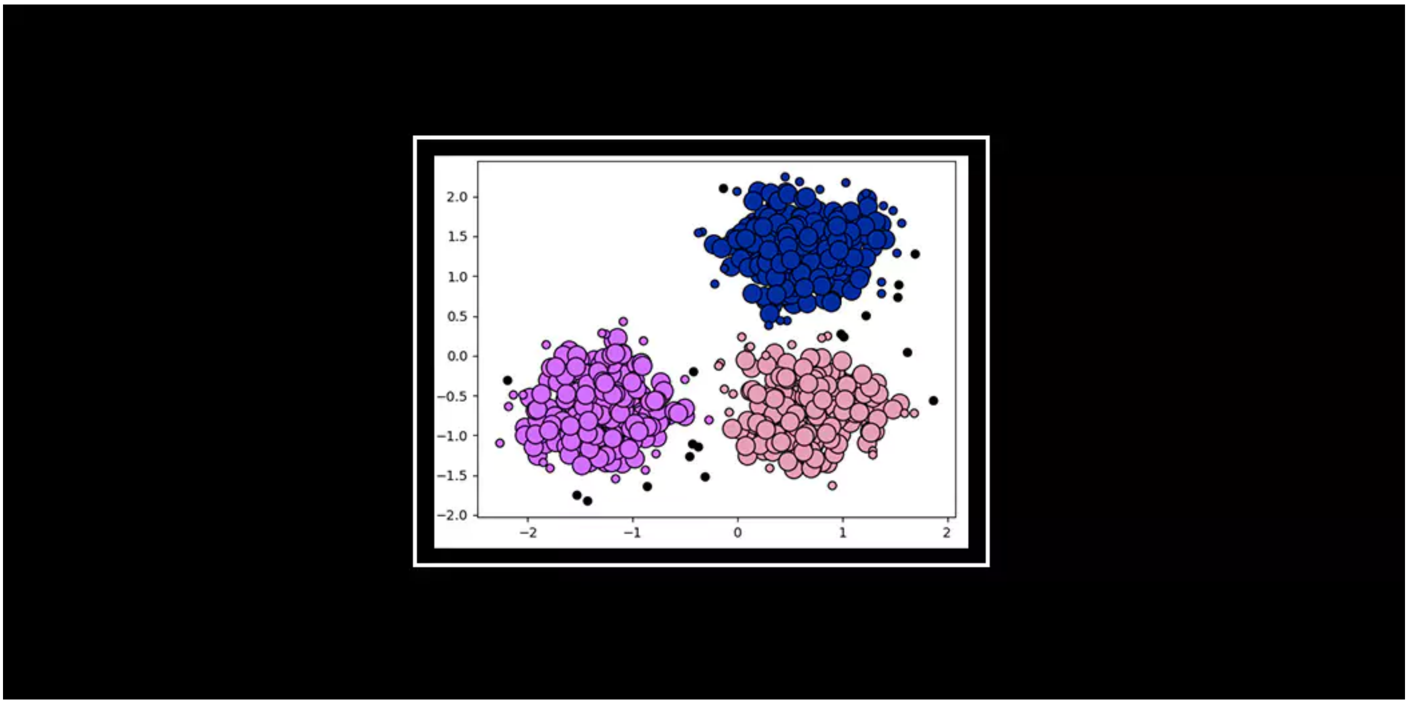
How to Master the Popular DBSCAN Clustering Algorithm for Machine Learning?

ALGORITHM BEGINNER CLUSTERING MACHINE LEARNING PYTHON PYTHON STRUCTURED DATA UNSUPERVISED

Mastering unsupervised learning opens up many avenues for a data scientist. There is so much scope in the vast expanse of unsupervised learning, yet many beginners in machine learning tend to shy away from it. I'm sure most newcomers will stick to basic clustering algorithms like K-Means clustering and hierarchical clustering.

While there's nothing wrong with that approach, it does limit what you can do when faced with clustering projects. And why limit yourself when you can expand your learning, knowledge, and skillset by learning the powerful **DBSCAN clustering** algorithm?

Clustering is an essential technique in **machine learning** and is used widely across domains and industries (think about Uber's route optimization, Amazon's recommendation system, Netflix's customer segmentation, and so on). This article is for anyone who wants to add an invaluable algorithm to their budding machine learning skillset – DBSCAN clustering!



Here, we'll learn about the popular and powerful DBSCAN clustering algorithm and how to implement it in Python. You will also understand the DBSCAN Algorithm and DB scanner, what they are, and how they are implemented.There's a lot to unpack, so let's get rolling!

In this article, you will understand what DBSCAN clustering is, how DBSCAN algorithm works, and how to implement Python DBSCAN to effectively analyze data based on density.

If you're new to machine learning and unsupervised learning, check out this popular resource:

- ***Introduction to Data Science***

Overview:

- Understand its advantages over traditional clustering algorithms like K-Means and Hierarchical Clustering, especially in handling noise and detecting clusters of various shapes.
- Learn about the core parameters—`epsilon` and `minPoints`—and how they define cluster formation based on density, enabling flexible, density-based clustering.
- Follow step-by-step instructions to apply DBSCAN algorithm on a dataset and visualize results, comparing its output with K-Means and Hierarchical methods.
- Grasp fundamental concepts behind DBSCAN clustering, such as core points, border points, and noise, along with connectivity and reachability within data.
- Understand DBSCAN's applications in various domains, from customer segmentation to anomaly detection, and how it enhances clustering capabilities in machine learning.

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Why do we need DBSCAN Clustering?

This is a pertinent question. We already have basic clustering algorithms, so why should you spend your time and energy learning about yet another clustering method? It's a fair question, so let me answer it before discussing what DBSCAN clustering is.

First, let's clear up the role of clustering.

Clustering is an **unsupervised learning** technique where we try to group the data points based on specific characteristics. There are various clustering algorithms with **K-Means** and **Hierarchical** being the most used ones. Some of the use cases of clustering algorithms include:

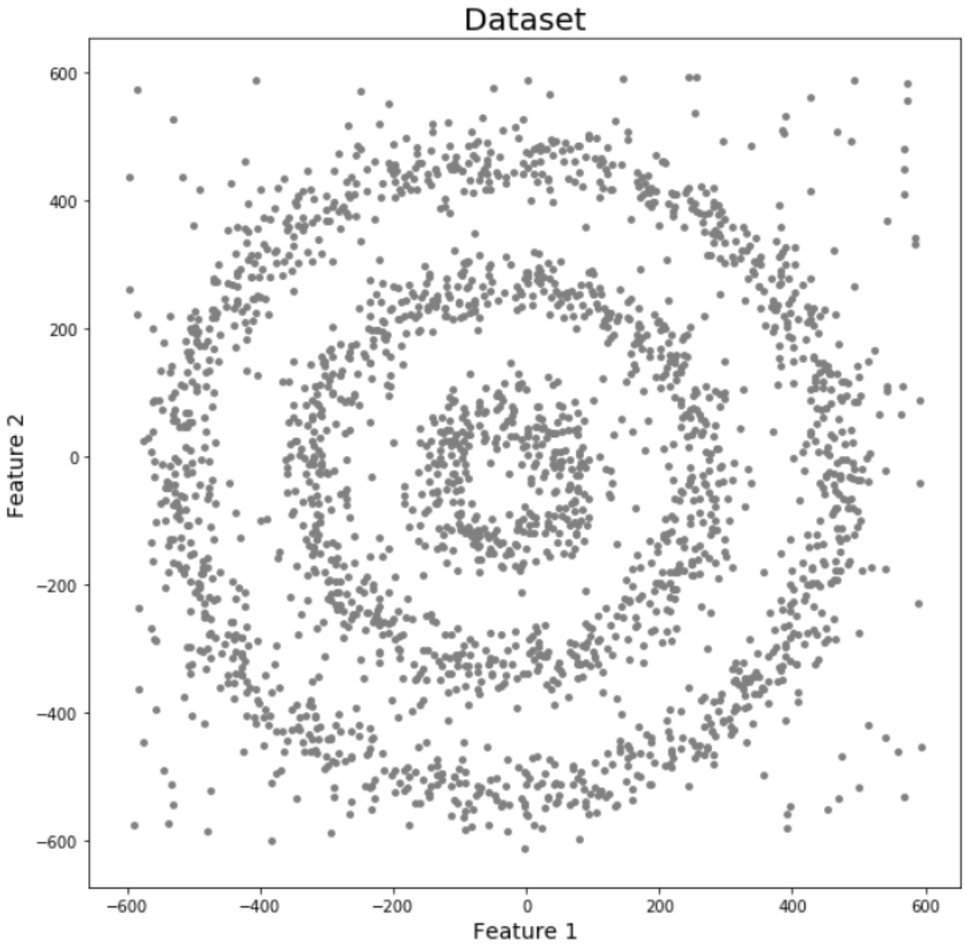
- Document Clustering
- Recommendation Engine
- Image Segmentation
- Market Segmentation
- Search Result Grouping
- and Anomaly Detection.

All these problems use the concept of clustering to reach their end goal. Therefore, it is crucial to understand the concept of clustering. But here's the issue with these two clustering algorithms.

K-Means and Hierarchical Clustering both fail to create clusters of arbitrary shapes. They are not able to form clusters based on varying densities. That's why we need DBSCAN clustering.

Example

Let's try to understand it with an example. Here we have data points densely present in the form of concentric circles:



We can see three different dense clusters in the form of concentric circles with some noise here. Now, let's run K-Means and Hierarchical clustering algorithms and see how they cluster these data points.

You might be wondering why there are four colors in the graph. As I said earlier, this data contains noise, too. Therefore, I have taken noise as a different cluster, which is represented by the purple color. Sadly, both of them failed to cluster the data points. Also, they were not able to detect the noise present in the dataset properly. Now, let's take a look at the results from DBSCAN clustering.

Awesome! DBSCAN cannot only cluster the data points correctly but also perfectly detect noise in the dataset.

Top [20 Questions to Test your Skills on DBSCAN Clustering]

What Parameters Required DBSCAN Algorithm?

The DBSCAN algorithm relies on two main parameters to identify clusters in your data:

1. **eps (ε):** This parameter defines the radius of a neighborhood around a data point. Points within this distance are considered neighbors of the central point.
2. **minPts:** This parameter represents the minimum number of points required within the ε-neighborhood of a point to classify it as a core point. A core point is considered to be dense enough to be part of a cluster.

These parameters work together to identify high-density regions in your data. Points with enough neighbors within the specified distance (core points) are grouped together as clusters, while points with insufficient neighbors are classified as noise.pen_sparktunesharemore_vert

What Exactly is DBSCAN Clustering?

DBSCAN stands for **D**ensity-**B**ased **S**patial **C**lustering of **A**pplications with **N**oise.

> It was proposed by Martin Ester et al. in 1996. DBSCAN Algorithm is a density-based clustering algorithm that works on the assumption that clusters are dense regions in space separated by regions of lower density.

It groups 'densely grouped' data points into a single cluster. It can identify clusters in large spatial datasets by looking at the local density of the data points. The most exciting feature of DBSCAN clustering is that it is robust to outliers. Unlike K-Means, where we have to specify the number of centroids, it also does not require the number of clusters to be told beforehand.

The DBSCAN algorithm requires only two parameters: epsilon and minPoints. Epsilon is the radius of the circle to be created around each data point to check its density, and ***minPoints*** is the minimum number of data points required inside that circle for that data point to be classified as a **Core** point.

In higher dimensions, the circle becomes a hypersphere, *epsilon* becomes its radius, and *minPoints* is the minimum number of data points required inside it.

Sounds confusing? Let's understand it with the help of an example.

Know More about the [Statistics for Data Science]()

Example

Here, we have some data points represented by grey color. Let's see how DBSCAN clusters these data points.

DBSCAN algorithm creates a circle of *epsilon* radius around every data point and classifies them into **Core** point, **Border** point, and **Noise**. A data point is a **Core** point if the circle around it contains at least '*minPoints'* number of points. If the number of points is less than *minPoints*, then it is classified as **Border** Point, and if there are no other data points around any data point within *epsilon* radius, then it treated as **Noise**.

The above figure shows a cluster created by DBCAN with *minPoints = 3*. Here, we draw a circle of equal radius *epsilon* around every data point. These two parameters help create spatial clusters.

All the data points with at least 3 points in the circle, including itself, are considered as **Core** points represented by red color. All the data points with less than 3 but greater than 1 point in the circle, including itself, are considered as Border points. They are represented by yellow color. Finally, data points with no point other than itself present inside the circle are considered Noise, represented by the purple colour.

DBSCAN uses **[Euclidean distance]to locate data points in space**, although other methods can also be used (like great circle distance for geographical data). It also needs to scan through the entire dataset once, whereas other algorithms require multiple scans.

Reachability and Connectivity

These are the two concepts that you need to understand before moving further. Reachability states if a data point can be accessed from another data point directly or indirectly, whereas Connectivity states whether two data points belong to the same cluster or not. In terms of reachability and connectivity, two points in DBSCAN can be referred to as:

- **Directly Density-Reachable**
- **Density-Reachable**
- **Density-Connected**

Let's understand what they are.

A point **X** is **directly density-reachable** from point **Y** w.r.t *epsilon, minPoints* if,

1. **X** belongs to the neighborhood of **Y**, i.e, *dist(X, Y) <= epsilon*
2. **Y** is a core point

Here, **X** is directly density-reachable from Y**,** but vice versa is not valid.

A point **X** is **density-reachable** from point **Y** w.r.t *epsilon, minPoints* if there is a chain of points p1, p2, p3, …, pn and p1=**X** and pn=**Y** such that pi+1 is directly density-reachable from pi.

Here, **X** is density-reachable from **Y** with **X** being directly density-reachable from **P2**, **P2** from **P3,** and **P3** from **Y.** But, the inverse of this is not valid.

A point **X** is **density-connected** from point **Y** w.r.t *epsilon and minPoints* if a point **O exists** such that both **X** and **Y** are density-reachable from **O** w.r.t to *epsilon and minPoints*.

Here, both **X** and **Y** are density-reachable from **O**, therefore, we can say that **X** is density-connected from **Y**.

Parameter Selection in DBSCAN Clustering

DBSCAN is very sensitive to the values of *epsilon* and *minPoints*. Therefore, it is very important to understand how to select these values. A slight variation in these values can significantly change the results produced by the DBSCAN algorithm.

The value of *minPoints* should be at least one greater than the number of dimensions of the dataset, i.e.,

minPoints>=Dimensions+1.

It does not make sense to take *minPoints* as 1 because each point will be a separate cluster. Therefore, it must be at least 3. Generally, it is twice the dimensions. But domain knowledge also decides its value.

The value of *epsilon* can be decided from the K-distance graph. The point of maximum curvature (elbow) in this graph tells us about the value of *epsilon*. If the value of *epsilon* chosen is too small, then more clusters will be created, and more data points will be taken as noise. However, if chosen too big, various small clusters will merge into a big cluster, and we will lose details.

Article You Should Read and Understand about the DBSCAN Clustering Algorithm

Implementing DBSCAN Clustering in Python

Now, it's implementation time! In this section, we'll apply DBSCAN clustering on a dataset and compare its result with K-Means and Hierarchical Clustering.

Step 1-

Let's start by importing the necessary libraries.

Python Code:

```
import numpy as np import pandas as pd import math import matplotlib.pyplot as plt import matplotlib
```

Step 2-

Here, I am creating a dataset with only two features so that we can visualize it easily. For creating the dataset, I have created a function *PointsInCircum*, which takes the radius and number of data points as arguments and returns an array of data points which, when plotted, forms a circle. We do this with the help of *sin* and *cosine* curves.

```
np.random.seed(42) # Function for creating datapoints in the form of a circle def PointsInCircum(r,n=100): return [(math.cos(2*math.pi/n*x)*r+np.random.normal(-30,30),math.sin(2*math.pi/n*x)*r+np.random.normal(-30,30)) for x in range(1,n+1)]
```

Step 3-

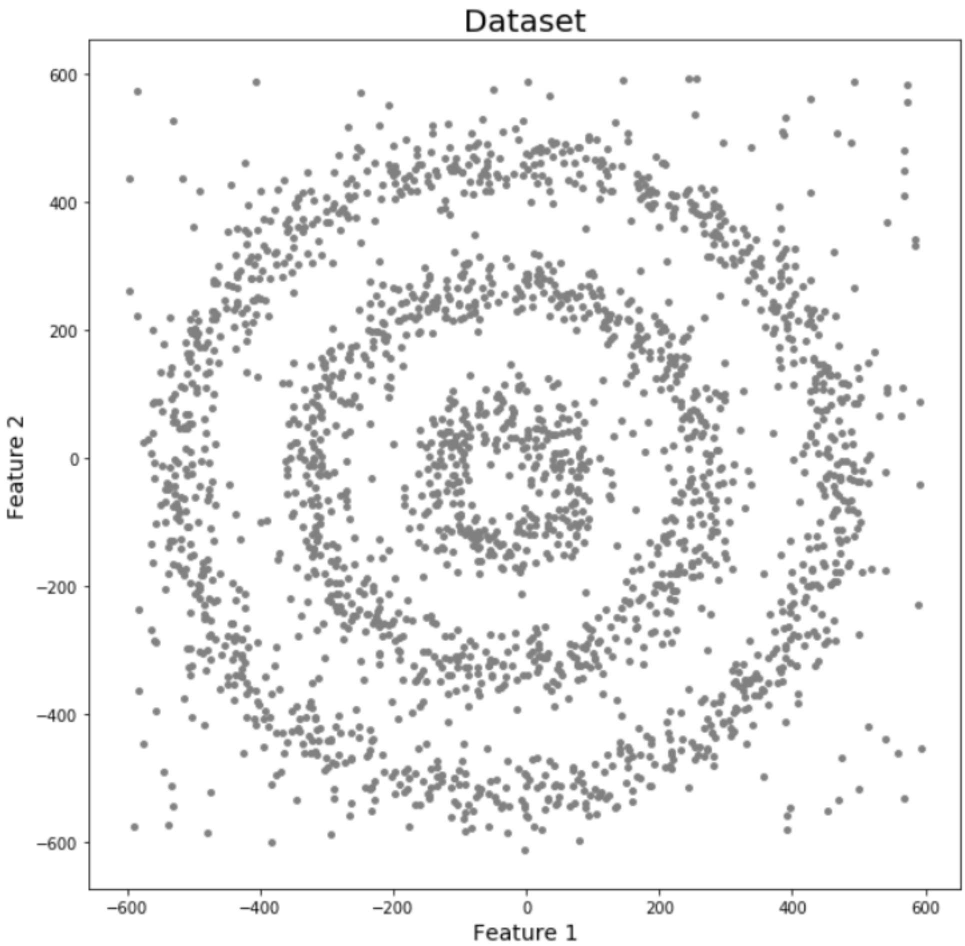
One circle won't be sufficient to show DBSCAN's clustering ability. Therefore, I have created three concentric circles of different radii. I will also add noise to this data so that we can see how different types of clustering algorithms deal with noise.

```
# Creating data points in the form of a circle df=pd.DataFrame(PointsInCircum(500,1000)) df=df.append(PointsInCircum(300,700)) df=df.append(PointsInCircum(100,300)) # Adding noise to the dataset df=df.append([(np.random.randint(-600,600),np.random.randint(-600,600)) for i in range(300)])
```

Step 4-

Let's plot these data points and see how they look in the feature space. Here, I use the scatter plot to plot these data points. Use the following syntax:

```
plt.figure(figsize=(10,10)) plt.scatter(df[0],df[1],s=15,color='grey') plt.title('Dataset',fontsize=20) plt.xlabel('Feature 1',fontsize=14) plt.ylabel('Feature 2',fontsize=14) plt.show()
```



Perfect! It's excellent for clustering a problem.

If you want to know more about visualization in Python you can read the following articles:

- *[A Beginner's Guide to matplotlib for Data Visualization and Exploration in Python]*
- *[Become a Data Visualization Whiz with this Comprehensive Guide to Seaborn in Python]*
- *[How to Create Beautiful, Interactive data visualizations using Plotly in R and Python?]*

K-Means vs. Hierarchical vs. DBSCAN Clustering

1. K-Means

We'll first start with **K-Means** because it is the easiest clustering algorithm

```
from sklearn.cluster import KMeans k_means=KMeans(n_clusters=4,random_state=42) k_means.fit(df[[0,1]])
```

It's time to see the results. Use **labels_** to retrieve the labels. I have added these labels to the dataset in the new column to make data management easier. But don't worry—I will only use two columns of the dataset for fitting other algorithms.

```
df['KMeans_labels']=k_means.labels_ # Plotting resulting clusters colors=['purple','red','blue','green'] plt.figure(figsize=(10,10))
plt.scatter(df[0],df[1],c=df['KMeans_labels'],cmap=matplotlib.colors.ListedColormap(colors),s=15)
plt.title('K-Means Clustering',fontsize=20) plt.xlabel('Feature 1',fontsize=14) plt.ylabel('Feature 2',fontsize=14) plt.show()
```

Here, K-means failed to cluster the data points into four clusters. It also didn't work well with noise. Therefore, it is time to try another popular clustering algorithm, **Hierarchical Clustering**.

2. Hierarchical Clustering

For this article, I am performing Agglomerative Clustering, but there is also another type of hierarchical clustering algorithm known as Divisive Clustering. Use the following syntax:

```
from sklearn.cluster import AgglomerativeClustering model = AgglomerativeClustering(n_clusters=4, affinity='euclidean') model.fit(df[[0,1]])
```

Here, I am taking labels from the Agglomerative Clustering model and plotting the results using a scatter plot, similar to what I did with KMeans.

```
df['HR_labels']=model.labels_ # Plotting resulting clusters plt.figure(figsize=(10,10))
plt.scatter(df[0],df[1],c=df['HR_labels'],cmap=matplotlib.colors.ListedColormap(colors),s=15)
```

```
plt.title('Hierarchical  Clustering',fontsize=20)  plt.xlabel('Feature  1',fontsize=14)  plt.ylabel('Feature
2',fontsize=14) plt.show()
```

Sadly, the hierarchical clustering algorithm also failed to cluster the data points properly.

Checkout this article about the [clustering its Different Methods, and Applications]()

3. DBSCAN Clustering

Now, it's time to implement DBSCAN algorithmand see its power. Import DBSCAN from **sklearn.cluster**. Let's first run DBSCAN without any parameter optimization and see the results.

```
from sklearn.cluster import DBSCAN
dbscan=DBSCAN()
dbscan.fit(df[[0,1]])
```

Here, *epsilon* is 0.5, and min_samples or *minPoints* is 5. Let's visualize the results from this model:df['DBSCAN_labels']=dbscan.labels_

```
#          Plotting          resulting          clusters          plt.figure(figsize=(10,10))
plt.scatter(df[0],df[1],c=df['DBSCAN_labels'],cmap=matplotlib.colors.ListedColormap(colors),s=15)
plt.title('DBSCAN   Clustering',fontsize=20)   plt.xlabel('Feature   1',fontsize=14)   plt.ylabel('Feature
2',fontsize=14) plt.show()
```

Interesting! All the data points are now purple, which means they are treated as noise. This is because the value of *epsilon* is very small, and we didn't optimize parameters. Therefore, we need to find the value of *epsilon* and *minPoints* and then train our model again.

For *Epsilon*, I am using the K-distance graph. To plot a K-distance Graph, we need the distance between a point and its nearest data point for all data points in the dataset. We obtain this using **NearestNeighbors** from **sklearn.neighbors.**

```
from sklearn.neighbors import NearestNeighbors neigh = NearestNeighbors(n_neighbors=2) nbrs = neigh.fit(df[[0,1]]) distances, indices = nbrs.kneighbors(df[[0,1]])
```

The distance variable contains an array of distances between a data point and its nearest data point for all data points in the dataset.

Let's plot our K-distance graph and find the value of *epsilon*. Use the following syntax:

Syntax:

```
# Plotting K-distance Graph distances = np.sort(distances, axis=0) distances = distances[:,1] plt.figure(figsize=(20,10)) plt.plot(distances) plt.title('K-distance Graph',fontsize=20) plt.xlabel('Data Points sorted by distance',fontsize=14) plt.ylabel('Epsilon',fontsize=14) plt.show()
```

The optimum value of *epsilon* is at the point of maximum curvature in the K-Distance Graph, which is 30 in this case. Now, it’s time to find the value of *minPoints*. The value of *minPoints* also depends on domain knowledge. This time I am taking minPoints as 6:

```
from sklearn.cluster import DBSCAN dbscan_opt=DBSCAN(eps=30,min_samples=6) dbscan_opt.fit(df[[0,1]])
```

```
df['DBSCAN_opt_labels']=dbscan_opt.labels_ df['DBSCAN_opt_labels'].value_counts()
```

The most amazing thing about DBSCAN is that it separates noise from the dataset pretty well. Here, 0, 1 and 2 are the three different clusters, and -1 is the noise. Let’s plot the results and see what we get.

```
# Plotting the resulting clusters plt.figure(figsize=(10,10)) plt.scatter(df[0],df[1],c=df['DBSCAN_opt_labels'],cmap=matplotlib.colors.ListedColormap(colors),s=15)
```

```
plt.title('DBSCAN Clustering',fontsize=20) plt.xlabel('Feature 1',fontsize=14) plt.ylabel('Feature 2',fontsize=14) plt.show()
```

DBSCAN amazingly clustered the data points into three clusters and detected noise in the dataset represented by the purple color.

One important point to note here is that, though DBSCAN creates clusters based on varying densities, it struggles with clusters of similar densities. Also, as the dimension of the data increases, it becomes difficult for DBSCAN to create clusters, and it falls prey to the Curse of Dimensionality.

Conclusion

So, in this article, I explained the DBSCAN clustering algorithm in-depth and showcased how it is useful compared to other clustering algorithms. Also, note that a much better and more recent version of this algorithm, HDBSCAN, uses Hierarchical Clustering combined with regular DBSCAN. It is much faster and more accurate than DBSCAN. Hope you like the article and get information about the dbscanner and dbscan algorithm. We cover all parts and information regarding the dbscan clustering.

Read More about the [Types of Clustering Algorithms in Machine Learning]()

Hope you found the information on density-based spatial clustering of applications with noise (DBSCAN) helpful! This powerful technique is essential for effective data analysis and clustering.

There is a lot of difference in the data science we learn in courses and self-practice and the one we work in the industry. I'd recommend you to go through these following crystal clear free courses to understand everything about analytics, machine learning, and artificial intelligence:

1. Introduction to AI/ML Free Course | Mobile app

2. [Introduction to AI/ML for Business Leaders Mobile app]
3. [Introduction to Business Analytics Free Course] | [Mobile app]

Frequently Asked Questions

Q1. What is DBSCAN Algorithm used for?

A. DBSCAN (Density-Based Spatial Clustering of Applications with Noise) is a popular clustering algorithm for data analysis and pattern recognition. It groups data points based on their density, identifying clusters of high-density regions and classifying outliers as noise. DBSCAN is effective in discovering arbitrary-shaped clusters in data and is widely used in data mining, spatial data analysis, and machine learning applications.

Q2. What is the DBSCAN algorithm?

A. The DBSCAN (Density-Based Spatial Clustering of Applications with Noise) algorithm is a density-based clustering technique. It groups data points based on their density and proximity to each other. It forms clusters by identifying core points (with sufficient nearby points) and expanding them to reach neighboring points. Points not part of any cluster are classified as noise or outliers.

Q3. What is a density-based spatial clustering of application with noise?

DBSCAN groups things by closeness. It's good for finding groups of different shapes and sizes, even with noise. It works by finding center points and adding nearby things. It's helpful for tasks like dividing customers, finding objects in pictures, finding unusual things, and understanding groups of people.

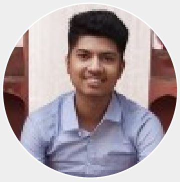
Q4.How does the algorithm resemble DBSCAN?

A technique like DBSCAN is OPTICS (Ordering Points To Identify the Clustering Structure). OPTICS also carries out density-based clustering, but it is able to manage clusters with different densities and offers a thorough ordering of points to comprehend the hierarchy of clustering.

Q5.Why is DBSCAN better than K-Means?

DBSCAN is better for irregular clusters and noise, while K-Means is better for spherical clusters and known cluster numbers.

Article Url - https://www.analyticsvidhya.com/blog/2020/09/how-dbscan-clustering-works/



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He is a data science aficionado, who loves diving into data and generating insights from it. He is always ready for making machines to learn through code and writing technical blogs. His areas of interest include Machine Learning and Natural Language Processing still open for something new and exciting.