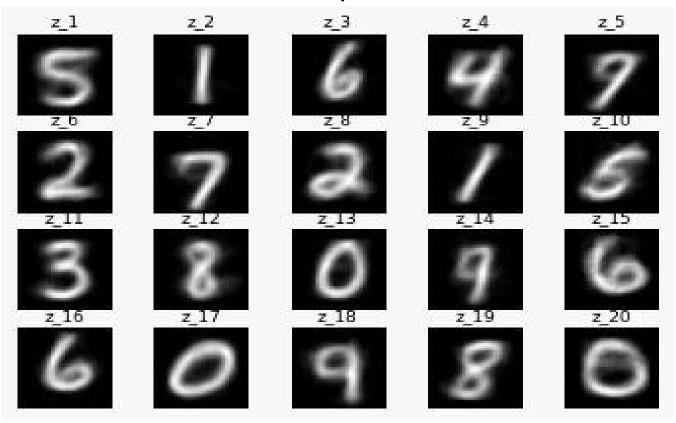
AI61003 LINEAR ALGEBRA FOR AI AND ML ASSIGNMENT 01 - PROBLEM 09

N (the number of training sample): 1000

n (the dimension of vectors to be clustered): 784

CASE 1 Random Initialization of Cluster Representatives



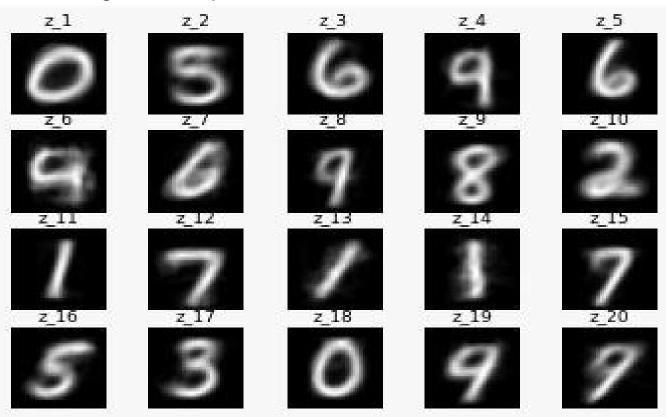
Number of iterations taken for the algorithm to converge: **18**Accuracy of cluster assignment for a randomly selected set of 50 images: **68.00%**

Number of clusters (k)	${\sf J}_{\sf clust}$
5	5.8968
6	5.8798
7	5.8824
8	5.8515
9	5.8549
10	5.8671
11	5.8752
12	5.9129
13	5.8592

14	5.8509
15	5.8954
16	5.8937
17	5.8979
18	5.8635
19	5.8869
20	5.8572

The optimal number of clusters is the one that gives the least value of the objective function J_{clust} . Therefore, **14** is the optimal cluster size.

CASE 2 Choosing Cluster Representatives from Given Dataset



Number of iterations taken for the algorithm to converge : **16**Accuracy of cluster assignment for a randomly selected set of 50 images : **72.00%**

Number of clusters (k)	${\sf J}_{\sf clust}$
5	6.5726
6	6.4847
7	6.4099
8	6.3861

9	6.3043
10	6.2270
11	6.1661
12	6.1165
13	6.1421
14	6.0424
15	6.0164
16	5.9788
17	5.9403
18	5.9260
19	5.9095
20	5.8953
·	

The optimal number of clusters is the one that gives the least value of the objective function J_{clust} . Therefore, **20** is the optimal cluster size.

The choice of initial condition definitely has an effect on the performance of the clustering algorithm.

- Firstly the <u>algorithm converges faster in the second case than in the first case</u>. The converged value of inertia (or *within-cluster sum-of-squares criterion*) in the first case (for k = 20) was 35668 and in the second case was 35658. It shows that not only does the number of iterations get affected by the initial condition, but <u>in the second case the algorithm may tend to find a more optimal clustering</u> (converges towards global minima) than in the first case (might converge towards local minima). Having said this, though both the number of iterations and the converged criterion value are better for *data-dependent initialization* of cluster representatives, the relative difference between these values for the two cases is quite small. So, <u>random initialization</u> of cluster representatives can <u>also give a good clustering of objects</u>.
- The accuracy of cluster assignments was evaluated in both the cases on the same test set (constructed by randomly choosing 50 images from MNIST dataset that were not seen in training). It is clear that the <u>accuracy of cluster assignment in the second case is 4% higher</u> than in the first case. This shows that the initial condition can also have an impact on the performance of the produced clusters on the unseen test samples.
- If you analyze the change in the converging value of J_{clust} with the number of clusters, you would find that the converging value decreases (almost) monotonically in the second case, whereas in the first case there is a very irregular pattern. As a result of this, their optimal cluster sizes also come out to be very different (14 for random initialization and 20 for data-dependent initialization).

```
1 import tensorflow as tf
In [1]:
         2 import numpy as np
         3 from matplotlib import pyplot as plt
         4 from random import shuffle, randint
         5 import sklearn.cluster as Clustering Algorithm
         1 mnist data = tf.keras.datasets.mnist
In [2]:
         2 (x train, y train), (x test, y test) = mnist data.load data()
         3 train data = list(zip(x train, y train))
         4 shuffle(train data)
         5 x train, y train = list(zip(*train_data))
         1 train images = [ [] for digit in range(10) ]
In [3]:
         2 sample count per digit = 100
         3 for i, label in enumerate(y train):
                if ( len(train images[label]) == sample count per digit ) : continue
                train images[label].append(x train[i].flatten().astype(np.float32) / 255)
         5
            def Get Random Test Data ( test samples count = 50 ) :
                global x test, y test
         8
         9
        10
                test data = list(zip(x test, y test))
                shuffle(train data)
        11
        12
                shuffle(test data)
        13
                x train, y train = list(zip(*train data))
                x test shuff, y test shuff = list(zip(*test data))
        14
        15
        16
                test images = [ [] for digit in range(10) ]
        17
                count = 0
        18
                for i, label in enumerate(y_test_shuff) :
        19
                    if count == test samples count : break
        20
                    count += 1
        21
                    test samples count
        22
                    test images[label].append(x test shuff[i].flatten().astype(np.float32) / 255)
        23
                return test images
```

```
In [4]:
        1 train = []
         2 do = [train.extend(img) for img in train images]
         3 N = len(train)
         4 n = train_images[0][0].shape[0]
         5 print ('N (number of training samples) :', N)
         6 print('n (dimension of vectors) :', n)
        N (number of training samples) : 1000
        n (dimension of vectors): 784
In [5]:
         1 def Get Distance ( a , b ) :
                return np.linalg.norm(b-a)
In [6]:
         1 def J clust ( train , kmeans ) :
                s = 0
                for img in train :
         3
                    cluster id = kmeans.predict(img.astype(np.float).reshape(1,-1))[0]
                    s += Get Distance(img, kmeans.cluster centers [cluster id])
         5
                return s / len(train)
```

CASE I: Random Initialization of Cluster Representatives

```
1 | k = 20
In [7]:
         2 kmeans = Clustering Algorithm.KMeans(n clusters = k, init='random', verbose=True, n init=1)
         3 kmeans.fit(train)
        Initialization complete
        Iteration 0, inertia 60732.524707579985
        Iteration 1, inertia 38050.91288994666
        Iteration 2, inertia 36886.65874578197
        Iteration 3, inertia 36505.343118868186
        Iteration 4, inertia 36233.53763940629
        Iteration 5, inertia 36055.34772788261
        Iteration 6, inertia 35925.409068793735
        Iteration 7, inertia 35836.56467969832
        Iteration 8, inertia 35781.09028613918
        Iteration 9, inertia 35733.11039512983
        Iteration 10, inertia 35708.260845345685
        Iteration 11, inertia 35688.57368506976
        Iteration 12, inertia 35678.89407890276
        Iteration 13, inertia 35675.8489286663
        Iteration 14, inertia 35672.49733949574
        Iteration 15, inertia 35671.12267063208
        Iteration 16, inertia 35669.257571344424
        Iteration 17, inertia 35668.07054899751
        Converged at iteration 17: strict convergence.
Out[7]: KMeans(init='random', n clusters=20, n init=1, verbose=True)
```

```
for cluster id, rep in enumerate(kmeans.cluster centers ) :
 In [8]:
                 plt.subplot(4, 5, cluster id+1)
                 cluster rep img = (rep*255).astype(np.int32).reshape((28,28))
                plt.imshow(cluster rep img, cmap='gray')
                 plt.title('z ' + str(cluster id+1), fontsize=9, pad=4)
                 plt.axis('off')
          7 plt.savefig('cluster representative plots part 1.png')
         1 digits represented by clusters = [5, 1, 6, 4, 9, 2, 7, 2, 1, 5, 3, 8, 0, 9, 6, 6, 0, 9, 8, 0]
In [10]:
          1 correctly classified = 0
          2 test images count = 50
          3 test_images = Get_Random_Test_Data(test_images_count)
          4 for dig in range(10):
                 for img in test images[dig] :
                     cluster id = kmeans.predict(img.astype(np.float).reshape(1,-1))[0]
                     correctly classified += (digits represented by clusters[cluster id] == dig)
          7
          9 accuracy = 100 * correctly classified / test images count
```

ACCURACY OF CLUSTER ASSIGNMENT: 68.0

10 print('ACCURACY OF CLUSTER ASSIGNMENT :', round(accuracy, 3))

```
1 least J value = float('inf')
In [11]:
          2 opt cluster size = -1
          3 for cluster size in range(5, 21):
                 kmeans = Clustering Algorithm.KMeans(n clusters = k, init='random', verbose=False, n init=1)
                 kmeans.fit(train)
                 J value = J clust(train, kmeans)
          6
                 print('CLUSTER SIZE :', cluster size, '\tJ clust :', round(J value, 5))
          8
          9
                 if J value < least J value :</pre>
         10
                     least J value = J value
                     opt cluster size = cluster size
         11
         12
         13 print('OPTIMAL CLUSTER SIZE :', opt cluster size)
         CLUSTER SIZE : 5
                                 J clust : 5.89679
                                 J clust : 5.87985
         CLUSTER SIZE : 6
                                 J clust : 5.8824
         CLUSTER SIZE : 7
                                 J clust : 5.85147
         CLUSTER SIZE : 8
                                 J clust : 5.8549
         CLUSTER SIZE : 9
         CLUSTER SIZE : 10
                                 J clust : 5.86706
                                 J clust : 5.8752
         CLUSTER SIZE : 11
                                 J clust : 5.91291
         CLUSTER SIZE : 12
                                 J clust : 5.85923
         CLUSTER SIZE : 13
         CLUSTER SIZE : 14
                                 J clust : 5.85086
                                 J clust : 5.89545
         CLUSTER SIZE : 15
                                 J clust : 5.8937
         CLUSTER SIZE : 16
                                 J clust : 5.89795
         CLUSTER SIZE : 17
                                 J clust : 5.86347
         CLUSTER SIZE: 18
                                 J clust: 5.88693
         CLUSTER SIZE : 19
         CLUSTER SIZE : 20
                                 J clust : 5.85719
```

CASE II: Data Dependent Initialization of Cluster Representatives

OPTIMAL CLUSTER SIZE : 14

```
In [12]:
         1 def Data_Dependent_Cluster_Representatives_Init ( train , k ) :
                clusters = []
          3
                 for i in range(k) : clusters.append([])
                 for img in train :
                     clusters[randint(0, k-1)].append(img)
          5
          6
          7
                 cluster_representatives = []
          8
                 for i in range(k):
                     rep = sum(clusters[i]) / len(clusters[i])
                     cluster_representatives.append(rep)
         10
         11
         12
                 cluster_representatives = np.array(cluster_representatives)
         13
                return cluster_representatives
```

```
In [13]:
          1 | k = 20
          2 kmeans = Clustering Algorithm.KMeans(n clusters = k, verbose=True, n init=1,
                                                  init=Data Dependent Cluster Representatives Init(train, k))
          4 kmeans.fit(train)
         Initialization complete
         Iteration 0, inertia 49601.48328326748
         Iteration 1, inertia 39424.78061696993
         Iteration 2, inertia 37262.66951403245
         Iteration 3, inertia 36526.05086918052
         Iteration 4, inertia 36129.293411810526
         Iteration 5, inertia 35995.34874088044
         Iteration 6, inertia 35928.17828729691
         Iteration 7, inertia 35885.53611488616
         Iteration 8, inertia 35829.41673297419
         Iteration 9, inertia 35792.76307584839
         Iteration 10, inertia 35752.53303179572
         Iteration 11, inertia 35721.684346373004
         Iteration 12, inertia 35687.63237248872
         Iteration 13, inertia 35672.999806197186
         Iteration 14, inertia 35664.05230663018
         Iteration 15, inertia 35658.41160480236
         Converged at iteration 15: strict convergence.
Out[13]: KMeans(init=array([[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.]], dtype=float32),

n clusters=20, n init=1, verbose=True)

```
for cluster id, rep in enumerate(kmeans.cluster centers ) :
In [15]:
                 plt.subplot(4, 5, cluster id+1)
                 cluster rep img = (rep*255).astype(np.int32).reshape((28,28))
                 plt.imshow(cluster rep img, cmap='gray')
                 plt.title('z ' + str(cluster id+1), fontsize=9, pad=4)
                 plt.axis('off')
          7 plt.savefig('cluster representative plots part 2.png')
         1 digits represented by clusters = [0, 5, 6, 9, 6, 9, 6, 9, 8, 2, 1, 7, 1, 1, 7, 5, 3, 0, 9, 9]
In [16]:
In [17]:
          1 correctly classified = 0
          2 test images count = 50
          3 for dig in range(10):
                 for img in test images[dig] :
                     cluster id = kmeans.predict(img.astype(np.float).reshape(1,-1))[0]
                     correctly classified += (digits represented by clusters[cluster id] == dig)
          8 accuracy = 100 * correctly classified / test images count
```

ACCURACY OF CLUSTER ASSIGNMENT: 72.0

9 print('ACCURACY OF CLUSTER ASSIGNMENT :', round(accuracy, 3))

```
In [18]:
          1 least J value = float('inf')
          2 opt cluster size = -1
          3 for cluster size in range(5, 21):
                 kmeans = Clustering Algorithm. KMeans (n clusters = cluster size, verbose=False, n init=1,
                                                       init=Data Dependent Cluster Representatives Init(train, cluster size))
           5
           6
                 kmeans.fit(train)
                 J value = J clust(train, kmeans)
           8
                 print('CLUSTER SIZE :', cluster size, '\tJ clust :', round(J value, 5))
          9
          10
                 if J value < least J value :</pre>
                     least J value = J value
         11
         12
                     opt cluster size = cluster size
         13
         14 print('OPTIMAL CLUSTER SIZE :', opt cluster size)
                                 J clust : 6.57261
         CLUSTER SIZE : 5
         CLUSTER SIZE : 6
                                 J clust : 6.48468
         CLUSTER SIZE : 7
                                 J clust: 6.40986
                                 J clust : 6.38606
         CLUSTER SIZE : 8
                                 J clust : 6.30426
         CLUSTER SIZE : 9
                                 J clust : 6.22705
         CLUSTER SIZE : 10
         CLUSTER SIZE : 11
                                 J clust : 6.16606
```

J clust : 6.11653

J clust : 6.14211

J clust : 6.04239

J clust : 6.0164

J_clust : 5.97875 J clust : 5.94029

J clust : 5.92599

J_clust : 5.90952 J clust : 5.8953

CLUSTER SIZE : 12

CLUSTER SIZE : 13 CLUSTER SIZE : 14

CLUSTER SIZE : 15

CLUSTER SIZE : 16

CLUSTER SIZE : 17 CLUSTER SIZE : 18

CLUSTER SIZE : 19

CLUSTER SIZE : 20

OPTIMAL CLUSTER SIZE : 20