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DBSCAN Clustering in ML | Density based clustering

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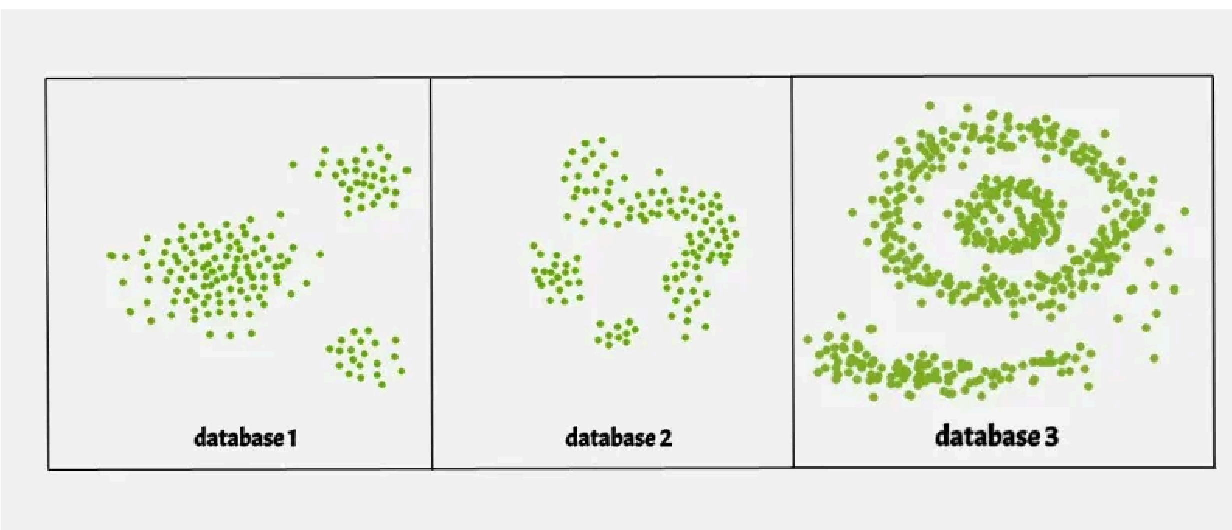
DBSCAN is a **density-based clustering algorithm** that **groups data points that are closely packed together and marks outliers as noise** based on their density in the feature space. It identifies clusters as dense regions in the data space, separated by areas of lower density.

Unlike K-Means or hierarchical clustering, which assume clusters are **compact and spherical**, DBSCAN excels in handling real-world data irregularities such as:

- **Arbitrary-Shaped Clusters**: Clusters can take any shape, not just circular or convex.
- **Noise and Outliers**: It effectively identifies and handles noise points without assigning them to any cluster.



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The figure above shows a data set with clustering algorithms: K-Means and Hierarchical **handling compact, spherical clusters with varying noise tolerance, while DBSCAN manages arbitrary-shaped clusters and excels in noise handling.**

Key Parameters in DBSCAN

- **1. eps**: This defines the radius of the neighborhood around a data point.

If the distance between two points is less than or equal to **eps**, they are considered neighbors. Choosing the right **eps** is crucial:

- If **eps** is too small, most points will be classified as noise.
- If **eps** is too large, clusters may merge, and the algorithm may fail to distinguish between them.

A common method to determine **eps** is by analyzing the **k-distance graph**.

- **2. MinPts**: This is the minimum number of points required within the **eps** radius to form a dense region.

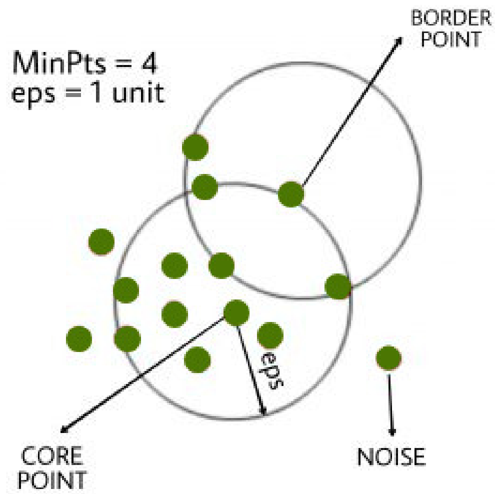
A general rule of thumb is to set MinPts >= D+1, where **D** is the number of dimensions in the dataset. For most cases, a minimum value of **MinPts = 3** is recommended.

How Does DBSCAN Work?

DBSCAN **works by categorizing data points into three types**:

1. core points, which have a sufficient number of neighbors within a specified radius (eplison)
2. border points, which are near core points but lack enough neighbors to be core points themselves
3. noise points, which do not belong to any cluster.

By iteratively expanding clusters from core points and connecting density-reachable points, DBSCAN forms clusters without relying on rigid assumptions about their shape or size.



Steps in the DBSCAN Algorithm

1. **Identify Core Points**: For each point in the dataset, count the number of points within its **eps** neighborhood. If the count meets or exceeds **MinPts**, mark the point as a **core point**.
2. **Form Clusters**: For each core point that is not already assigned to a cluster, create a new cluster. Recursively find all **density-connected points** (points within the **eps** radius of the core point) and add them to the cluster.
3. **Density Connectivity**: Two points, **a** and **b**, are **density-connected** if there exists a chain of points where each point is within the **eps** radius of the next, and at least one point in the chain is a core point. This chaining process ensures that all points in a cluster are connected through a series of dense regions.
4. **Label Noise Points**: After processing all points, any point that does not belong to a cluster is labeled as **noise**.

Pseudocode For DBSCAN Clustering Algorithm

```
DBSCAN(dataset, eps, MinPts){
# cluster index
C = 1
for each unvisited point p in dataset {
         mark p as visited
         # find neighbors
         Neighbors N = find the neighboring points of p
```

```
          if |N|>=MinPts:
              N = N U N'
              if p' is not a member of any cluster:
                  add p' to cluster C
 }
```

Implementation Of DBSCAN Algorithm In Python

Here, we'll use the Python library sklearn to compute DBSCAN. We'll also use the matplotlib.pyplot library for visualizing clusters.

Import Libraries

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

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```
from sklearn import datasets
```

Prepare dataset

We will create a dataset using sklearn for modeling. We make_blob for creating the dataset

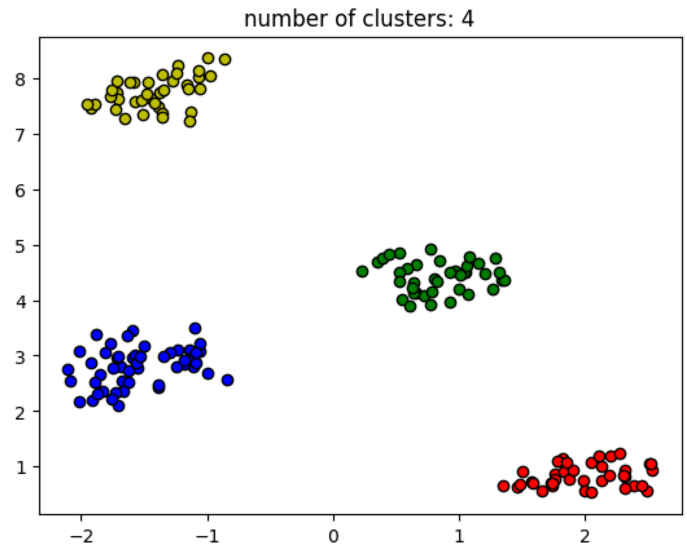
```
# Load data in X
X, y_true = make_blobs(n_samples=300, centers=4,
                       cluster_std=0.50, random_state=0)
```

Modeling The Data Using 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)

# Plot result

# Black removed and is used for noise instead.
unique_labels = set(labels)
colors = ['y', 'b', 'g', 'r']
print(colors)
for k, col in zip(unique_labels, colors):
    if k == -1:
        # Black used for noise.
```

```
        col = 'k'

    class_member_mask = (labels == k)

    xy = X[class_member_mask & core_samples_mask]
    plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=col,
             markeredgecolor='k',
             markersize=6)

    xy = X[class_member_mask & ~core_samples_mask]
    plt.plot(xy[:, 0], xy[:, 1], 'o', markerfacecolor=col,
             markeredgecolor='k',
             markersize=6)

plt.title('number of clusters: %d' % n_clusters_)
plt.show()
```

Output:



Cluster of dataset

Evaluation Metrics For DBSCAN Algorithm In Machine Learning

We will use the **Silhouette score** and **Adjusted rand score** for evaluating clustering algorithms.

- Silhouette's score is in the range of -1 to 1. A score near 1 denotes the best meaning that the data point i is very compact within the cluster to which it belongs and far away from the other clusters. The worst value is -1. Values near 0 denote overlapping clusters.
- Absolute Rand Score is in the range of 0 to 1. More than 0.9 denotes excellent cluster recovery, and above 0.8 is a good recovery. Less than 0.5 is considered to be poor recovery.

```
# evaluation metrics
sc = metrics.silhouette_score(X, labels)
print("Silhouette Coefficient:%0.2f" % sc)
ari = adjusted_rand_score(y_true, labels)
print("Adjusted Rand Index: %0.2f" % ari)
```

Output:

```
Coefficient:0.13
Adjusted Rand Index: 0.31:
```

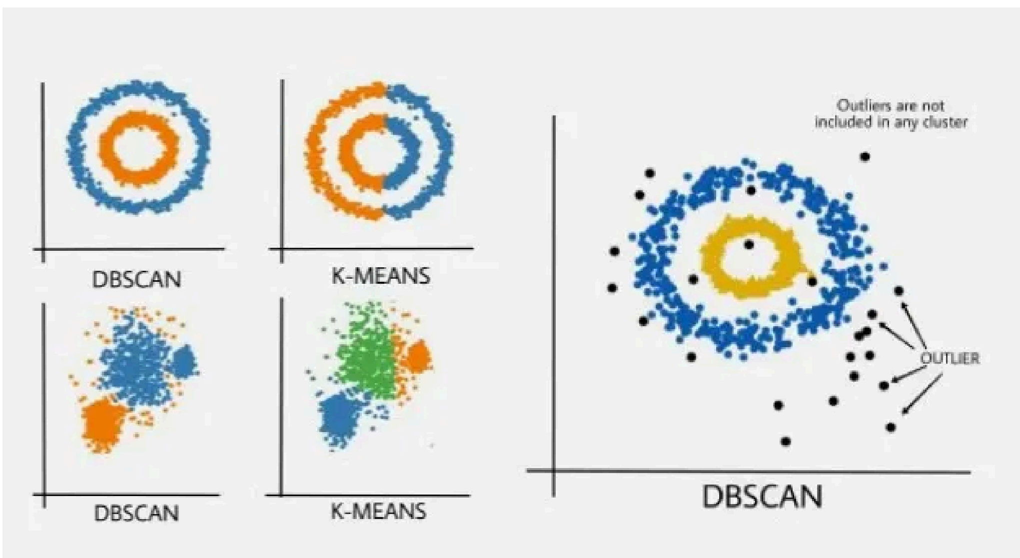
Black points represent outliers. By changing the *eps* and the *MinPts*, we can change the cluster configuration. **Now the question that should be raised is —**

When Should We Use DBSCAN Over K-Means In Clustering Analysis?

DBSCAN(Density-Based Spatial Clustering of Applications with Noise) and K-Means are both clustering algorithms that group together data that have the same characteristic. However, They work on different principles and are suitable for different types of data. We prefer to use DBSCAN **when the data is not spherical in shape or the number of classes is not known beforehand.**

DBSCAN	K-Means
In DBSCAN we need not specify the number of clusters.	K-Means is very sensitive to the number of clusters so it need to specified
Clusters formed in DBSCAN can be of any arbitrary shape.	Clusters formed in K-Means are spherical or convex in shape

DBSCAN	K-Means
DBSCAN can work well with datasets having noise and outliers	K-Means does not work well with outliers data. Outliers can skew the clusters in K-Means to a very large extent.
In DBSCAN two parameters are required for training the Model	In K-Means only one parameter is required is for training the model



As it can identify clusters of arbitrary shapes **and effectively handle noise**. K-Means, on the other hand, is better suited for data with well-defined, spherical clusters and is less effective with noise or complex cluster structures. More differences between these two algorithms can be found here

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