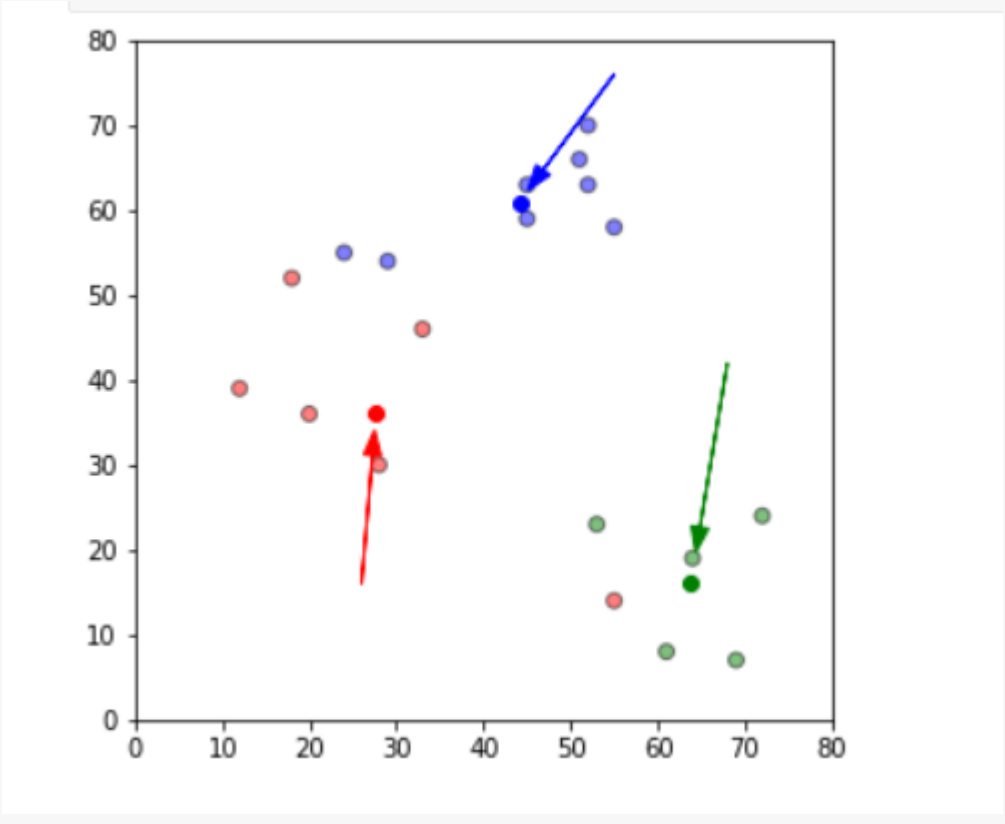


Step 3:

```
## 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
```

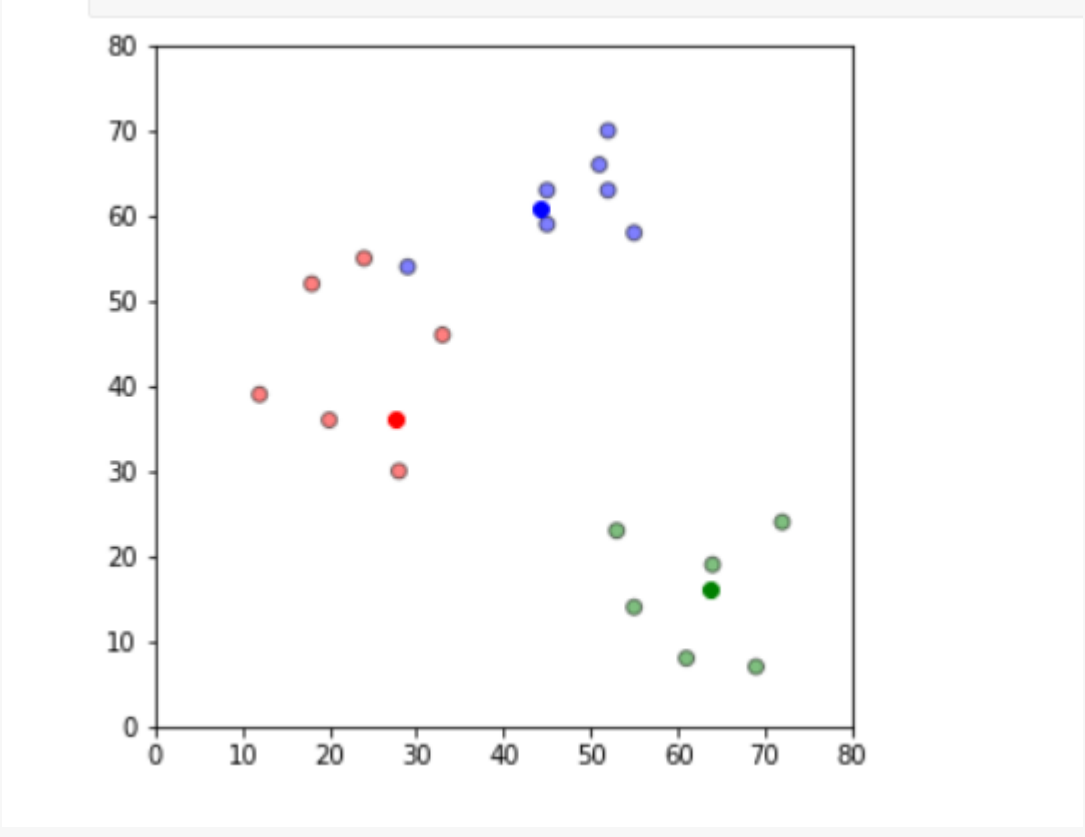
```
ax.arrow(old_x, old_y, dx, dy, head_width=2, head_length=3,
fc=colmap[i], ec=colmap[i])

plt.show()
```



Step 4:

```
## Repeat Assignment 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()
```



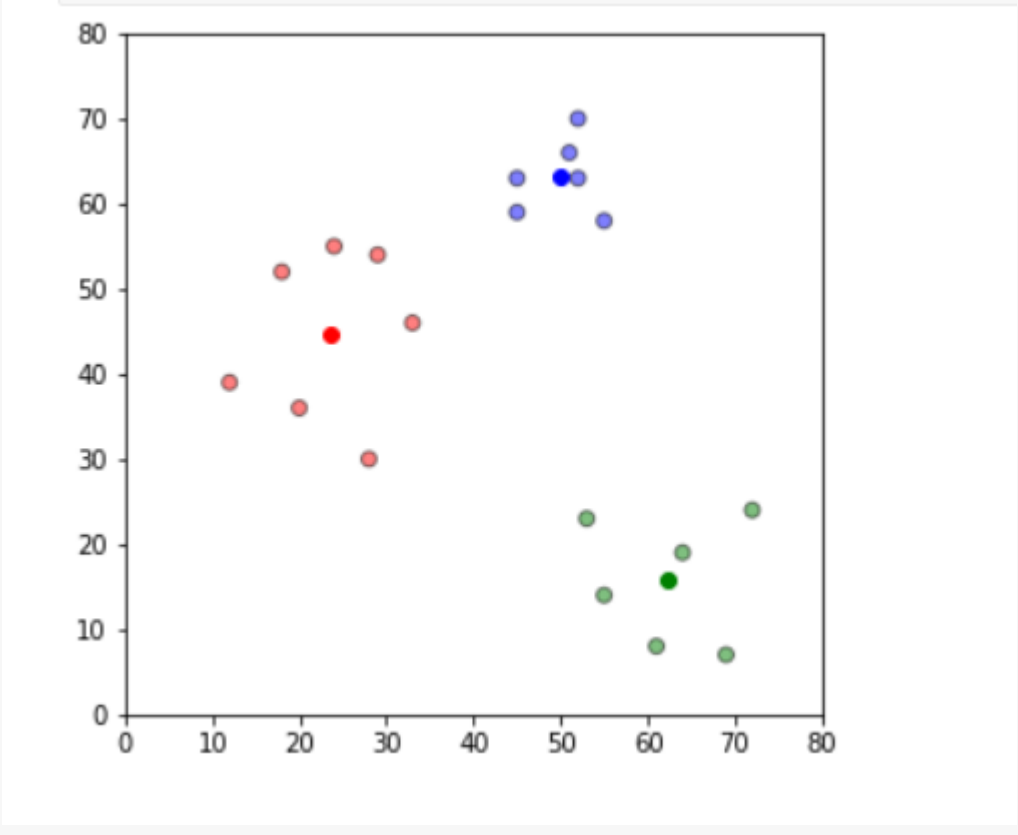
We now repeat until there are no changes to any of the clusters.

Step 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()
```

Final Output



CONCLUSION

So,we have successfully created three clusters from our random data set. All data clusters are shown in different colors. We can use the same code for making clusters on other data also and can even change the number of clusters in the algorithm. Also It is now clear that more centroids can improve the clustering. So after choosing more clusters we get better clusters with improved information again.