Data Warehousing & Data Mining LAB - G2
EXPERIMENT 7

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- 2K18/SE/041

Aim:- Write a program to implement DBSCAN Clustering Algorithm in any Language.

Theory: -

Density-Based Clustering refers to unsupervised learning methods that identify distinctive groups/clusters in the data, based on the idea that a cluster in data space is a contiguous region of high point density, separated from other such clusters by contiguous regions of low point density.

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is a base algorithm for density-based clustering. It can discover clusters of different shapes and sizes from a large amount of data, which is containing noise and outliers.

Algorithmic steps for DBSCAN clustering:-

- The algorithm proceeds by arbitrarily picking up a point in the dataset (until all points have been visited).
- If there are at least 'minPoint' points within a radius of 'ε' to the point then we consider all these points to be part of the same cluster.
- The clusters are then expanded by recursively repeating the neighborhood calculation for each neighboring point.

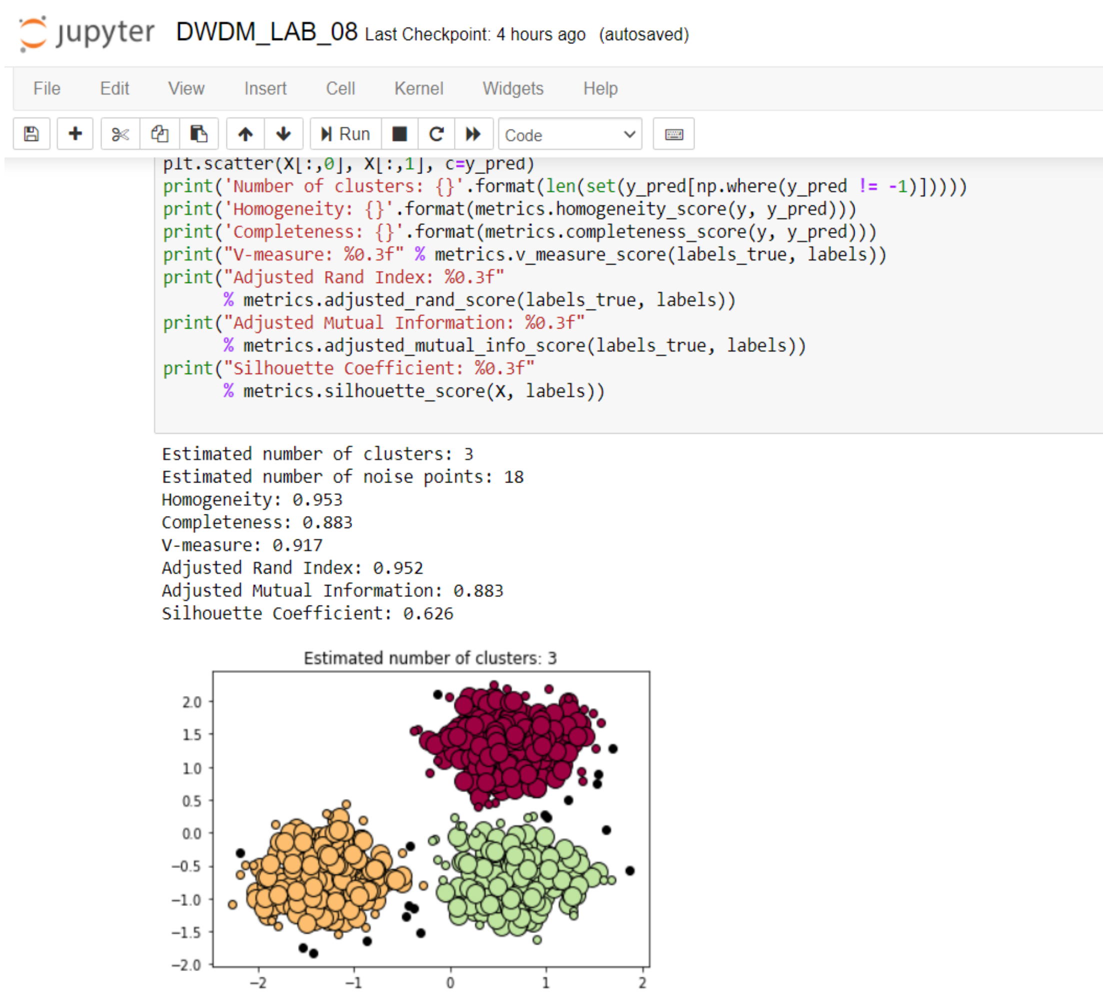
Source Code (in python):

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import metrics
from sklearn.datasets import make_circles
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import DBSCAN
from sklearn.datasets import make_blobs

# Generate sample data
centers = [[1, 1], [-1, -1], [1, -1]]
X, labels_true = make_blobs(n_samples=750, centers=centers, cluster_std=0.4,
                    random_state=0)
X = StandardScaler().fit_transform(X)
```

```
# Compute DBSCAN
db = DBSCAN(eps=0.3, min_samples=10).fit(X)
core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_

# Number of clusters in labels, ignoring noise if present.
n_clusters_ = len(set(labels)) - (1 if -1 in labels else 0)
n_noise_ = list(labels).count(-1)

print('Estimated number of clusters: %d' % n_clusters_)
print('Estimated number of noise points: %d' % n_noise_)
print("Homogeneity: %0.3f" % metrics.homogeneity_score(labels_true, labels))
print("Completeness: %0.3f" % metrics.completeness_score(labels_true, labels))
print("V-measure: %0.3f" % metrics.v_measure_score(labels_true, labels))
print("Adjusted Rand Index: %0.3f"
      % metrics.adjusted_rand_score(labels_true, labels))
print("Adjusted Mutual Information: %0.3f"
      % metrics.adjusted_mutual_info_score(labels_true, labels))
print("Silhouette Coefficient: %0.3f"
      % metrics.silhouette_score(X, labels))

# Plot result
import matplotlib.pyplot as plt
%matplotlib inline

# Black removed and is used for noise instead.
unique_labels = set(labels)
colors = [plt.cm.Spectral(each)
          for each in np.linspace(0, 1, len(unique_labels))]
for k, col in zip(unique_labels, colors):
    if k == -1:
        # Black used for noise.
        col = [0, 0, 0, 1]

    class_member_mask = (labels == k)

    xy = X[class_member_mask & core_samples_mask]
    plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col),
             markeredgecolor='k', markersize=14)

    xy = X[class_member_mask & ~core_samples_mask]
    plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=tuple(col),
             markeredgecolor='k', markersize=6)
plt.title('Estimated number of clusters: %d' % n_clusters_)
plt.show()
```

```
X, y = make_circles(n_samples=750, factor=0.3, noise=0.1)
X = StandardScaler().fit_transform(X)
y_pred = DBSCAN(eps=0.3, min_samples=10).fit_predict(X)

plt.scatter(X[:,0], X[:,1], c=y_pred)
print('Number of clusters: {}'.format(len(set(y_pred[np.where(y_pred != -1)]))))
print('Homogeneity: {}'.format(metrics.homogeneity_score(y, y_pred)))
print('Completeness: {}'.format(metrics.completeness_score(y, y_pred)))
print("V-measure: %0.3f" % metrics.v_measure_score(labels_true, labels))
print("Adjusted Rand Index: %0.3f"
    % metrics.adjusted_rand_score(labels_true, labels))
print("Adjusted Mutual Information: %0.3f"
    % metrics.adjusted_mutual_info_score(labels_true, labels))
print("Silhouette Coefficient: %0.3f"
    % metrics.silhouette_score(X, labels))
```

<u>OUTPUT-</u>



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```
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print('Number of clusters: {}'.format(len(set(y_pred[np.where(y_pred != -1)]))))
print('Homogeneity: {}'.format(metrics.homogeneity_score(y, y_pred)))
print('Completeness: {}'.format(metrics.completeness_score(y, y_pred)))
print("V-measure: %0.3f" % metrics.v_measure_score(labels_true, labels))
print("Adjusted Rand Index: %0.3f"
      % metrics.adjusted_rand_score(labels_true, labels))
print("Adjusted Mutual Information: %0.3f"
      % metrics.adjusted_mutual_info_score(labels_true, labels))
print("Silhouette Coefficient: %0.3f"
      % metrics.silhouette_score(X, labels))
```
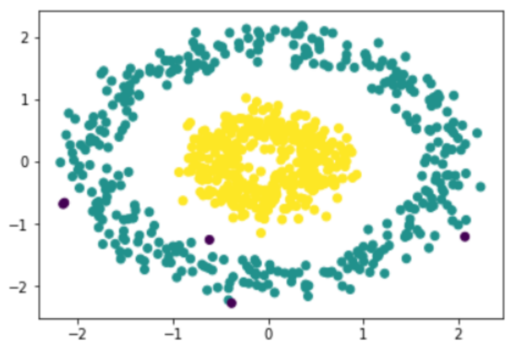

```
Number of clusters: 2
Homogeneity: 1.0
Completeness: 0.9514032557784387
V-measure: 0.917
Adjusted Rand Index: 0.952
Adjusted Mutual Information: 0.883
Silhouette Coefficient: -0.036
```



Findings and Learning:

- We have successfully implemented DBSCAN clustering in Python.
- DBSCAN algorithm is somewhat more arduous to tune contrasted to parametric clustering algorithms like K-Means.