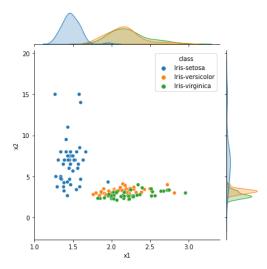
Problem 4

```
In [1]: import numpy as np
         import pandas as pd
         import seaborn as sns
         import matplotlib.pyplot as plt
         %matplotlib inline
         import sys
         import random
         random.seed(0)
         np.random.seed(0)
In [2]: column_names = ['sepal length', 'sepal width', 'petal length', 'petal width', 'class']
In [3]: # read iris dataset
         iris = pd.read_csv('iris.data',names=column_names,index_col=False)
In [4]: iris.head()
Out[4]:
             sepal length sepal width petal length petal width
                                                            class
                    5.1
                               3.5
                                                    0.2 Iris-setosa
          0
                    4.9
                               3.0
                                          1.4
                                                    0.2 Iris-setosa
                    4.7
                               3.2
                                          1.3
                                                    0.2 Iris-setosa
          2
                    4.6
                                          1.5
                                                    0.2 Iris-setosa
                               3.6
                                                    0.2 Iris-setosa
                    5.0
                                          1.4
In [5]: iris_df_new = pd.DataFrame() # creating new dataframe
In [6]: # this function assigns values
         def get_class(x):
              if x=='Iris-setosa': # Iris-setosa =0
                  return 0
              elif(x=='Iris-versicolor'): # Iris-versicolor =1
                  return 1
              else:
                  return 2 # Iris Virginica =3
In [7]: # Assgning x1 and x2
         iris_df_new['x1']=iris['sepal length']/iris['sepal width']
iris_df_new['x2']=iris['petal length']/iris['petal width']
         iris_df_new['class']=iris['class']
         iris_df_new['class_enc']=iris_df_new['class'].apply(lambda x: get_class(x))
In [8]: iris_df_new.head()
Out[8]:
          o 1.457143 7.0 Iris-setosa
                                          n
          1 1.633333 7.0 Iris-setosa
          2 1.468750 6.5 Iris-setosa
                                          0
          3 1.483871 7.5 Iris-setosa
                                          0
          4 1.388889 7.0 Iris-setosa
In [9]: # showing the clusters
         plt.figure(figsize=(12,8))
         data = iris_df_new.drop('class_enc',axis=1)
sns.jointplot(x='x1',y='x2',data=data,hue='class')
```

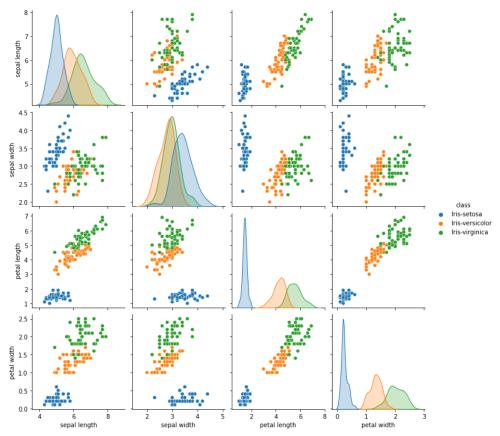
```
Out[9]: <seaborn.axisgrid.JointGrid at 0x7fb85005bcd0>
```

<Figure size 864x576 with 0 Axes>



In [10]: sns.pairplot(data=iris,hue='class')

Out[10]: <seaborn.axisgrid.PairGrid at 0x7fb85005be90>



2) KMeans++ Source Code Documentation:

- 1. Using Euclidean Distance for calculating distance between data points (get_distance function)
- 2. initialize_kmeans_plus_plus -> Initializes Centroids (takes "K" as argument) and returns initial K centroids

We initialize a list of centroids

centroids=[]

- a. First we randomly select a point and append to the centroids list b. Then for rest (K-1) times,
 - i. We loop through all the points $% \left\{ 1,2,...,n\right\}$
 - .> Then determine minimum distance of the point from all current centroids in the centroids list
 - ii. Among those minimum distances, we now select the distance with max value and select the corresponding data point as new centroid.
 - iv. Append the new centroid data point to centroids list
- 3. KMeans Plus Plus Algorithm:

kmeans_plus_plus -> (takes current centroids, "K" value), (returns new centroids,point to cluster centroids mapping)

a. (initialization)

```
\label{lem:cent_map=[]} $$ stores centroids and corresponding assigned points mapping $$ sums_x1=[] $$ $$ stores sum of x1 feature of all points within a cluster $$ sums_x2=[] $$ $$ $$ stores sum of x2 feature of all points within a cluster $$
```

b. For each of the points,

- i. we calculate the distance from all the current centroids.
- ii. we map the data point to the centroid with which it has minimum distance
- c. For each of the cluster, we calculate the new centroids by

```
new_cx1[k] = sums_x1[k]/length(cent_map[k])
new_cx2[k] = sums_x2[k]/length(cent_map[k])
append this values to new centroids list
```

 $\mbox{d.}$ Returns the new centroids list and mapping of points to centroids.

```
In [12]: ## Initialize the centroids function
           num_rows = iris_df_new.shape[0]
def initialize_kmeans_plus_plus(k):
                centroids_x1=[]
                centroids_x2=[]
                # first point is selected randomly
                rand_num = np.random.randint(num_rows-1)
                first_centroid x1 = iris_df_new['x1'].iloc[rand_num]
first_centroid_x2 = iris_df_new['x2'].iloc[rand_num]
                centroids_x1.append(first_centroid_x1)
                centroids_x2.append(first_centroid_x2)
                for k id in range(k-1):
                     dist=[]
                     # for each of the point
                     for ind in range(num rows):
                          x1=iris_df_new['x1'].iloc[ind]
x2=iris_df_new['x2'].iloc[ind]
                          min_dist = sys.maxsize
                          # we determine the minimum distance from current all centroids
                          for cd in range(len(centroids_x1)):
                               y1=centroids_x1[cd]
                               y2=centroids x2[cd]
                               distance = get_distance(x1,x2,y1,y2)
min_dist = min(min_dist,distance)
                          dist.append(min_dist)
                     # then select the data point which is at maximum distance,
                     # and assign that data point as new centroid
                     mx_ind = np.argmax(np.array(dist))
                     centroids_x1.append(iris_df_new['x1'].iloc[mx_ind])
centroids_x2.append(iris_df_new['x2'].iloc[mx_ind])
                return centroids x1, centroids x2
```

```
In [13]: ## Kmean++ algorithm
          def kmeans_plus_plus(k,centroids_x1,centroids_x2):
               # number of datapoints
               num_rows = iris_df_new.shape[0]
               cent_map=[] # stores centroids and corresponding assigned points mapping
               sums x1=[] # stores sum of x1 feature of all points within a cluster sums x2=[] # stores sum of x2 feature of all points within a cluster
               for ind in range(k):
                   cent_map.append([])
                   sums_x1.append(0)
                   sums_x2.append(0)
               # for each data point
               for ind in range(num_rows):
                   x1=iris_df_new['x1'].iloc[ind]
x2=iris_df_new['x2'].iloc[ind]
                   min_dist = sys.maxsize
                   mid=-1
                   # we calculate the distances between point and all centroids
                   # point will be mapped to the centroid with minimum distance from it
                   for cd in range(len(centroids_x1)):
                       y1=centroids_x1[cd]
                        y2=centroids_x2[cd]
                       distance = get_distance(x1,x2,y1,y2)
                       if mid==-1:
                            mid=cd
                            min_dist = distance
                       else:
                            if(distance<min dist):</pre>
                                mid=cd
                                min_dist = distance
                   cent_map[mid].append(ind)
               # calculating new centroids
               for ind in range(len(cent_map)):
                   for cd in range(len(cent_map[ind])):
                        index = cent_map[ind][cd]
                       sums_x1[ind]+=iris_df_new['x1'].iloc[index]
sums_x2[ind]+=iris_df_new['x2'].iloc[index]
               for ind in range(len(cent_map)):
                   length = len(cent_map[ind])
                   #print(length)
                   if(length>0):
                       sums_x1[ind]=sums_x1[ind]/float(length)
                       sums_x2[ind]=sums_x2[ind]/float(length)
               centroids x1=sums x1
              centroids x2=sums x2
               # returning new centroids, mapping of points to corresponding centroids
               return centroids_x1,centroids_x2,cent_map
```

```
In [14]: # 3. K=1 to 5 and 50 iterations for each
    maps_of_points=[]
    final_centroids=[]
    initial_centroids=[]
    for k_value in range(1,6):
        centroids_x1,centroids_x2=initialize_kmeans_plus_plus(k_value)
        first_cent=[]
        first_cent.append(centroids_x1)
        first_cent.append(centroids_x2)
        initial_centroids.append(first_cent)
        final_map=[]
        for turn in range(50):
            centroids_x1,centroids_x2,cent_map = kmeans_plus_plus(k_value,centroids_x1,centroids_x2)
            final_map=cent_map
        maps_of_points.append(final_map)
        centroids =[]
        centroids_append(centroids_x2)
        final_centroids_append(centroids_x2)
        final_centroids.append(centroids)
```

```
In [15]: for k in range(len(final_centroids)):
              print("centroids for k_value = ",k+1)
print("Initial Centroids")
              for t in range(len(initial_centroids[k][0])):
                  print(initial_centroids[k][0][t],initial_centroids[k][1][t])
              print("\nFinal Centroids")
              for t in range(len(final_centroids[k][0])):
                  print(final_centroids[k][0][t],final_centroids[k][1][t])
              print("\n\n*****\n\n")
          centroids for k_value = 1
          Initial Centroids
          1.437499999999998 6.99999999999999
          Final Centroids
          1.9551444308694617 4.367166423691872
          centroids for k_value = 2
          Initial Centroids
          2.0263157894736845 3.0454545454545454
          1.2682926829268295 15.0
          Final Centroids
          1.9777366323385024 3.920104640236229
          1.4936180294304975 13.5
          *****
          centroids for k_value = 3
          Initial Centroids
          2.148148148148148 4.1
          1.2682926829268295 15.0
          1.411764705882353 9.49999999999998
          Final Centroids
          2.0928950450949397 3.1673129041992576
          1.5220456333595596 14.8
1.4788141804347774 7.3678160919540225
          centroids for k_value = 4
          Initial Centroids
          2.1724137931034484 3.111111111111111107 1.2682926829268295 15.0
          1.411764705882353 9.49999999999998 1.5714285714285714 6.5
          Final Centroids
          2.1066310718427834 3.1351604990097712
          1.5220456333595596 14.8
          1.4838758832268053 8.625
          1.4623690090317294 6.724637681159421
```

Final Centroids 1.5220456333595596 14.8

centroids for k_value = 5
Initial Centroids
1.5806451612903227 15.0
2.0714285714285716 2.125
1.5882352941176472 8.5
1.27777777777777 5.0
1.433333333333333 11.0

1.4225490196078432 10.25

2.172285144648706 2.984749635537806 1.48232743051511 7.211538461538462 1.5910182803613162 4.3882352941176475

```
In [16]: # calculating inertia (sum of square of distance of points from their cluster centroids)
         for u in range(len(maps_of_points)):
             fmap=maps_of_points[u]
centroids = final_centroids[u]
              sum dist=0
              for t in range(len(fmap)):
                 pts = fmap[t]
                  mn_dist=0
                  for y in range(len(pts)):
                      dist = get_distance(centroids[0][t],centroids[1][t],
                                                iris\_df\_new['x1'].iloc[pts[y]], iris\_df\_new['x2'].iloc[pts[y]])
                      mn dist+=dist
                  sum dist+=mn dist
              acc.append(sum_dist)
             print("mean =", sum_dist, "for K = ",u+1)
         mean = 1071.228686156884 for K = 1
         mean = 457.22352154601197  for K = 2
         mean = 89.17750273047949 for K = 3
         mean = 70.1996474420087 for K = 4
         mean = 42.03957396126128 for K = 5
In [17]: plt.figure(figsize=(10,4))
          index=range(1,6)
         sns.lineplot(x=index, y=acc)
         plt.xlabel('No of Clusters')
         plt.ylabel('Clustering Objective - Intertia')
Out[17]: Text(0, 0.5, 'Clustering Objective - Intertia')
            1000
          Clustering Objective - Intertia
             800
             600
             400
```

4) From K =1 to 3, the inertia (sum of square of distance of points from their cluster centroids) decreases highly, then the decrease rate is very less. So, I will choose K=3

5.0

4.5

3.5

4.0

200

10

1.5

1.411764705882353 9.49999999999999

2.0

```
In [18]: #chosen cluster = 3
          centroids_x13,centroids_x23=initialize_kmeans_plus_plus(3)
          print("initial chosen centroids with k=3 ")
          for u in range(len(centroids_x13)):
                  print(centroids_x13[u],centroids_x23[u])
          initial chosen centroids with k=3
          1.3783783783783783 3.75
1.5806451612903227 15.0
```

```
In [19]: final_map3=[]
                                 cent_map3=[]
                                 accuracv3=[1
                                 for u in range(3):
                                              cent map3.append([])
                                 num rows = iris df new.shape[0]
                                  # initial assignment of points to initial cluster centers
                                 for ind in range(num_rows):
                                                             x1=iris_df_new['x1'].iloc[ind]
                                                              x2=iris_df_new['x2'].iloc[ind]
                                                              min_dist = sys.maxsize
                                                             mid=-1
                                                              for cd in range(len(centroids x13)):
                                                                           y1=centroids_x13[cd]
                                                                            y2=centroids x23[cd]
                                                                            distance = get distance(x1,x2,y1,y2)
                                                                             if mid==-1:
                                                                                          mid=cd
                                                                                          min_dist = distance
                                                                                          if(distance<min_dist):</pre>
                                                                                                        mid=cd
                                                                                                        min dist = distance
                                                              cent_map3[mid].append(ind)
                                 for turn in range(50):
                                                #print("iteration = ",turn+1)
                                                sum dist=0
                                                for u in range(len(cent_map3)):
                                                             pts=cent_map3[u]
                                                              mn dist=0
                                                              for j in range(len(pts)):
                                                                           x1=iris_df_new['x1'].iloc[pts[j]]
x2=iris_df_new['x2'].iloc[pts[j]]
                                                                           dist = get_distance(centroids_x13[u],centroids_x23[u],x1,x2)
                                                                           mn_dist+=dist
                                                              sum_dist+=mn_dist
                                                #print(sum_dist, "\n\n")
                                                accuracy3.append(sum_dist)
                                                centroids_x13,centroids_x23,cent_map3 = kmeans_plus_plus(3,centroids_x13,centroids_x23)
                                                final_map3=cent_map3
                                 print("objective function (accuracy) changes for 50 iterations and K =3")
                                 print(accuracy3)
                                 objective function (accuracy) changes for 50 iterations and K =3
                                 047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.1775027304794, 89.1775027304794
                                 50273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.177502730479490,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.177502
                                 9.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.17750273047949,\ 89.1750273047949,\ 89.175027304949,\ 89.175027304949,\ 89.1750273049490,\ 89.17502730
                                  3047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949
                                 750273047949, 89.17750273047949, 89.17750273047949, 89.17750273047949]
In [20]: plt.figure(figsize=(10,4))
                                 index3=range(1,51)
                                 sns.lineplot(x=index3, y=accuracy3)
                                 plt.xlabel('No of Iterations')
                                 plt.ylabel('Clustering Objective - Inertia')
                                 plt.title('No of Clusters = 3')
Out[20]: Text(0.5, 1.0, 'No of Clusters = 3')
                                                                                                                                                    No of Clusters = 3
                                           275
                                          250
                                           225
                                    Clustering Objective - 125
                                          100
                                                                                                                                                            No of Iterations
In [21]: print(final map3)
                                 print("Final Cluster Centers for K=3")
                                  for u in range(len(centroids_x13)):
                                              print(centroids_x13[u],centroids_x23[u])
                                 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 1
                                 06,\ 107,\ 108,\ 109,\ 110,\ 111,\ 112,\ 113,\ 114,\ 115,\ 116,\ 117,\ 118,\ 119,\ 120,\ 121,\ 122,\ 123,\ 124,\ 125,\ 126,\ 127,\ 128,\ 129,\ 130,\ 131,\ 132,\ 133,\ 134,\ 138,\ 134,\ 138,\ 134,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\ 138,\
                                 5, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149], [9, 12, 32, 34, 37], [0, 1, 2, 3, 4, 7, 8, 10, 11, 13, 14, 18, 20, 24, 2 5, 27, 28, 29, 30, 33, 35, 36, 38, 39, 42, 46, 47, 48, 49]]
                                 Final Cluster Centers for K=3
                                 2.0928950450949397 3.1673129041992576
                                 1.5220456333595596 14.8
```

1.4788141804347774 7.3678160919540225

```
In [22]: x3=[]
y3=[]
for t in range(len(final_map3)):
    pts = fmap[t]
    lx=[]
    ly=[]
    for y in range(len(pts)):
        lx.append(iris_df_new['x1'].iloc[pts[y]])
        ly.append(iris_df_new['x2'].iloc[pts[y]])
    x3.append(lx)
    y3.append(ly)
```

```
In [23]: # centroids are in + sign

plt.figure(figsize=(10,4))
for u in range(len(x3)):
    plt.scatter(x3[u],y3[u])

plt.scatter(centroids_x13,centroids_x23,marker='+',s=400)
plt.title('Data Colored by Assignment with Clusters=3')
plt.show()
```

