Lab 5: Clustering Part 2

```
In [1]:
    import numpy as np
    import pandas as pd
    import math
    import matplotlib.pyplot as plt
    import matplotlib
    import sklearn.datasets as skl_data
    from jupyterthemes import jtplot
    jtplot.style(theme = "monokai",context = "notebook", ticks =
    True,grid = False)
```

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:

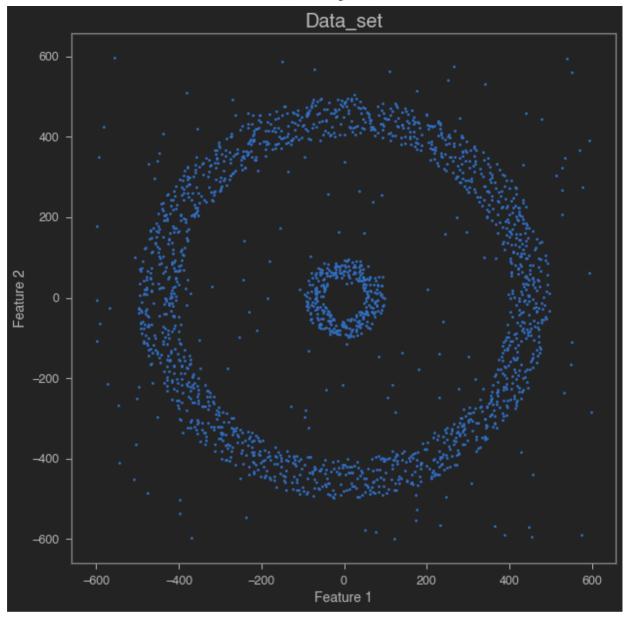
- a. The algorithm proceeds by arbitrarily picking up a point in the dataset (until all points have been visited).
- b. If there are at least 'minPoint' points within a radius of ' ϵ ' to the point then we consider all these points to be part of the same cluster.
- c. The clusters are then expanded by recursively repeating the neighborhood calculation for each neighboring point
- A. Generate "N" spherical training data points.

```
In [2]: ## write your code here

def circles(R,width,num):
    r = np.random.rand(num)*width+R
    phi = np.linspace(0,2.*np.pi, len(r))
    x= r * np.sin(phi)
    y = r* np.cos(phi)
    return x,y

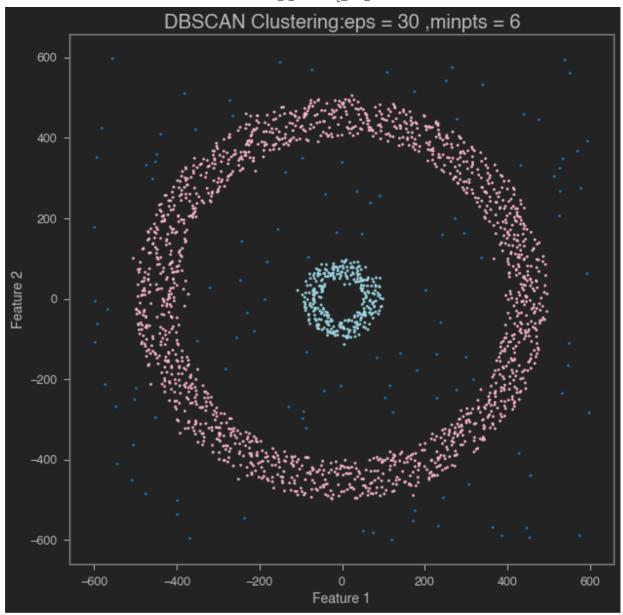
def uniform(num,a):
    x = np.random.uniform(-a,a,num)
    y = np.random.uniform(-a,a,num)
```

```
return x,y
def dtset(num):
    x,y = circles(400,100,num)
   data = np.array([x,y])
    x,y = circles(50,50,int(num/5))
    data = np.append(data,[x,y],axis=1)
    x,y = uniform(int(num/7.5),600)
    data = np.append(data,[x,y],axis=1)
    return data
data = dtset(1500)
data = np.unique(data,axis=0)
plt.figure(figsize=[10,10])
plt.scatter(data[0,:],data[1,:],marker='o',s=7)
plt.title('Data_set', fontsize=20);
plt.xlabel('Feature 1', fontsize=14);
plt.ylabel('Feature 2', fontsize=14);
data = data.T
```



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

```
if len(neighbours) < minpts:</pre>
            labels[i] = -1
        else:
            curr cl +=1
            cluster(data, labels, i, neighbours, curr cl, eps, minpts)
    return labels
def core(data,i,eps):
    neighbours = np.array([])
    for j in range(len(data[:,0])):
        if dist(data[i,:],data[j,:],eps) == 1:
            neighbours = np.append(neighbours,j)
    return(neighbours)
def cluster(data, labels, i, neighbours, curr cl, eps, min pts):
    labels[i] = curr cl
    j=0
    while j < len(neighbours):</pre>
        p = int(neighbours[j])
        if labels[p] == -1:
            labels[p] = curr cl
        elif labels[p] == 0:
            labels[p] = curr cl
            N neighbours = core(data,p,eps)
            if len(N neighbours) >= min pts:
                neighbours = np.append(neighbours, N neighbours)
        j+=1
eps = 30
min pts = 6
clusters = dbscan(data,eps,min pts)
print(np.max(clusters))
plt.figure(figsize=[10,10])
plt.scatter(data[:,0],data[:,1],c= clusters,s=7,cmap = 'tab20')
plt.title('DBSCAN Clustering:eps = '+str(eps)+" ,minpts =
"+str(min pts), fontsize=20);
plt.xlabel('Feature 1', fontsize=14);
plt.ylabel('Feature 2', fontsize=14);
```



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

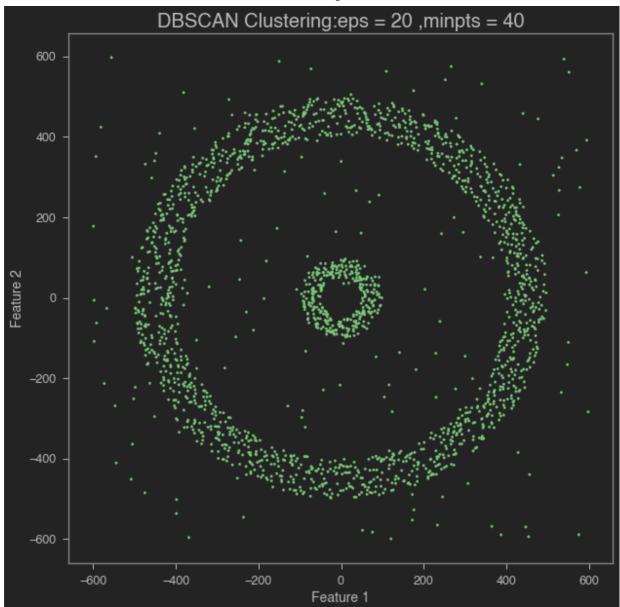
```
print(np.max(clusters2))
plt.figure(figsize=[10,10])
plt.scatter(data[:,0],data[:,1],c= clusters2,s=7,cmap = 'tab20')
plt.title('DBSCAN Clustering:eps = '+str(eps)+" ,minpts =
"+str(min pts), fontsize=20);
plt.xlabel('Feature 1',fontsize=14);
plt.ylabel('Feature 2', fontsize=14);
eps = 50
min pts = 10
clusters3 = dbscan(data,eps,min pts)
print(np.max(clusters3))
plt.figure(figsize=[10,10])
plt.scatter(data[:,0],data[:,1],c= clusters3,s=7,cmap = 'Set1')
plt.title('DBSCAN Clustering:eps = '+str(eps)+" ,minpts =
"+str(min pts), fontsize=20);
plt.xlabel('Feature 1', fontsize=14);
plt.ylabel('Feature 2', fontsize=14);
eps = 35
min pts = 20
clusters5 = dbscan(data,eps,min pts)
print(np.max(clusters5))
plt.figure(figsize=[10,10])
plt.scatter(data[:,0],data[:,1],c= clusters5,s=7,cmap = 'Set2')
plt.title('DBSCAN Clustering:eps = '+str(eps)+" ,minpts =
"+str(min pts), fontsize=20);
plt.xlabel('Feature 1', fontsize=14);
plt.ylabel('Feature 2', fontsize=14);
```

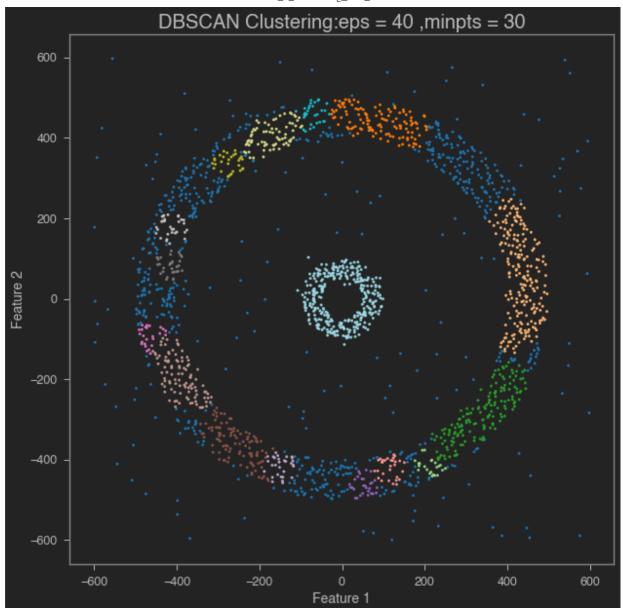
```
-1.0
```

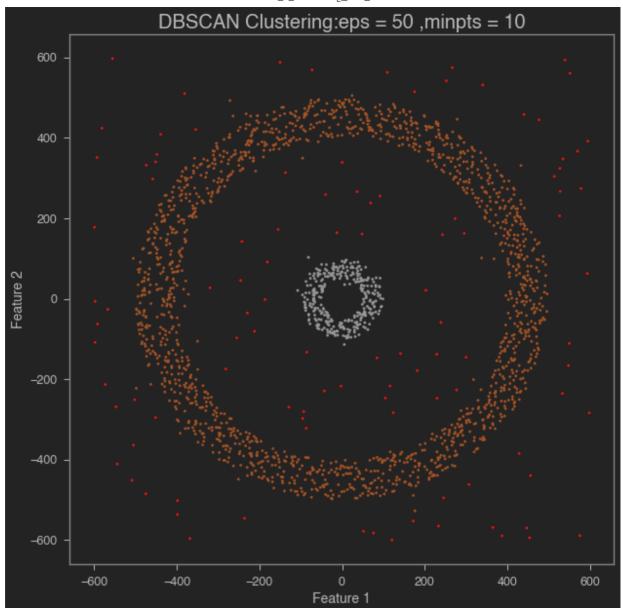
6.0

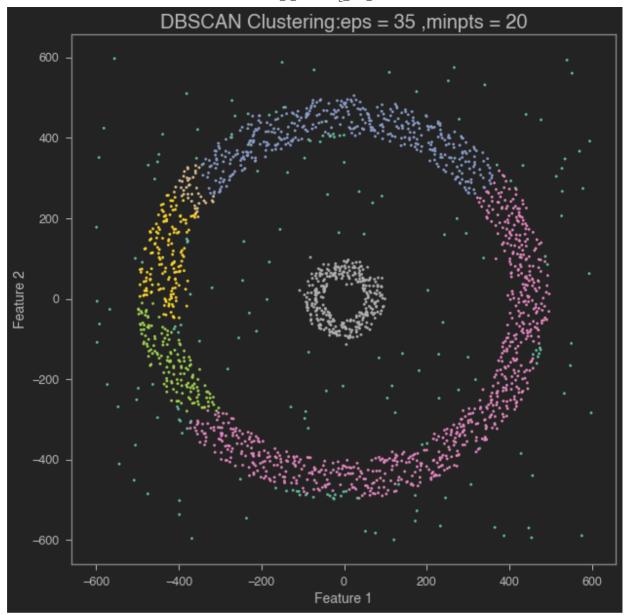
^{16.0}

^{2.0}



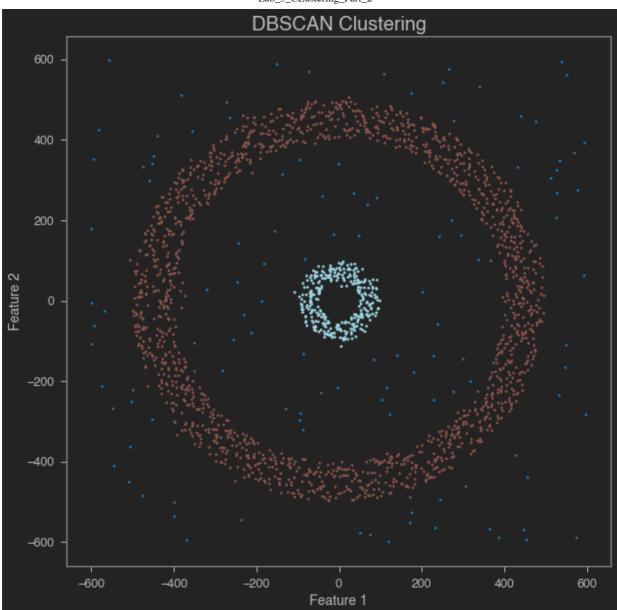


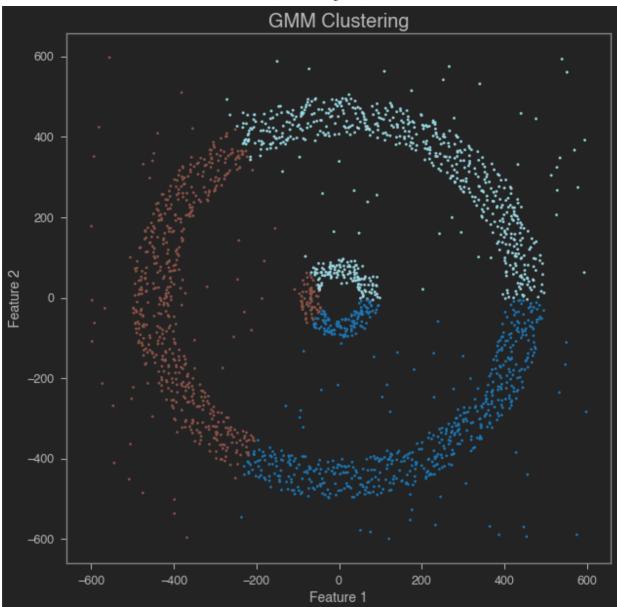


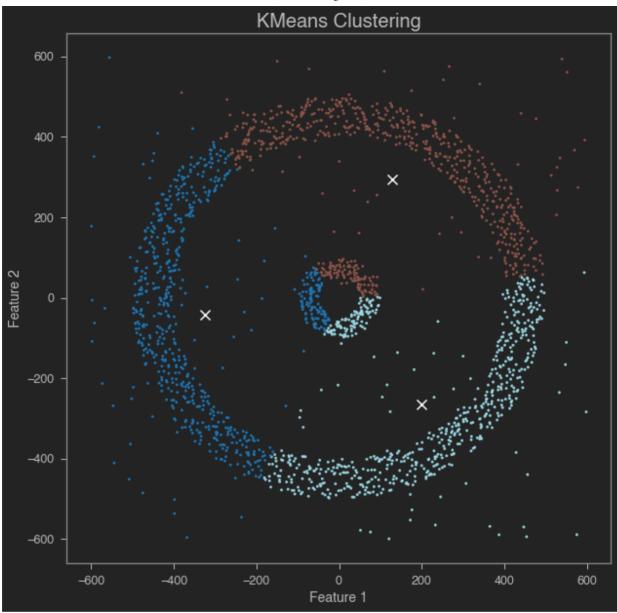


D. Compare your model with the built in DBSCAN in Sci-kit Learn. Also compare you results with GMM and the K-means Algorithm

```
from sklearn.mixture import GaussianMixture
## write your code here
plt.figure(figsize=(10,10))
gmm = GaussianMixture(n components=3).fit(data)
labels = gmm.predict(data)
plt.scatter(data[:, 0], data[:, 1], c=labels, s=7, cmap='tab20')
plt.title('GMM Clustering',fontsize=20)
plt.xlabel('Feature 1', fontsize=14)
plt.ylabel('Feature 2', fontsize=14)
plt.show()
from sklearn.cluster import KMeans
## write your code here
plt.figure(figsize=(10,10))
kmeans = KMeans(n clusters=3)
kmeans.fit(data)
y kmeans = kmeans.predict(data)
plt.scatter(data[:, 0], data[:, 1], c=y kmeans, s=7, cmap='tab20')
centers = kmeans.cluster centers
plt.scatter(centers[:, 0], centers[:, 1], c='white', s=100, marker
= 'x');
plt.title('KMeans Clustering', fontsize=20)
plt.xlabel('Feature 1', fontsize=14)
plt.ylabel('Feature 2', fontsize=14)
plt.show()
```







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:

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

$$x_1=\left[egin{array}{c}1\1\end{array}
ight]$$
 , $x_2=\left[egin{array}{c}2\1\end{array}
ight]$, $x_3=\left[egin{array}{c}5\4\end{array}
ight]$, $x_4=\left[egin{array}{c}6\5\end{array}
ight]$, $x_5=\left[egin{array}{c}6.5\6\end{array}
ight]$

Steps to perform Agglomerative Clustering:

- 1. Compute Distance matrix (N imes 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 $x_{min(l,k)}=.5 imes[x_l+x_m]$ 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 [6]:
        def Euclidian Dist(x,y):
        ##write your code here
            dist = np.sqrt((x[0]-y[0])**2 + (x[1]-y[1])**2)
            return dist
        def Dist mat(X):
         ## write your code here
            dist mat = np.array([])
            for i in range(len(X[:,0])):
                for j in range(len(X[:,0])):
                    tmp = np.round(Euclidian Dist(X[i,:],X[j,:]),1)
                     if i == j:
                        dist mat = np.append(dist mat,np.inf)
                    else:
                        dist mat = np.append(dist mat, tmp)
            dist mat = np.reshape(dist mat,[len(X[:,0]),len(X[:,0])])
            return dist mat
        def combine(X):
          ## write your code here
            mn = np.min(dist)
            ind = np.where(dist == np.min(dist))
            X[ind[0][0]] = 0.5*(X[ind[0][0]] + X[ind[0][1]])
            newX = np.delete(X, ind[0][1], 0)
            return newX
```

```
In [7]: X=np.array([[1,1],[2,1],[5,4],[6,5],[6.5,6]])
    X=X.transpose()
    Y = X.T
    i = len(Y[:,0])
```

```
## write your code here
while i>1:
    dist = Dist_mat(Y)
    Y = combine(Y)
    i = len(Y[:,0])
    ind = np.where(dist == np.min(dist))
    print(dist,"\n","Mean after every iteration:\n",Y.T,"\n")

## validate from inbuilt Dendogram
import plotly.figure_factory as ff

lab=np.linspace(1,X.shape[1],X.shape[1])
fig = ff.create_dendrogram(X.T, labels=lab)
fig.update_layout(width=800, height=300)
fig.show()
```

```
[[inf 1. 5. 6.4 7.4]
[1. inf 4.2 5.7 6.7]
[5. 4.2 inf 1.4 2.5]
[6.4 5.7 1.4 inf 1.1]
[7.4 6.7 2.5 1.1 inf]]
Mean after every iteration:
[[1.5 5. 6. 6.5]
[1. 4. 5. 6.]]
[[inf 4.6 6. 7.1]
[4.6 inf 1.4 2.5]
[6. 1.4 inf 1.1]
[7.1 2.5 1.1 inf]]
Mean after every iteration:
[[1.5 5. 6.25]
[1. 4. 5.5]]
[[inf 4.6 6.5]
[4.6 inf 2.]
[6.5 2. inf]]
Mean after every iteration:
[[1.5
       5.625]
[1.
      4.75 ]]
[[inf 5.6]
[5.6 inf]]
Mean after every iteration:
[[3.5625]
[2.875]]
```



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 [8]: pip install idx2numpy
```

Requirement already satisfied: idx2numpy in /Library/Frameworks/Python.framework/Versions/3.8/lib/python3.8/site-packages (1.2.3)

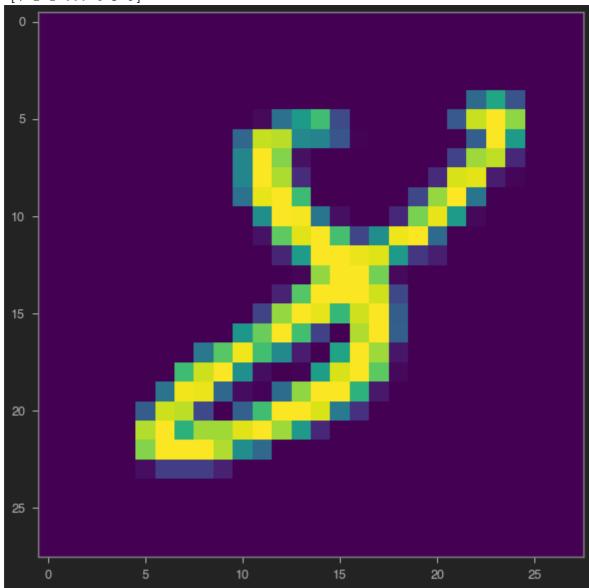
Requirement already satisfied: numpy in /Library/Frameworks/Python.framework/V ersions/3.8/lib/python3.8/site-packages (from idx2numpy) (1.19.2)

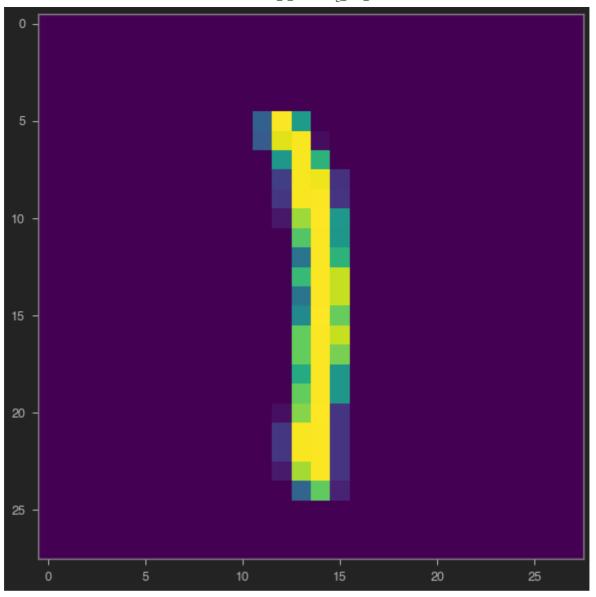
Requirement already satisfied: six in /Library/Frameworks/Python.framework/Ver sions/3.8/lib/python3.8/site-packages (from idx2numpy) (1.15.0)

```
In [9]:
        import idx2numpy
        from keras.utils import np utils
        img path = 't10k-images-idx3-ubyte'## write your code here
        label path = 't10k-labels-idx1-ubyte'## write your code here
        Images = idx2numpy.convert from file(img path)
        labels = idx2numpy.convert from file(label path)
        ## write your code here
        images = np.reshape(Images , (Images.shape[0],-1))
        print(images.shape)
        print(labels)
        plt.figure(figsize=[10,10])
        plt.imshow(Images[np.random.randint(0,Images.shape[0]),:,:])
        plt.figure(figsize=[10,10])
        plt.imshow(Images[np.random.randint(0,Images.shape[0]),:,:])
        plt.show()
```

(10000, 784)







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

```
In [10]:
         ## write your code here
         data = np.array([])
         img = np.array([])
         cnt 7 = 0
         cnt 9 = 0
         for i in range(len(labels)):
             if labels[i] == 7:
                 data = np.append(data,images[i,:],axis = 0)
                 cnt_7 +=1
             if labels[i] == 9:
                 data = np.append(data,images[i,:],axis = 0)
                 cnt 9 +=1
         data=np.reshape(data,(int(len(data)/784),784))
         print(data.shape)
         kmeans = KMeans(n clusters=2)
         kmeans.fit(data)
```

```
labels1 = kmeans.predict(data)
cntnw_7 = 0
cntnw_9 = 0

for i in range(len(labels1)):
    if labels1[i] == 0:
        cntnw_7 +=1
    if labels1[i] == 1:
        cntnw_9 +=1
print(cnt_7,cntnw_7)
print(cnt_9,cntnw_9)
```

(2037, 784) 1028 1095 1009 942

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

```
In [11]:
    ## write your code here
    gmm = GaussianMixture(n_components=2).fit(data)
    labels2 = gmm.predict(data)

cntnw_7 = 0
    cntnw_9 = 0

for i in range(len(labels2)):
    if labels2[i] == 0:
        cntnw_7 +=1

    if labels2[i] == 1:
        cntnw_9 +=1

    print(cnt_7,cntnw_7)
    print(cnt_9,cntnw_9)
```

1028 927 1009 1110

In []: