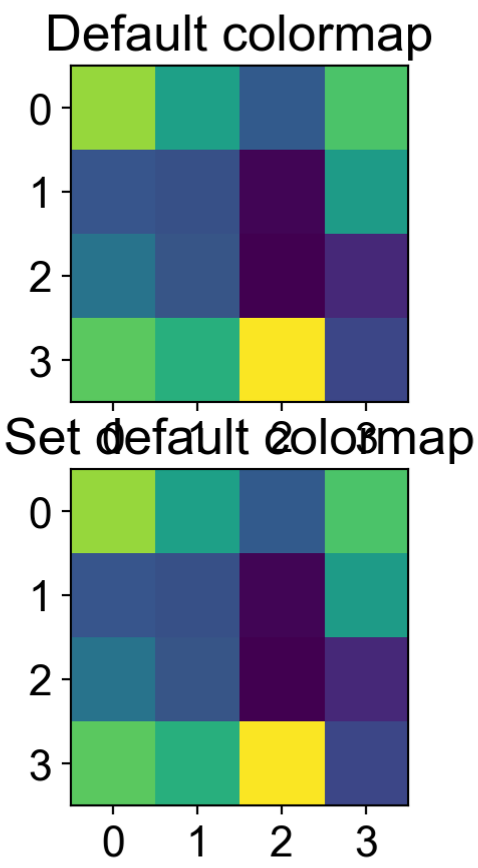
CPSC 330 Lecture 16: DBSCAN, Hierarchical Clustering

Happy Halloween

Announcements

- HW5 extension: Was due yesterday
- HW6 is due next week Wednesday.
  - Computationally intensive
  - You need to install many packages

Imports



iClicker Exercise 16.1

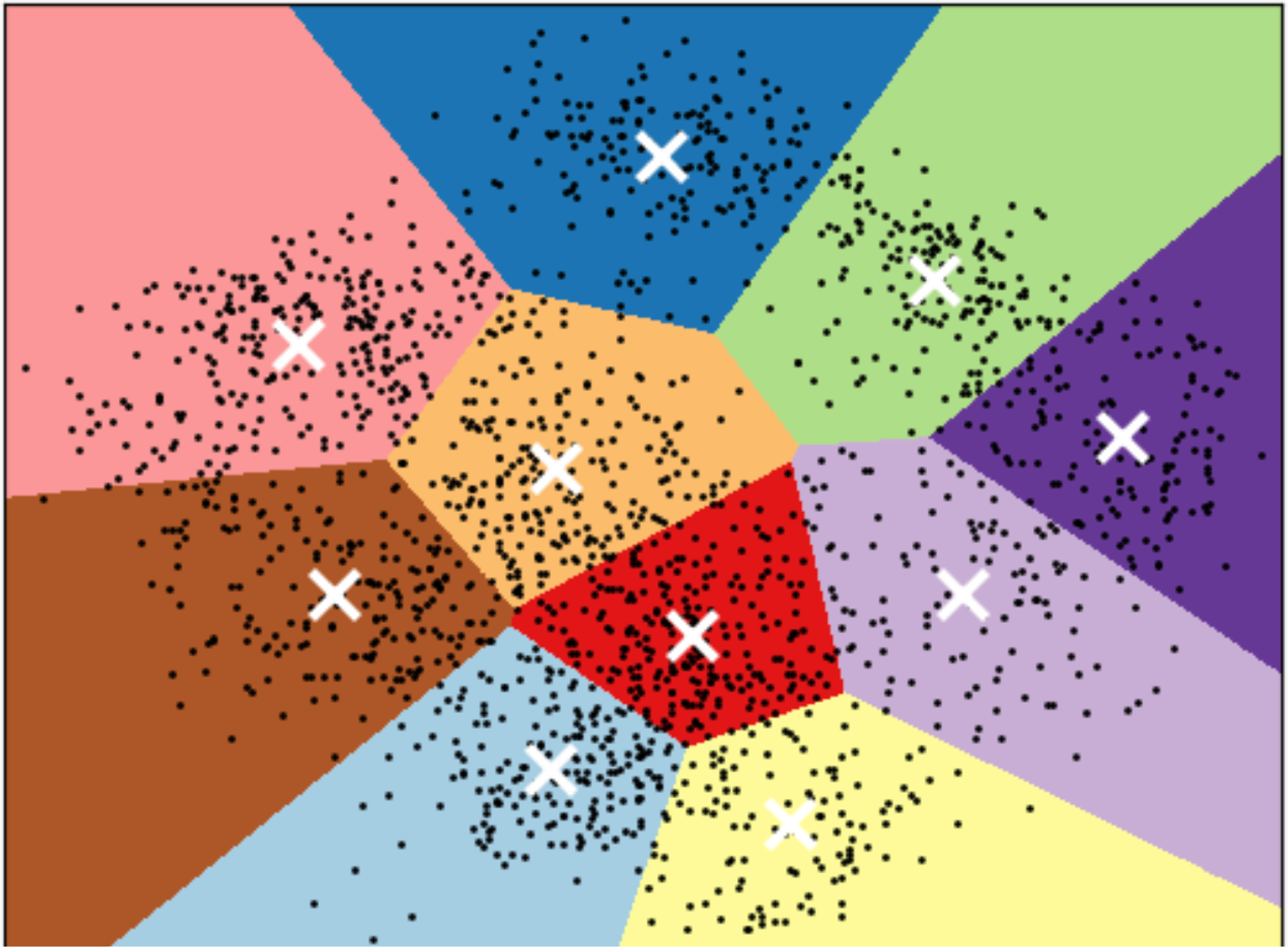
Select all of the following statements which are TRUE.

- a. Similar to K-nearest neighbours, K-Means is a non parametric model.
- b. The meaning of K in K-nearest neighbours and K-Means clustering is very similar.
- c. Scaling of input features is crucial in clustering.
- d. In clustering, it’s almost always a good idea to find equal-sized clusters.

K-means Limitations

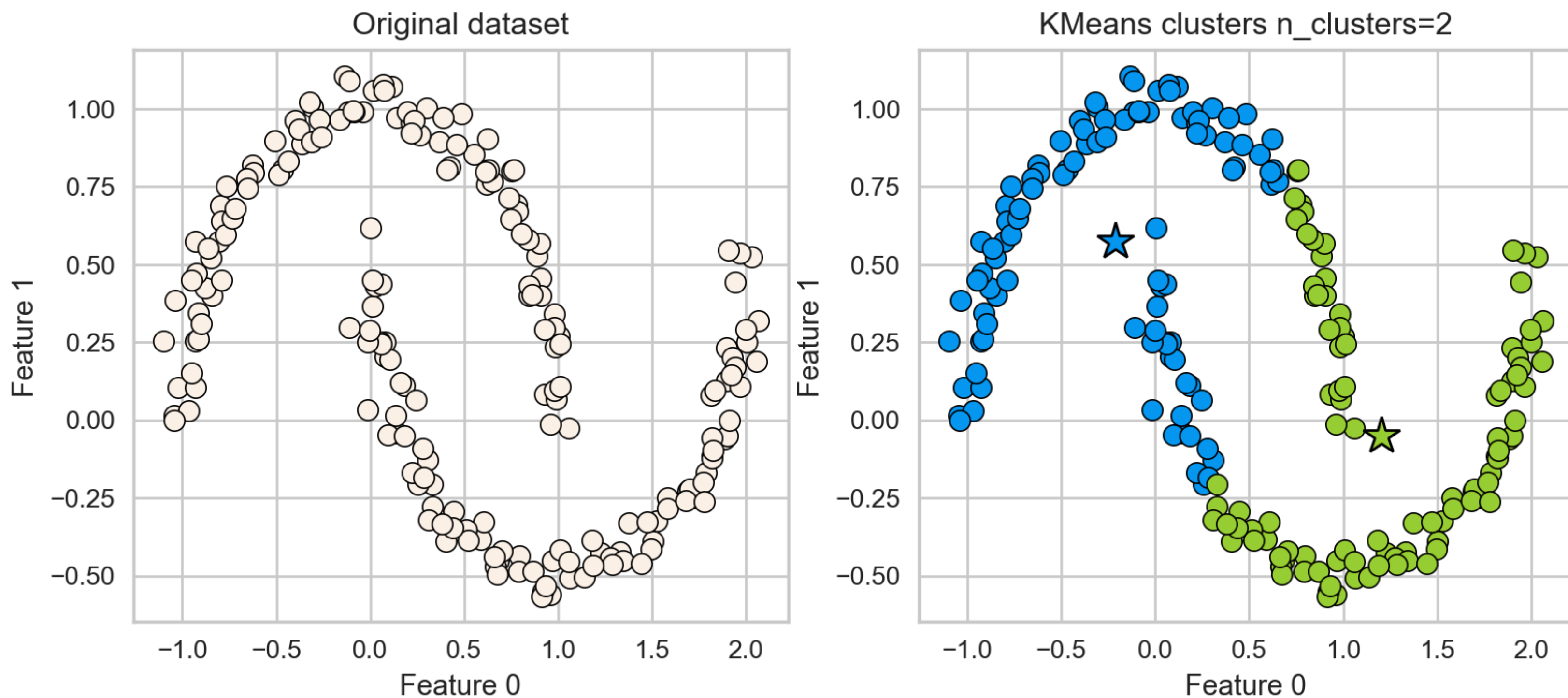
Shape of clusters

- Good for spherical clusters of more or less equal sizes



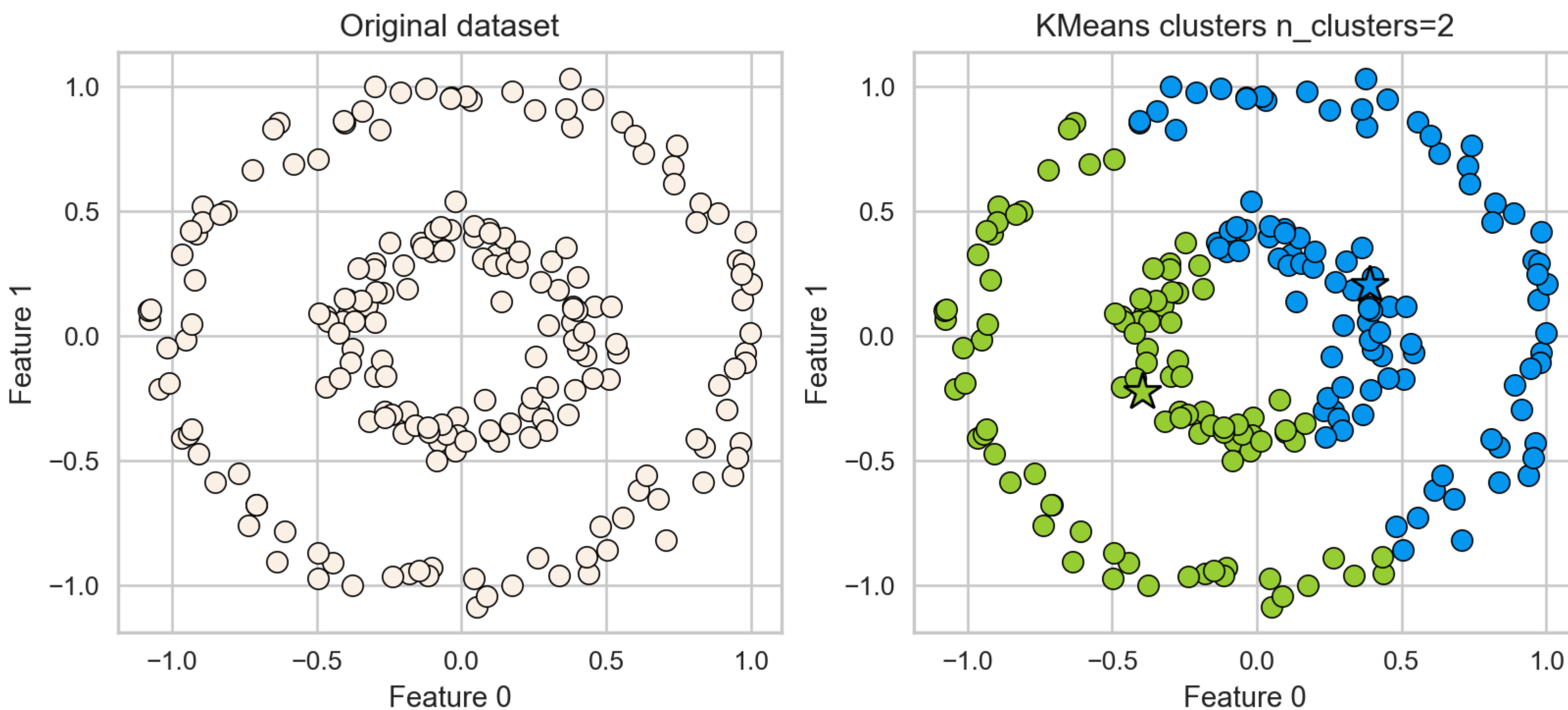
K-Means: failure case 1

- K-Means performs poorly if the clusters have more complex shapes (e.g., two moons data below).



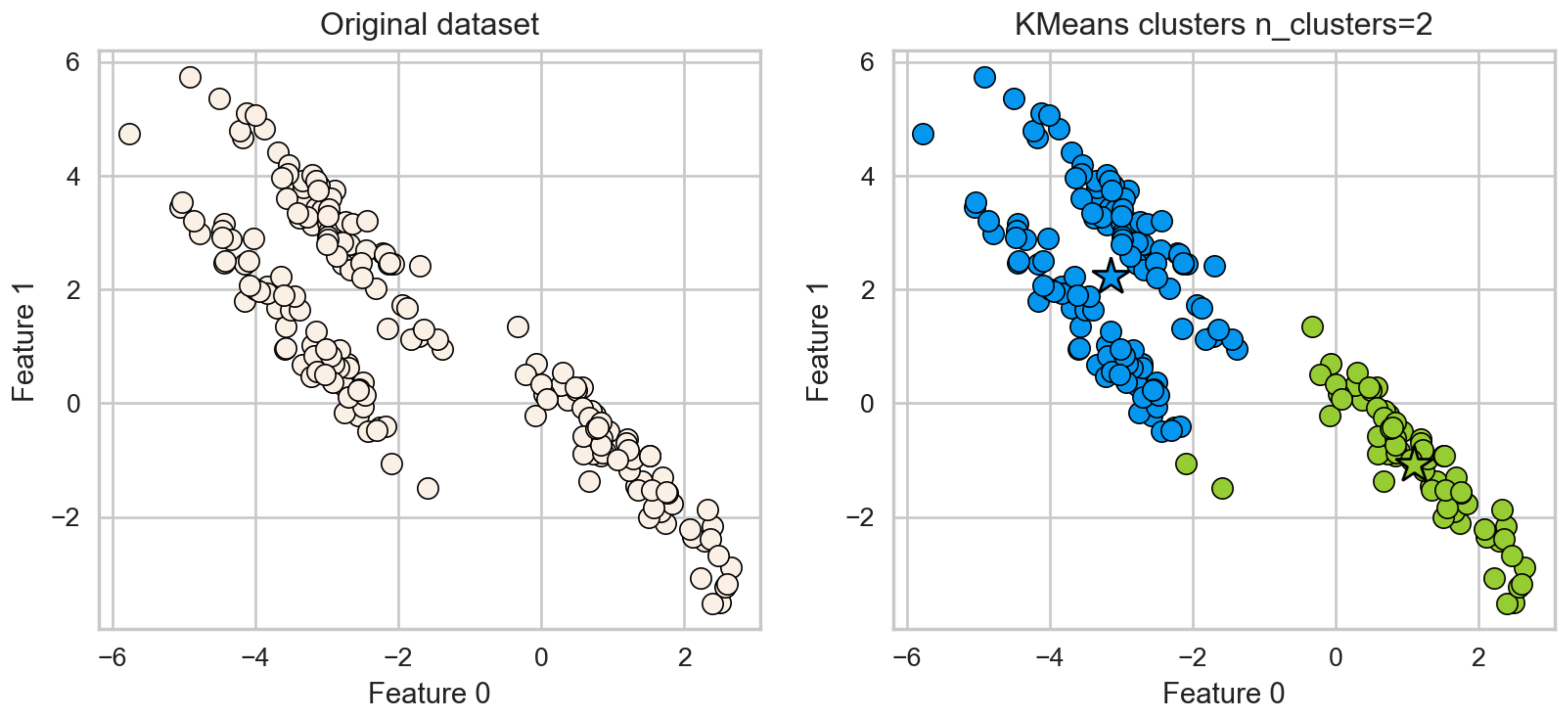
K-Means: failure case 2

- Again, K-Means is unable to capture complex cluster shapes.



K-Means: failure case 3

- It assumes that all directions are equally important for each cluster and fails to identify non-spherical clusters.

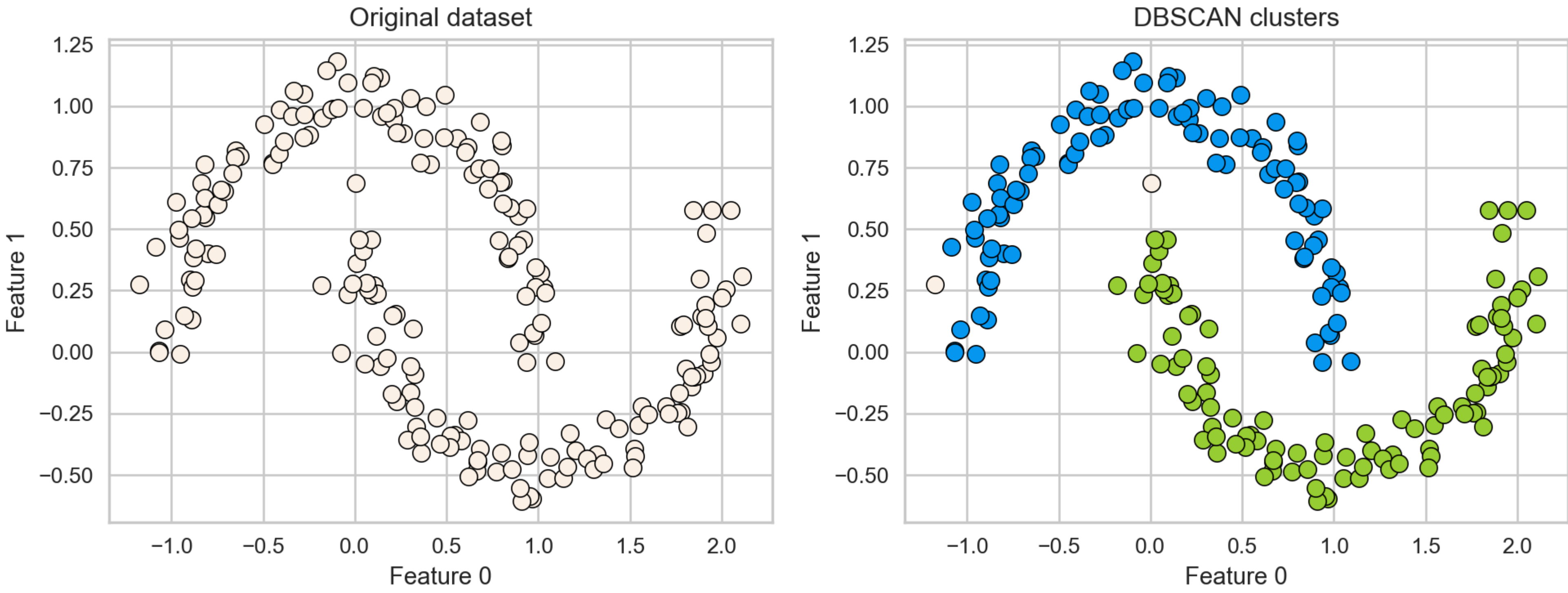


Can we do better?

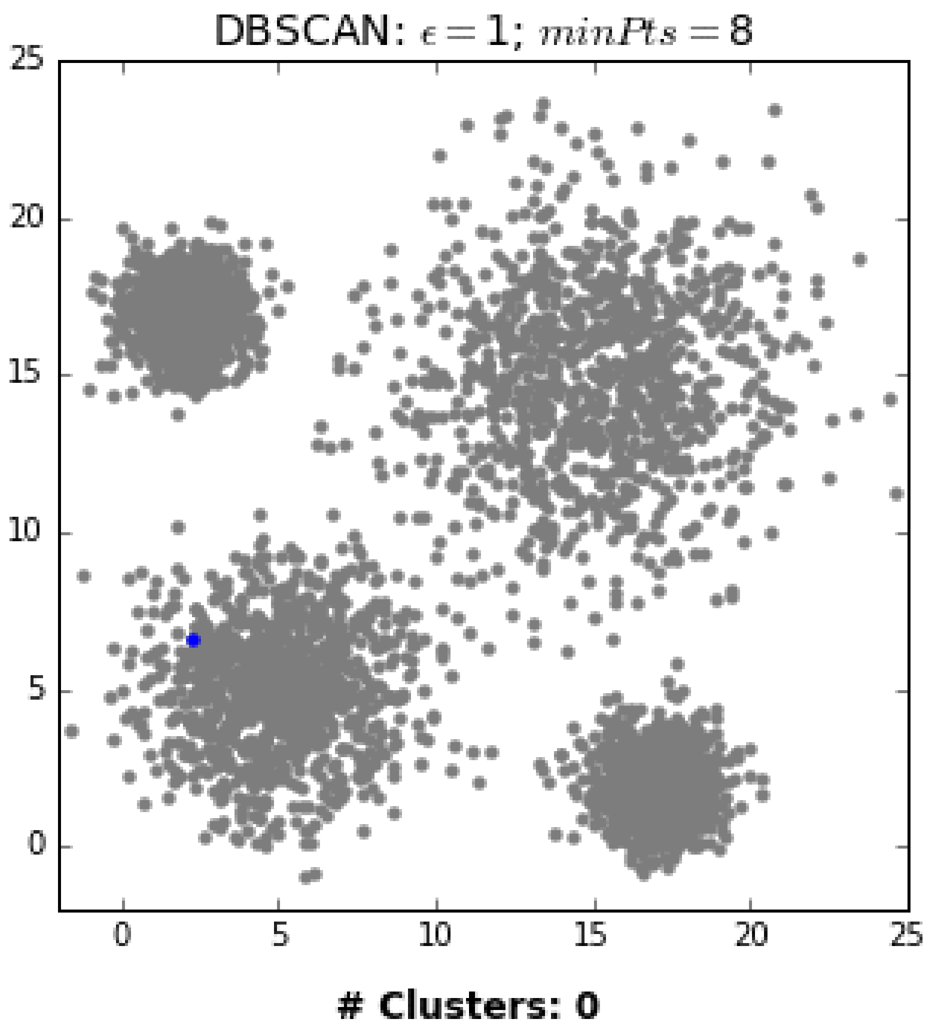
DBSCAN

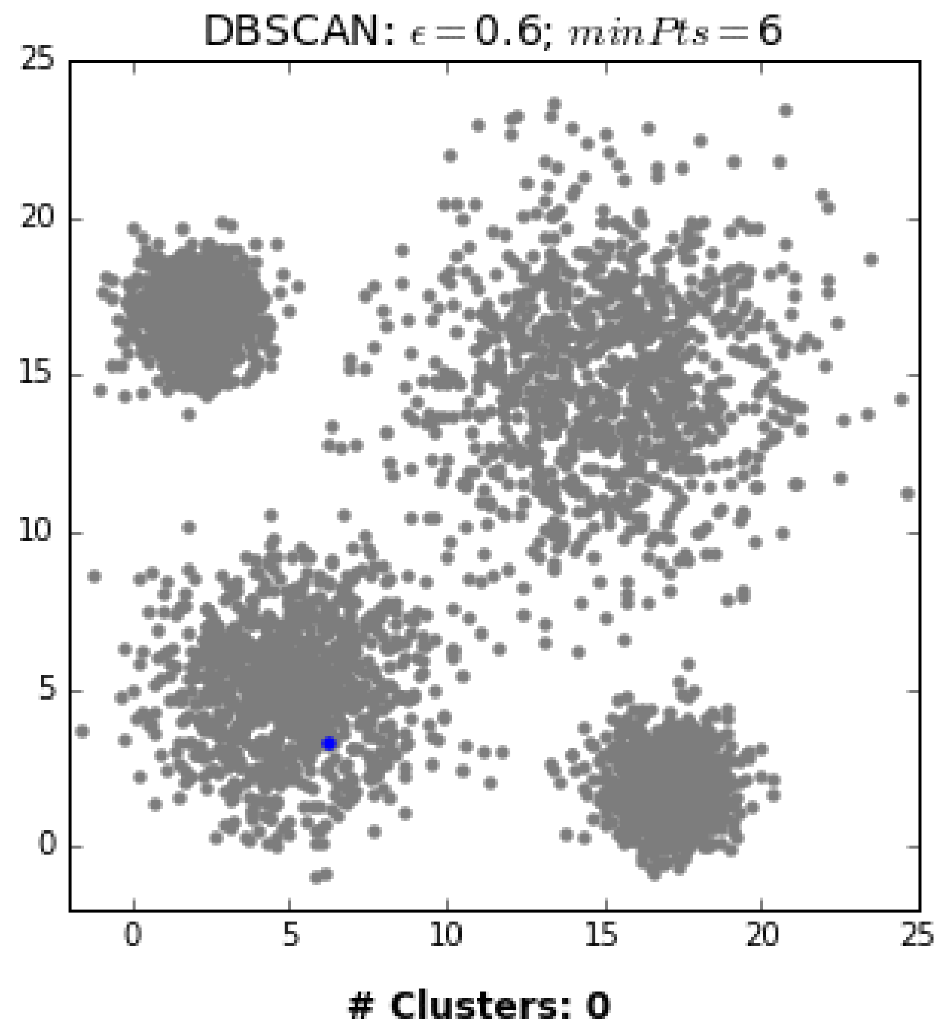
- **D**ensity-**B**ased **S**patial **C**lustering of **A**pplications with **N**oise
- A density-based clustering algorithm

```
X, y = make_moons(n_samples=200, noise=0.08, random_state=42)
dbscan = DBSCAN(eps=0.2)
dbscan.fit(X)
plot_original_clustered(X, dbscan, dbscan.labels_)
```

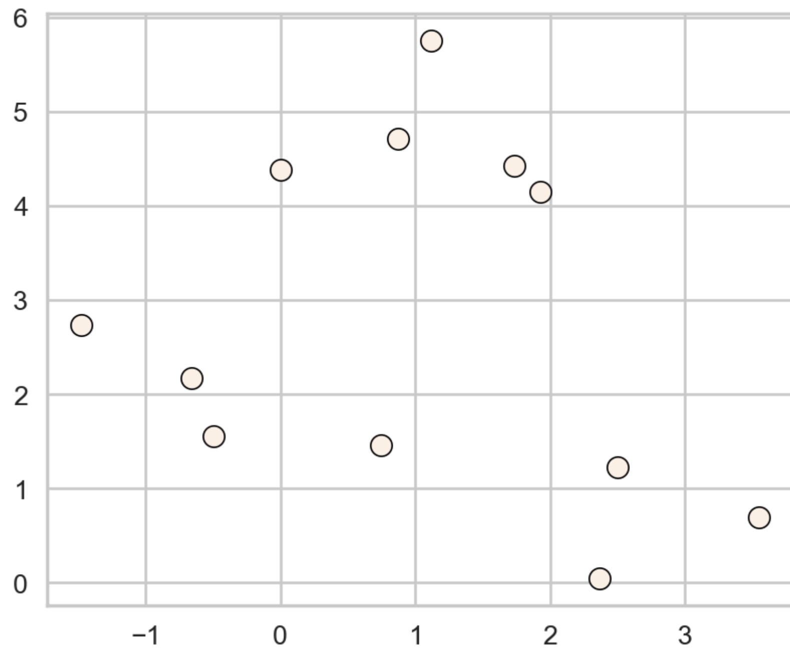

Original dataset
DBSCAN clusters
Feature 0
Feature 1
1.25
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0

How does it work?





DBSCAN Analogy



Consider DBSCAN in a social context:

- Social butterflies (🦋): Core points
- Friends of social butterflies who are not social butterflies: Border points
- Lone wolves (🐺): Noise points

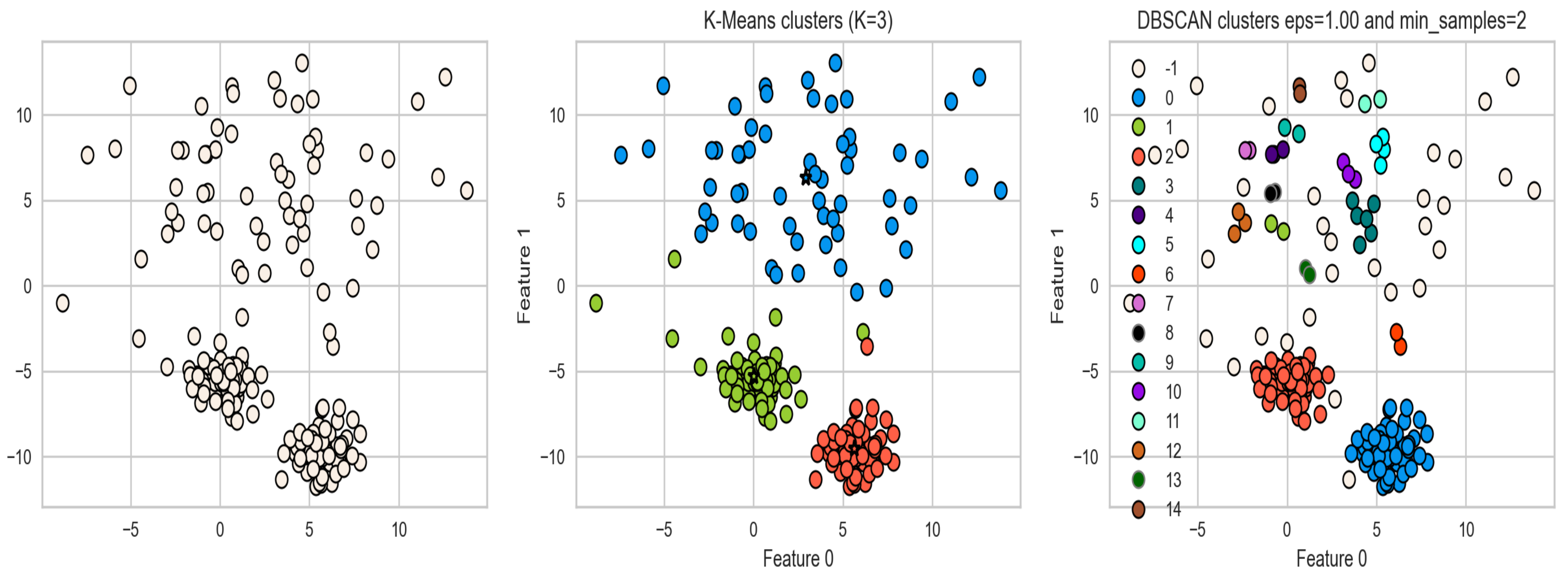
Two main hyperparameters

- `eps`: determines what it means for points to be "close"
- `min_samples`: determines the number of **neighboring points** we require to consider in order for a point to be part of a cluster

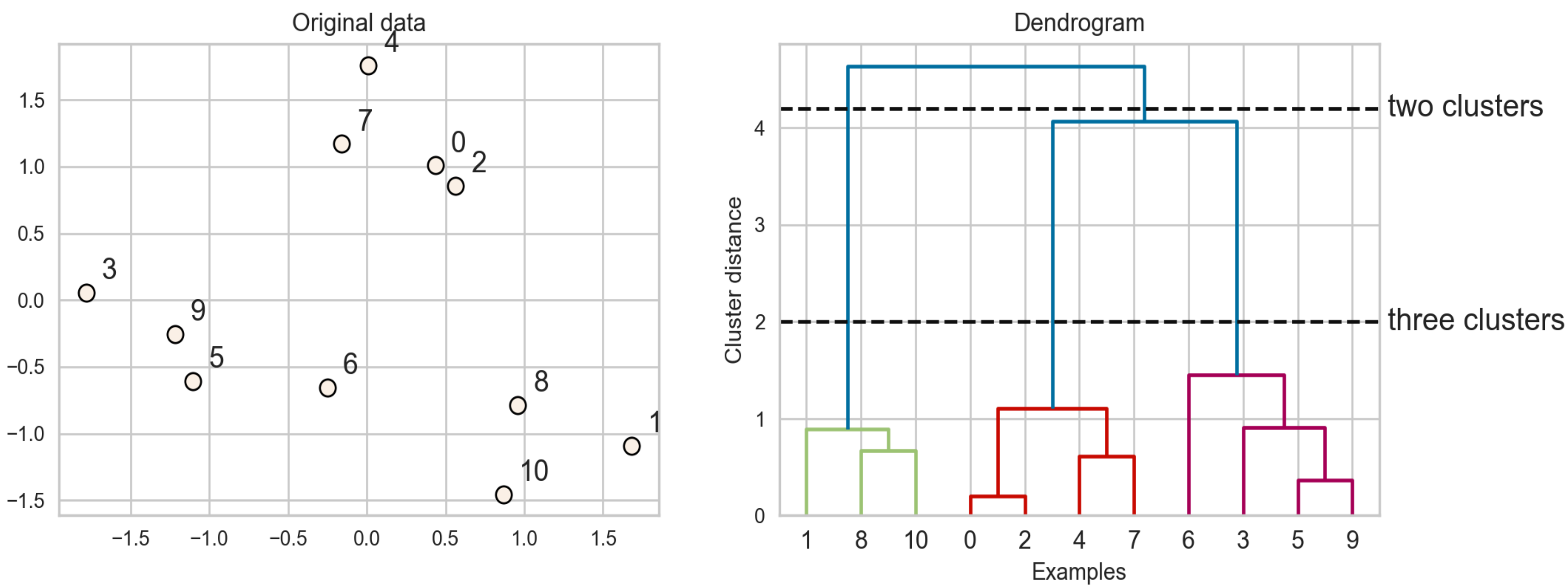
DBSCAN: failure cases

- Let's consider this dataset with three clusters of varying densities.
- K-Means performs better compared to DBSCAN. But it has the benefit of knowing the value of *K* in advance.

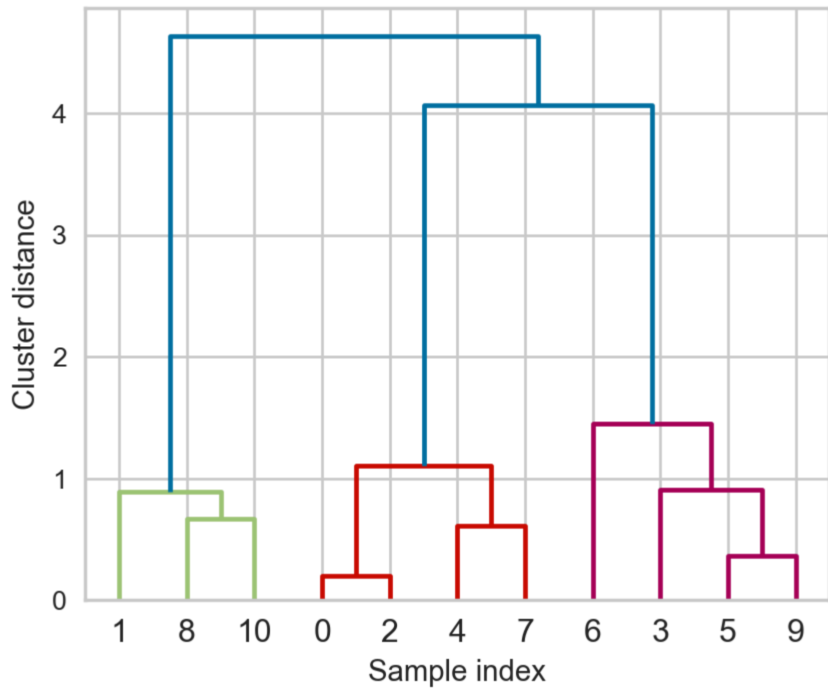
```
[ 0  1  2  3  4  5  6  7  8  9 10 11 12 13 14 15]
```



Hierarchical clustering



Dendrogram



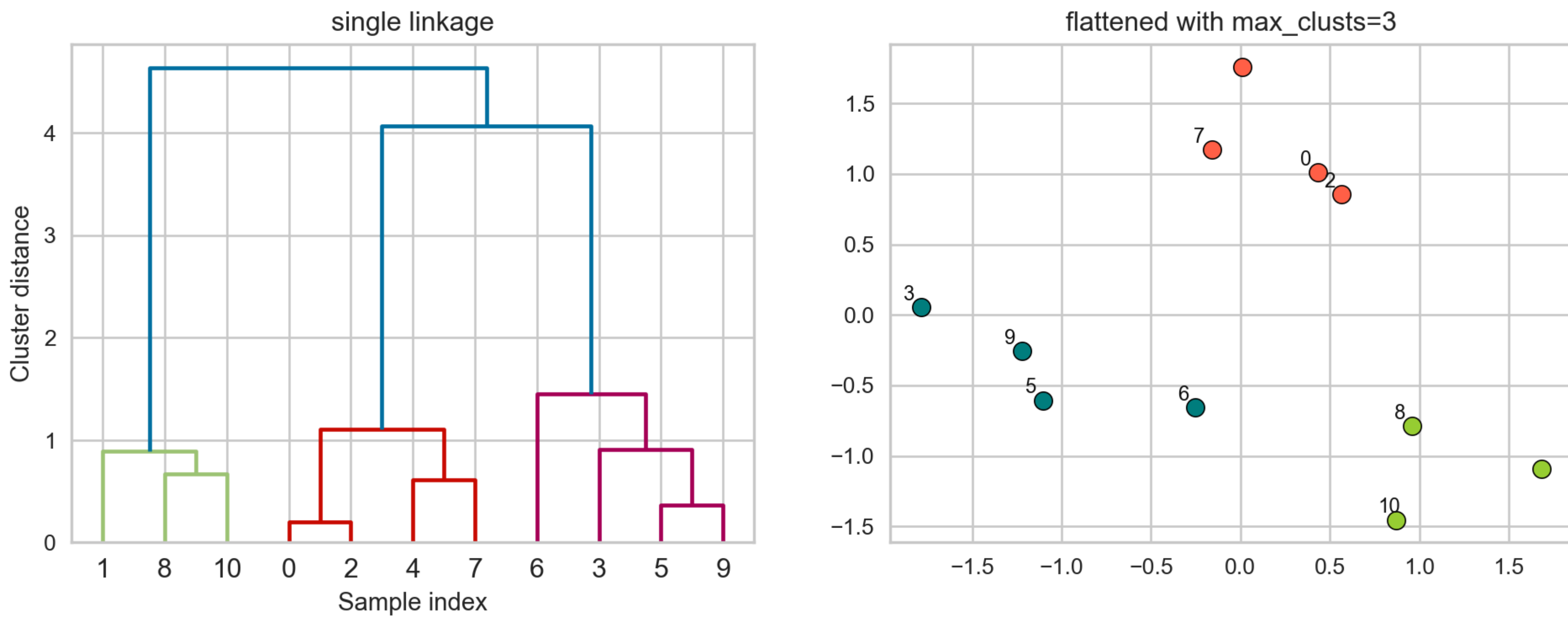
- Dendrogram is a tree-like plot.
- On the x-axis we have data points.
- On the y-axis we have distances between clusters.

Flat clusters

- This is good but how can we get cluster labels from a dendrogram?
- We can bring the clustering to a “flat” format use `fcluster`

Flat clusters

```python
from scipy.cluster.hierarchy import fcluster
# flattening the dendrogram based on maximum number of clusters.
hier_labels1 = fcluster(linkage_array, 3, criterion="maxclust")
plot_dendrogram_clusters(X, linkage_array, hier_labels1, title="flattened w
```



Linkage criteria

- When we create a dendrogram, we need to calculate distance between clusters. How do we measure distances between clusters?
- The **linkage criteria** determines how to find similarity between clusters:
- Some example linkage criteria are:
  - Single linkage → smallest minimal distance, leads to loose clusters
  - Complete linkage → smallest maximum distance, leads to tight clusters
  - Average linkage → smallest average distance between all pairs of points in the clusters
  - Ward linkage → smallest increase in within-cluster variance, leads to equally sized clusters

Activity

- Fill in the table below in this Google doc: https://shorturl.at/3yOdg

Clustering Method	KMeans	DBSCAN	Hierarchical Clustering
Approach			
Hyperparameters			
Shape of clusters			
Handling noise			
Examples			

Class demo