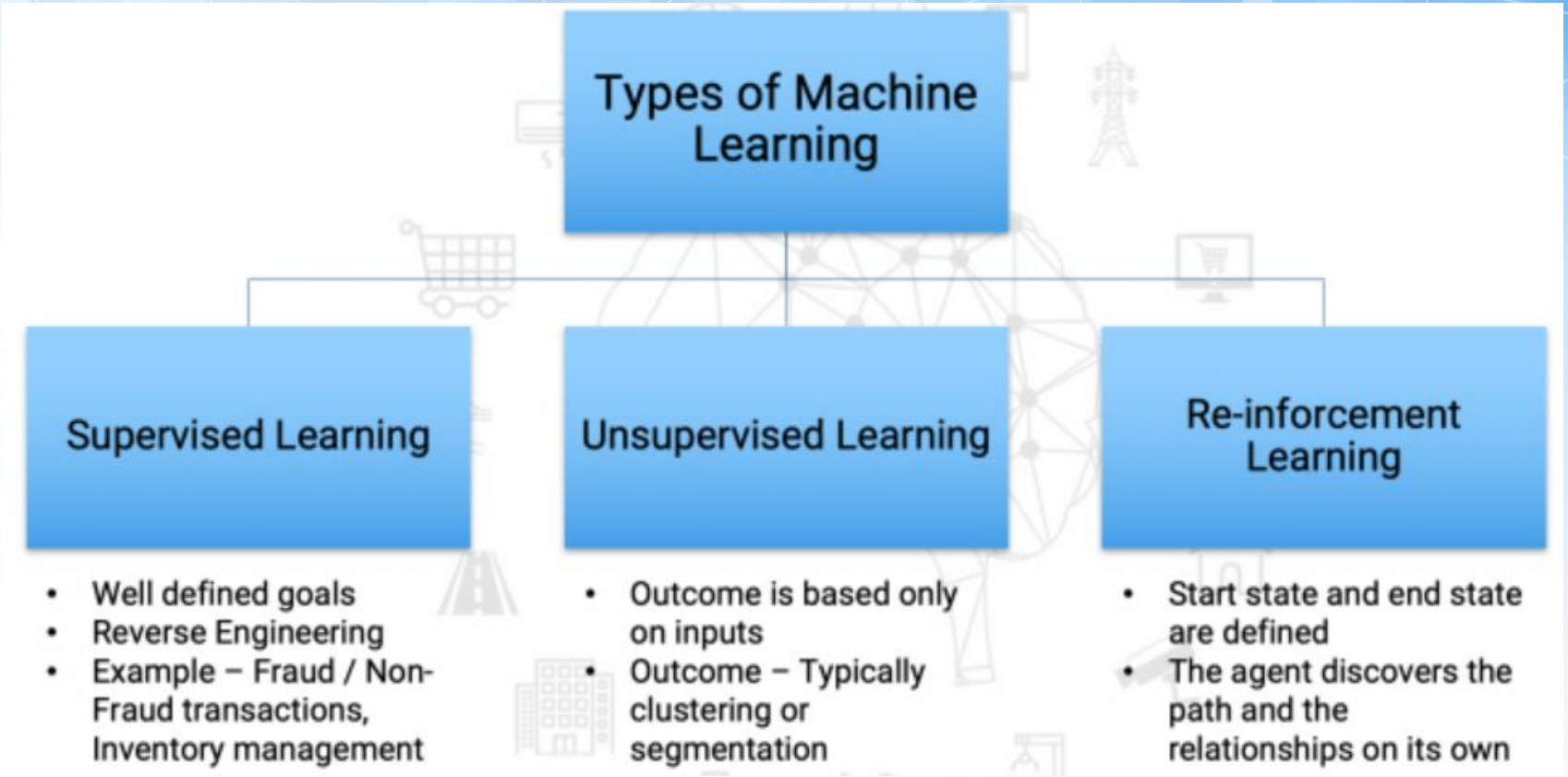
ICT Academy of Kerala

Building the Nation's Future

Unsupervised learning & K-Means Clustering

A **GOVT. OF INDIA** SUPPORTED, **GOVT. OF KERALA** PARTNERED SOCIAL ENTERPRISE.



Supervised vs Unsupervised

Supervised Learning

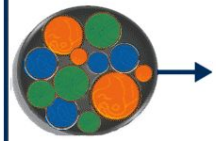
- Known number of classes
- Based on training set
- Used to classify future observations

Unsupervised Learning

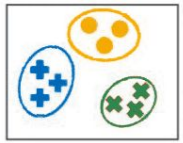
- Unknown number of classes
- No prior knowledge
- Used to understand data

UNSUPERVISED LEARNING

Raw Data



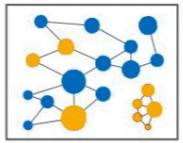
EXAMPLES



CLUSTERING

Identifies similarities in groups:

Are there patterns in the data that indicate which groups to target?



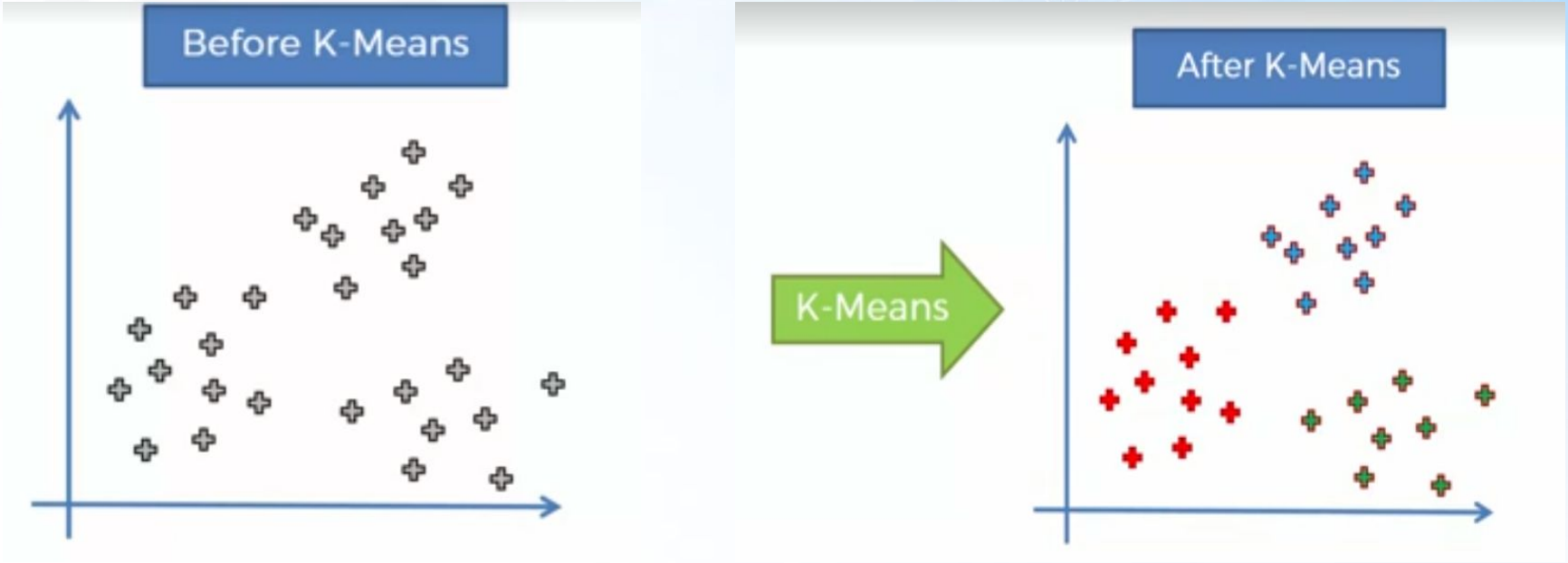
ANOMALY DETECTION

Identifies abnormalities in dataset:

Is the user behaving as it should? Is a hacker intruding the network?

K-Means Clustering

What K-Means does for you?



How K-Means works?

Step 1: Choose the Number of K-Clusters

Step 2: Select at Random K-Points, the centroids (Not necessarily from your dataset.)

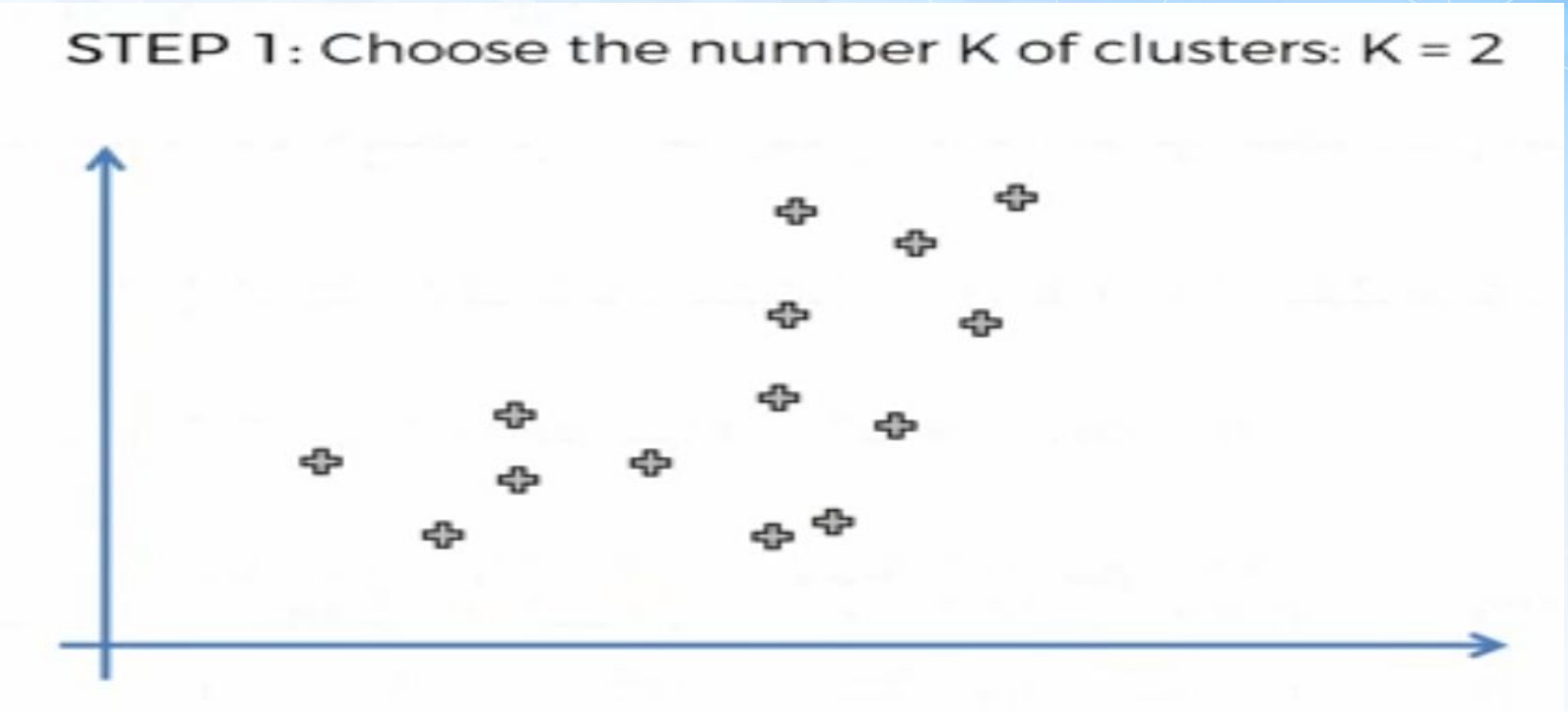
Step 3: Assign each data point to the closest centroid (That forms K-Clusters.)

Step 4: Compute and place the new Centroid of each other

Step 5: Reassign each data point to the new closest Centroid.
(If any reassignment took place, go to Step 4, otherwise FINISH)

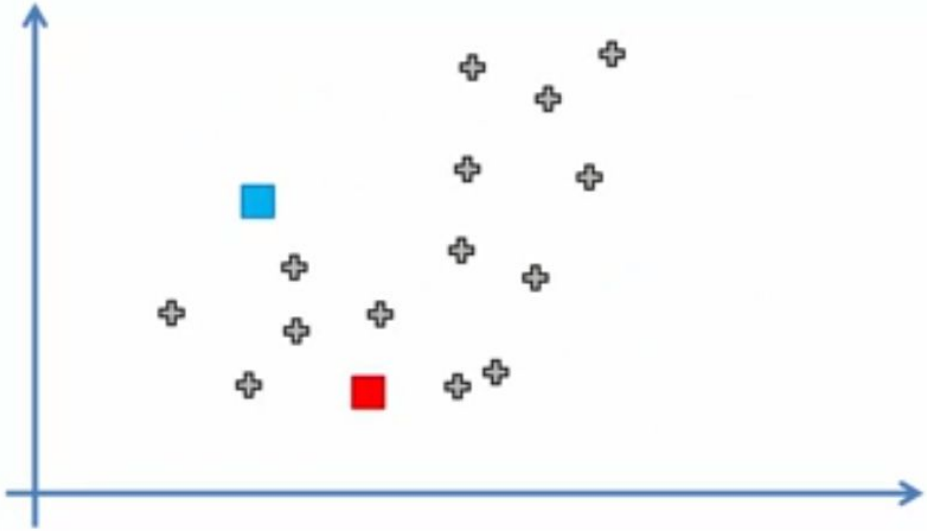
Model is READY!

K-Means Clustering



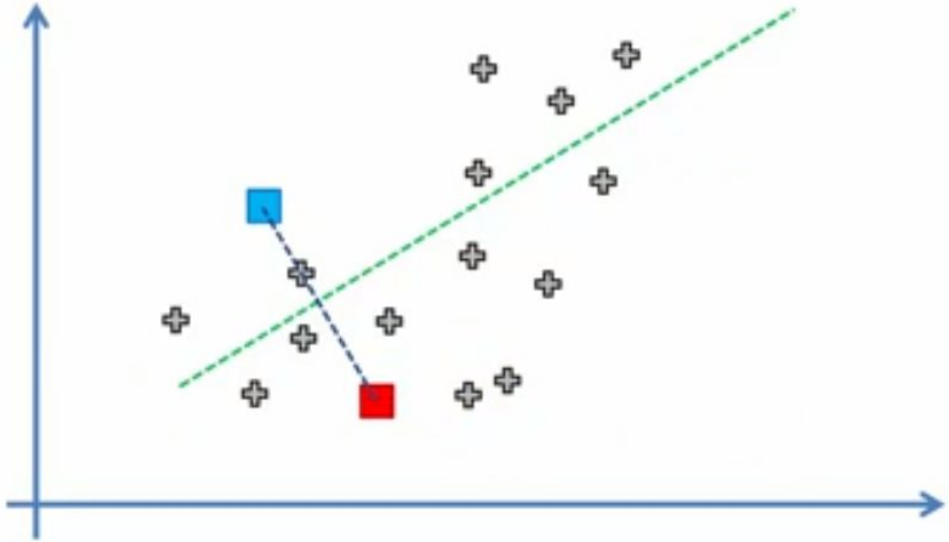
K-Means Clustering

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

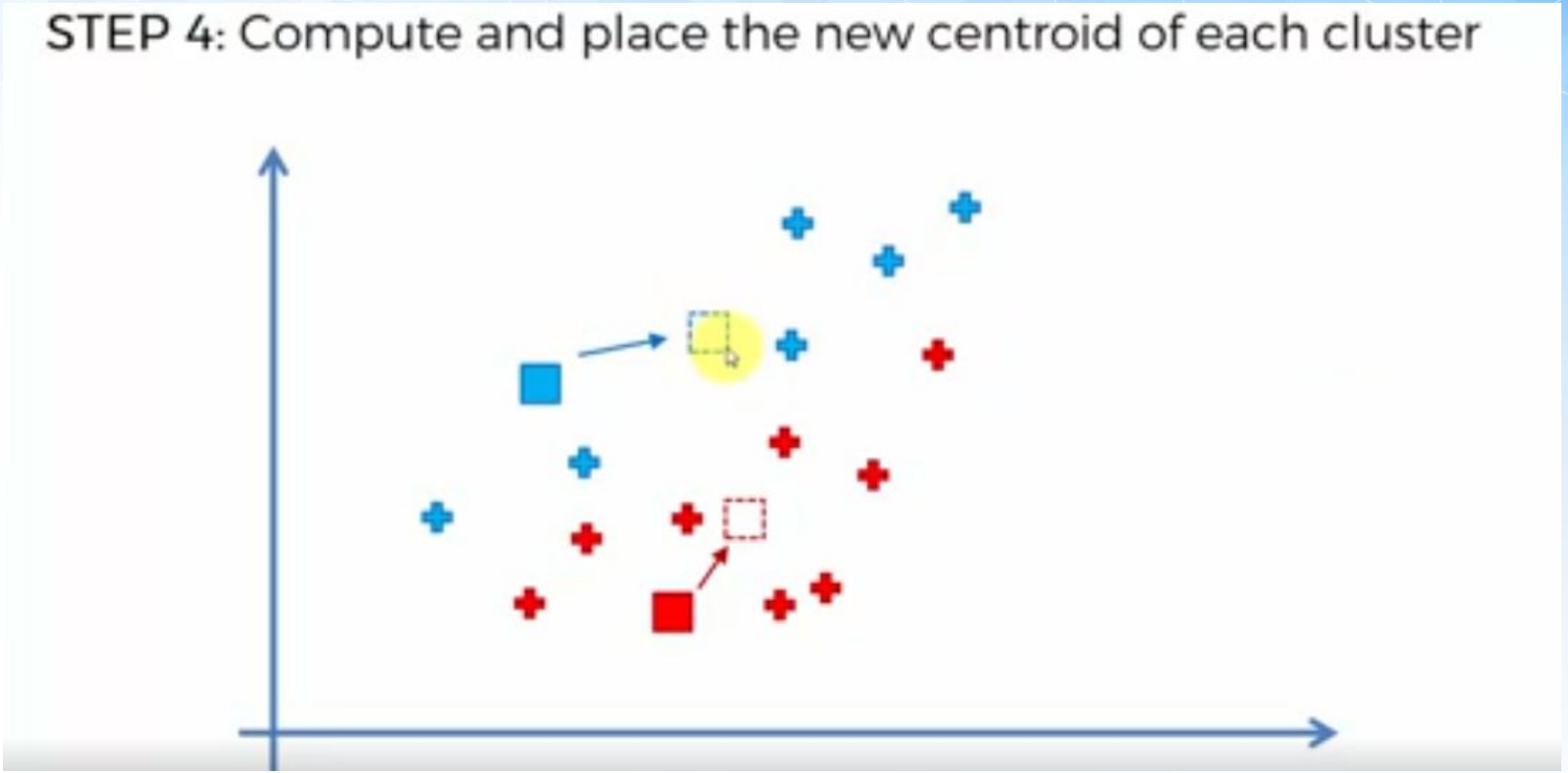


K-Means Clustering

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



K-Means Clustering



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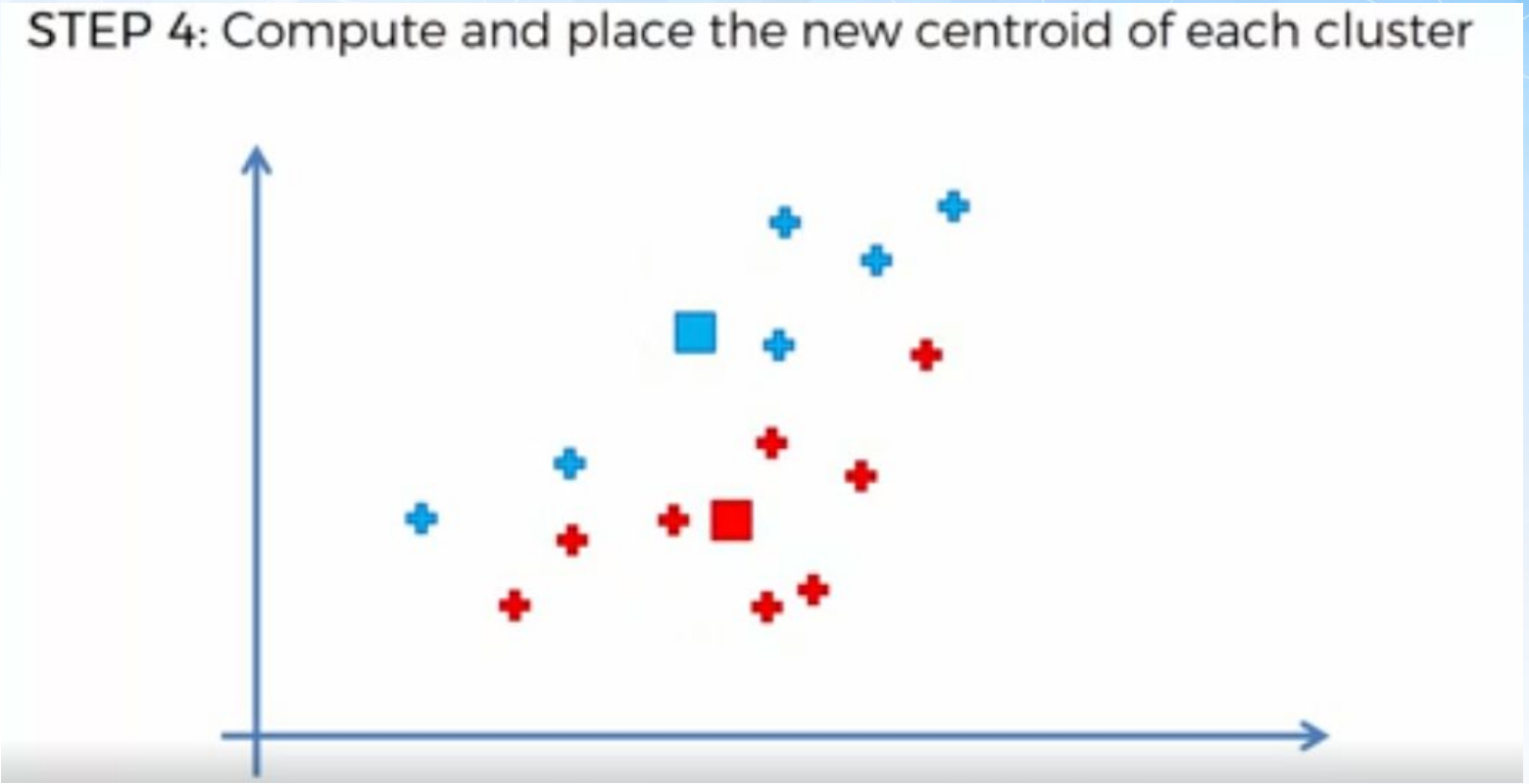

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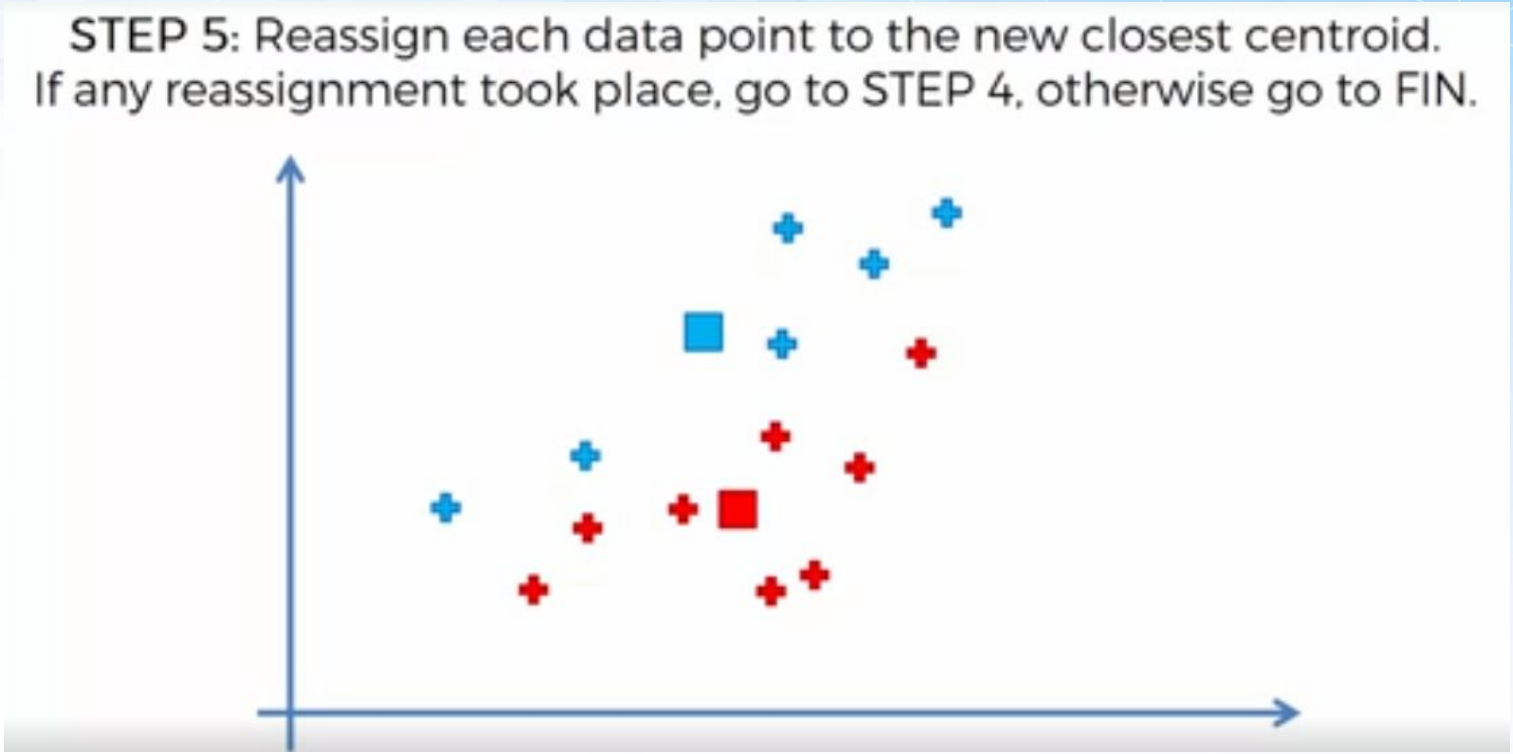
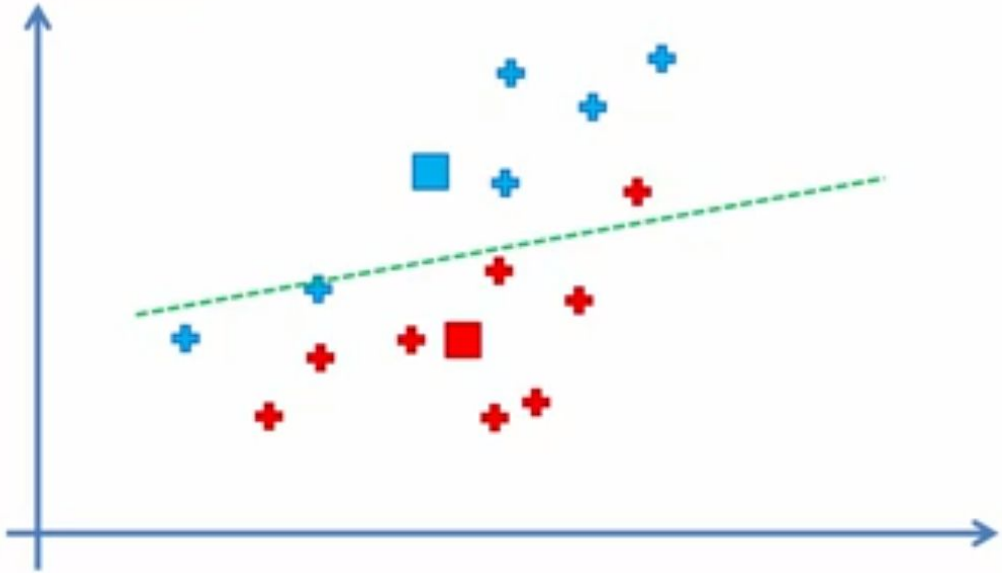


K-Means Clustering

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



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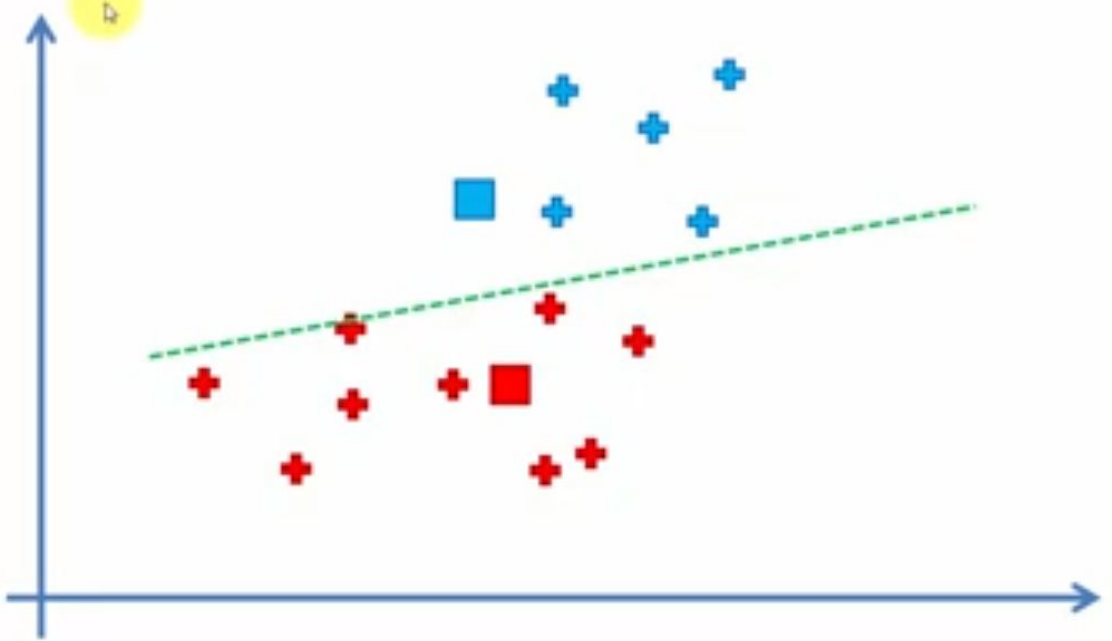
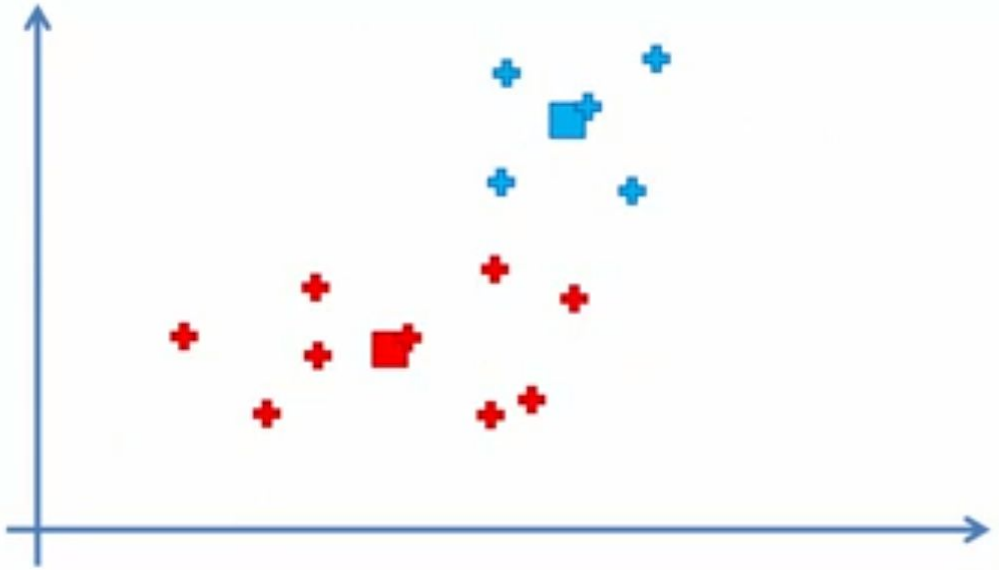


K-Means Clustering

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



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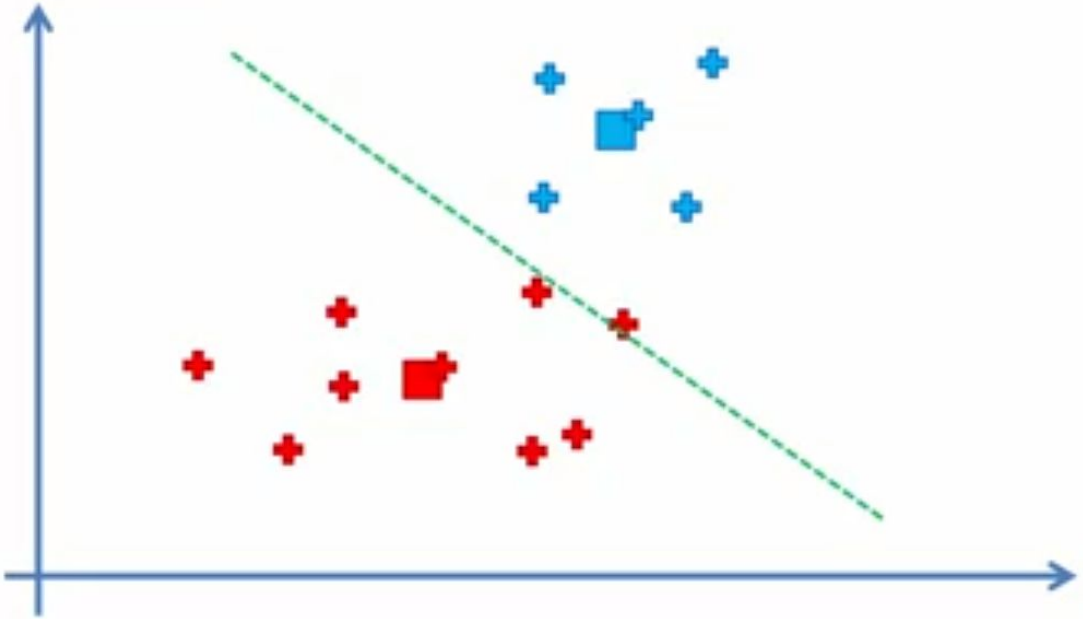

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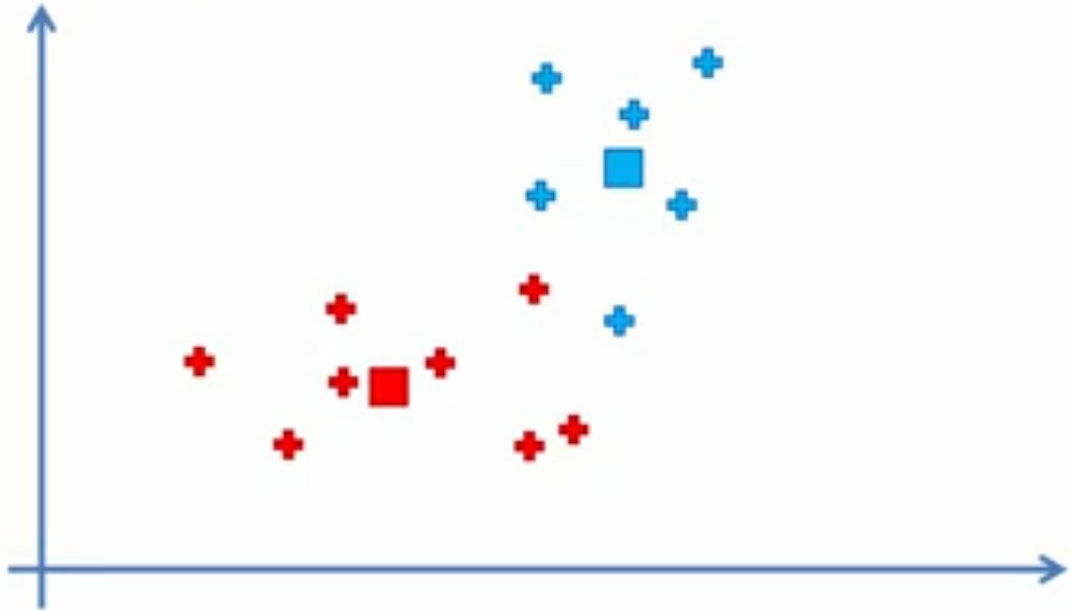

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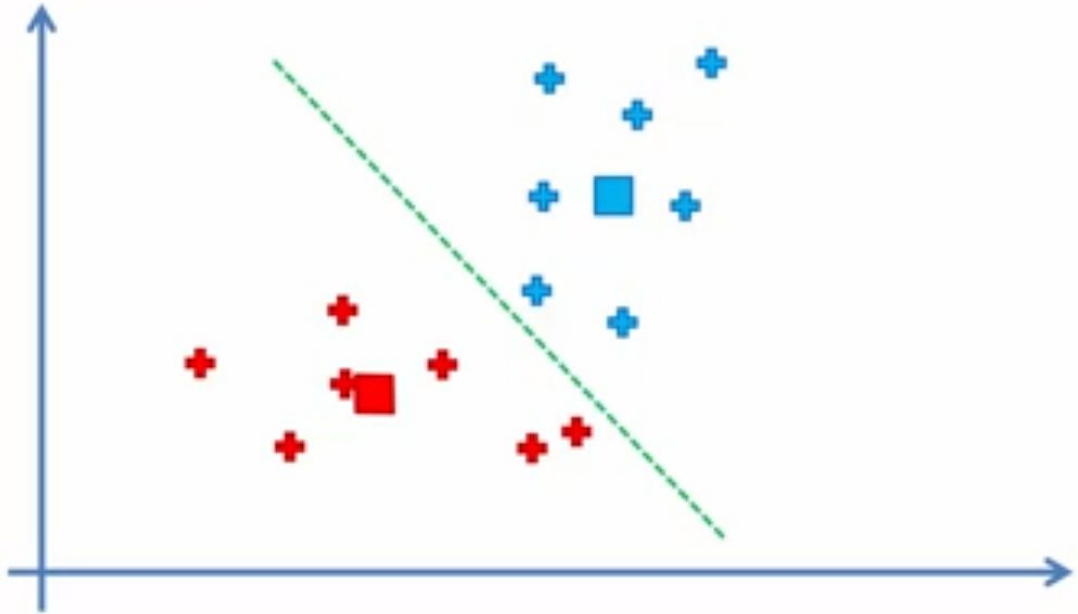

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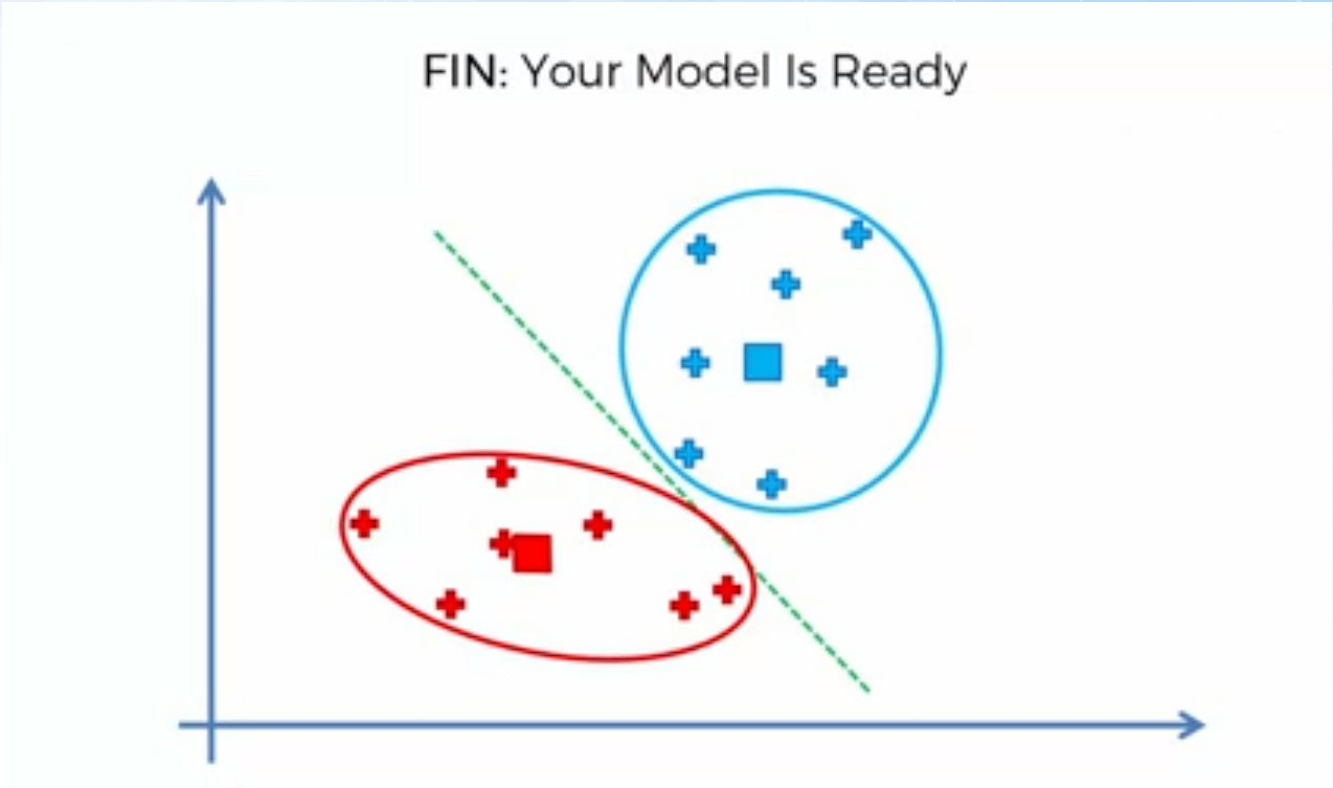
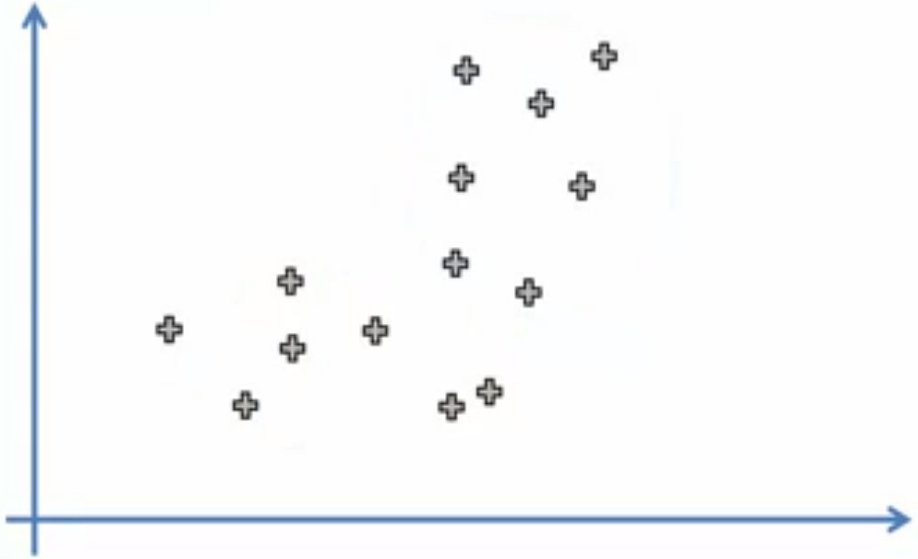


K-Means Clustering

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



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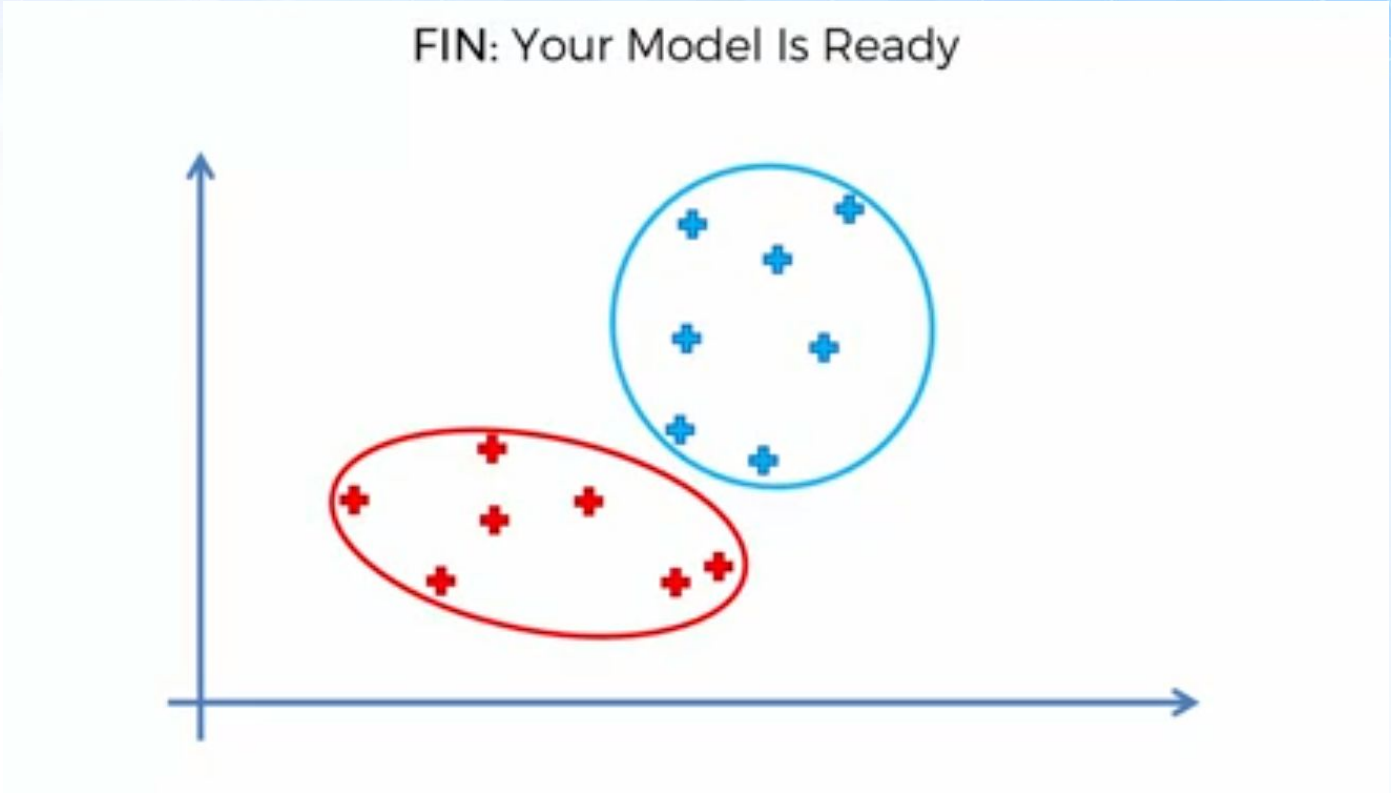
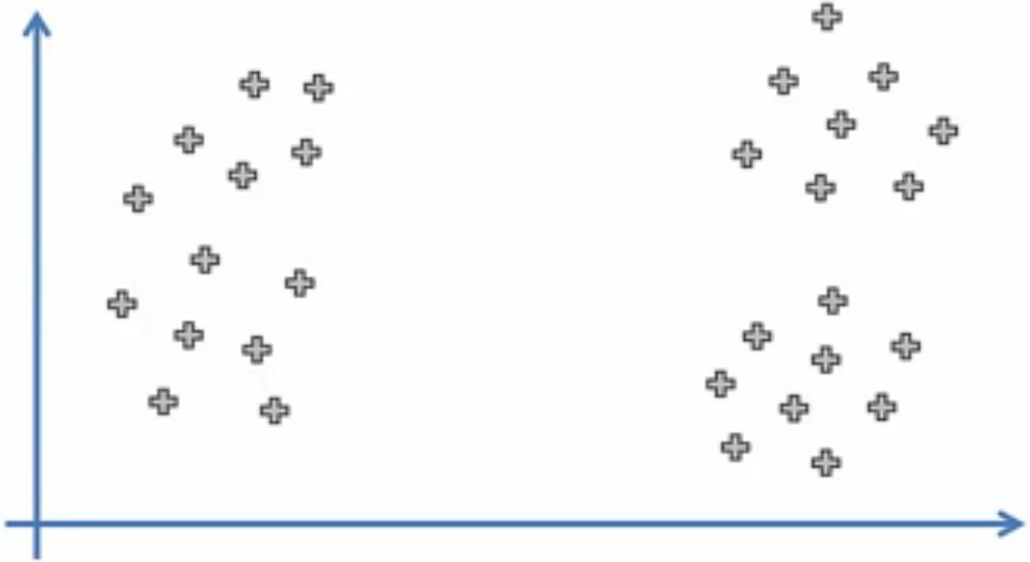
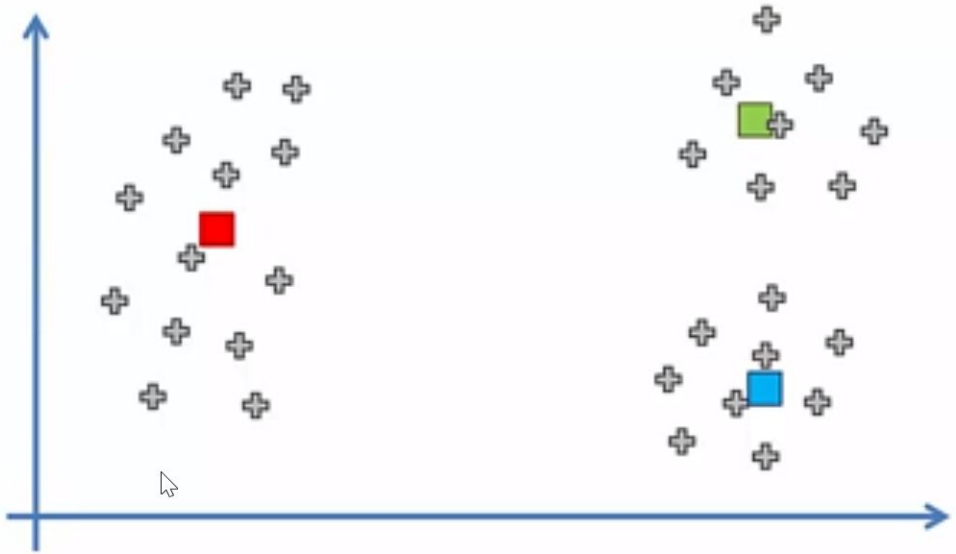


Random Initialization Trap



If we choose K = 3 clusters...

Random Initialization Trap



...this correct random initialisation would lead us to...

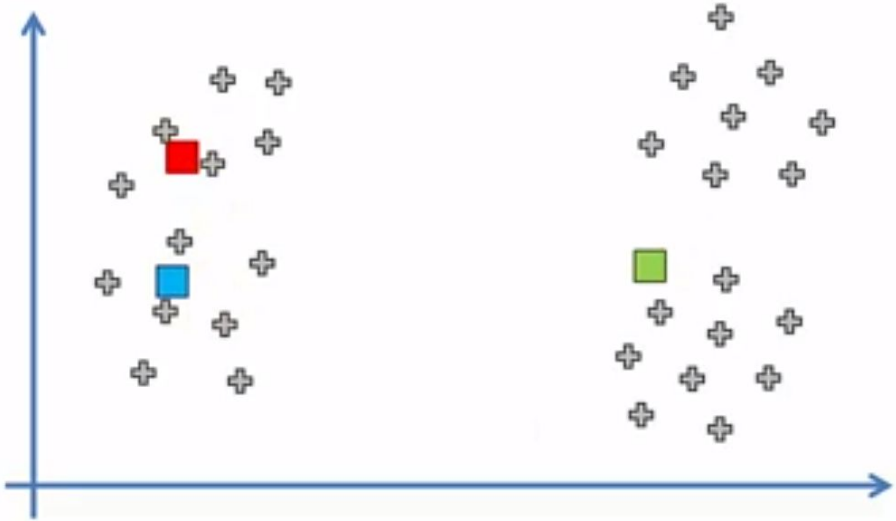
Random Initialization Trap

Random Initialization Trap

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

Random Initialization Trap

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



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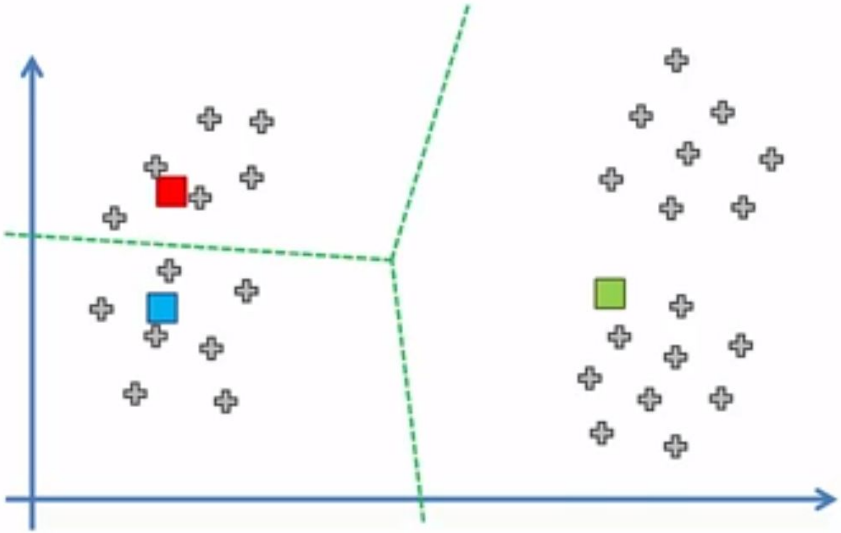
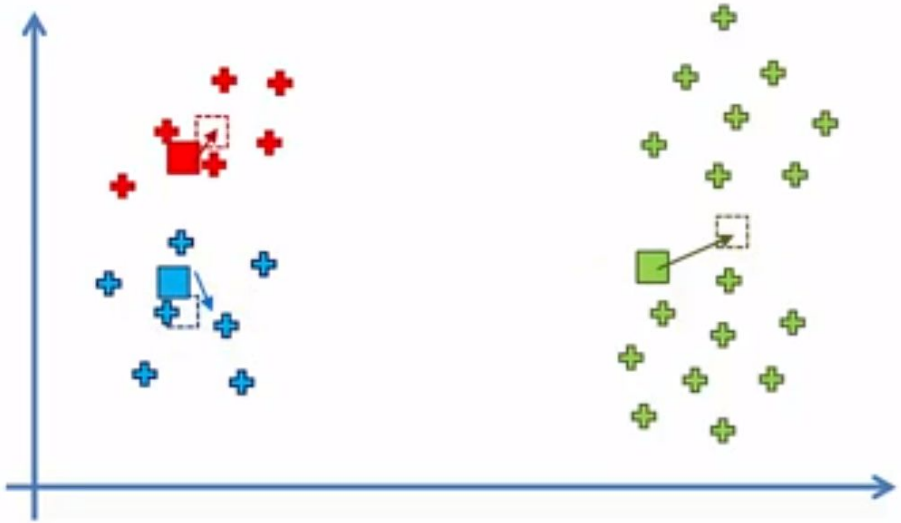


Random Initialization Trap

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



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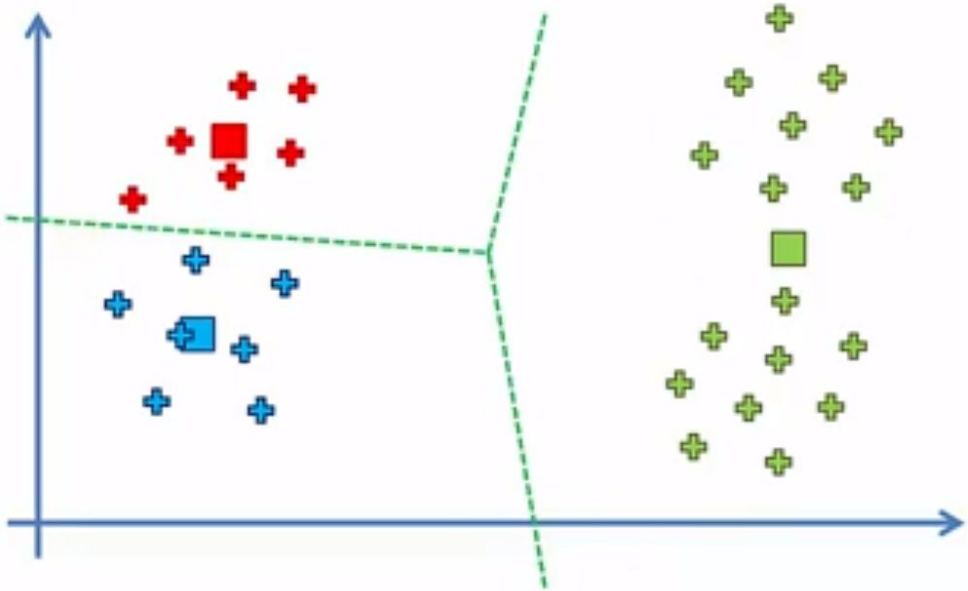

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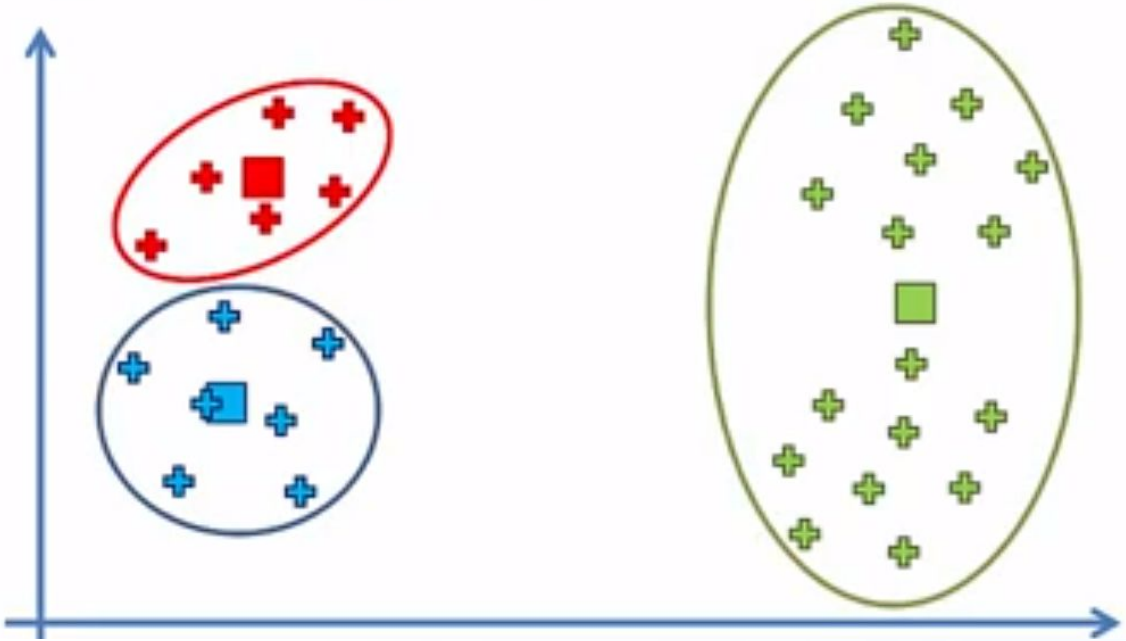

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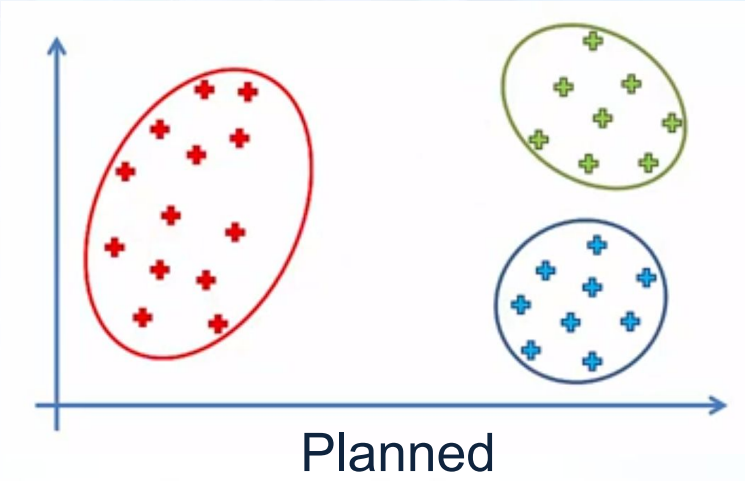
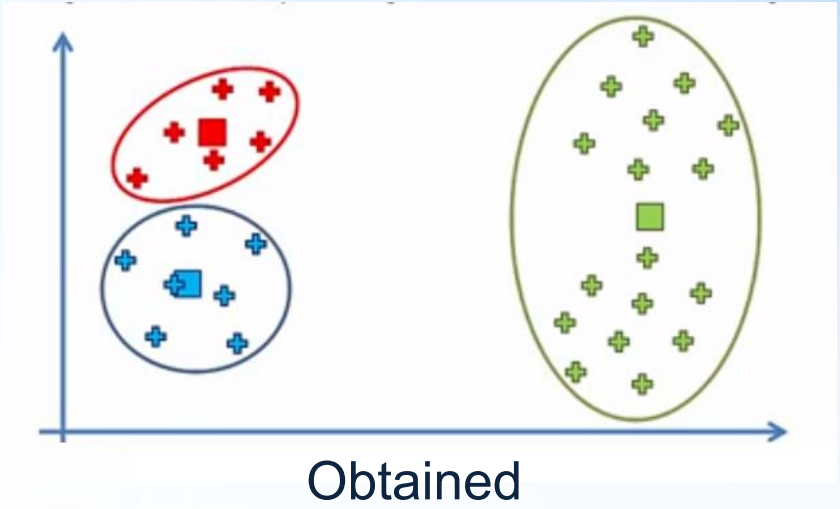
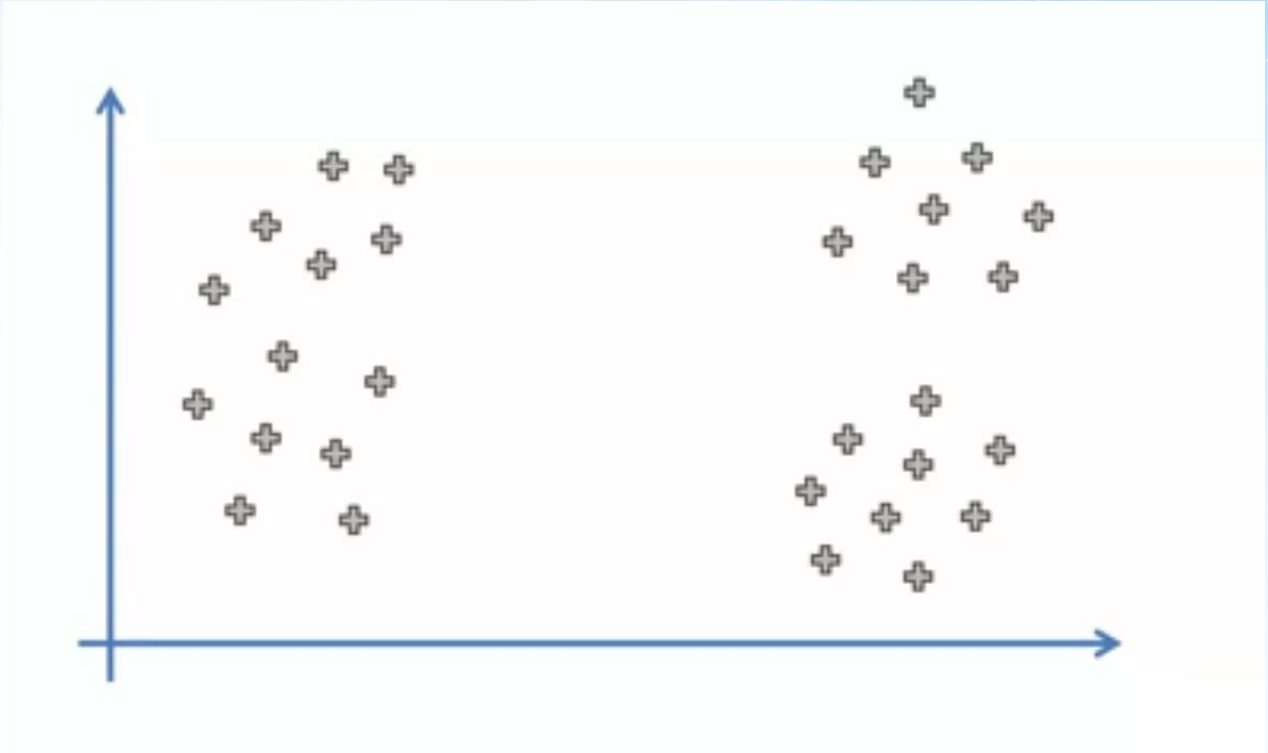




Random Initialization Trap

Choosing Right Number of Clusters



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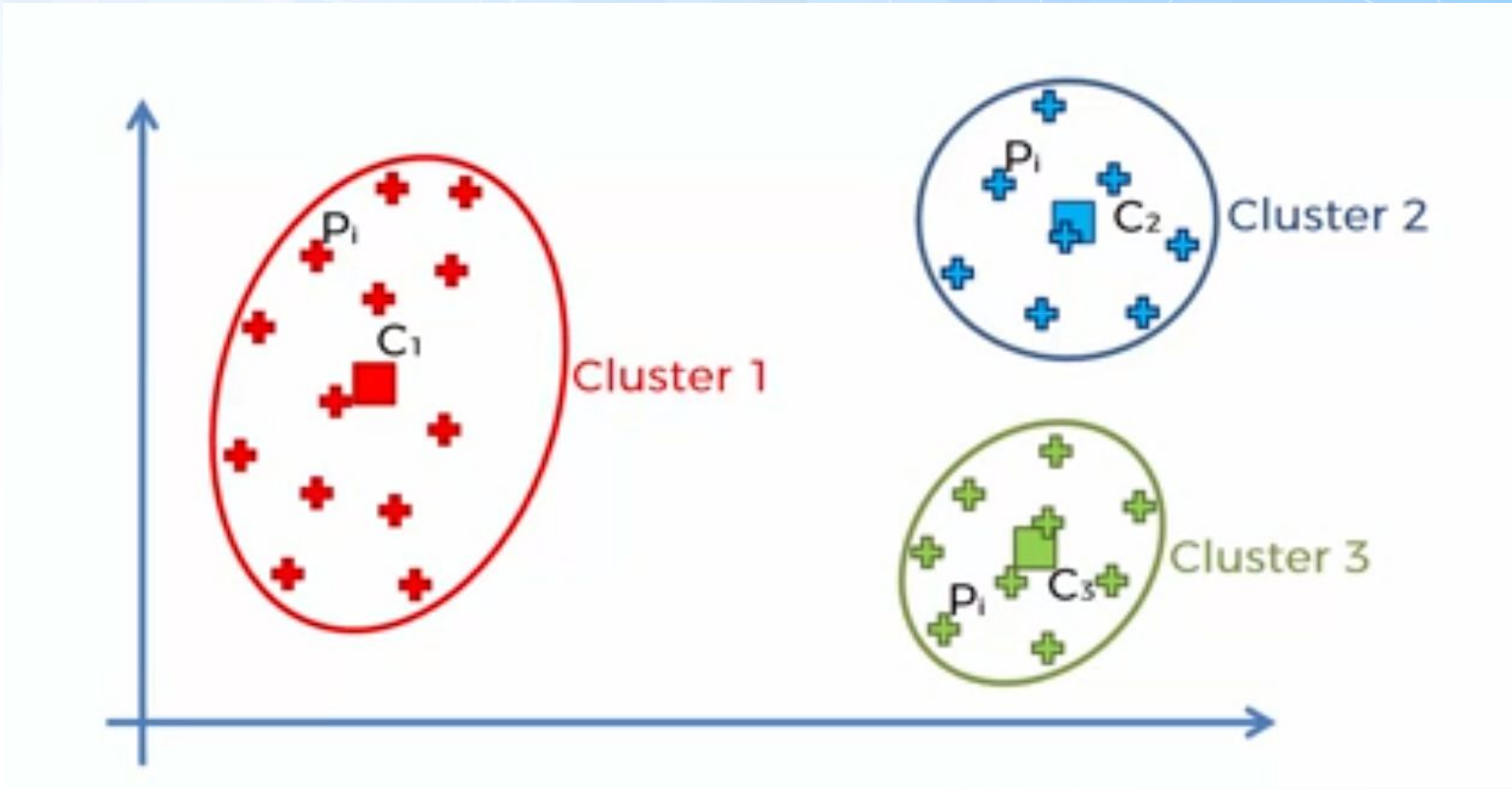
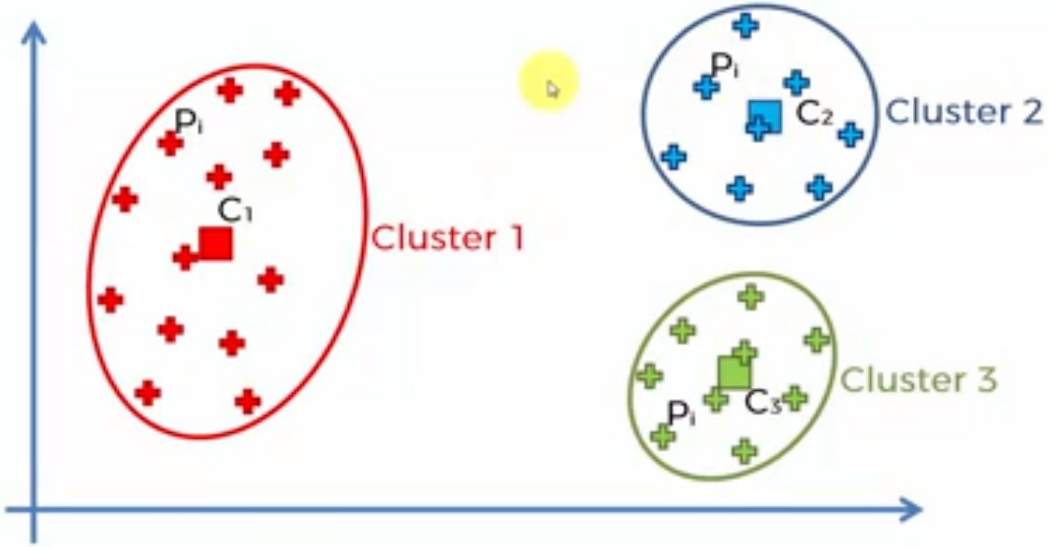


Choosing Right Number of Clusters

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

*** within-cluster sums of squares**

Choosing Right Number of Clusters



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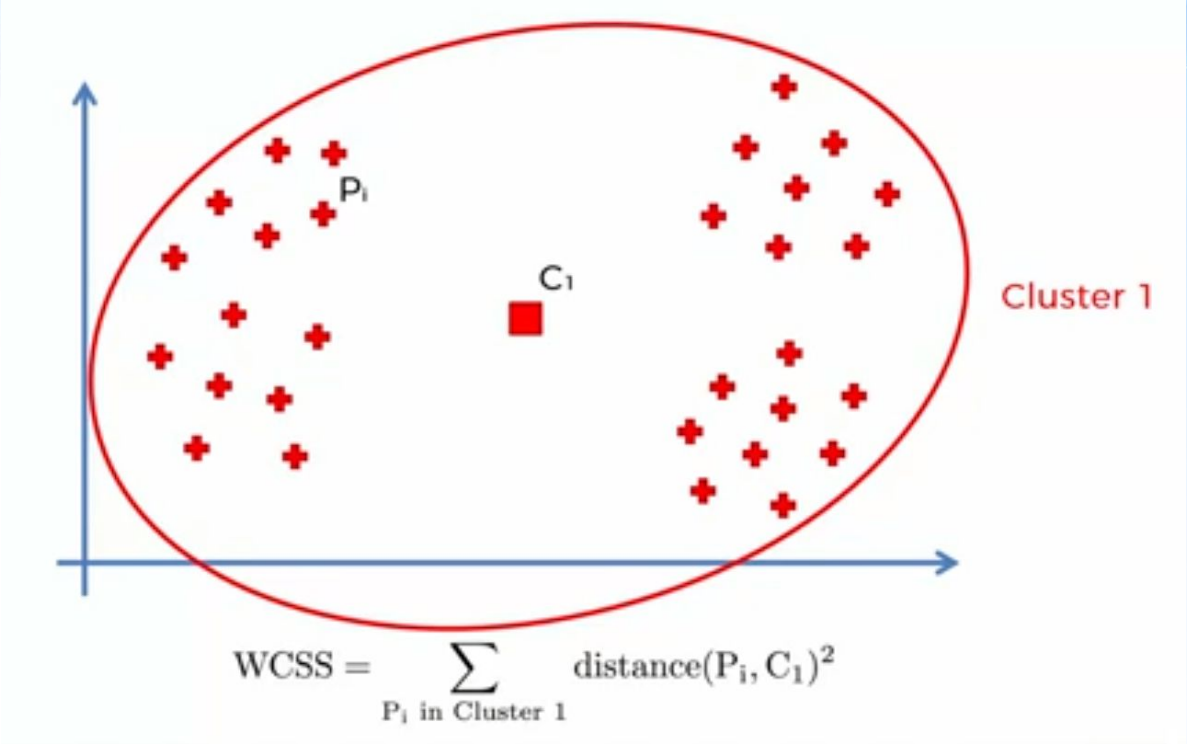

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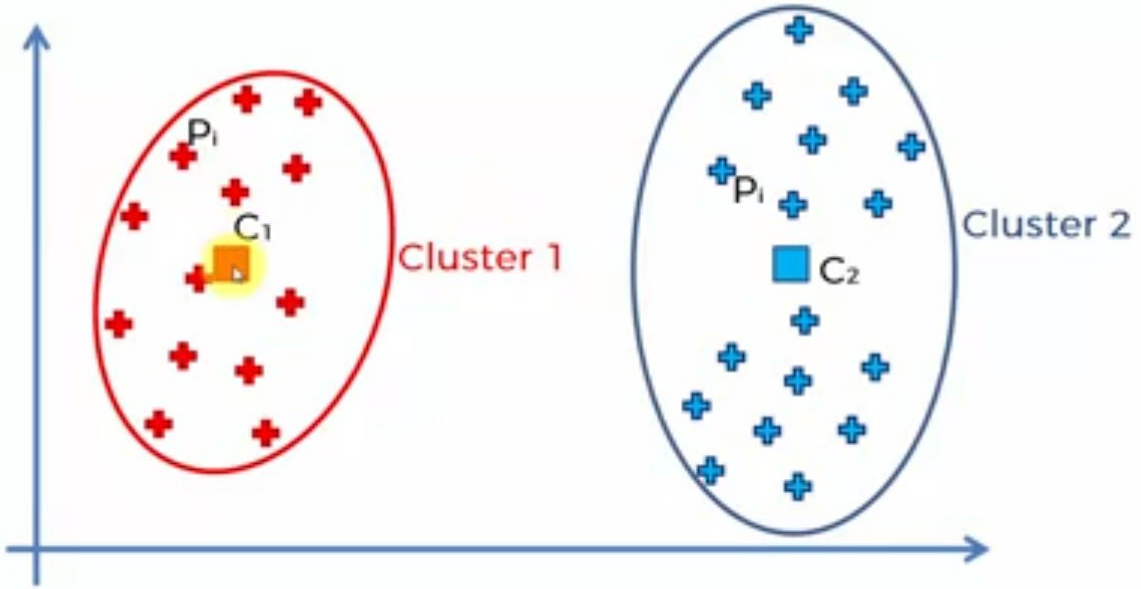

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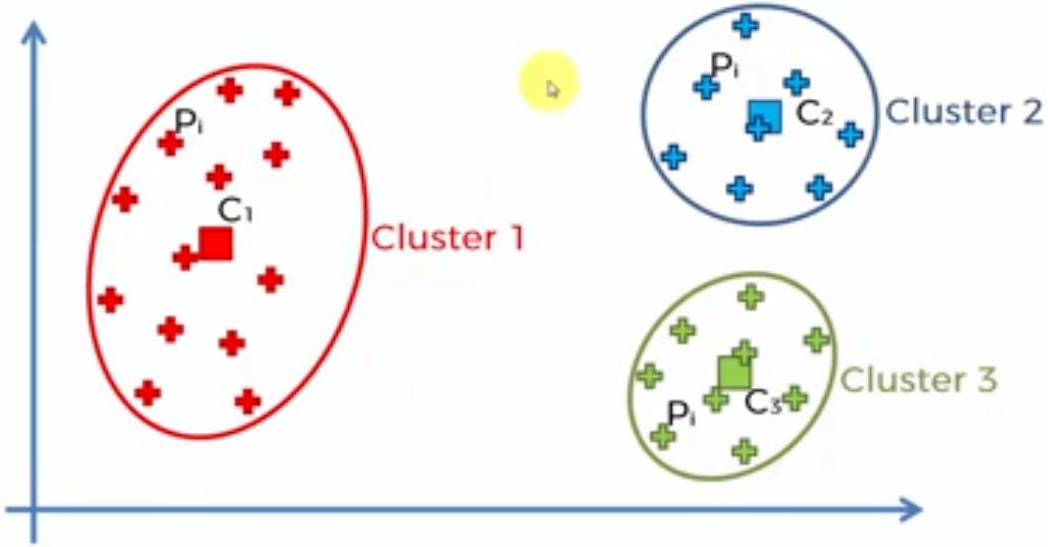

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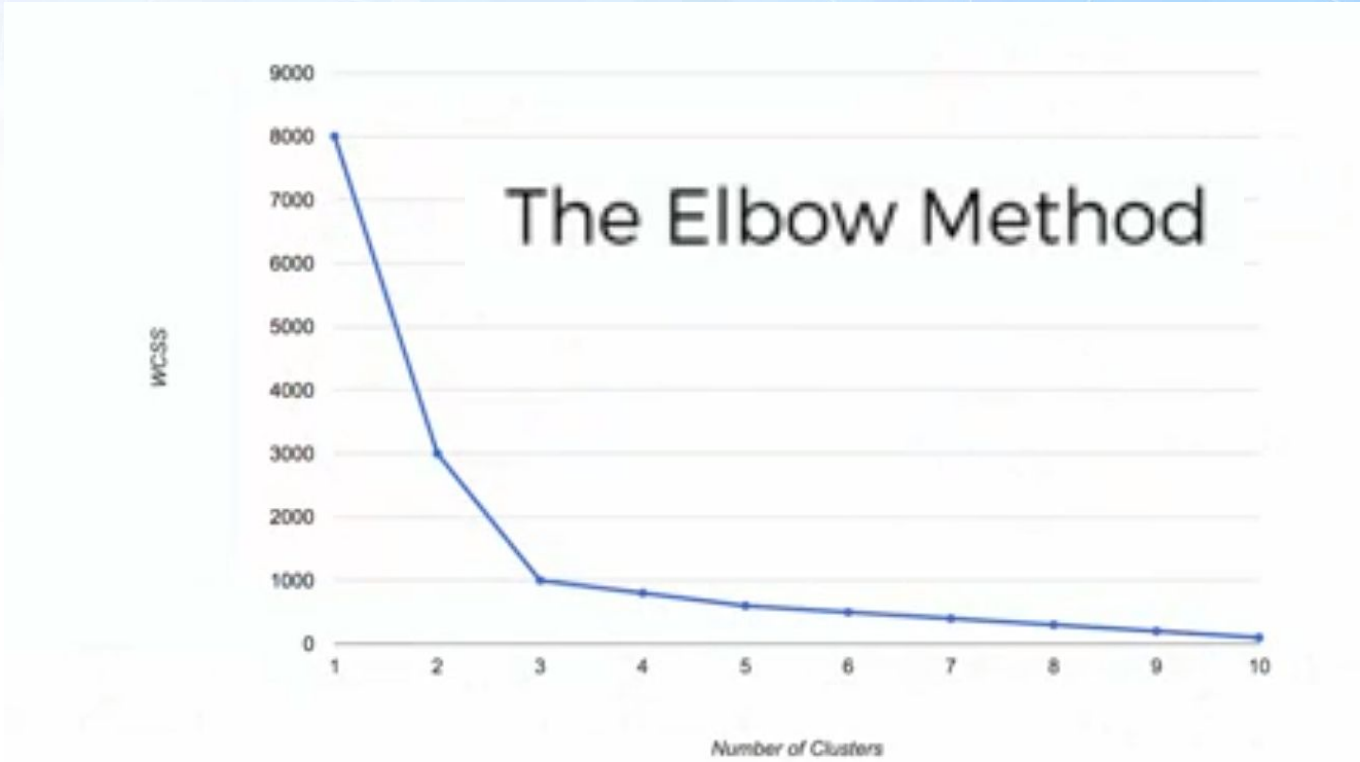

Choosing Right Number of Clusters