Clustering Part 2

In [ ]:
```
import numpy as np
import pandas as pd
import math
import matplotlib.pyplot as plt
import matplotlib
```

DBSCAN Algorithm

DBSCAN(Density-Based Spatial Clustering of Applications with Noise) is a commonly used unsupervised clustering algorithm. DBSCAN does not need to specify the number of clusters. It can automatically detect the number of clusters based on your input data and parameters. More importantly, DBSCAN can find arbitrary shape clusters that k-means are not able to find.

Algorithm:

a. The algorithm proceeds by arbitrarily picking up a point in the dataset (until all points have been visited).

b. If there are at least 'minPoint' points within a radius of 'ε' to the point then we consider all these points to be part of the same cluster.

c. The clusters are then expanded by recursively repeating the neighborhood calculation for each neighboring point

A. **Generate "N" spherical training data points.**

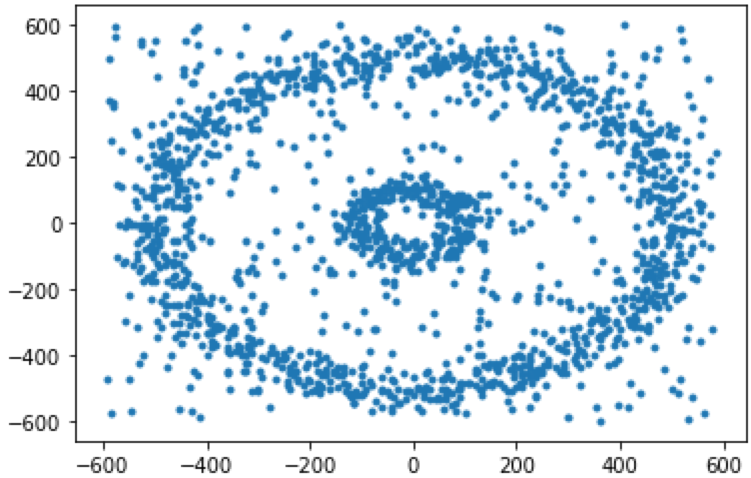
General form for points on a circle:

$$(x, y) = (rcos\theta, rsin\theta)$$

For n such points, ith point would have $\theta = \frac{2\pi i}{n}$, i = 0, 1, 2, 3, ... n-1

In [ ]:
```
## write your code here
def circularData(radius, noise, n):
    dataset = []
    for i in range(n):
        x = math.cos(2*math.pi*i/n)*radius + np.random.normal(0, noise)
        y = math.sin(2*math.pi*i/n)*radius + np.random.normal(0, noise)
        dataset.append((x, y))
    return dataset

def uniformNoise(bound, n):
    dataset = []
    for i in range(n):
        x = np.random.uniform(-bound, bound)
        y = np.random.uniform(-bound, bound)
        dataset.append((x, y))
```

```
    return dataset

outerC = circularData(500, 35, 1000)
innerC = circularData(100, 25, 250)
noisyPts = uniformNoise(600, 400)

plt.figure()
data = pd.DataFrame(outerC)
data = data.append(innerC)
data = data.append(noisyPts)
plt.plot(data[0], data[1], '.')
plt.show()
```



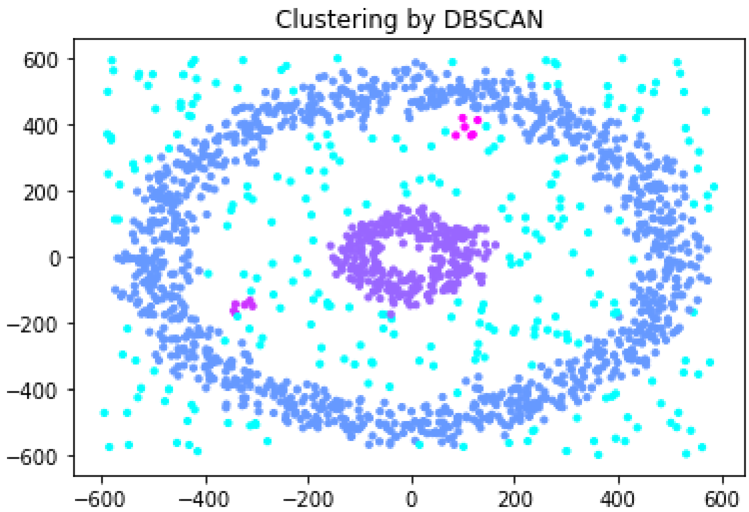
B. **Perform DBSCAN Algorithm on the above generated data to obtain clusters**

In [ ]:

```
## Write your code here

eps = 35
minpts = 6
x = np.array(data)

def getNeighbours(x, i, eps):
    neighbours = []
    for j in range(0, len(x)):
        # If d<eps , add it to the neighbors list.
        if np.linalg.norm(x[i] - x[j]) < eps:
           neighbours.append(j)
    return neighbours

def populateCluster(x, seed, labels, cluster_id, neighbours, eps, minpts):
    labels[seed] = cluster_id
    i = 0
    while i < len(neighbours):                # sort of Breadth-First-Search
        j = neighbours[i]
        if labels[j] == -1:                   # was earlier labelled as noise
            labels[j] = cluster_id
        elif labels[j] == 0:                  # undiscovered point
            labels[j] = cluster_id
            jNeighbours = getNeighbours(x, j, eps)
            if len(jNeighbours) >= minpts:  # else it's a border point!
                neighbours = neighbours + jNeighbours
        i = i + 1

def MyDBSCAN(eps, minpts, x):
    labels = np.zeros((x.shape[0]))
    # print(labels)
    cluster_id = 0
```

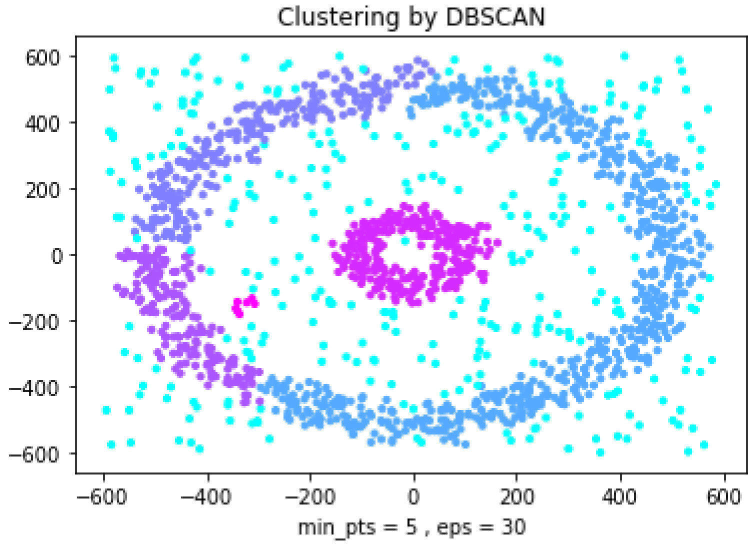
```
    for i in range(len(x)):
        if labels[i] != 0:
            continue
        neighbours = getNeighbours(x, i, eps)
        if len(neighbours) < minpts:
            labels[i] = -1         # noise:-1, not considered:0
        else:
            cluster_id = cluster_id + 1
            populateCluster(x, i, labels, cluster_id, neighbours, eps, minpts)
    return labels

# function call
pred_labels = MyDBSCAN(eps, minpts, x)

print(pred_labels)
plt.figure()
plt.scatter(x[:,0], x[:,1], c=pred_labels, s=10, cmap = 'cool')
plt.title("Clustering by DBSCAN")
plt.show()
```

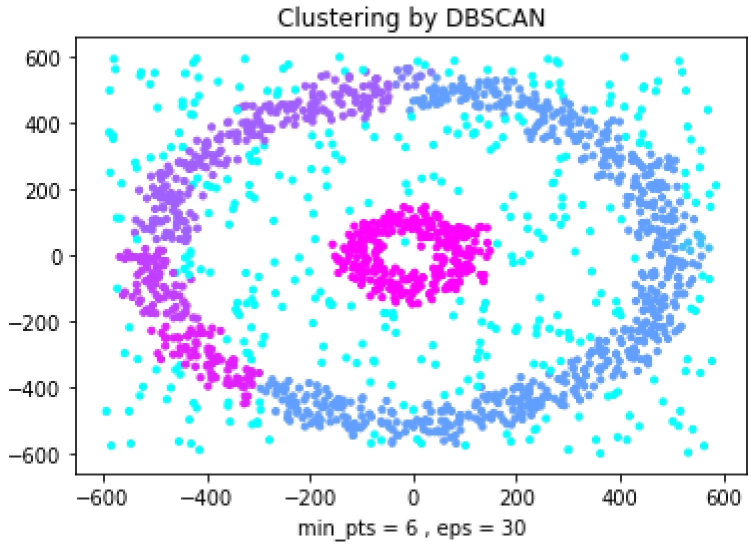
```
[-1.  1.  1. ...  1. -1.  1.]
```

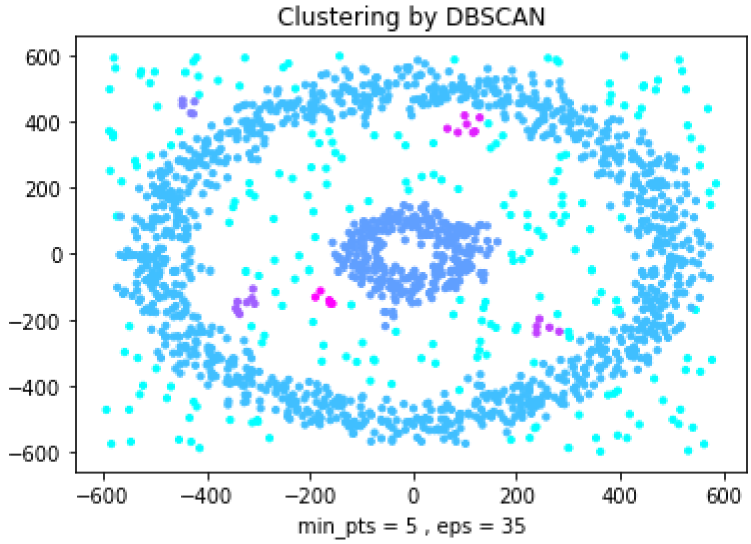


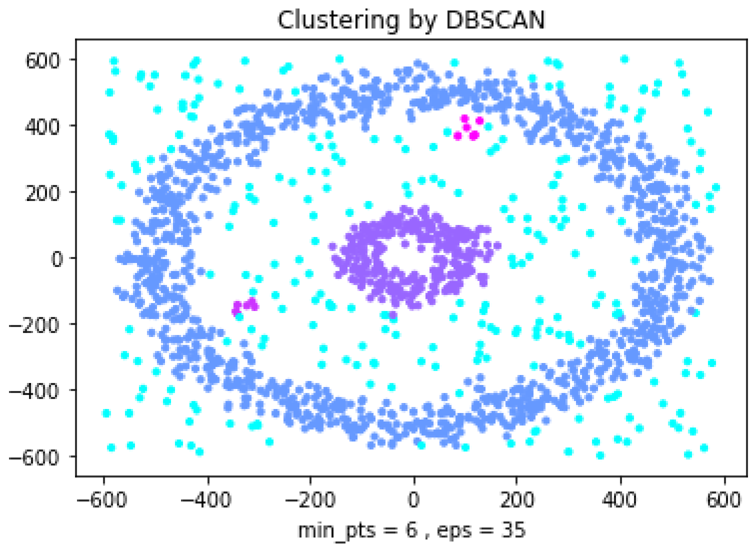
C. **Experiment by varying the number of min points and epsilon radius and plot your observations**

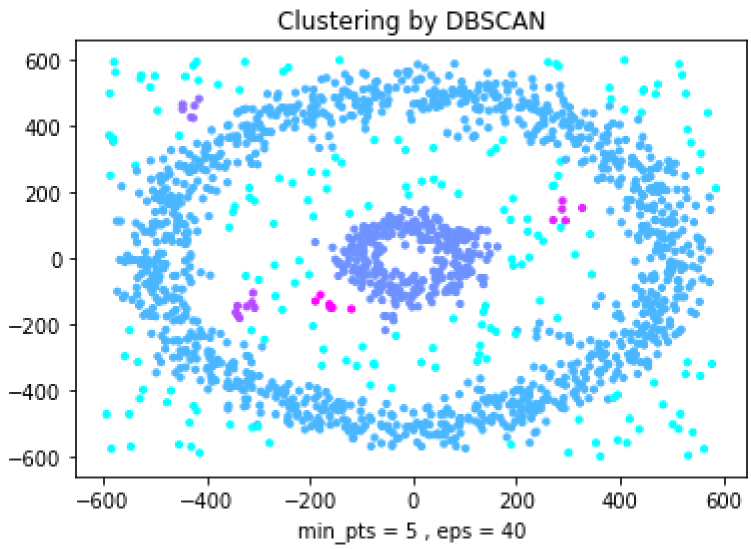
In [ ]:
```
## write your code here
min_pts = [5, 6]
eps_rad = [30, 35, 40]
for i in eps_rad:
    for j in min_pts:
        plabels = MyDBSCAN(i, j, x)
        plt.figure()
        plt.scatter(x[:,0], x[:,1], c=plabels, s=10, cmap = 'cool');
        plt.title("Clustering by DBSCAN")
        plt.xlabel("min_pts = "+str(j)+" , eps = "+str(i))
        plt.show()
```

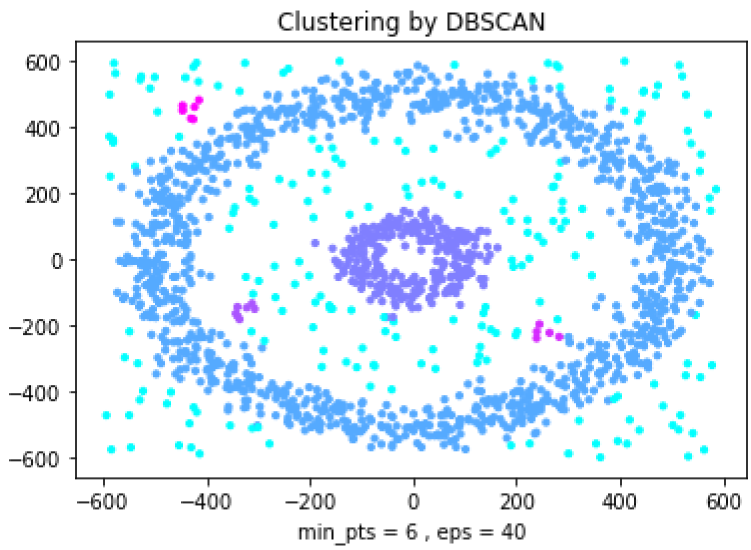

Clustering by DBSCAN
min_pts = 5 , eps = 30


Clustering by DBSCAN
min_pts = 6 , eps = 30


Clustering by DBSCAN
min_pts = 5 , eps = 35



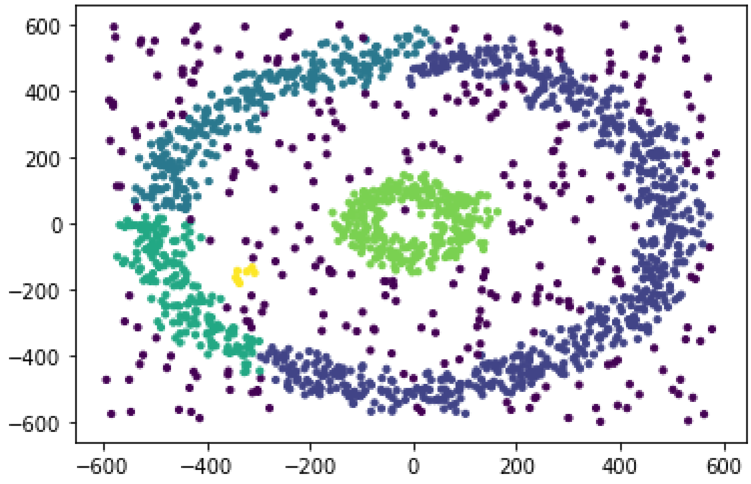




D. **Compare your model with the built in DBSCAN in Sci-kit Learn. Also compare you results with GMM and the K-means Algorithm**

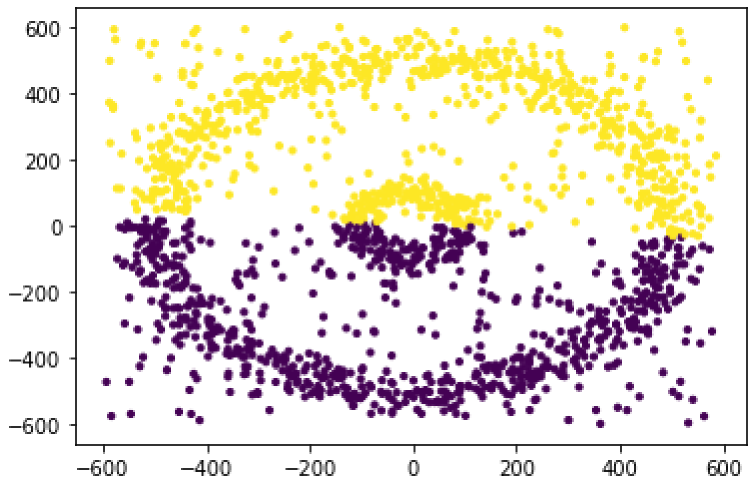
In [ ]:

```
from sklearn.cluster import DBSCAN
## write your code here
dBSCAN = DBSCAN(eps=30, min_samples=5).fit(x)
labels = dBSCAN.labels_
plt.figure()
plt.scatter(x[:, 0], x[:, 1], s=10, c=labels)
plt.show()
```



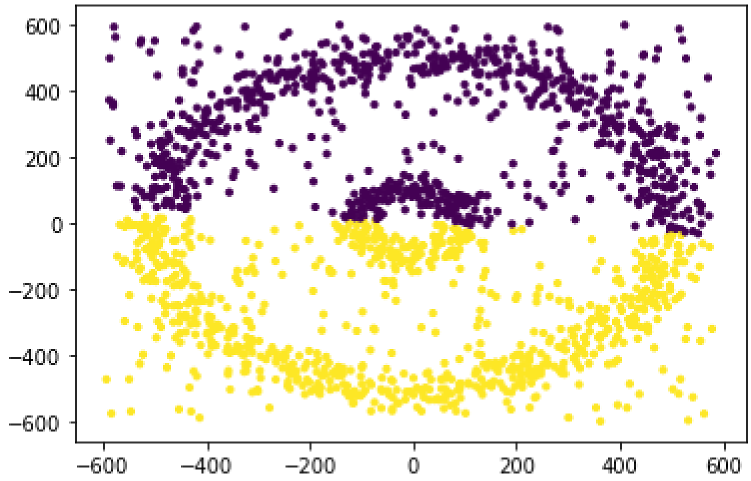
In [ ]:
```
##########################################################################
from sklearn.mixture import GaussianMixture
## write your code here
gaussMix = GaussianMixture(n_components=2, random_state=0).fit(x)
labels = gaussMix.predict(x)
plt.scatter(x[:, 0], x[:, 1], s=10, c=labels)
```

Out[ ]:
```
<matplotlib.collections.PathCollection at 0x198003e71f0>
```



In [ ]:
```
##########################################################################
from sklearn.cluster import KMeans
## write your code here
kMeans = KMeans(n_clusters=2, random_state=0).fit(x)
y = kMeans.fit_predict(x)
labels = kMeans.predict(x)
plt.scatter(x[:,0], x[:,1], s=10, c=labels)
```

Out[ ]:
```
<matplotlib.collections.PathCollection at 0x1980049e3a0>
```



Fuzzy C-Means Based clustering

1. Randomly initialize the centroids and clusters K, and compute the probability that each data point xi is a member of a given cluster k, P(point xi has label k|xi, k).
2. Iteration: Recalculate the centroids of the clusters as the weighted centroid given the probabilities of membership of all data points xi:

$$\mu_k(n+1) = \frac{\sum_{x_i \in k} x_i * P(\mu_k \mid x_i)^b}{\sum_{x_i \in k} P(\mu_k \mid x_i)^b}$$

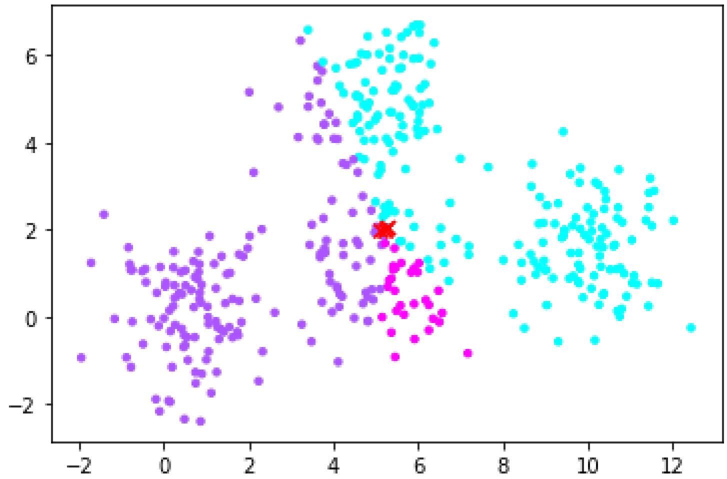
1. Implement it on the data for which Kmeans was implemented.

In [ ]:
```
import random
import numpy as np
import math
import matplotlib.pyplot as plt


d1 = np.random.multivariate_normal((0.5, 0.0), np.identity(2), 100)
d2 = np.random.multivariate_normal((5.0, 5.0), np.identity(2), 100)
d3 = np.random.multivariate_normal((5.0, 1.0), np.identity(2), 100)
d4 = np.random.multivariate_normal((10.0, 1.5), np.identity(2), 100)
zeroarr = np.zeros(100)
onearr = np.ones(100)
twoarr = 2*onearr
threearr = 3*onearr
# concatenate all this to form an unlabelled dataset
real_labels = np.concatenate((zeroarr, onearr, twoarr, threearr))
data = np.concatenate((d1,d2,d3,d4))

class FuzzyC:
    # func for euclidean distance
    def dist(self, a, b):
        d = (a[1] - b[1])**2 + (a[0] - b[0])**2
        return d

    # initialization parameters
    def __init__(self, c, data):
        self.data = data
        self.b = 2              # fuzzification parameter
        self.n = len(data)
```

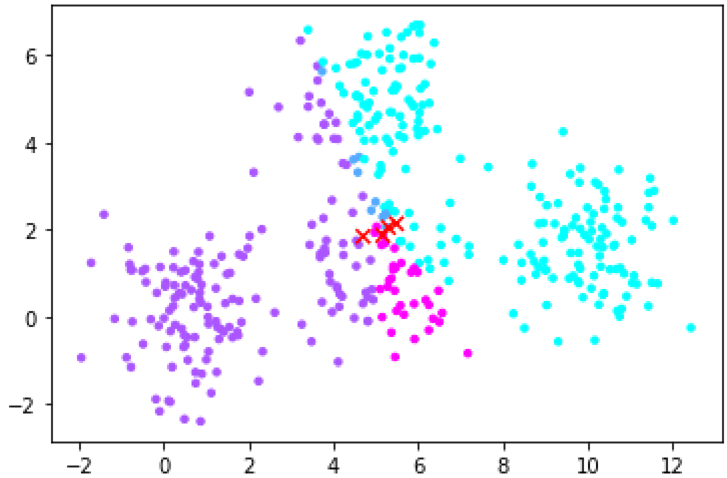
```
        self.c = c
        self.p=len(data[0])
        self.max_iter=100

    # initialize the membership matrix
    def initialize_membership_matrix(self, n, c):
        mem_mat = list()
        # generate c random numbers in [0,1), sum them and divide (w.r.t. each poi
        for i in range(n):
            random_list = [random.random() for x in range(c)]
            summation = sum(random_list)
            for i in range(len(random_list)):
                random_list[i] = random_list[i]/summation
            mem_mat.append(random_list)
        return mem_mat

    # update centroids
    # (can also be used for cluster initialization, since we let mem matrix be rand
    def update_centroid(self, mem_mat):
        data = self.data
        centroids = {}
        for j in range(self.c):                                   # consider jth clu
            temp=[]
            for k in range(self.p):                               # w.r.t each featu
                add = 0
                for i in range(self.n):                           # get sum(p^b)
                    add = add + mem_mat[i][j]**self.b
                x = 0
                for i in range(self.n):                           # sum(x * p^b)
                    x = x + (mem_mat[i][j]**self.b)*(data[i][k])
                val = x/add
                temp.append(val)
            centroids[j] = temp
        return centroids

    # update membership matrix
    def update_membership_matrix(self, mem_mat,centroids):
        ratio = float(2/(self.b-1))
        data = self.data
        for i in range(self.n):
            distances = list()
            for j in range(self.c):
                distances.append(self.dist(data[i],centroids[j]))
            for j in range(self.c):
                den = sum([math.pow(float(distances[j]/distances[q]), ratio) for q
                mem_mat[i][j] = float(1/den)
        return mem_mat

    # labelling based on final clustering
    def find_cluster(self,mem_mat):
        clusters=list()
        for i in range(self.n):
            max_val, idx = max((val, idx) for (idx, val) in enumerate(mem_mat[i]))
            clusters.append(idx)
        return clusters

    # check if membership matrix isn't changing much
    def check(self,prev_mat,mem_mat):
        diff=0
        for i in range(self.n):
            for j in range(self.c):
                diff+=prev_mat[i][j]-mem_mat[i][j]
        if(diff<0.01):
            return True
```

```
        return False

    # main thing here!!!!!
    def fuzzy_c_mean(self):
        print(self.n)
        print(self.p)
        print(self.b)
        mem_mat=self.initialize_membership_matrix(self.n,self.c)
        for i in range(self.max_iter):
            centroids=self.update_centroid(mem_mat)
            prev_mat=mem_mat
            mem_mat=self.update_membership_matrix(mem_mat,centroids)
            cluster=self.find_cluster(mem_mat)
            if i<=10:
                self.showGraphs(cluster, centroids, i)
            if(self.check(prev_mat,mem_mat))<0.01:
                print(i)
                break
        return cluster,centroids

    def showGraphs(self, clusters, centroids, i):
        print("Iteration ",i)
        plt.figure()
        plt.scatter(self.data[:,0], self.data[:,1], c=clusters, s=12, cmap="cool")
        x = []
        y = []
        for i in range(len(centroids)):
            cent = centroids[i]
            x.append(cent[0])
            y.append(cent[1])
        plt.scatter(x, y, marker='x', color='r', s=50*np.ones(len(centroids)))
        plt.show()


fcm = FuzzyC(4, data)
clusters, centroids = fcm.fuzzy_c_mean()
x = []
y = []
for i in range(len(centroids)):
    cent = centroids[i]
    x.append(cent[0])
    y.append(cent[1])

plt.figure()
plt.scatter(data[:,0], data[:,1], c=clusters, s=12, cmap="cool")
plt.scatter(x, y, marker='x', color='r', s=50*np.ones(len(centroids)))
plt.show()
```

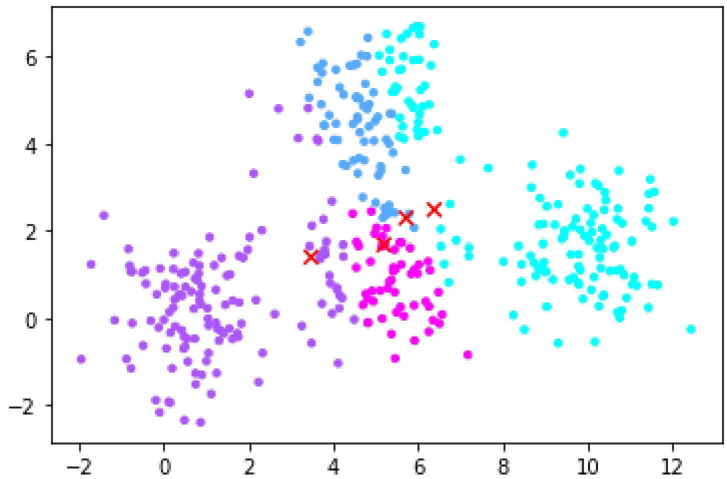
```
400
2
2
Iteration  0
```



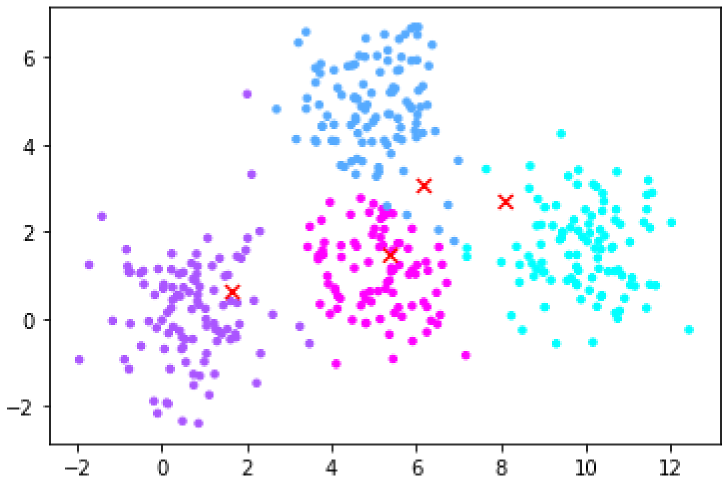
Iteration 1



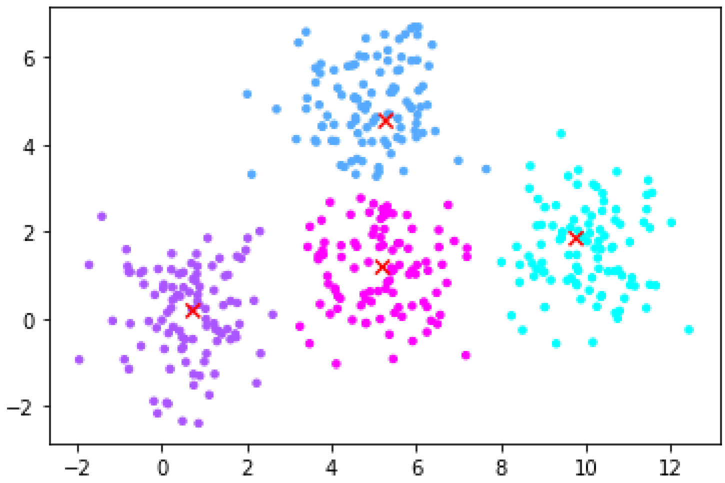
Iteration 2



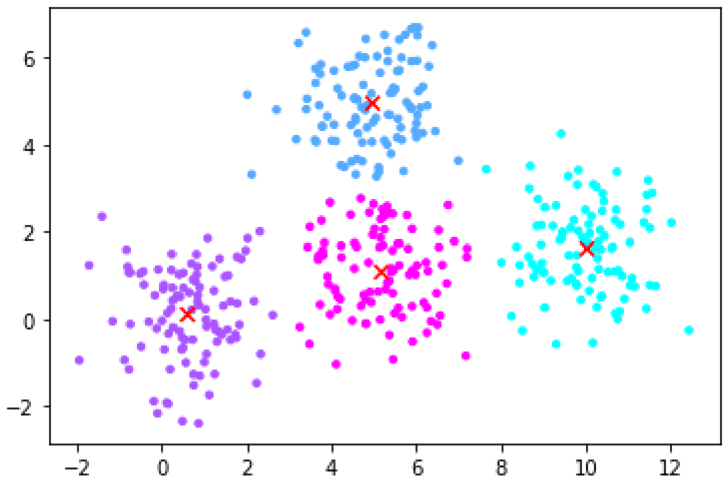
Iteration 3



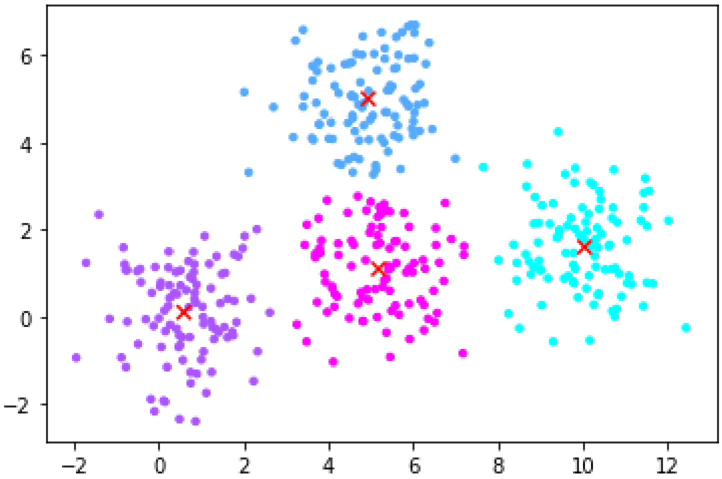
Iteration 4



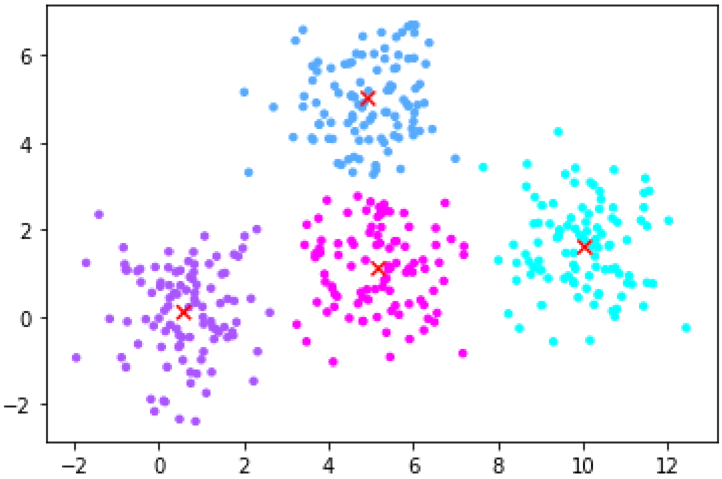
Iteration 5



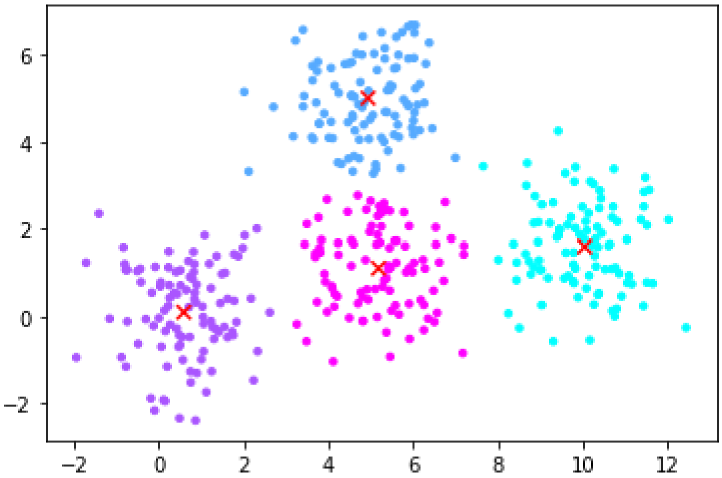
Iteration 6



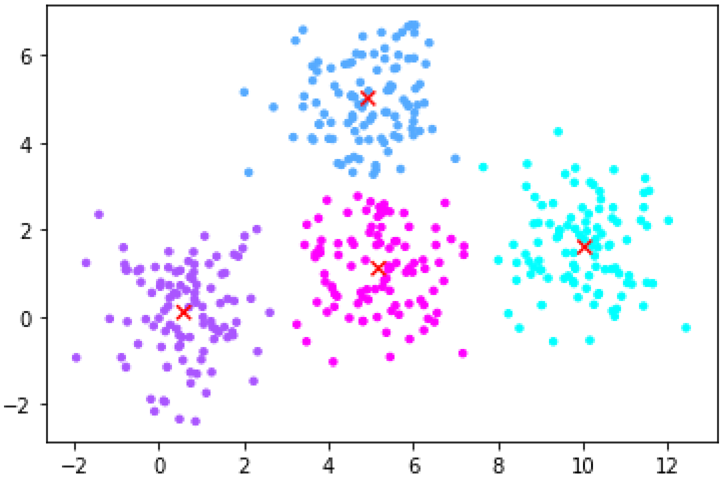
Iteration 7



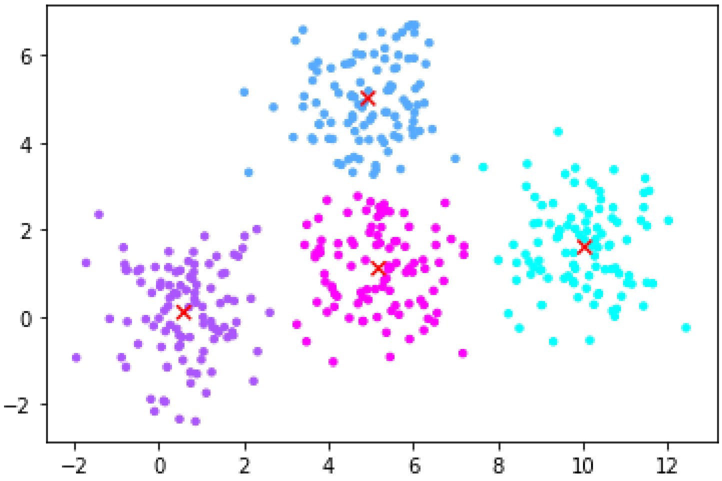
Iteration 8

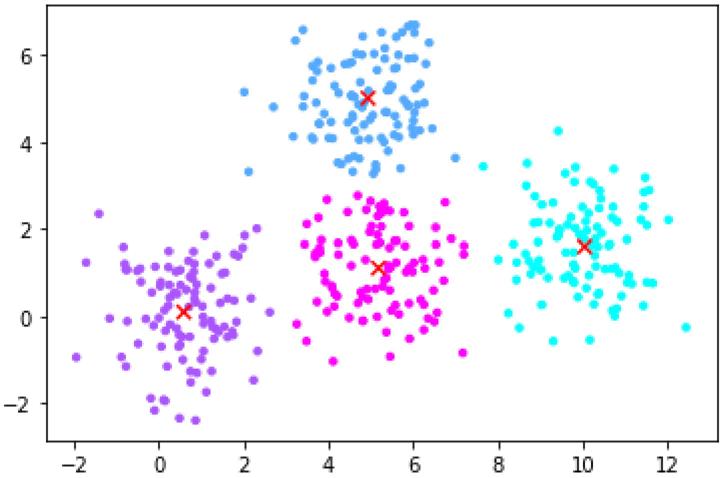


Iteration 9



```
Iteration  10
```





Hierarchical Clustering

Hierarchical clustering is an unsupervised clustering technique which groups together the unlabelled data of similar characteristics.

There are two types of hierarchical clustering:

- Agglomerative Clustering
- Divisive Clustering

Agglomerative Clustering:

In this type of hierarchical clustering all data set are considered as indivisual cluster and at every iterations clusters with similar characteristics are merged to give bigger clusters. This is repeated untill one single cluster is reached. It is also called bottem-top approach.

Agglomerative Clustering:

Lets start with some dummy example :

X=$[x_1, x_2, \ldots, x_5]$, with

$x_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$, $x_2 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$, $x_3 = \begin{bmatrix} 5 \\ 4 \end{bmatrix}$, $x_4 = \begin{bmatrix} 6 \\ 5 \end{bmatrix}$, $x_5 = \begin{bmatrix} 6.5 \\ 6 \end{bmatrix}$

Steps to perform Agglomerative Clustering:

1. Compute Distance matrix ($N \times N$ matrix, where N number of vectors present in the dataset): $D(a, b) = ||x_a - x_b||_2$
2. Replace the diagonal elements with inf and find the index of the minimum element present in the distance matrix (suppose we get the location (l, k)).
3. Replace $x_{min(l,k)} = .5 \times [x_l + x_m]$ and delete $x_{max(l,m)}$ vector from X(i.e now $(N = N - 1)$),

repeat from step 1 again untill all the vectors combined to a single cluster.

In [ ]:
```
from cmath import inf
from turtle import position


def Euclidian_Dist(x,y):
  return ((x[0]-y[0])**2+(x[1]-y[1])**2)**0.5

def Dist_mat(X):
 ## write your code here
  dist_mat=np.empty(shape=(X.shape[0],X.shape[0]))
  for i in range(X.shape[0]):
    for j in range(X.shape[0]):
      dist_mat[i][j]=Euclidian_Dist(X[i,:],X[j,:])
  for i in range(X.shape[0]):
    dist_mat[i][i]=inf
  return dist_mat

def combine(X,cluster):
  dist_mat=Dist_mat(X=X)
  points=np.where(dist_mat == np.amin(dist_mat))[0]
  minx=points[0]
  miny=points[1]
  if(minx>miny):
    minx,miny=miny,minx
  cluster.append([minx,miny])
  X[minx]=0.5*(X[minx]+X[miny])
  X=np.delete(X,miny,0)
  return X,cluster
```

In [ ]:
```
X=np.array([[1,1],[2,1],[5,4],[6,5],[6.5,6]])
import plotly.figure_factory as ff
## write your code here
cluster=[]
```

```
print(X)
while X.shape!=(1,2):
  X1=X.transpose()
  lab=np.linspace(1,X1.shape[1],X1.shape[1])
  fig = ff.create_dendrogram(X1.T, labels=lab)
  fig.update_layout(width=800, height=300)
  fig.show()
  X,cluster = combine(X,cluster)
  print("Combined Points",cluster[-1]+np.ones((1,2)))


  print('\nMean of clusters after every iteration: \n\n',X)
print('\ncluster combination order: \n\n',cluster+np.ones((len(cluster),2)))

## validate from inbuilt Dendogram
```

```
[[1.  1. ]
 [2.  1. ]
 [5.  4. ]
 [6.  5. ]
 [6.5 6. ]]

Combined Points [[1. 2.]]

Mean of clusters after every iteration:

 [[1.5 1. ]
 [5.  4. ]
 [6.  5. ]
 [6.5 6. ]]

Combined Points [[3. 4.]]

Mean of clusters after every iteration:

 [[1.5  1.  ]
 [5.   4.  ]
 [6.25 5.5 ]]

Combined Points [[2. 3.]]

Mean of clusters after every iteration:

 [[1.5   1.   ]
 [5.625 4.75 ]]

Combined Points [[1. 2.]]

Mean of clusters after every iteration:

 [[3.5625 2.875 ]]

cluster combination order:

 [[1. 2.]
 [3. 4.]
 [2. 3.]
 [1. 2.]]
```

Clustering Algorithms on MNIST Digit dataset

Perform Kmeans and gmm clustering on MNIST dataset

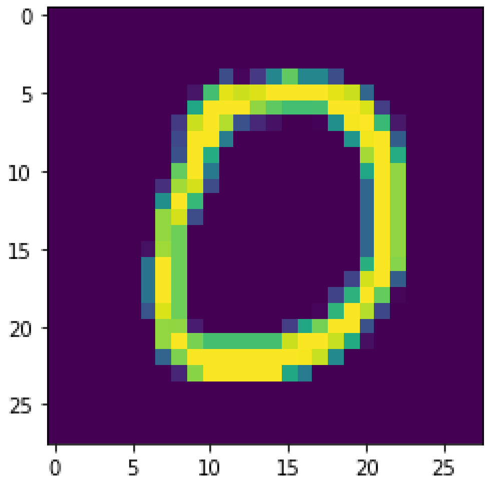
1. Load MNIST data from the given images and labels
2. Consider any 2 classes

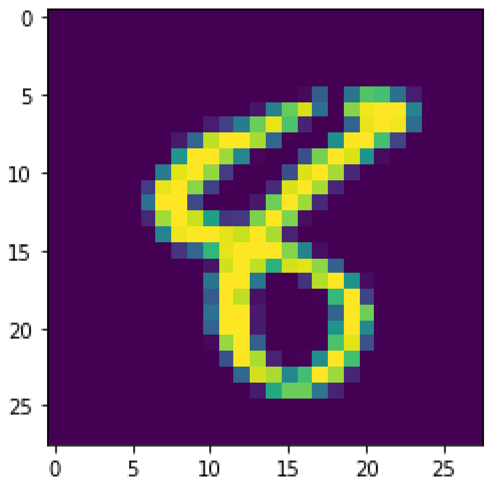
In [ ]:
```
# !pip install idx2numpy
```

In [ ]:
```
import idx2numpy
from keras.utils import np_utils
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
img_path = r"C:\Users\Asus\Documents\GitHub\PRML-Lab\Lab 07\t10k-images-idx3-ubyte'
label_path = r"C:\Users\Asus\Documents\GitHub\PRML-Lab\Lab 07\t10k-labels-idx1-ubyt

Images = idx2numpy.convert_from_file(img_path)
labels = idx2numpy.convert_from_file(label_path)

## write your code here
```

In [ ]:
```
id_0 = np.where(labels==0)
id0 = id_0[0]
Im_0 = Images[id0,:,:]
label_0=labels[id0]
plt.figure()
plt.imshow(Im_0[1,:,:])

id_8=np.where(labels==8)
id8=id_8[0]
Im_8=Images[id8,:,:]
label_8=labels[id8]
plt.figure()
plt.imshow(Im_8[1,:,:])

data=np.concatenate((Im_0, Im_8))
data=np.reshape(data,(data.shape[0],data.shape[1]*data.shape[2]))
# print(data.shape)
G_lab=np.concatenate((label_0,label_8))




print(data.shape)
# just for checking
# data=1-(data+10**(-12))
d=data[1,:]
im=np.reshape(d,(28,28))
# plt.figure()
# plt.imshow(im)
print(data)
```

```
(1954, 784)
[[0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 ...
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]
 [0 0 0 ... 0 0 0]]
```





Use the K-means clustering algorithm from the last lab to form the clusters

In [ ]:
```
from sklearn import metrics
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=2)
kmeans.fit(data)

pred_lab=kmeans.predict(data)
print(pred_lab)
print('performance=',metrics.homogeneity_score(pred_lab,G_lab))
```

```
[0 0 0 ... 1 1 1]
performance= 0.7387783429447129
```

Use the GMM clustering algorithm from the last lab to form the clusters

In [ ]:
```
from sklearn.mixture import GaussianMixture as Gmm
gmm=Gmm(n_components=2, init_params='kmeans',covariance_type='diag',verbose=1)
gmm.fit(data)
pred_lab=gmm.predict(data)
print(pred_lab)
print('performance=',metrics.homogeneity_score(pred_lab,G_lab))
```

```
Initialization 0
  Iteration 10
Initialization converged: True
[0 0 0 ... 0 0 0]
performance= 0.1213186660952875
```