DBScan Clustering Algorithm in Machine Learning

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The DBScan Clustering Algorithm is used to build clusters with high density separated by low density areas. The DBScan algorithm clusters can be of any shape while the KMeans algorithm assumes that the clusters are convex in shape. The basic principle of DBScan is that cluster are built of some core samples which belong to an area of high density. Each sample in the cluster are close to each other based on a distance measure (eps) and samples which are in vicinity of a core sample based on the distance but are not core sample themselves, these samples are called border points.

In this post we will generate a DBScan cluster using SKLearn DBSCAN module and will generate the following

1. List of noise/outlier points (not readily available in DBSCAN model output)
2. Index of noise/outlier points
3. View the clusters by cluster label and identify all the core points in the clusters
4. All the core points, count of core point, indexes of the core points
5. Estimated number of clusters
6. Silhouette Score of the Clustering
7. Silhouette Score of the Clustering by ignoring the noise points

Note: the noise points are those with label -1

DBScan Clustering Algorithm using SKLearn

```
import numpy as np
from sklearn.cluster import DBSCAN
from sklearn.metrics import silhouette_samples, silhouette_score
import matplotlib.pyplot as plt

epsilon = 3
min_samples = 2

X = [
[1,2],
[2,2],
[2,3],
[8,7],
[8,8],
[25,80]]

# plot
A = np.array(X)
plt.scatter(
   A[:, 0], A[:, 1],
   c='white', marker='o',
   edgecolor='red', s=50
)
print("The points prior to running DBScan Clustering")
plt.show()



db = DBSCAN(eps=epsilon, min_samples=min_samples).fit(X)

core_samples_mask = np.zeros_like(db.labels_, dtype=bool)
core_samples_mask[db.core_sample_indices_] = True
labels = db.labels_
no_clusters = len(np.unique(labels) )
no_noise = np.sum(np.array(labels) == -1, axis=0)

noise_index = []
for i in range(len(labels)):
    if labels[i] == -1:
        noise_index.append(i)
print("Noise/Outliers Index are at the following indexes ",noise_index)
for obj in noise_index:
    print("Noise/outlier point = ",X[obj])

print("-"*20)
unique_labels = set(labels)
print("unique labels are ",unique_labels)
print("-"*20)
for label in unique_labels:
    print("cluster points for ", label)
    cluster_indexes = []
    for i in range(len(labels)):
```

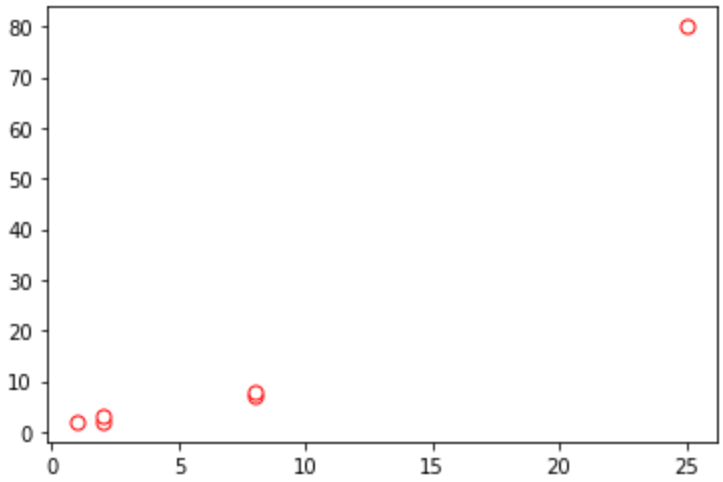
```
        if labels[i] == label:
            cluster_indexes.append(i)
    print("cluster_indexes = ",cluster_indexes)
    for obj in cluster_indexes:
        print("exact point = ",X[obj])
    print("-"*10)

silhouette_avg = silhouette_score(X, labels)

print("-"*20)
print("Labels ",labels)
print("Indices of Core Samples = ",db.core_sample_indices_)
print("Copy of each core sample found by training = ",db.components_)
print("Count of Core Samples ",len(db.core_sample_indices_))
print('Estimated no. of clusters: %d' % no_clusters)
print('Estimated no. of noise points: %d' % no_noise)
print("-"*20)
print("silhouette_avg = ",silhouette_avg)
print("Silhoutter Avg ignoring noise points ",(silhouette_avg *
len(labels))/(len(labels)-no_noise) )
```

Output

```
Noise/Outliers Index are at the following indexes  [5]
Noise/outlier point =  [25, 80]
--------------------
unique labels are  {0, 1, -1}
--------------------
cluster points for  0
cluster_indexes =  [0, 1, 2]
exact point =  [1, 2]
exact point =  [2, 2]
exact point =  [2, 3]
----------
cluster points for  1
cluster_indexes =  [3, 4]
exact point =  [8, 7]
exact point =  [8, 8]
----------
cluster points for  -1
cluster_indexes =  [5]
exact point =  [25, 80]
----------
--------------------
Labels  [ 0  0  0  1  1 -1]
Indices of Core Samples =  [0 1 2 3 4]
Copy of each core sample found by training =  [[1 2]
 [2 2]
 [2 3]
 [8 7]
 [8 8]]
Count of Core Samples  5
Estimated no. of clusters: 3
Estimated no. of noise points: 1
--------------------
silhouette_avg =  0.7227526416896678
Silhoutter Avg ignoring noise points  0.8673031700276013
```



DBScan SKLearn

References

https://scikit-learn.org/stable/modules/clustering.html#clustering