機器學習
K-Means

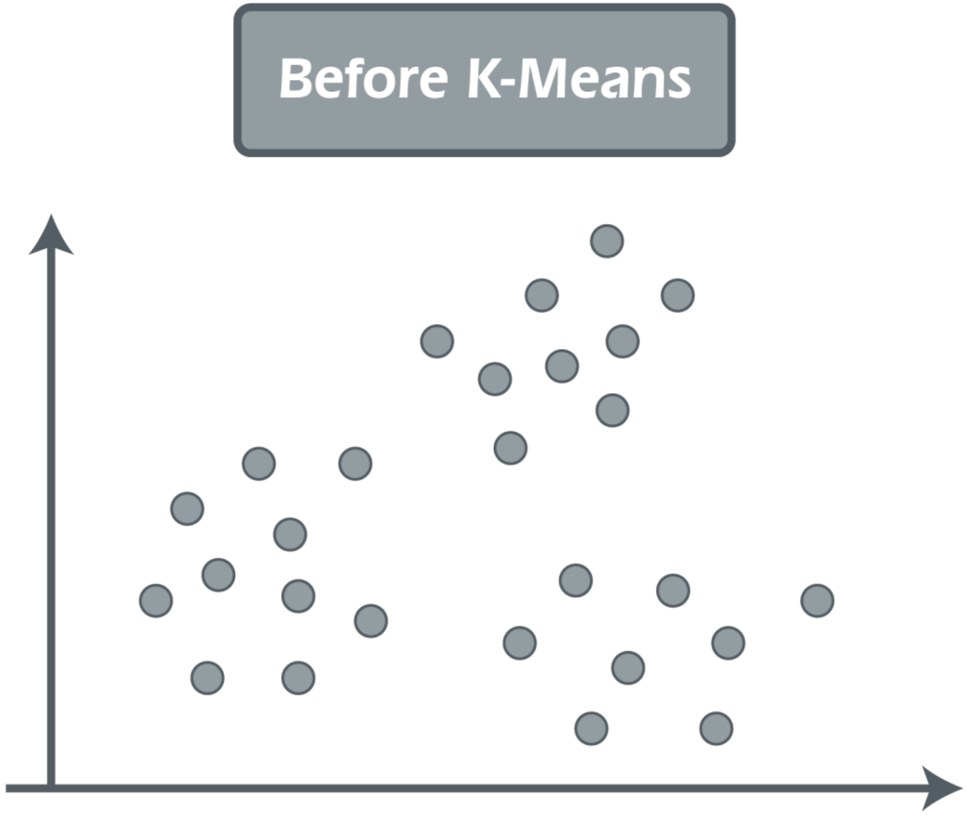
授課老師：林彥廷

K-Means

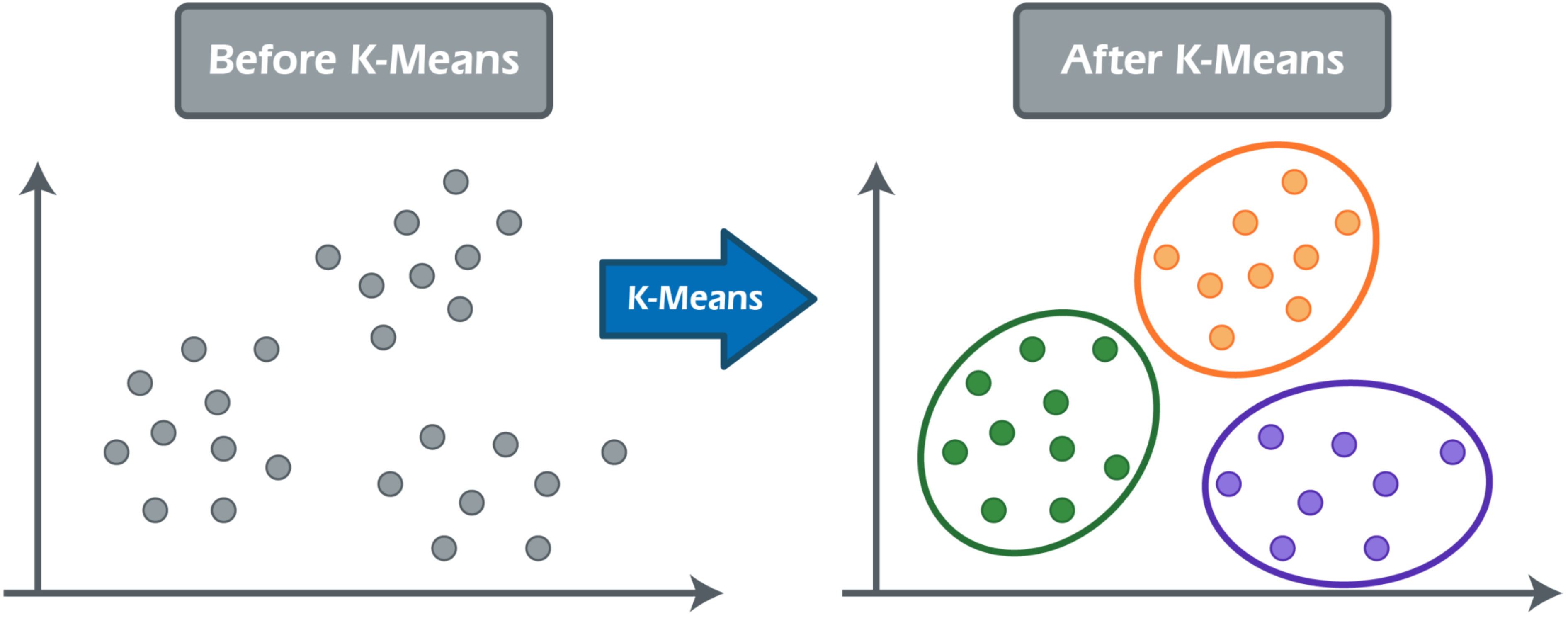
- K-Means是常見的分群(Clustering)演算法之一
- K-Means屬於非監督式學習演算法
- 非監督式學習是資料並沒有標籤，讓機器直接從資料中學習出規則

K-Means Intuition: Understanding K-Means

What K-Means does for you



What K-Means does for you



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 → That forms K clusters

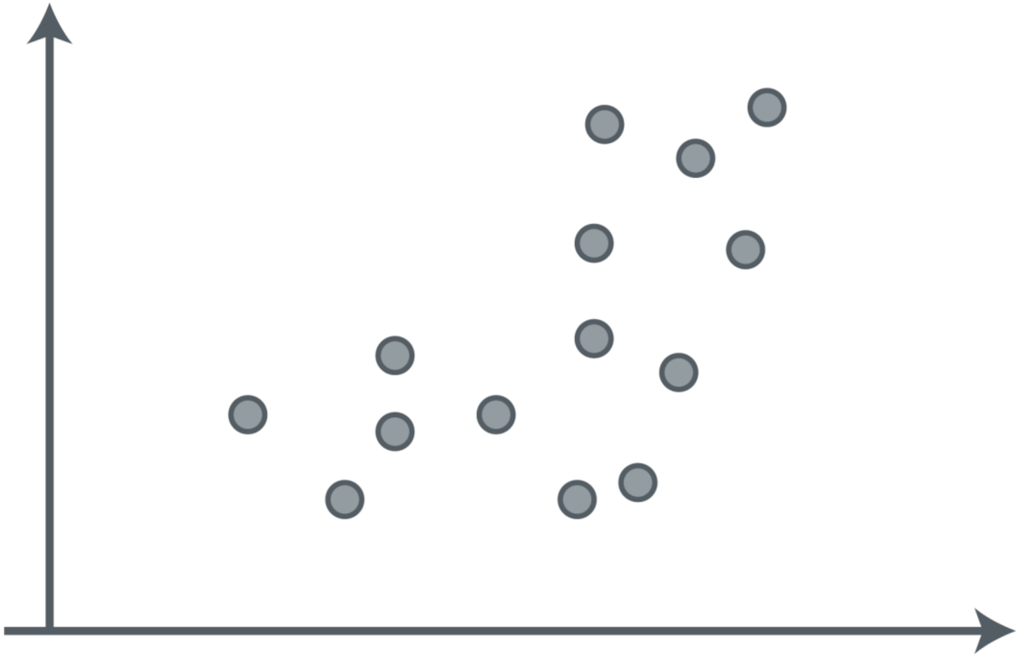
STEP 4: Compute and place the new centroid of each cluster

STEP 5: Reassign each data point to the new closest centroid.

If any reassignment took place, go to STEP 4, otherwise go to FIN.

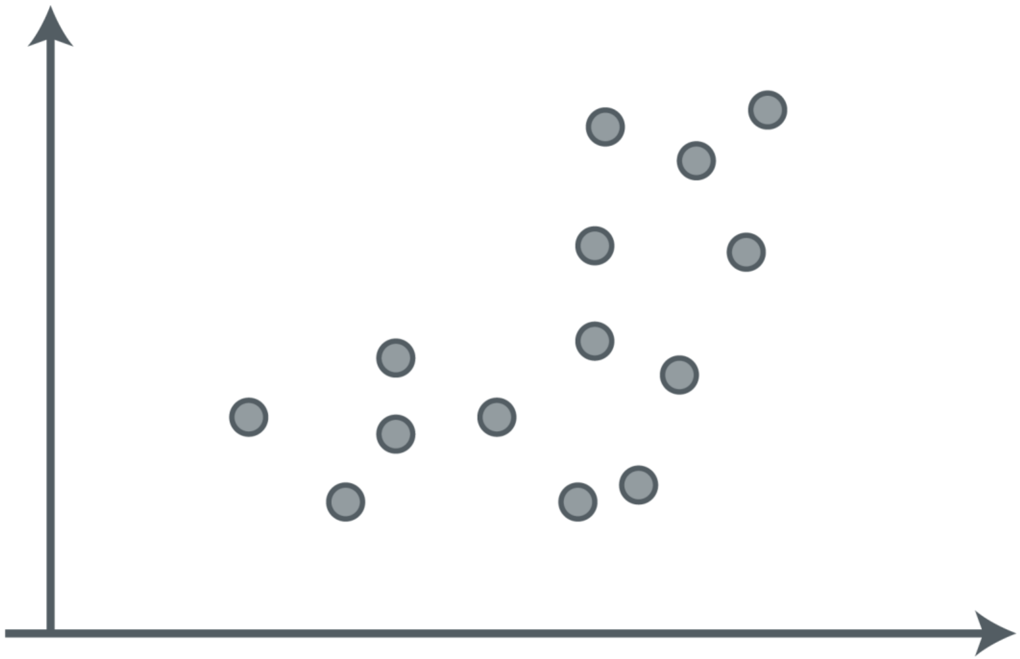
K-Means algorithm

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



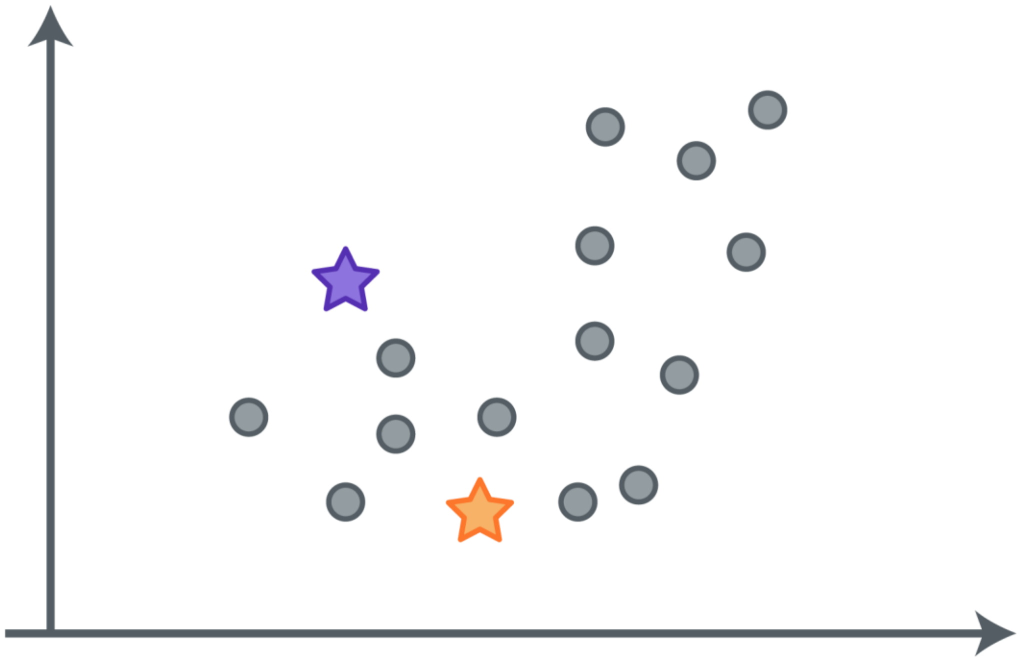
K-Means algorithm

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



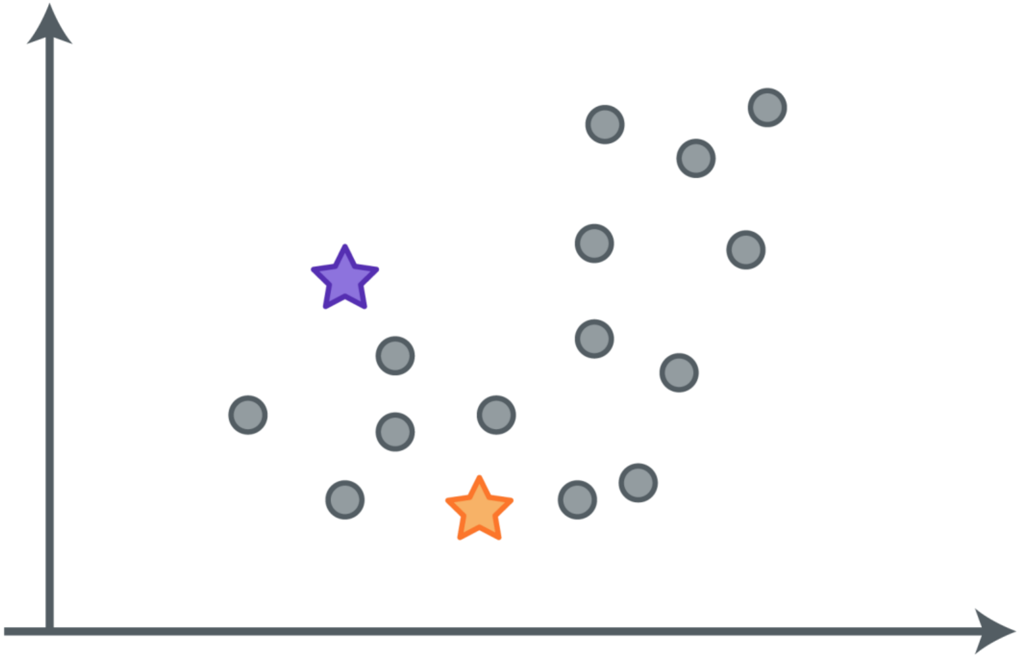
K-Means algorithm

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



K-Means algorithm

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



K-Means algorithm

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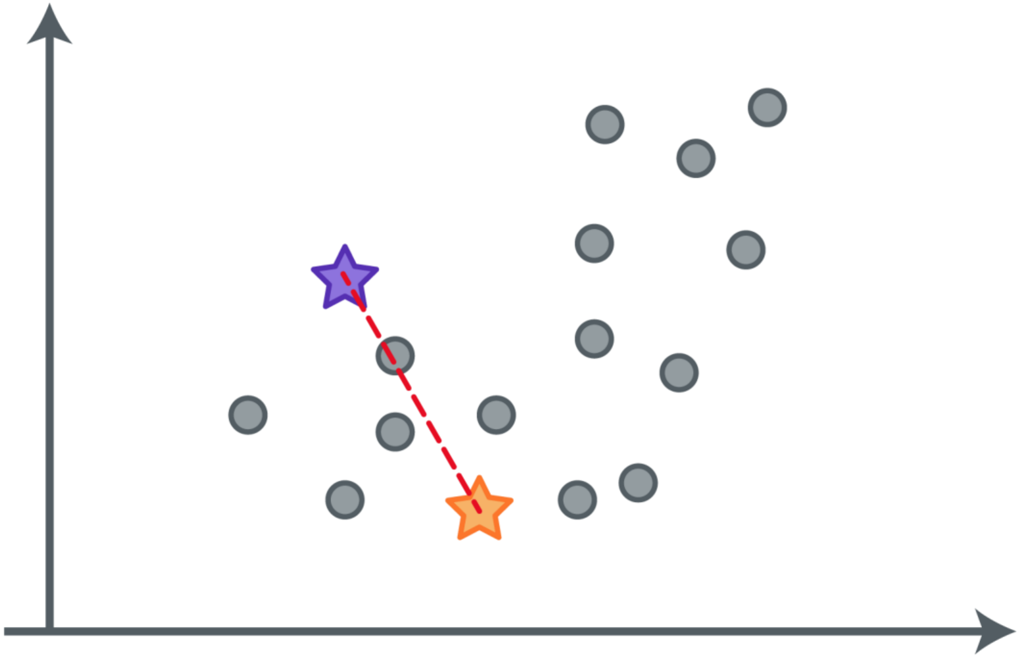

K-Means algorithm

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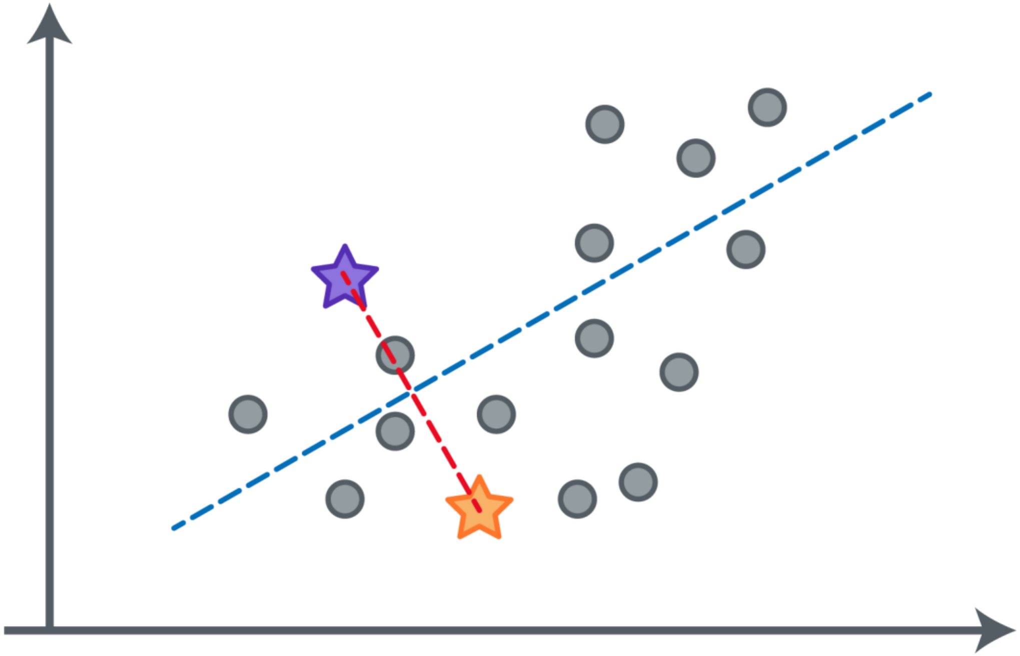

K-Means algorithm

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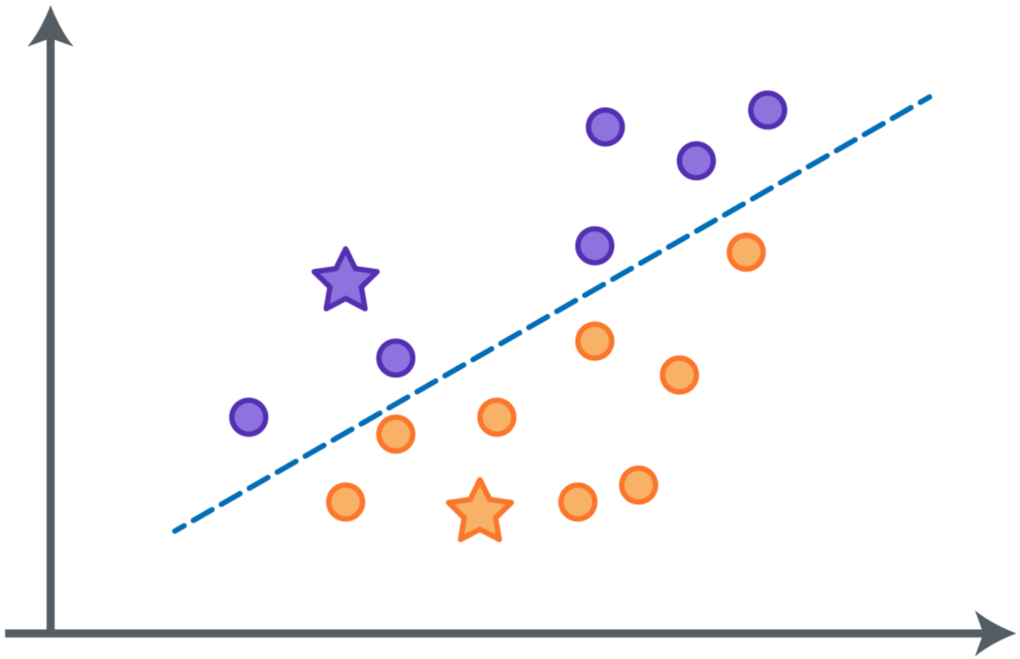
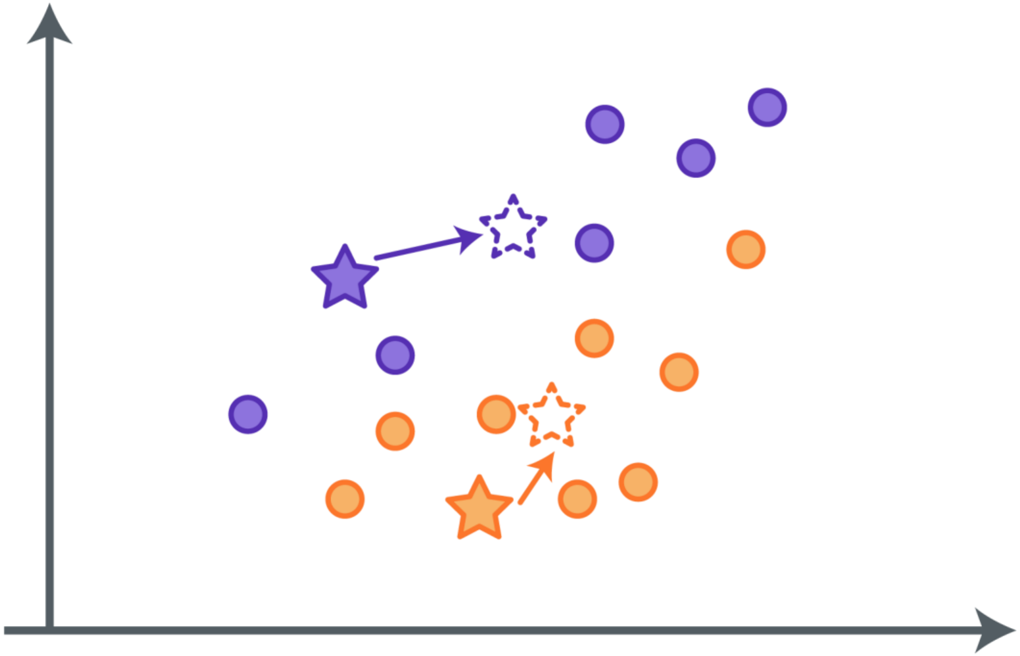


K-Means algorithm

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



K-Means algorithm

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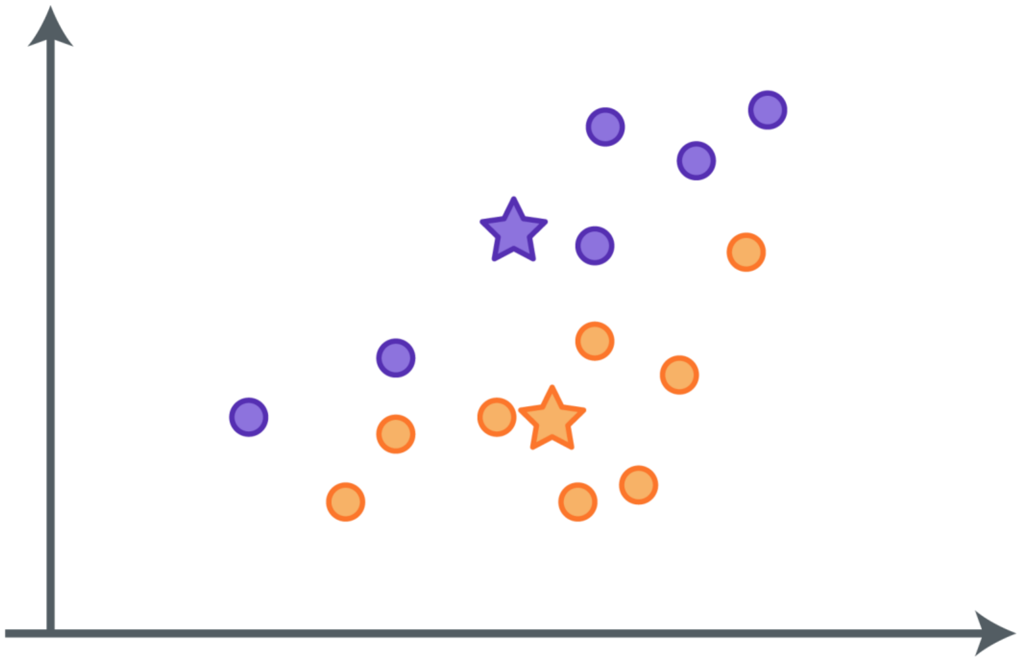

K-Means algorithm

STEP 5: Reassign each data point to the new closest centroid.

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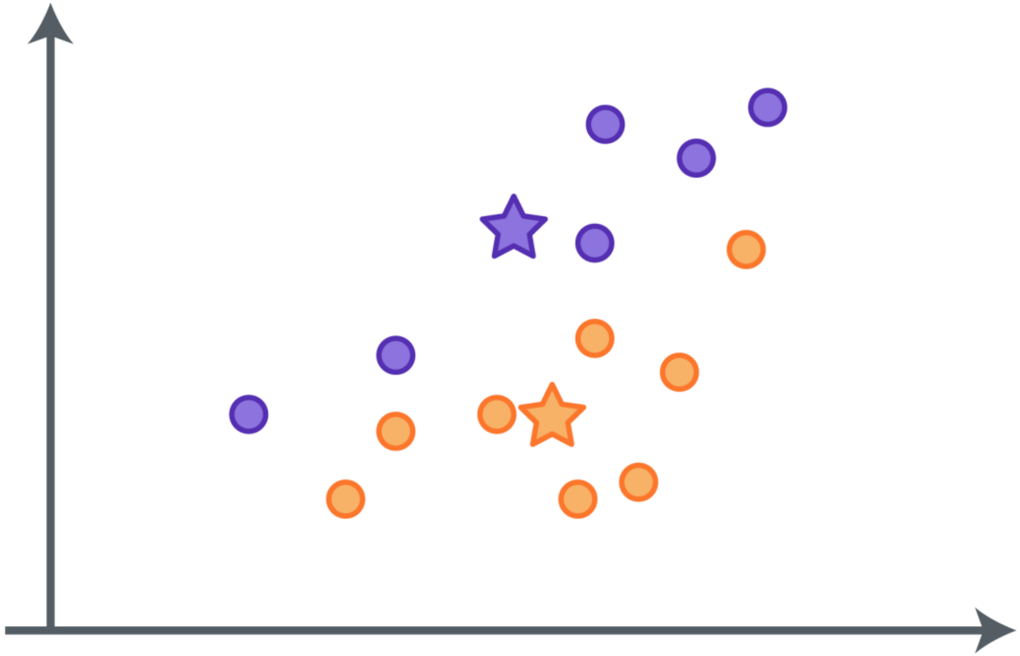

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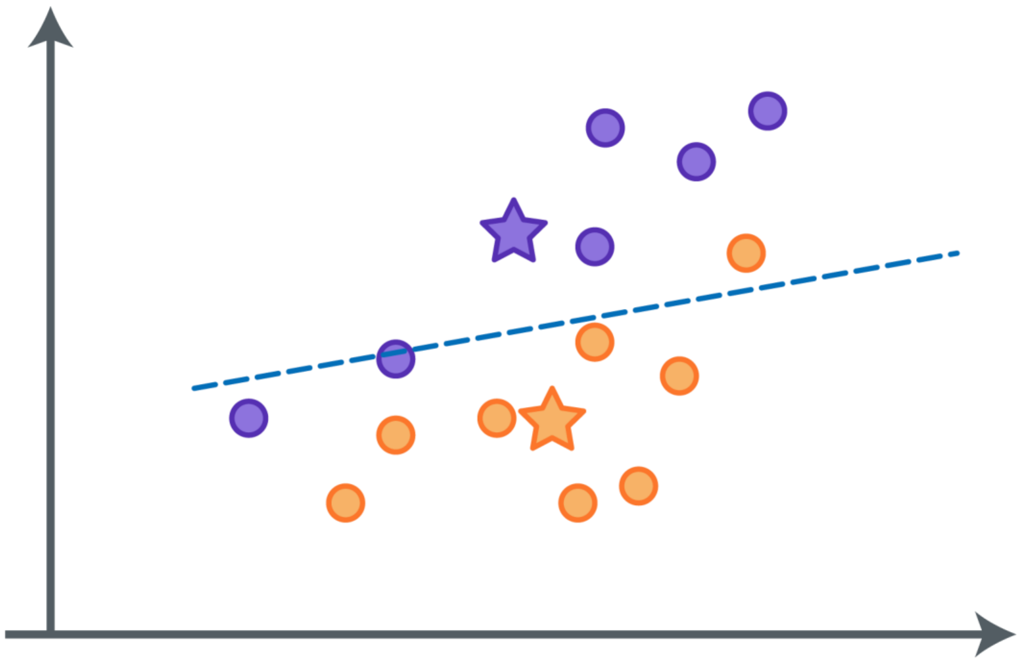

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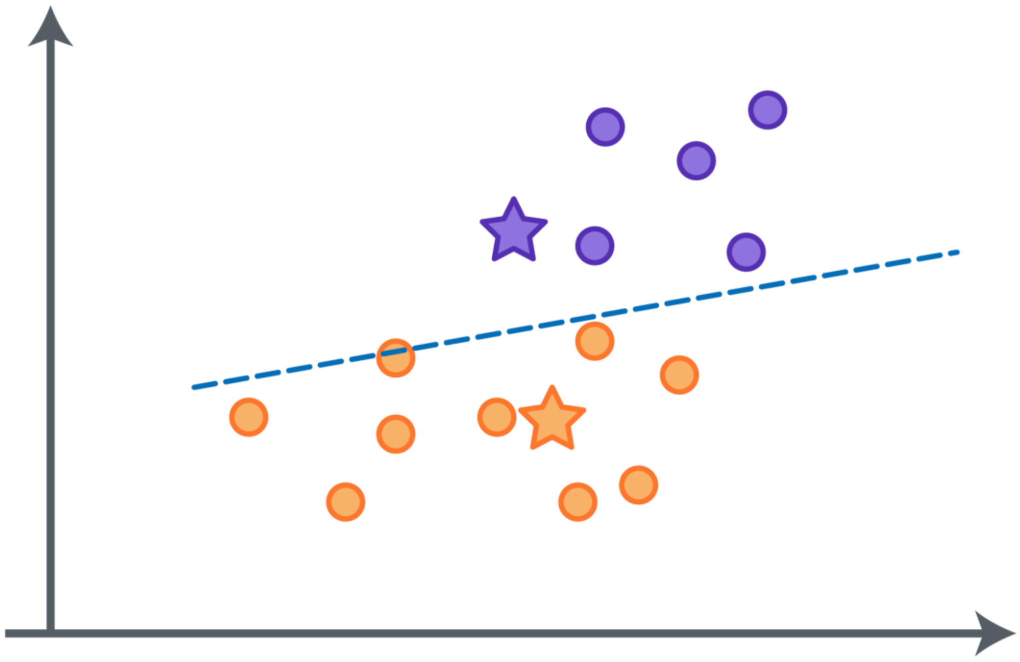

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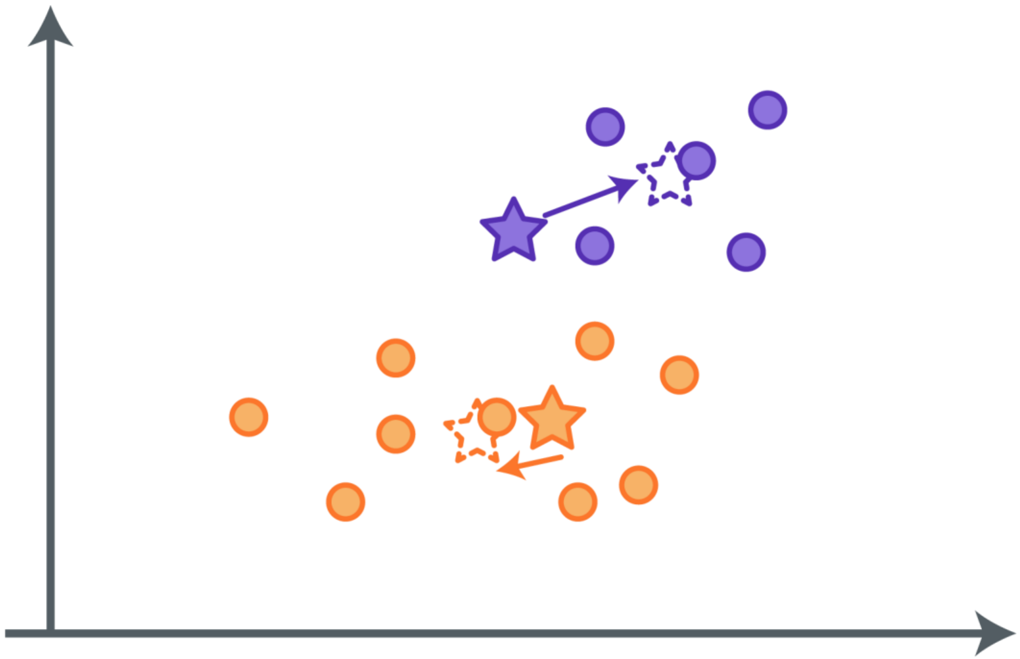

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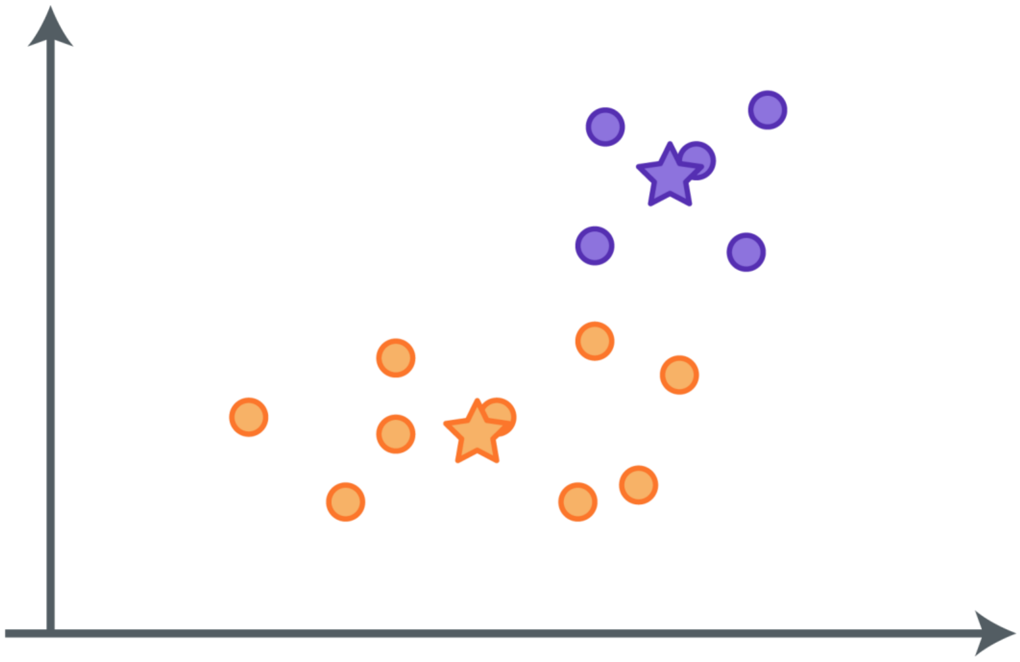

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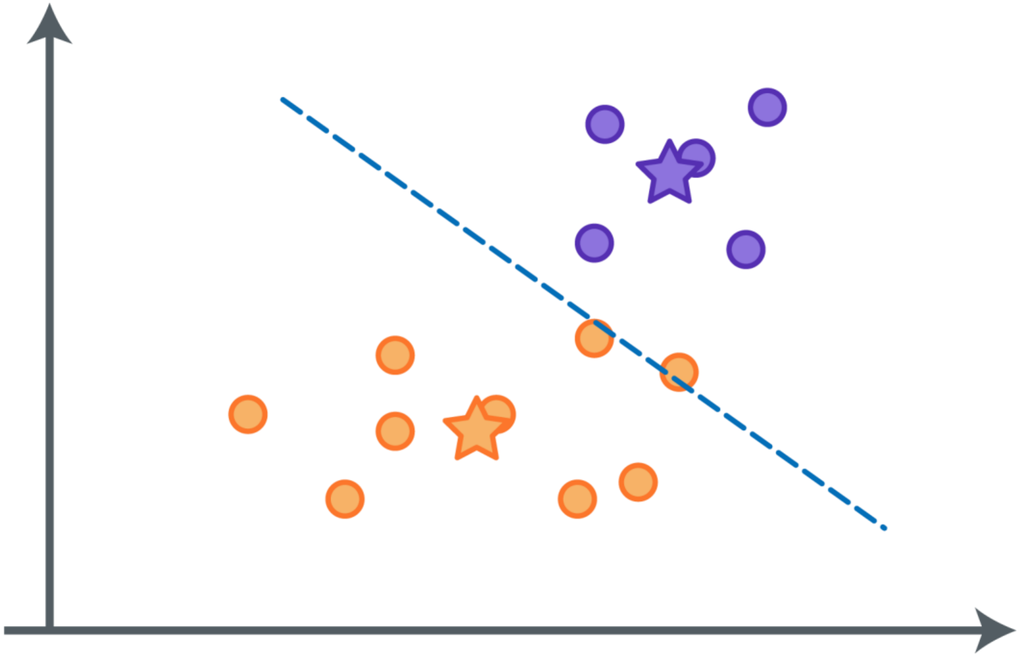

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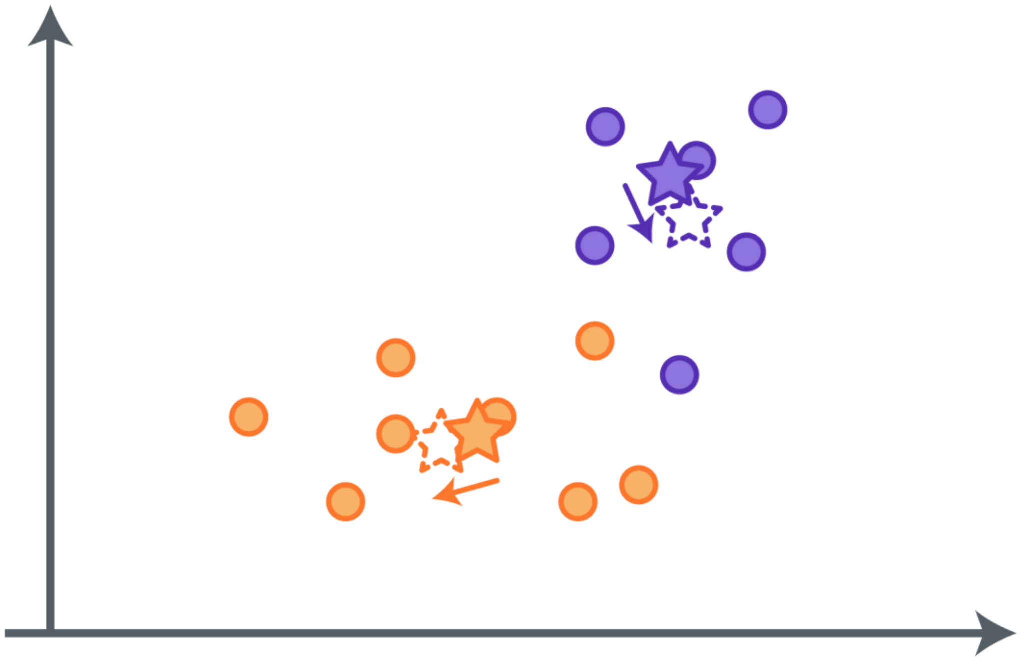

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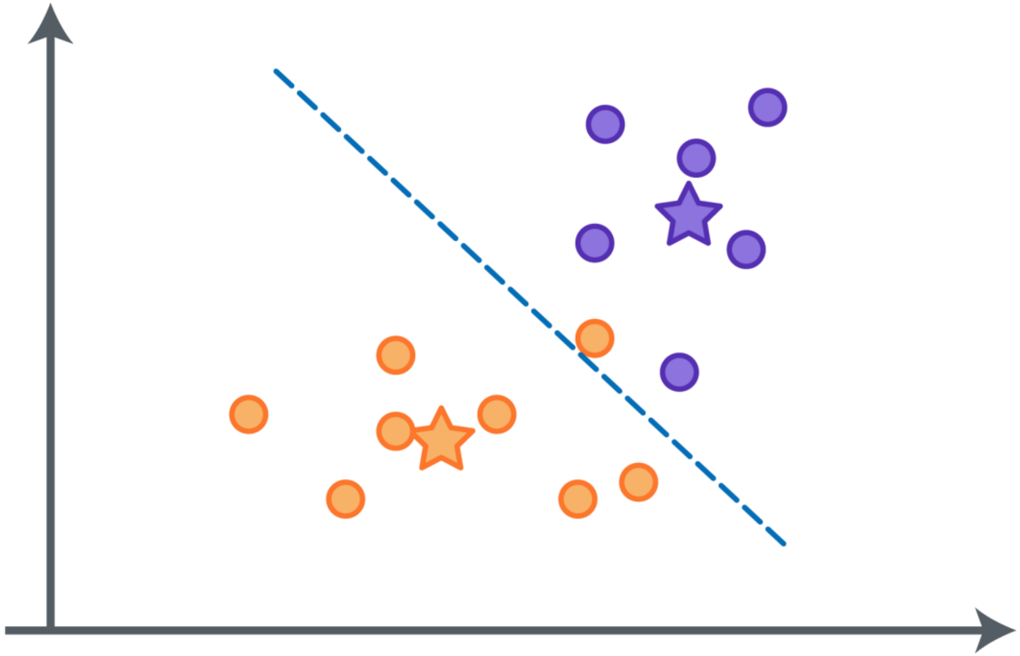

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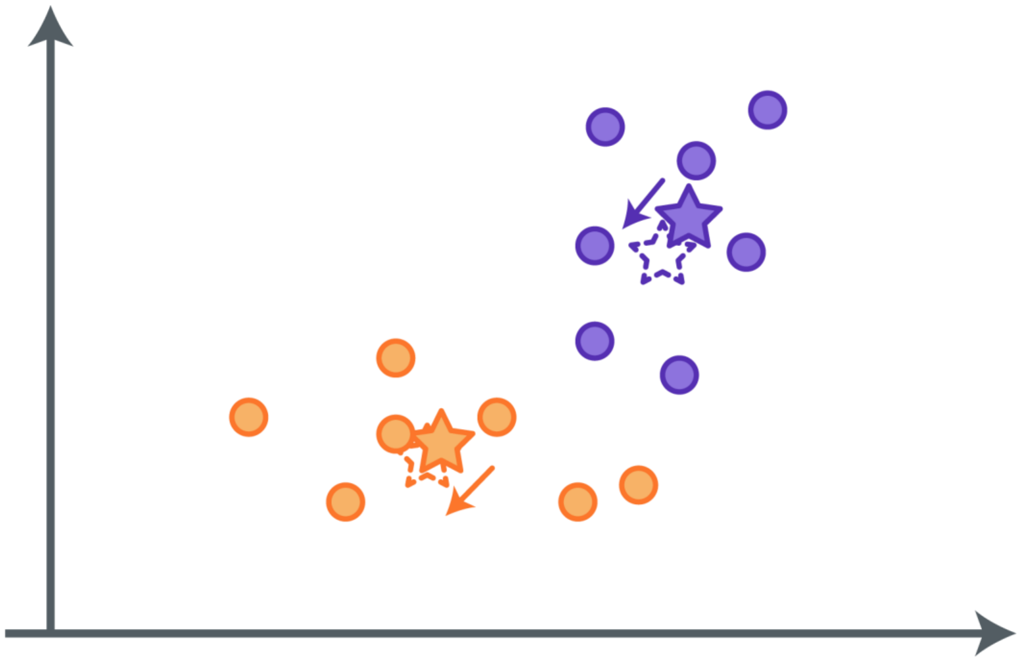

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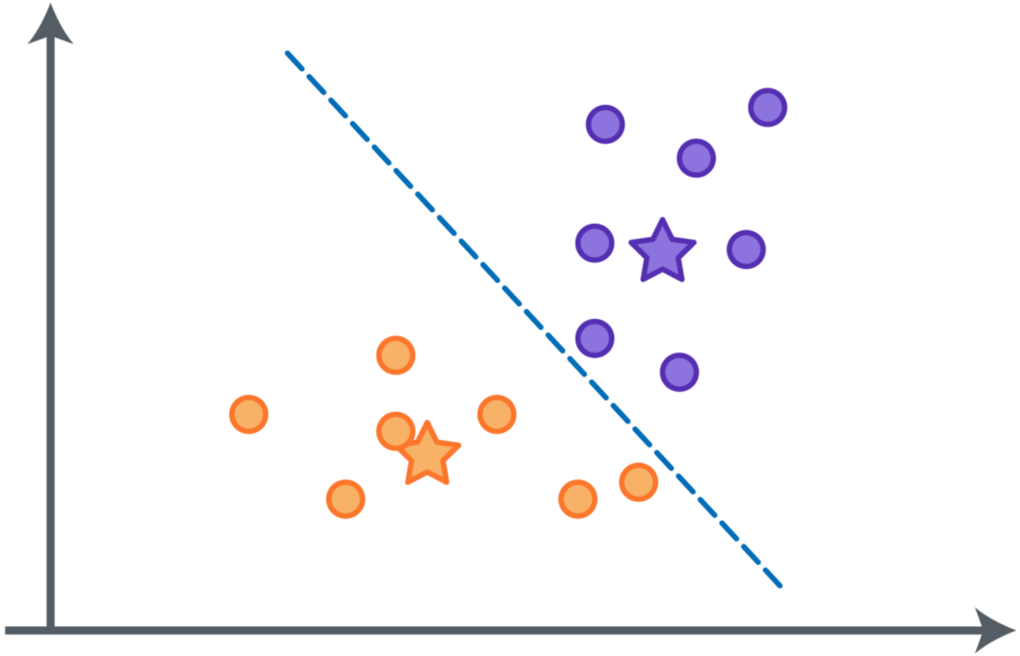
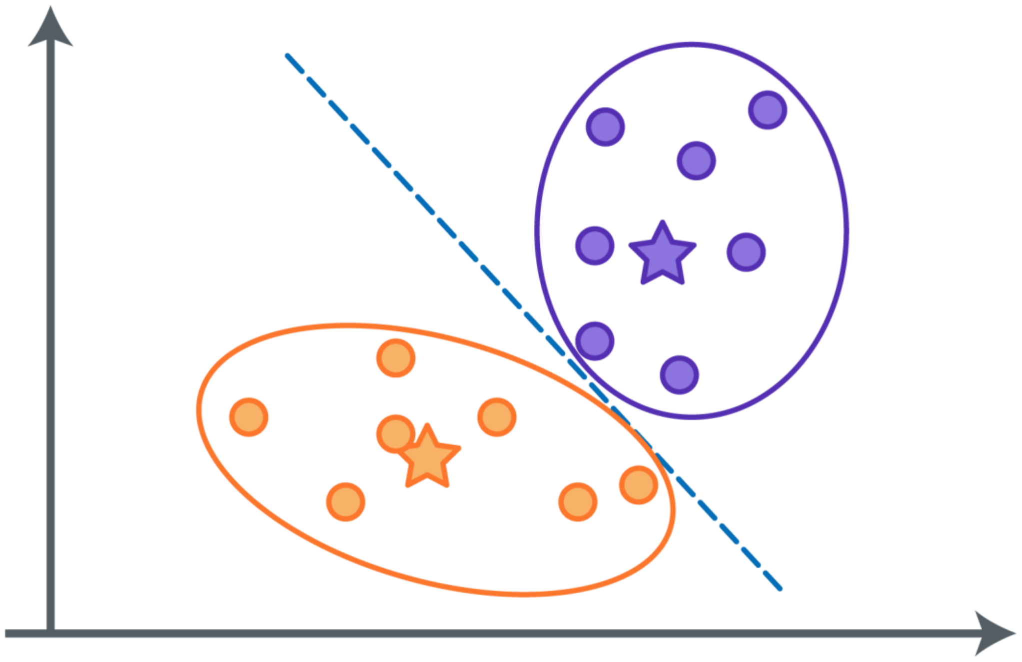


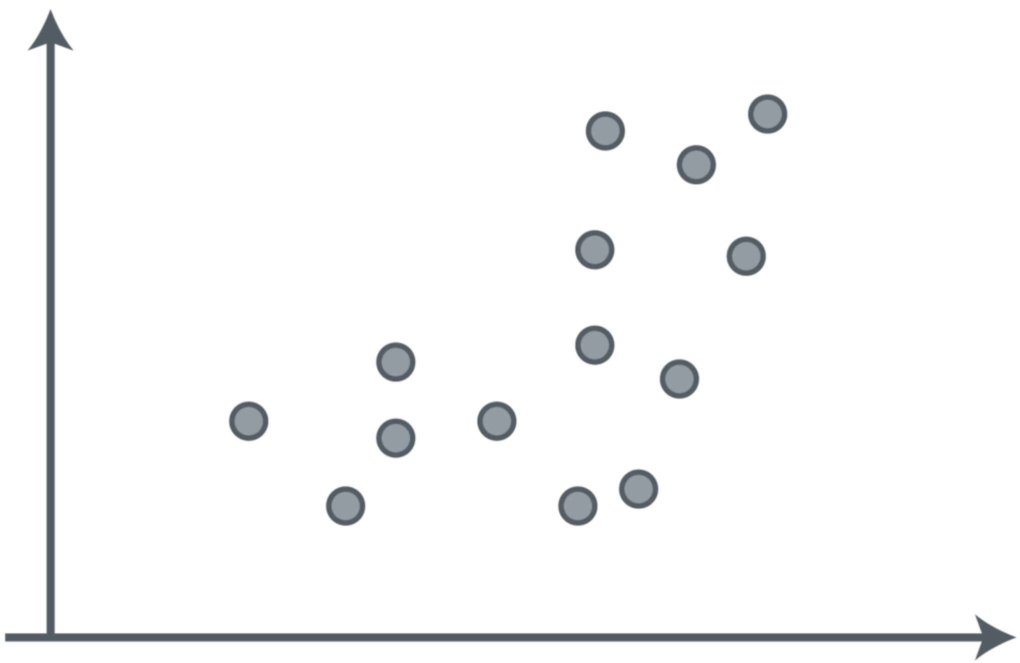
K-Means algorithm

FIN: Your Model Is Ready



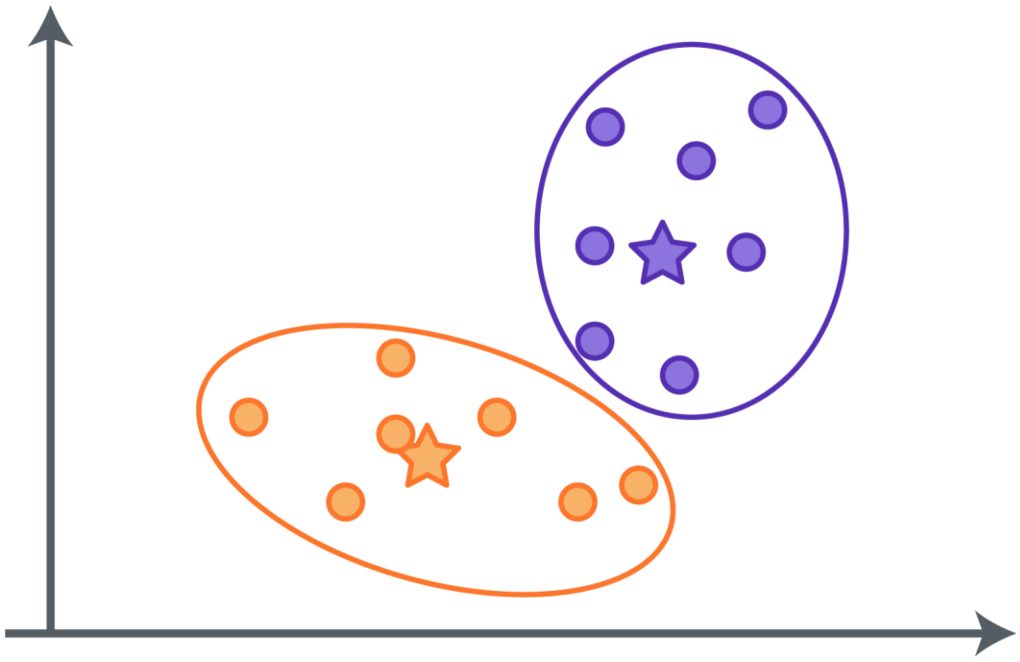
K-Means algorithm

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



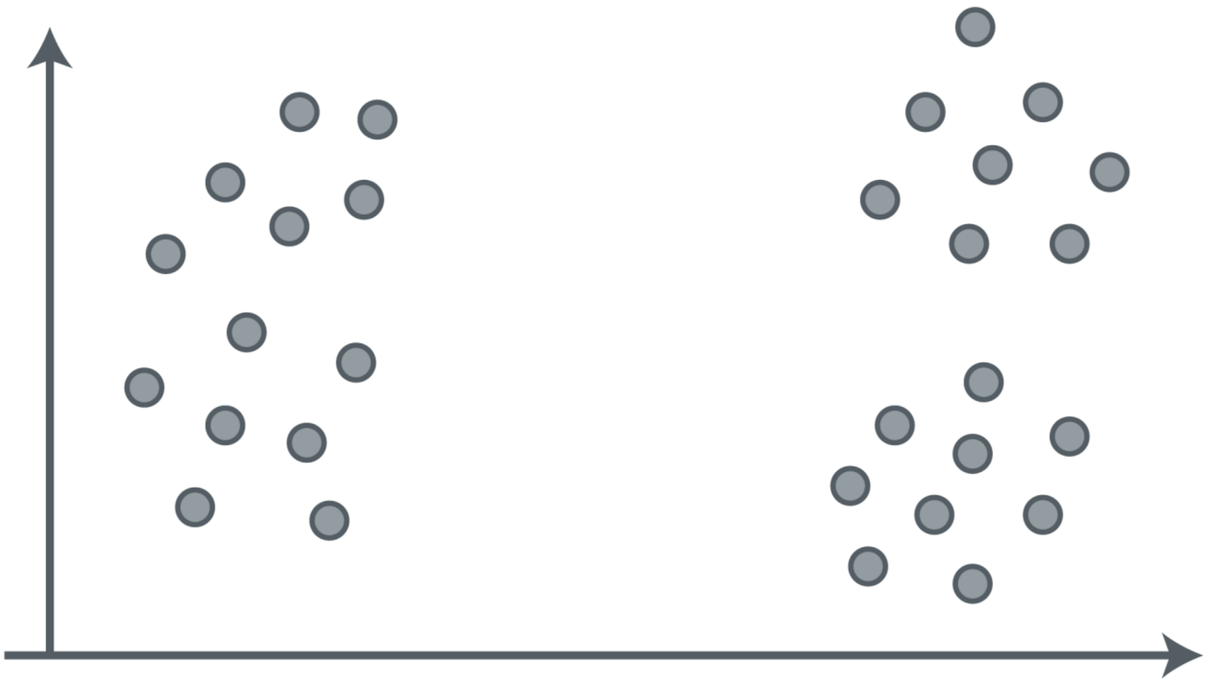
K-Means algorithm

FIN: Your Model Is Ready



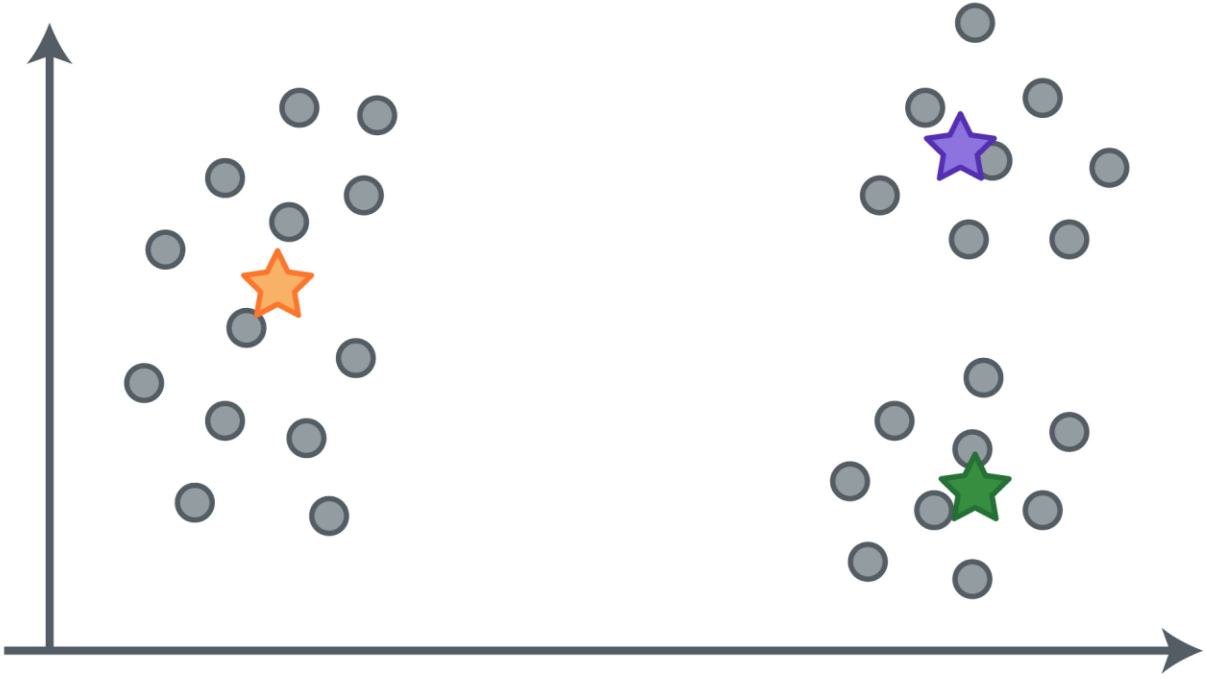
K-Means Intuition:
Random Initialization Trap

Random Initialization Trap



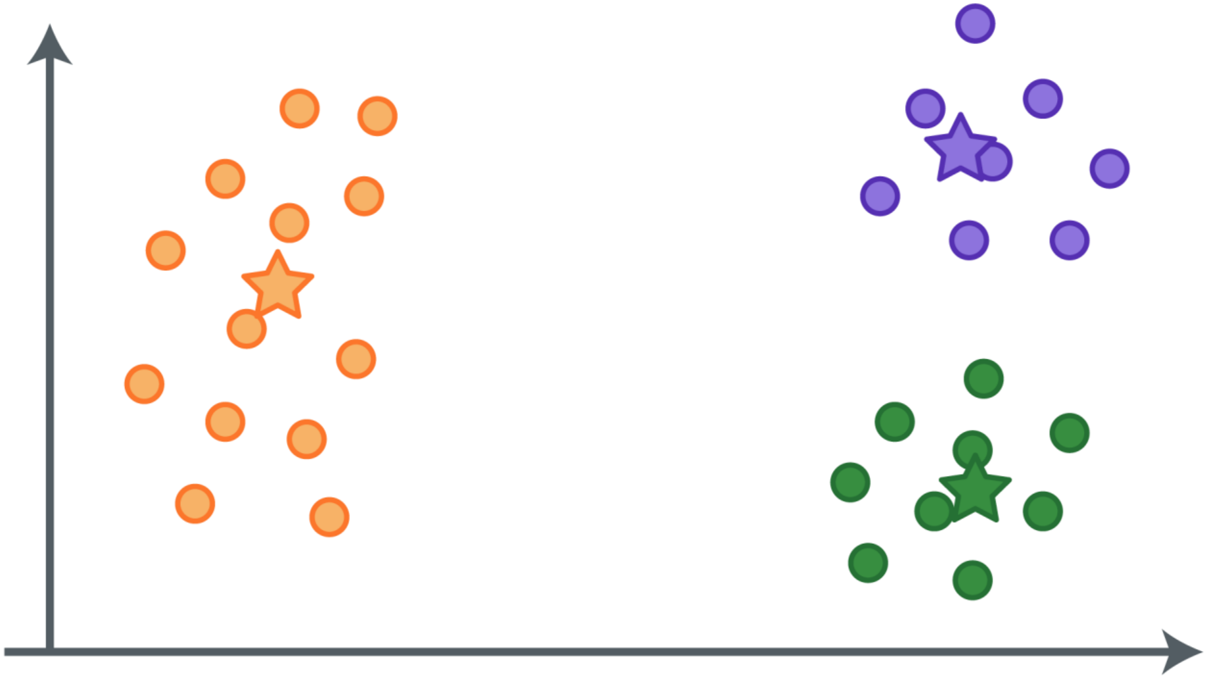
If we choose K = 3 clusters…

Random Initialization Trap



…this correct random initialization would lead us to…

Random Initialization Trap



…the following three clusters

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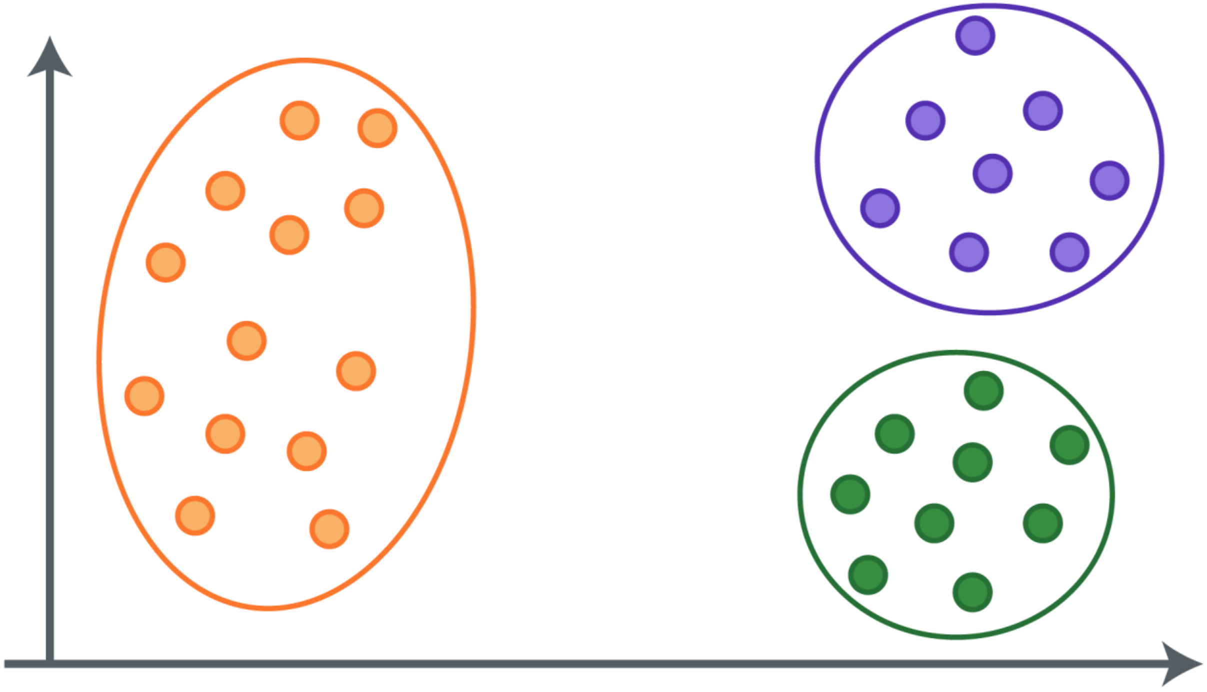

…the following three clusters

Random Initialization Trap

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

Random Initialization Trap

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Your Model is Ready

Random Initialization Trap

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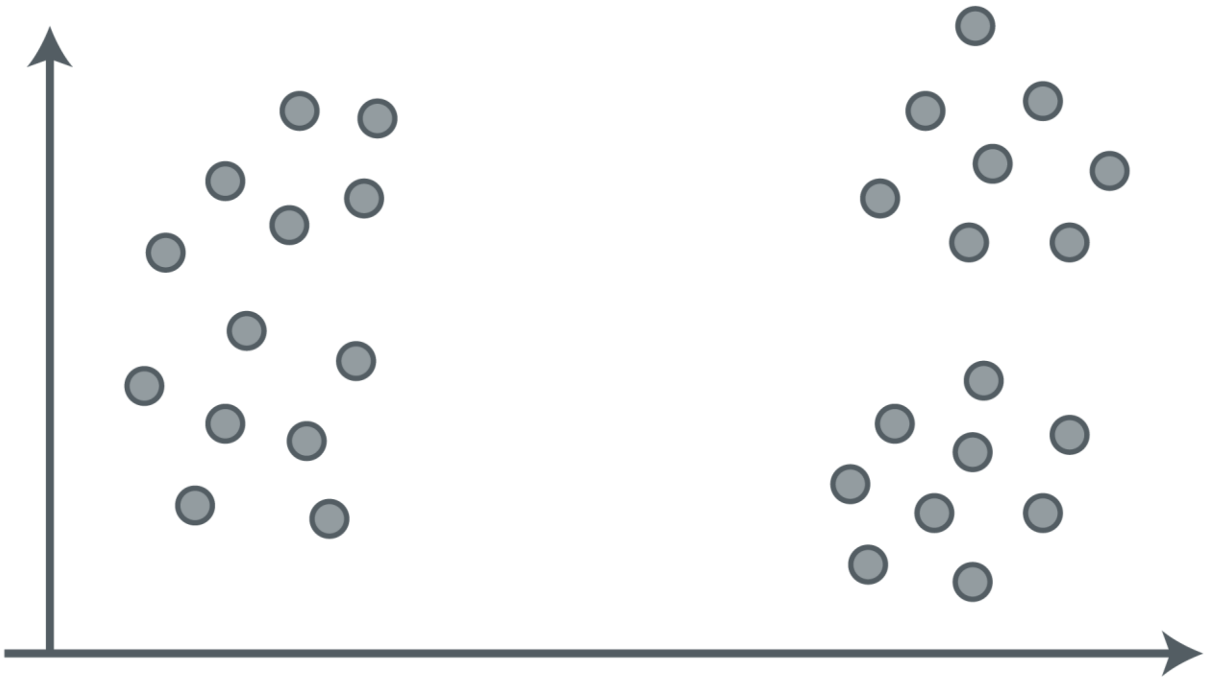

Random Initialization Trap

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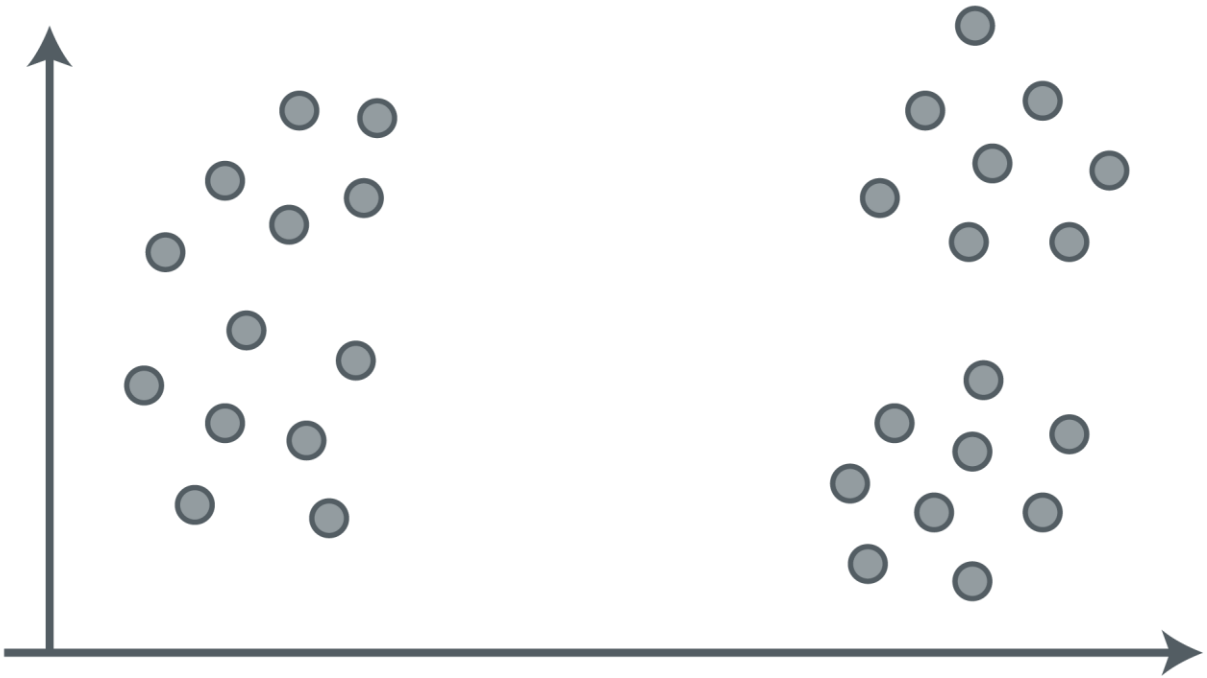

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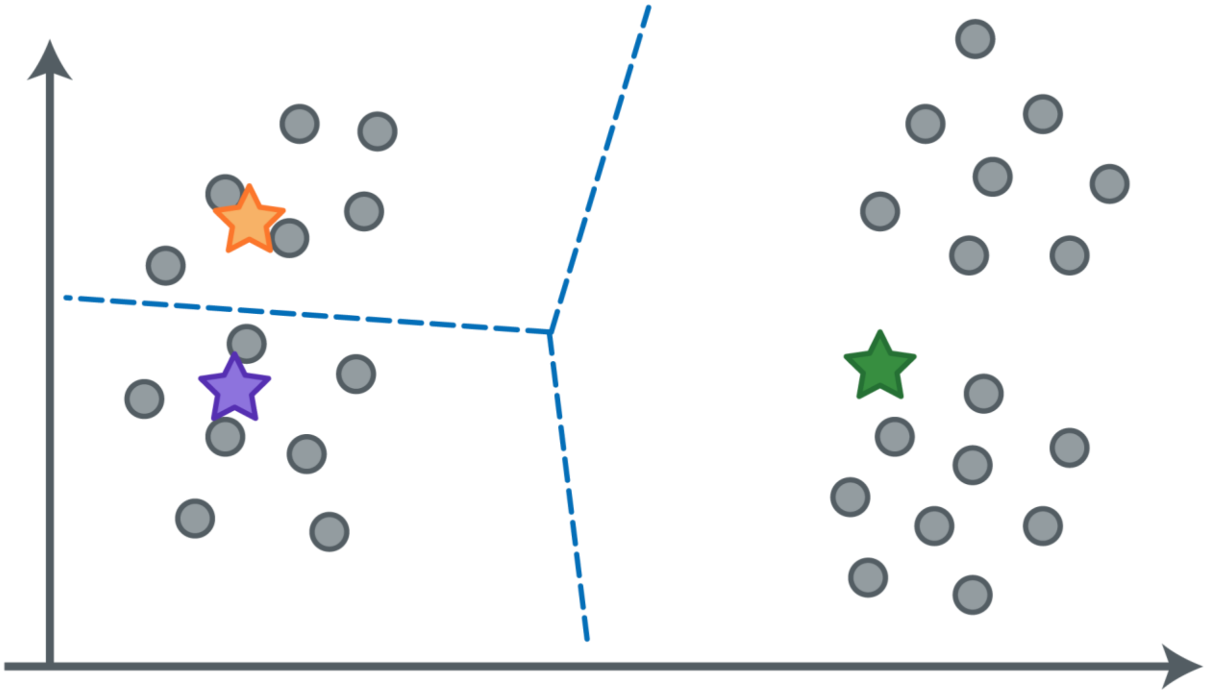
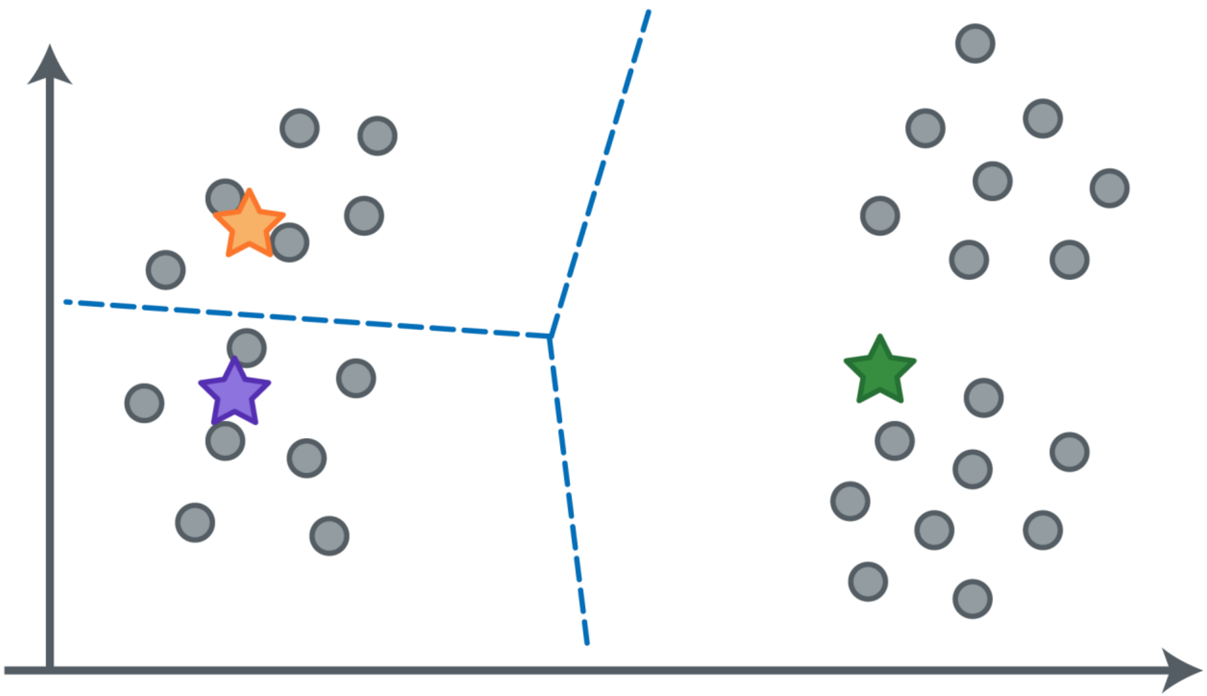


Random Initialization Trap

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



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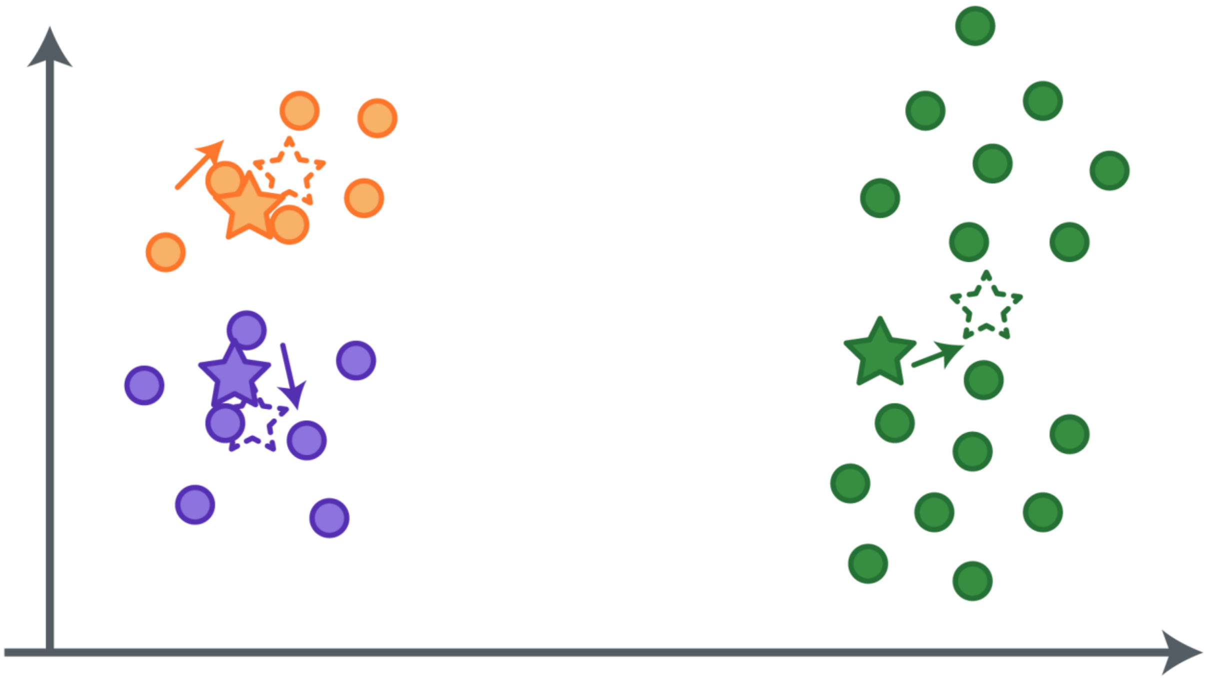

Random Initialization Trap

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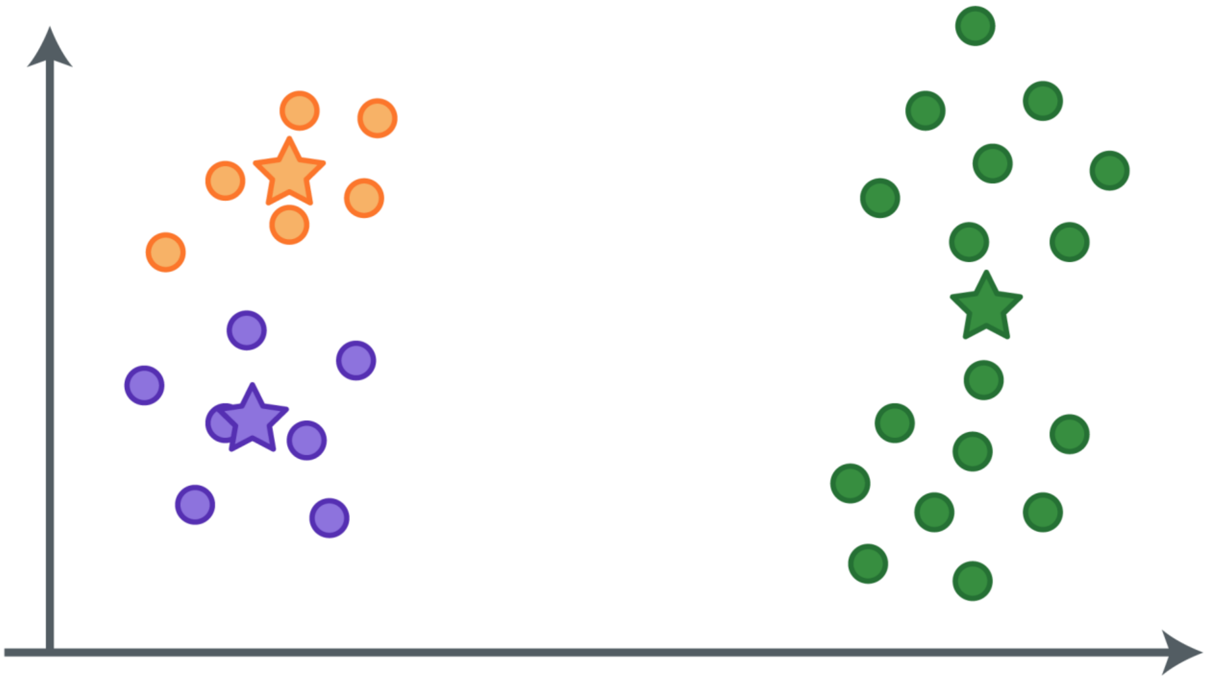

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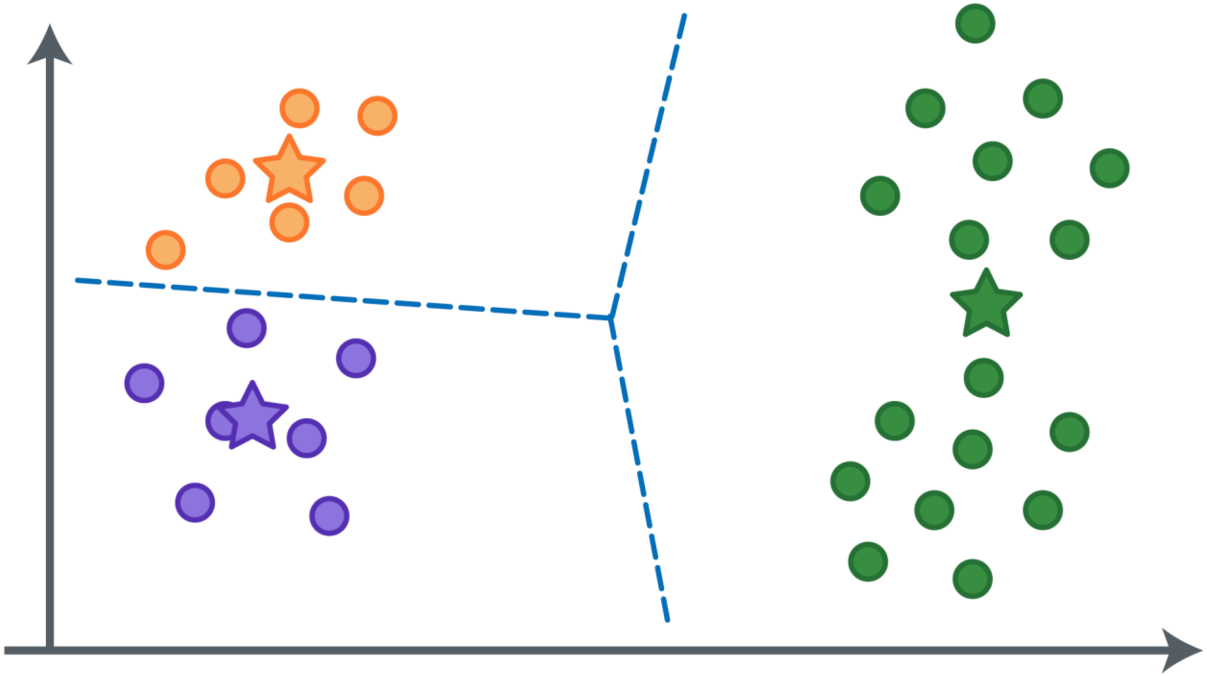

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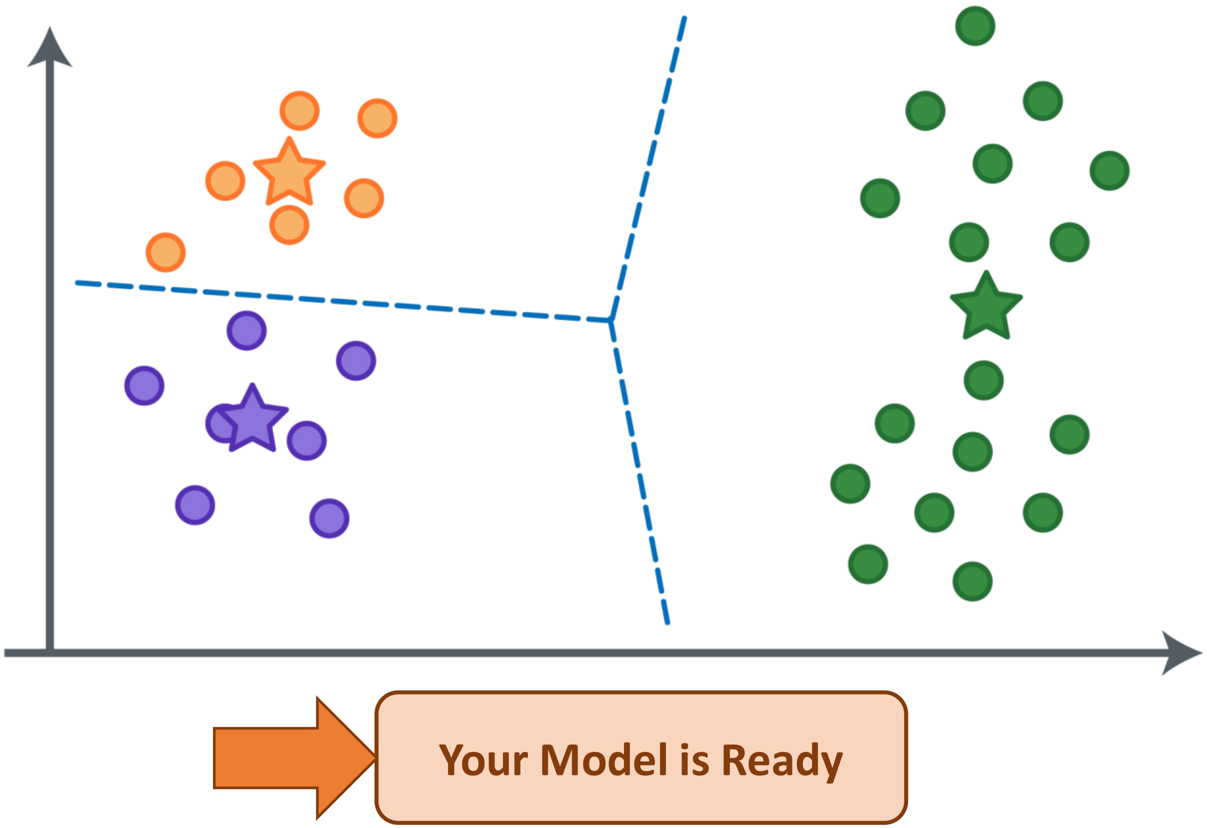

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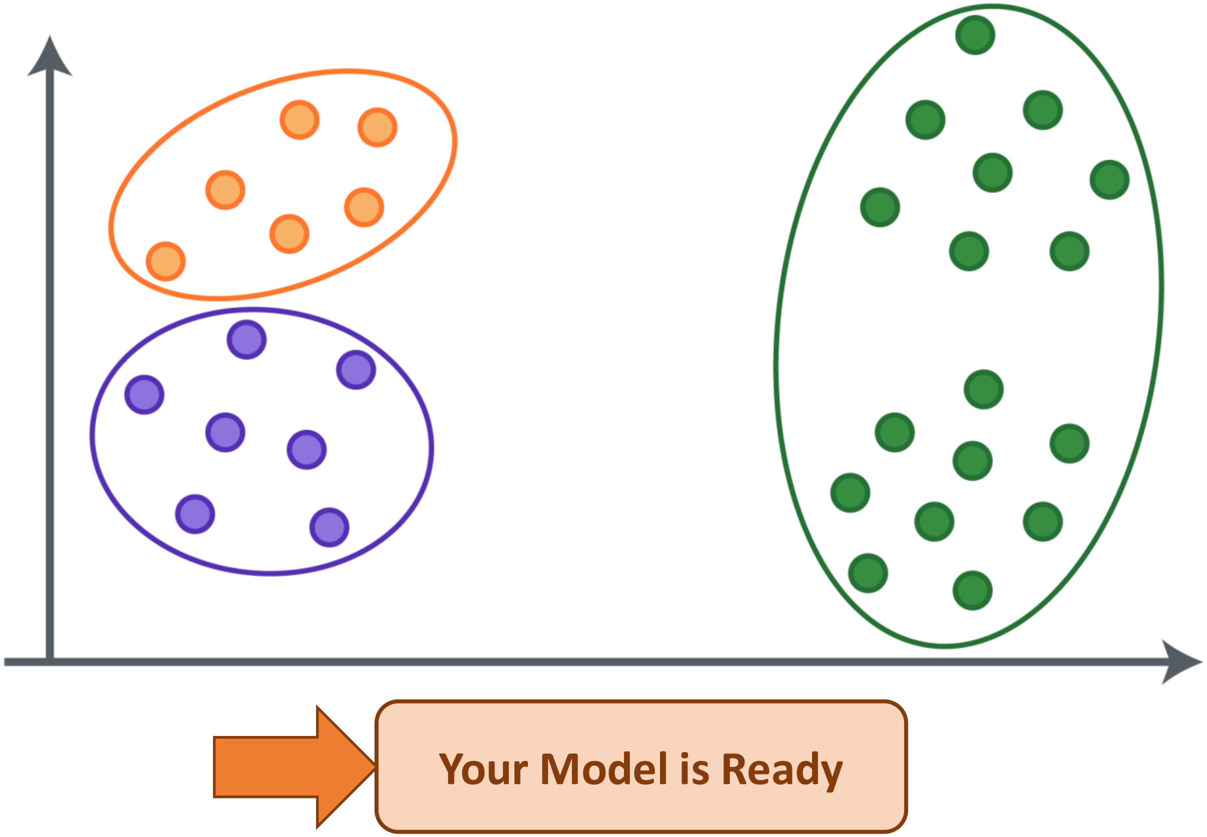

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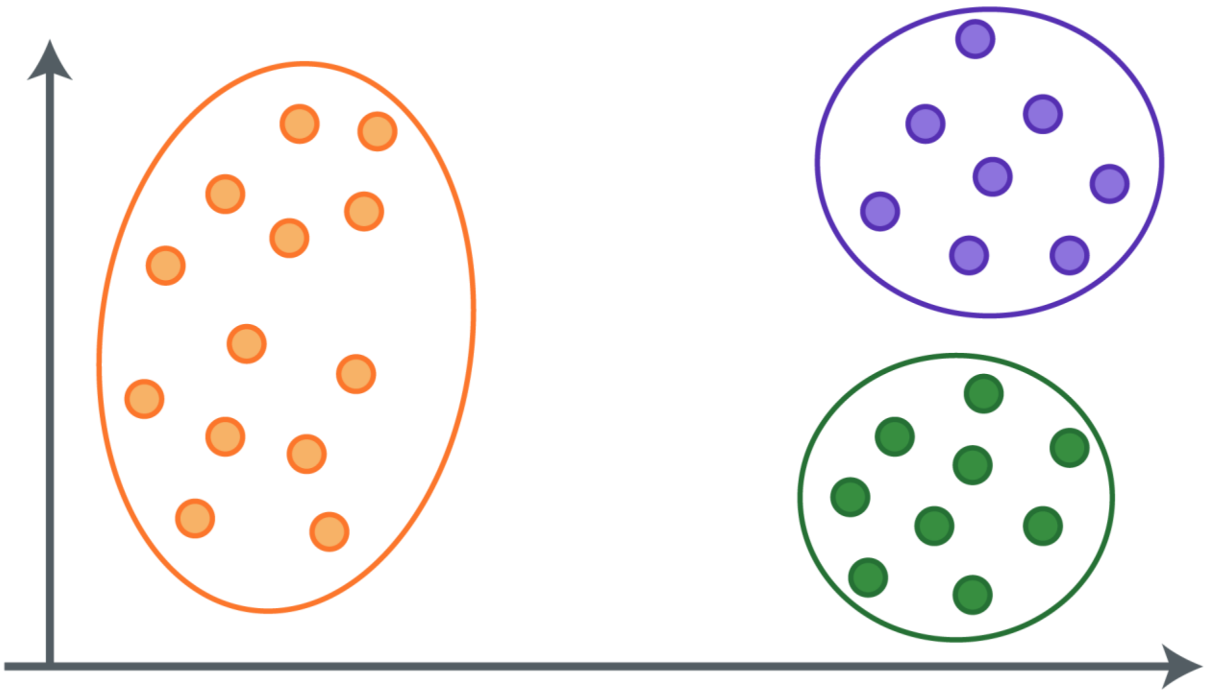

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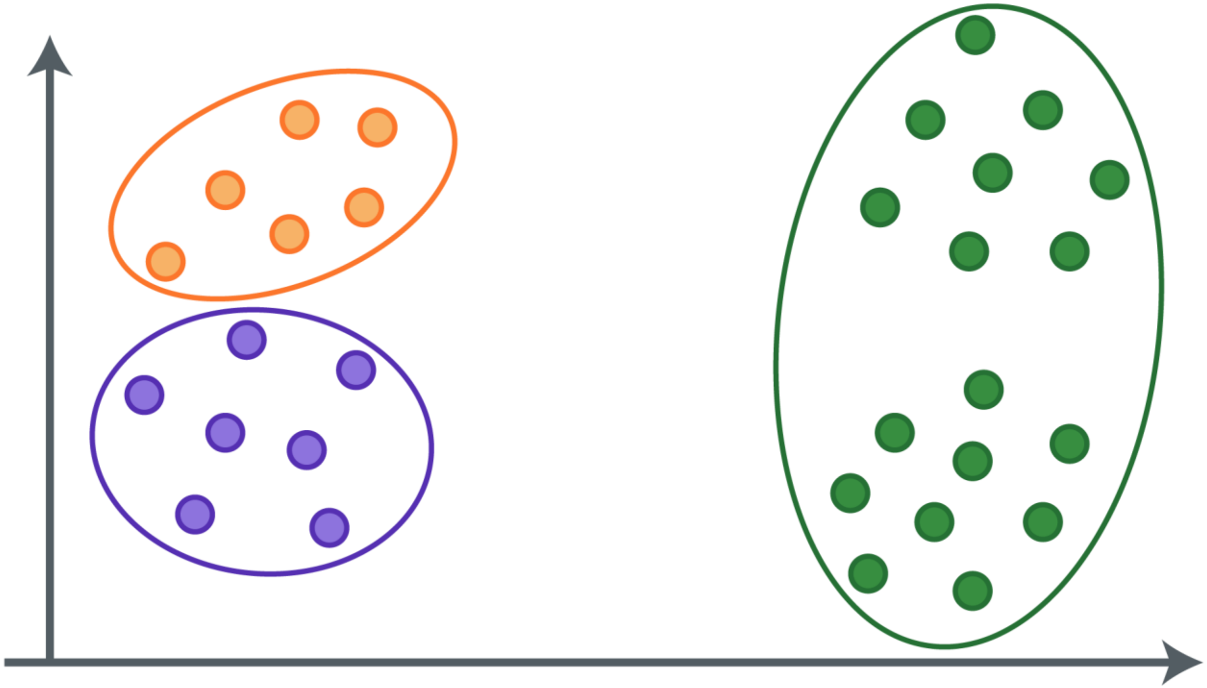
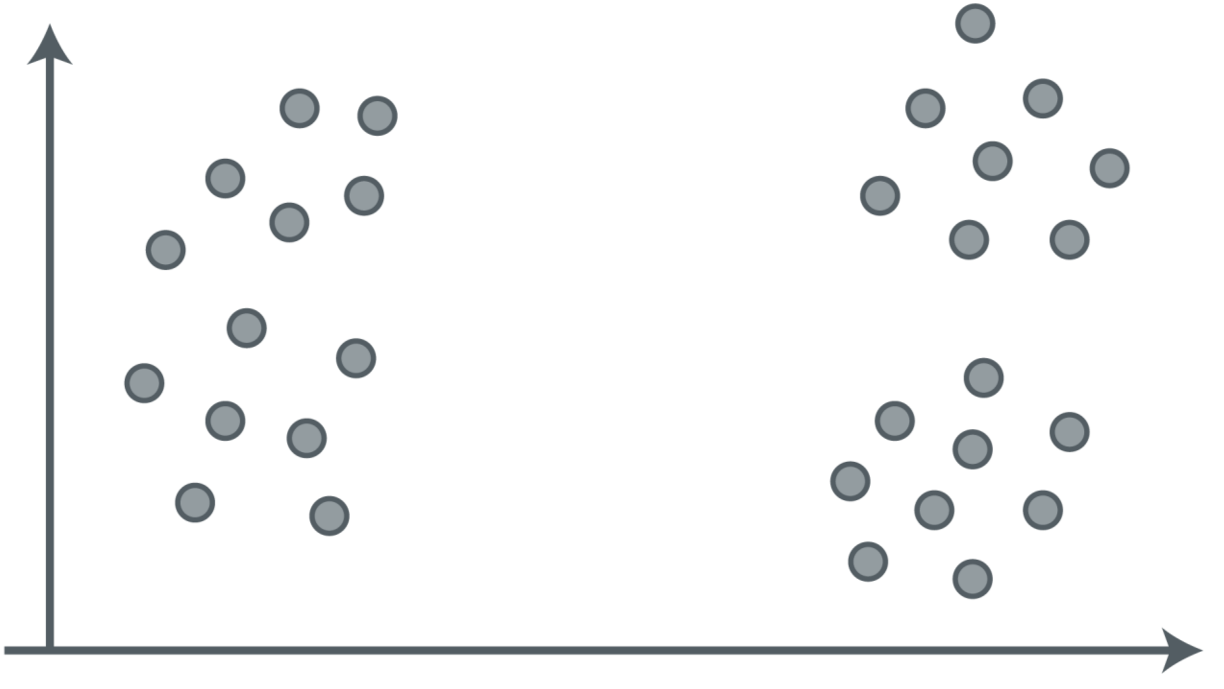


Random Initialization Trap

Solution → **K-Means++**

K-Means Intuition:
Choosing the right number of clusters

Choosing the right number of clusters



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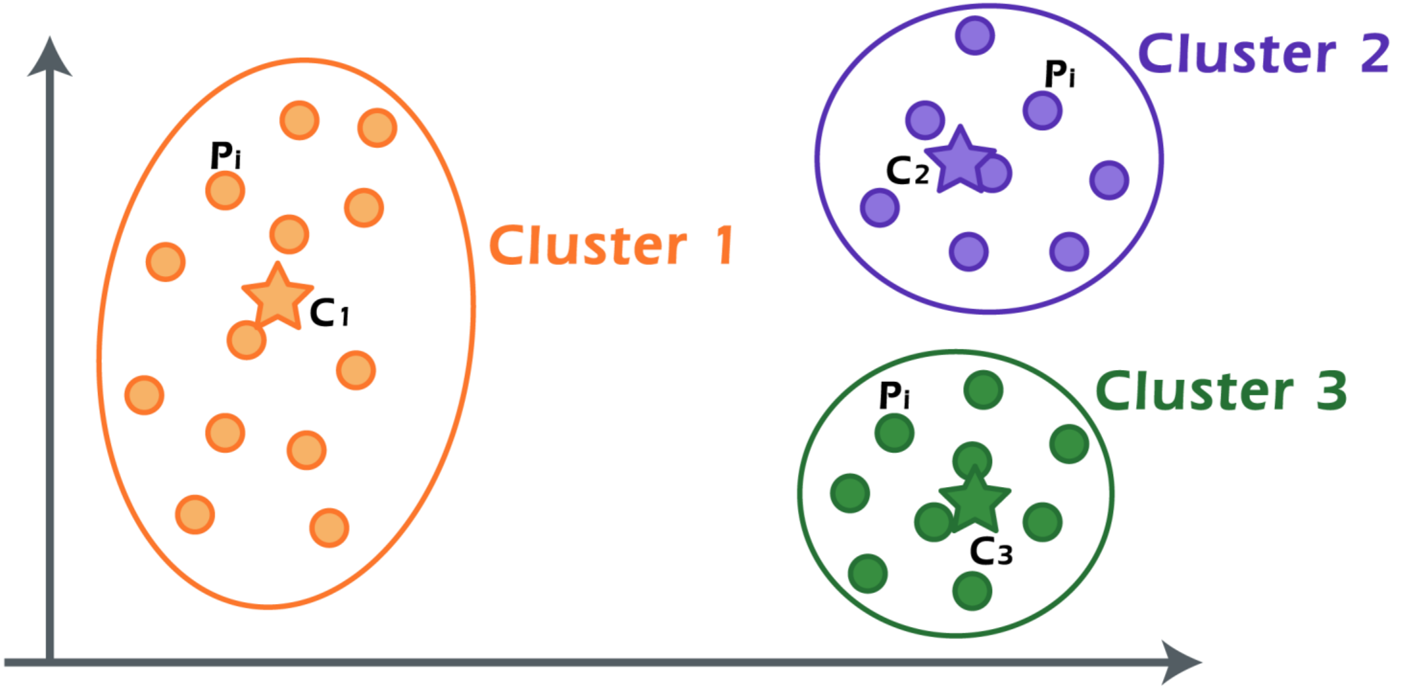

Choosing the right number of clusters

组内平方和

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

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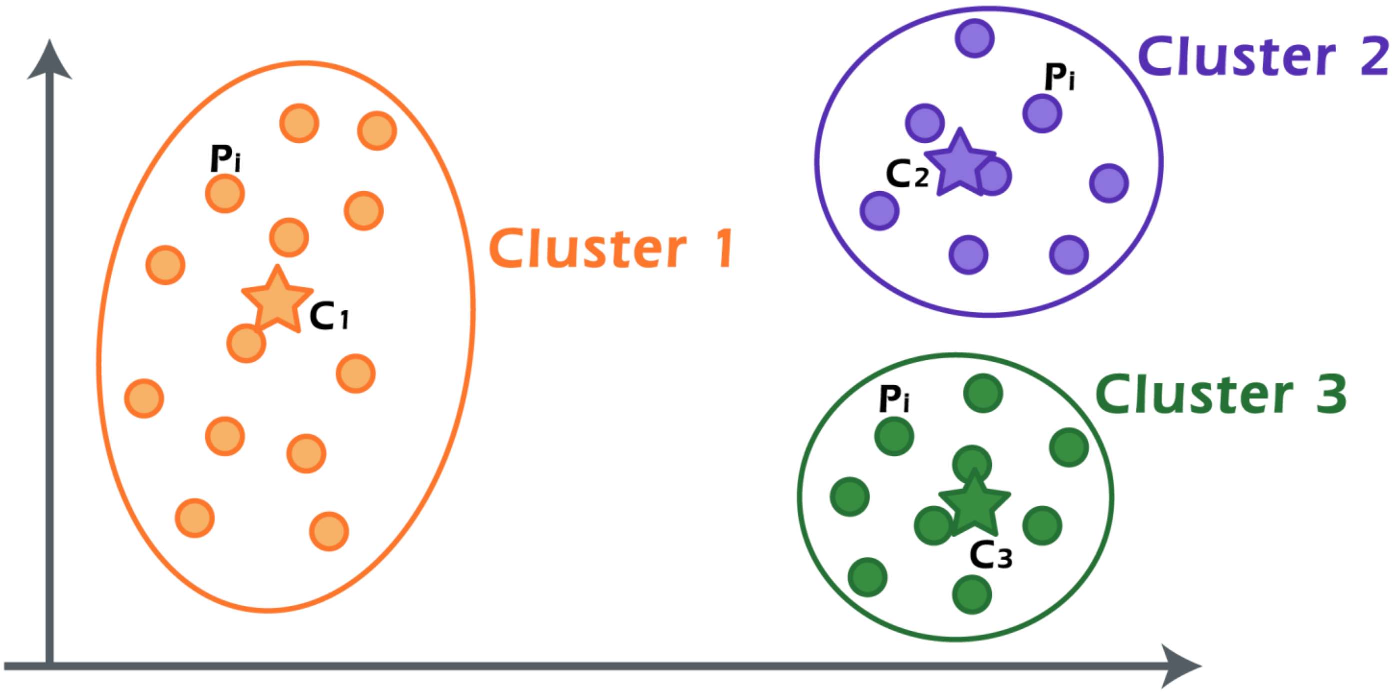

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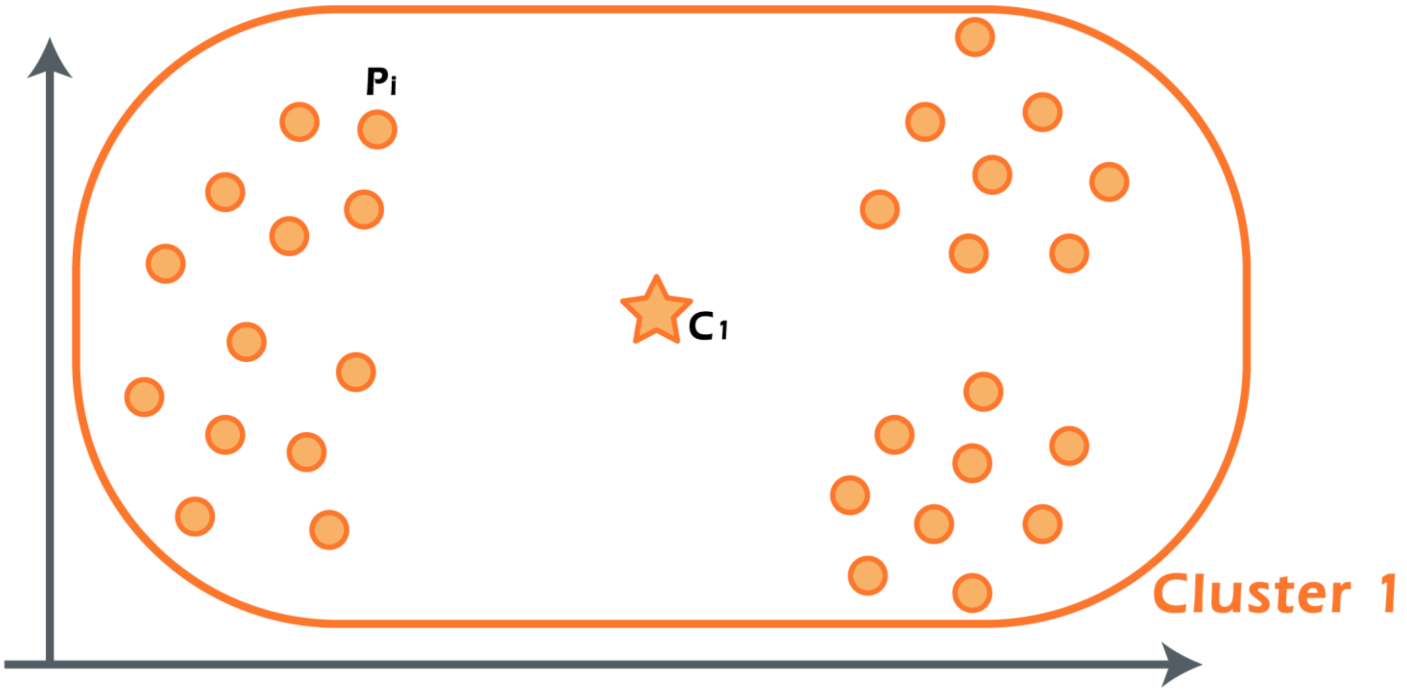

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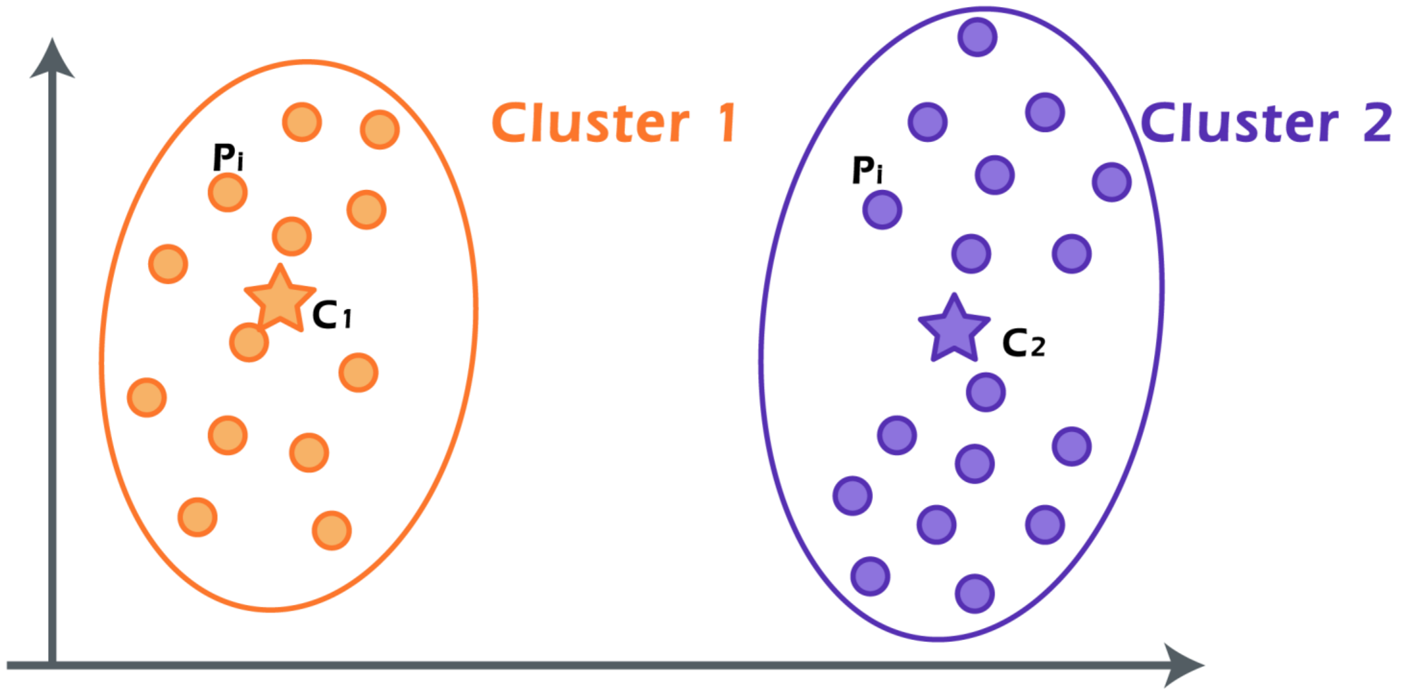
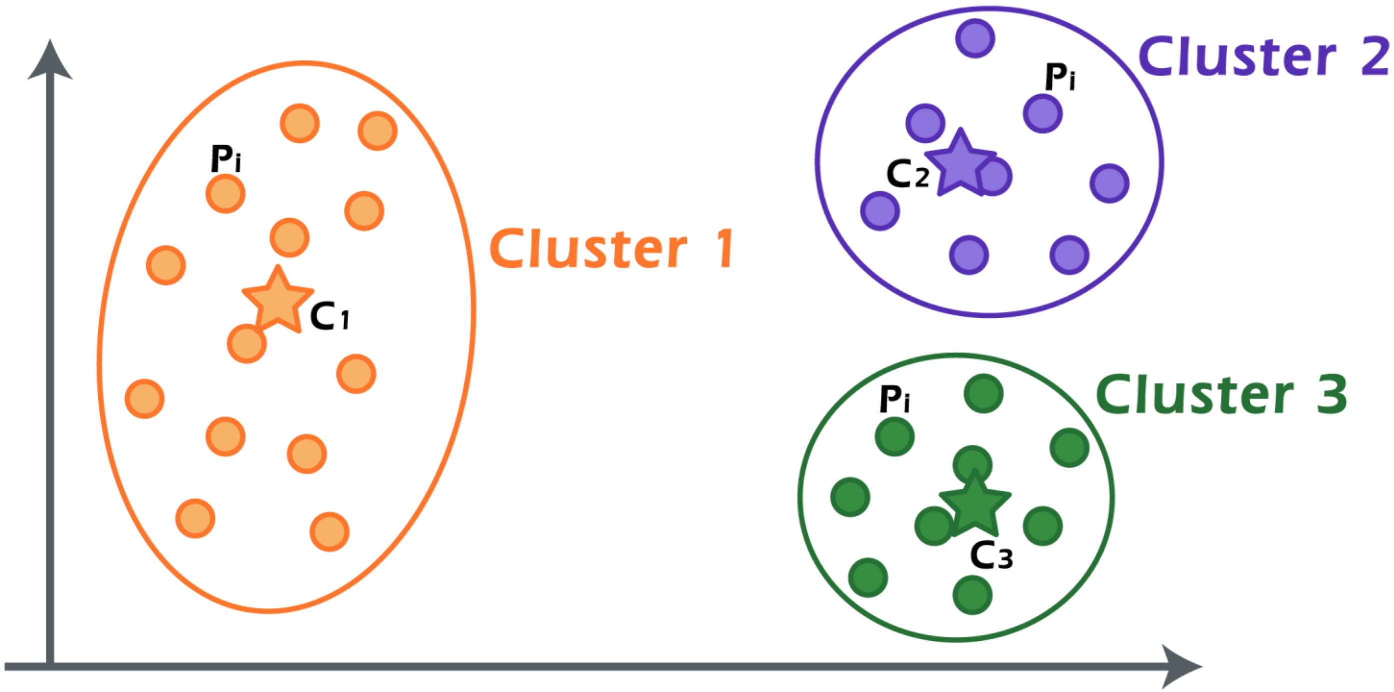


$$\mathrm{WCSS} = \sum_{P_i \text{ in Cluster 1}} \mathrm{distance}(P_i, C_1)^2 + \sum_{P_i \text{ in Cluster 2}} \mathrm{distance}(P_i, C_2)^2$$

Choosing the right number of clusters



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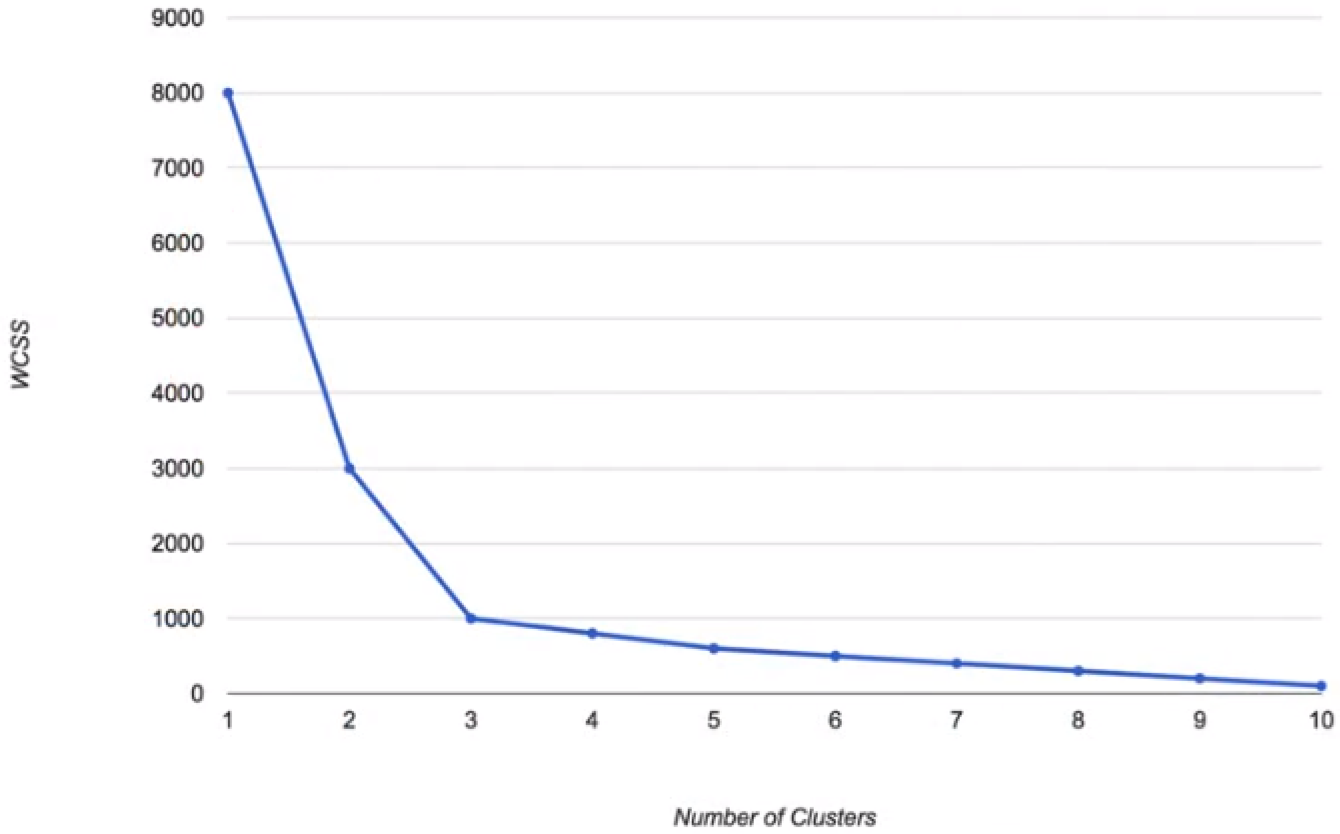
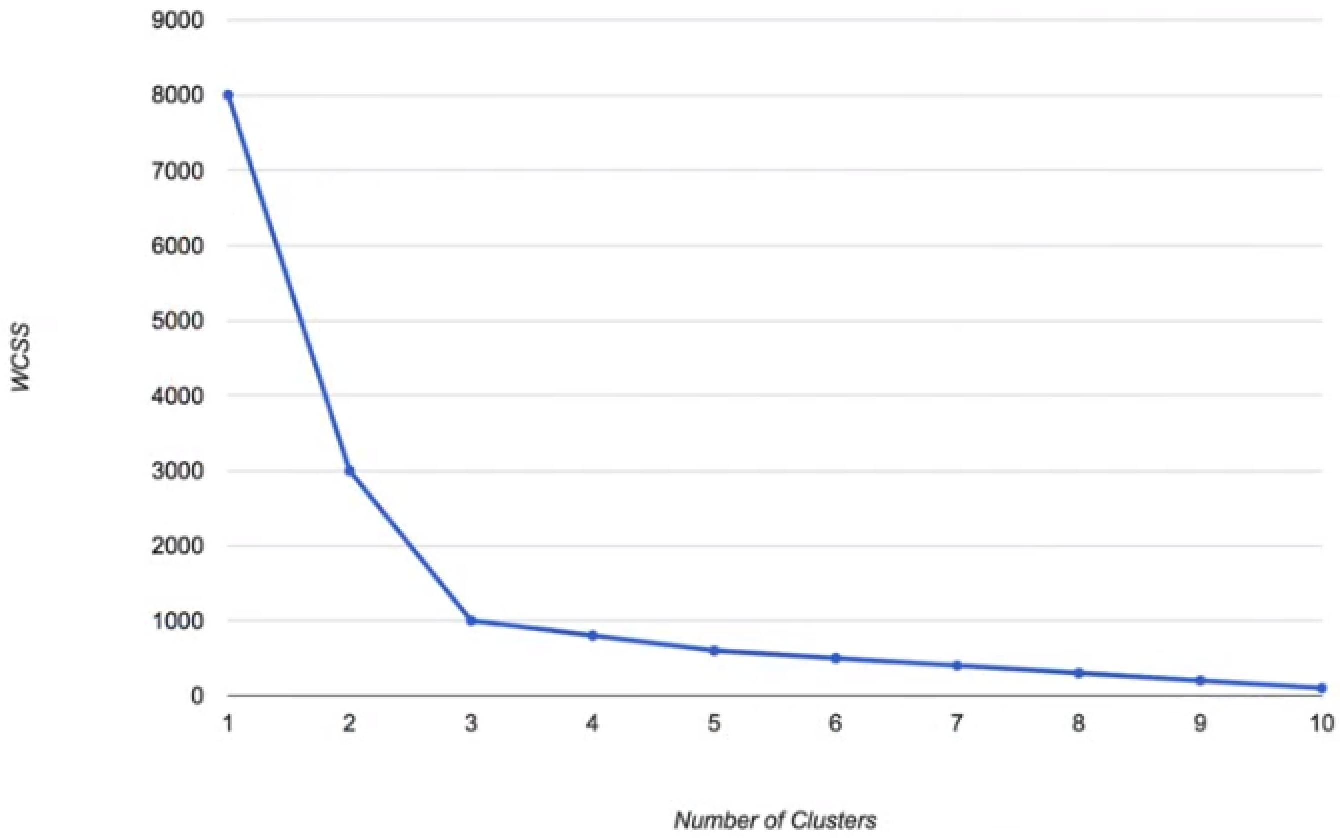
Choosing the right number of clusters



Choosing the right number of clusters

- The Elbow Method 手肘法則



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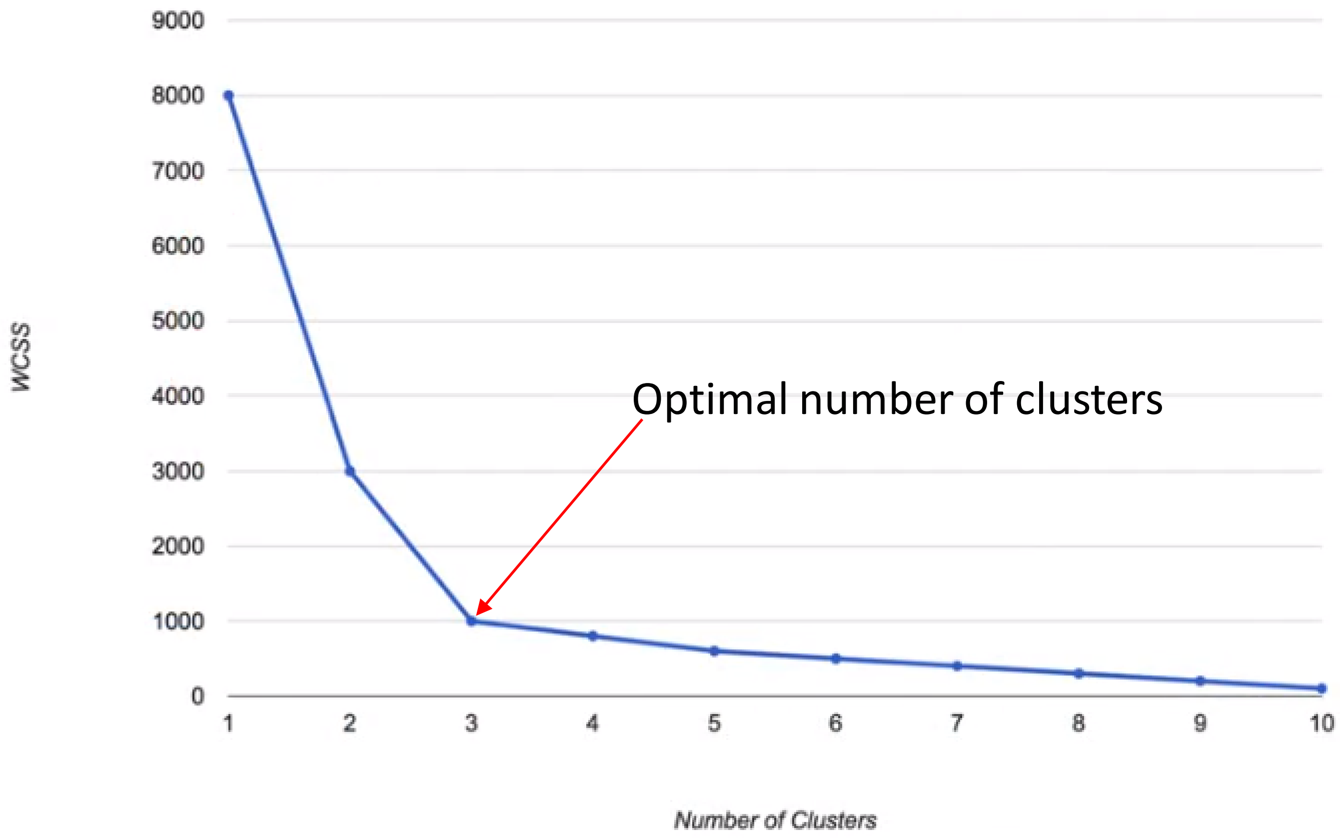

THE END

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