Assignment 2. Date of Submission: Date of Completion 27.8.2020 Title: Visualize the clusters using suitable toll Problem Statement: - Consider a suitable Sataset. For clustering of data instances in different groups apply different dustering techniques. Visualize the clusters using suitable took Learning Objective: Understand dustering and different algorithms used for clustering clara Joanning Outcomes - Students will be able to understand different clustering methods and interement them. Theor. Software / Hardware

suguirements: - Python, Murupy, sklearn (packages) Theory :-Clustering Algorithms: 1. Chustoring is a machine Learning technique that involves the grouping of points

2. It is a unsupervised learning algorithm. Types of the chustering algorithms: 
2) Kneans clustering

3) Hierarchical clustering 3) Mean shift chisterings 2) Fuzzy C dustering 5) spectral Custering etc. Clustering Methods: r Density Bosed 2. Herarchical Based 3. Partitioning based 4. Grid - based K-Mains algorithm: · simplest unsupervised clustering algorithm. 2. It partions nothervation into kither clusters where each observation belongs to clusters nearest mean serving as a prototype cluster. Applications: -Biology, Earthquake studies etc

Hierarchical clustering:

It builds a hierarchy of chusters. 2 types:

a) Agglometric: Bottom up" approach

b) Divisive: "Top down" approach.

fundts are unally presented in a dendogram. Linkage Criteria:

To compute the distance behoven two similar clusters many linkage critoria have developed. Patalet Used: K-means :- juis dataset Hierarchical :- Mall Customers. Conclusion: - Thus I have unclustood different elustering algorithms and implemented K-means & hilocordiical clustering algorithm.

#### **CODE:**

y = iris.data[:, :2]

## **Heriarical Clustering:**

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
dataset = pd.read csv('Mall Customers.csv')
X = dataset.iloc[:, [3, 4]].values
#using dendogram for finding optimal number of clusterings
import scipy.cluster.hierarchy as sch
dendrogram = sch.dendrogram(sch.linkage(X, method='ward'))
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Eucladian Distances')
plt.show()
#training the cluster Using HC
from sklearn.cluster import AgglomerativeClustering
hc = AgglomerativeClustering(n clusters = 3, affinity='euclidean', linkage='ward')
y hc = hc.fit predict(X)
plt.scatter(X[y | hc == 0, 0], X[y | hc == 0, 1], s = 100, c = 'red', label = 'Cluster 1')
plt.scatter(X[y | hc == 1, 0], X[y | hc == 1, 1], s = 100, c = 'blue', label = 'Cluster 2')
plt.scatter(X[y | hc == 2, 0], X[y | hc == 2, 1], s = 100, c = 'green', label = 'Cluster 3')
plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
KMeans Clustering:
# Importing the libraries
from sklearn import datasets
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
#Dataset
iris = datasets.load iris()
# Importing the dataset
x = iris.data[:, :2]
```

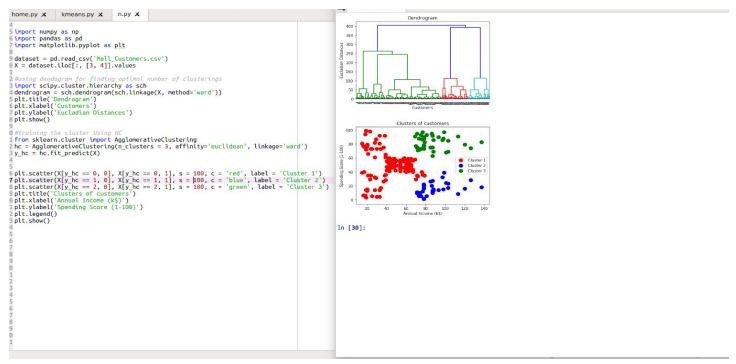
```
# Using the elbow method to find the optimal number of clusters from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=4)
y_kmeans = kmeans.fit_predict(x)

# print(y_kmeans)
kmeans.cluster_centers_

# Fitting K-Means to the dataset
plt.scatter(x[:,0], x[:,1], c=y_kmeans, cmap='gist_rainbow')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
```

# **OUTPUT:**

### **HIERARCHICAL CLUSTERING**



# **K-MEANS CLUSTERING:**

