

# EI320A(3) 深度學習使用 Python

Instructors

Tipajin Thaipisutikul ([t.greentip@gmail.com](mailto:t.greentip@gmail.com))

Prof. Huang-Chia Shih ([hcshih@Saturn.yzu.edu.tw](mailto:hcshih@Saturn.yzu.edu.tw))

# Course Syllabus

## Evaluation Criteria

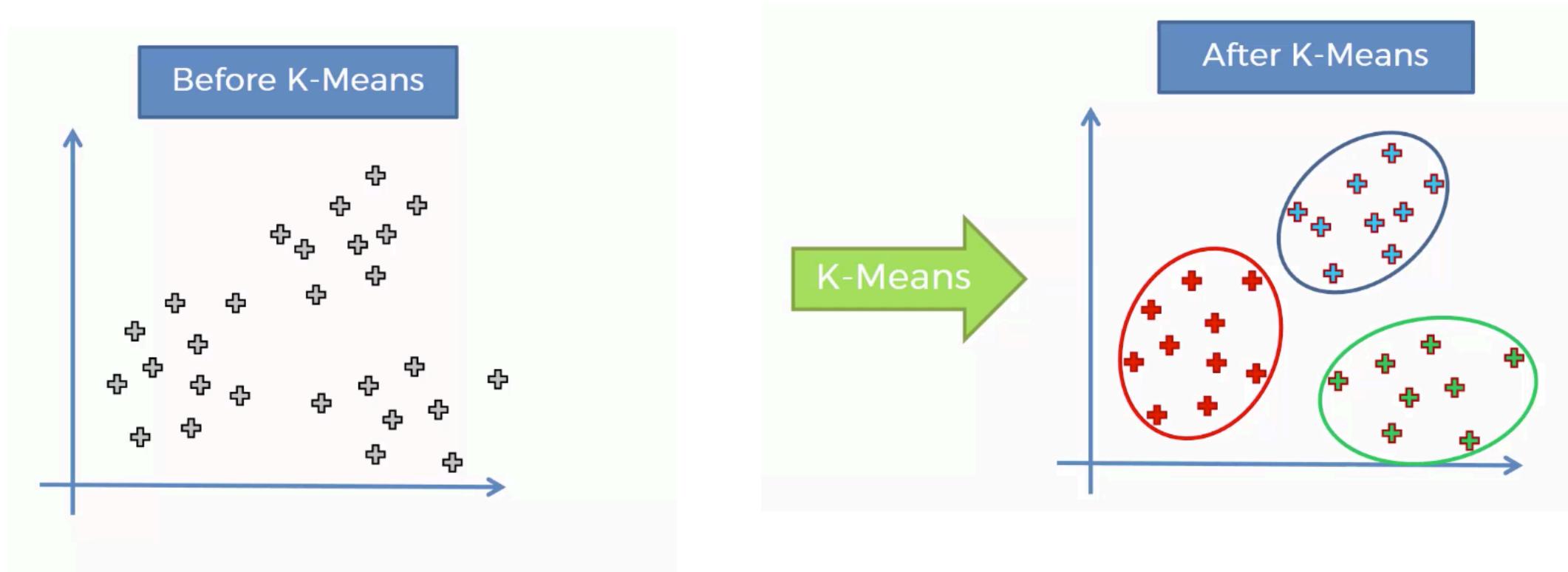
Tasks	Percentage
In Class Hands-on	60
Project Proposal Presentation	10
Project Final Presentation	30
Bonus (In Class Participation)	5
Total	110/100

Week	Date	Content	Note	Total
1	2/26	Welcome to the course	Download & Install Anaconda Homework (1)	1
2	3/5	Crash Course of Python, <u>Numpy</u> , <u>Pandas</u> , and <u>Matplotlib</u>	In class hands-on (4)	5
3	3/12	Get to know about Data <u>ML</u> : <u>Classification Models</u>	In class hands-on (5)	10
4	3/19	<u>ML</u> : <u>Regression Models</u>	<u>In class hands-on (5)</u>	<u>15</u>
5	3/26	<u>ML</u> : <u>Clustering /Apriori Models</u>	In class hands-on (5)	20
6	4/2	Holiday		
7	4/9	Introduction to Deep Learning (ANN)	In class hands-on (5)	25
8	4/16	Convolutional Neural Network (CNN)	In class hands-on (5)	30
9	4/23	Convolutional Neural Network (CNN)	In class hands-on (5)	35
10	4/30	Recurrent Neural Network (RNN)	In class hands-on (5)	40
11	5/7	Recurrent Neural Network (RNN)	In class hands-on (5)	45
12	5/14	Project Proposal Presentation	Proposal Presentation (10)	55
13	5/21	Time series with DNN, CNN, RNN	In class hands-on (5)	60
14	5/28	Attention Neural Network	In class hands-on (5)	65
15	6/4	Generative Adversarial Network (GAN)	In class hands-on (5)	70
16	6/11	Reinforcement Learning (RL)	In class hands-on (5)	75
17	6/18	Final Project Presentation	Final Presentation (30)	105

Bonus: 5 For class participation.

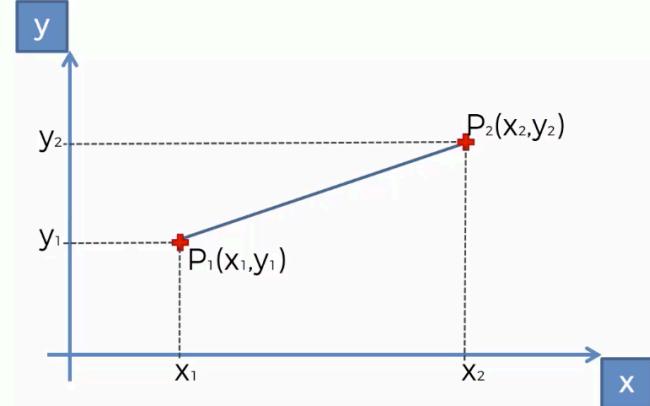
# K-Means Clustering

## Intuition



# K-Means Clustering

## Intuition (How did it do that?)



STEP 1: Choose the number K of clusters



STEP 2: Select at random K points, the centroids (not necessarily from your dataset)



STEP 3: Assign each data point to the closest centroid  $\rightarrow$  That forms K clusters



STEP 4: Compute and place the new centroid of each cluster



STEP 5: Reassign each data point to the new closest centroid.  
If any reassignment took place, go to STEP 4, otherwise go to FIN.



Your Model is Ready

$$\text{Euclidean Distance between } P_1 \text{ and } P_2 = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

# K-Means Clustering

## 1. Intuition

STEP 1: Choose the number K of clusters:  $K = 2$



# K-Means Clustering

## 1. Intuition

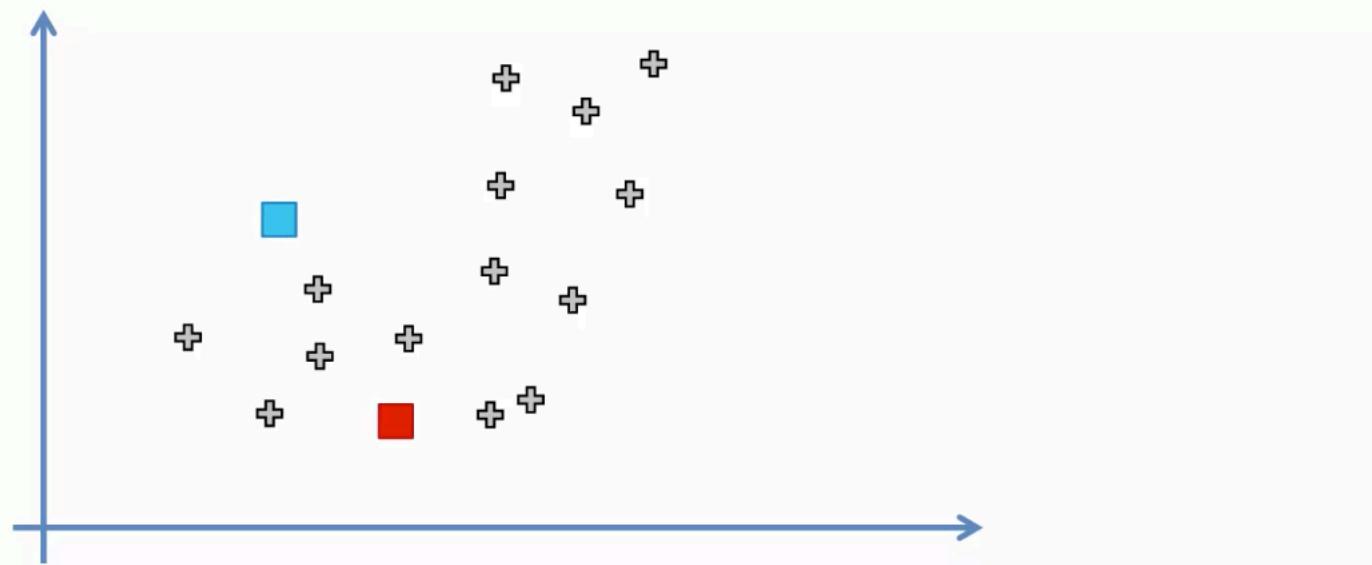
STEP 2: Select at random K points, the centroids (not necessarily from your dataset)



# K-Means Clustering

## 1. Intuition

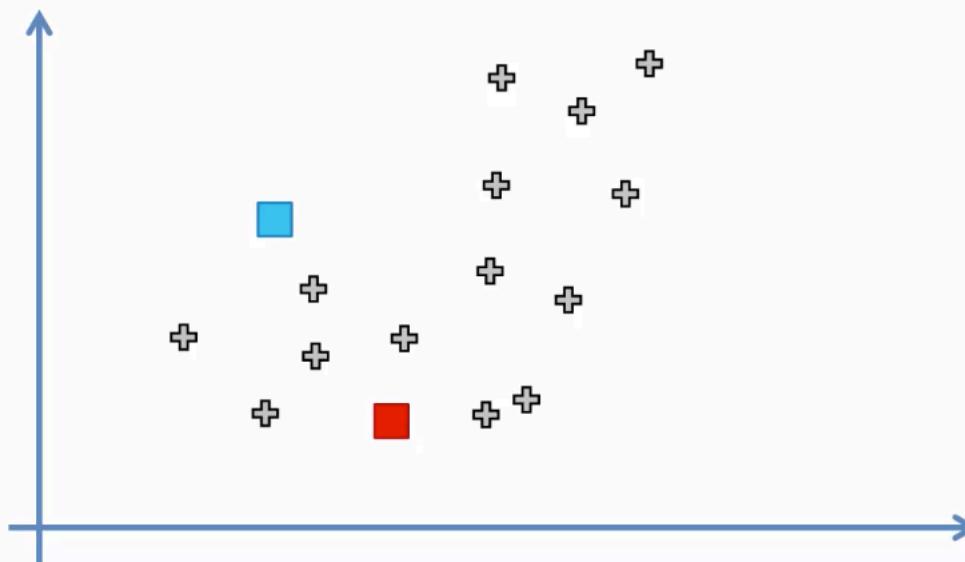
STEP 2: Select at random K points, the centroids (not necessarily from your dataset)



# K-Means Clustering

## 1. Intuition

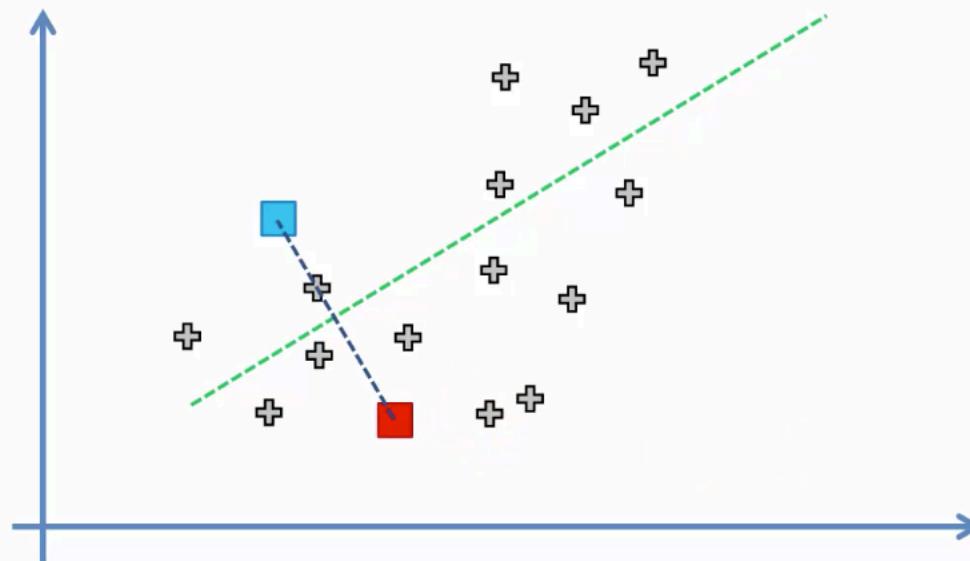
STEP 3: Assign each data point to the closest centroid ➔ That forms K clusters



# K-Means Clustering

## 1. Intuition

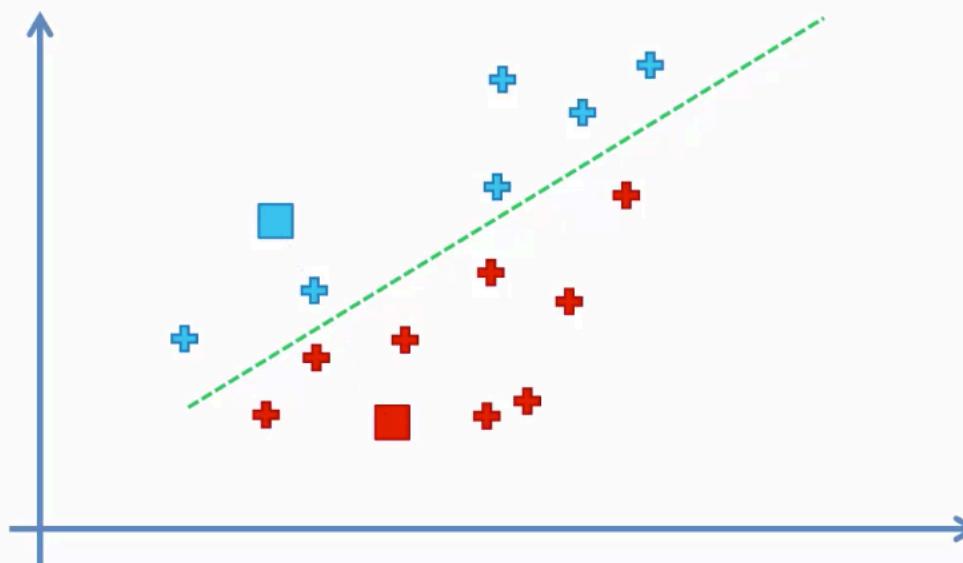
STEP 3: Assign each data point to the closest centroid → That forms K clusters



# K-Means Clustering

## 1. Intuition

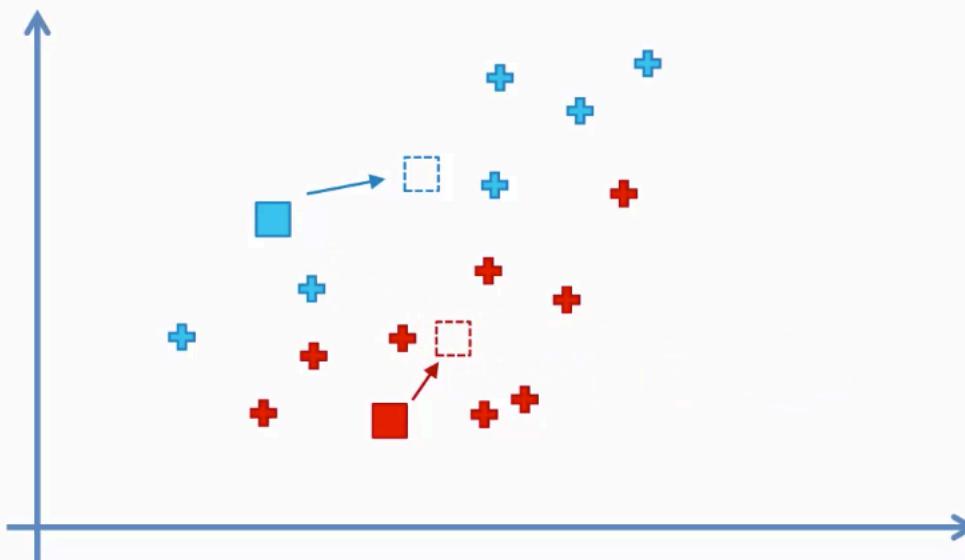
STEP 3: Assign each data point to the closest centroid ➔ That forms K clusters



# K-Means Clustering

## 1. Intuition

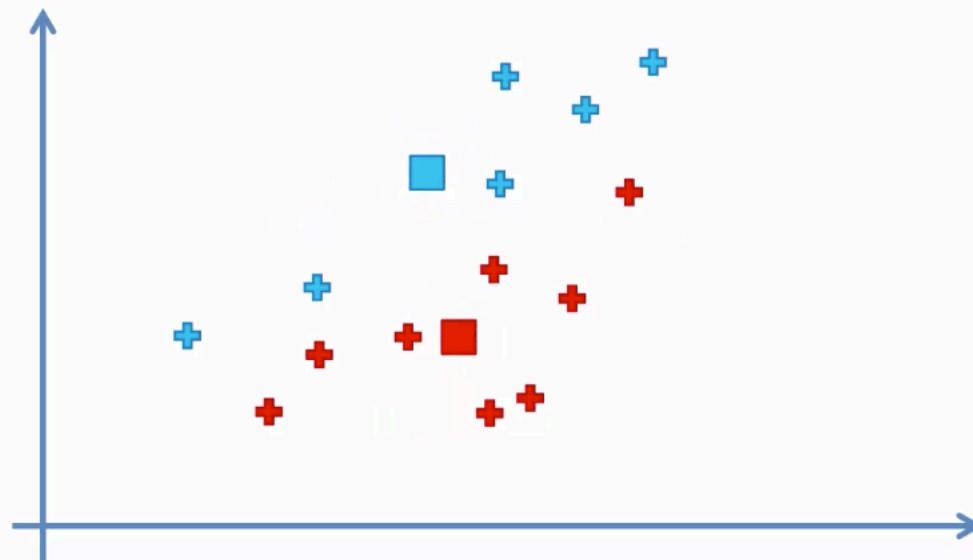
STEP 4: Compute and place the new centroid of each cluster



# K-Means Clustering

## 1. Intuition

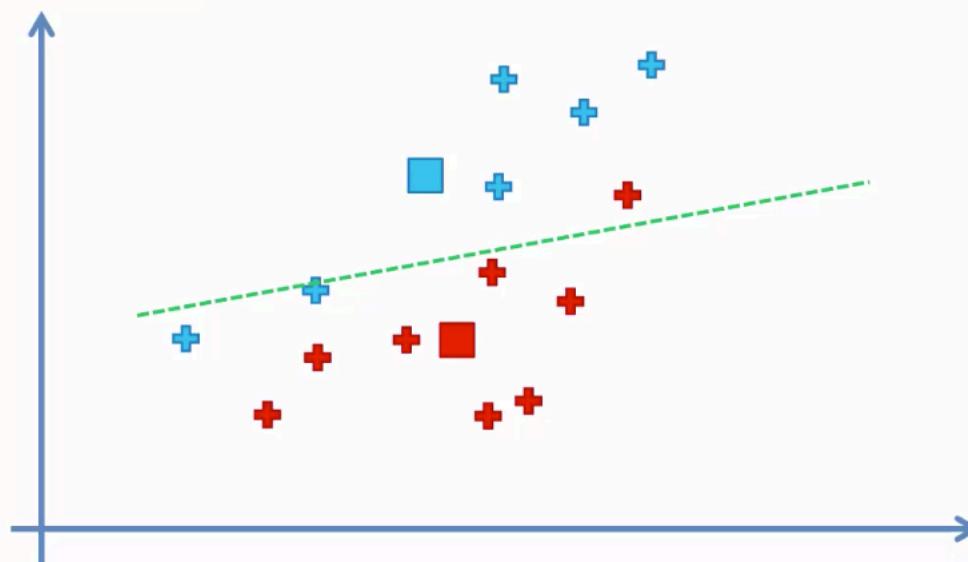
STEP 4: Compute and place the new centroid of each cluster



# K-Means Clustering

## 1. Intuition

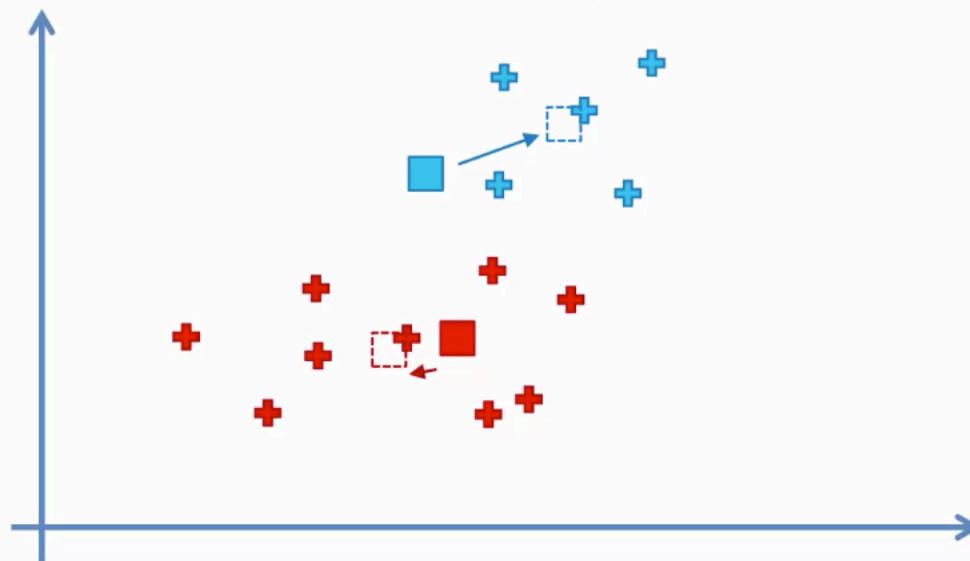
STEP 5: Reassign each data point to the new closest centroid.  
If any reassignment took place, go to STEP 4, otherwise go to FIN.



# K-Means Clustering

## 1. Intuition

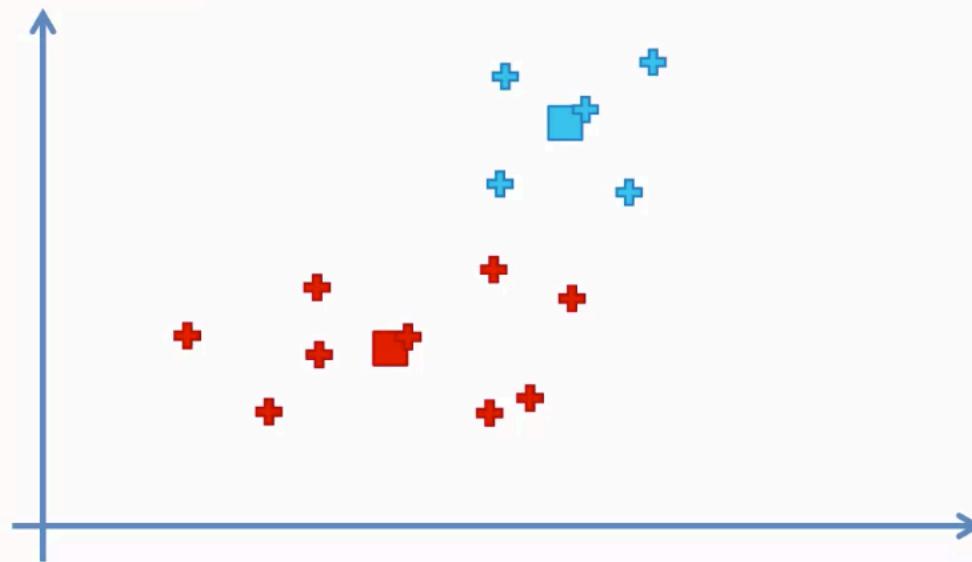
STEP 4: Compute and place the new centroid of each cluster



# K-Means Clustering

## 1. Intuition

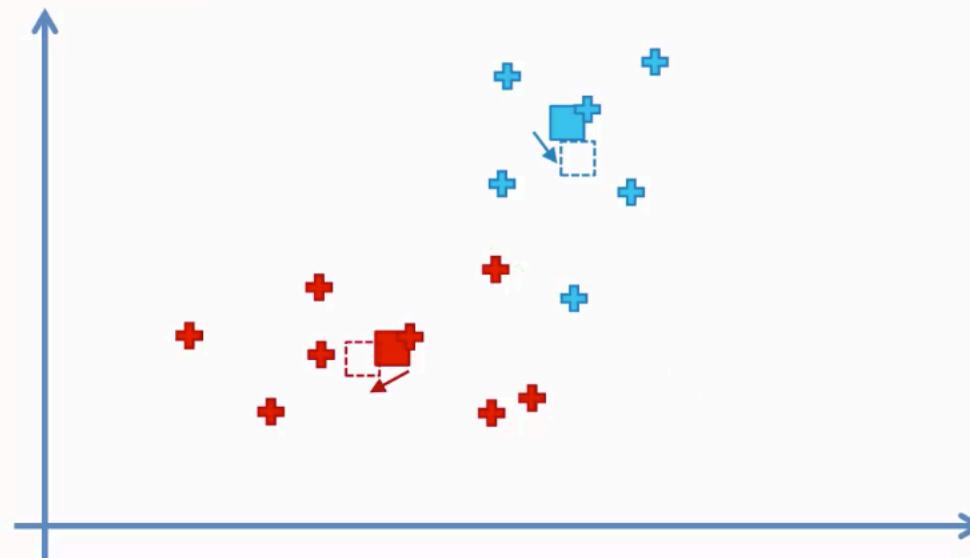
STEP 5: Reassign each data point to the new closest centroid.  
If any reassignment took place, go to STEP 4, otherwise go to FIN.



# K-Means Clustering

## 1. Intuition

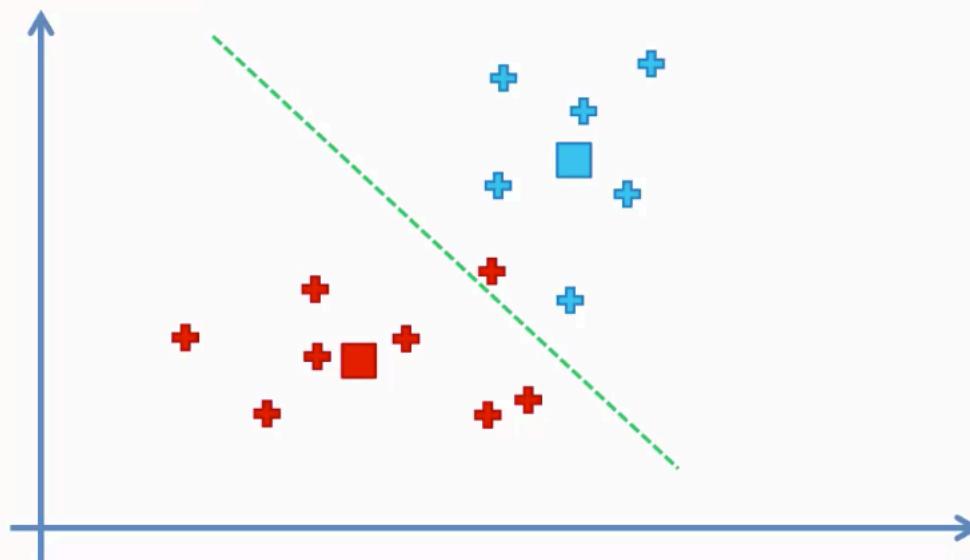
STEP 4: Compute and place the new centroid of each cluster



# K-Means Clustering

## 1. Intuition

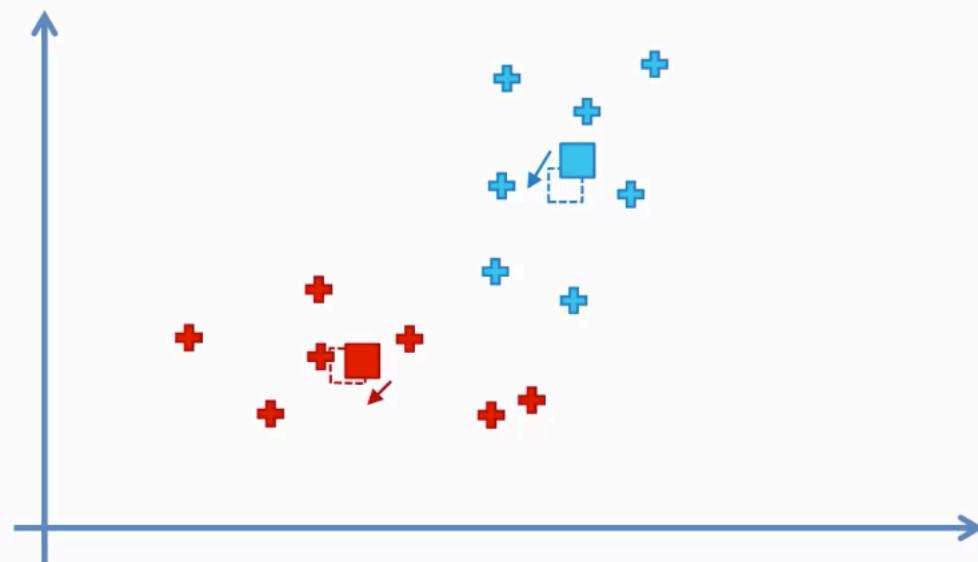
STEP 5: Reassign each data point to the new closest centroid.  
If any reassignment took place, go to STEP 4, otherwise go to FIN.



# K-Means Clustering

## 1. Intuition

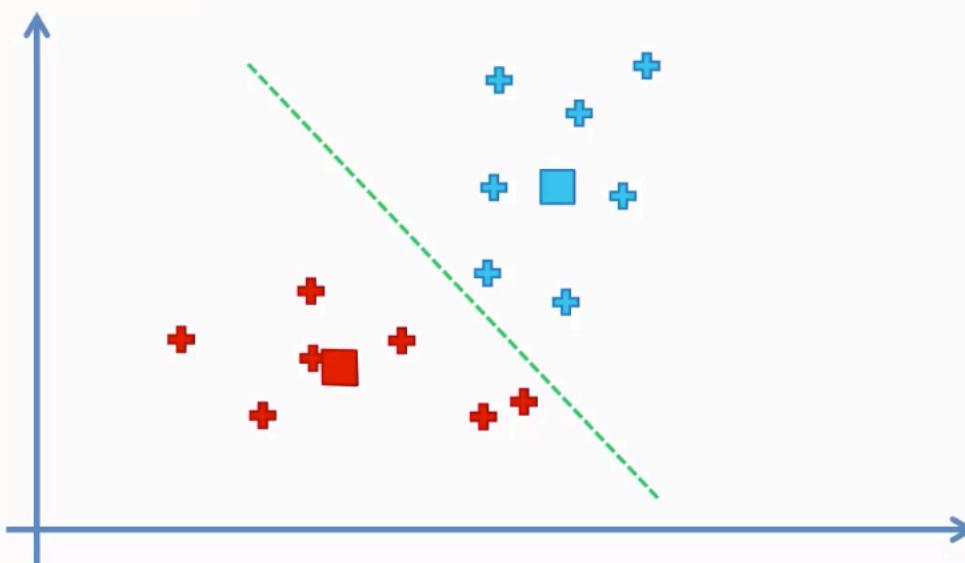
STEP 4: Compute and place the new centroid of each cluster



# K-Means Clustering

## 1. Intuition

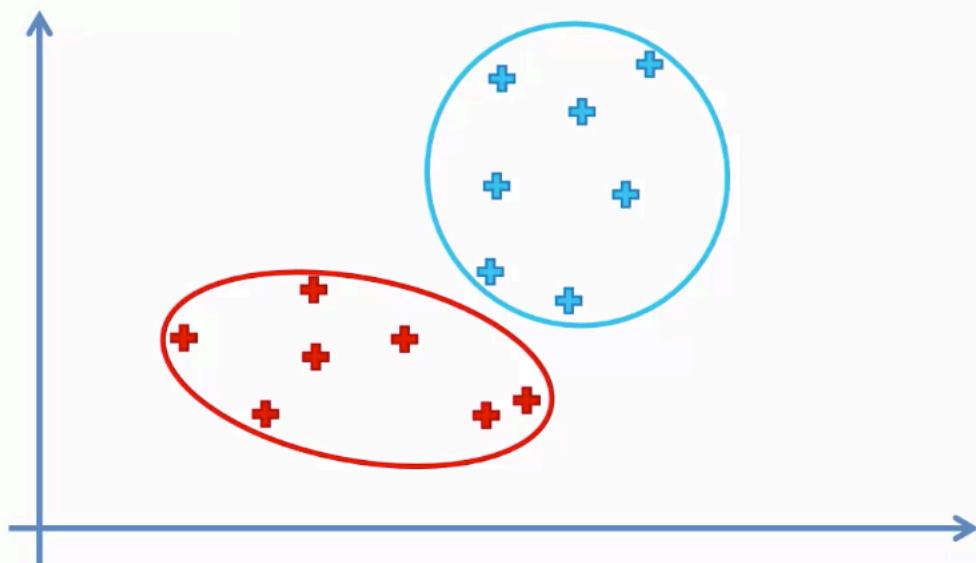
STEP 5: Reassign each data point to the new closest centroid.  
If any reassignment took place, go to STEP 4, otherwise go to FIN.



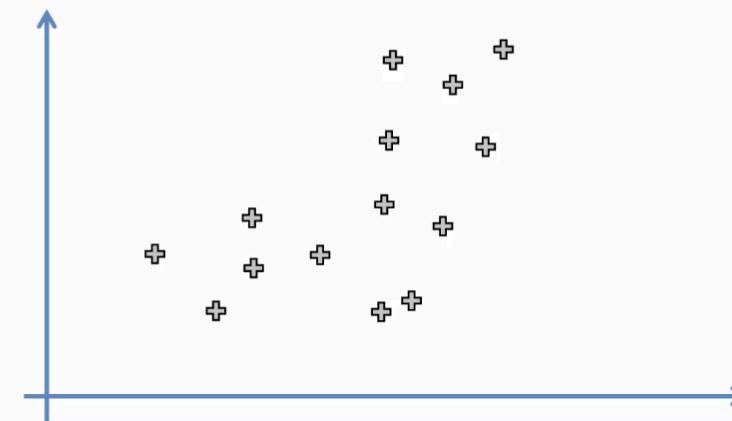
# K-Means Clustering

## 1. Intuition

FIN: Your Model Is Ready

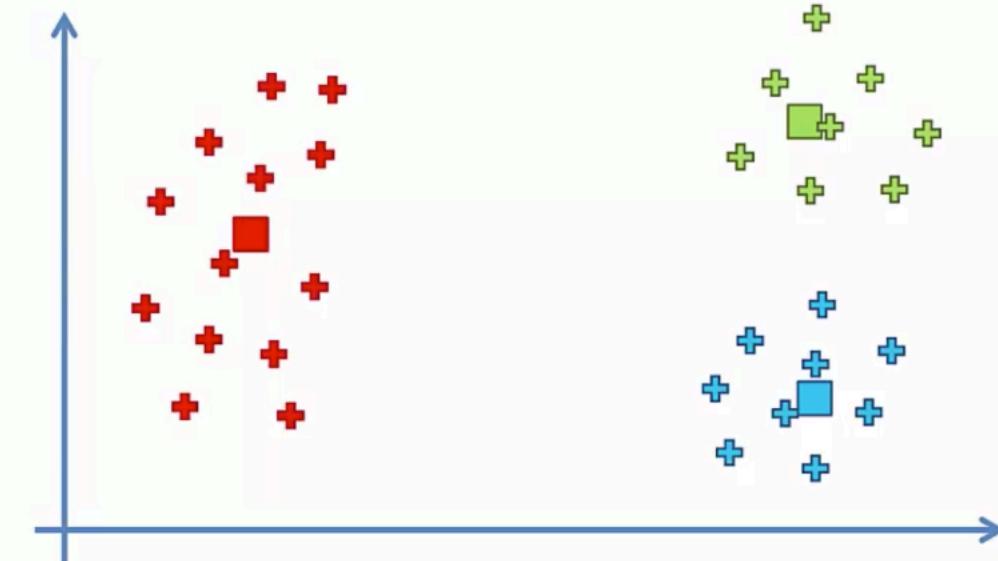
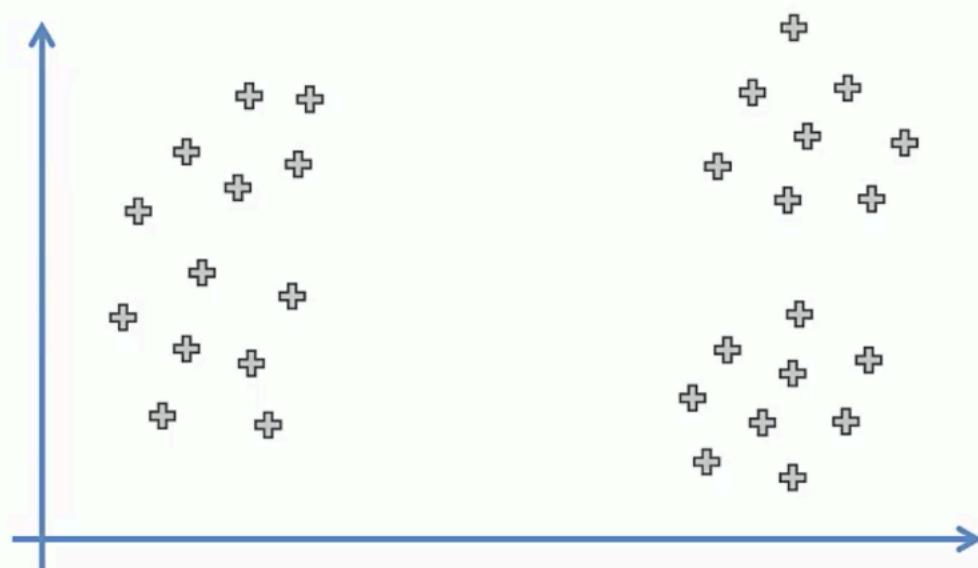


2: Select at random K points, the centroids (not necessarily from your dataset)



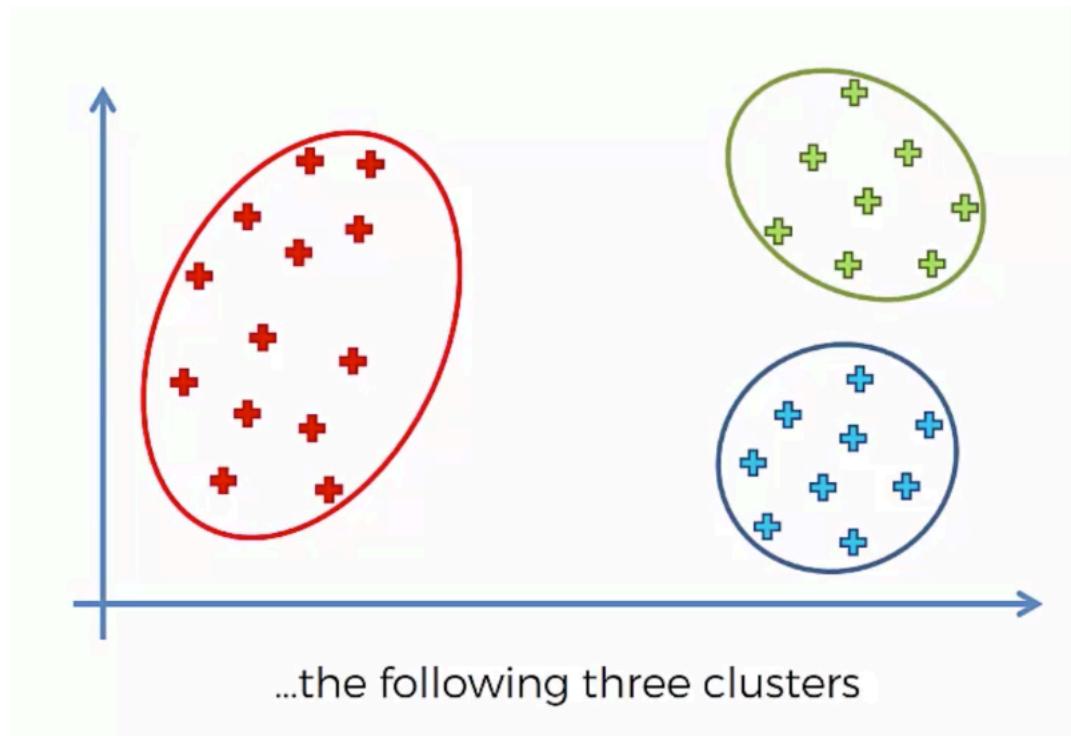
# K-Means Clustering

## 2. Random Initialization Trap



# K-Means Clustering

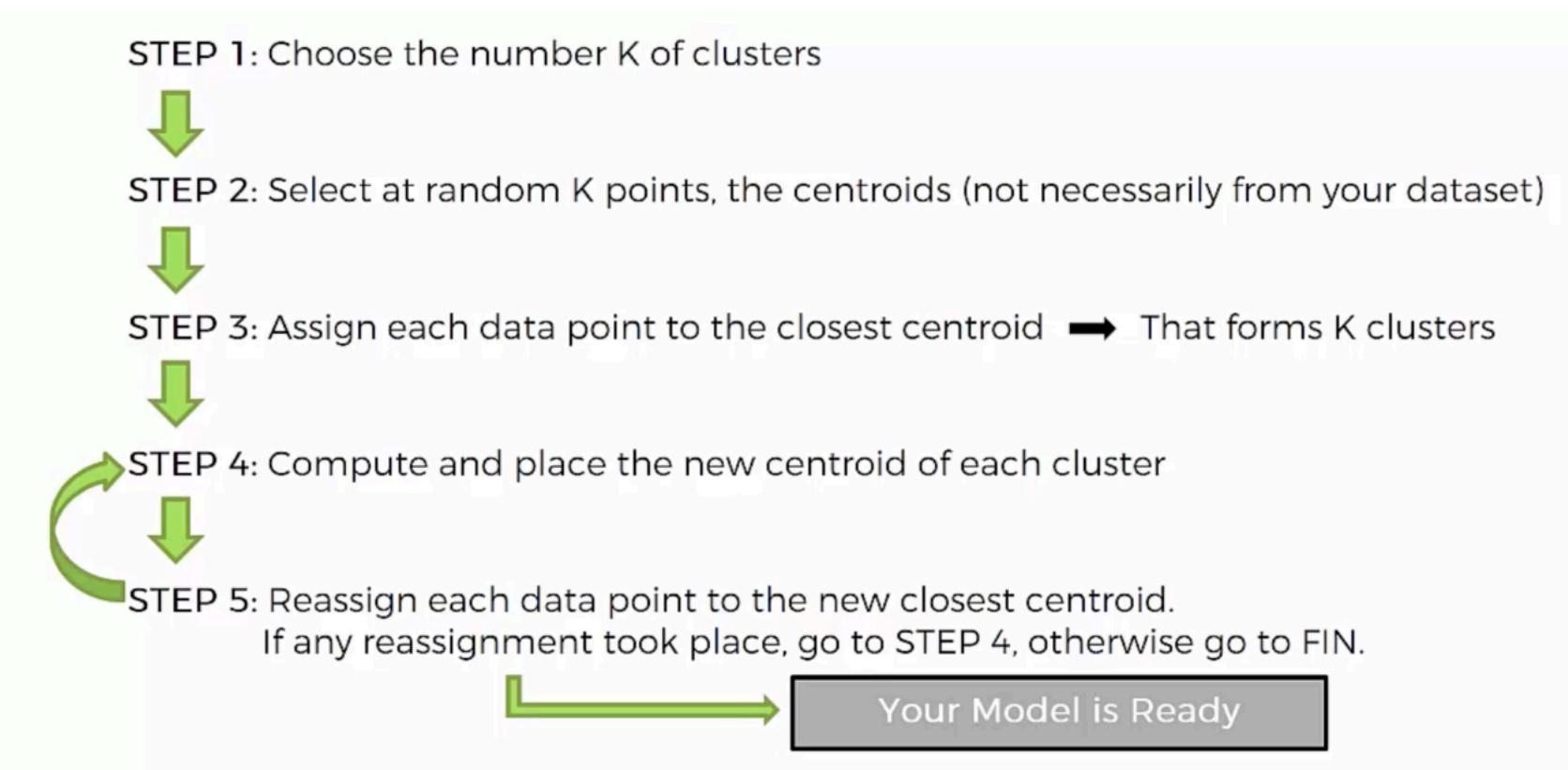
## 2. Random Initialization Trap



But what would happen if we had a bad random initialisation ?

# K-Means Clustering

## 2. Random Initialization Trap



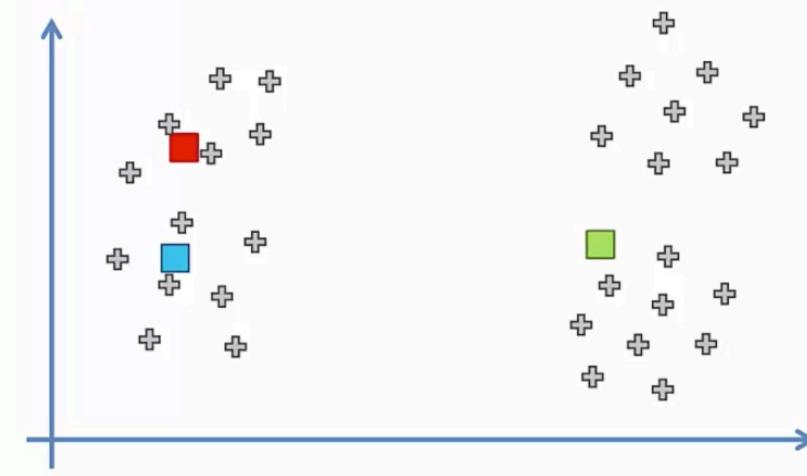
# K-Means Clustering

## 2. Random Initialization Trap

STEP 1: Choose the number K of clusters:  $K = 3$



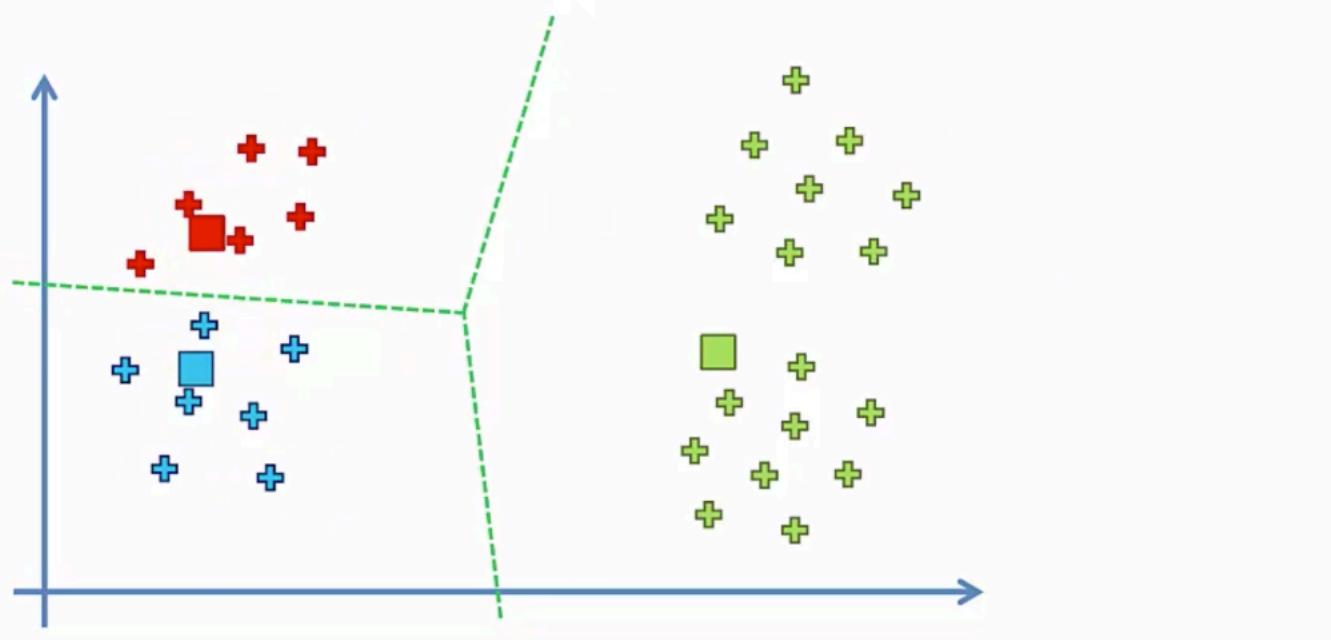
STEP 2: Select at random K points, the centroids (not necessarily from your dataset)



# K-Means Clustering

## 2. Random Initialization Trap

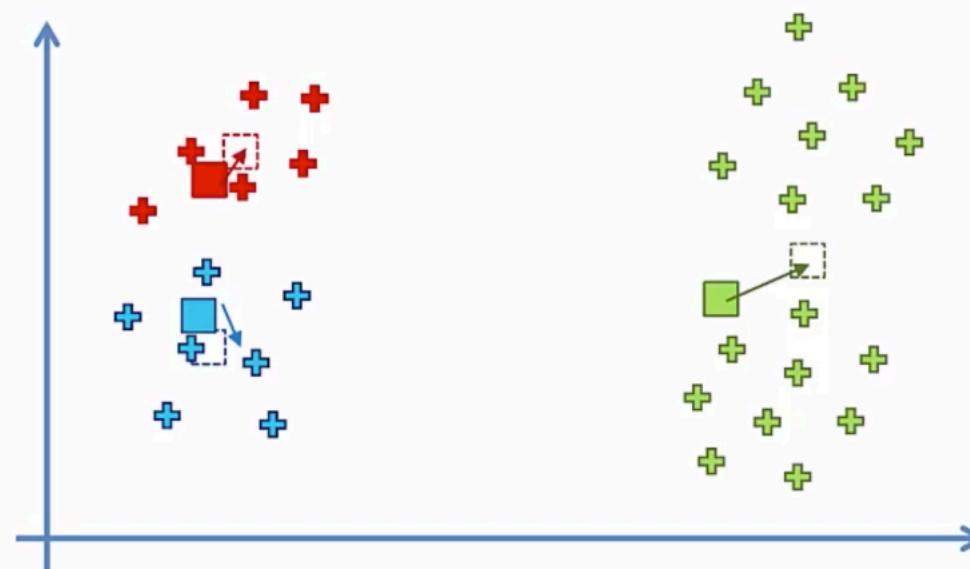
STEP 3: Assign each data point to the closest centroid  $\rightarrow$  That forms K clusters



# K-Means Clustering

## 2. Random Initialization Trap

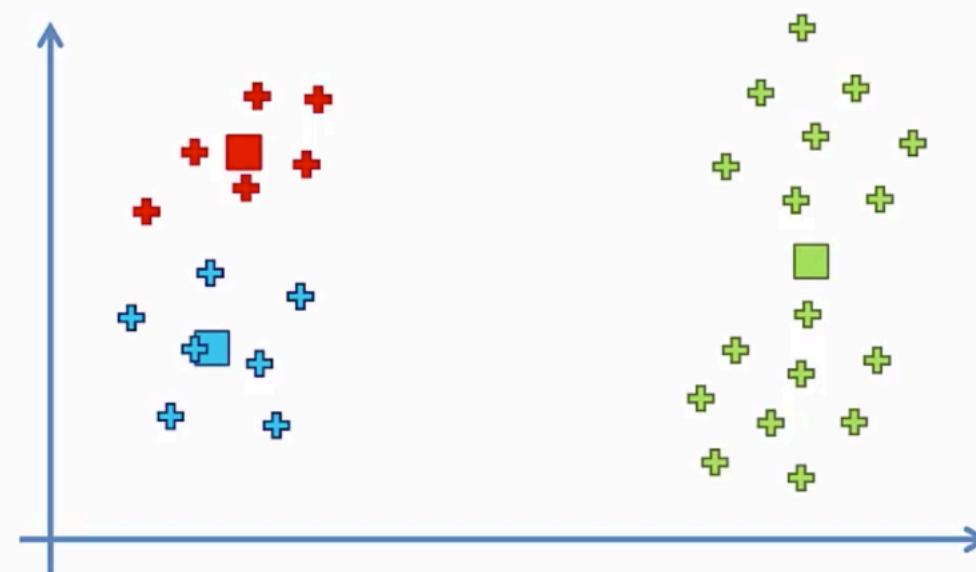
STEP 3: Assign each data point to the closest centroid  $\rightarrow$  That forms K clusters



# K-Means Clustering

## 2. Random Initialization Trap

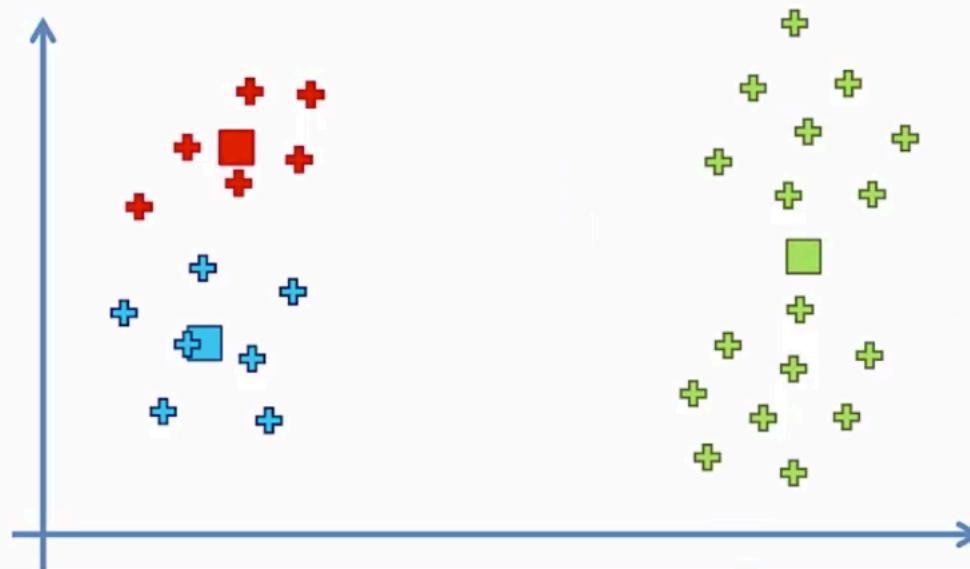
STEP 4: Compute and place the new centroid of each cluster



# K-Means Clustering

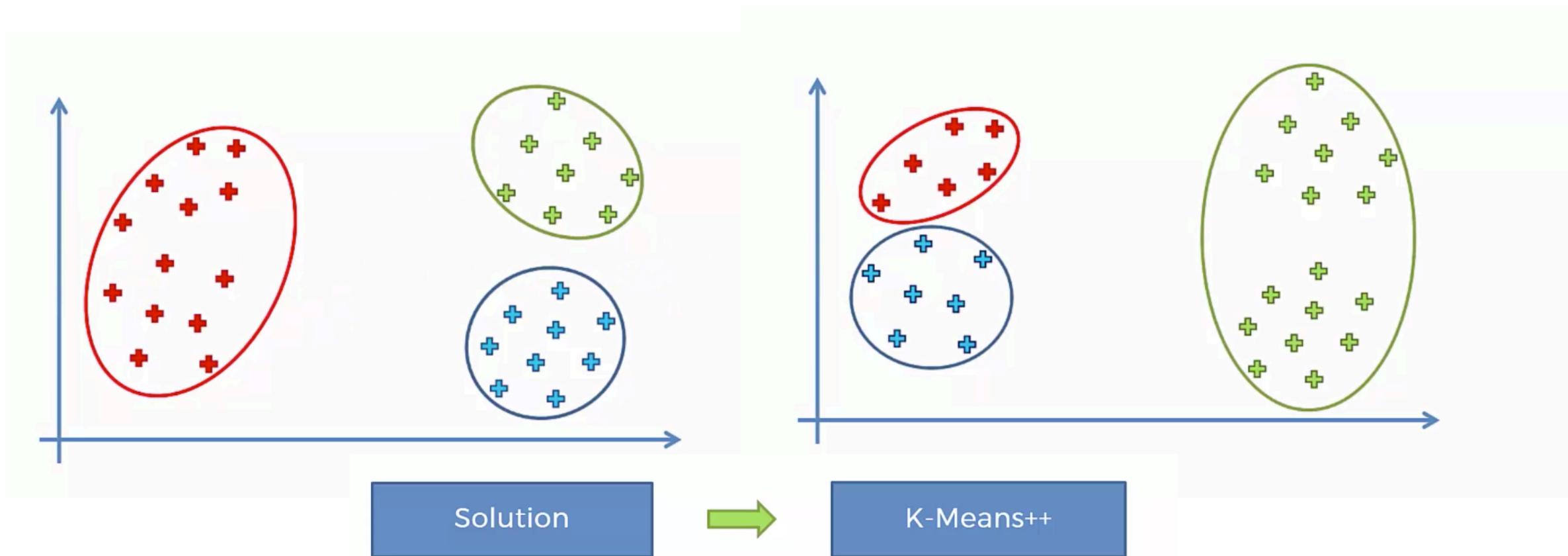
## 2. Random Initialization Trap

STEP 5: Reassign each data point to the new closest centroid.  
If any reassignment took place, go to STEP 4, otherwise go to FIN.



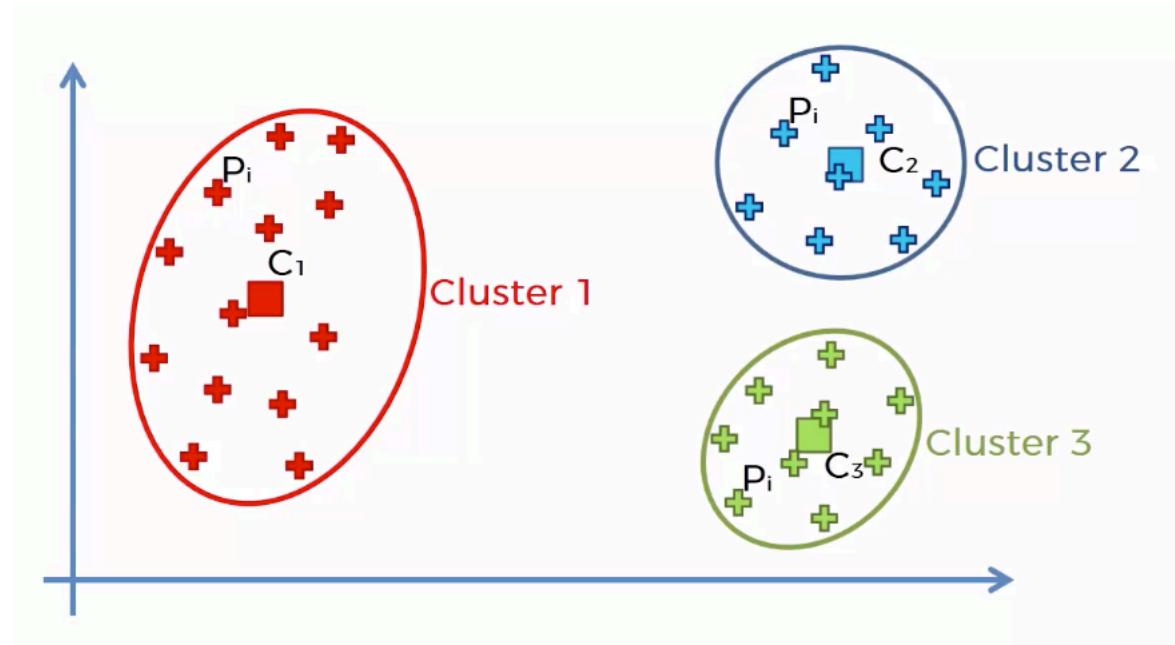
# K-Means Clustering

## 2. Random Initialization Trap



# K-Means Clustering

## 3. Selecting The Number Of Clusters



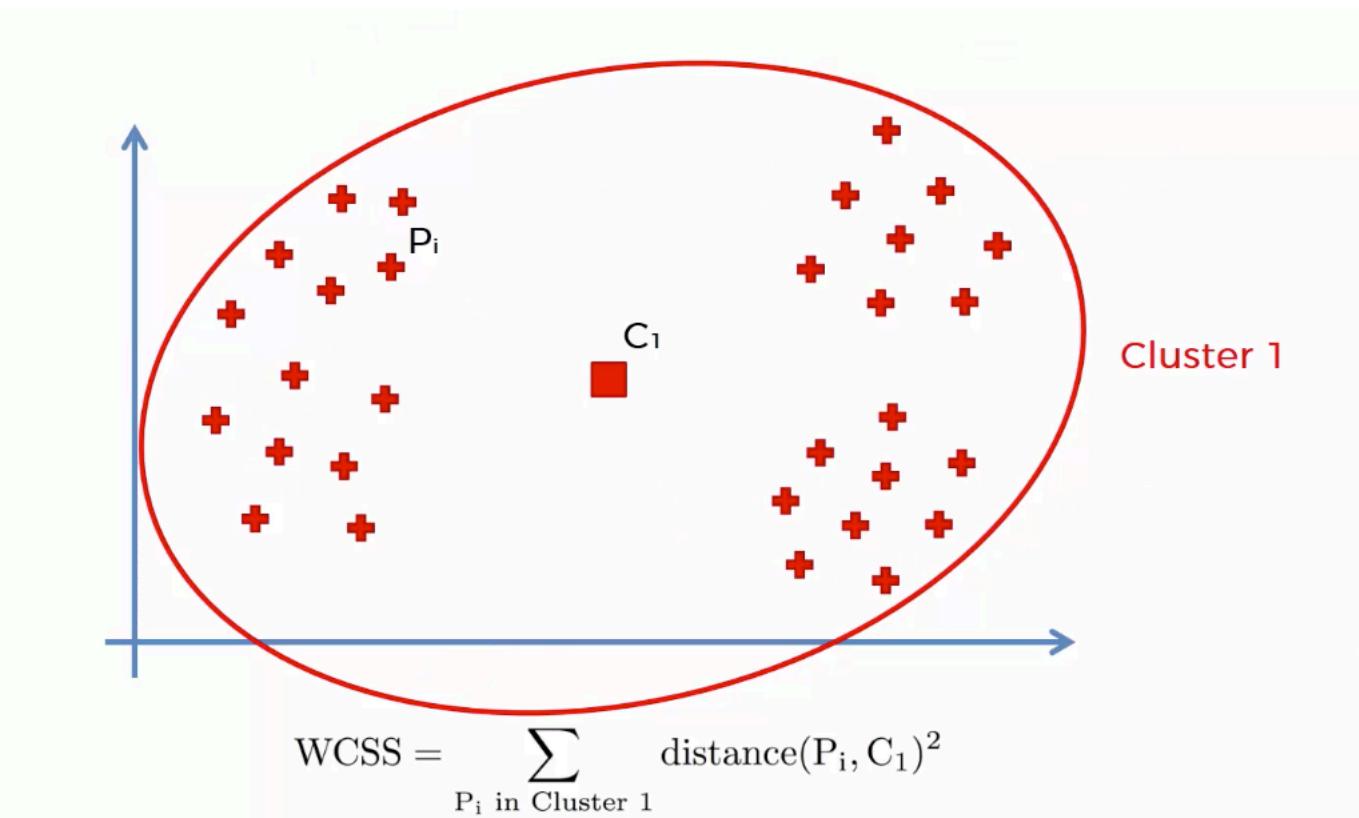
Within-Cluster-Sum-of-Squares (WCSS)

$$\text{WCSS} = \sum_{P_i \text{ in Cluster 1}} \text{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in Cluster 2}} \text{distance}(P_i, C_2)^2 + \sum_{P_i \text{ in Cluster 3}} \text{distance}(P_i, C_3)^2$$

Let's rewind to see how does WCSS change if #cluster is increasing

# K-Means Clustering

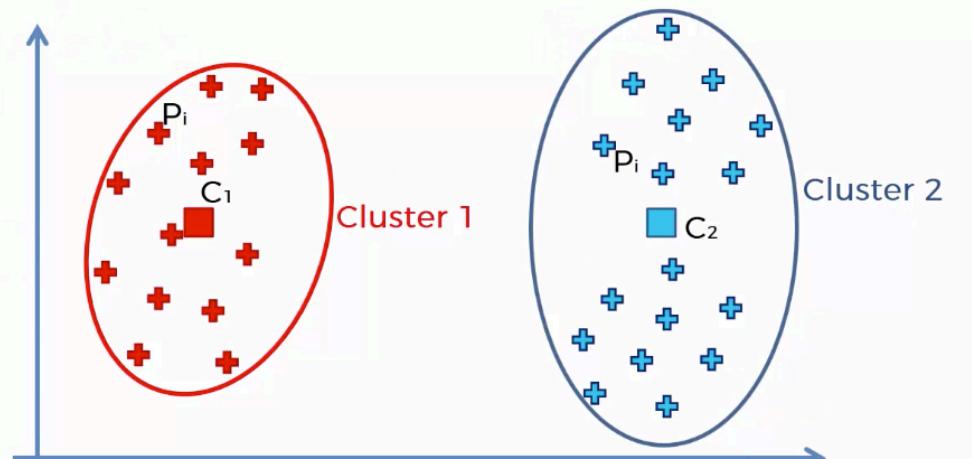
## 3. Selecting The Number Of Clusters



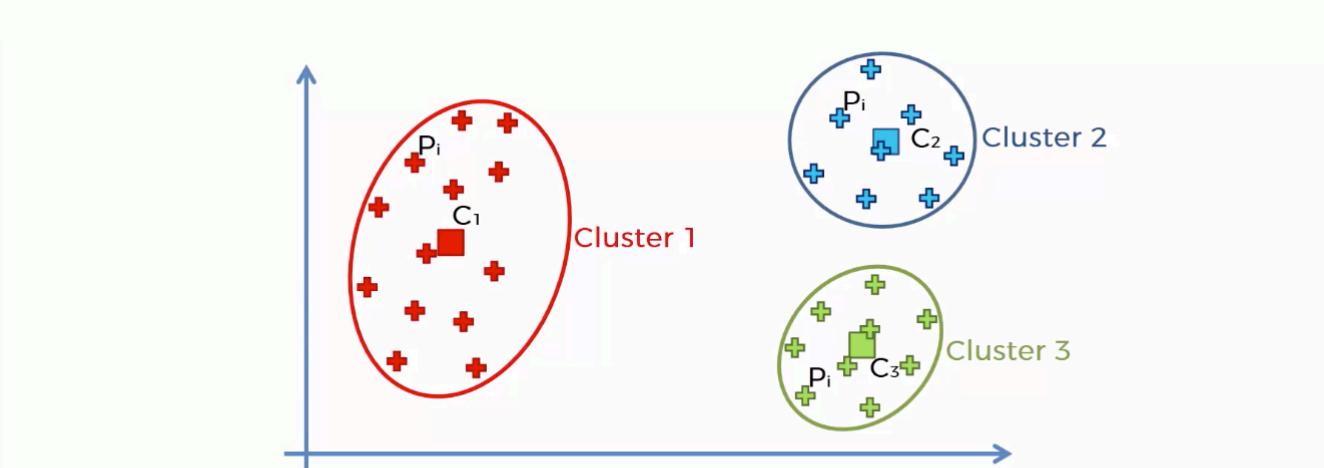
**Large Distance, Large WCSS!!**

# K-Means Clustering

## 3. Selecting The Number Of Clusters



$$WCSS = \sum_{P_i \text{ in Cluster 1}} \text{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in Cluster 2}} \text{distance}(P_i, C_2)^2$$

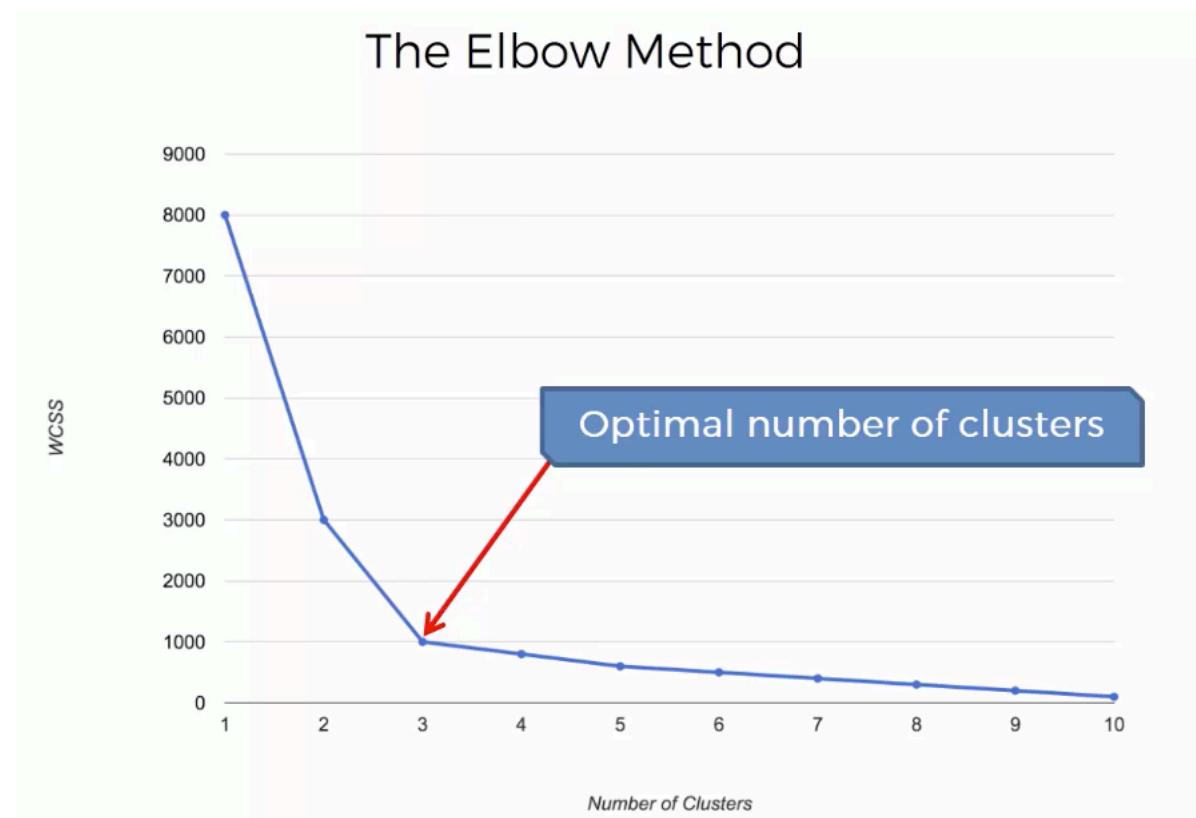


$$WCSS = \sum_{P_i \text{ in Cluster 1}} \text{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in Cluster 2}} \text{distance}(P_i, C_2)^2 + \sum_{P_i \text{ in Cluster 3}} \text{distance}(P_i, C_3)^2$$

**Smaller Distance, Smaller WCSS!!**

# K-Means Clustering

## 3. Selecting The Number Of Clusters



# K-Mean Demo

**Revise** How do Train&Test Datasets impact the model?

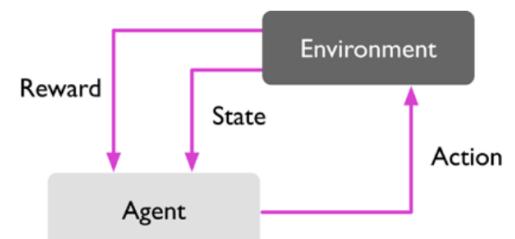
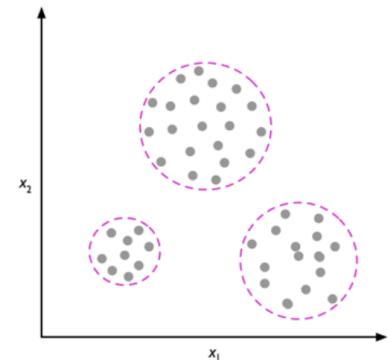
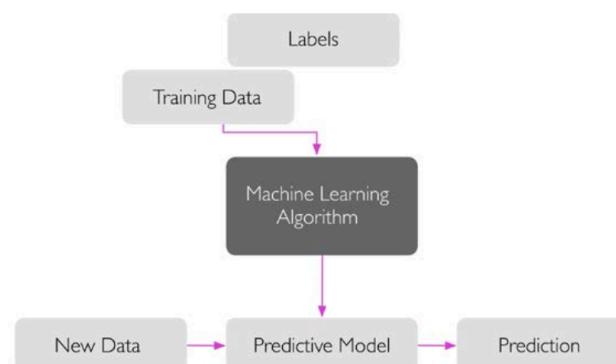
**ARTIFICIAL INTELLIGENCE**  
Science that enables computers to mimic human intelligence.  
Subfields: Machine Learning, robotics, and computer vision

**MACHINE LEARNING**  
Subset of AI that enable machines to improve at tasks with experience

## The three different types of machine learning



- Machine learning uses algorithms to parse data, learn from that data, and make informed decisions based on what it has learned
- Deep learning structures algorithms in layers to create an artificial “neural network” that can learn and make intelligent decisions on its own
- Deep learning is a subfield of machine learning. While both fall under the broad category of artificial intelligence, deep learning is usually what’s behind the most human-like artificial intelligence



# Association Rule Learning

## Apriori Intuition: What is it all about?



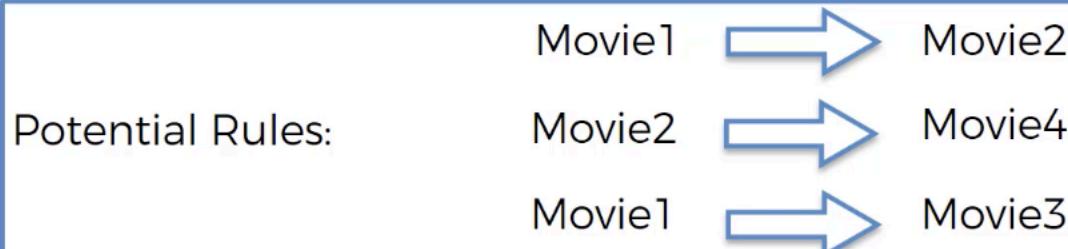
People who bought also bought ...

- Market Basket Analysis is one of the key techniques used by large retailers to uncover associations between items.
- It works by looking for combinations of items that occur together frequently in transactions.
- To put it another way, it allows retailers to identify relationships between the items that people buy.
- Association Rules are widely used to analyze retail basket or transaction data, and are intended to identify strong rules discovered in transaction data using measures of interestingness, based on the concept of strong rules.

# Association Rule Learning

## Apriori Intuition: Movie Recommendation

User ID	Movies liked
46578	Movie1, Movie2, Movie3, Movie4
98989	Movie1, Movie2
71527	Movie1, Movie2, Movie4
78981	Movie1, Movie2
89192	Movie2, Movie4
61557	Movie1, Movie3



# Association Rule Learning

## Apriori Intuition: Market Basket Optimization

Transaction ID	Products purchased
46578	Burgers, French Fries, Vegetables
98989	Burgers, French Fries, Ketchup
71527	Vegetables, Fruits
78981	Pasta, Fruits, Butter, Vegetables
89192	Burgers, Pasta, French Fries
61557	Fruits, Orange Juice, Vegetables
87923	Burgers, French Fries, Ketchup, Mayo



# Association Rule Learning

$$\text{Rule: } X \Rightarrow Y$$
$$\text{Support} = \frac{\text{frq}(X, Y)}{N}$$
$$\text{Confidence} = \frac{\text{frq}(X, Y)}{\text{frq}(X)}$$
$$\text{Lift} = \frac{\text{Support}}{\text{Supp}(X) \times \text{Supp}(Y)}$$



Rule	Support	Confidence	Lift
$A \Rightarrow D$	2/5	2/3	10/9
$C \Rightarrow A$	2/5	2/4	5/6
$A \Rightarrow C$	2/5	2/3	5/6
$B \& C \Rightarrow D$	1/5	1/3	5/9

# Association Rule Learning

$$\text{Rule: } X \Rightarrow Y$$
$$\begin{array}{c} \xrightarrow{\quad\quad\quad} \\ \text{Support} = \frac{frq(X, Y)}{N} \\ \text{Confidence} = \frac{frq(X, Y)}{frq(X)} \\ \downarrow \\ Lift = \frac{\text{Support}}{\text{Supp}(X) \times \text{Supp}(Y)} \end{array}$$

## An example of Association Rules

- Assume there are 100 customers
- 10 of them bought milk, 8 bought butter and 6 bought both of them.
- bought milk  $\Rightarrow$  bought butter
- support =
- confidence =
- lift =

Note: this example is extremely small. In practice, a rule needs the support of several hundred transactions, before it can be considered statistically significant, and datasets often contain thousands or millions of transactions.

# Association Rule Learning

## Apriori Algorithm

Step 1: Set a minimum support and confidence



Step 2: Take all the subsets in transactions having higher support than minimum support



Step 3: Take all the rules of these subsets having higher confidence than minimum confidence



Step 4: Sort the rules by decreasing lift

# Association Rule Demo

