03 - DBSCAN

- We studied two clustering methods; K-Means which is a centroid-based algorithm, and Agglomerative Clustering which is a hierarchical system.
- There's one more approach to clustering known as DBSCAN which is a density-based approach.

- DBSCAN refers to Density-based spatial clustering of applications with noise
- DBSCAN works fairly well with large data and is able to handle noise and outliers very efficiently.
- First things first, here are some key ideas that build the DBSCAN.

Density and Dense Region

- DBSCAN uses a concept of density, which can be defined as;
  - at a certain point P, density at point P is the number of points within a hypersphere centered at P with a radius of $epsilon$
- Now, consider any region around the point P within eps radius, if there are more data points than $minpts$, we call the region a **Dense** region.
- For example, let's say we have eps=1 and $minpts$=10. Consider two points P_1 and P_2, both with a radius of eps
  - Suppose there are 20 points around point P_1, and only 6 points around point P_2, within the radius of eps, then we say the region around point P_1 is dense and the region around point P_2 as non-dense.

Min Points($minpts$) and Epsilon(eps)

- $minpts$ are the minimum number of points that we need in a hypersphere around point P with the radius of eps for considering the region as a **Dense** region.
- $minpts$ acts like a certain threshold and eps are the radius of the hypersphere

Core Point

- If a point P has points $\geq minpts$ within the radius of eps, then P is a core point.
- This also implies that point P has a dense region around it

Border Point

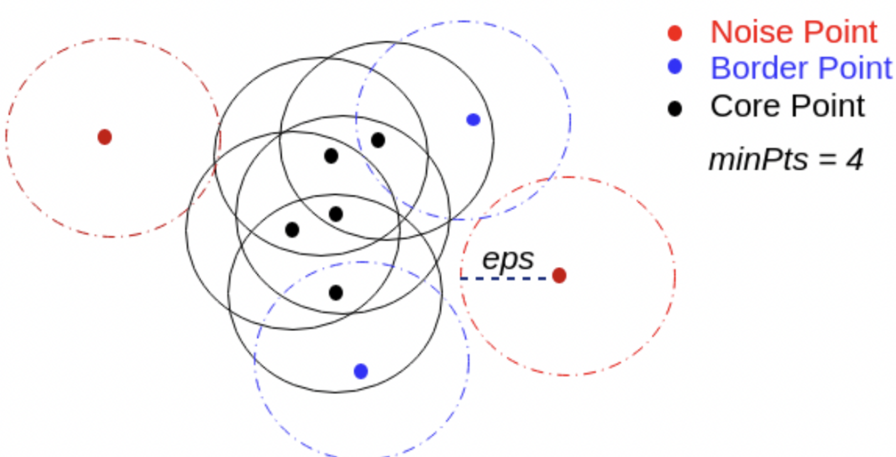
- A point P can be defined as a border point if:
  1. P is not a core point
  2. Point P lies in the neighborhood of point Q such that point Q is a core-point

Neighborhood

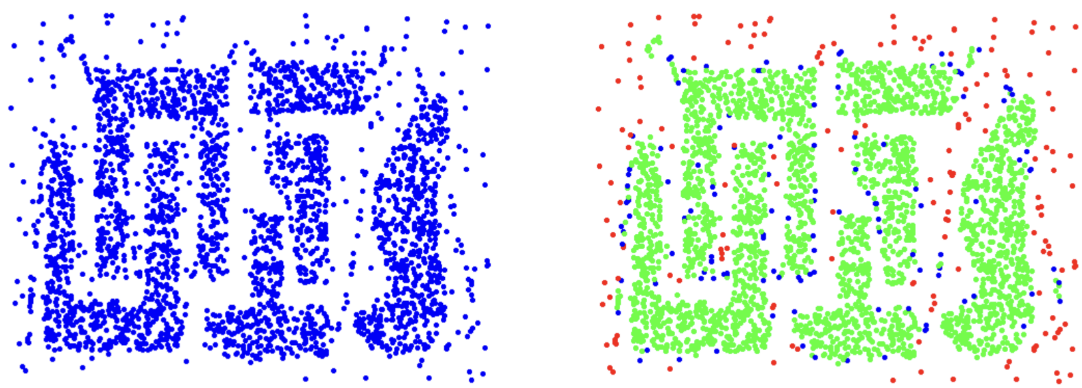
- A point P is said to be in the neighborhood of point Q if distance between point P and Q is less than eps value; i.e. $dist(P,Q) \leq eps$

Noise Point

- It is a point that is neither a core point nor a border point.
- Suppose around core point P, a border point Q, and a point R which is in a non-dense region, the point R is said to be a noise point



- One thing to understand is that, when using DBSCAN, we fix two things:
    1. Min Points
    2. Epsilon.
- By fixing these hyperparameters, we get core points, border points, and noise points as well



Original Points

Point types: core, border and noise

Density Edges and Density Connected Points

- If points P and Q are two core points and the distance between point P and Q is less than or equal to eps value, then an edge between point P and Q is known as a **density edge.**

- Points P and Q can be said as density-connected points;
    - if both points are core points
    - if there exist other density edges connecting the points P and Q
    -
- Imagine we have two core points, point P, and Q, and there are other core points connecting point P with point Q; say $P_1, P_2, \ldots . P_n$, where the distance between each point $P_1, P_2, \ldots . P_n$ is less than eps
- Then point P and point Q are said to be density connected points.

DBSCAN Algorithm

Step-1:

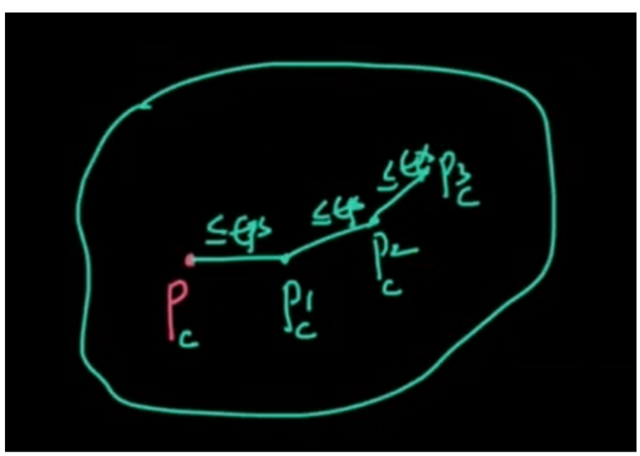
- For each point xi that belongs to the dataset D, label it as either core point, border point, or noise point.
- Time complexity of this step would be $O(n*logN)$

Step-2:

- Remove all the noise points from the dataset
- Time complexity of this step would be $O(n)$
- This is basically a noise removal step

Step-3:

- For each core point P that is not yet assigned to any clustered:
  - create a new cluster with point P
  - Add all points that are density connected to point P, to the P's cluster
- To understand this with an example, Consider a core point P and there are three core points P_1,P_2 and P_3 which are density connected.
- Then, we group all the three points in the cluster of point P
- Time complexity of this step would be $O(n*logN)$



Step-4:

- For each border point, we assign it to the nearest core points' cluster.
    - For example, if we're having a cluster having core points $P_1, P_2 .... P_9$, and a border point P_{10} which is near the cluster.
    - We merge border point P_{10}, into the cluster of core points $P_1, P_2 .... P_9$
- Time complexity of this step would be $O(n) * logN$
- **DBSCAN Animation Links:**
    - [DBSCAN Animation]()
    - [DBSCAN Animation Statquest]()

Adjusting Min Points

- So there are some rules of thumb that people have made over the past years, which typically works well. They are:
    - value of $minpts$ should be greater than or equal to $d+1$; where d is dimensionality of the data
    - lot of libraries use the value of $minpts$ approximately equal to $2*d$
- The points mentioned above are typically rules of thumb and these are used because they tend to work fairly good in most of the cases
- Given an epsilon value, if the dataset is noisy, we pick larger $minpts$

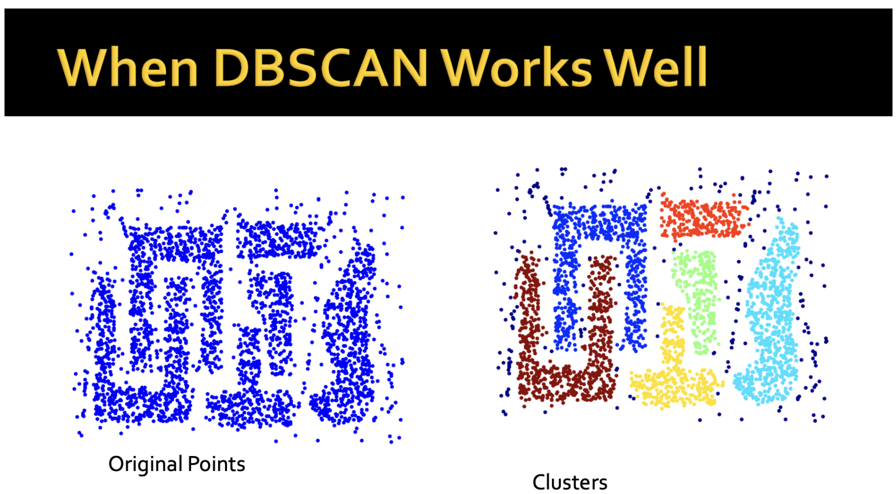
Adjusting Epsilon

- Let's assume we've fixed the value of $minpts$ = 4.
- **Step 1:**
    - for every point x_i in dataset, we compute a distance d_i
    - d_i refers to the distance from x_i to x_i's 4_{th} nearest neighbor (because we've set $minpts$ = 4)
- **Step 2:**
    - Sort the values of d_i's and plot them. You'll notice that the distance will increase graudally and then suddenlly, at a certain point, the value of distance will get boosted
    - So, the index at which the value of d_i distance got boosted will be used as the value of eps

- The indices having higher values of di's will be outliers

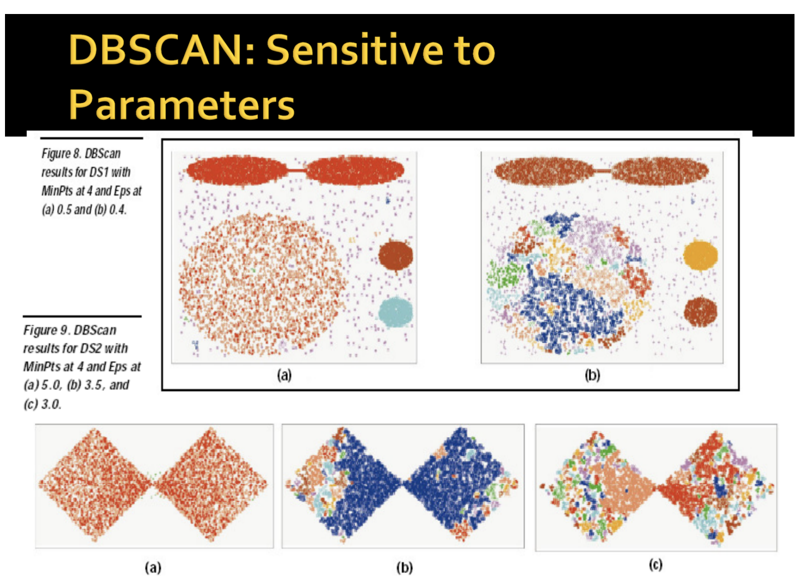
Advantages of DBSCAN

- It's resistant to noise
- Can handle clusters of different shapes and sizes.
- It doesn't require one to specify the number of clusters a priori.
- It requires only two parameters: MinPts and Epsilon.
- It is designed for use with databases as it's created by the database community.

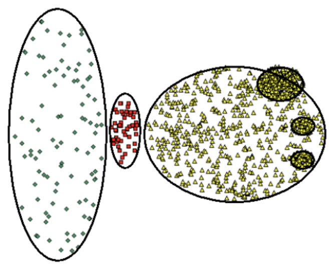


Limitations of DBSCAN

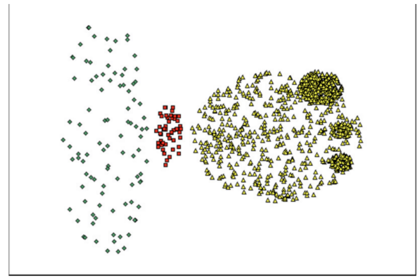
- Even a small change in the hyperparameters, we can get a completely different type of clusters. So, it's quite sensitive to the choice of hyperparameters.



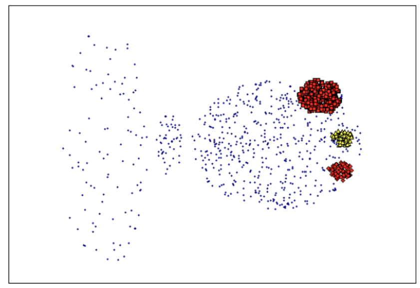
- Cannot handle varying densities and data with higher dimensions.



Original Points



(MinPts=4, Eps=9.75).



(MinPts=4, Eps=9.92)

- Varying densities
- High-dimensional data