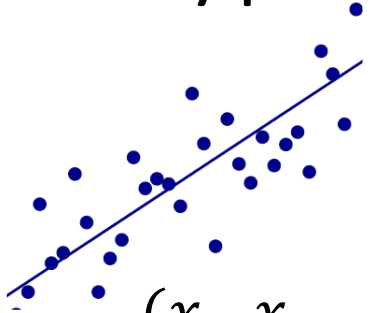


# Supervised vs Unsupervised Learning

By Francisco Mendoza

[mentofran@gmail.com](mailto:mentofran@gmail.com)

# Type of problems, data types

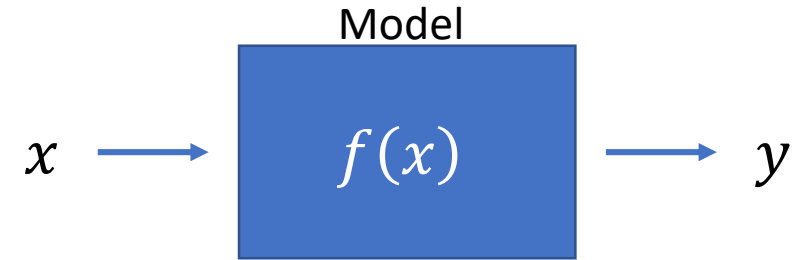


$$x \rightarrow y$$

$$(x_1, x_2, \dots, x_n) \rightarrow y$$

$$(x_1, x_2, \dots, x_n) \rightarrow (y_1, y_2, \dots, y_k)$$

**Supervised**



$$f: X \rightarrow Y$$

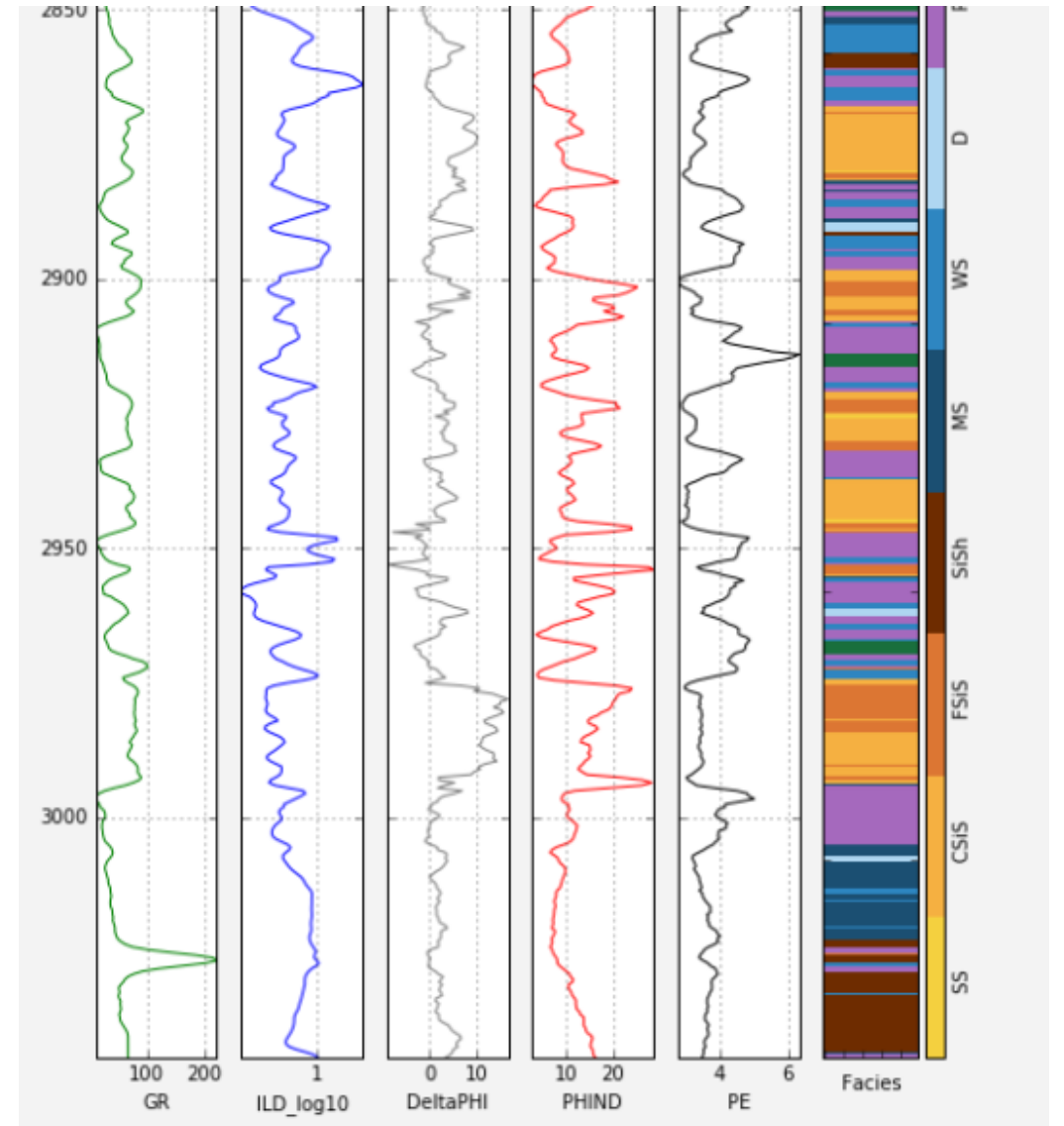
**Unsupervised**

ID	$x_1$	...	$x_n$	Category
1	3.532		A	Catx
2	7.234		H	Caty
⋮	⋮		⋮	⋮



ID	Cat y
1	aaa
2	hhh
⋮	⋮

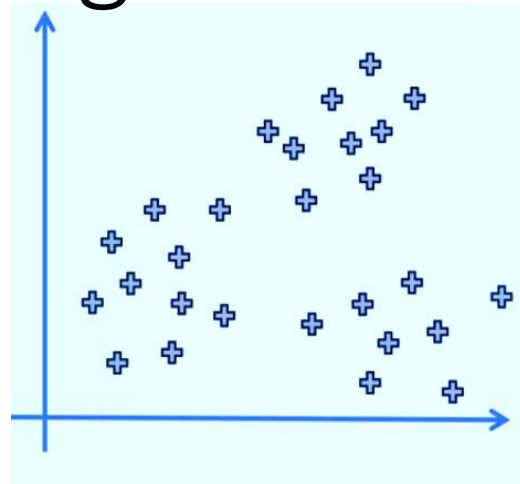
# Supervised Vs Unsupervised learning



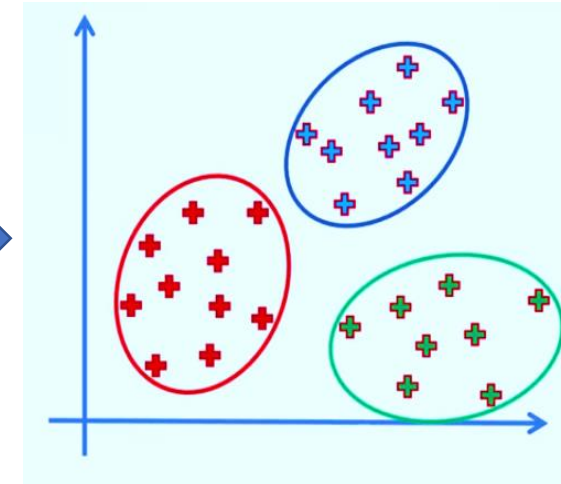
# Unsupervised learning

- Clustering

- K-means
- DBSCAN
- Hierarchical Cluster Analysis

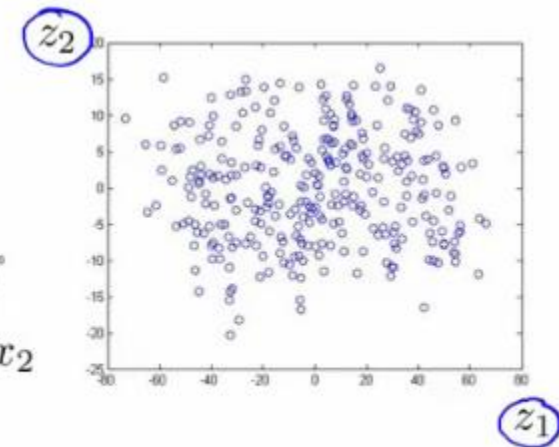
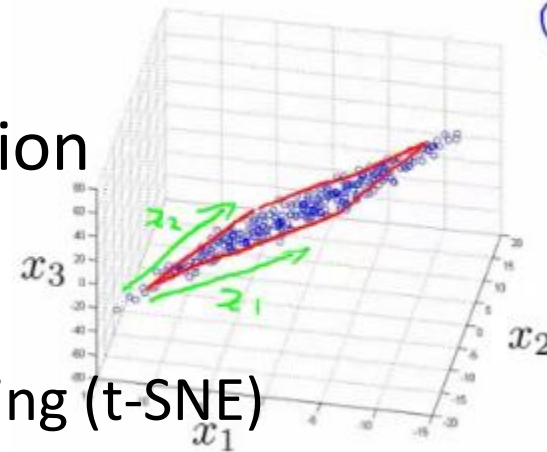


Clustering



- Visualization and dimensionality reduction

- Principal Component Analysis (PCA)
- Locally-Linear Embedding (LLE)
- t-distributed Stochastic Neighbor Embedding (t-SNE)



K-means

# K-means

## Assumptions

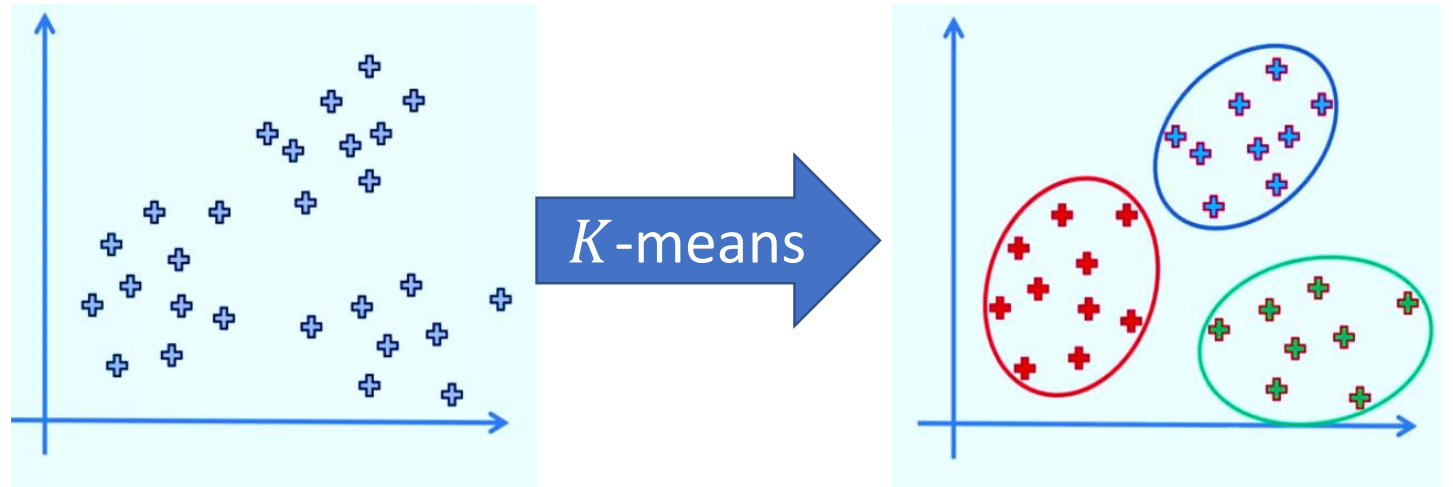
- $K$  –clusters
- $n$  instances

$$1. C_1 \cup C_2 \cup \dots \cup C_K = \{1, \dots, n\}$$

$$2. C_i \cap C_j = \emptyset \quad \forall i \neq j$$

## Requirements

Similarity or Dissimilarity (Distance) measure

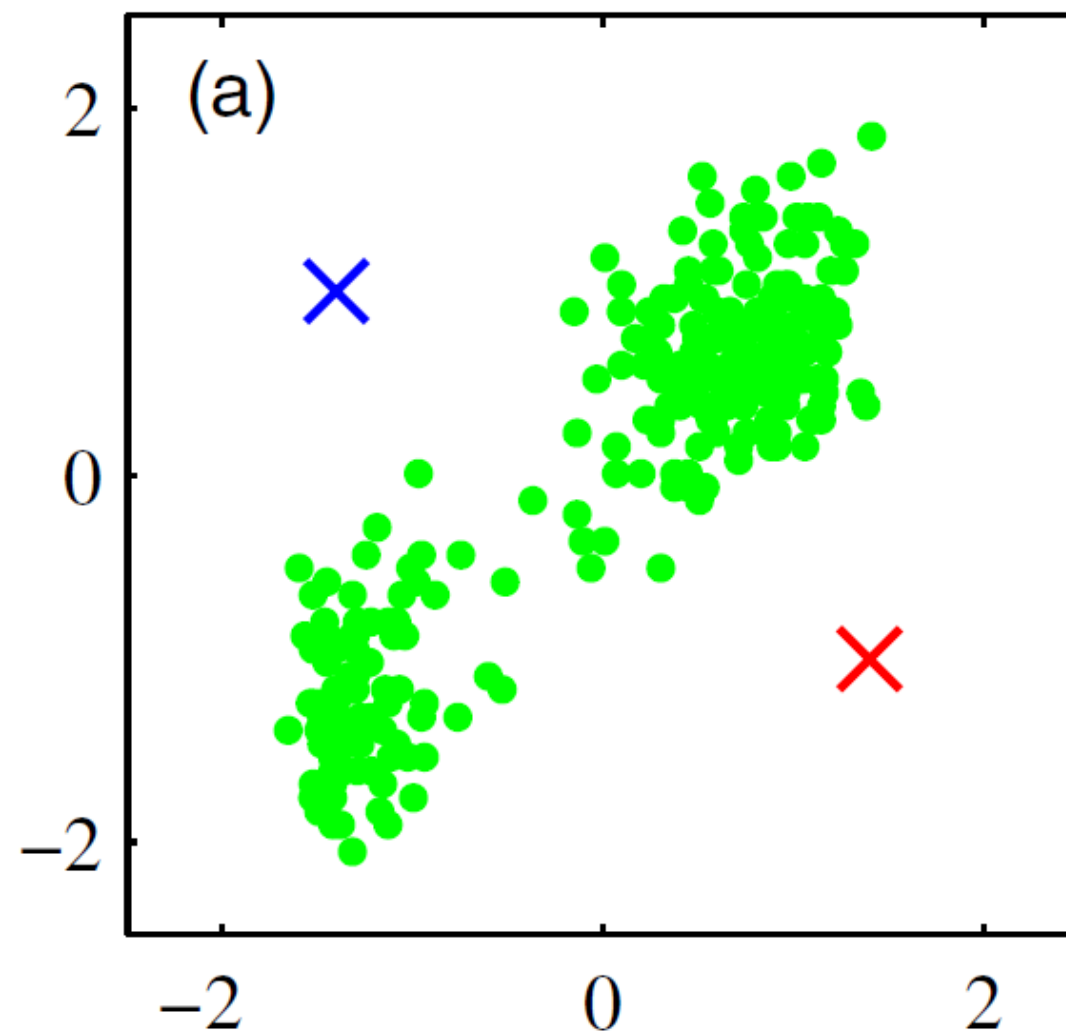


# Similarity vs Dissimilarity

- The **similarity** between two objects is a numeral measure of the degree to which the two objects are alike. Consequently, similarities are higher for pairs of objects that are more alike. Similarities are usually non-negative and are often between 0 (no similarity) and 1 (complete similarity).
- The **dissimilarity** between two objects is the numerical measure of the degree to which the two objects are different. Dissimilarity is lower for more similar pairs of objects.
- Frequently, the term **distance** is used as a synonym for dissimilarity. Dissimilarities sometimes fall in the interval  $[0,1]$ , but it is also common for them to range from 0 to  $\infty$ .

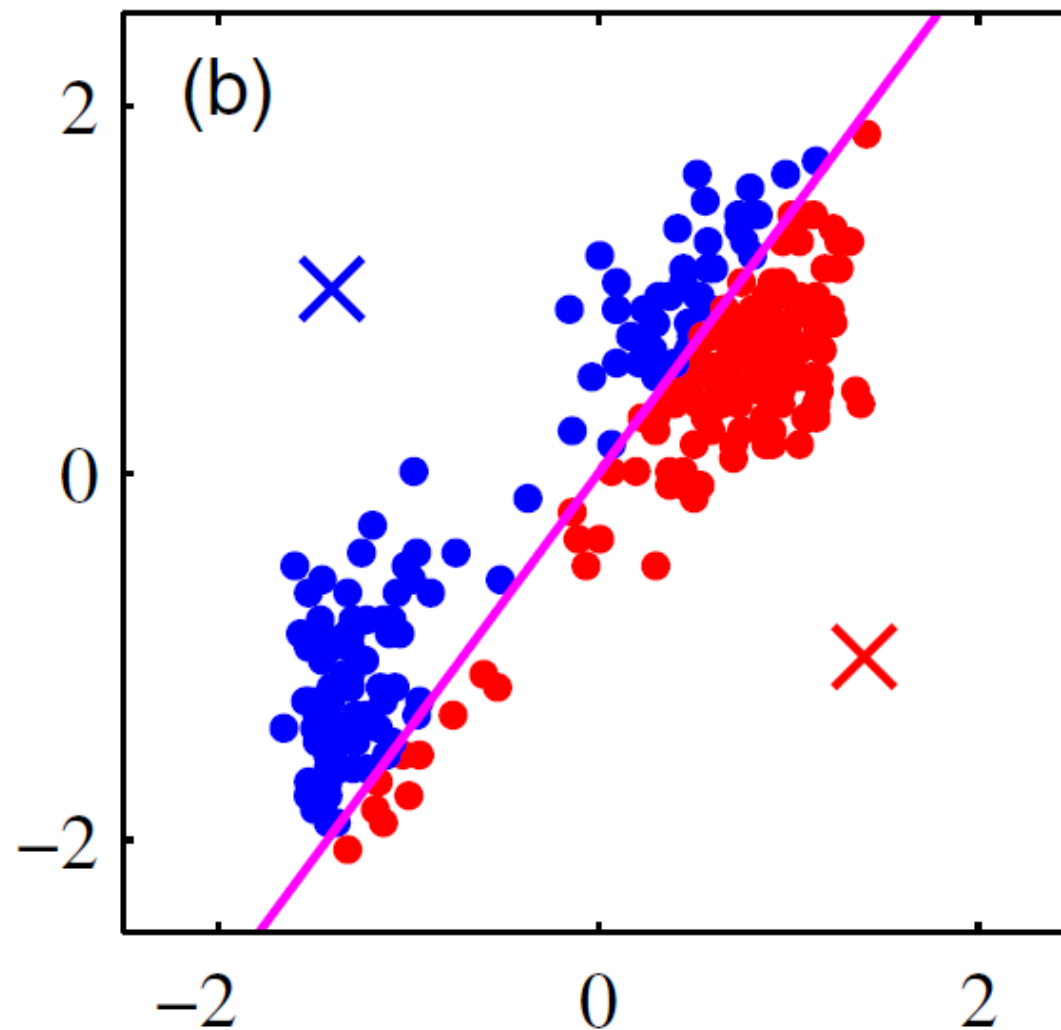


# $K$ -means algorithm

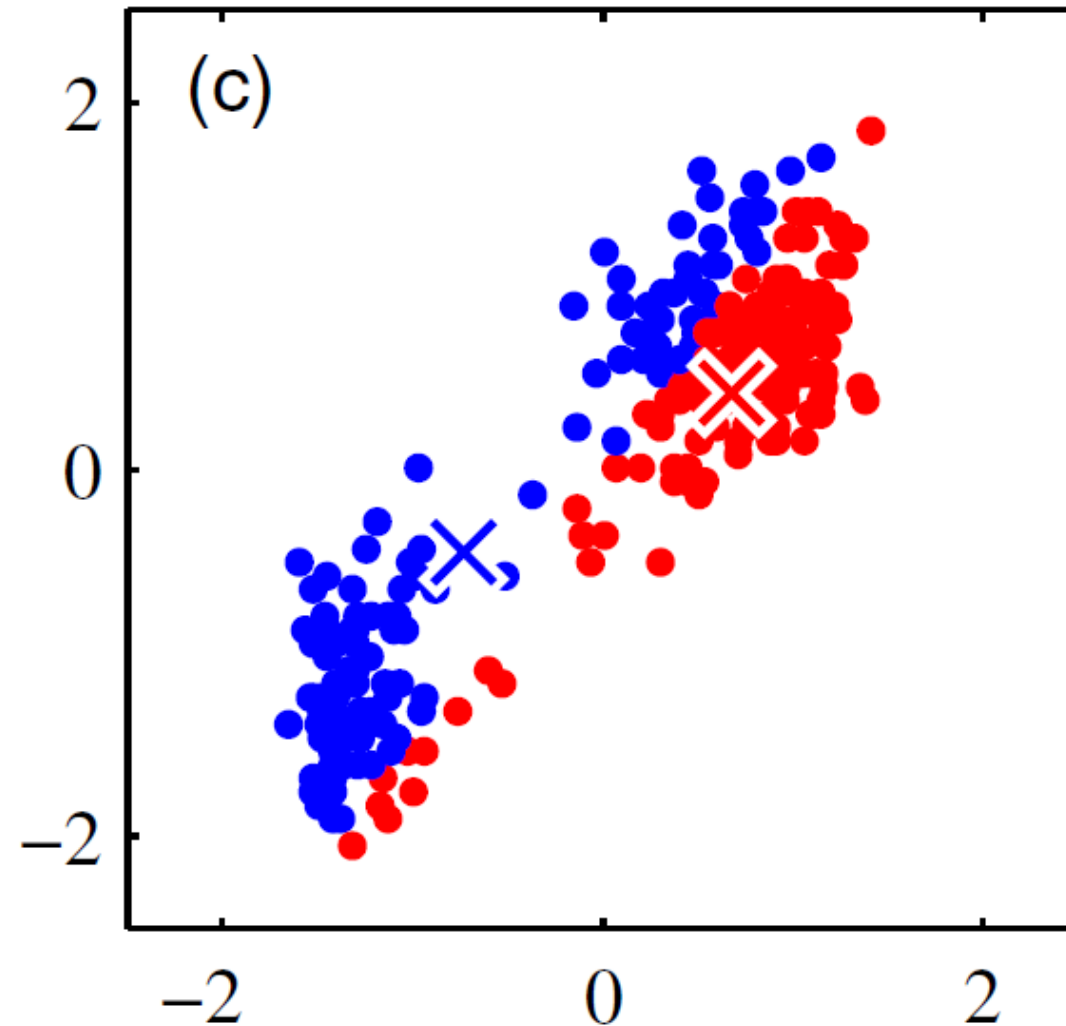




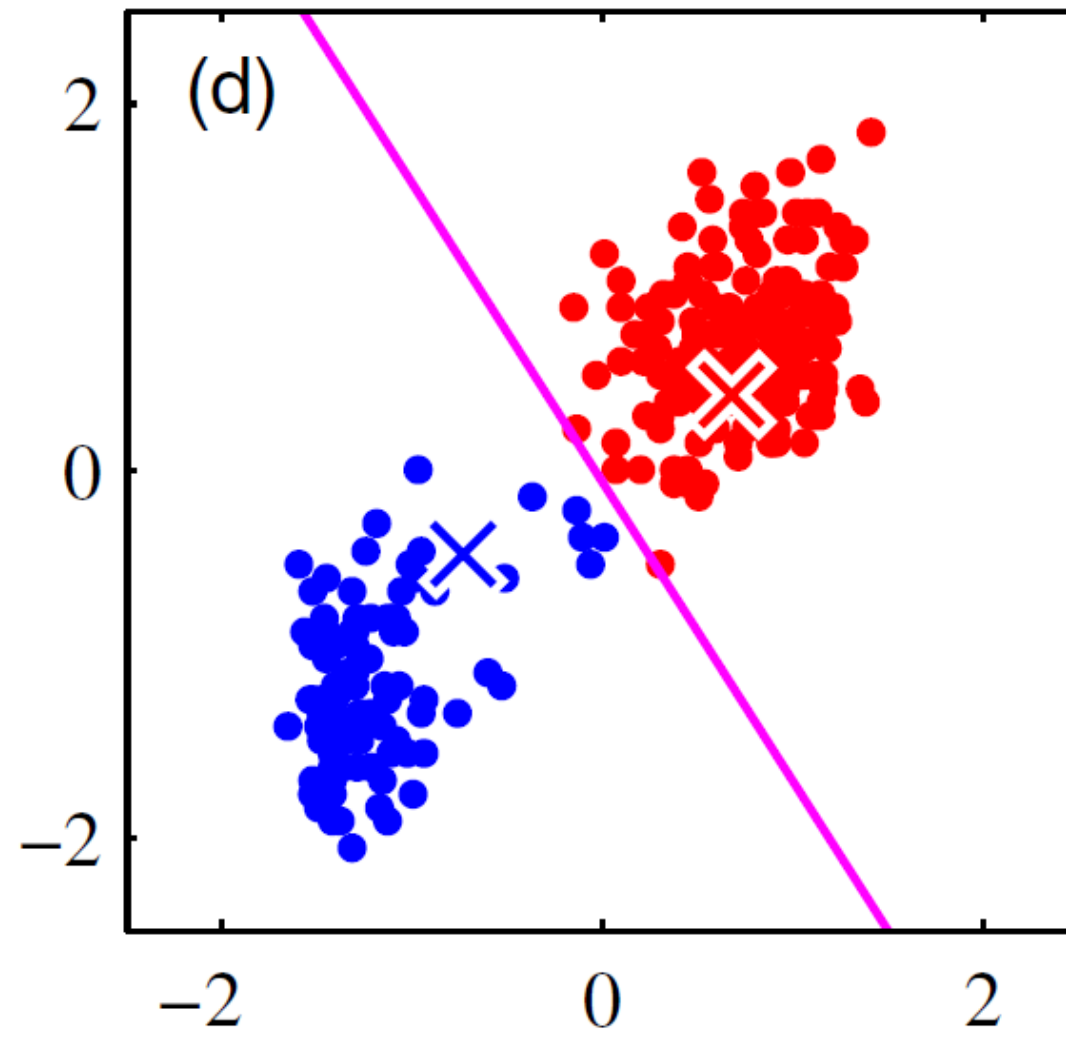
# $K$ -means algorithm



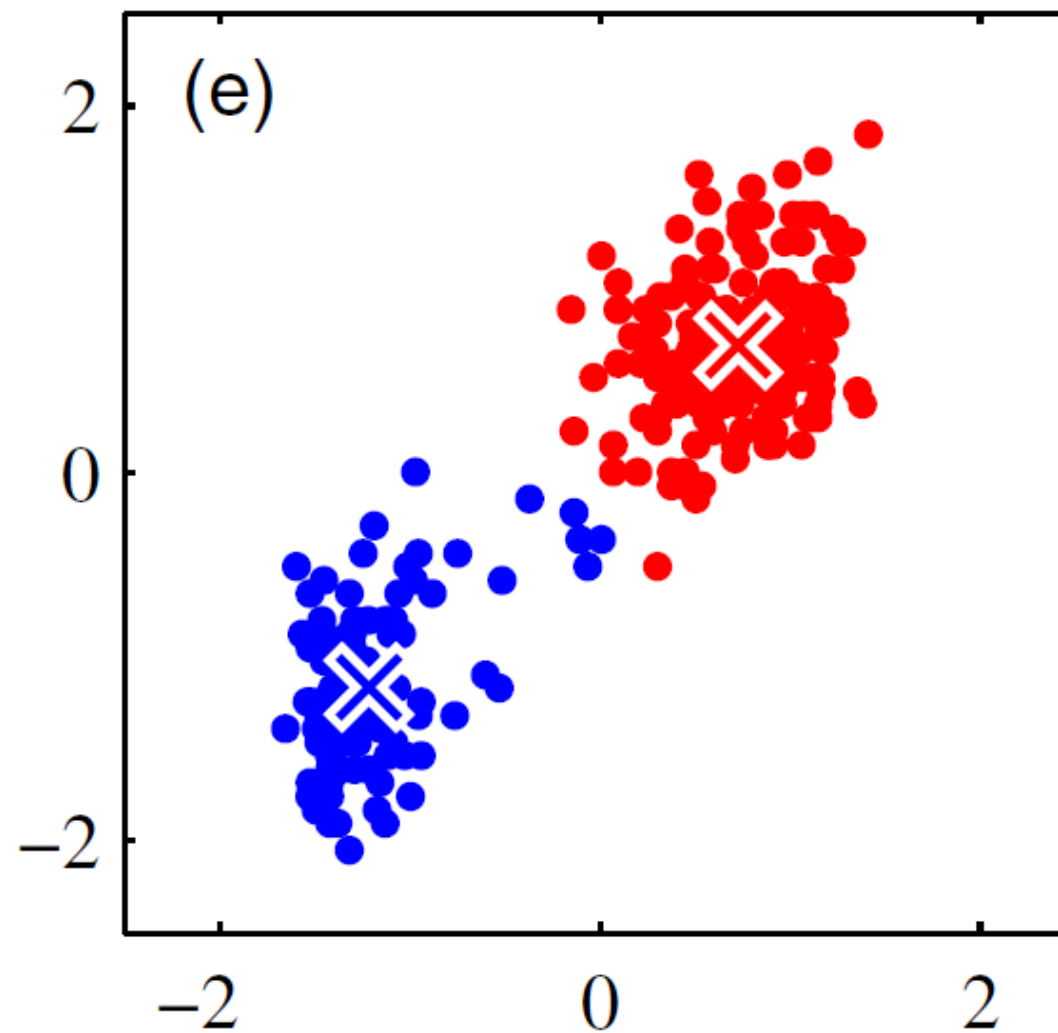
# $K$ -means algorithm



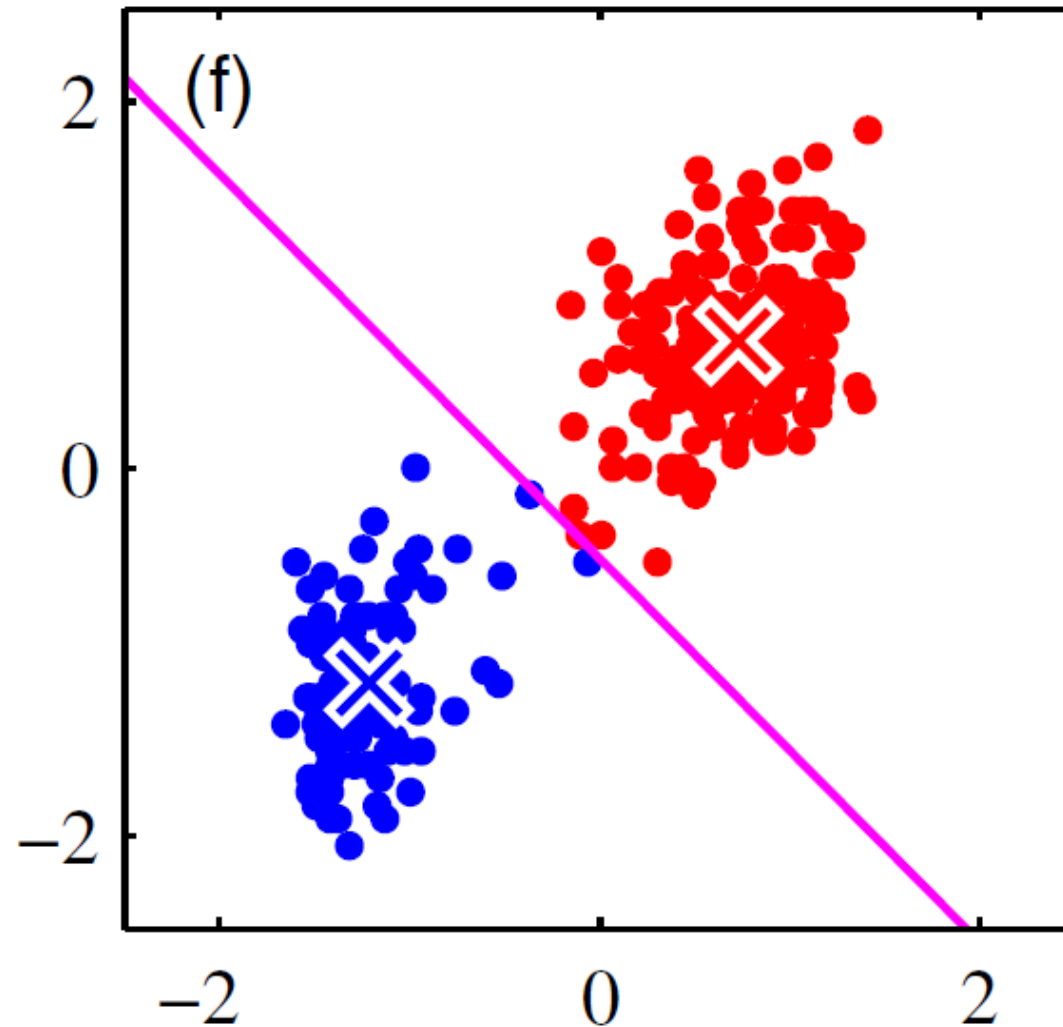
# $K$ -means algorithm



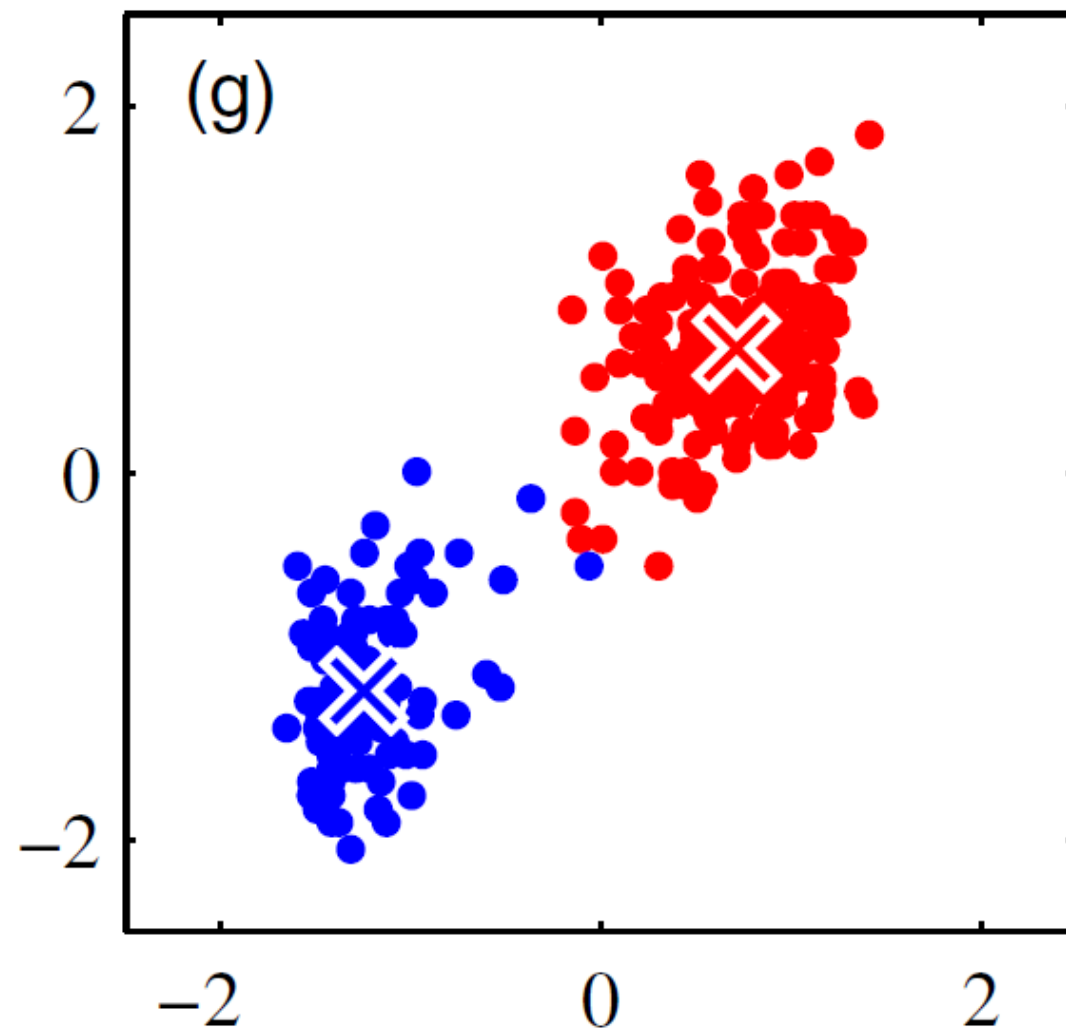
# $K$ -means algorithm



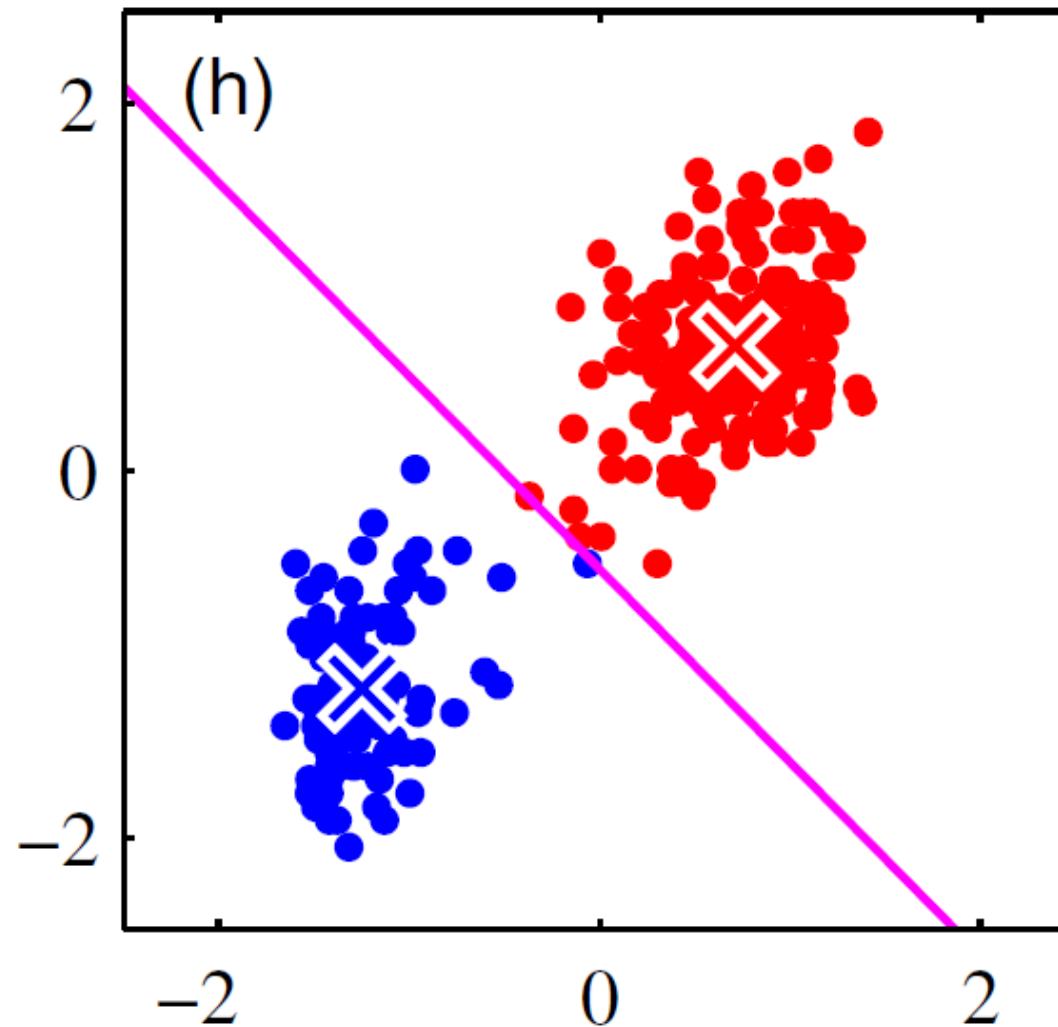
# $K$ -means algorithm



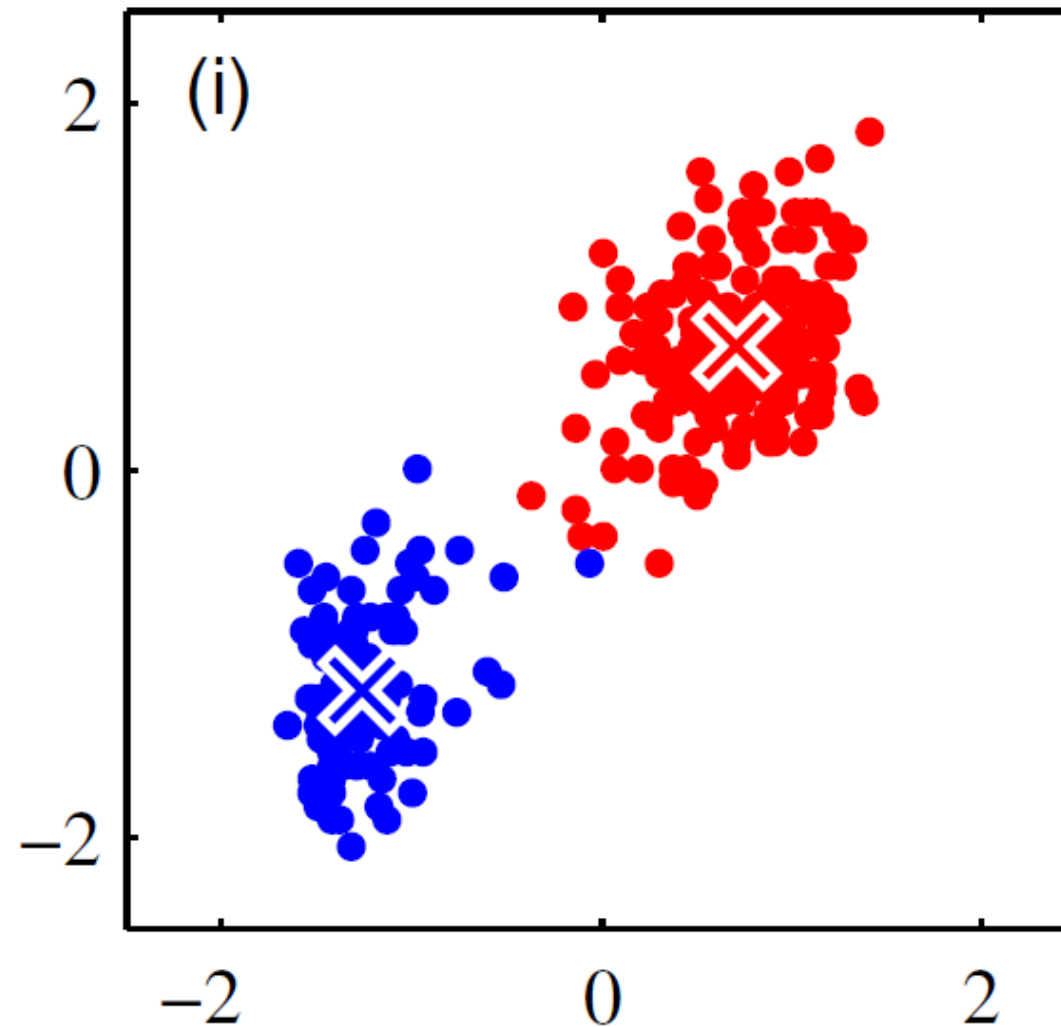
# $K$ -means algorithm



# $K$ -means algorithm



# $K$ -means algorithm





# Exercise

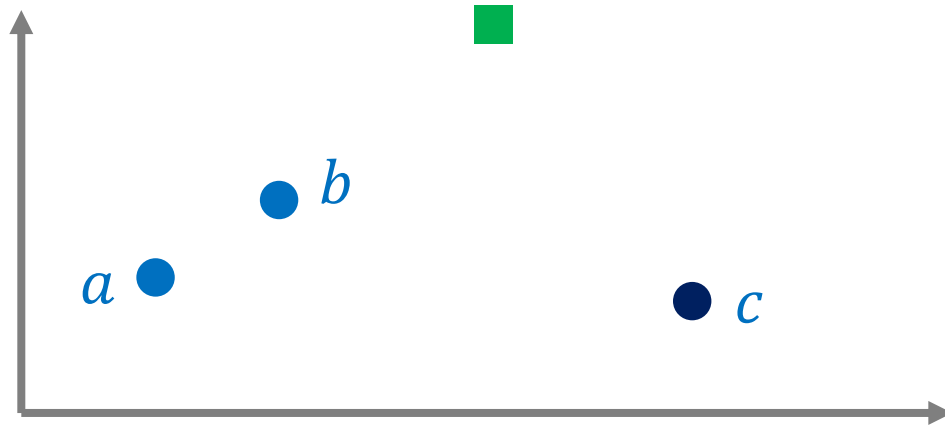
Data

	$x$	$y$
$a$	1	1
$b$	3	2
$c$	7	1

Initial Centroids

	$x$	$y$
$c_1$	5	3
$c_2$	5	1

$$\begin{pmatrix} \begin{smallmatrix} \square & \square \\ \square & \square \end{smallmatrix} & \begin{smallmatrix} \square & \square \\ \square & \square \end{smallmatrix} \end{pmatrix}$$



>\_ Code

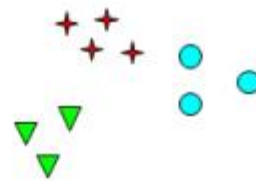
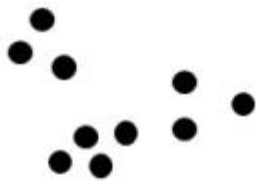
# Homework assignment

- Generate a bivariate dataset with  $K = 3$  groups and then use `sklearn.cluster.KMeans()` to get clusters of the dataset
- Plot the scatterplot identifying each cluster with a different color

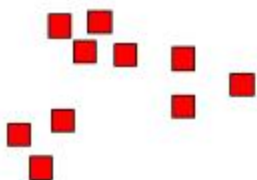
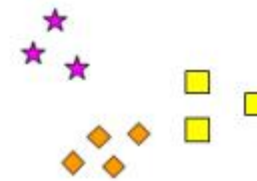
# Choosing $K$ . Silhouette coefficient/score



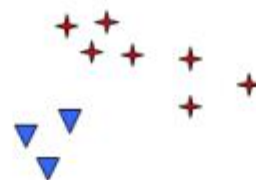
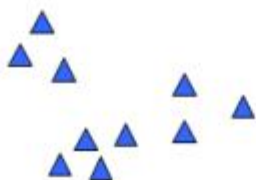
How many clusters?



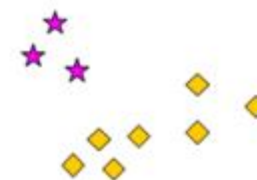
Six Clusters



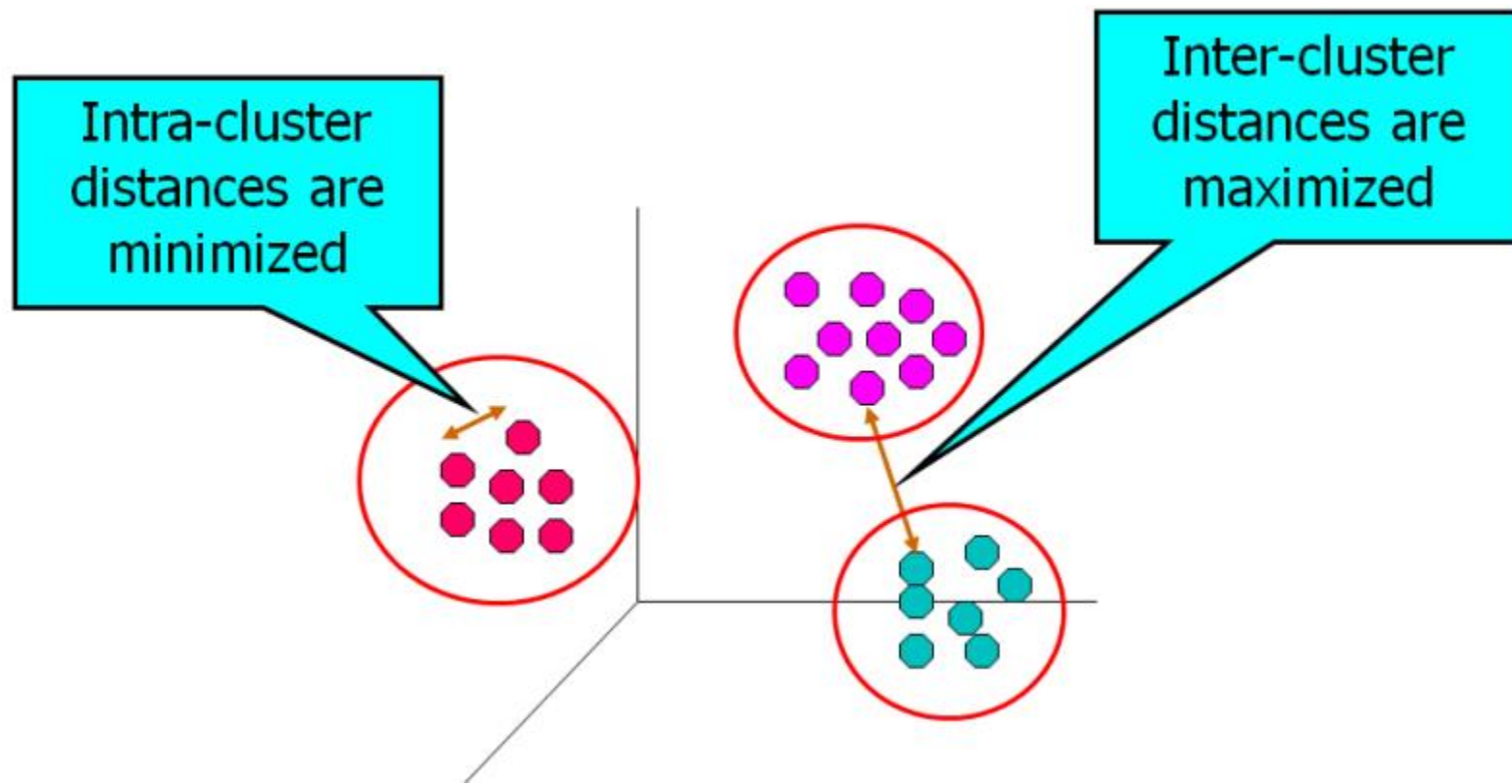
Two Clusters



Four Clusters

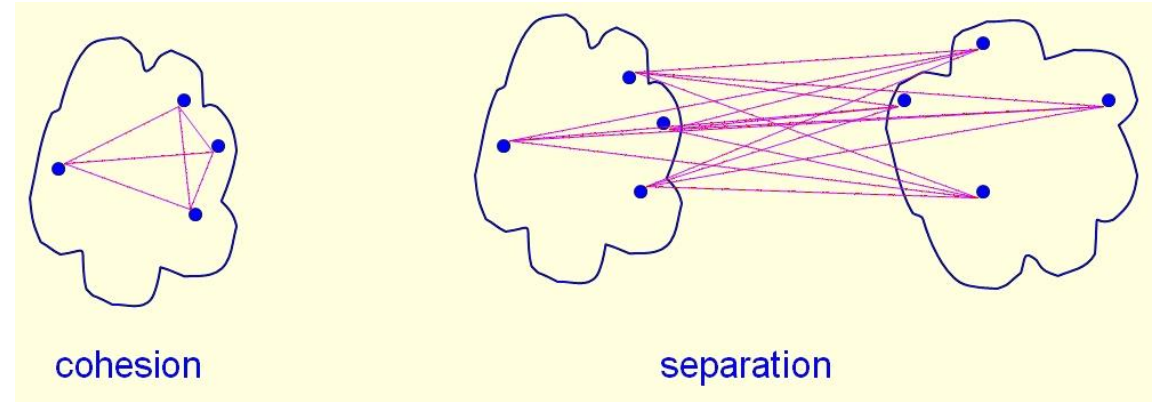


# Choosing $K$ . Silhouette coefficient/score



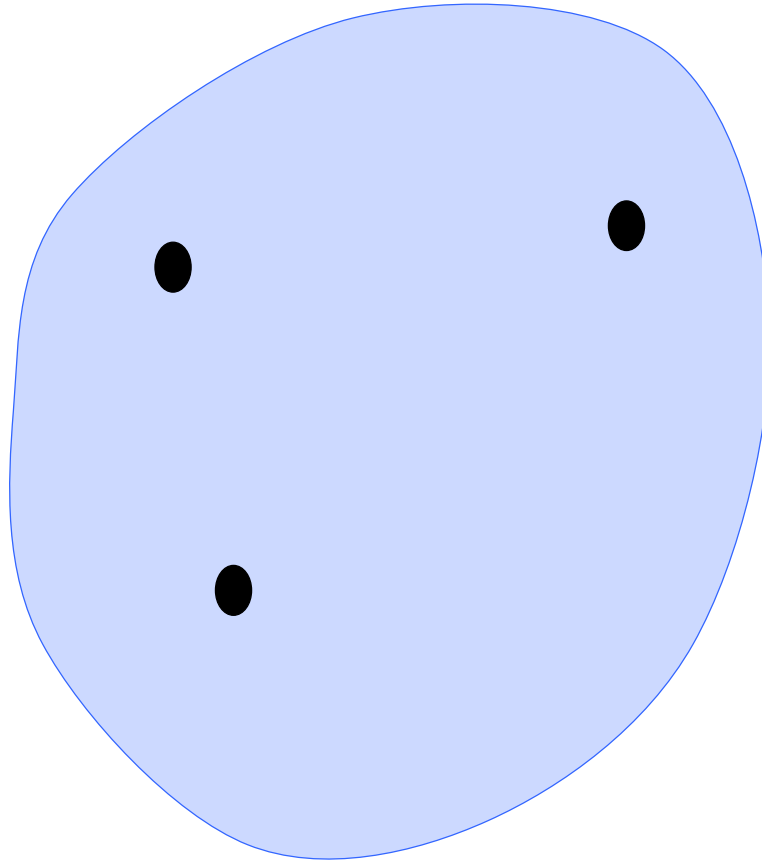
# Cohesion and Separation

- Cluster cohesion
  - How tightly packed is a cluster
  - More cohesive clusters is more better
- Cluster separation
  - Distance between clusters
  - The more separation, the better
- Can we measure these things?
  - Yes



# Cohesion (intra-cluster)

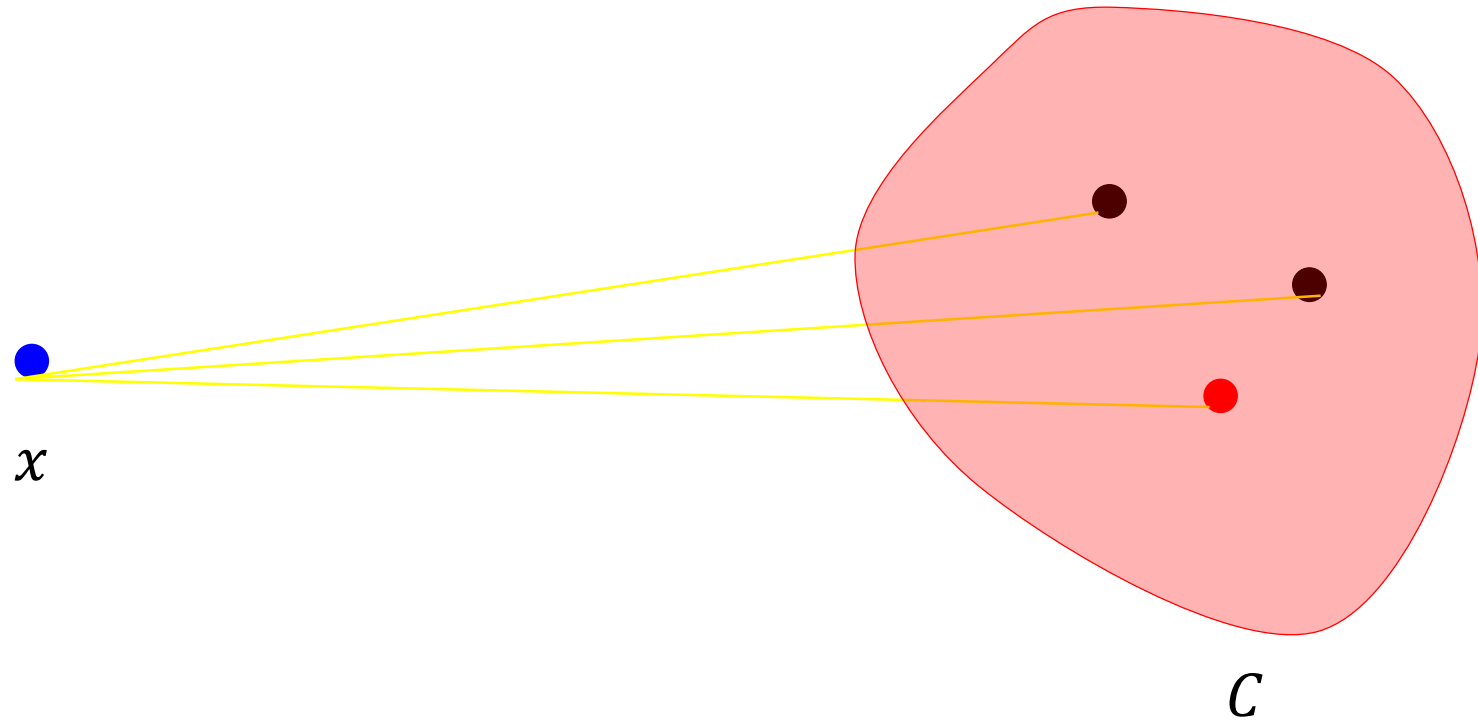
- For a data point  $x_i$  in the cluster  $C_i$



$$a(i) = \frac{1}{|C_i| - 1} \sum_{j \in C_i, i \neq j} d(i, j)$$

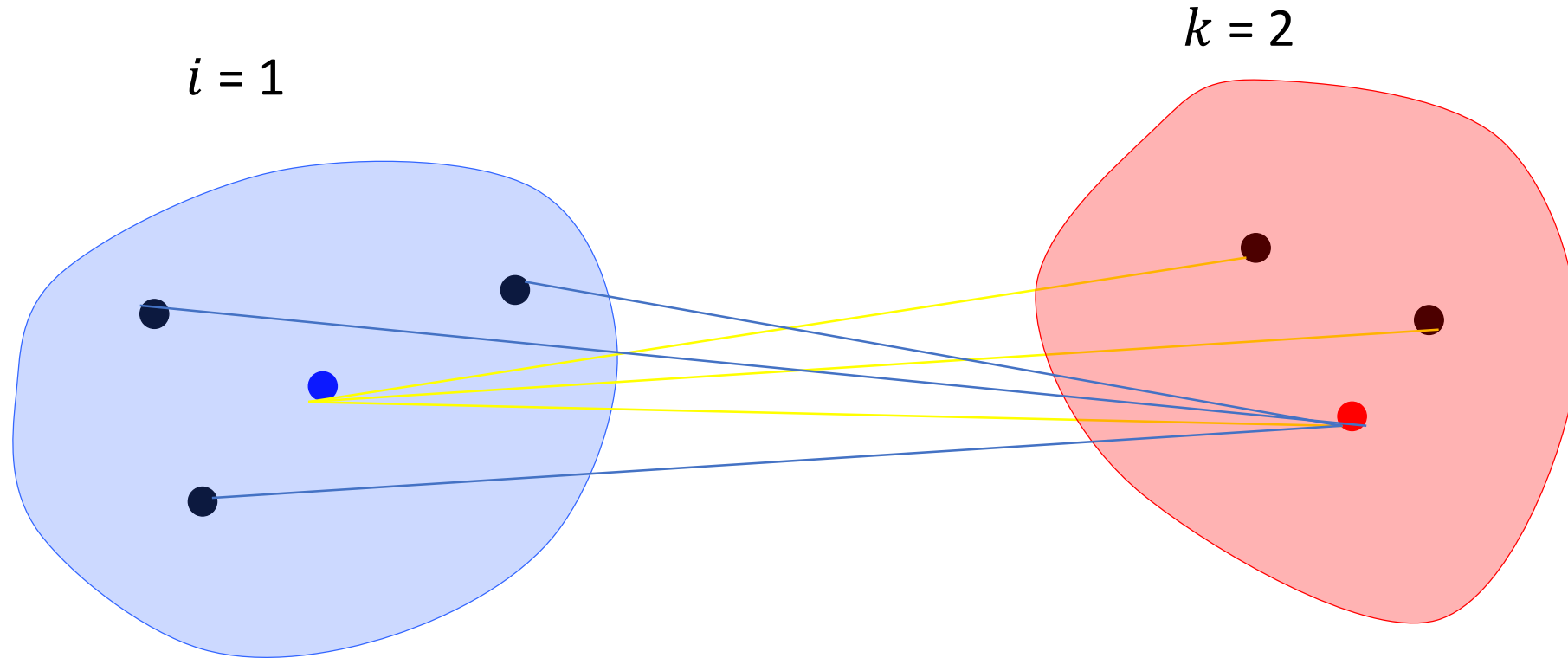
# Separation (inter-cluster)

Distance  $d$  from a point  $x$  to a set  $C$  is defined as  $d(x, C)$



# Separation (inter-cluster)

$K = 2$



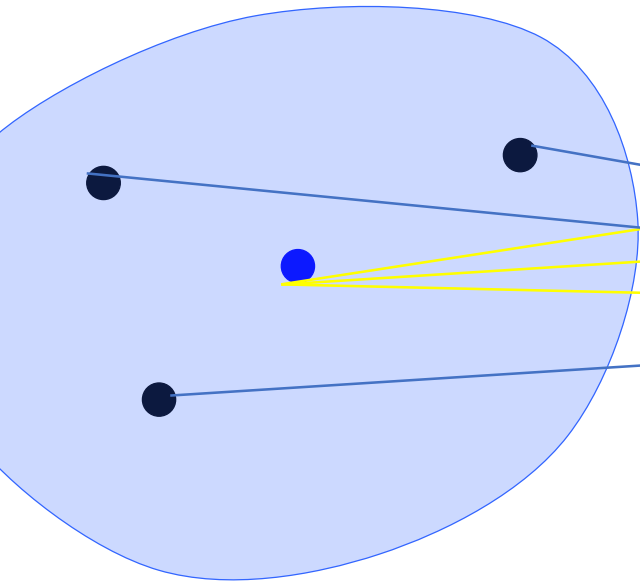
$$b(i) = \min_{k \neq i} \frac{1}{|C_k|} \sum_{j \in C_k} d(i, j)$$



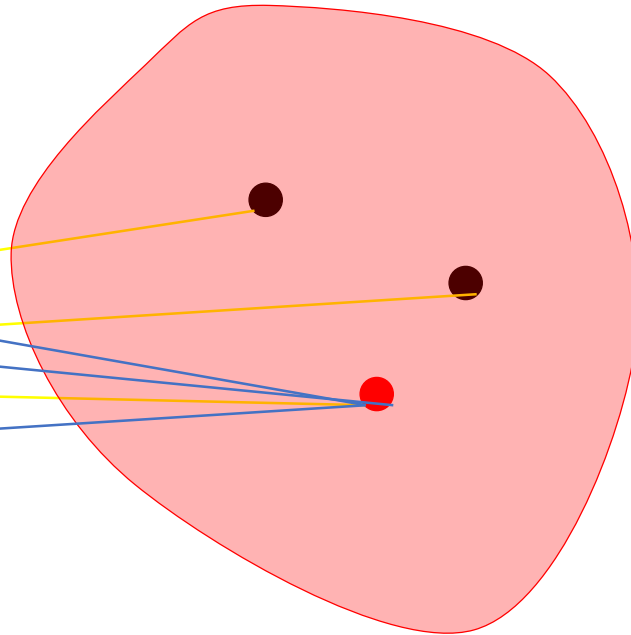
# Separation (inter-cluster)

$K = 3$

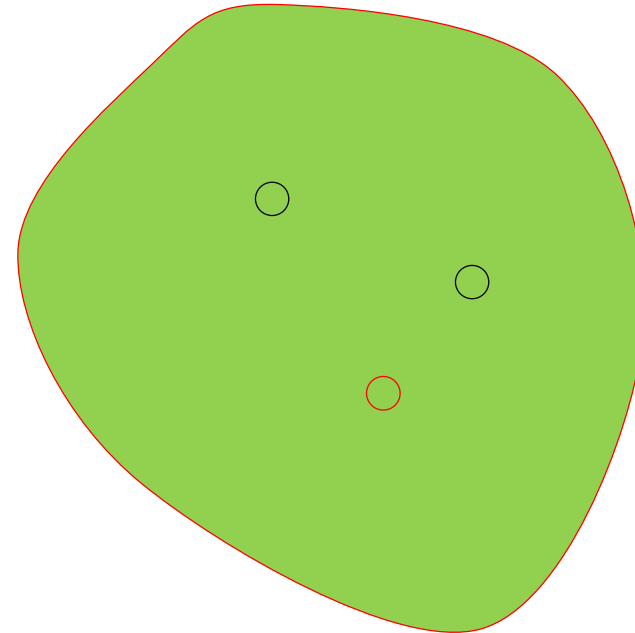
$i = 1$



$k = 2$



$k = 3$



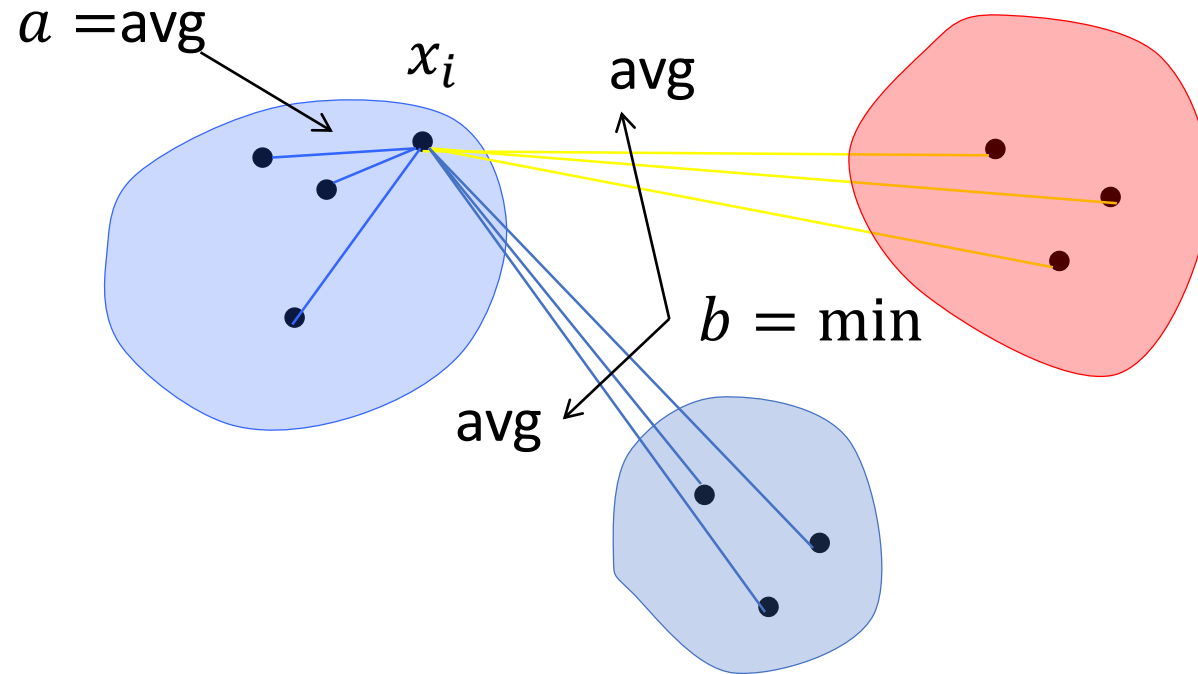
$$b(i) = \min_{k \neq i} \frac{1}{|C_k|} \sum_{j \in C_k} d(i, j)$$

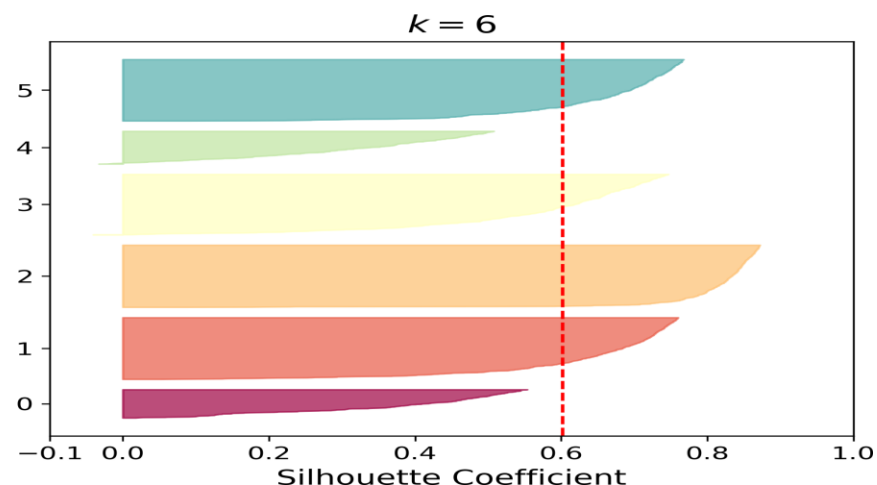
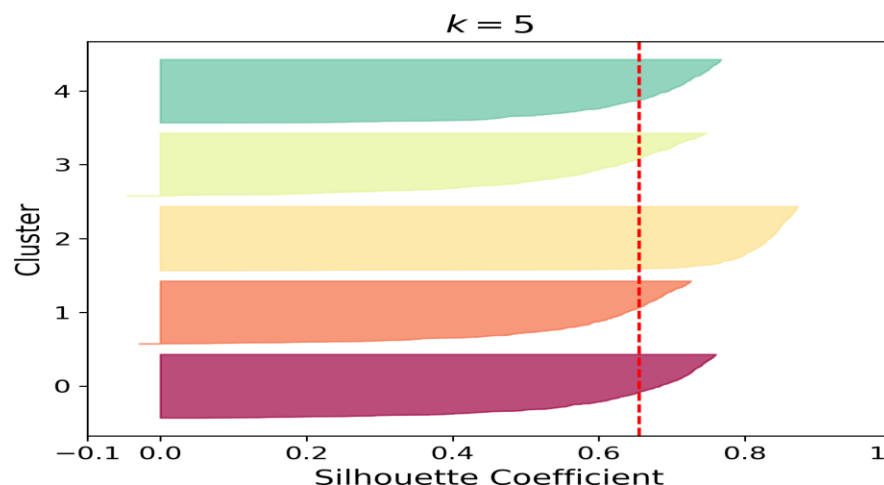
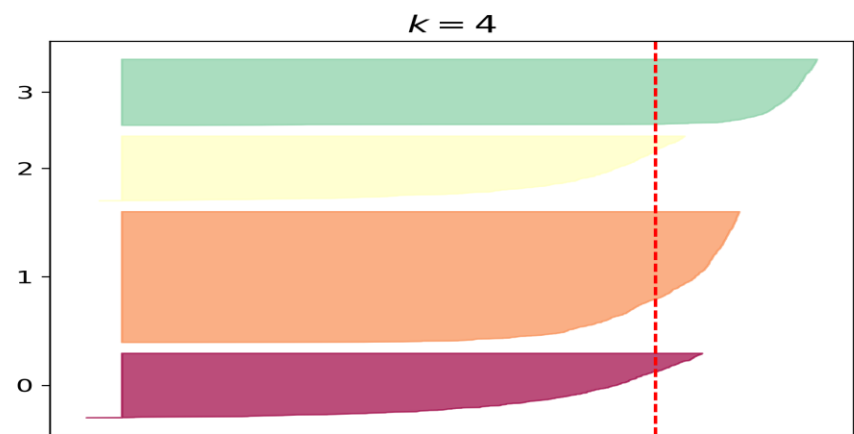
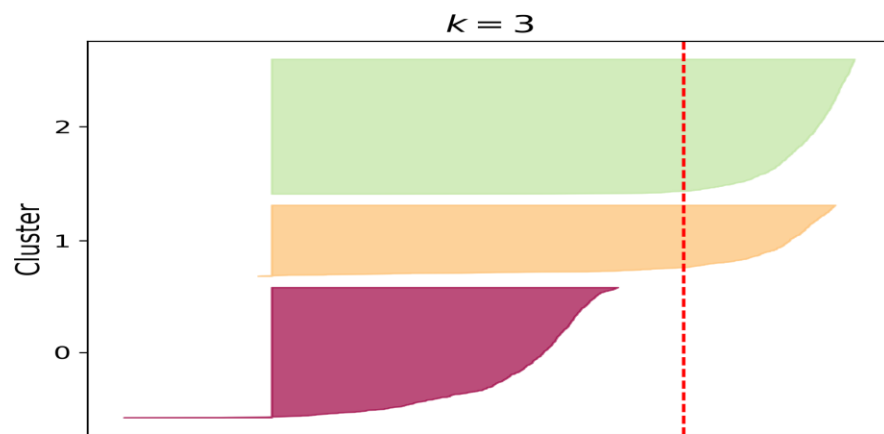
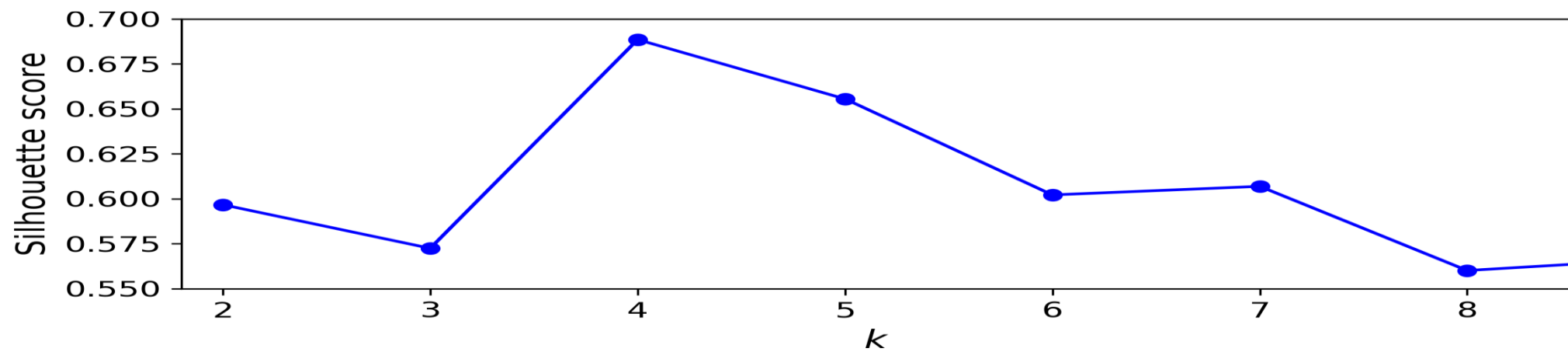
# Silhouette Coefficient

- Essentially, combines cohesion and separation into a single number
- Let  $C_i$  be cluster of point  $x_i$ 
  - Let  $a$  be average of  $d(x_i, y)$  for all  $y$  in  $C_i$
  - For  $C_i \neq C_j$ , let  $b_j$  be avg  $d(x_i, y)$  for  $y$  in  $C_j$
  - Let  $b$  be minimum of  $b_j$
- Then,  $S(x_i) = \frac{b-a}{\max(a,b)}$
- if  $|C_i| > 1$ , else  $S(x_i) = 0$

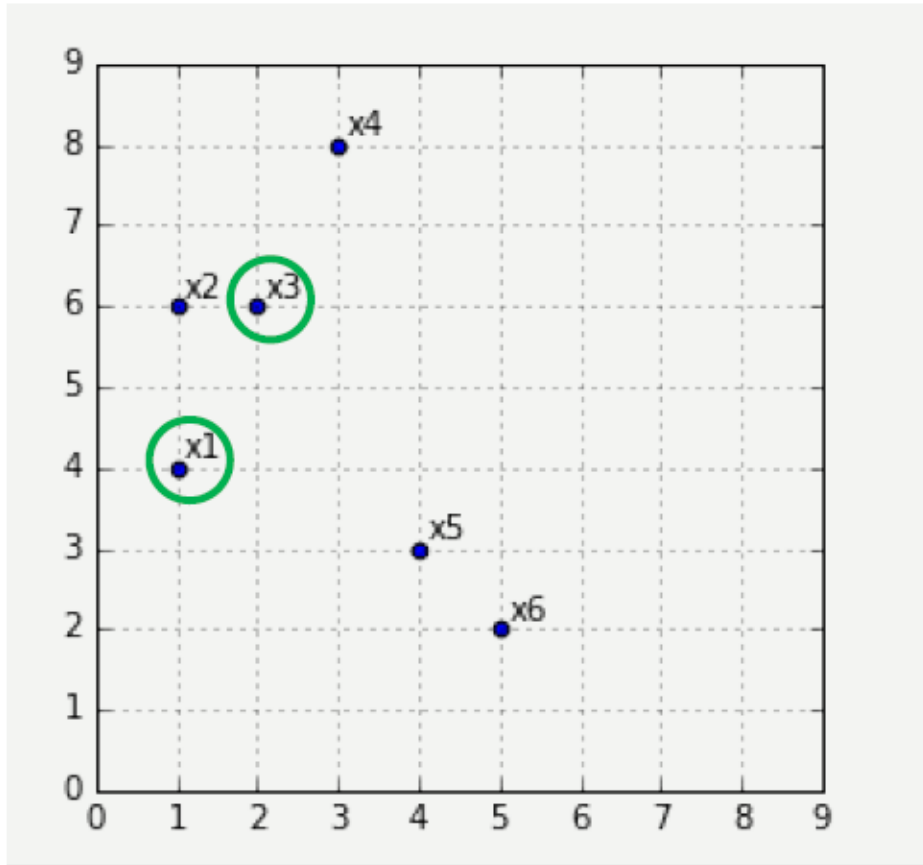
# Silhouette Coefficient

- The idea...





- Compute the Silhouette coefficient for



$$\begin{pmatrix} \begin{matrix} \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \end{matrix} & \begin{matrix} \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \end{matrix} \\ \begin{matrix} \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \end{matrix} & \begin{matrix} \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot \end{matrix} \end{pmatrix}$$

>\_ Code

# Homework assignment

- Using Scikit learn, find the Silhouette coefficient for of the dataset in the previous homework assignment  $K = 2, 3, 4, 5, 6$ . Plot the Silhouette coefficient as function of  $K$ .