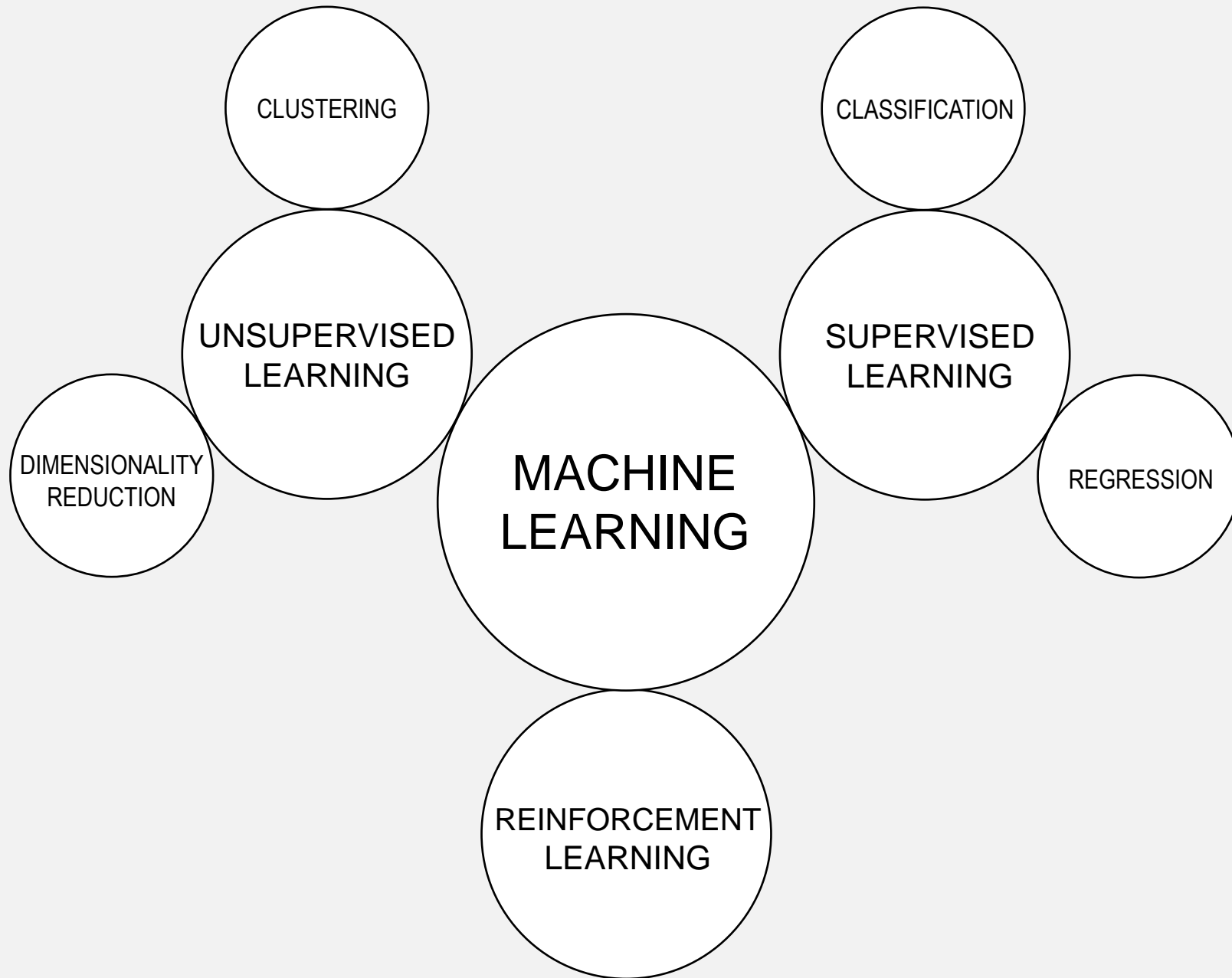


CLUSTERING

Lecture 10
MALI, 2024



CLUSTERING

CLUSTERING

- What is clustering?
- *k*-means clustering
- Agglomerative clustering
- DBSCAN
- Application

WHAT IS CLUSTERING?

grouping data: unlabeled version of classification

↓
most data in the world is

REVERSE IMAGE SEARCH

I want to know what this bird in my garden is



The corresponding websites
tell me it's a common linnet

REVERSE IMAGE SEARCH



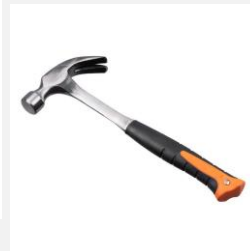
All the images in the dataset ...

REVERSE IMAGE SEARCH



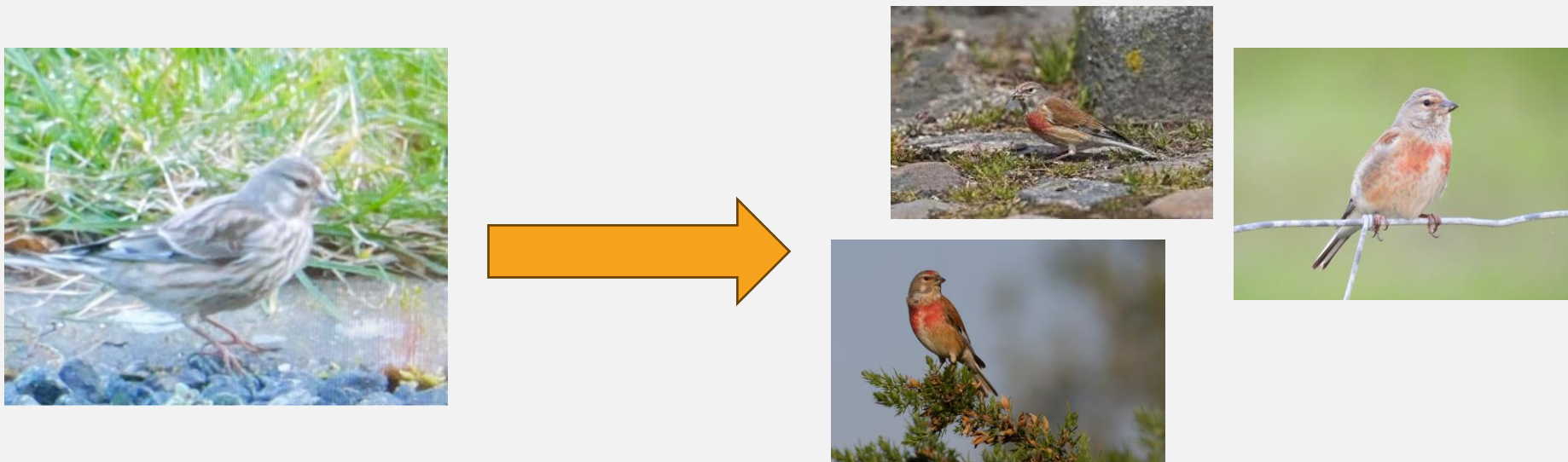
... are **clustered** into groups.

REVERSE IMAGE SEARCH



The image we search with is assigned to a cluster ...

REVERSE IMAGE SEARCH



... and the other images in the cluster are returned.

DIFFERENCE FROM CLASSIFICATION?

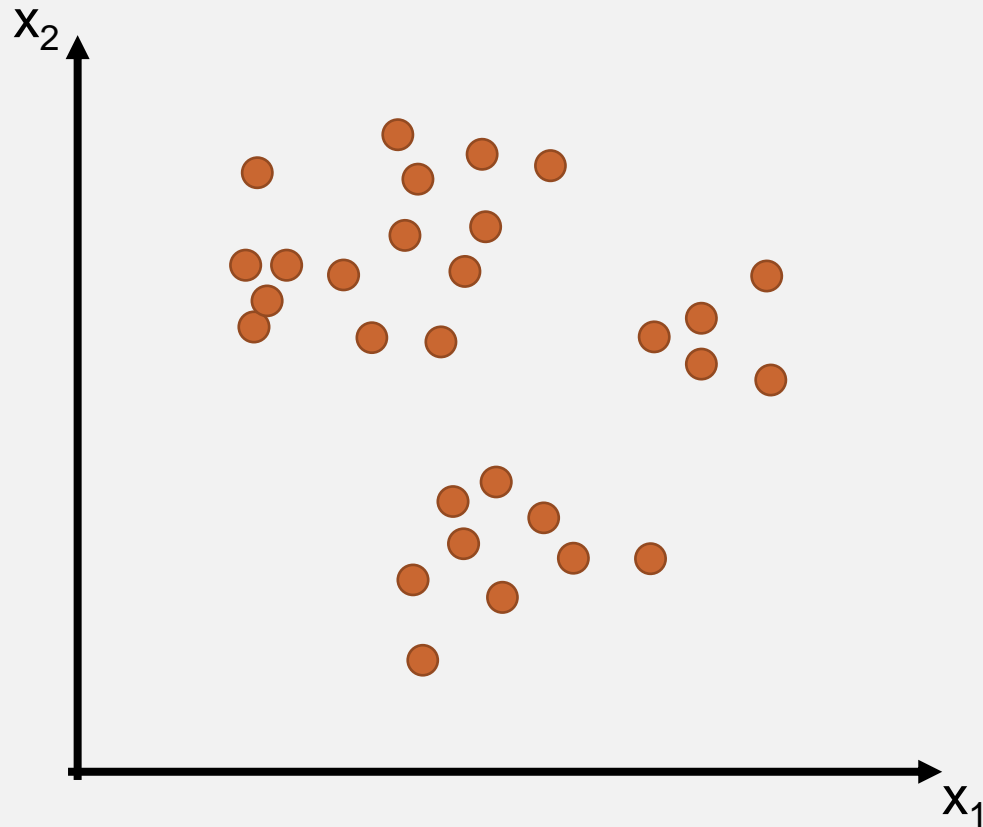
At no point did we label
the images - we only care
about the fact that some are similar

measure of similarity??

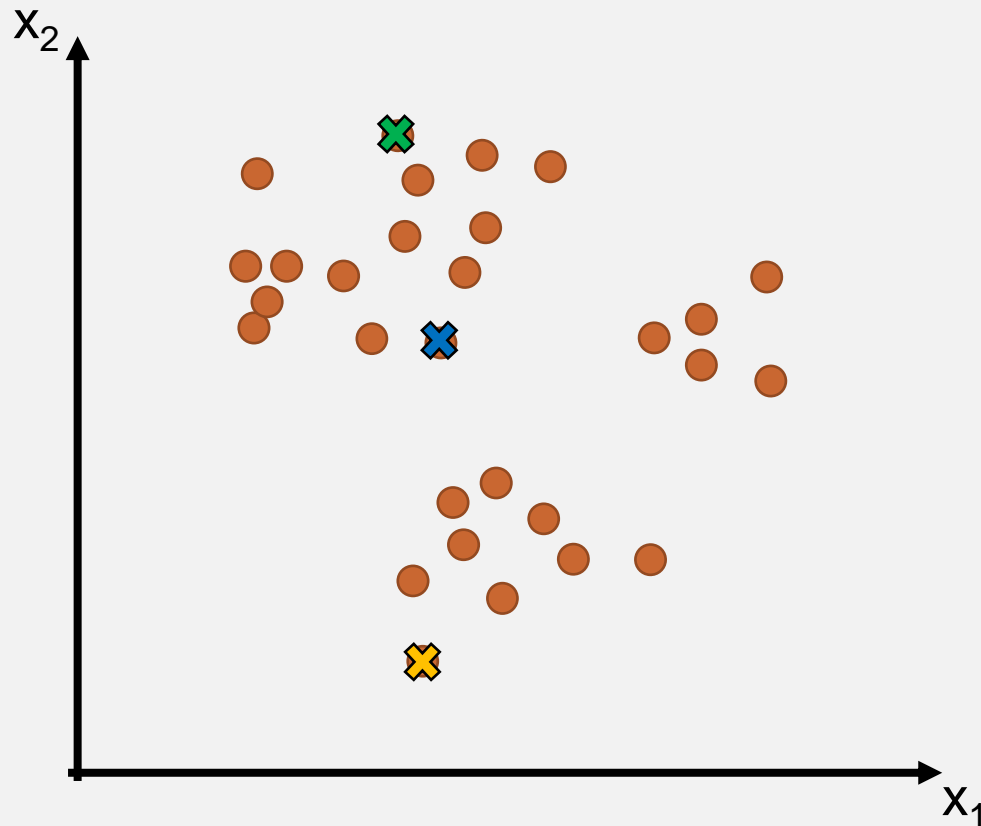
CLUSTERING

- What is clustering?
- ***k*-means clustering**
- Agglomerative clustering
- DBSCAN
- Application

k -MEANS CLUSTERING

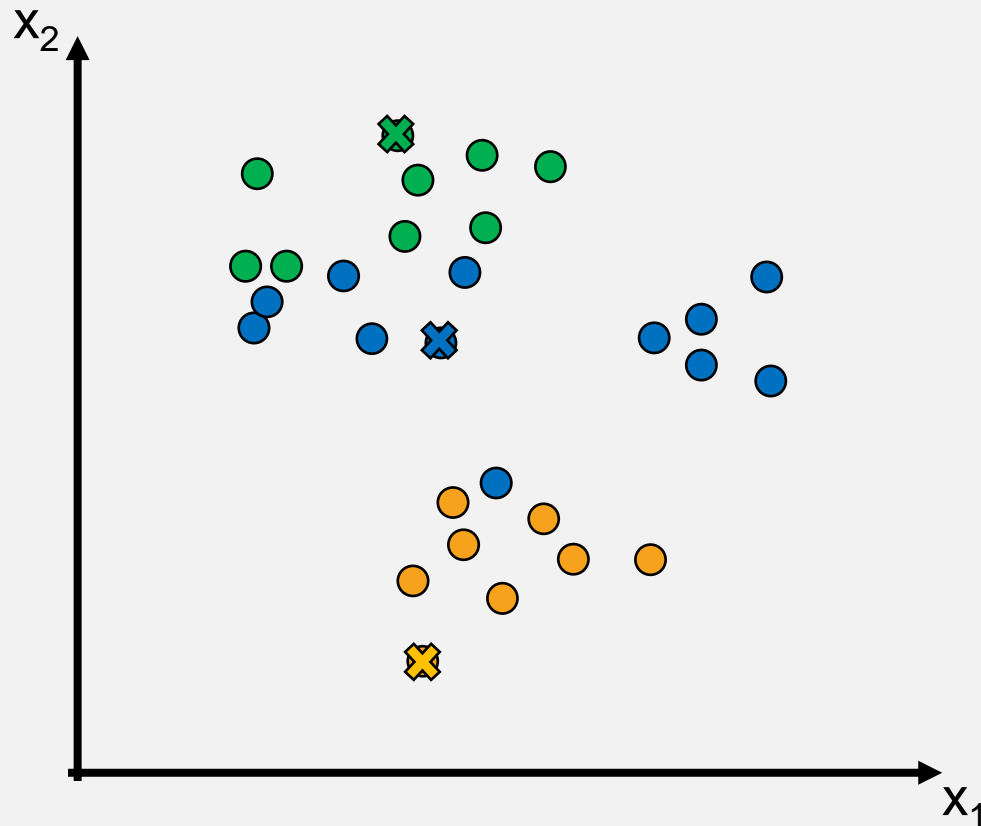


k -MEANS CLUSTERING



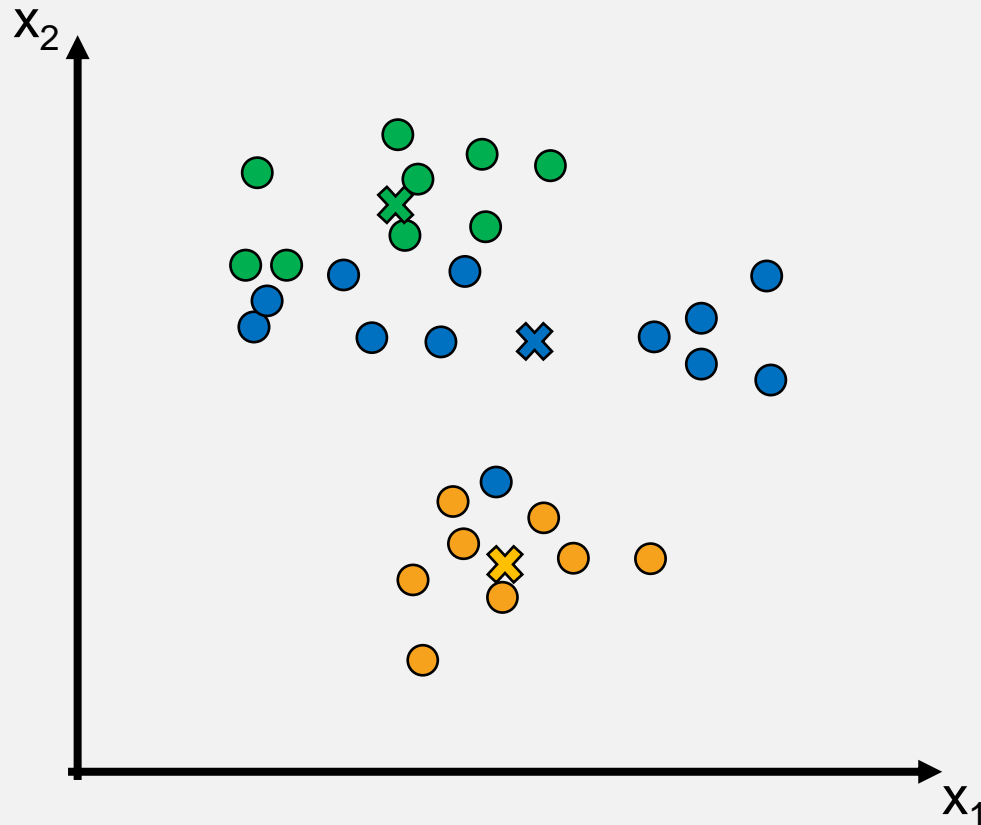
I. Assign $k(=3)$ random points as **centroids**

k -MEANS CLUSTERING



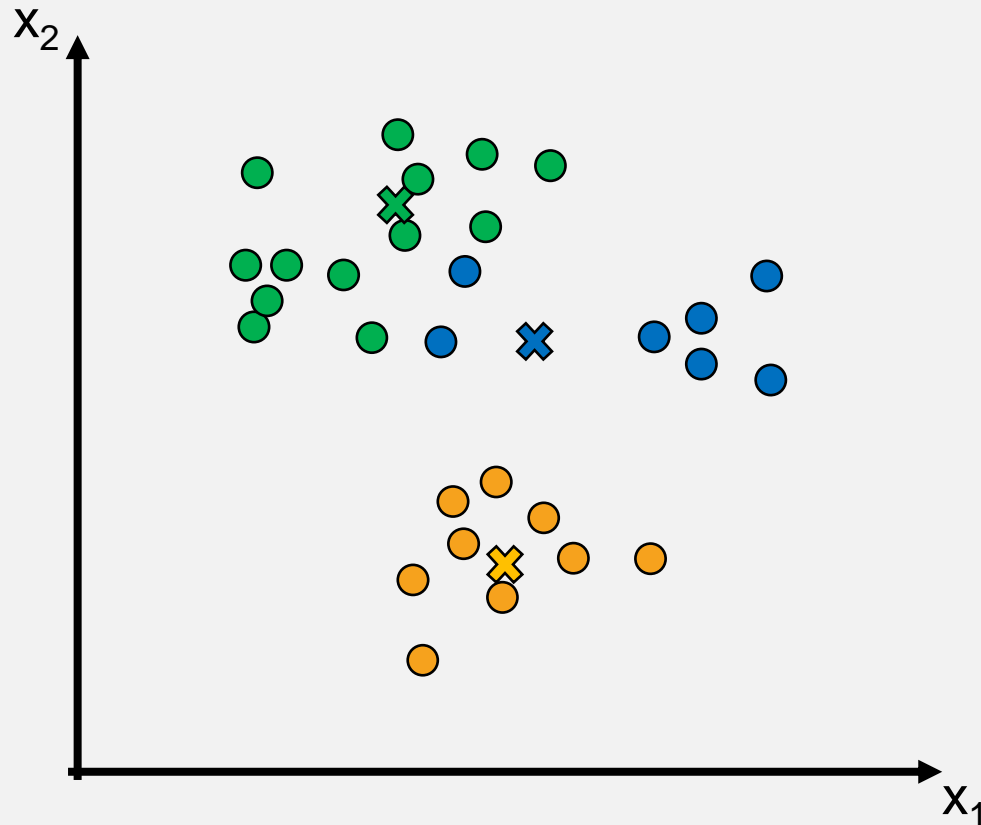
1. Assign $k(=3)$ random points as **centroids**
2. Group the data by their distance to the centroids

k -MEANS CLUSTERING



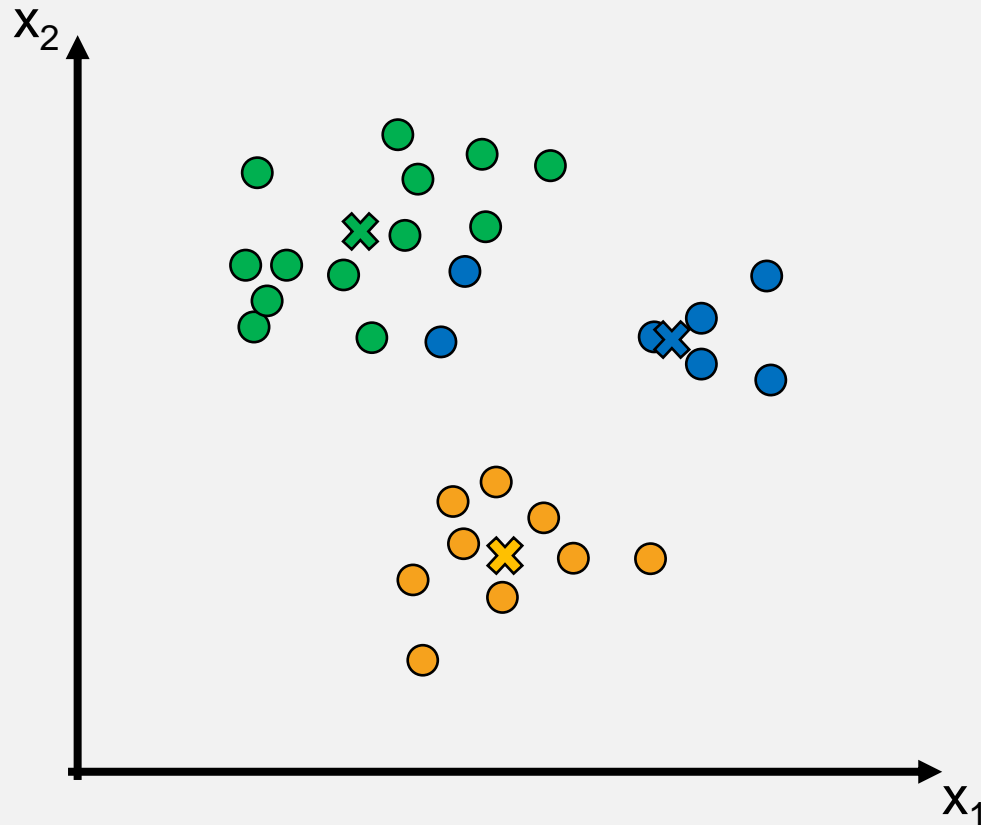
1. Assign $k(=3)$ random points as **centroids**
2. Group the data by their distance to the centroids
3. Move the centroids to the cluster centers

k -MEANS CLUSTERING



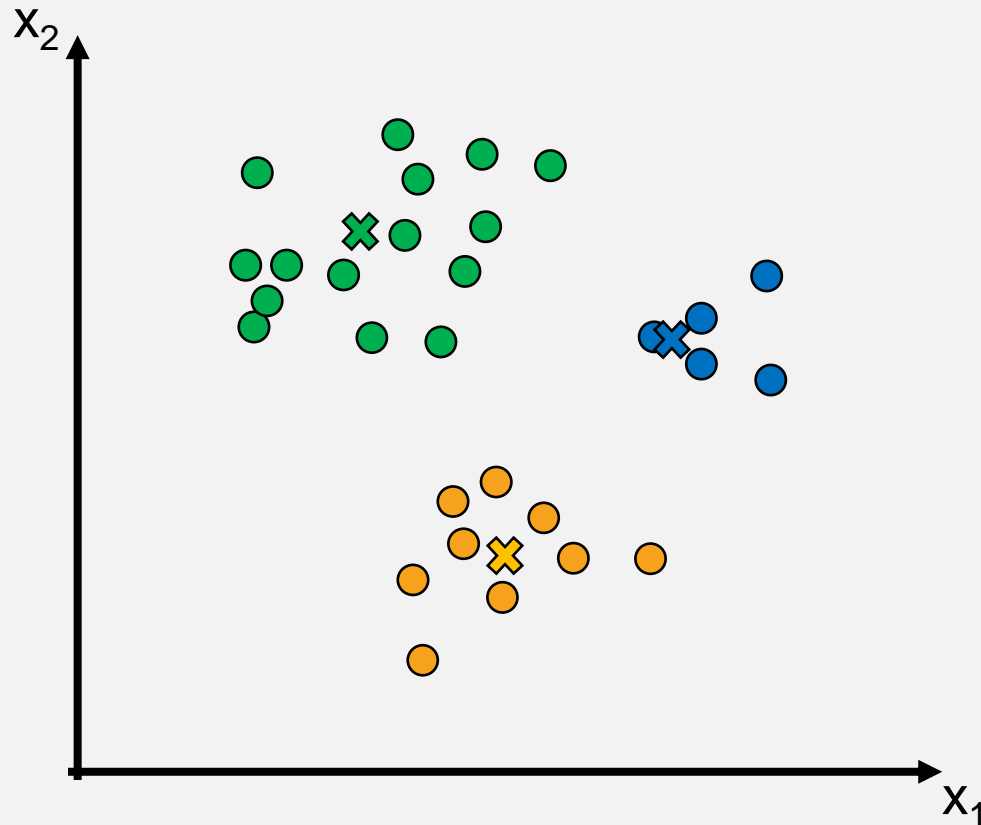
1. Assign $k(=3)$ random points as **centroids**
2. Group the data by their distance to the centroids
3. Move the centroids to the cluster centers
4. Regroup the data

k -MEANS CLUSTERING



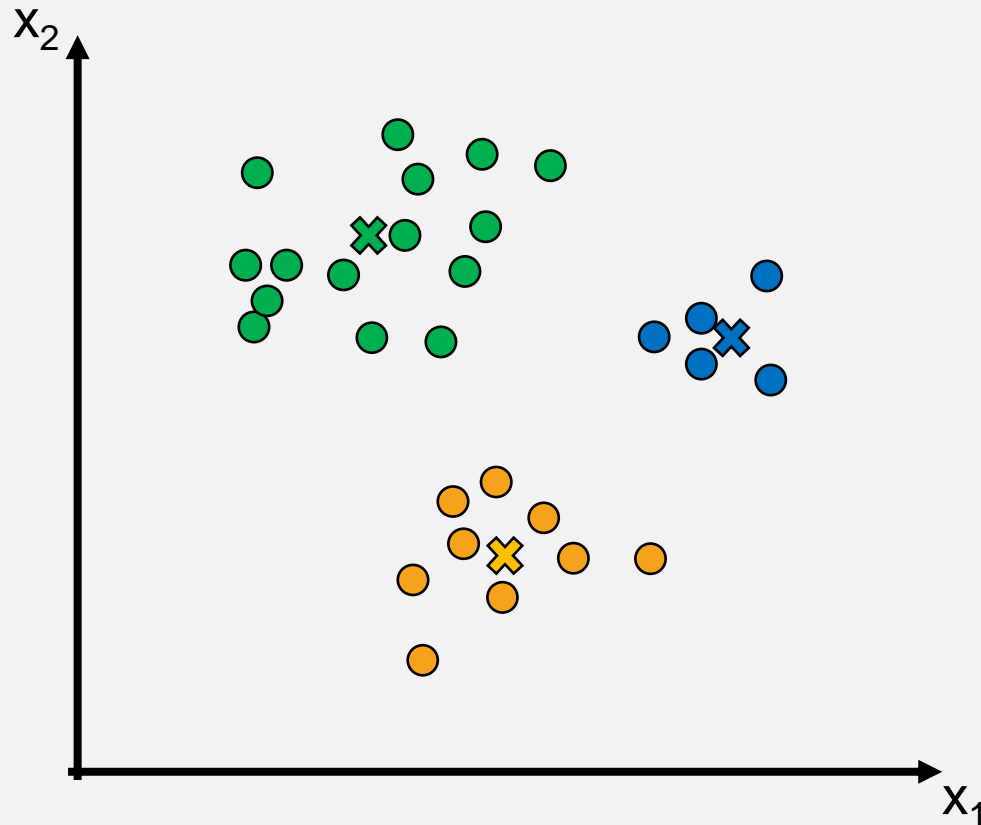
1. Assign $k(=3)$ random points as **centroids**
2. Group the data by their distance to the centroids
3. Move the centroids to the cluster centers
4. Regroup the data
5. Repeat 3-4 until nothing changes

k -MEANS CLUSTERING



1. Assign $k(=3)$ random points as **centroids**
2. Group the data by their distance to the centroids
3. Move the centroids to the cluster centers
4. Regroup the data
5. Repeat 3-4 until nothing changes

k -MEANS CLUSTERING



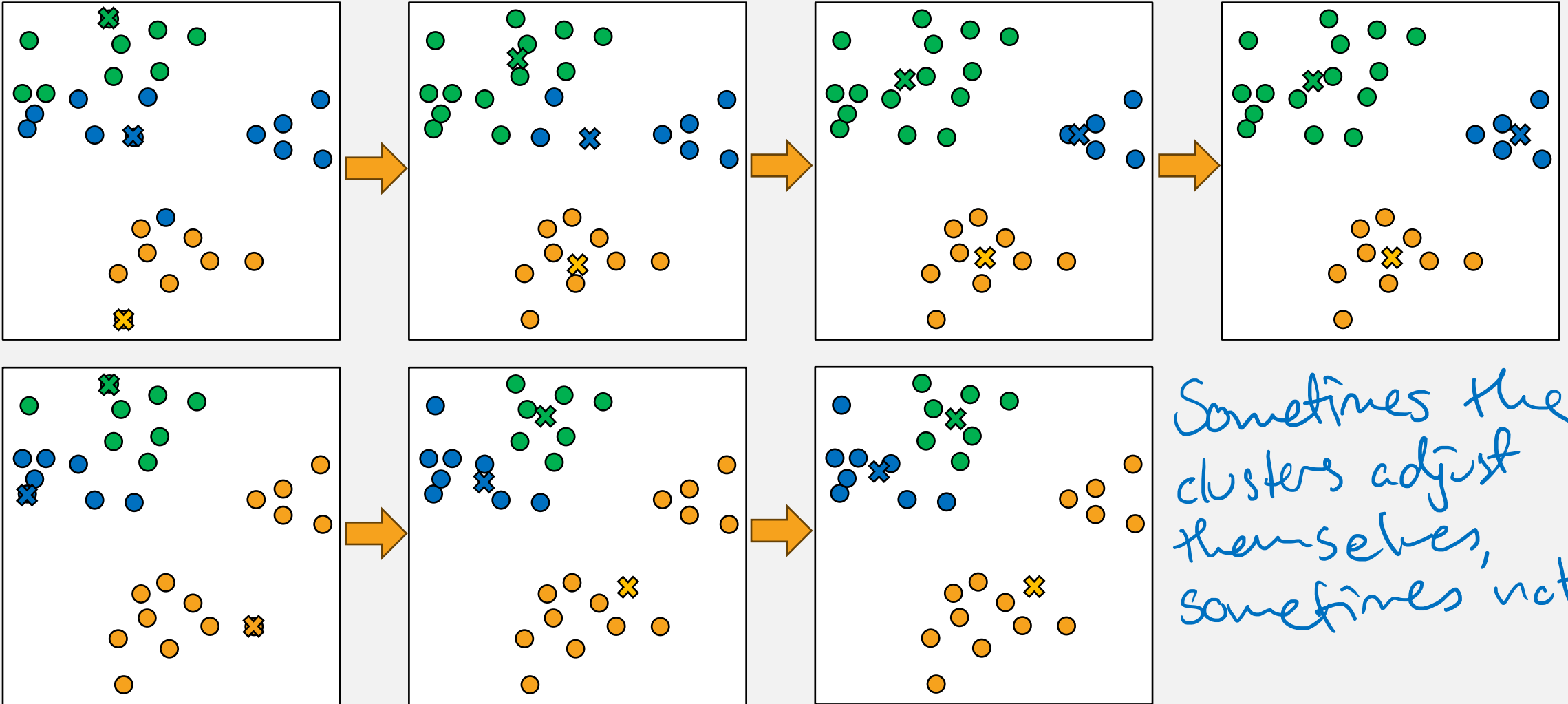
1. Assign $k(=3)$ random points as **centroids**
2. Group the data by their distance to the centroids
3. Move the centroids to the cluster centers
4. Regroup the data
5. Repeat 3-4 until nothing changes

A FEW THINGS WE HAVE TO DEAL WITH

The value of k

The initial centroids

THE INITIAL CENTROIDS



Sometimes the clusters adjust themselves, sometimes not

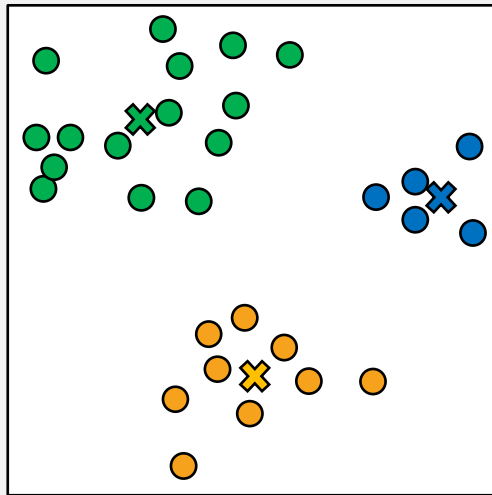
THE INITIAL CENTROIDS

Solution 1: Try different, randomized initializations and compare the **costs** of the final clusterings

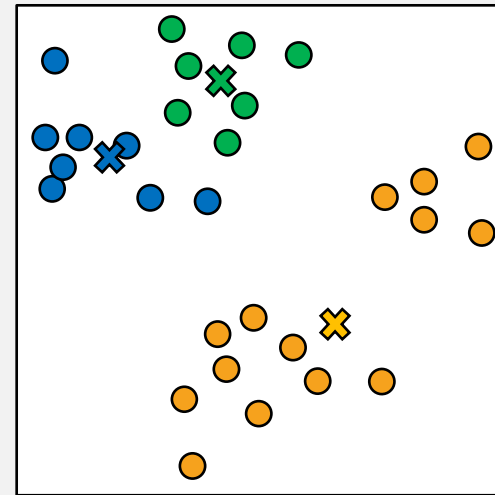
cost function $C = \sum_i \|x_i - \mu(x_i)\|^2$

data point *associated centroid*

lower cost
⇒ better



$C = 157.6$

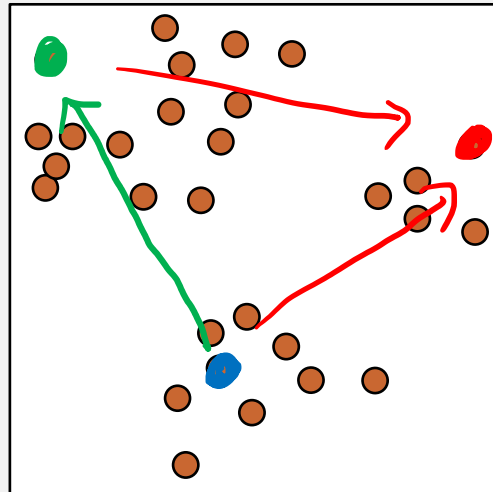


$C = 223.2$

THE INITIAL CENTROIDS

Solution 2: Choose the initial centroids based on the distance to the previous ones

Start randomly then choose point furthest away
and do the same again

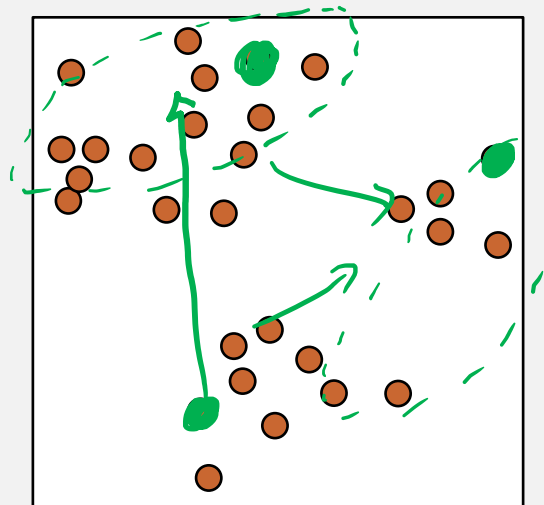


may choose outliers!

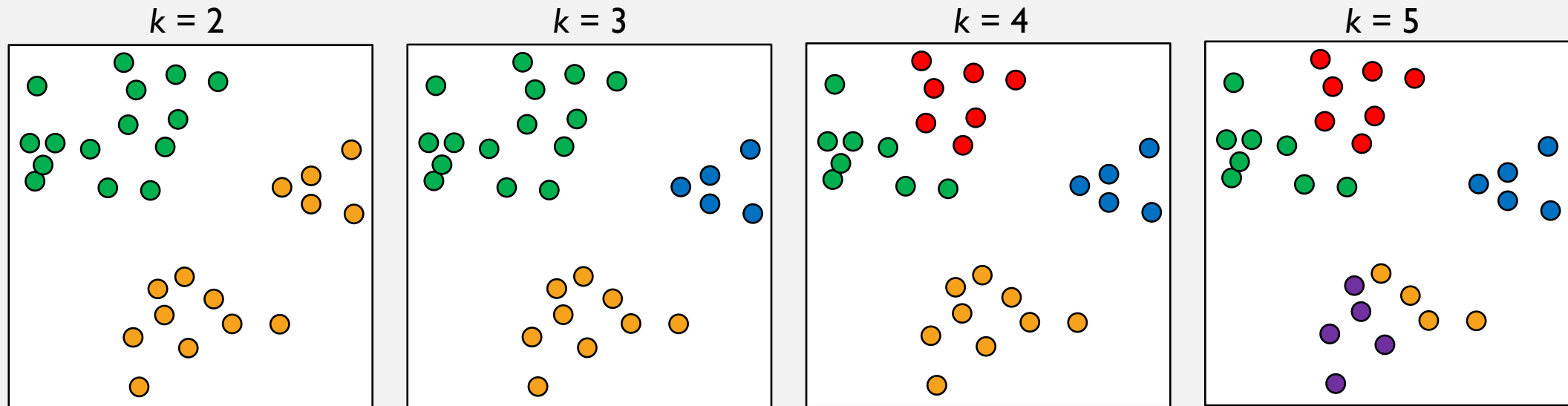
THE INITIAL CENTROIDS

Solution 3: Choose "far away but random" points ("k-means++")

probability of next point high
when far away



THE NUMBER OF CLUSTERS (k)



How do we decide appropriate k ?

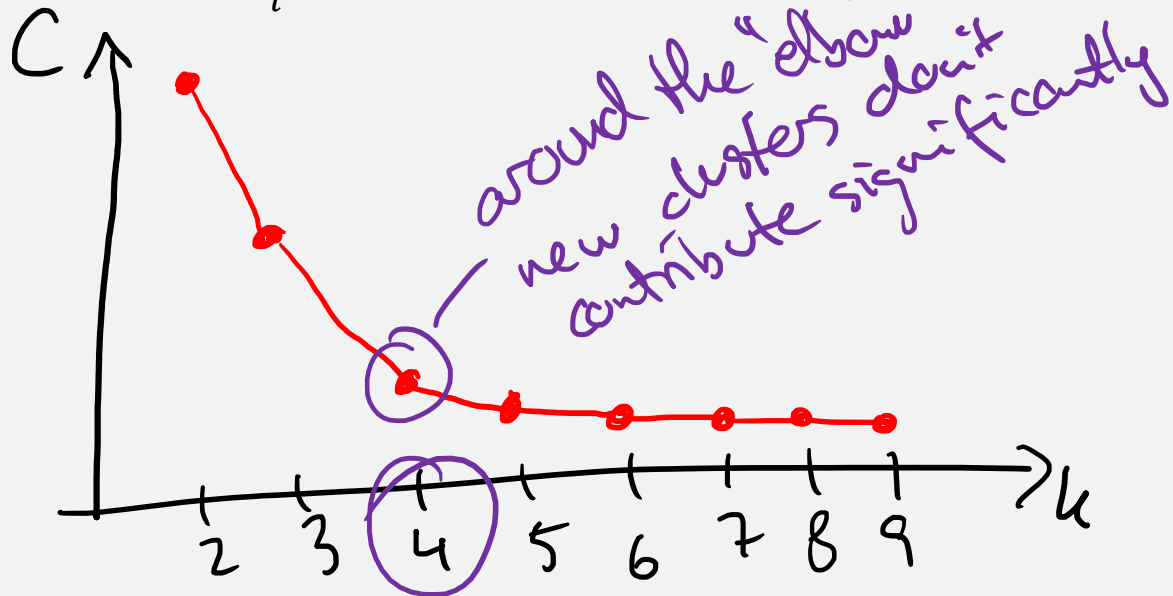
THE NUMBER OF CLUSTERS (k)

The easy way: We already know it (domain knowledge)

The hard way:

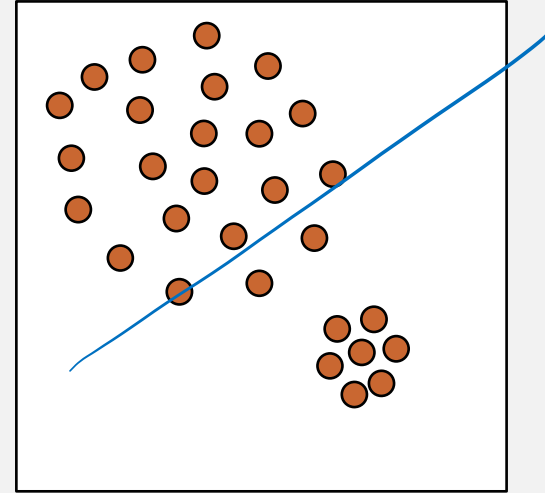
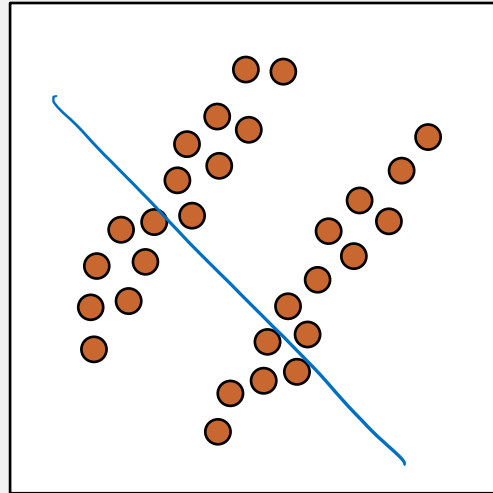
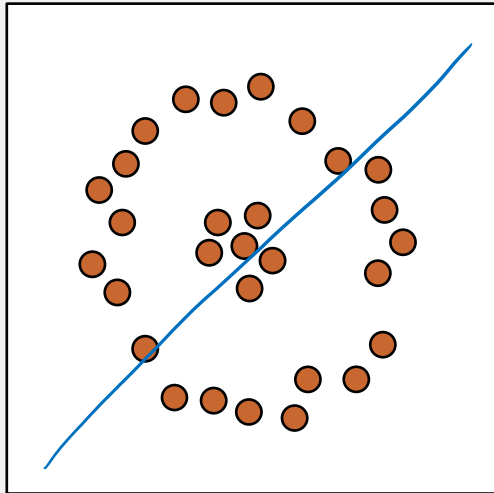
$$C = \sum_i ||x_i - \mu(x_i)||^2$$

always decreases with k

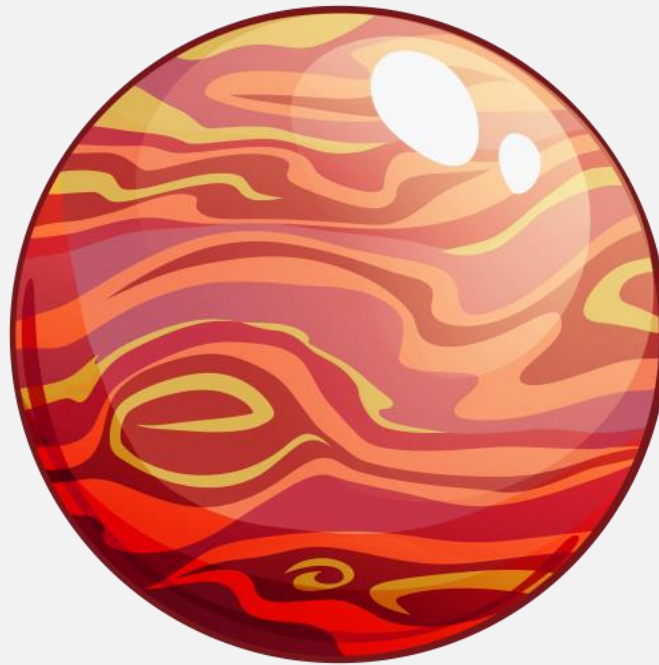


"The elbow method"

WHERE k -MEANS FAILS



CODE EXAMPLE



Jupyter Notebook **Clustering methods**

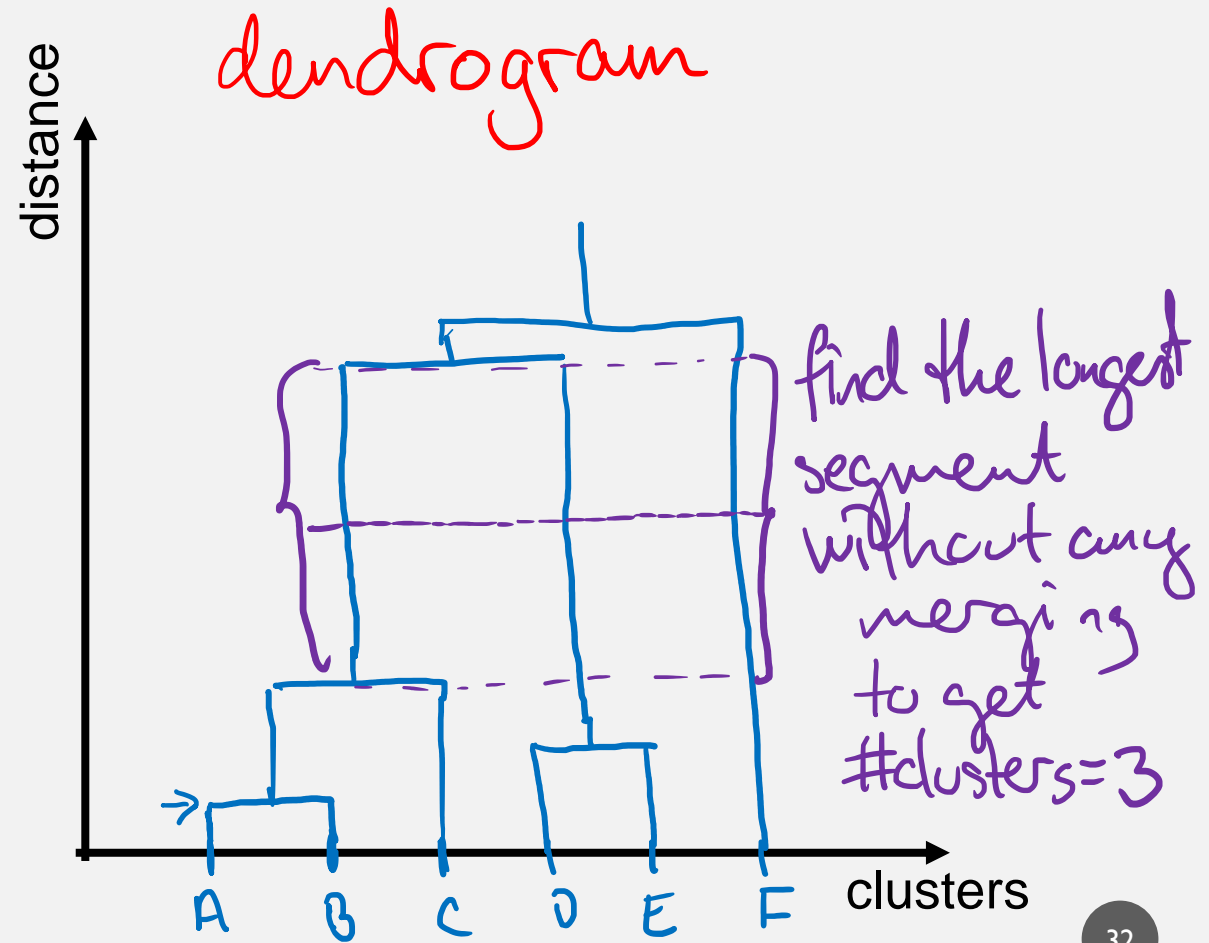
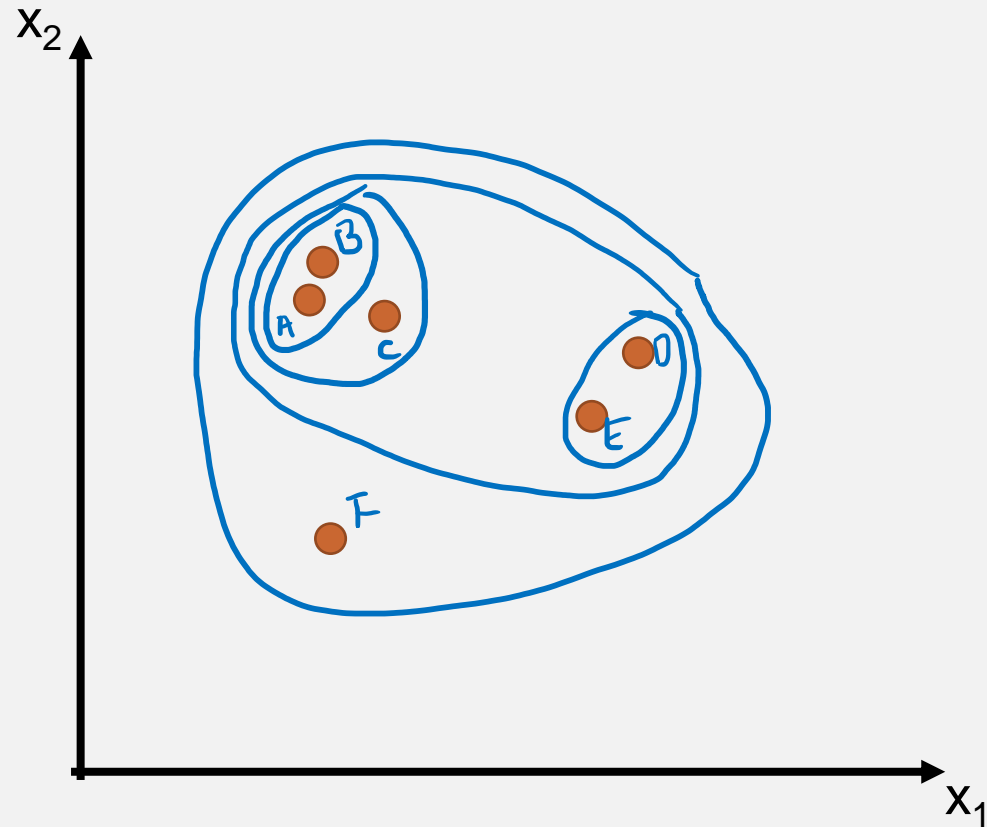
CLUSTERING

- What is clustering?
- *k*-means clustering
- **Agglomerative clustering**
- DBSCAN
- Application

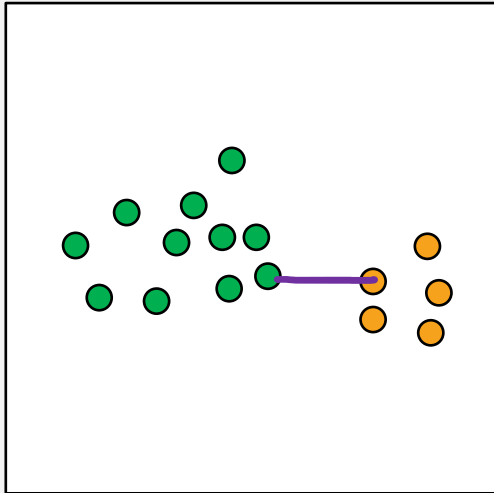
AGGLOMERATIVE CLUSTERING

let each point be its own cluster
while there is more than 1 cluster:
merge the two closest clusters

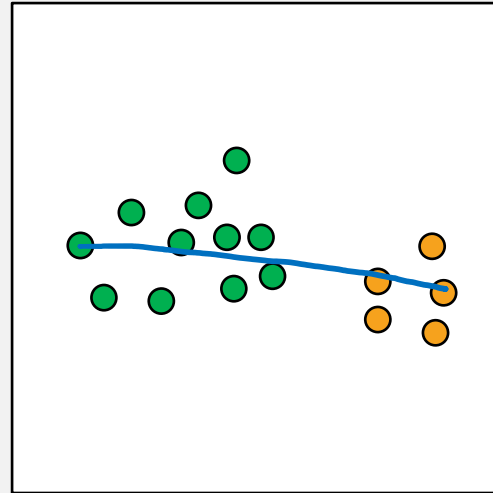
AGGLOMERATIVE CLUSTERING



THE DISTANCE BETWEEN CLUSTERS

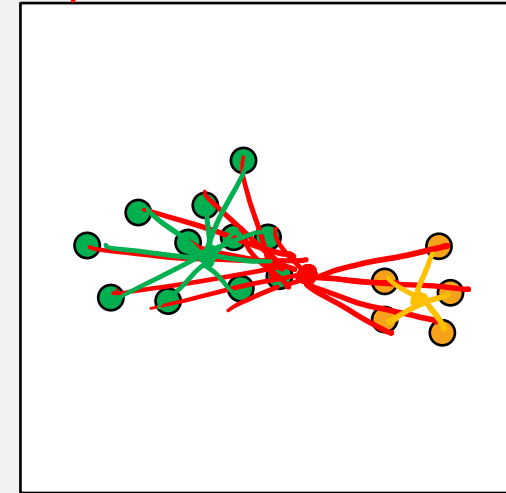


"single link"
(min distance)
→ sensitive to
outliers/noise



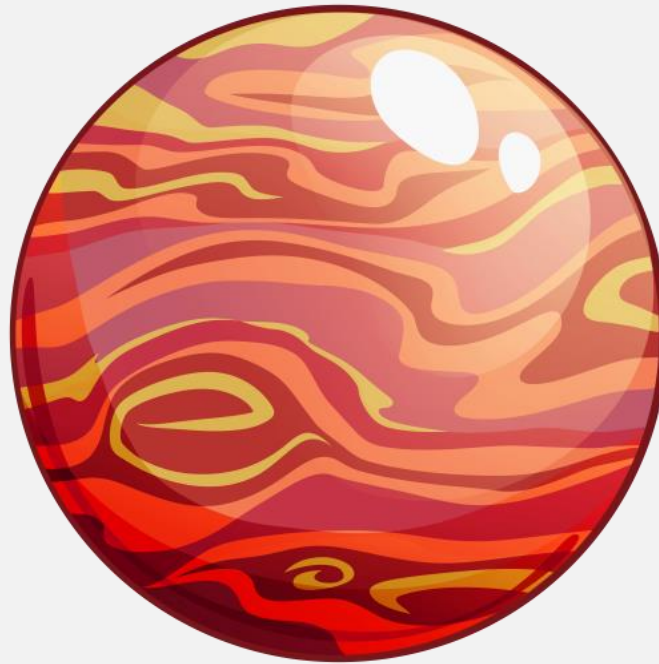
"complete link"
(max distance)
→ may break
large clusters
many more: different choices ⇒ different results

$$\text{red lines} - (\text{green star} + \text{yellow star})$$



"Ward's method"
(change in cost
function upon merging)
→ difficulty with
odd shapes/different
sizes

CODE EXAMPLE



Jupyter Notebook **Clustering methods**

CLUSTERING

- What is clustering?
- *k*-means clustering
- Agglomerative clustering
- **DBSCAN**
- Application

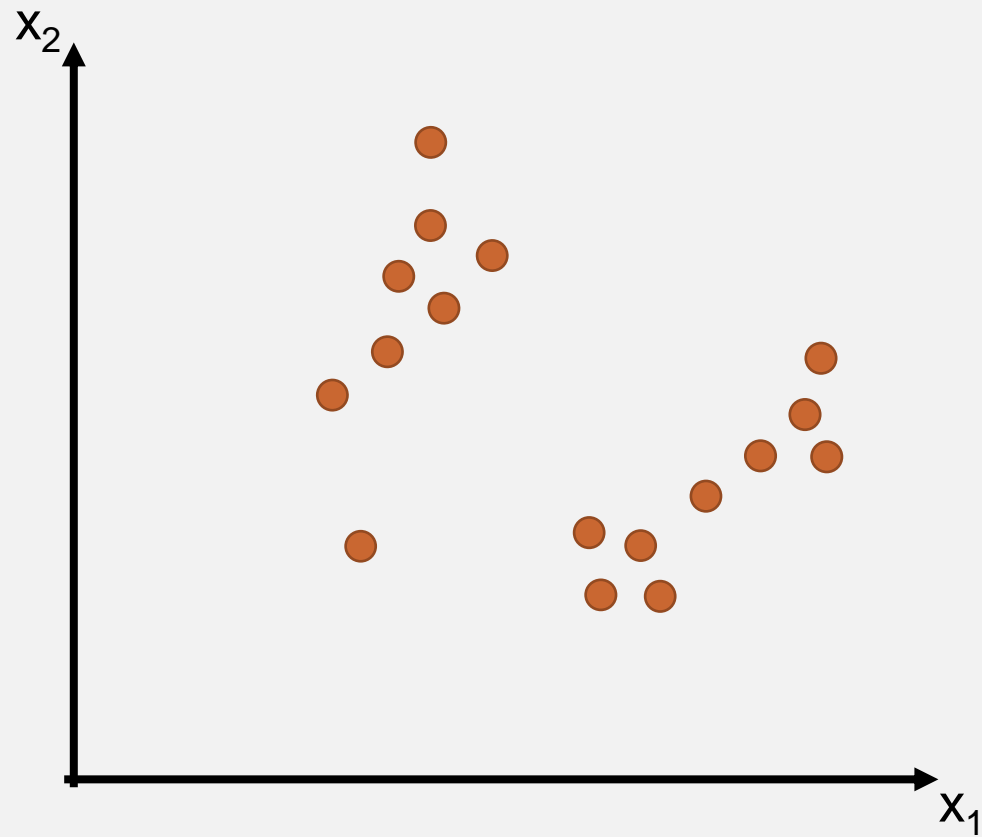
DBSCAN

"density-based spatial clustering of applications with noise"

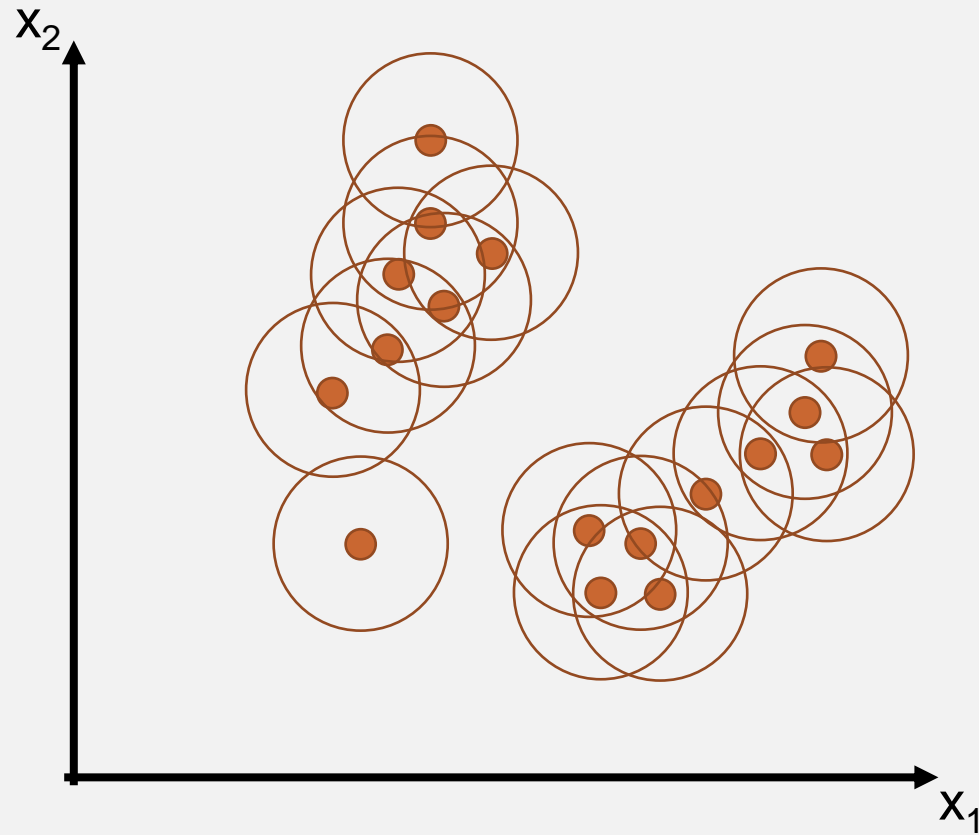
Partition points into dense regions
separated by not-so-dense regions

- How do we measure density?
= number of points in a circle of radius ϵ
- What is a dense region?
= density of at least n points

DBSCAN

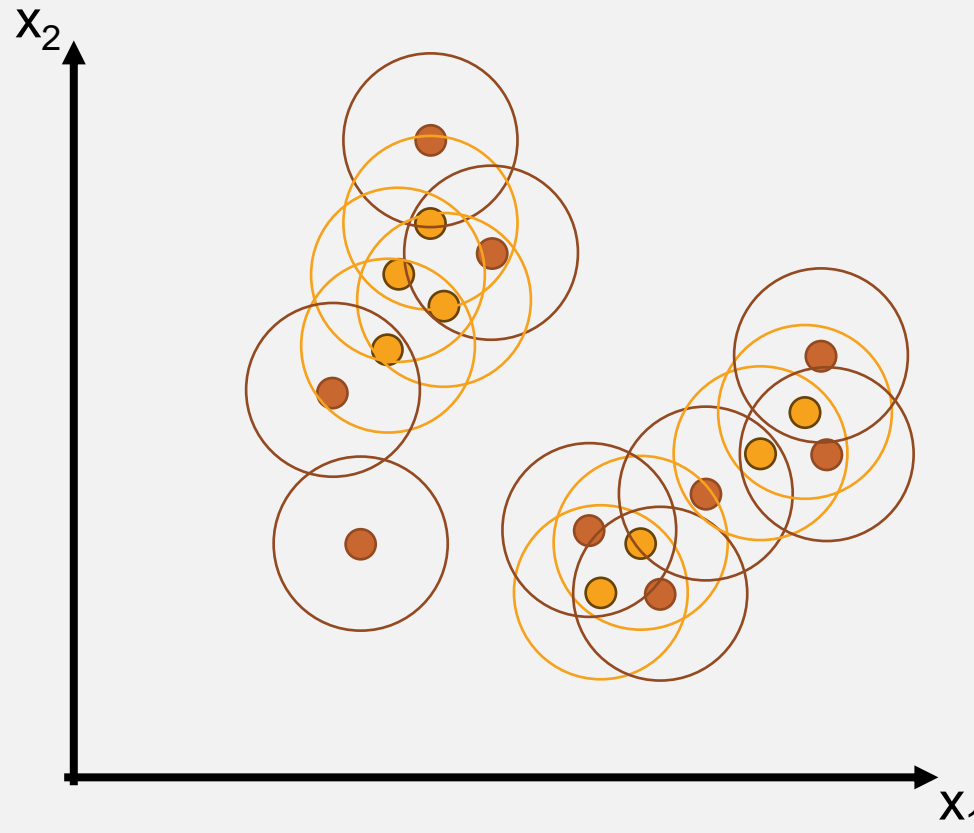


DBSCAN



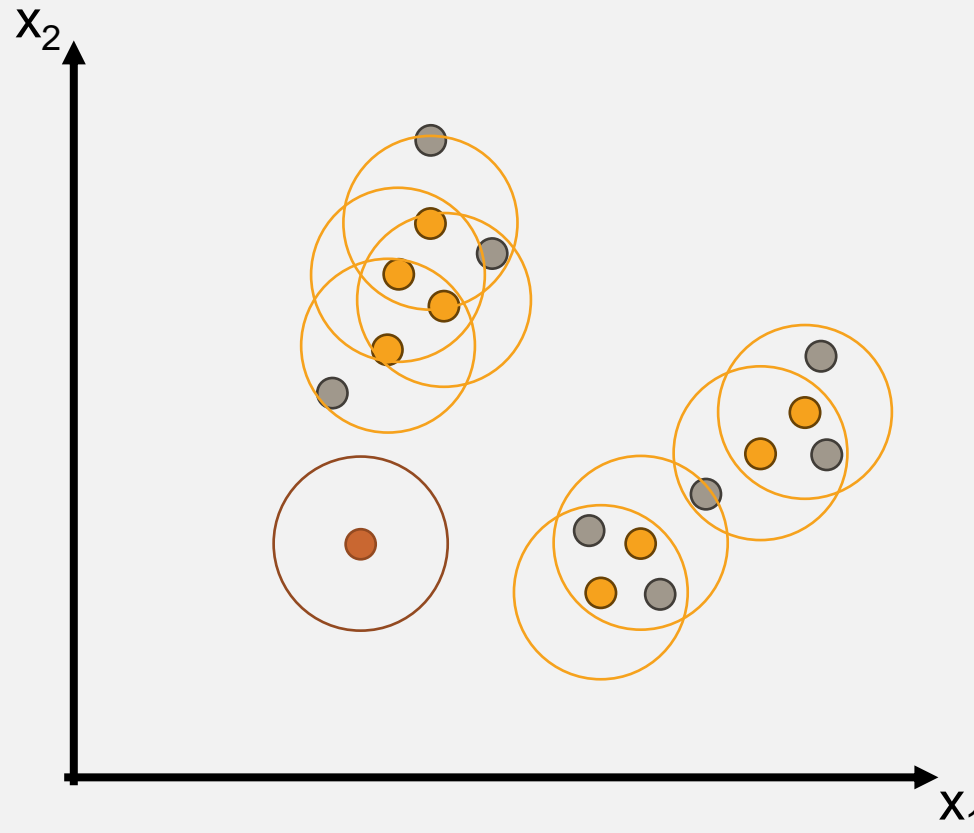
- I. Draw a circle of radius ϵ around every point.
This region is the ϵ -neighbourhood.

DBSCAN



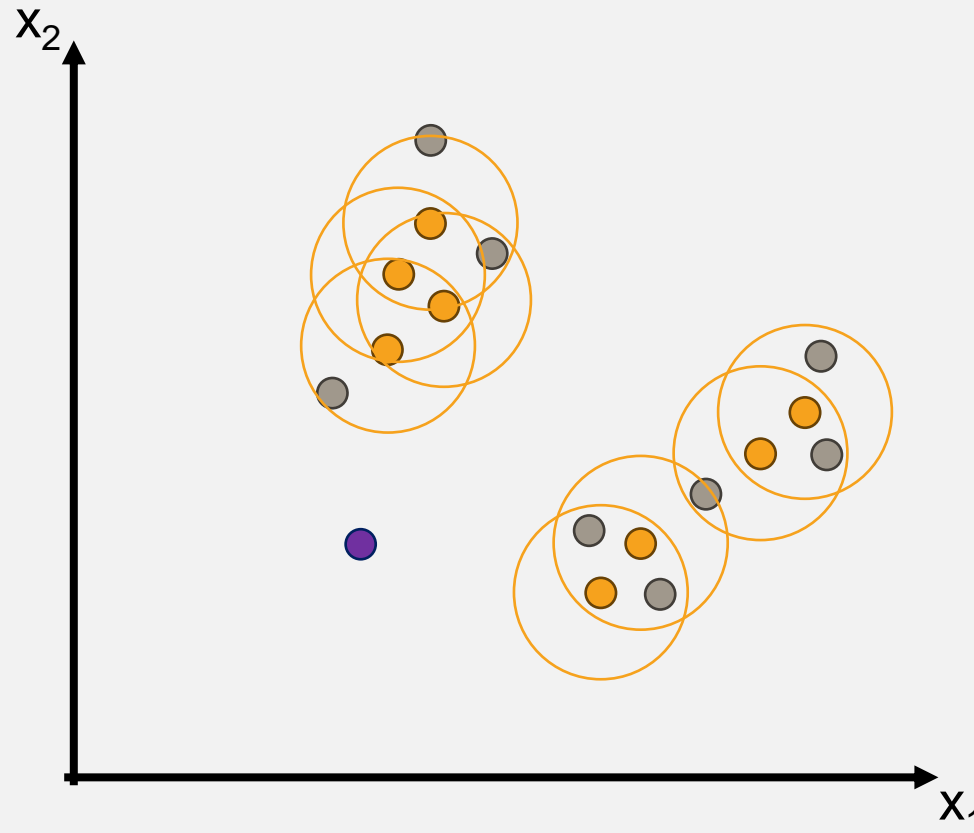
1. Draw a circle of radius ϵ around every point.
This region is the ϵ -neighbourhood.
2. If the ϵ -neighbourhood contains at least n ($=4$) points, we consider the point a **core** point ●.

DBSCAN



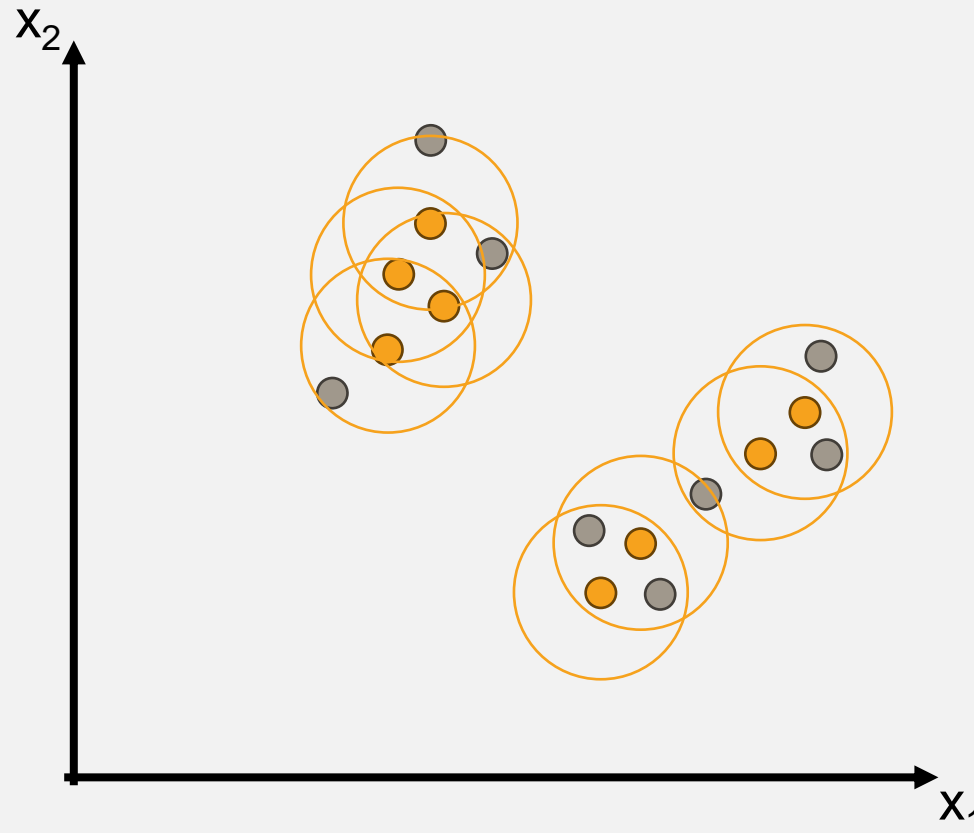
1. Draw a circle of radius ϵ around every point.
This region is the ϵ -neighbourhood.
2. If the ϵ -neighbourhood contains at least n ($=4$) points, we consider the point a **core** point ●.
3. If the point is not a core point, but is in the ϵ -neighbourhood of one, it is a **border** point ●.

DBSCAN



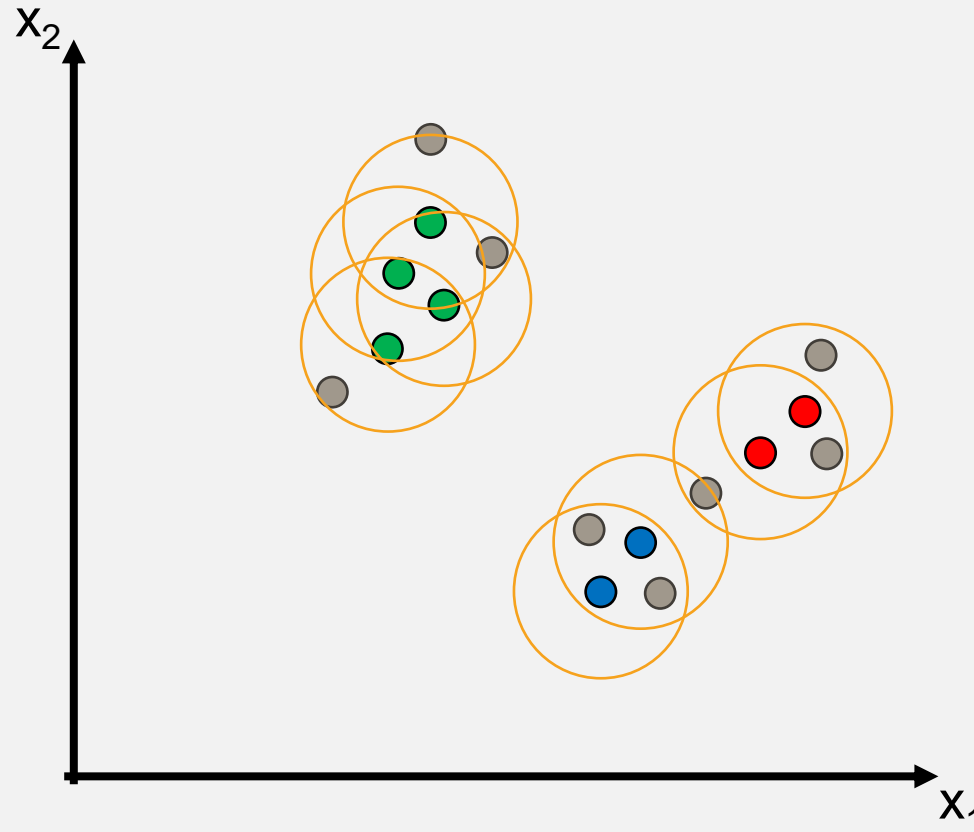
1. Draw a circle of radius ϵ around every point.
This region is the ϵ -neighbourhood.
2. If the ϵ -neighbourhood contains at least n ($=4$) points, we consider the point a **core** point ●.
3. If the point is not a core point, but is in the ϵ -neighbourhood of one, it is a **border** point ●.
4. Otherwise, it is a **noise** point ●.

DBSCAN



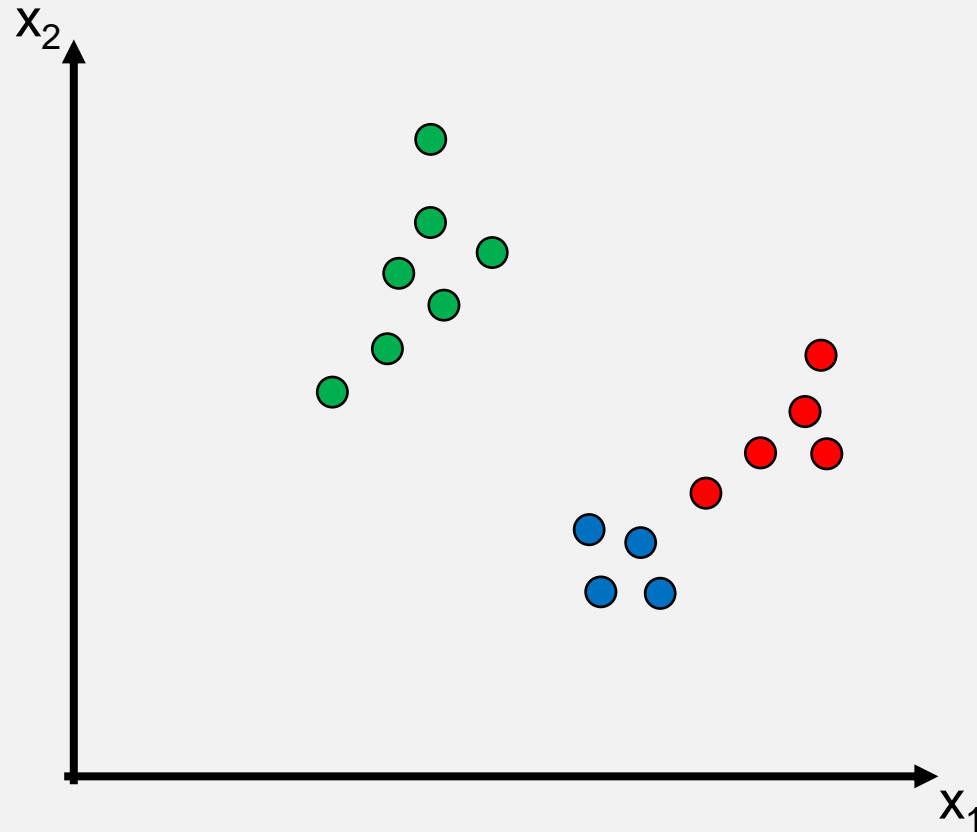
1. Draw a circle of radius ϵ around every point.
This region is the ϵ -neighbourhood.
2. If the ϵ -neighbourhood contains at least n ($=4$) points, we consider the point a **core** point ●.
3. If the point is not a core point, but is in the ϵ -neighbourhood of one, it is a **border** point ●.
4. Otherwise, it is a **noise** point ●.
5. Get rid of **noise** points.




DBSCAN



1. Draw a circle of radius ϵ around every point.
This region is the ϵ -neighbourhood.
2. If the ϵ -neighbourhood contains at least n ($=4$) points, we consider the point a **core** point (orange).
3. If the point is not a core point, but is in the ϵ -neighbourhood of one, it is a **border** point (grey).
4. Otherwise, it is a **noise** point (blue).
5. Get rid of **noise** points.
6. All **core** points reachable through each other's ϵ -neighbourhoods belong to the same cluster.

DBSCAN



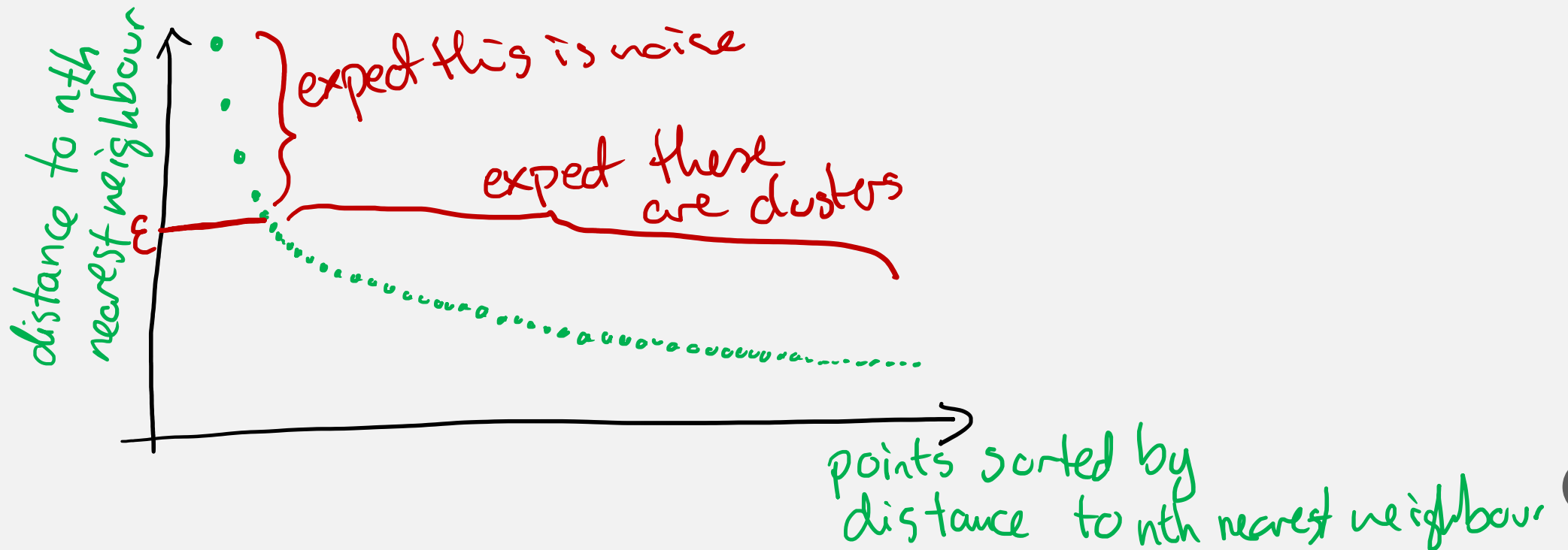
1. Draw a circle of radius ϵ around every point.
This region is the ϵ -neighbourhood.
2. If the ϵ -neighbourhood contains at least n ($=4$) points, we consider the point a **core** point .
3. If the point is not a core point, but is in the ϵ -neighbourhood of one, it is a **border** point .
4. Otherwise, it is a **noise** point .
5. Get rid of **noise** points.
6. All **core** points reachable through each other's ϵ -neighbourhoods belong to the same cluster.
7. All **border** points are assigned to the cluster of closest core point.

DETERMINING ϵ AND n (recommendation)

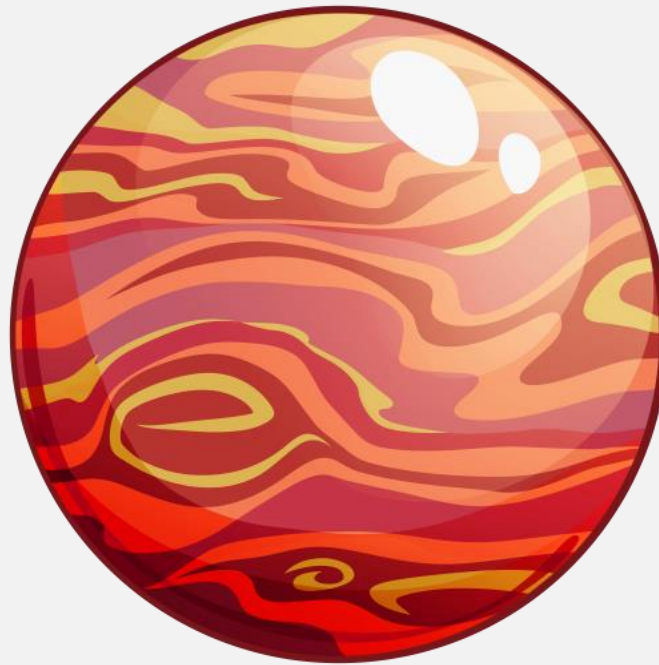
$$n \text{ (minPts)} = 2 \times \textcircled{d} - \text{dimensionality}$$

2D data $\Rightarrow n=4$
3D data $\Rightarrow n=6$
- - -

②



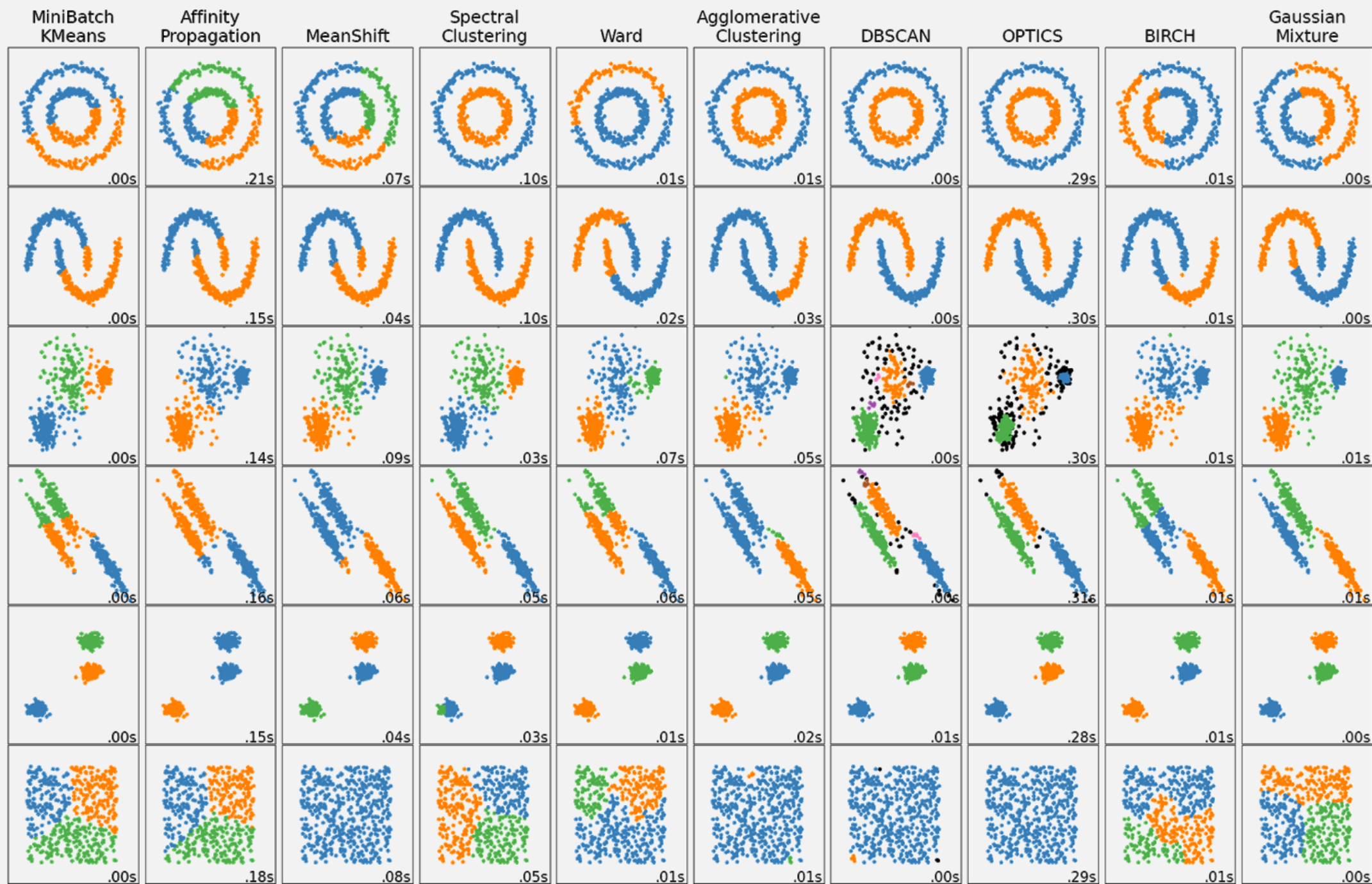
CODE EXAMPLE



Jupyter Notebook **Clustering methods**

COMPARING THE MODELS

	Pros	Cons
k-means clustering	Efficient	Cannot handle outliers Cannot handle weird shapes User must provide k (could be ok) Initialization
Agglomerative clustering	No a priori knowledge about #clusters	Each distance metric has its own problem Computationally heavy Dendrograms can be ambiguous
DBSCAN	Arbitrary shapes Deals with outliers No a priori knowledge about #clusters	Trouble w/ diff. densities



CLUSTERING

- What is clustering?
- *k*-means clustering
- Agglomerative clustering
- DBSCAN
- Application

APPLICATION: IMAGE SEGMENTATION



Jupyter Notebook **Image segmentation**

OUR ANALYSIS SHOWS THAT THERE ARE
THREE KINDS OF PEOPLE IN THE WORLD:
THOSE WHO USE K-MEANS CLUSTERING
WITH $K=3$, AND TWO OTHER TYPES WHOSE
QUALITATIVE INTERPRETATION IS UNCLEAR.

