Master Degree in Artificial Intelligence for Science and Technology

Cluster Analysis: Density-Based Clustering

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OUTLOOK

- Concept
- DBSCAN
  - Core point
  - Border point
  - Noise point
- Advantages
- Limitations
- DBSCAN vs K-means
- Additional algorithms

DENSITY-BASED CLUSTERING TECHNIQUES

- Density-based clustering techniques aim to find dense regions of objects that are surrounded by low-density regions.
- **DBSCAN** is a simple and effective density-based clustering algorithm that illustrates a number of important concepts that are typical of the density-based approach.
- Several methods exist to define density, we describe the center-based approach on which DBSCAN is based.

density of the red filled circle object is the number of objects within a specific radius (Eps) of that object

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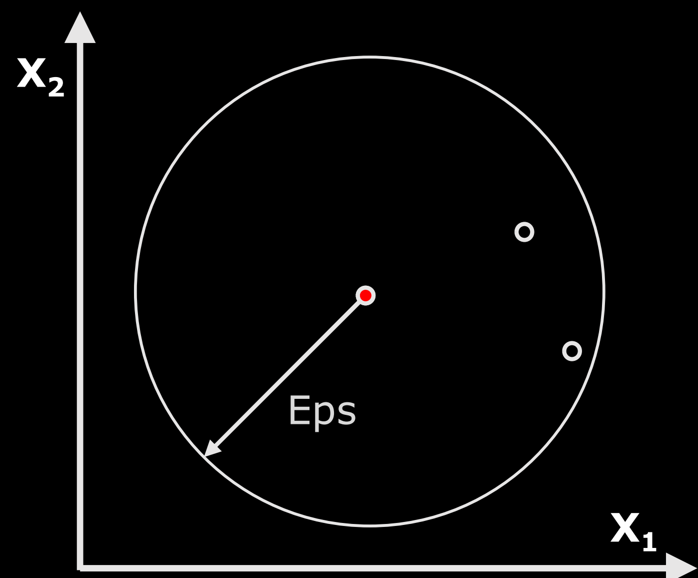


density of any point will depend on the specified radius (Eps).

DBSCAN

- Density-based Clustering Techniques allow to classify a point (record) as being:
  - **CORE POINT**
  - **BORDER POINT**
  - **NOISE POINT**

DBSCAN

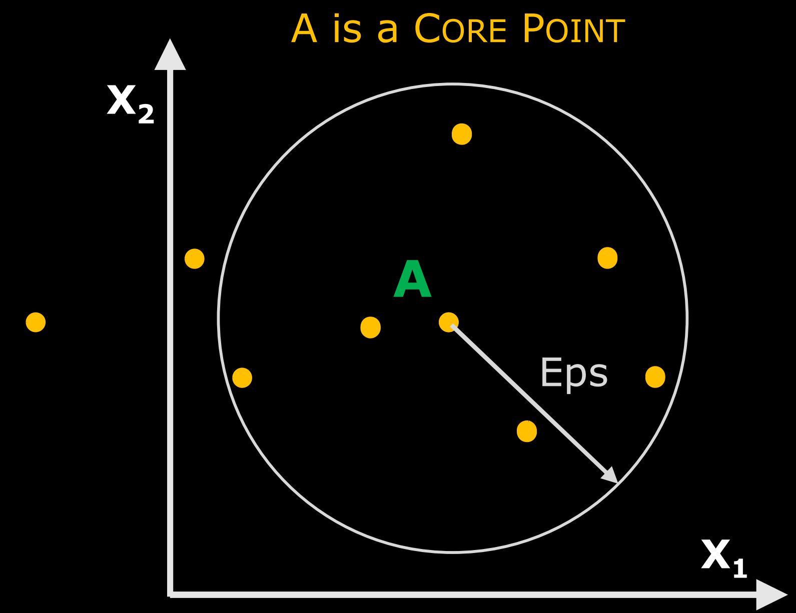
- Density-based Clustering Techniques allow to classify a point (record) as being:

  — **CORE POINT :** is in the interior of a density-based cluster.

  A point is a core point if the number of points within a given neighborhood around the point as determined by the distance function and a user-specified distance parameter, **Eps**, exceeds a certain threshold, **MinPts**, which is also a user-specified parameter.

We set **MinPts=6** and use

the selected **Eps** value



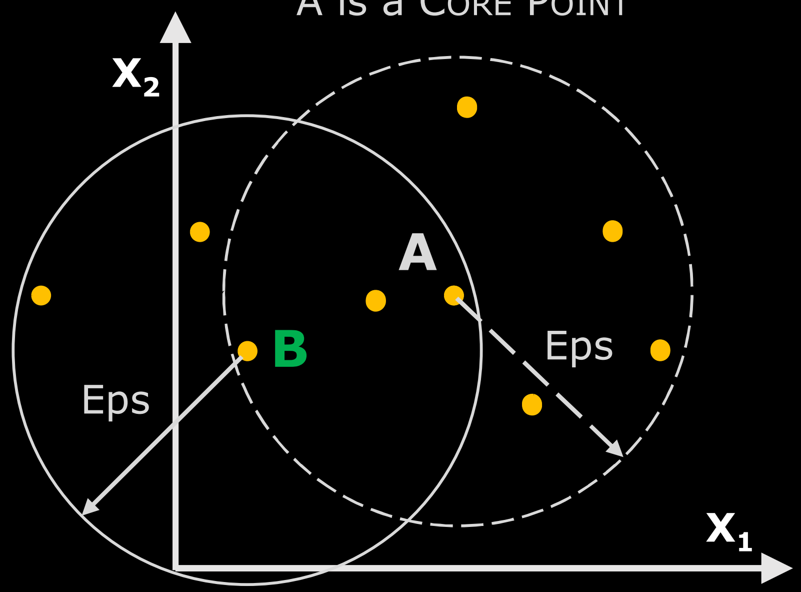
DBSCAN

- Density-based Clustering Techniques allow to classify a point (record) as being:
  - **BORDER POINT :** is not a core point, but falls within the neighborhood of a core point. A border point can fall in the neighborhood of several core points.

We set **MinPts=6** and use the selected **Eps** value

B is a Border Point

A is a Core Point



B is not a core point

B is a border point

DBSCAN

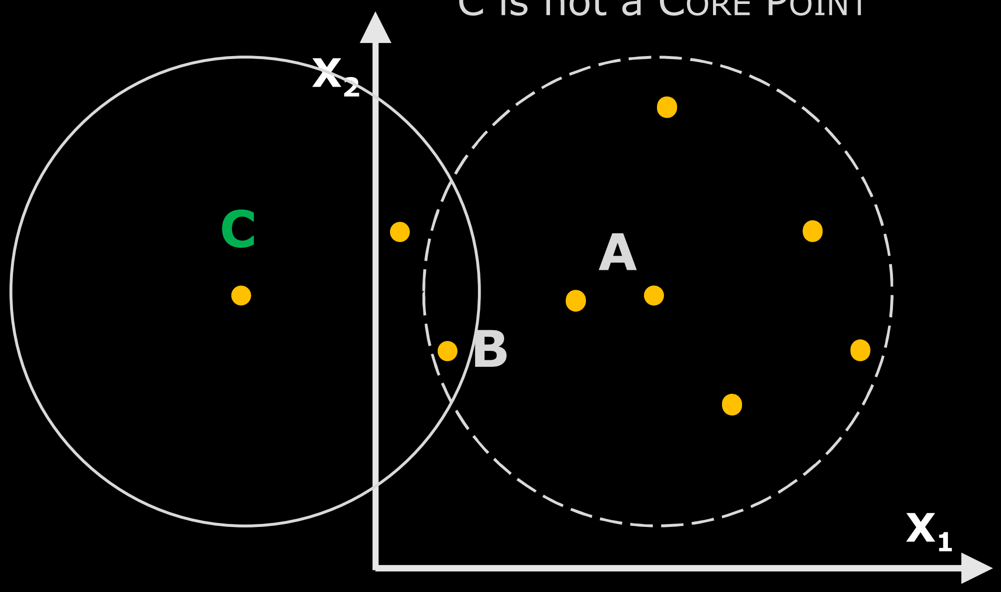
- Density-based Clustering Techniques allow to classify a point (record) as being:
  - **NOISE POINT :** is any point that is neither a core nor a border point

C is a NOISE POINT

C is not a BORDER POINT

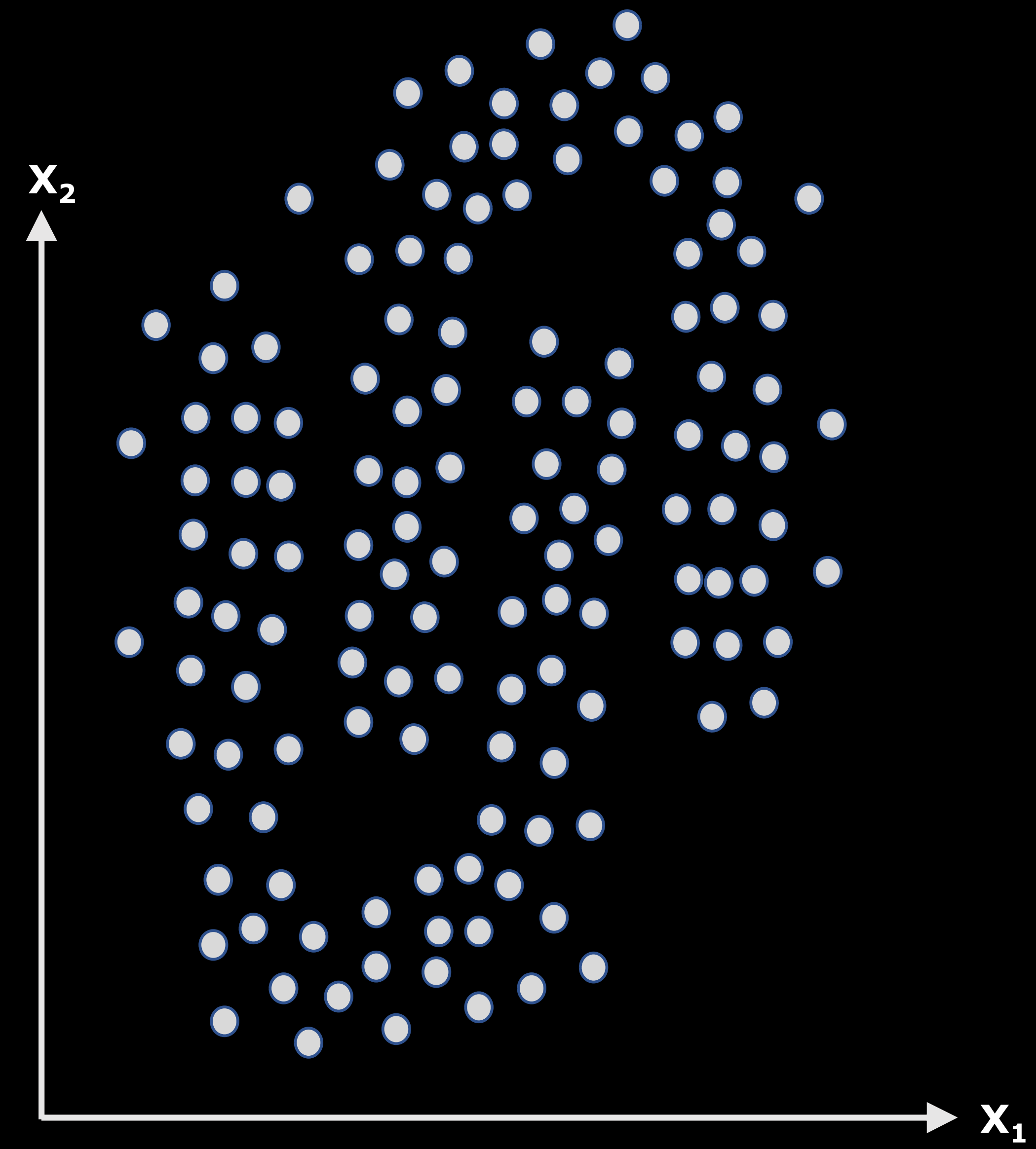
C is not a CORE POINT

We set **MinPts=6** and use the selected **Eps** value



DBSCAN

1. Label all points as core, border, or noise points
2. Eliminate noise points
3. Put an edge between all core points that are within *Eps* of each other
4. Make each group of connected core points into a separate cluster
5. Assign each border point to one of the clusters of its associated core points



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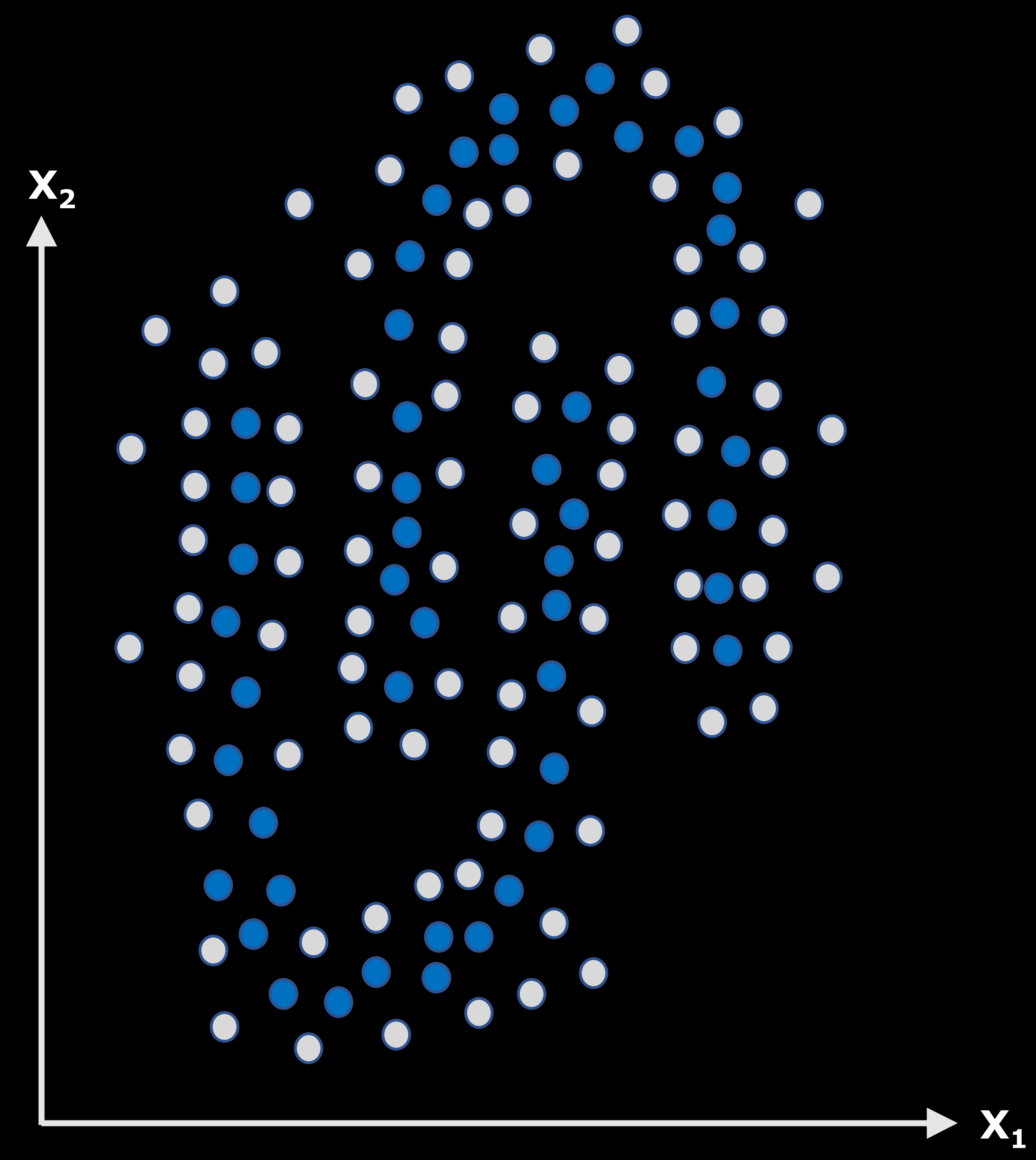

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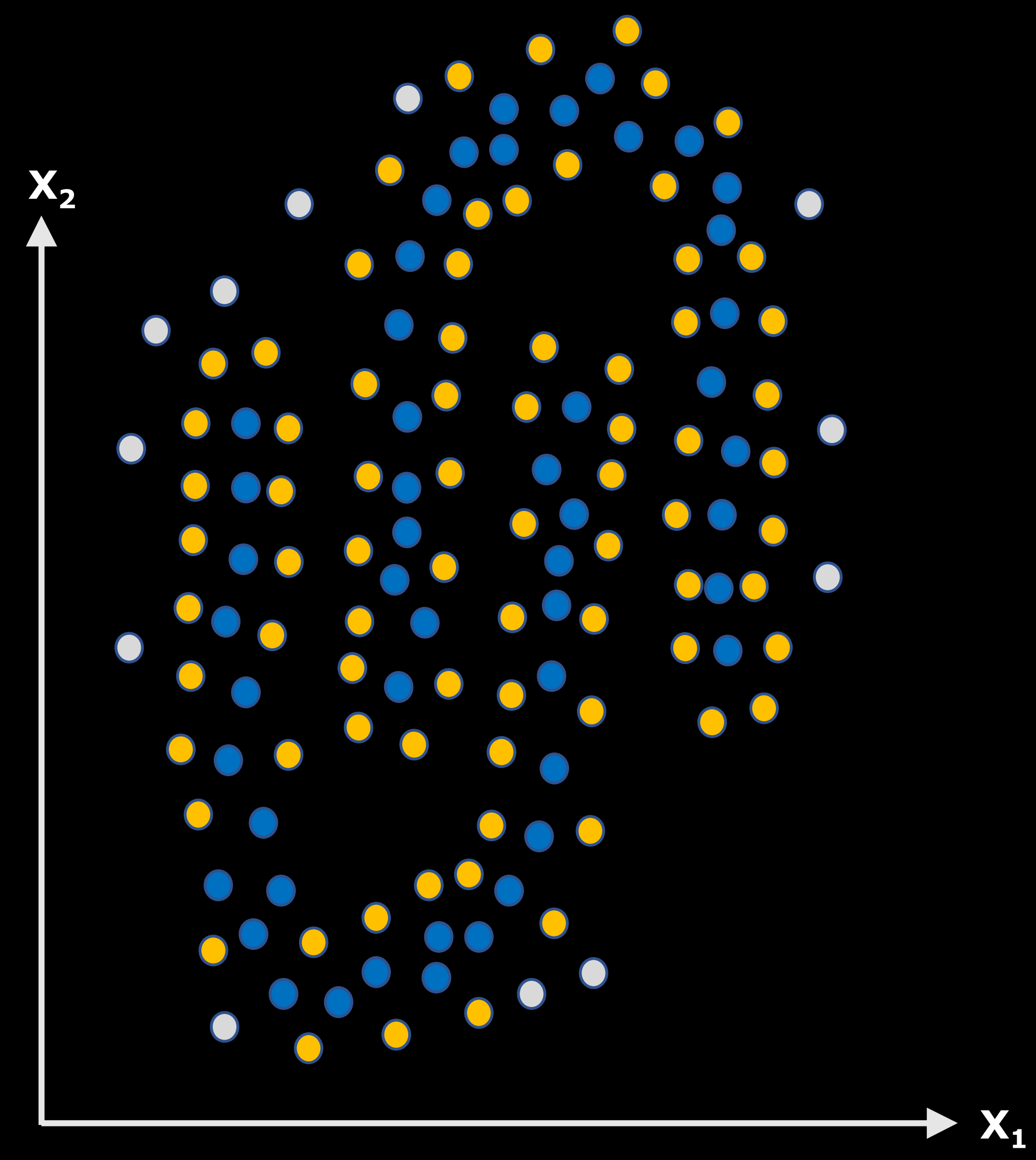

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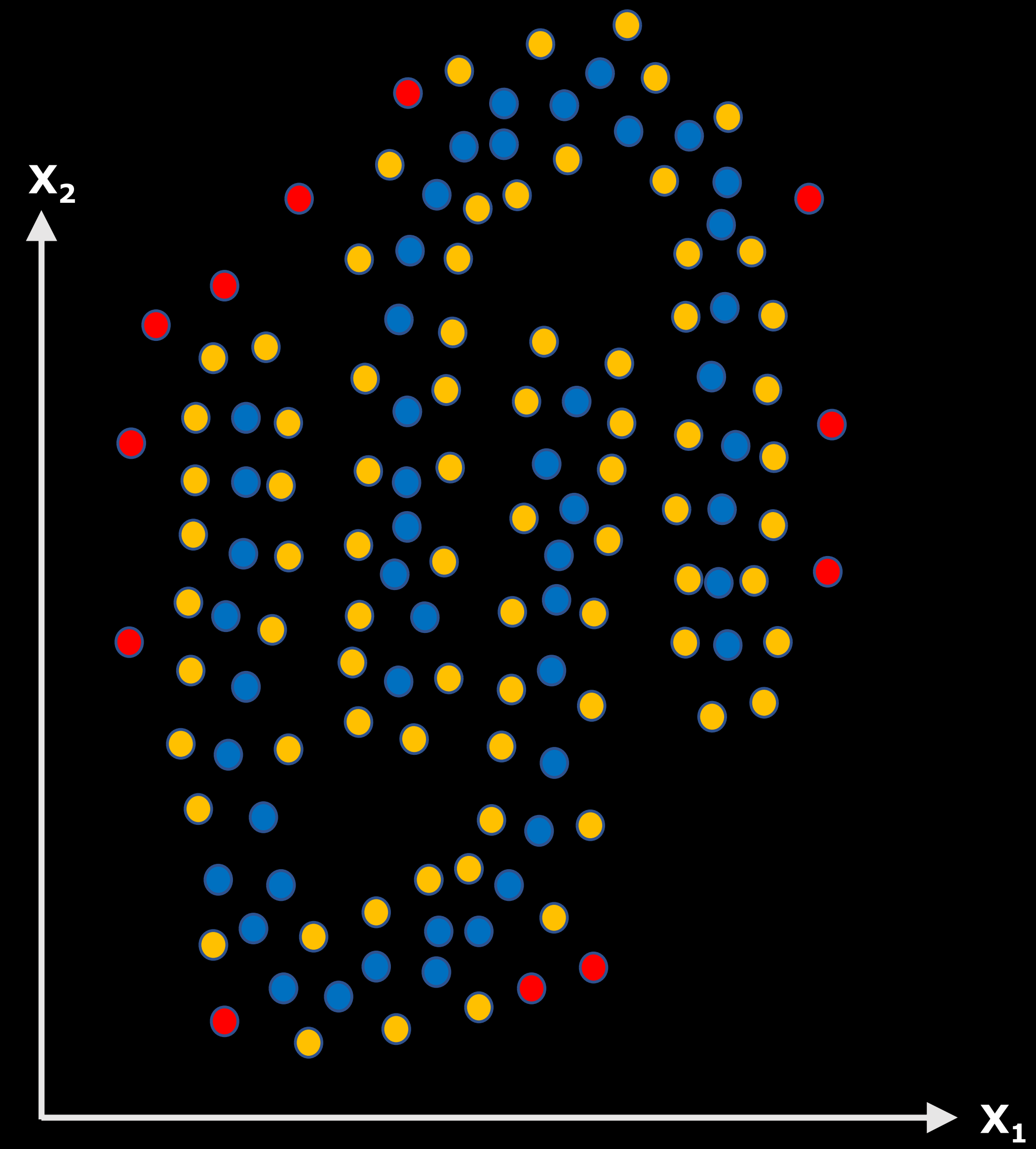

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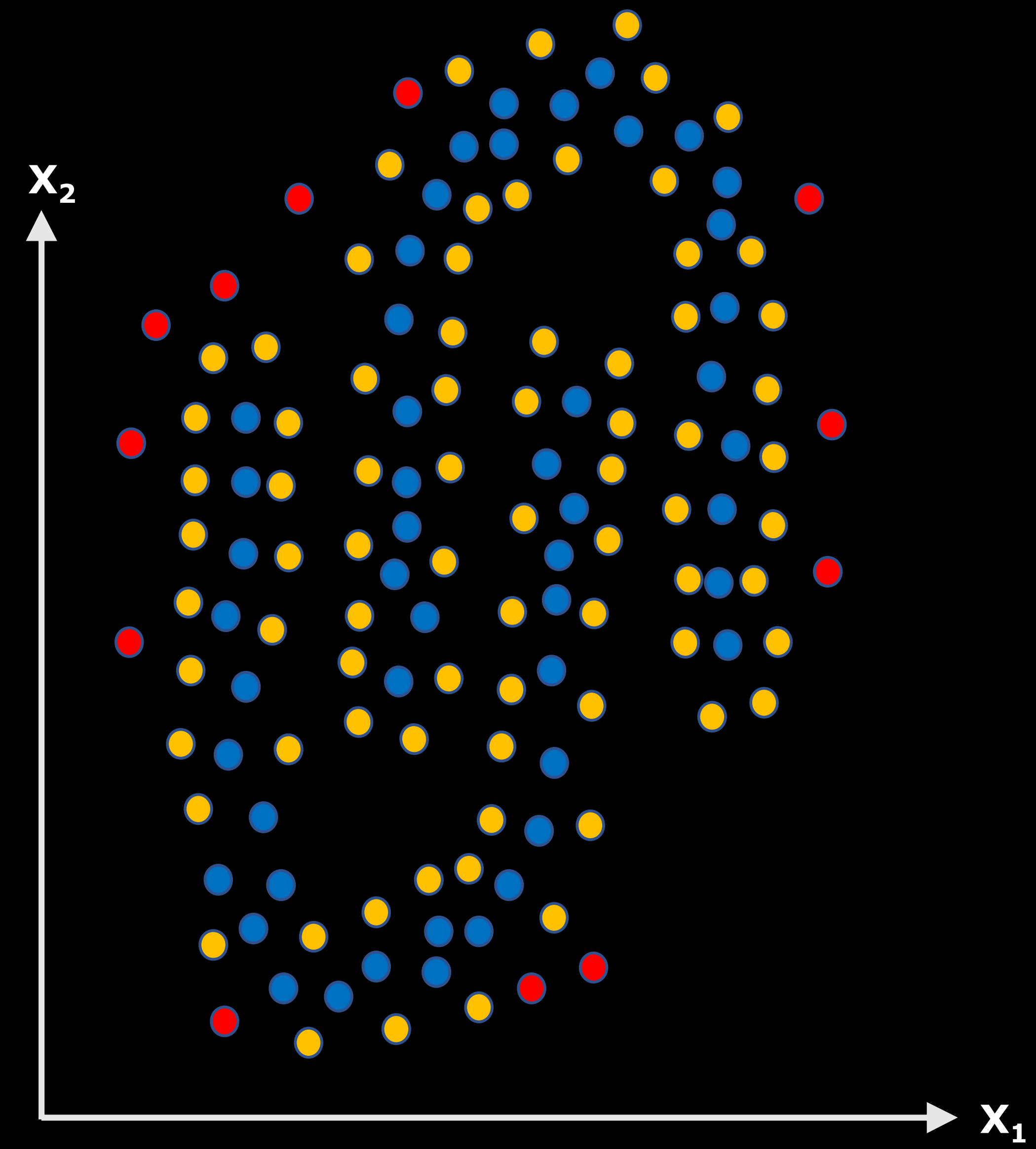

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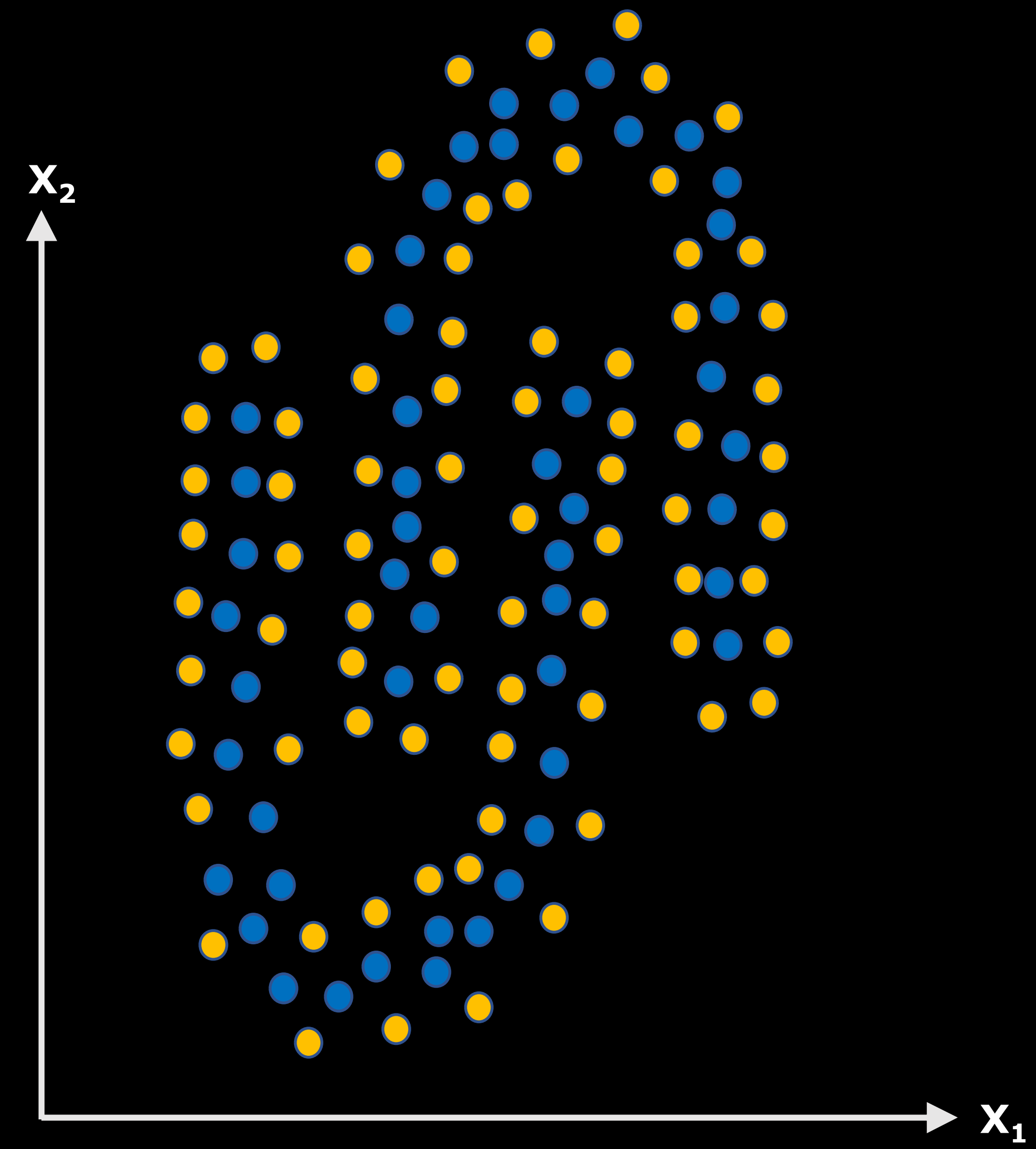

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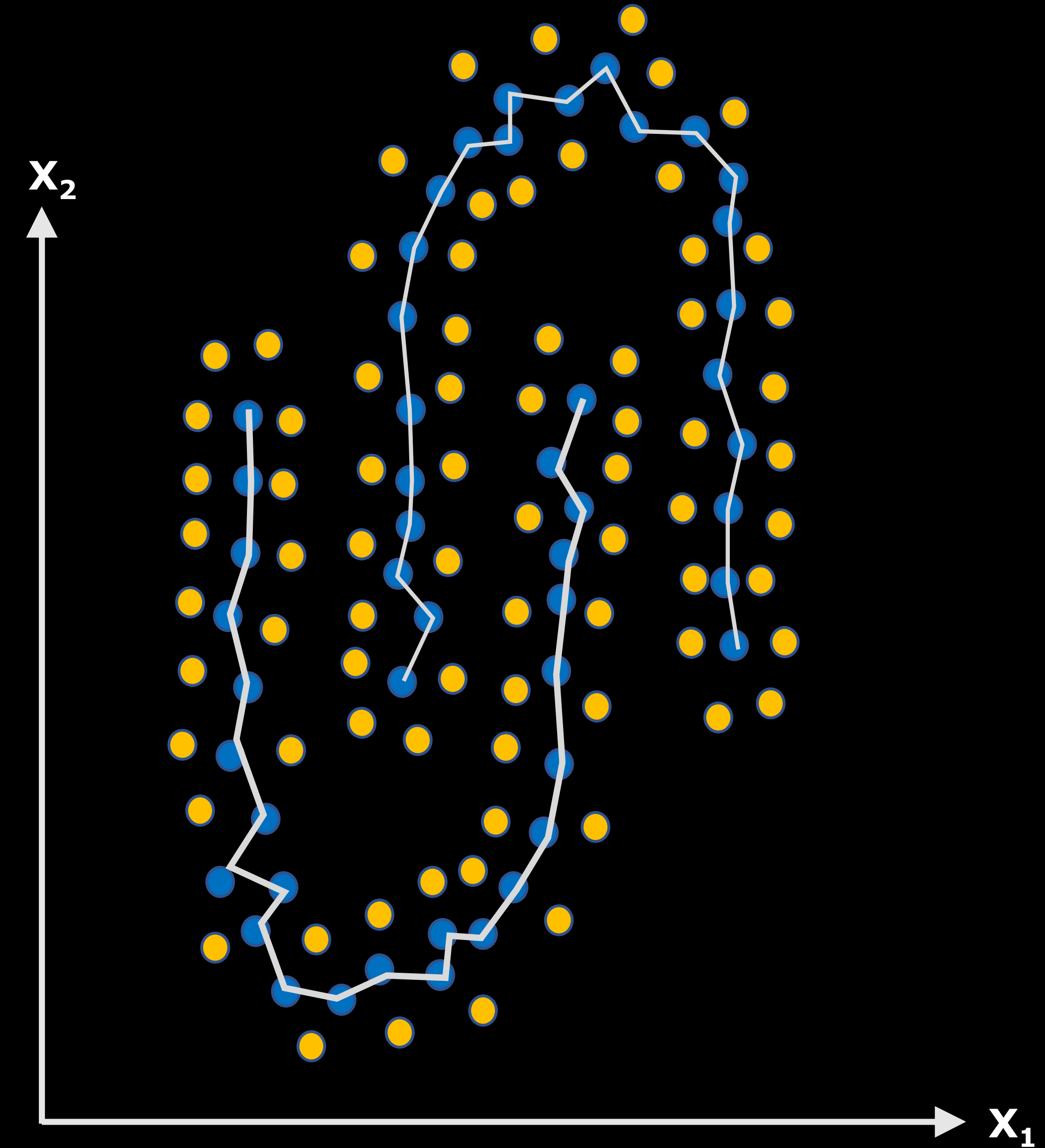

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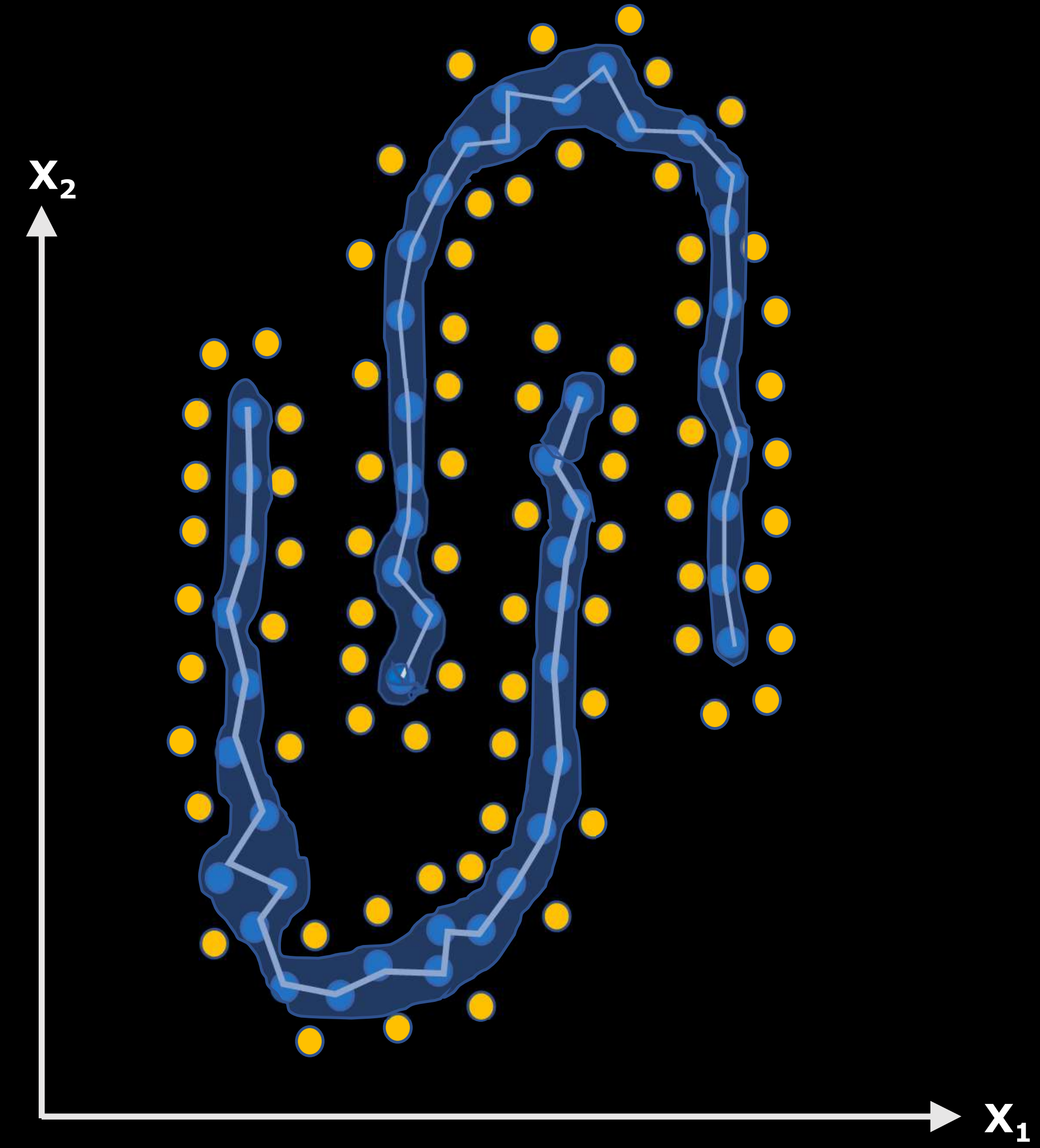

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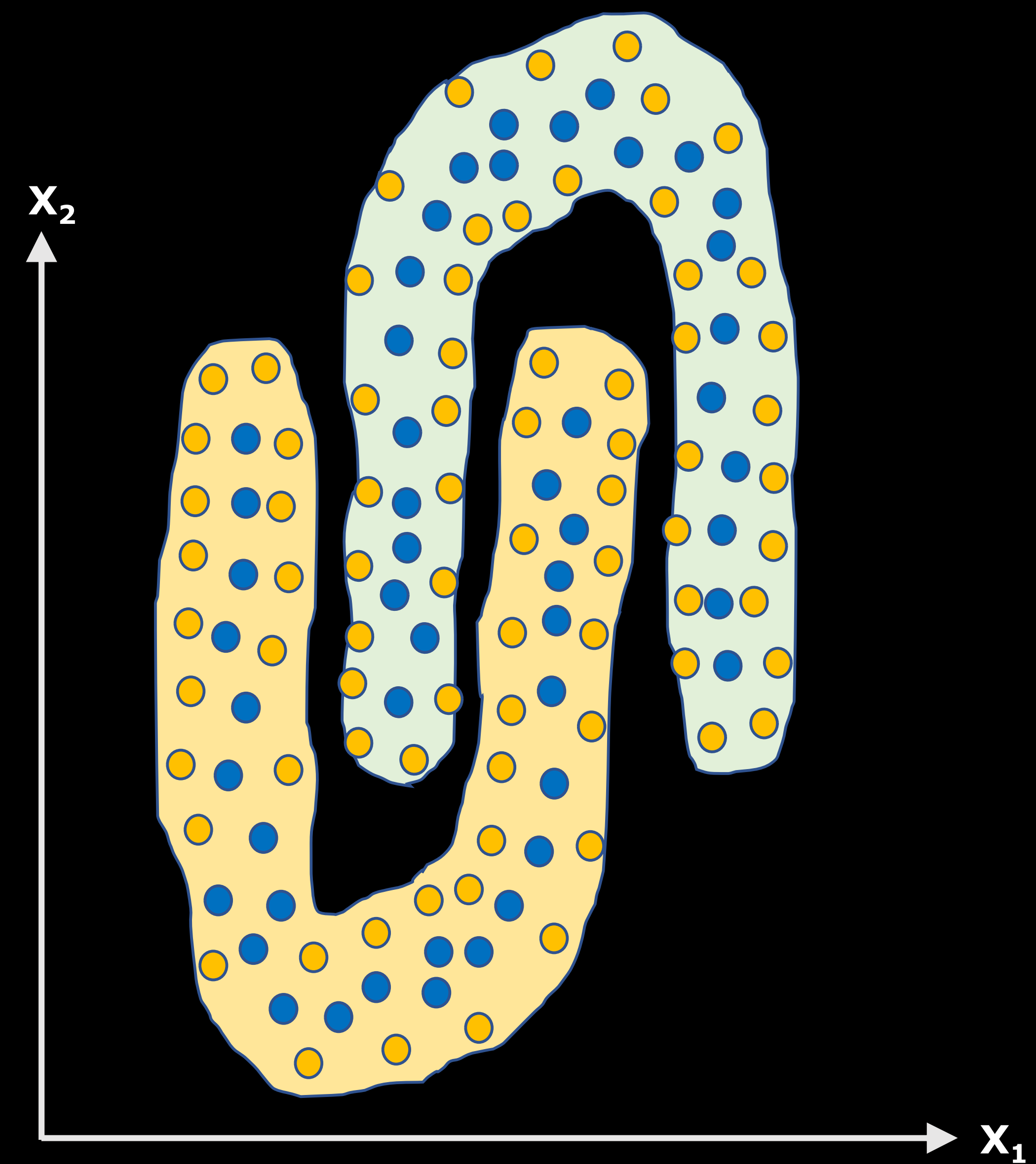
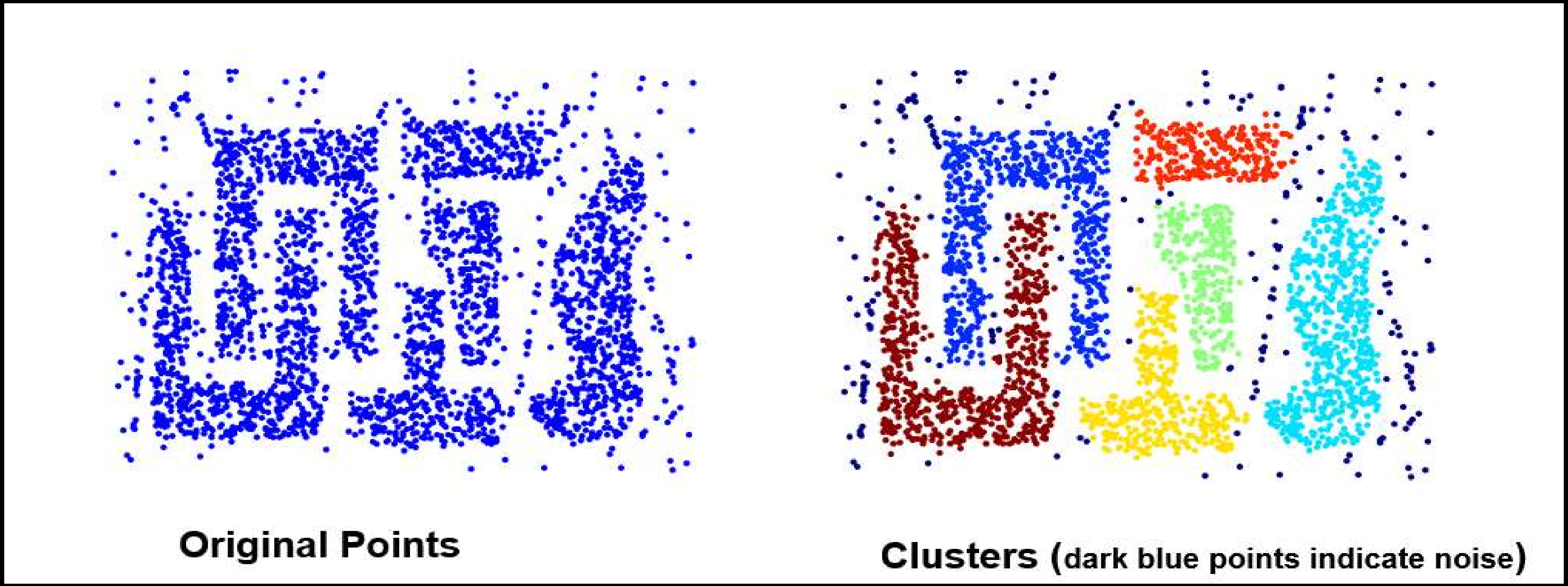
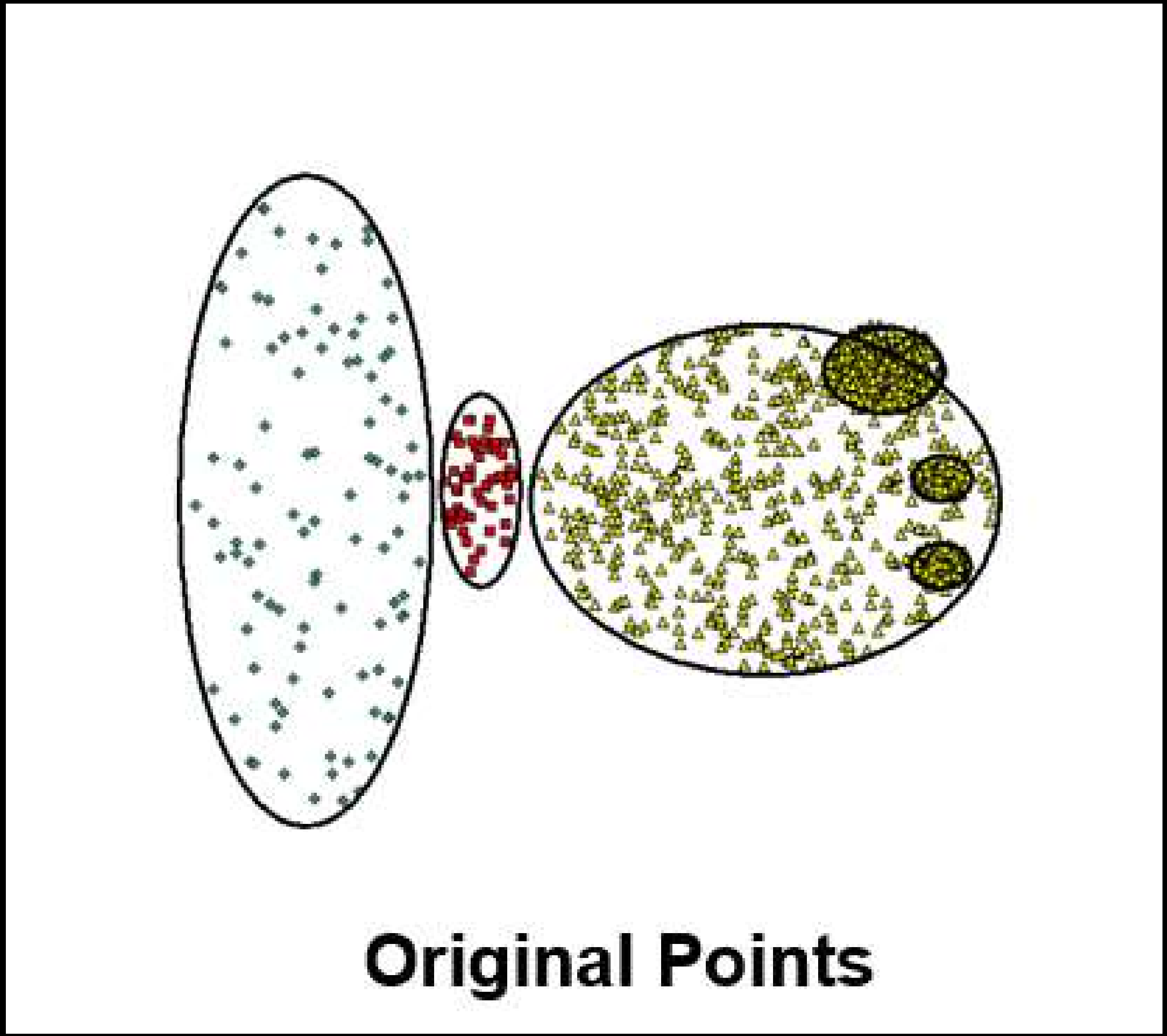


DBSCAN WORKS WELL WHEN …

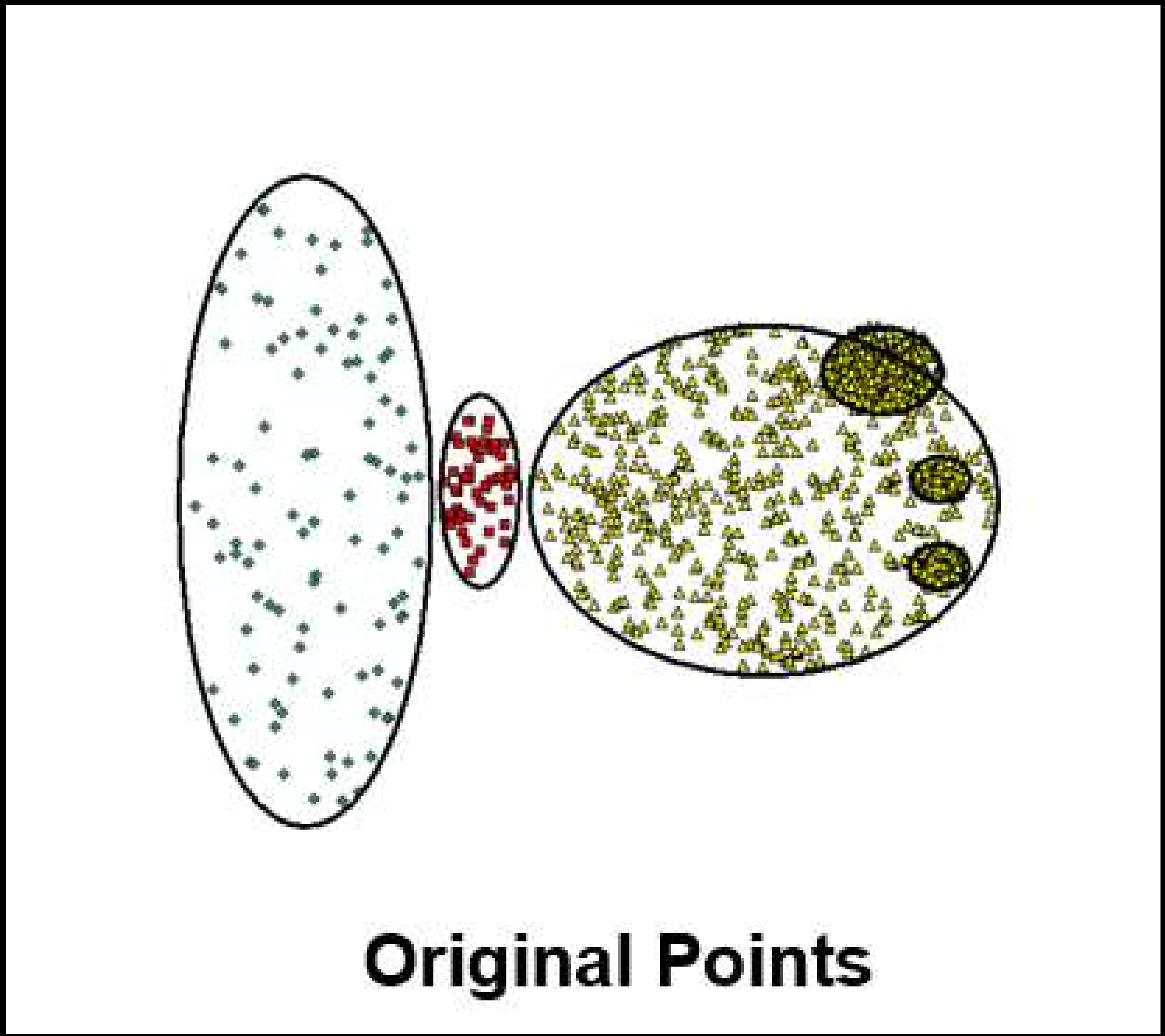


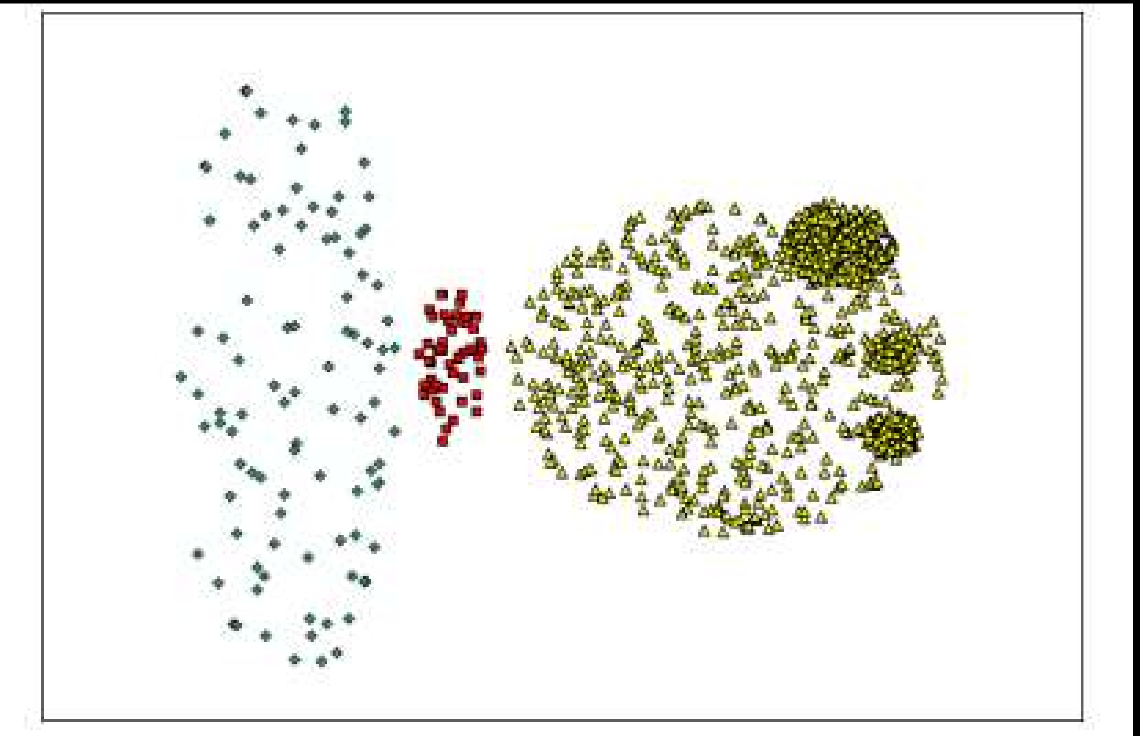
- Can handle clusters of different shapes and sizes
- Resistant to noise

DBSCAN DOES NOT WORK WELL WHEN …



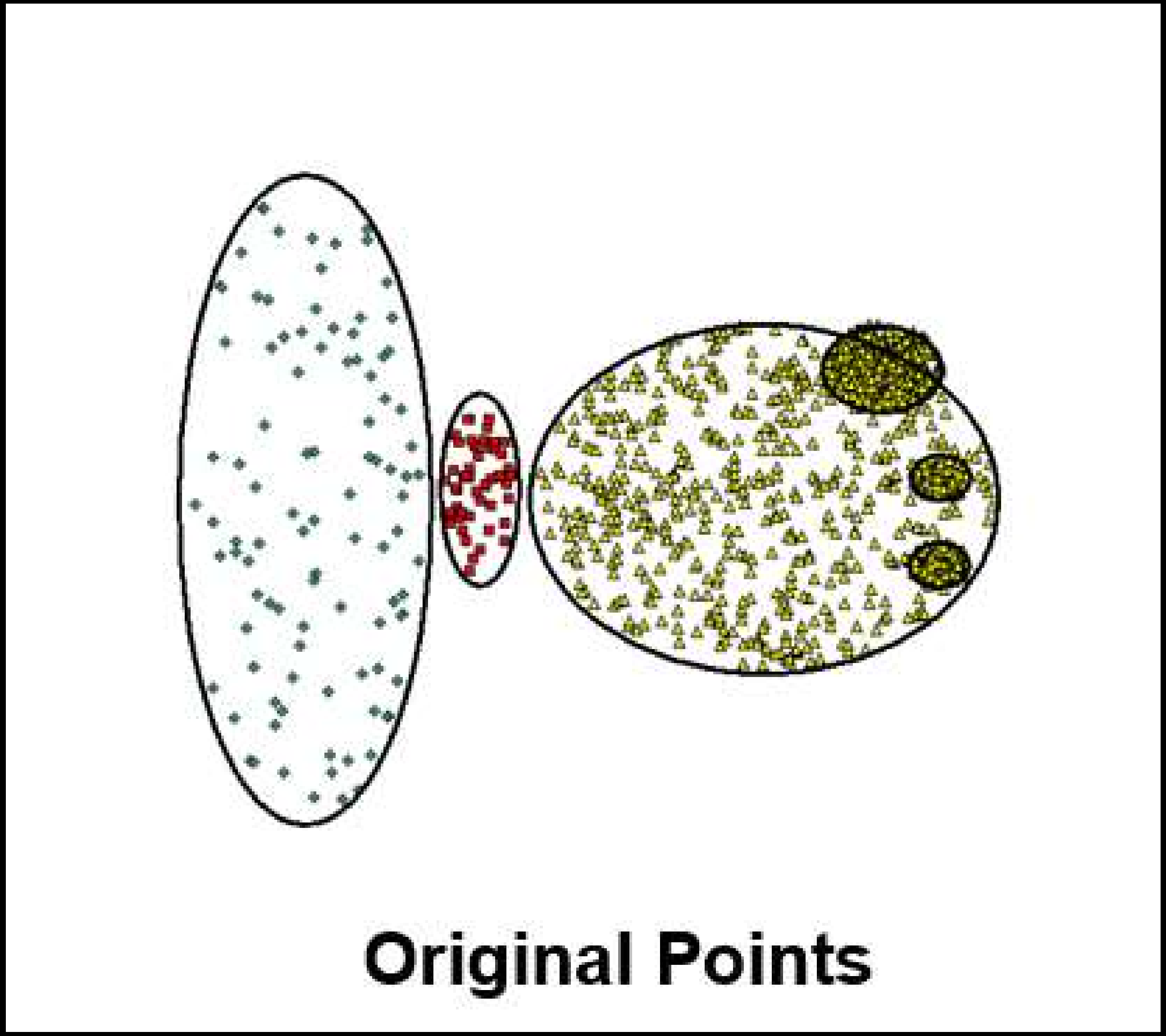
DBSCAN DOES NOT WORK WELL WHEN …

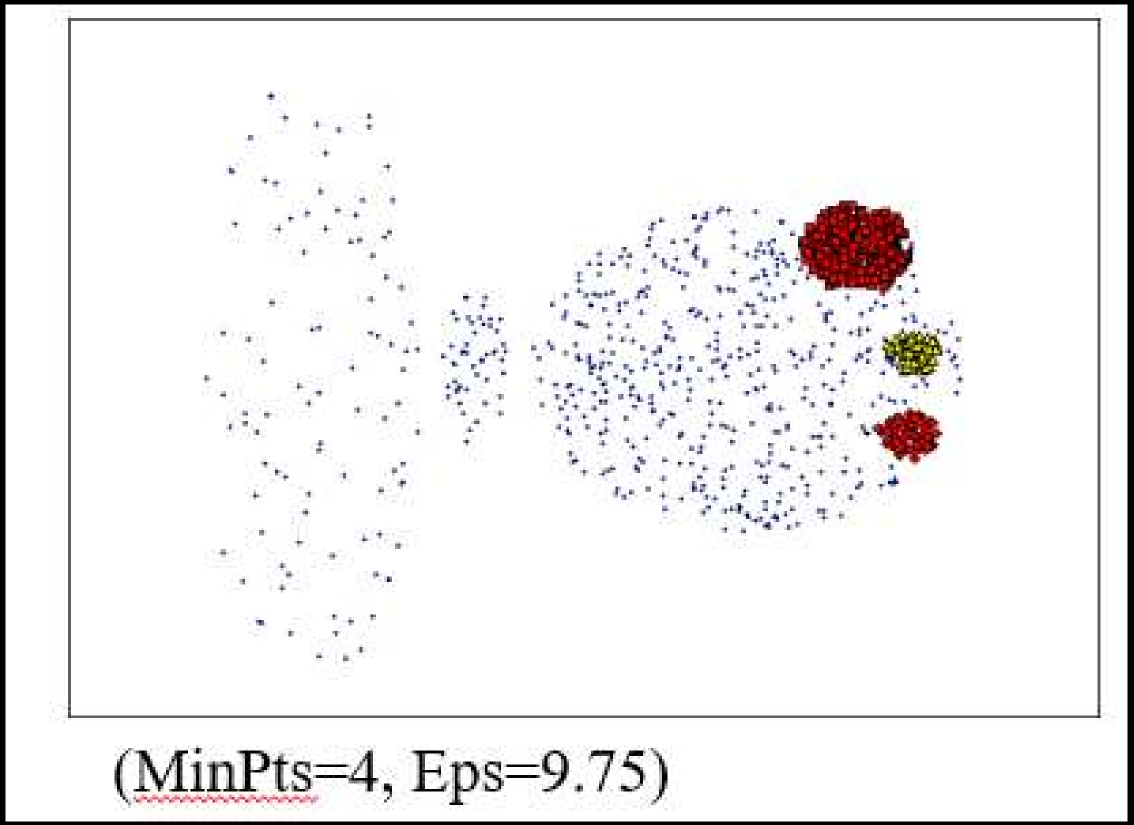




(MinPts=4, Eps=9.92).

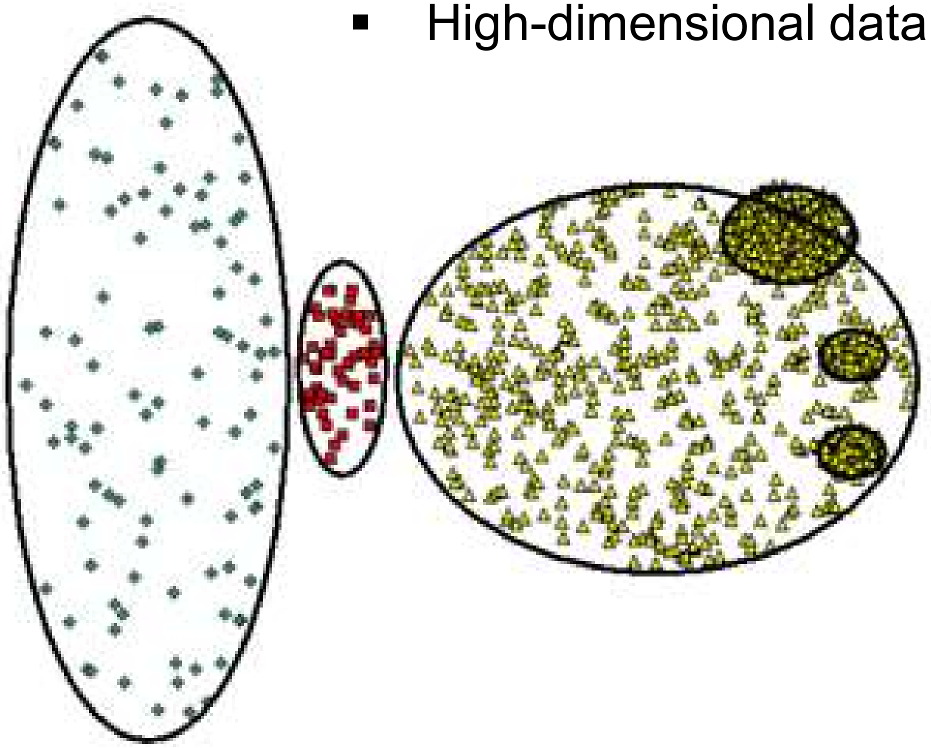
DBSCAN DOES NOT WORK WELL WHEN …



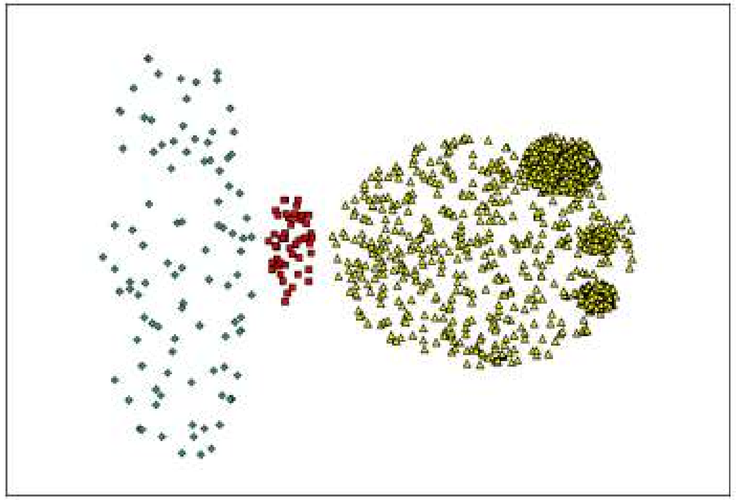


DBSCAN DOES NOT WORK WELL WHEN …

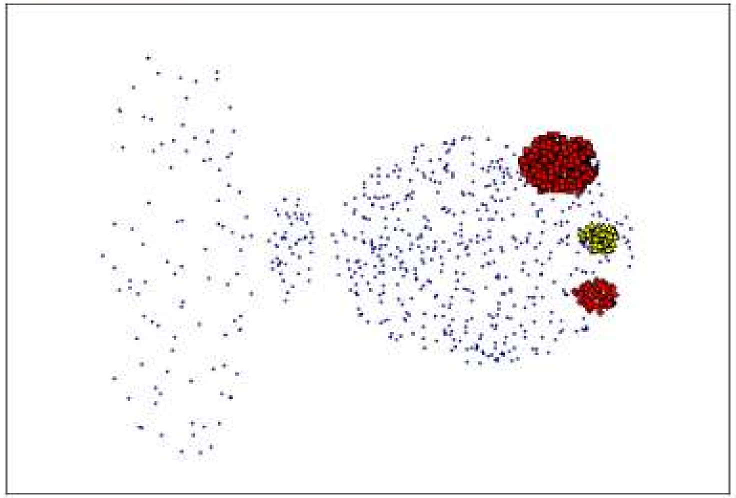
- Varying densities
- High-dimensional data



Original Points



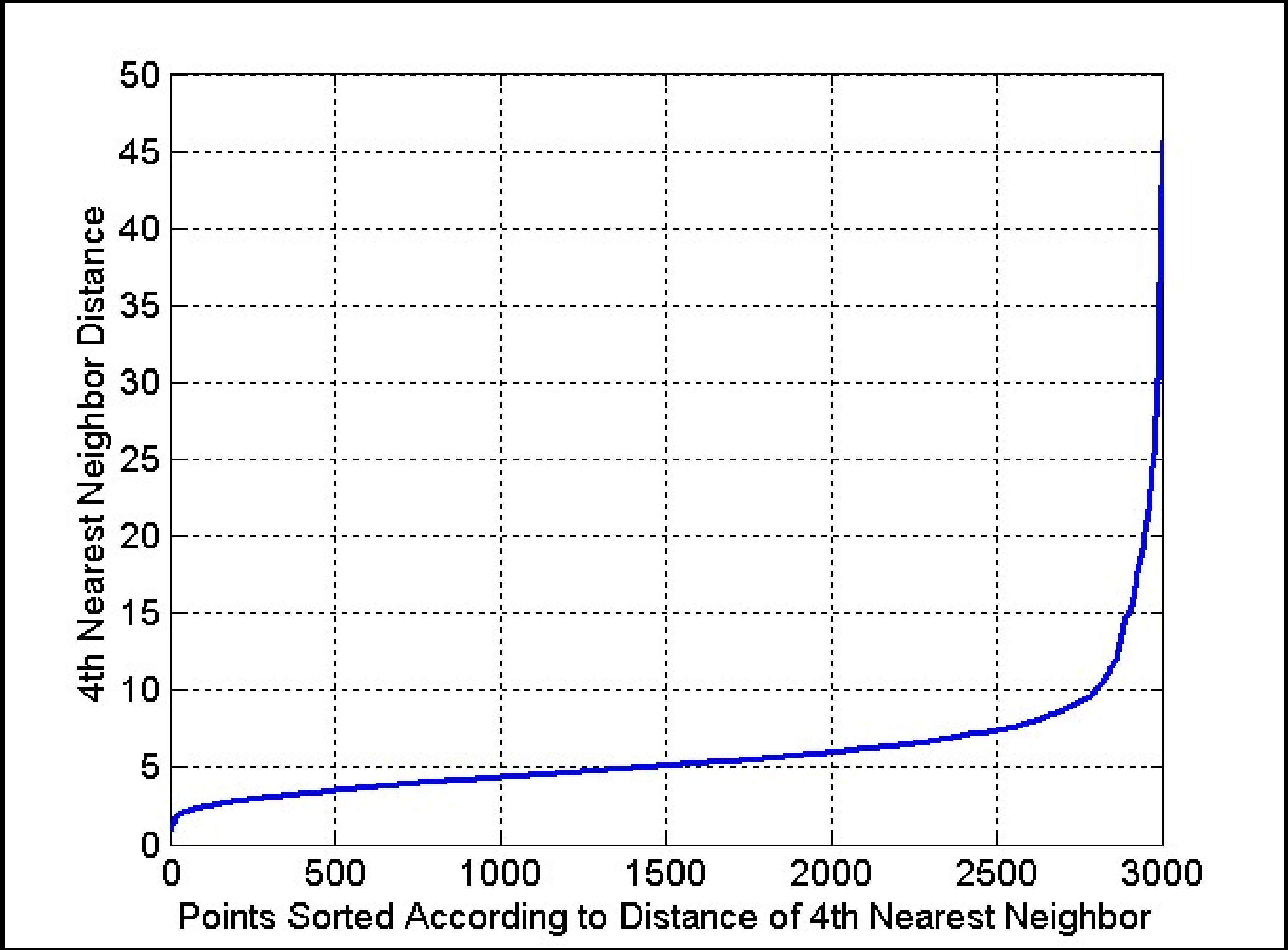
(MinPts=4, Eps=9.92).



(MinPts=4, Eps=9.75)

DBSCAN – How to set parameters (Eps and MinPts)?

- Idea is that for points in a cluster, their k^{th} nearest neighbors are at close distance
- Noise points have the k^{th} nearest neighbor at farther distance
- So, plot sorted distance of every point to its k^{th} nearest neighbor



DBSCAN VS K-MEANS

We assume that there are no ties in distances for either DBSCAN and K-means, we also assume that DBSCAN always assigns a border point which is associated with more core points to the closest core point.

- DBSCAN and K-means assign objects to a single cluster, but K-means assigns all objects while DBSCAN can discard noise objects
- DBSCAN can handle clusters of different sizes and shapes and it is not strongly affected by noise or outliers. K-means has difficulties with non-globular clusters and clusters of different sizes. Both algorithms perform poorly when clusters have widely differing densities
- K-means can only be used for data that has a well defined centroid, such as mean or median. DBSCAN requires that its definition of density, which is based on the traditional Euclidean notion of density, be meaningful for the data
- K-means can be applied to sparse, high-dimensional data, such as document data. DBSCAN typically performs poorly for such data because the traditional Euclidean definition of density does not work well for high-dimensional data

DBSCAN vs K-means

We assume that there are no ties in distances for either DBSCAN and K-means, we also assume that DBSCAN always assigns a border point which is associated with more core points to the closest core point.

- DBSCAN makes no assumption about the distribution of the data. The basic K-means is equivalent to a statistical clustering approach (Mixture Model) that assumes all clusters come from spherical Gaussian distributions with different means but the same covariance matrix
- DBSCAN and K-means both look for clusters using all attributes, that is, they do not look for clusters that may involve only a sub-set of the attributes
- K-means can find clusters that are not well separated, even if they overlap, but DBSCAN merges clusters that overlap
- K-means has complexity $O(N)$ while DBSCAN is $O(N^2)$ (except for low dimensional Euclidean data.)
- DBSCAN produces the same set of clusters from one run to another while K-means, which is typically used with random initialization of centroids, does not
- DBSCAN automatically determines the number of clusters, for K-means the number of clusters needs to be specified as a parameter

ADDITIONAL DENSITY-BASED CLUSTERNG ALGORITHMS

Many additional Density-based clustering techniques exist that address the issues of efficiency, finding clusters in subspaces, and more accurately modelling density.

They can be grouped in

- **GRID-BASED CLUSTERING**; they break the data space into grid cells and then form clusters from cells that are sufficiently dense. They can be effective and efficient at least for low-dimensional data (**CLIQUE**)
- **SUBSPACE CLUSTERING**; they look for clusters (dense regions) in subsets of all dimensions. For a data space with “n” attributes, potentially 2^{n-1} subspaces need to be searched, and thus an efficient technique is needed to do this (**COSA**)
- **KERNEL DENSITY FUNCTION**; they use kernel density functions to model density as the sum of the influences of individual data objects (**DENCLUE**)

RECAP

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