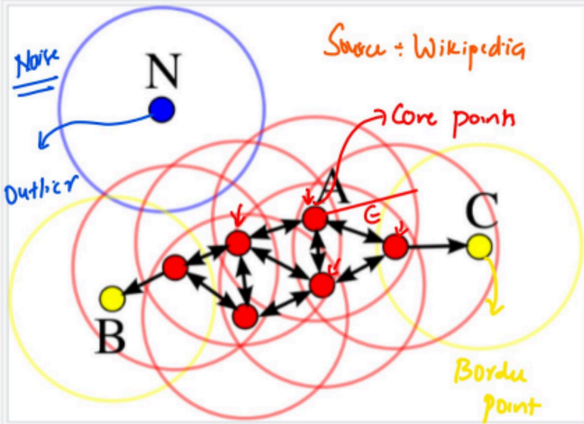
DBSCAN: Density-Based Spatial Clustering of Applications with Noise

- **Core Idea:** DBSCAN groups together data points that are closely packed in high-density regions, while marking points in low-density regions as outliers or noise. It doesn't require you to specify the number of clusters beforehand.
- **Key Parameters:**
  - **`eps` (ϵ):** Defines the maximum distance between two points for one to be considered as in the neighborhood of the other.
  - **`minPts`:** The minimum number of data points required to form a dense region (i.e., points within the `eps` radius of a point).
- **How it Works & Point Types:**
  - The algorithm picks an arbitrary unvisited point.
  - It finds all neighbor points within the `eps` distance.
  - If a point has at least `minPts` neighbors (including itself), it's marked as a **Core Point**, and a new cluster is started.
  - All reachable points from the core point (within `eps` distance) are added to the cluster. If any of these neighbors are also core points, their neighbors are also added recursively (density-connected).
  - If a point has fewer than `minPts` neighbors but is within the `eps` distance of a core point, it's marked as a **Border Point**. Border points belong to a cluster but aren't used to expand it further.
  - If a point is neither a core point nor a border point, it's marked as **Noise**.
  - The process continues until all points have been visited.
- **Advantages:**
  - Doesn't require specifying the number of clusters (k) in advance.
  - Can find arbitrarily shaped clusters (unlike K-Means which assumes spherical clusters).
  - Robust to outliers and can identify them as noise.
- **Disadvantages:**
  - Can be sensitive to the choice of `eps` and `minPts` parameters; tuning them can be challenging.
  - Struggles with datasets where clusters have significantly varying densities, as a single (`eps`, `minPts`) combination might not work well for all clusters.
  - Performance can degrade on high-dimensional data due to the "curse of dimensionality" affecting distance measurements.
- **Common Applications:**
  - Anomaly detection (e.g., fraud detection).
  - Spatial data analysis (e.g., identifying geographic points of interest).
  - Image segmentation.
  - Recommendation systems (grouping users with similar behavior).

DBSCAN Clustering.



In this diagram, minPts = 4. Point A and the other red points are core points, because the area surrounding these points in an ε radius contain at least 4 points (including the point itself). Because they are all reachable from one another, they form a single cluster. Points B and C are not core points, but are reachable from A (via other core points) and thus belong to the cluster as well. Point N is a noise point that is neither a core point nor directly-reachable.

- ● → Core point
- ● → border point
- ● → Outlier

} Non linear Clustering

minpts = 4 ϵ = radius

Core point

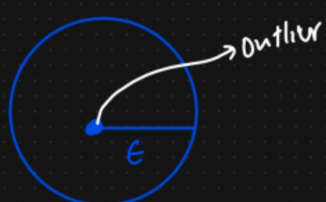
minpts = 4

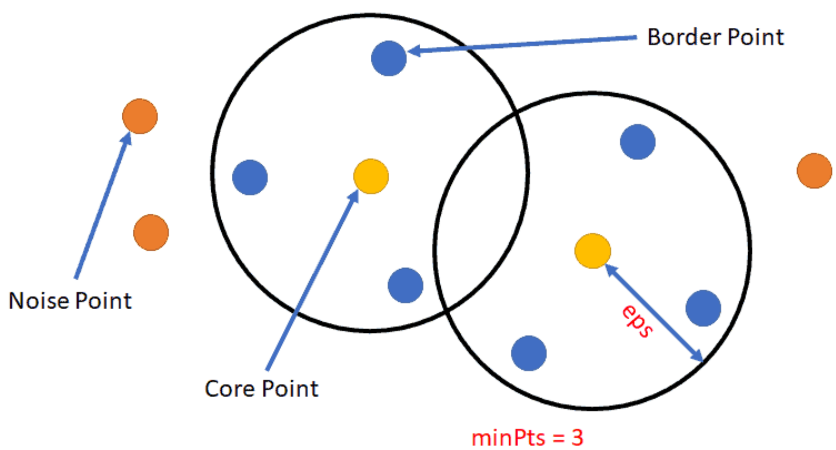
① No. of points within the ϵ should be greater ≥ 4

Border point

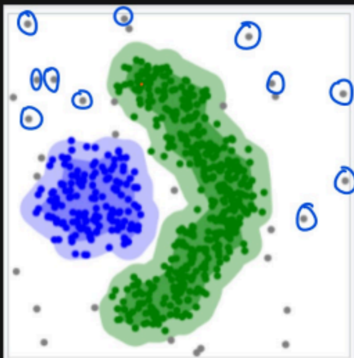
no. of data points within this radius will be less than minpts

Outlier (Noise)

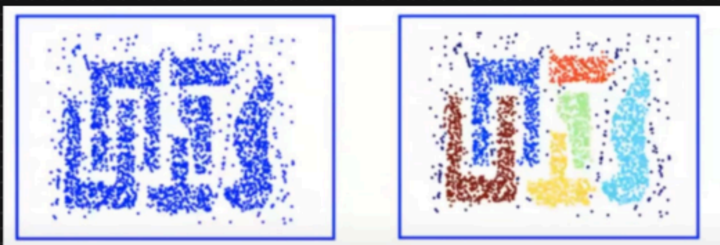




Some Examples after we apply DBScan Clustering



DBSCAN can find non-linearly separable clusters. This dataset cannot be adequately clustered with k-means or Gaussian Mixture EM clustering.



The left image depicts a more traditional clustering method that does not account for multi-dimensionality. Whereas the right image shows how DBSCAN can contort the data into different shapes and dimensions in order to find similar clusters.