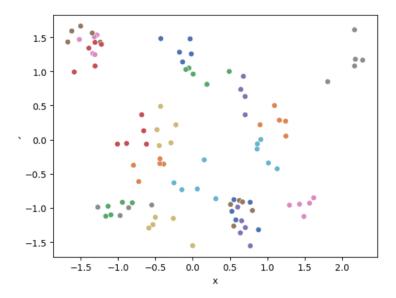
<u>Aim:</u> Write a program to cluster a set of points using K-means. Consider, K=3, clusters. Consider Euclidean distance as the distance measure. Randomly initialize a cluster mean as one of the data points. Iterate for 10 iterations. After iterations are over, print the final cluster means for each of the clusters. Use the ground truth cluster label present in the data set to compute and print the Jacquard distance of the obtained clusters with the ground truth clusters for each of the three clusters.

```
[3]: from sklearn.cluster import KMeans
     KMeans = KMeans(n_clusters=2, n_init=10)
     KMeans.fit(X)
[3]: 🔻
                  KMeans
     KMeans(n_clusters=2, n_init=10)
[4]: KMeans.cluster_centers_
[4]: array([[-0.95128646, -0.89978266],
            [ 1.99434749, 2.03518682]])
[5]: plt.scatter(X[:,0], X[:,1], s = 50, c = 'b')
     plt.scatter(-0.98362533, -1.09744804 , s=200, c='g', marker='s')
     plt.scatter(2.06708619, 1.99208978, s=200, c='r', marker='s')
     plt.show()
         3
         2
         1
         0
       ^{-1}
       -2
       import numpy as np
[6]:
       import matplotlib.pyplot as plt
       from sklearn.preprocessing import StandardScaler
       from numpy.random import uniform
       from sklearn.datasets import make_blobs
       import seaborn as sns
       import random
[7]: def euclidean (point, data):
           return np.sqrt(np.sum((point - data)**2, axis=1))
```

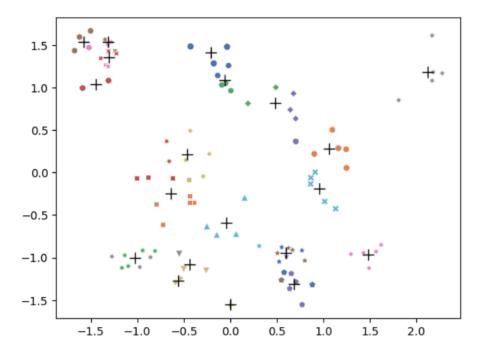
```
[8]: class KMeans:
         def __init__(self, n_clusters=8, max_iter=300):
             # Initialization
             self.n_clusters = n_clusters
             self.max_iter = max_iter
         def fit(self, X_train):
             self.centroids = [random.choice(X_train)]
             for _ in range(self.n_clusters - 1):
                  # Calculate distances from points to the centroids
                 dists = np.sum([euclidean(centroid, X_train) for centroid in self.centroids], axis=0)
                 # Normalize the distances
                 dists /= np.sum(dists)
                  # Choose remaining points based on their distances
                  new_centroid_idx = np.random.choice(range(len(X_train)), size=1, p=dists)
                  self.centroids += [X_train[new_centroid_idx[0]]]
             # Iterative adjustment of centroids until convergence or max iterations
             iteration = 0
             prev_centroids = None
             while np.not_equal(self.centroids, prev_centroids).any() and iteration < self.max_iter:</pre>
                  # Sort each datapoint, assigning to the nearest centroid
                  sorted_points = [[] for _ in range(self.n_clusters)]
                 for x in X_train:
                     dists = euclidean(x, self.centroids)
                     centroid_idx = np.argmin(dists)
                     sorted_points[centroid_idx].append(x)
                 # Push current centroids to previous, reassign centroids as means
                  prev centroids = self.centroids
                  self.centroids = [np.mean(cluster, axis=0) if cluster else self.centroids[i] for i, cluster in enumerate(sorted points)]
                  iteration += 1
```

```
def evaluate(self, X):
    centroids = []
    centroid_idxs = []
    for x in X:
        dists = euclidean(x, self.centroids)
        centroid_idx = np.argmin(dists)
        centroids.append(self.centroids[centroid_idx])
        centroid_idxs.append(centroid_idx)
    return centroids, centroid_idxs
```

```
[9]: import matplotlib.pyplot as plt
     import seaborn as sns
     from sklearn.datasets import make_blobs
     from sklearn.preprocessing import StandardScaler
     # Create a dataset with 20 clusters
     centers = 20
     X_train, true_labels = make_blobs(n_samples=100, centers=centers, random_state=42)
     # Standardize the data
     X_train = StandardScaler().fit_transform(X_train)
     # Scatter plot
     sns.scatterplot(x=[X[0] for X in X_train],
                     y=[X[1] for X in X_train],
                     hue=true_labels,
                     palette="deep",
                     legend=None
                    )
     plt.xlabel("x")
     plt.ylabel("y")
     plt.show()
```



```
[10]: #Fit centroids to dataset
       kmeans = KMeans(n clusters=centers)
      kmeans.fit(X_train)
[11]: #View results
      class_centers, classification = kmeans.evaluate(X_train)
      sns.scatterplot(x=[X[0] for X in X train],
                       y=[X[1] for X in X_train],
                       hue=true_labels,
                       style=classification,
                       palette="deep",
                       legend=None
      plt.plot([x for x, _ in kmeans.centroids],
               [y for _, y in kmeans.centroids],
                'k+',
               markersize=10,
      plt.show()
```



[12]: #Import Libraries
import numpy as np # Linear algebra
import pandas as pd # data processing, CSV file 1/0 (e.g. pd.read_csv)
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import StandardScaler
df = pd.read_csv('breast-cancer.csv')
df.head ()

[12]:		id	diagnosis	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	 radius_worst
	0	842302	М	17.99	10.38	122.80	1001.0	0.11840	0.27760	0.3001	0.14710	 25.38
	1	842517	М	20.57	17.77	132.90	1326.0	0.08474	0.07864	0.0869	0.07017	 24.99
	2 8	34300903	М	19.69	21.25	130.00	1203.0	0.10960	0.15990	0.1974	0.12790	 23.57
	3 8	34348301	М	11.42	20.38	77.58	386.1	0.14250	0.28390	0.2414	0.10520	 14.91
	4 8	34358402	М	20.29	14.34	135.10	1297.0	0.10030	0.13280	0.1980	0.10430	 22.54

5 rows × 32 columns

[13]: df.describe()

	id	radius_mean	texture_mean	perimeter_mean	area_mean	smoothness_mean	compactness_mean	concavity_mean	concave points_mean	symmetry_mean	
count	5.690000e+02	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	569.000000	ŀ
mean	3.037183e+07	14.127292	19.289649	91.969033	654.889104	0.096360	0.104341	0.088799	0.048919	0.181162	
std	1.250206e+08	3.524049	4.301036	24.298981	351.914129	0.014064	0.052813	0.079720	0.038803	0.027414	
min	8.670000e+03	6.981000	9.710000	43.790000	143.500000	0.052630	0.019380	0.000000	0.000000	0.106000	
25%	8.692180e+05	11.700000	16.170000	75.170000	420.300000	0.086370	0.064920	0.029560	0.020310	0.161900	
50%	9.060240e+05	13.370000	18.840000	86.240000	551.100000	0.095870	0.092630	0.061540	0.033500	0.179200	
75%	8.813129e+06	15.780000	21.800000	104.100000	782.700000	0.105300	0.130400	0.130700	0.074000	0.195700	
max	9.113205e+08	28.110000	39.280000	188.500000	2501.000000	0.163400	0.345400	0.426800	0.201200	0.304000	

8 rows × 31 columns

```
[14]: df['diagnosis'] = df['diagnosis'].map({'B': 0, 'M': 1})
[15]: X = df.drop('diagnosis', axis=1)
       y = df['diagnosis']
[16]: X.head(5)
[16]:
                                                                                                                                       concave
                id radius_mean texture_mean perimeter_mean area_mean smoothness_mean compactness_mean concavity_mean
                                                                                                                                                symmetry_mean ... radius_
                                                                                                                                   points_mean
           842302
                           17.99
                                         10.38
                                                         122.80
                                                                     1001.0
                                                                                      0.11840
                                                                                                          0.27760
                                                                                                                           0.3001
                                                                                                                                        0.14710
                                                                                                                                                          0.2419 ...
            842517
                           20.57
                                          17.77
                                                         132.90
                                                                     1326.0
                                                                                      0.08474
                                                                                                          0.07864
                                                                                                                           0.0869
                                                                                                                                        0.07017
                                                                                                                                                          0.1812
       2 84300903
                           19.69
                                         21.25
                                                         130.00
                                                                     1203.0
                                                                                      0.10960
                                                                                                          0.15990
                                                                                                                           0.1974
                                                                                                                                        0.12790
                                                                                                                                                          0.2069 ...
       3 84348301
                                                                                      0.14250
                                                                                                          0.28390
                                                                                                                           0.2414
                                                                                                                                        0.10520
                                                                                                                                                          0.2597
                           11.42
                                         20.38
                                                          77.58
                                                                      386.1
       4 84358402
                           20.29
                                         14.34
                                                         135.10
                                                                     1297.0
                                                                                      0.10030
                                                                                                          0.13280
                                                                                                                           0.1980
                                                                                                                                        0.10430
                                                                                                                                                          0.1809 ...
      5 rows × 31 columns
            y.head(5)
  [17]:
 [17]:
            0
                      1
             1
                      1
             2
                      1
             3
                      1
             4
                      1
             Name: diagnosis, dtype: int64
 [18]: import seaborn as sns
             plt.figure(figsize=(10,16))
             dataplot= sns.heatmap(df.corr(), annot=True)
             plt.show()
                                                                                                                                                 1.0
                                     id - 1).04076.0.07.39.39.5549.05564.402.29534.40754.0509.783.46597.901.782.68.276508.10.401.0062.393.5440
                             diagnosis -0.04 10.70.40,74.70.36.60.0.70.380 03.7008 36.3506 29.25.40 0655 770.40,76.70.40.59.60,70.40.3
                          radius_mean - 07/5731 ).32 10.99.10.50.60.89.16.30
                                                                           6B09.50.7<mark>0.2</mark>220.19.380-0.0<sup>4</sup>,9<mark>70.39.97,94</mark>.12.40.50.74.0.60
                         texture_mean -0.10.40.30 1 0.30.3020 032 40.30.2000 10 0620.39.28.0.6006.69.14.0.60090.043 0.90.30.000 000.00.30.10.1
                      perimeter_mean -07/741 ).31 10.9).20.50.70.8).16.2689.06.50.7-0.0.26.20.40.0020).970.3).97.9-0.16.46.50.70.0905
                                                                                                                                                 0.8
                                                  3)<mark>.991</mark>).18).5,60,8).1<mark>5,2</mark>).70,0 <mark>6,73).5).10/20,20,37</mark>,0020<mark>).9</mark>)
                                                                                                          29.96.90.10.39.50.70.0.40
                    smoothness_mean -.0036.10700220.1 1 1 0.66.50.56.50.0.066.0.2.26.30.30.20.26.30.20.20.20.03624.2 0.80.40.4 0.50.3 9.5
                   compactness_mean -5e-050.50.20.50.50.50.6(10.80.83).0.570.6.04656.4614.70.50.60.20.50.50.50.50.50.80.80.80.80.80.50.
                                            ). D. 6<mark>1</mark>9. 3). 70, 69. 5<mark>0, 88 10. 97</mark>0. 10. 34. 11<mark>30 1</mark>766 6. 11<mark>20 1</mark>967. 69. 68. 18. 45. 6 10. 10, 70, 68. 40, 75, 88. 80, 41. 5
                       concavity_mean →.05
                 concave points_mean -04,476.8),20,85.8),50,85.921 ),45.1 0,0,02170,6302849.44 (20,952),80,20,85.0,45.60,75.9),36.3
                                                                                                                                                - 0.6
                      68.507.368.107.48<mark>.1.</mark>00.001.106.049.049.56.405.349.305.649.2050-61201.249.50.46.305.108.34).77
              fractal_dimension_mean -.05.B-D3B10-D626.20
                                          14.507.68.208.60.7 (0.30.50.63).700.8000 1 ().2 ().907.9 ().106.36.30.50.204.2 ().7 ().1 ().702.7 ().104.29.308.509.50
                            perimeter_se -).14.56.60,28.60.7 0.30.56.60.7 0.30.0 0.9).21 10.90.16.40.36.56.20.2 40.70.20.70.10.30.40.56.00.0
                                                                                                                                                 0.4
                               area_se -0.10550.70.20.70.80.26.40.60.69.20.00.90.11).941 017526.20.40.10.10.70.70.70.80.10.26.39.5000.01
```

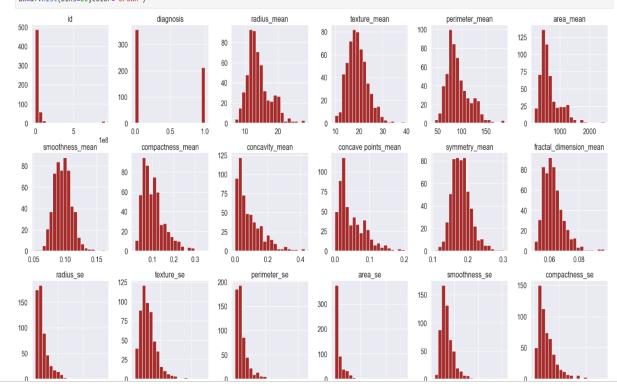
smoothness se - 09.70-072/2006/20.10736.1409.9781.9.4.16.40.1507 1

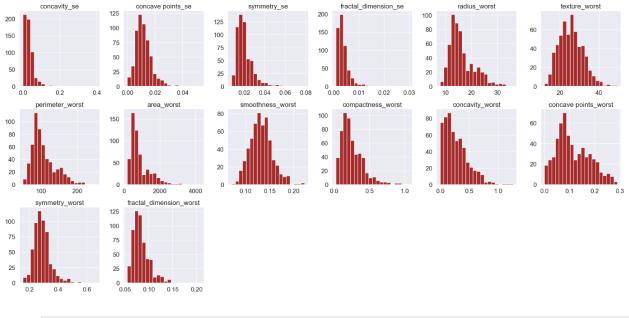
[19]: df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 569 entries, 0 to 568
Data columns (total 32 columns):

#	Column	Non-Null Count	Dtype
0	id	569 non-null	int64
1	diagnosis	569 non-null	int64
2	radius_mean	569 non-null	float64
3	texture_mean	569 non-null	float64
4	perimeter_mean	569 non-null	float64
5	area_mean	569 non-null	float64
6	smoothness_mean	569 non-null	float64
7	compactness_mean	569 non-null	float64
8	concavity_mean	569 non-null	float64
9	concave points_mean	569 non-null	float64
10	symmetry_mean	569 non-null	float64
11	fractal_dimension_mean	569 non-null	float64
12	radius_se	569 non-null	float64
13	texture_se	569 non-null	float64
14	perimeter_se	569 non-null	float64
15	area_se	569 non-null	float64
16	smoothness_se	569 non-null	float64
17	compactness_se	569 non-null	float64
18	concavity_se	569 non-null	float64
19	concave points_se	569 non-null	float64
20	symmetry_se	569 non-null	float64
21	fractal_dimension_se	569 non-null	float64
22	radius_worst	569 non-null	float64
23	texture_worst	569 non-null	float64
24	perimeter_worst	569 non-null	float64
25	area_worst	569 non-null	float64
26	smoothness_worst	569 non-null	float64
27	compactness_worst	569 non-null	float64
28	concavity_worst	569 non-null	float64
29	concave points_worst	569 non-null	float64
30	examinal revenues of	56911	Clualey

[20]: #Draw Hostogram For Each Feature sns.set(style='darkgrid', font_scale=1.3, rc={'figure.figsize':(25,25)}) ax=df.hist(bins=20,color='brown')





```
[22]: plt.figure(figsize=(12,10))
  mask=np.tril(df.corr())
  sns.heatmap(df.corr(), cmap="coolwarm", annot=True, fmt='.1g', square=True)
```

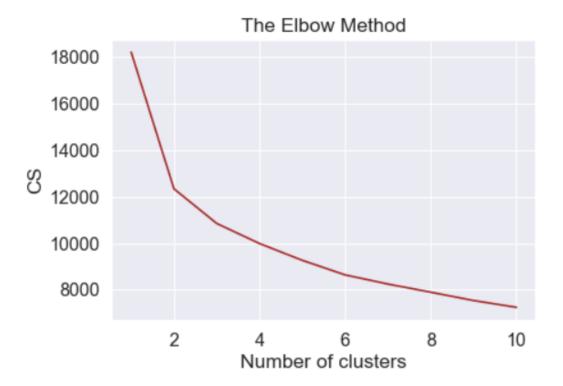
[23]: sc= StandardScaler()

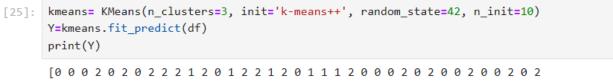
```
df=sc.fit_transform(df)

from sklearn.cluster import KMeans
import matplotlib.pyplot as plt

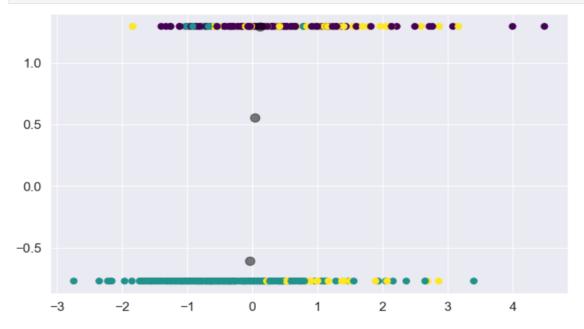
# Assuming df is your dataset
cs = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10, random_state=42)
    kmeans.fit(df)
    cs.append(kmeans.inertia_)

# Plotting outside the loop
plt.figure(figsize=(6, 4), dpi=80)
plt.plot(range(1, 11), cs, color='brown')
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('CS')
plt.show()
```





```
plt.figure(figsize=(10,6), dpi=80)
plt.scatter(df[:, 10], df[:, 1], c=Y, s=50, cmap='viridis')
centers = kmeans.cluster_centers_
plt.scatter(centers[:,0], centers[:,1], c='black', s=100, alpha=0.5);
```



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