DBSCAN

DBSCAN

- DBSCAN - Density-based spatial clustering of applications with noise is a powerful technique which can be used for clustering and outlier detection.
- Let's review what this section will cover!

DBSCAN

- Section Overview:
  - Intuition of DBSCAN
  - DBSCAN vs. K-Means Clustering
  - DBSCAN Hyperparameters Theory
  - DBSCAN Hyperparameters Coding
  - Outlier Project Exercise
  - Project Solutions

DBSCAN

Theory and Intuition

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- DBSCAN stands for **D**ensity-**b**ased **s**patial **c**lustering of **a**pplications with **n**oise.
- Let's review a brief history of the algorithm and then explore an intuition based approach to understanding how it works.

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- Questions to consider:
  - How does DBSCAN work?
  - Advantages and disadvantages of DBSCAN?
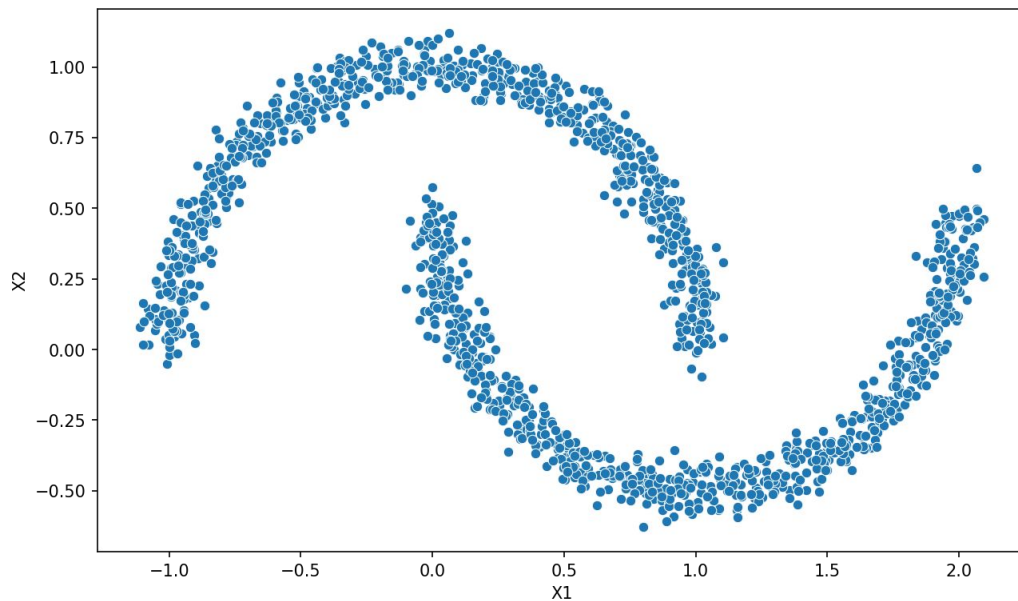 - How does it deal with outliers and noise?

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- DBSCAN Key Ideas
  - DBSCAN focuses on using **density** of points as its main factor for assigning cluster labels.
  - This creates the ability to find cluster segmentations that other algorithms have difficulty with.
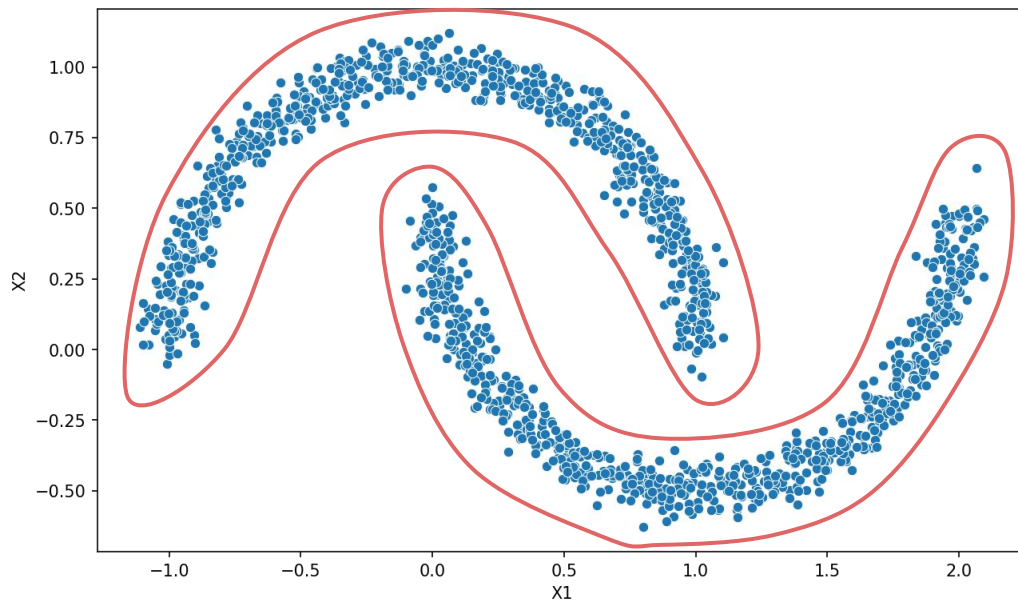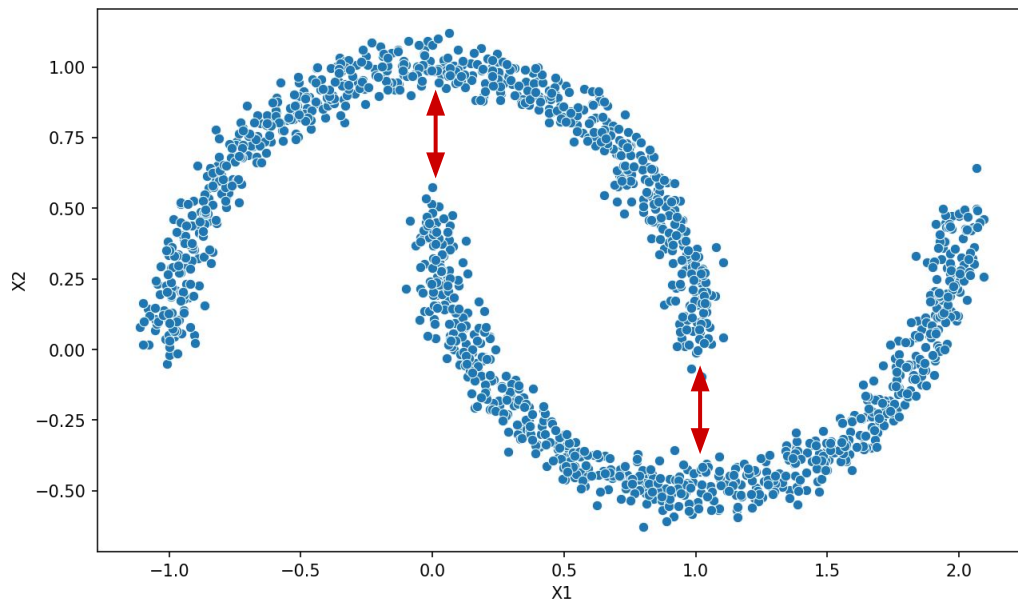
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● Consider the following data set:
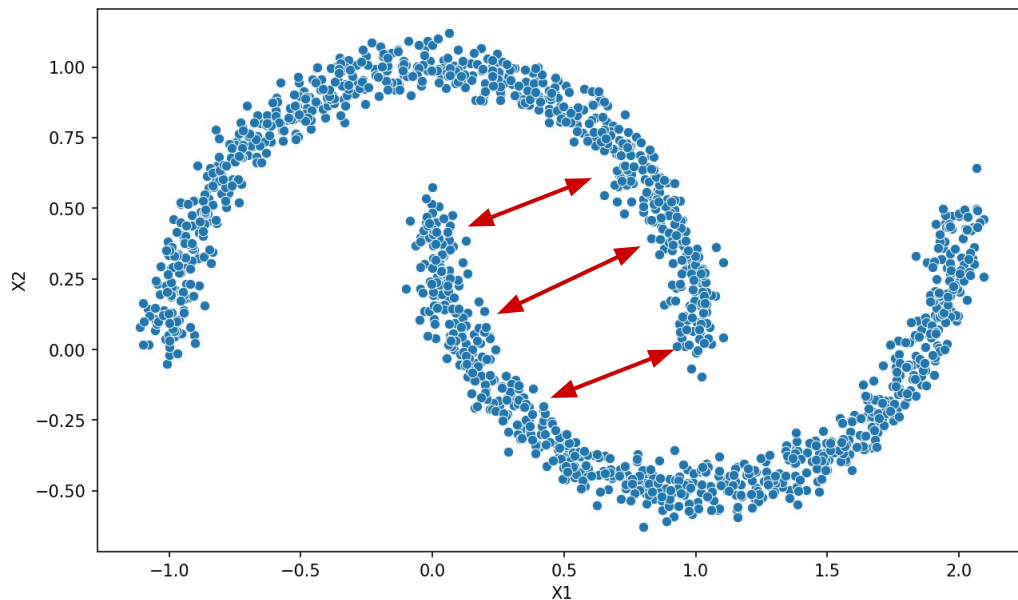
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- Cleary two "moon" shaped clusters:
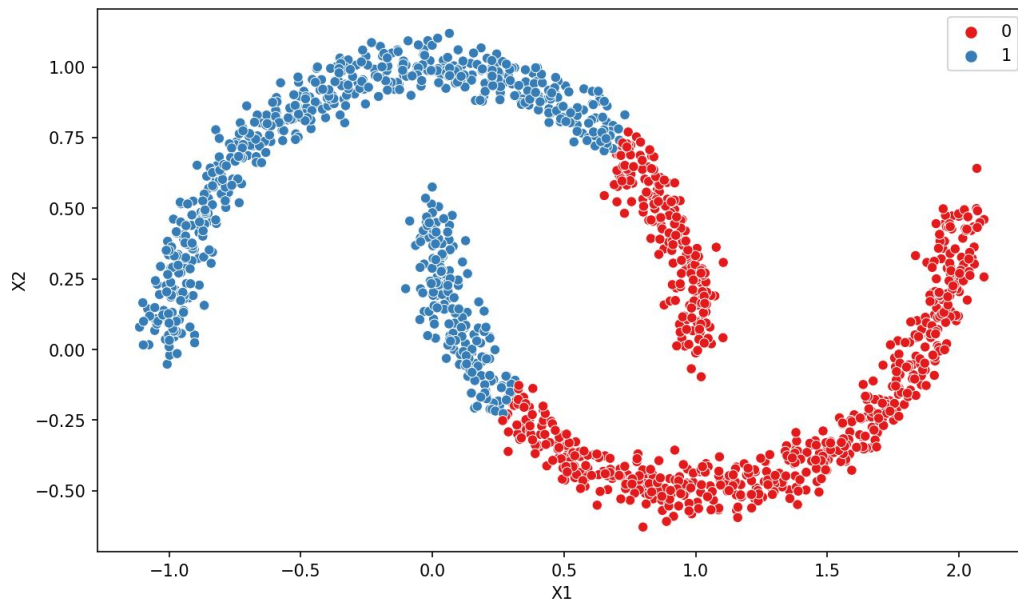
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- But distance based clustering has issues:

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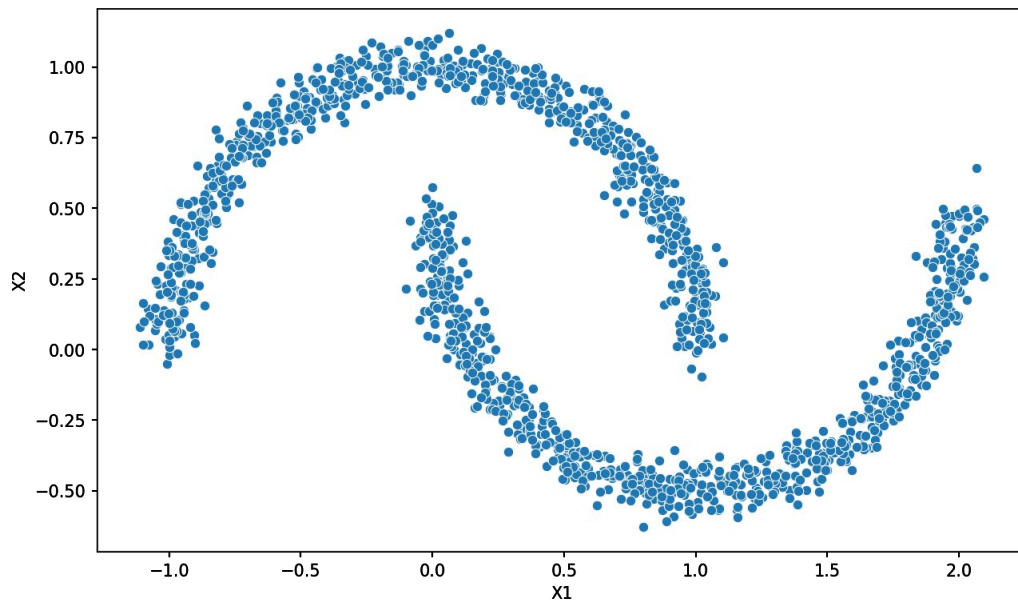- But distance based clustering has issues:
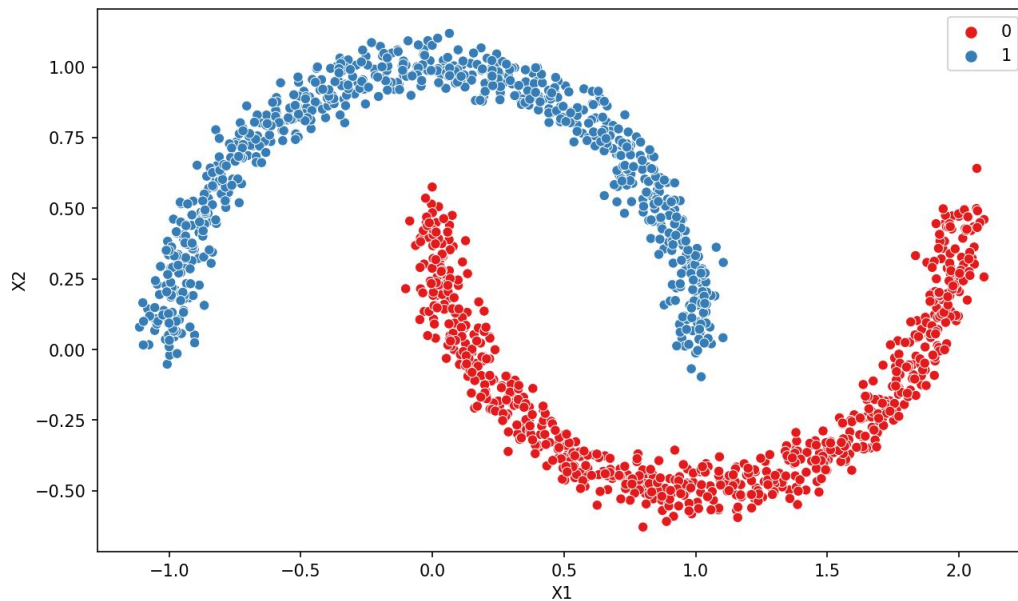
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- Results of K-Means:

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- Results of DBSCAN:

DBSCAN

- Results of DBSCAN:

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- DBSCAN iterates through points and uses two key hyperparameters (epsilon and minimum number of points) to assign cluster labels.
- Unlike K-Means, it focuses on density as the main factor for cluster assignment of points.

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- DBSCAN Key Hyperparameters:
  - Epsilon:
    - Distance extended from a point.
  - Minimum Number of Points:
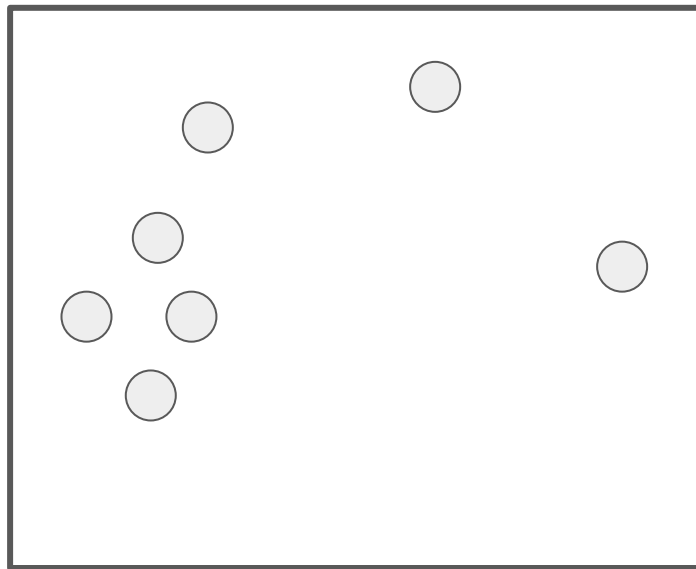   - Minimum number of points in an epsilon distance.

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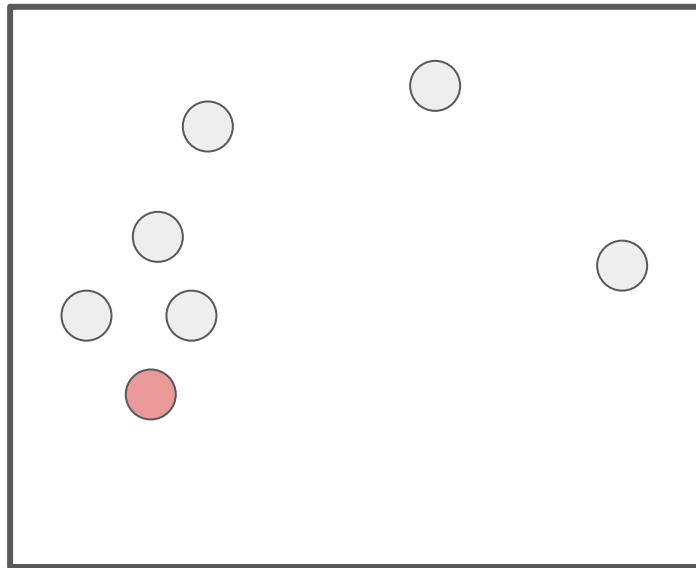- DBSCAN Point Types:
  - Core
  - Border
  - Outlier

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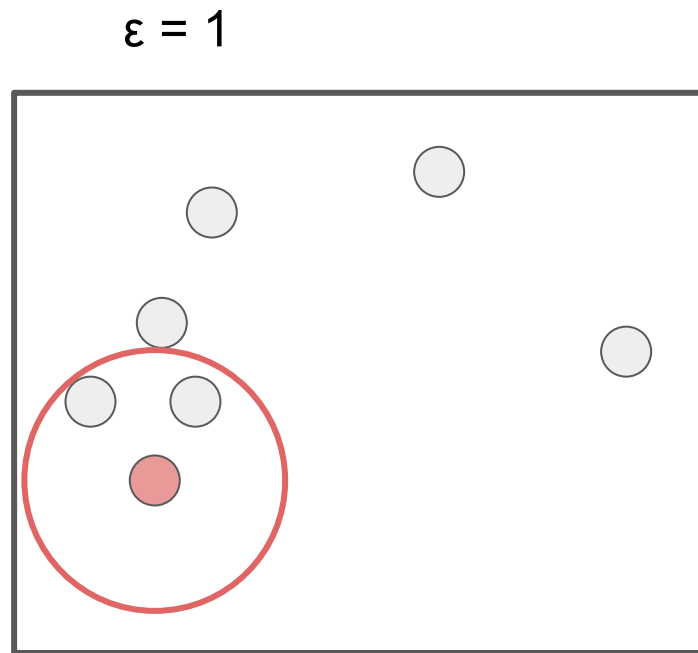- DBSCAN Point Types:
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DBSCAN

- DBSCAN Point Types:
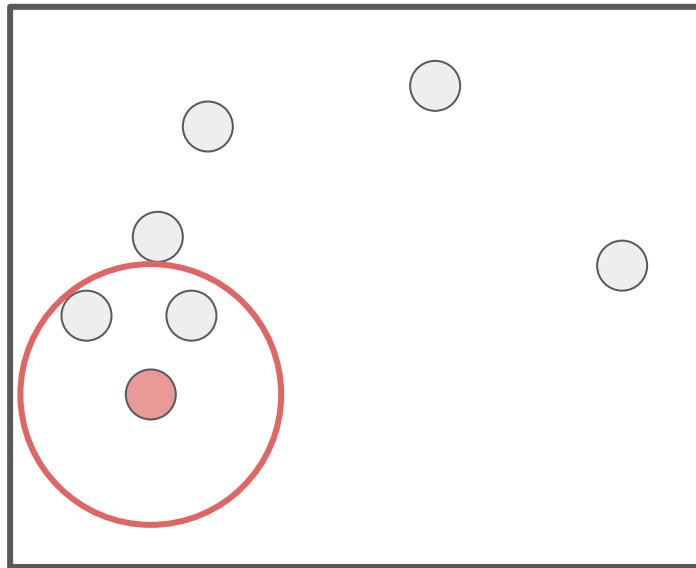 - Core

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- DBSCAN Point Types:
  - Core

ε = 1

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● DBSCAN Point Types:
  ○ Core

ε = 1 and Min Points = 2
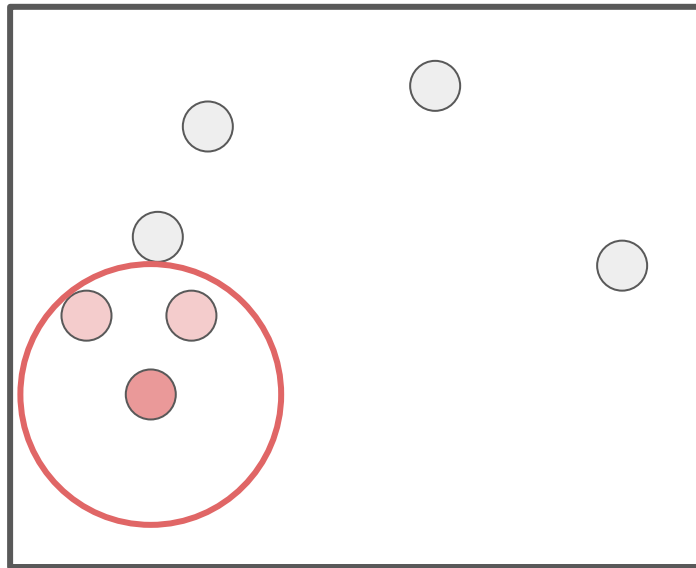
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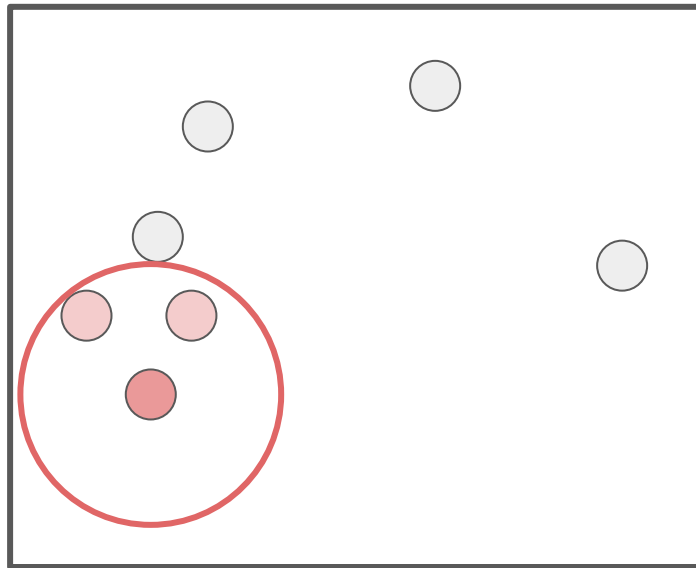- ● DBSCAN Point Types:
  - ○ Core

ε = 1 and Min Points = 2

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- DBSCAN Point Types:
  - Core:
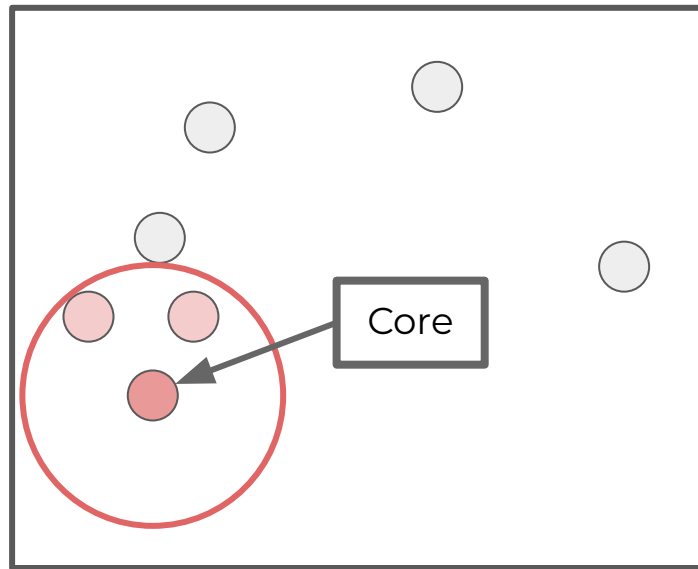   - Point with min. points in epsilon range.

ε = 1 and Min Points = 2

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- DBSCAN Point Types:
  - Core:
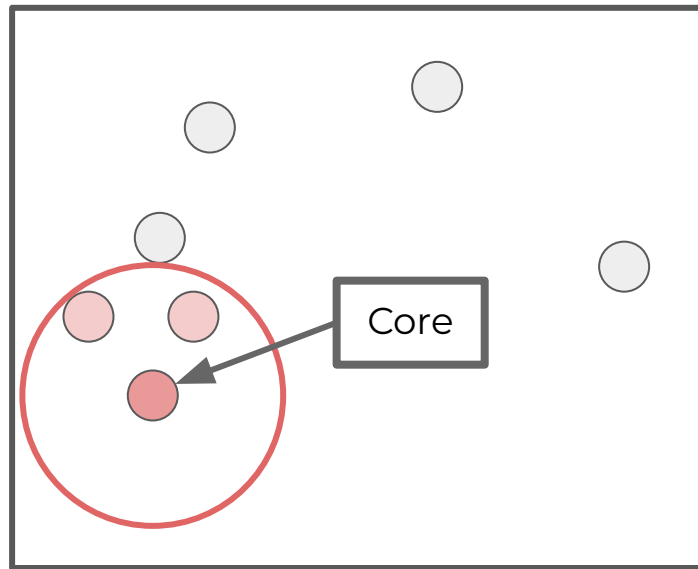   - Point with min. points in epsilon range.

ε = 1 and Min Points = 2

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- DBSCAN Point Types:
  - Core:
    - Point with min. points in epsilon range (including itself).

ε = 1 and Min Points = 3

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- DBSCAN Point Types:
  - Border:
    - In epsilon range of core point, but does not contain min. number of points.

ε = 1 and Min Points = 3

DBSCAN

- DBSCAN Point Types:
  - Border:
    - In epsilon range of core point, but does not contain min. number of points.

ε = 1 and Min Points = 3

DBSCAN

- DBSCAN Point Types:
  - Border:
    - In epsilon range of core point, but does not contain min. number of points.

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Border
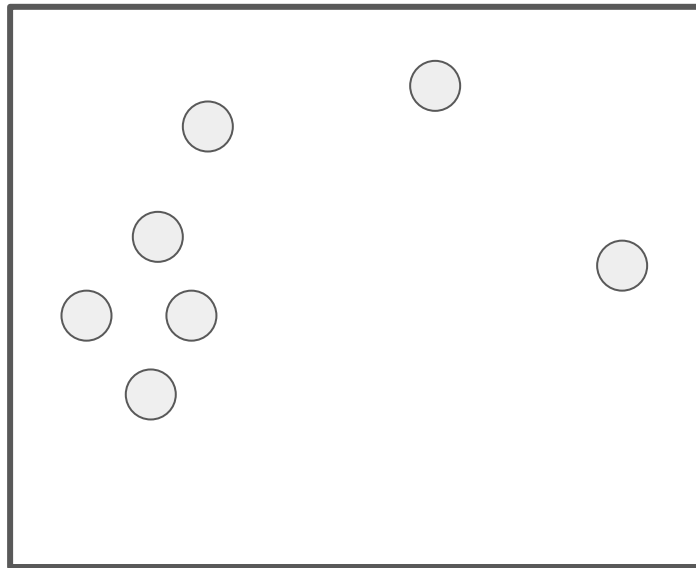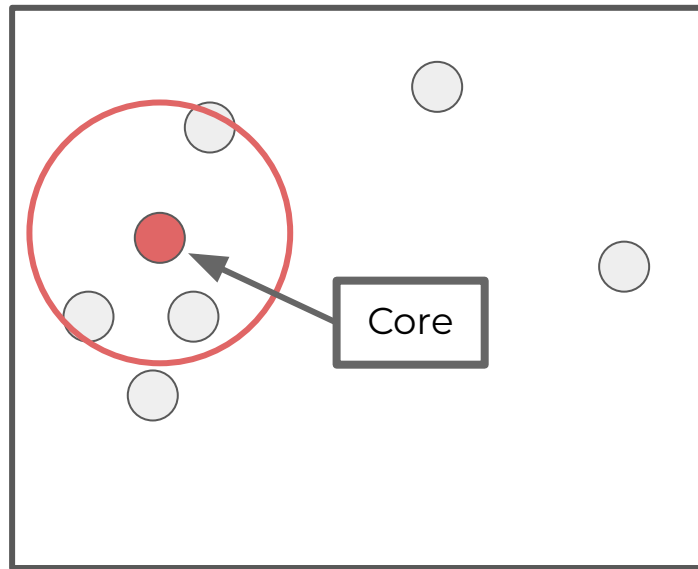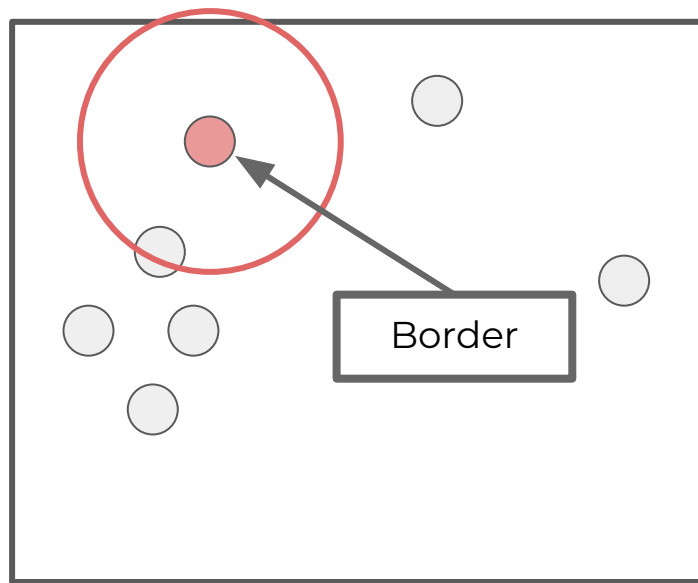
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- DBSCAN Point Types:
  - Border:
    - In epsilon range of core point, but does not contain min. number of points.
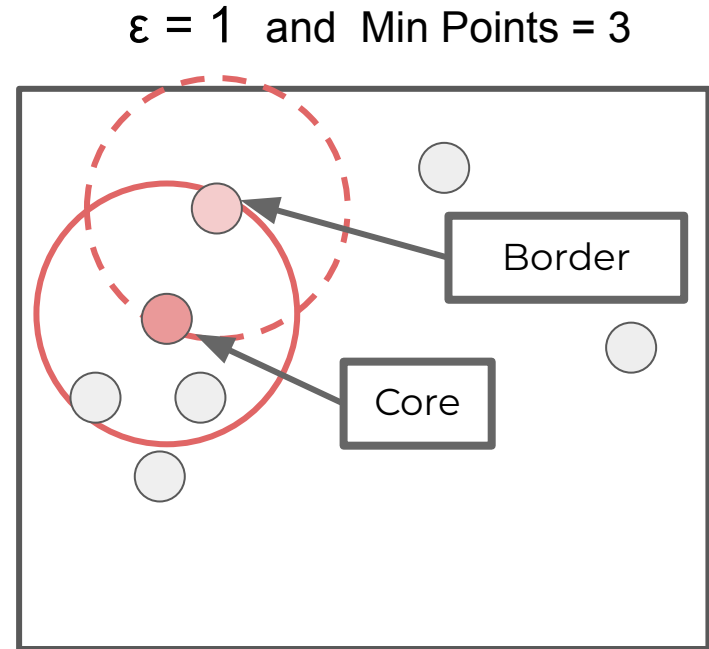
ε = 1 and Min Points = 3

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- DBSCAN Point Types:
  - Outlier:
    - Can not be "reached" by points in a cluster assignment.

ε = 1 and Min Points = 3
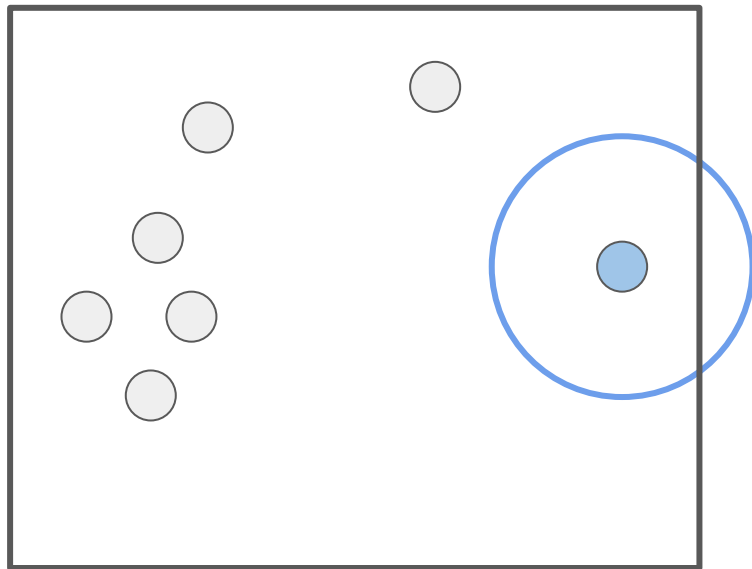
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- We will discuss neighborhoods, epsilon, and minimum number of points in further detail later on, but let's review the actual process of DBSCAN for assigning clusters.

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- DBSCAN Procedure:
    - Pick a random point not yet assigned.
    - Determine the point type.
    - Once a **core** point has been found, add all directly reachable points to the same cluster as core.
    - Repeat until all points have been assigned to a cluster or as an outlier.

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Coding Example on Data Sets

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- Let's explore how DBSCAN compares to K-Means clustering on some unique data sets to get an intuitive understanding of the density based approach of DBSCAN versus a distance based clustering approach of K-Means.

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Key Hyperparameters

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- As we've seen already, there are two key hyperparameters to consider for DBSCAN:
  - Epsilon:
    - Distance extended from a point to search for Min. Number of Points.
  - Min. Number of Points:
    - Min. Number of Points within Epsilon distance to be a core point.
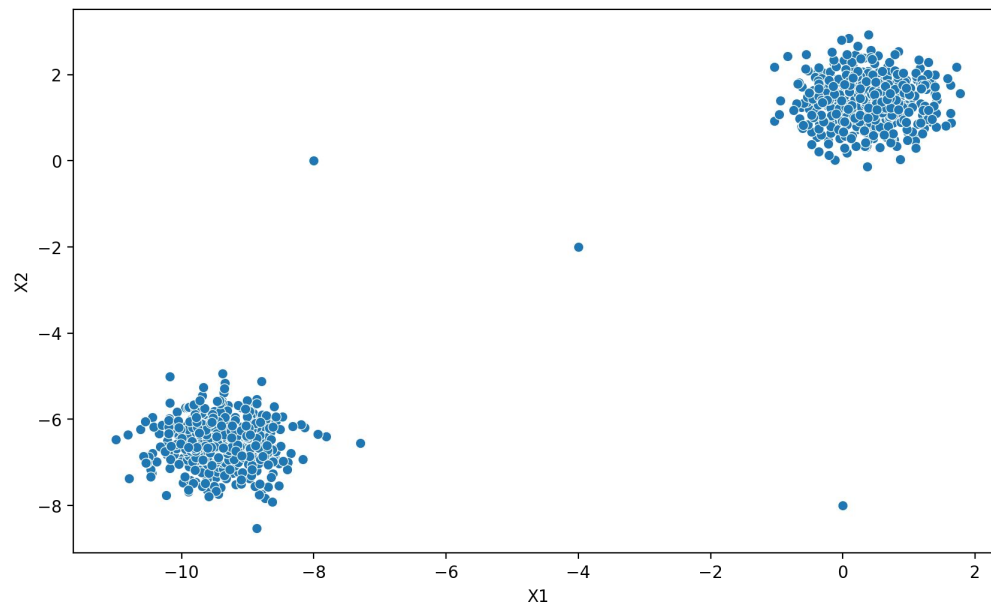
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- Adjusting these hyperparameters have two main outcomes:
    - Changing number of clusters.
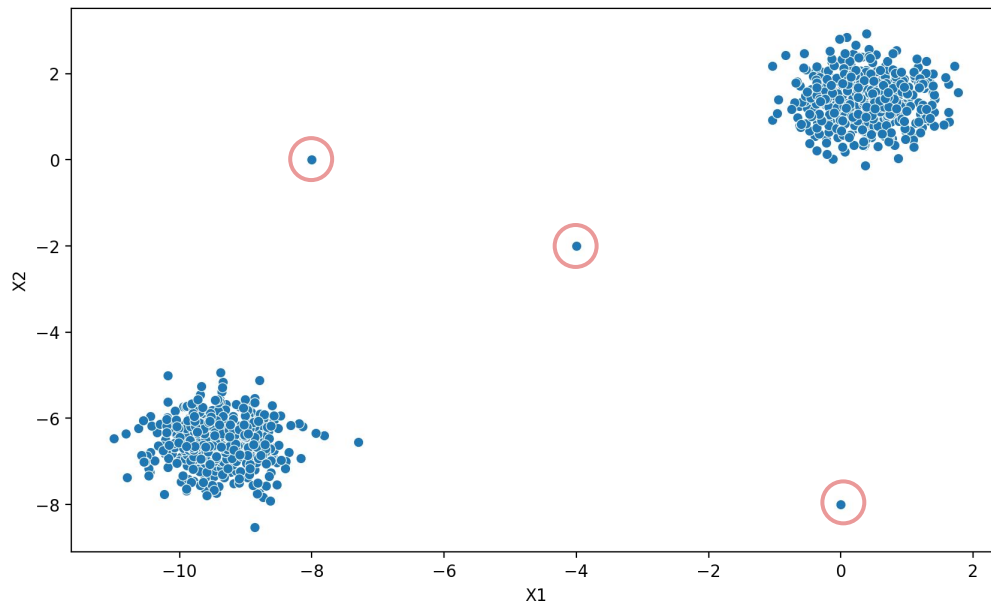   - Changing what is an outlier point.
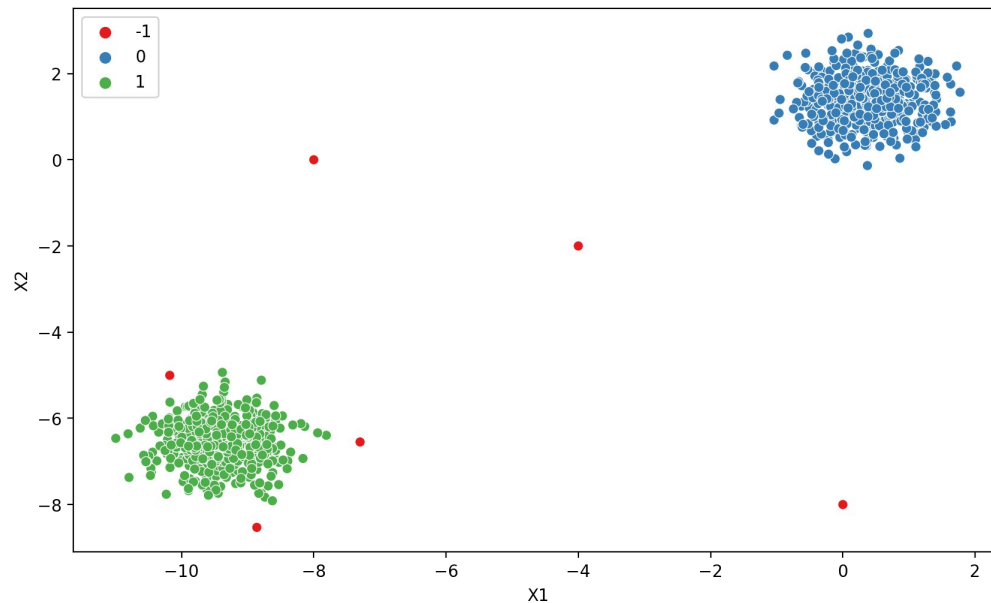
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- Example Data Set:

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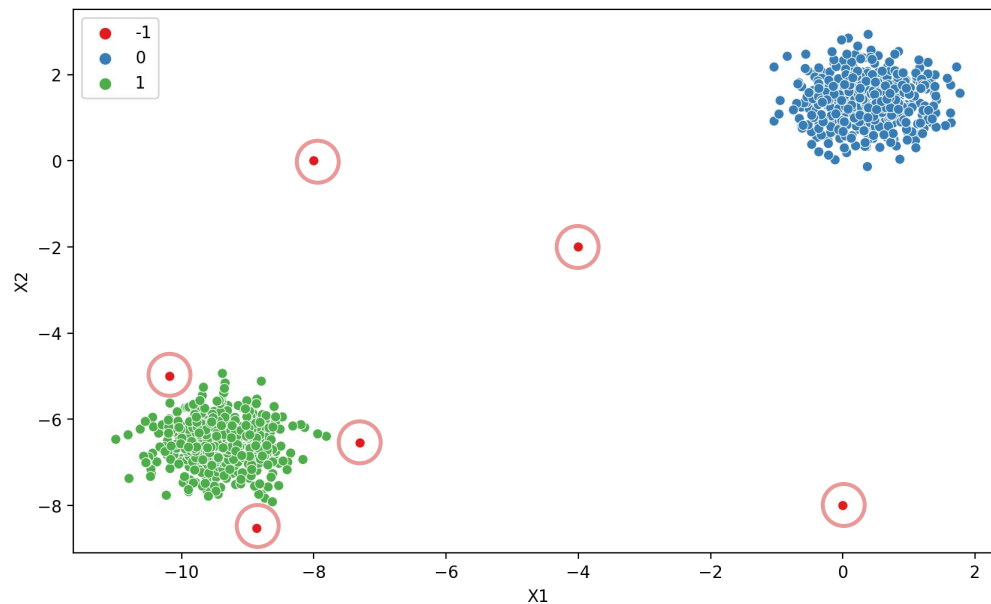
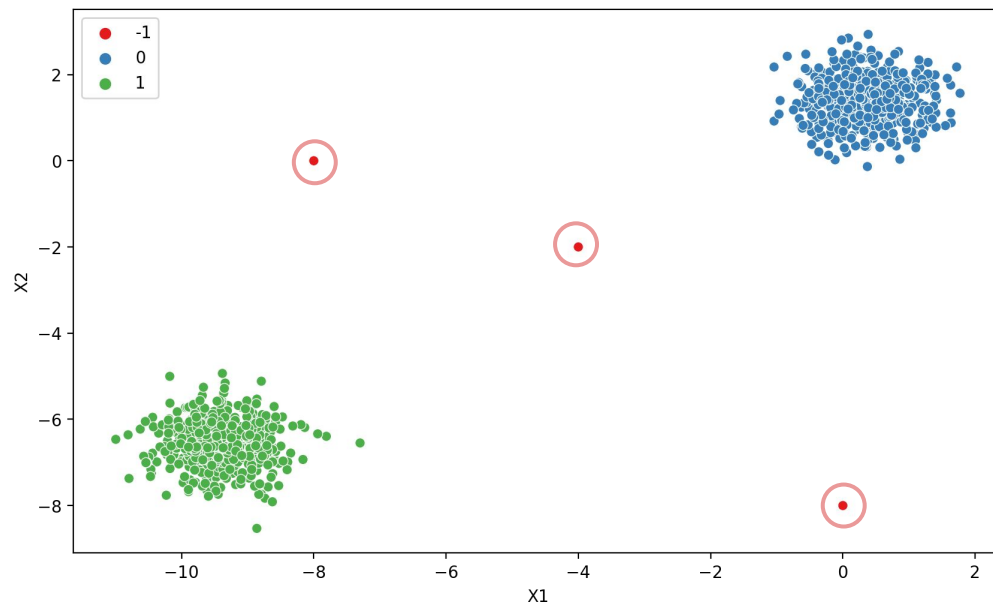- Example Data Set:

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- DBSCAN Results:

DBSCAN

- DBSCAN Results:

DBSCAN

● DBSCAN Results:

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- Epsilon Intuition:
    - Increasing epsilon allows more points to be **core** points which also results in more **border** points and less outlier points.
    - Imagine a huge epsilon, all points would be within the neighborhood and classified as the same cluster!

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- Epsilon Intuition:
  - Decreasing epsilon causes more points not to be in range of each other, creating more unique clusters.
  - Imagine a tiny epsilon, the range would not extend far out enough to come into contact with any other points!

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- Methods for finding an epsilon value:
  - Run multiple DBSCAN models varying epsilon and measure:
    - Number of Clusters
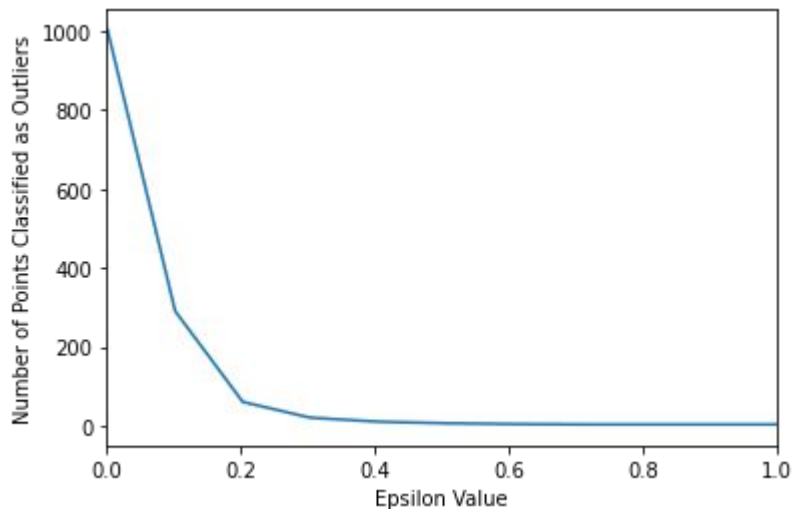   - Number of Outliers
    - Percentage of Outliers

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- Methods for finding an epsilon value:
    - Extremely dependent on the particular data set and domain space.
    - Requires user to have some expectation or intuition about number of clusters and relative percentage of outliers.

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- Plot "elbow/knee" diagram comparing epsilon values:

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- Minimum Number of Samples/Points:
  - Number of samples in a neighborhood for a point to be considered as a **core** point (including the point itself).

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- Min. Number of Samples Intuition:
  - Increasing to a larger number of samples needed to be considered a core point, causes more points to be considered unique outliers.

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- Min. Number of Samples Intuition:
  - Imagine if min. number of samples was close to total number of points available, then very likely all points would become outliers.
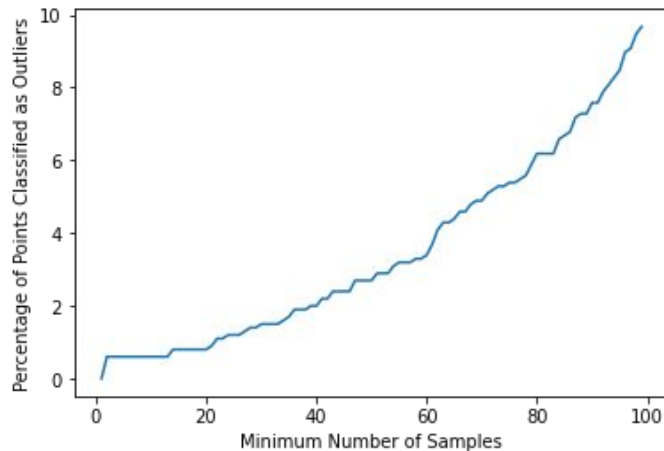
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- Choosing Min. Number of Samples:
    - Test multiple potential values and chart against number of outliers labeled.

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  - Test multiple potential values and chart against number of outliers labeled.

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- Min. Number of Samples Note:
  - Useful to increase to create potential new small clusters, instead of complete outliers.

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