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· . '	DEC Lab Assignment 8
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	Problem Statement: Consider a suitable dataset and
• ,	apply different clustering techniques.
	in a cini
	Objectives: To build the cluster using different clus-
	-ter techniques et ale reclinic mon
. r	· To implement the k-means and Hierarchical clustering
, .	· To check the performance of clustering algorithm
	Comment of the figure of the ship of the s
0 0	Conclusion :
	In conclusion the clustering is a powerful technique
	in machine learning that helps uncover hidden
• 🗘	patterns and structures within datasets Demonstr-
Trans.	-ated their implementation using Python programming language and the sci-kit learn library.
	language and the sci-kit learn library.
	0:0
	FAQ'S AND PROPERTY OF ASSETT OF
	The state of the s
(1)	Differentiate bet unsupervised and supervised
	learning.
-	In supervised learning the algo is trained on a
	labeled dataset, where the Input data: is paired
	with corresponding output labels. The goal is to
	learn a mapping from inputs to outputs and the model makes predictions based on this learned
	model makes predictions based on this learned
	mapping

Page	No.		
Date			

In unsupervised learning the algorithm is given unlabelled data and must find patterns or relationships within the data without explicit guidance. The goal is often to discover the under lying structure or distribution of the data.

- 92) What is the purpose of using cluster analysis in data science?
- -) Cluster analysis in data science is used to group similar data points together on their inherent characteristics. The purpose is to uncover patterns, identify natural groupings and gain insights into the structure of the data, facilitating tasks like segmentation, aromaly detection and pattern recognition:
- 3) What are the different types of clustering algorithms available?

 There are several types of clustering algorithms, including

 - 1) K-means clustering
 2) Hierarchical clustering
 3) DBSCAN (Density based Spatial Clustering of Applications with noise)
 4) Gaussian Mixture: Models

 - 5) Agglomerative Clustering

 6) Affinity propagation

 7) Mean shift clustering

 8) Self Organizing Maps (SOM:)

```
In [1]:
         import pandas as pd
         import numpy as np
         housing = pd.read_csv("HousingData.csv")
In [2]:
         housing.columns
In [3]:
        Index(['CRIM', 'ZN', 'INDUS', 'CHAS', 'NOX', 'RM', 'AGE', 'DIS', 'RAD', 'TAX',
Out[3]:
                'PTRATIO', 'B', 'LSTAT', 'MEDV'],
               dtype='object')
         housing.dropna(inplace=True)
In [4]:
In [5]:
         housing.isnull().sum()
        CRIM .
                    0
Out[5]:
         ΖN
                    0
        INDUS
                    0
        CHAS
                    0
        NOX
                    0
        RM
                    0
        AGE
                    0
        DIS
        RAD
                    0
        TAX
                    0
        PTRATIO
                    0
        В
                    0
        LSTAT
                    0
        MEDV
                    0
        dtype: int64
In [6]: import seaborn as sns
         import matplotlib.pyplot as plt
         plt.figure(figsize=(10, 10))
In [7]:
         sns.heatmap(housing.corr(), annot=True , linewidths=1);
```



```
In [8]: from sklearn.cluster import KMeans
k = 3
In [9]: data_sample= housing.loc[:,['CRIM','MEDV']]
```

```
In [10]: model = KMeans(n_clusters=3)
    model.fit(data_sample)
    labels = model.predict(data_sample)
```

C:\Users\91902\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:1416: FutureWa rning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the v alue of `n_init` explicitly to suppress the warning

super()._check_params_vs_input(X, default_n_init=10)

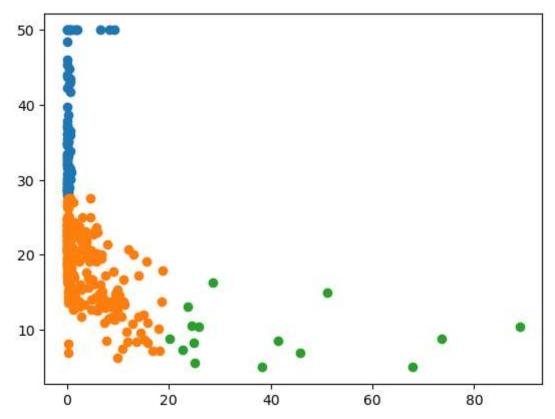
C:\Users\91902\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:1440: UserWarn ing: KMeans is known to have a memory leak on Windows with MKL, when there are less chunks than available threads. You can avoid it by setting the environment variable OMP_NUM_THREADS=2.

warnings.warn(

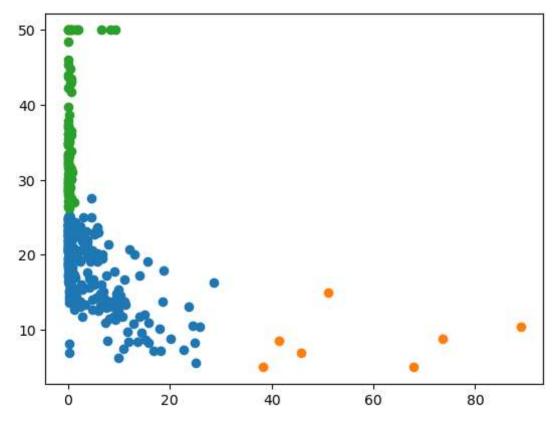
```
In [11]: data_sample['Label_data']=labels
```

```
In [12]:
          data_sample
Out[12]:
                CRIM MEDV Label_data
            0.00632
                         24.0
                                      1
            1 0.02731
                         21.6
                                      1
            2 0.02729
                                      0
                         34.7
            3 0.03237
                         33.4
                                     0
            5 0.02985
                         28.7
                                     0
                          •••
          499 0.17783
                         17.5
                                      1
          500 0.22438
                         16.8
          502 0.04527
                         20.6
                                      1
          503 0.06076
                         23.9
          504 0.10959
                         22.0
                                      1
         394 rows × 3 columns
In [13]:
          clusters= {}
          for i in range(k):
            clusters[i] = []
          for i in range(k):
            clusters[i].append(data_sample[data_sample['Label_data'] == i])
In [14]: print(clusters[1][0]['MEDV'])
          0
                 24.0
          1
                 21.6
          7
                 27.1
          8
                 16.5
          10
                 15.0
                 . . .
          499
                 17.5
          500
                 16.8
          502
                 20.6
                 23.9
          503
          504
                 22.0
          Name: MEDV, Length: 298, dtype: float64
In [15]: for i in range(k):
            plt.scatter(clusters[i][0]['CRIM'],clusters[i][0]['MEDV'])
```

plt.show()



```
from sklearn.cluster import AgglomerativeClustering
In [16]:
         data_sample2 = data_sample
         # Create Hierarchical clustering object
         hierarchical = AgglomerativeClustering(n_clusters=3)
         # Fit the model
         hierarchical.fit(data_sample2)
         # Get cluster labels
         labels = hierarchical.labels_
In [17]: data_sample2['Label_data']=labels
         clusters= {}
         for i in range(k):
           clusters[i] = []
         for i in range(k):
           clusters[i].append(data_sample2[data_sample2['Label_data'] == i])
In [18]:
        for i in range(k):
           plt.scatter(clusters[i][0]['CRIM'],clusters[i][0]['MEDV'])
         plt.show()
```



In []: