UNIT 5
K-MEANS CLUSTERING

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FOR THIS UNIT...

01
What is K-Means Clustering?

02
How does it work?

03
How to choose the optimal number of clusters?

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FOR THIS UNIT...

04

Applications

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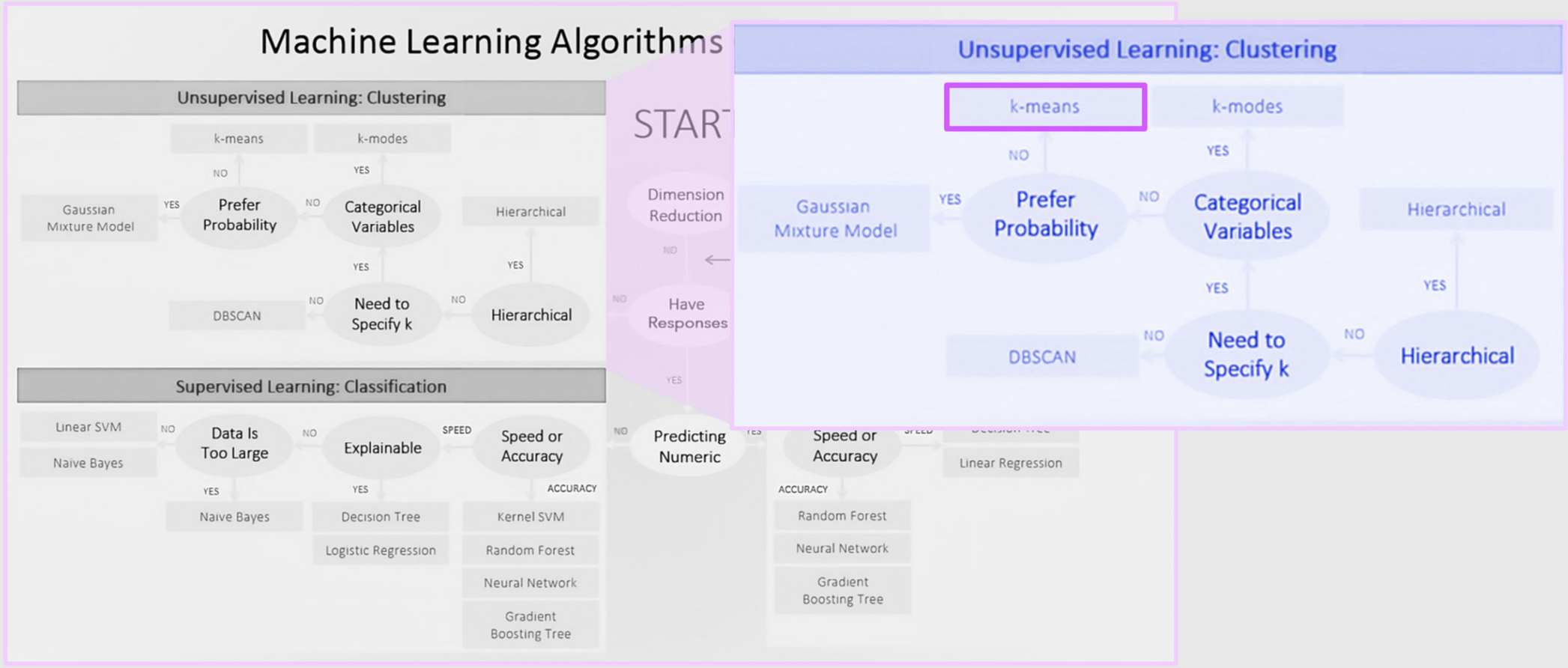
K-Means Clustering



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https://blogs.sas.com/content/subconsciousmusings/2020/12/09/machine-learning-algorithm-use

K-Means Clustering

An unsupervised learning algorithm used for data clustering, which groups unlabeled data points into groups or clusters.

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https://www.ibm.com/topics/k-means-clustering

K-Means Clustering

Petal Width	Petal Length	Iris Plant
5.8	2.2	Iris-virginica
1.5	0.2	Iris-setosa
4.9	1.5	Iris-versicolor
1.4	0.3	Iris-setosa
4.3	1.3	Iris-versicolor
5.6	1.8	Iris-virginica
5.4	2.3	Iris-virginica
4.2	1.2	Iris-versicolor
4.1	1.3	Iris-versicolor
5.8	2.2	Iris-virginica

Petal Width	Petal Length	Iris Plant
4.0	1.3	Iris-versicolor
1.4	0.2	Iris-setosa
1.4	0.2	Iris-setosa
1.3	0.2	Iris-setosa
1.4	0.2	Iris-setosa
5.0	1.9	Iris-virginica
1.5	0.2	Iris-setosa
1.4	0.2	Iris-setosa
4.5	1.5	Iris-versicolor
6.0	2.5	Iris-virginica

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1.4	0.2	Iris-setosa
1.6	0.2	Iris-setosa
3.0	1.1	Iris-versicolor
4.2	1.3	Iris-versicolor
5.2	2.3	Iris-virginica
5.1	1.8	Iris-virginica
5.1	1.9	Iris-virginica
4.7	1.4	Iris-versicolor

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https://archive.ics.uci.edu/dataset/53/iris

K-Means Clustering

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5.4	2.3	Iris-virginica
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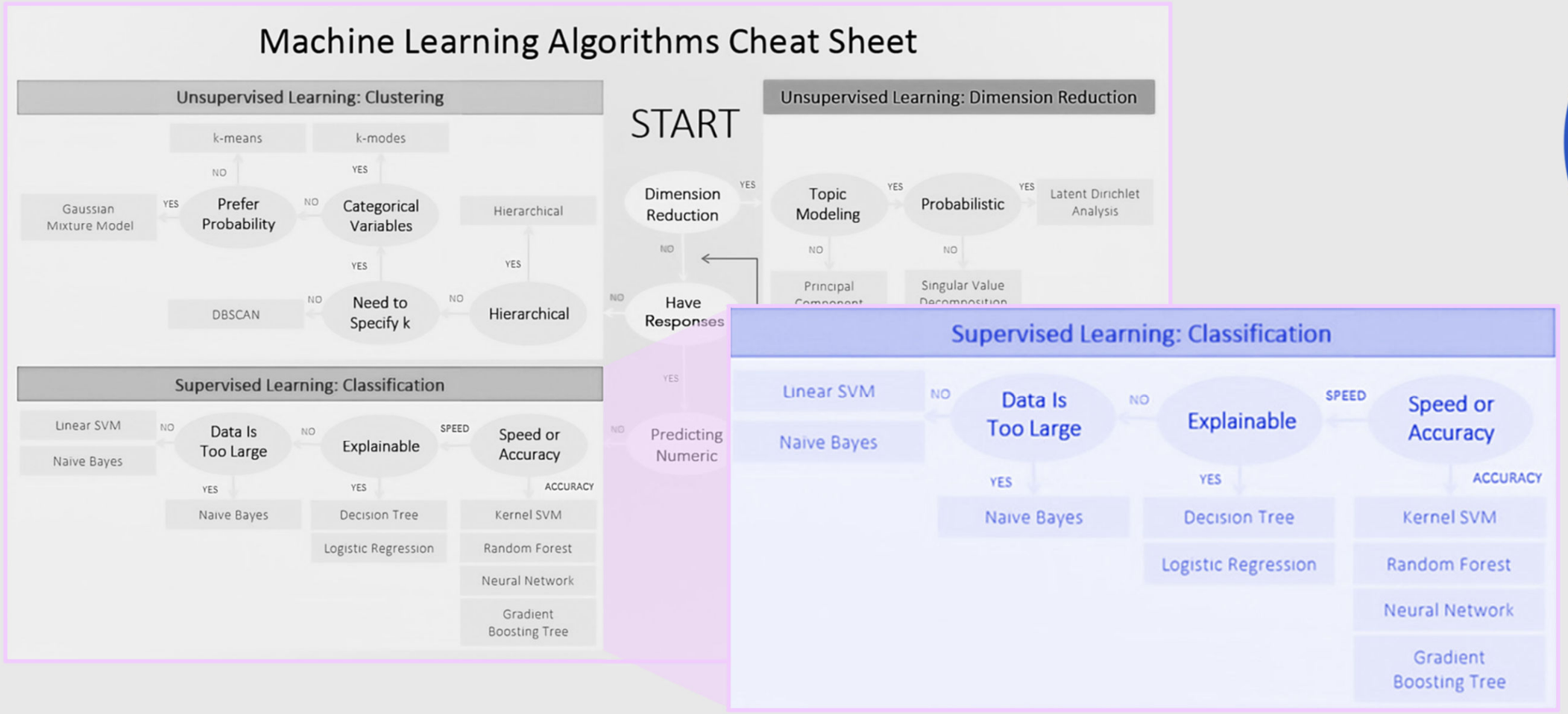
https://archive.ics.uci.edu/dataset/53/iris

Classification Algorithms



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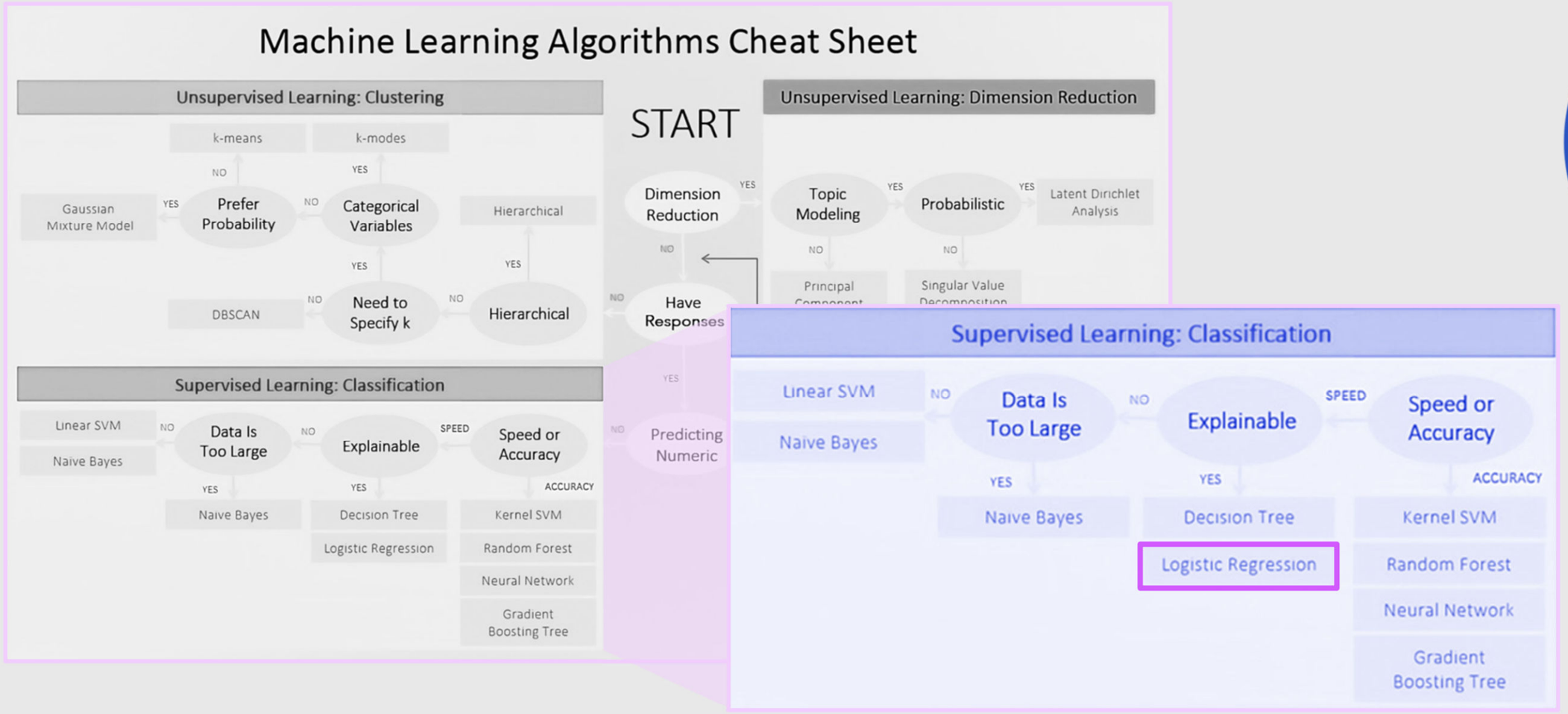
Classification Algorithms



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K-Means Clustering

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K-Means Clustering

Petal Width	Petal Length
5.8	2.2
1.5	0.2
4.9	1.5
1.4	0.3
4.3	1.3
5.6	1.8
5.4	2.3
4.2	1.2
4.1	1.3
5.8	2.2

Petal Width	Petal Length
4.0	1.3
1.4	0.2
1.4	0.2
1.3	0.2
1.4	0.2
5.0	1.9
1.5	0.2
1.4	0.2
4.5	1.5
6.0	2.5

Petal Width	Petal Length
5.9	2.1
5.2	2.0
1.4	0.2
1.6	0.2
3.0	1.1
4.2	1.3
5.2	2.3
5.1	1.8
5.1	1.9
4.7	1.4

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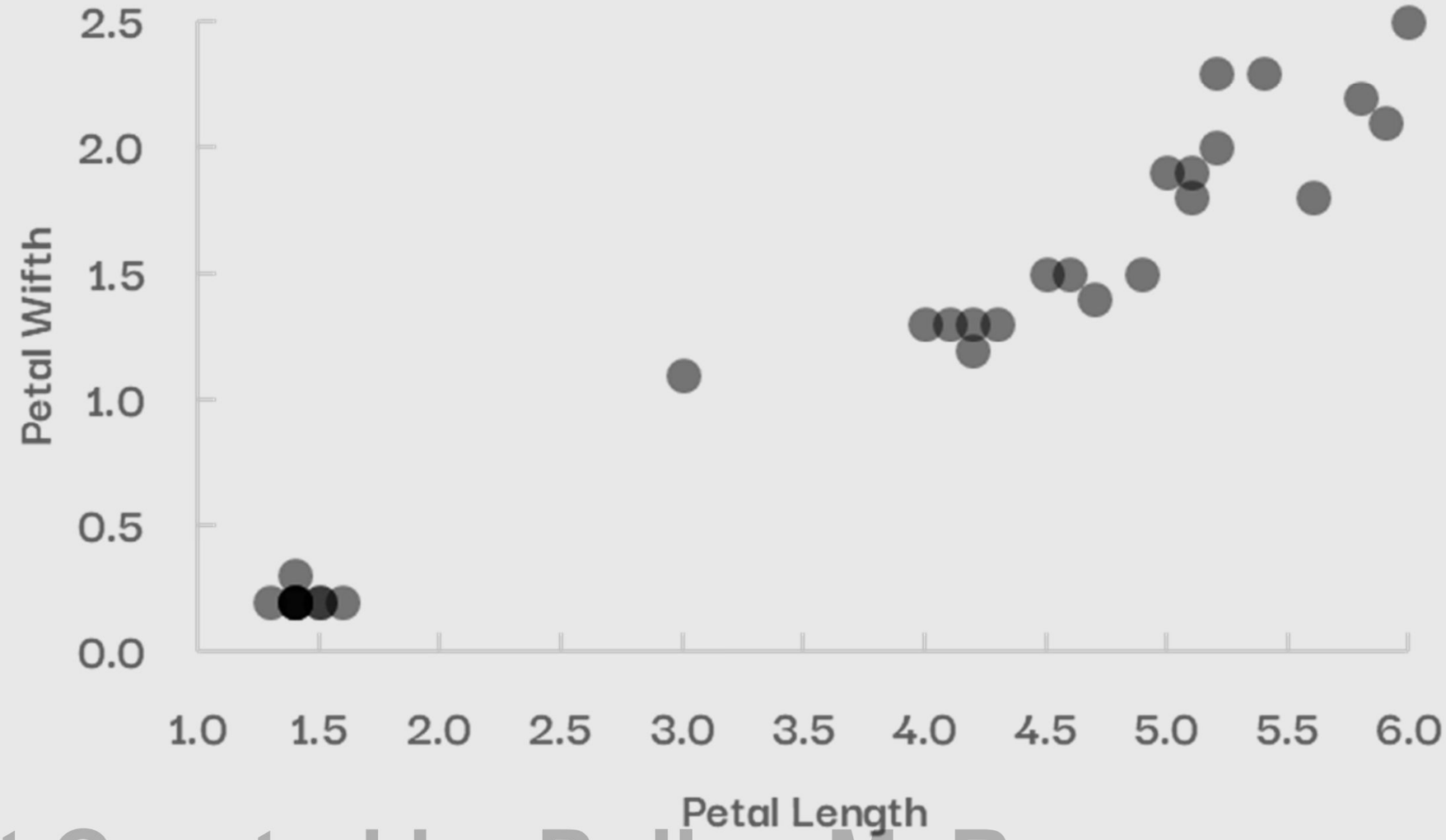
K-Means Clustering



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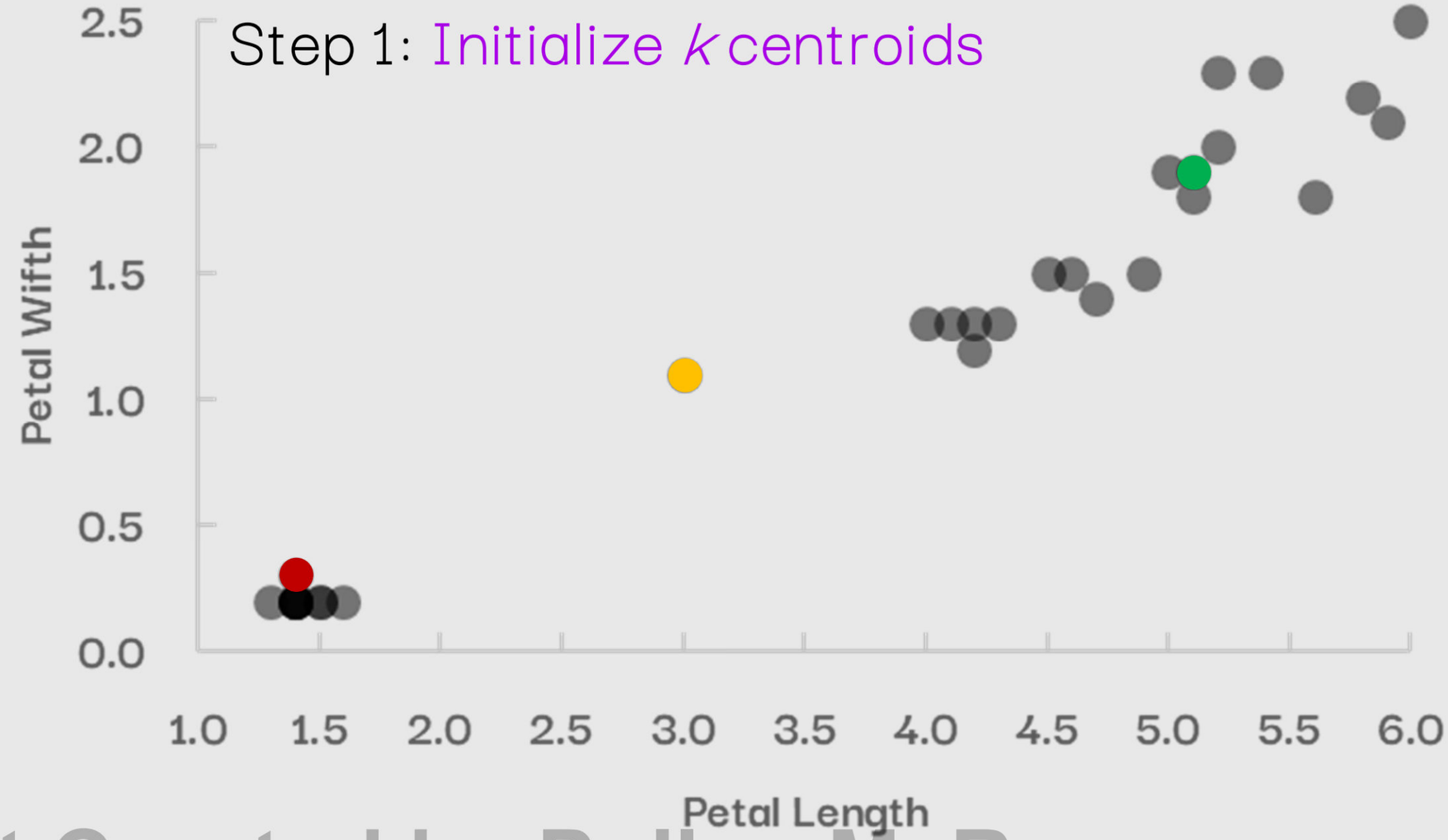
K-Means Clustering



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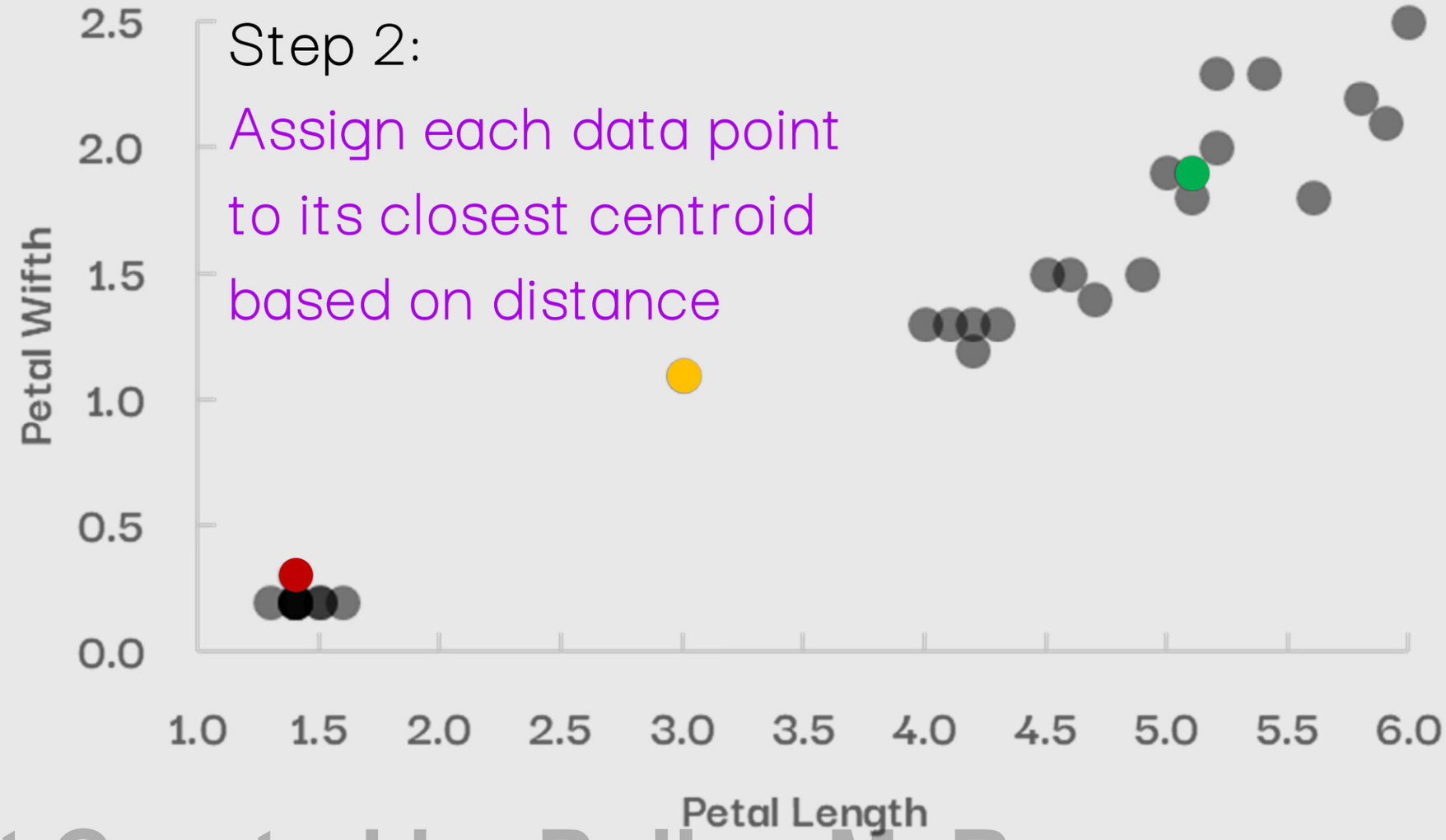
K-Means Clustering



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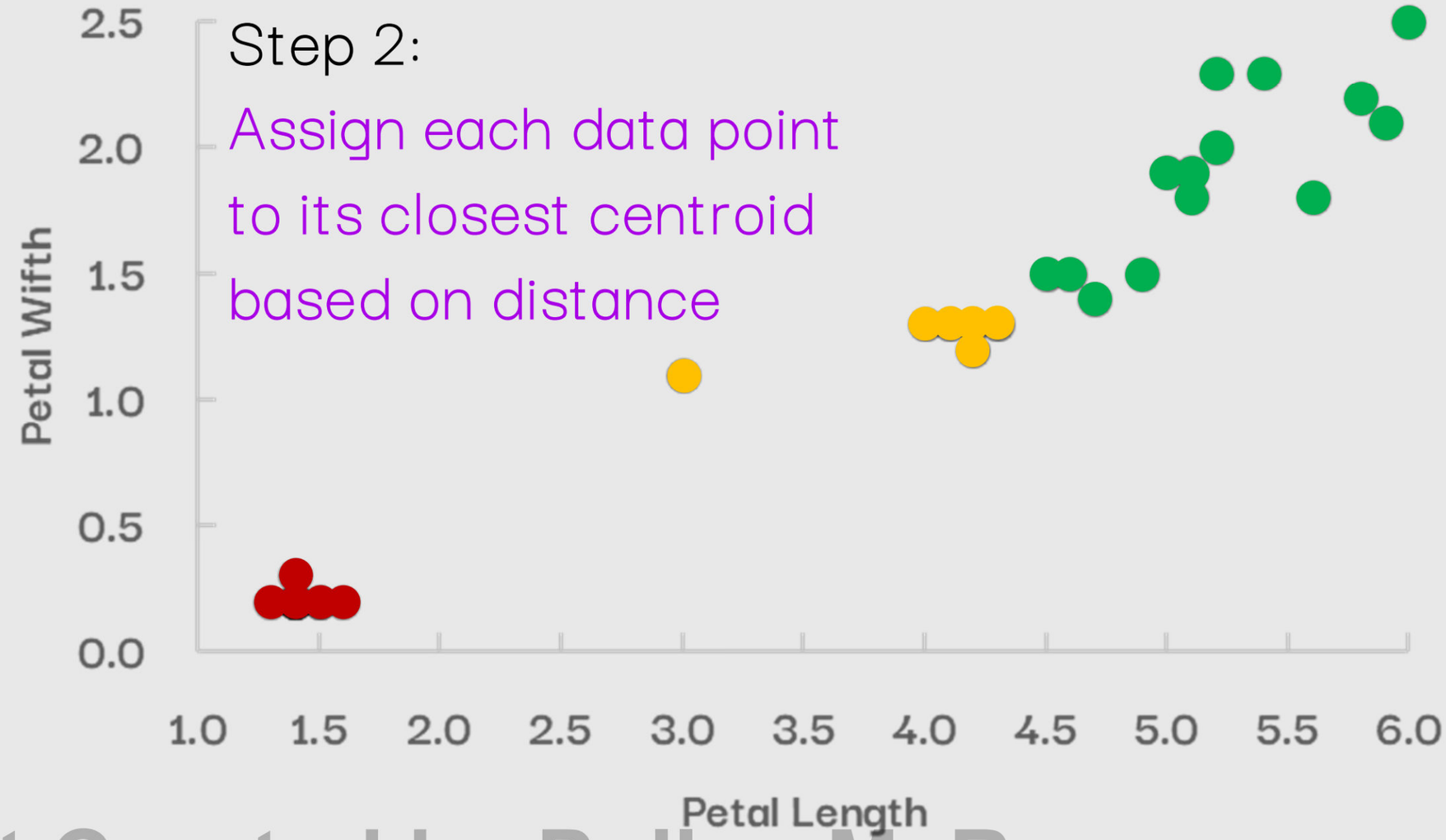
K-Means Clustering



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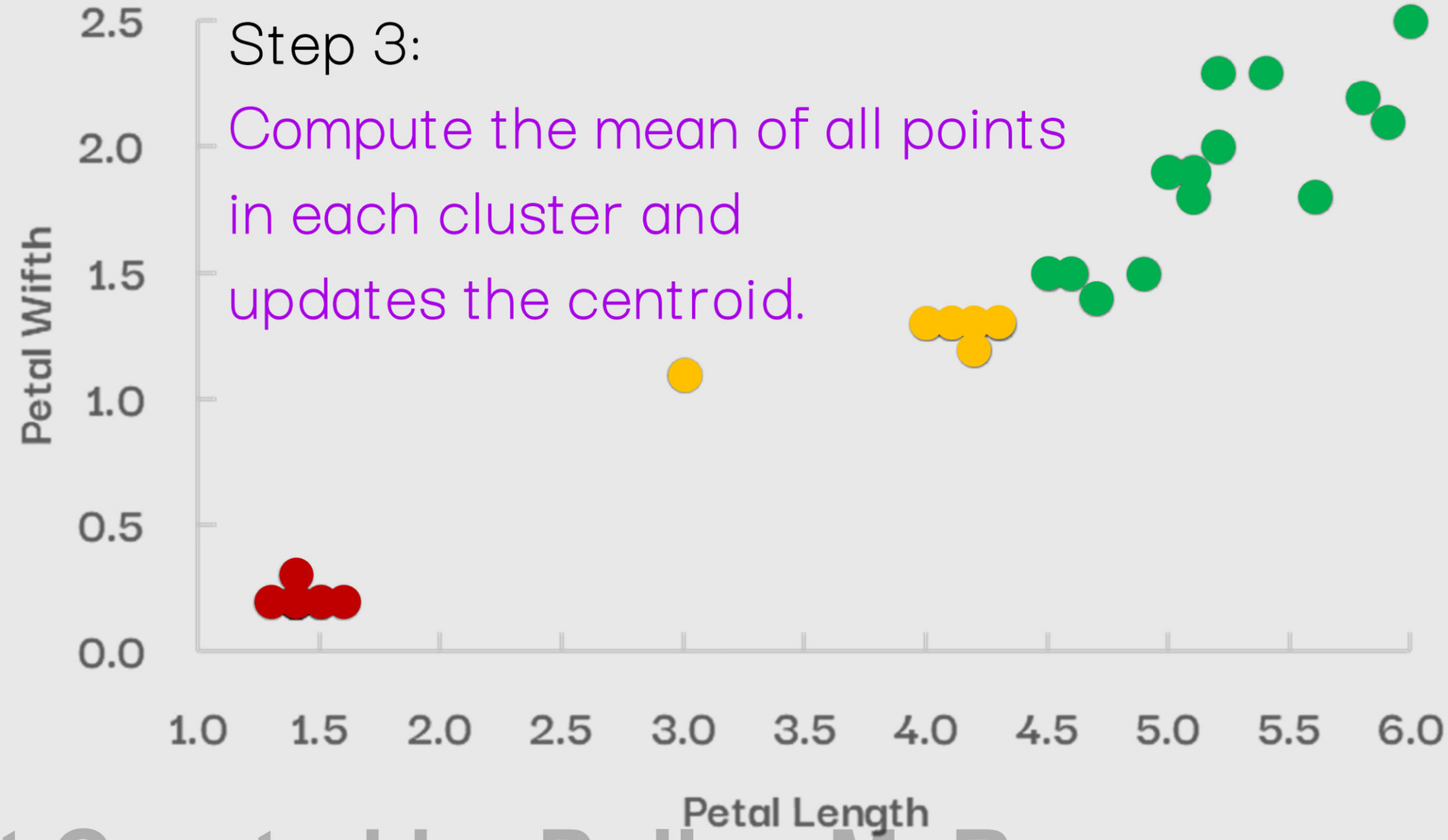
K-Means Clustering



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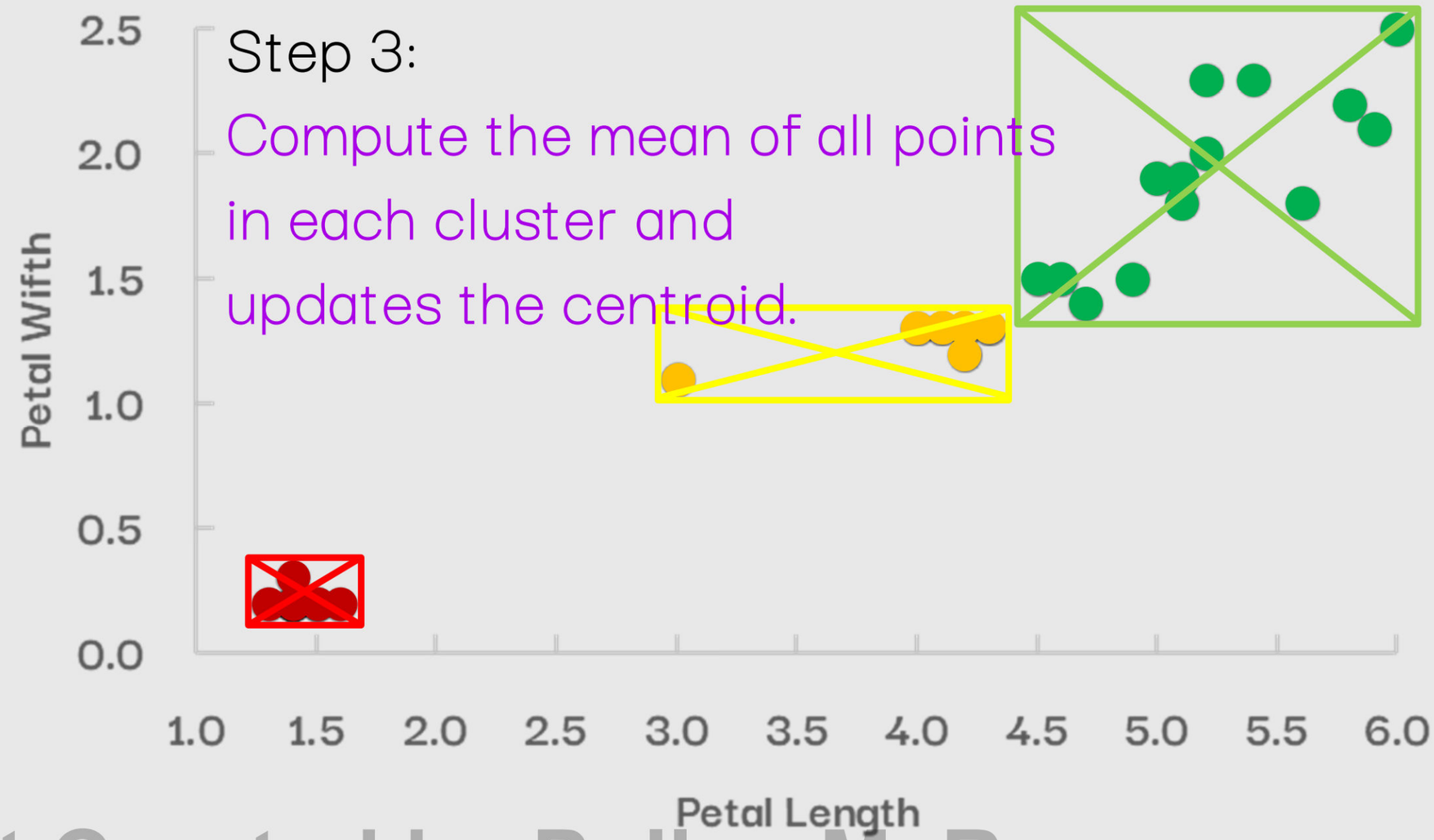
K-Means Clustering

Step 3:

Compute the mean of all points in each cluster and updates the centroid.



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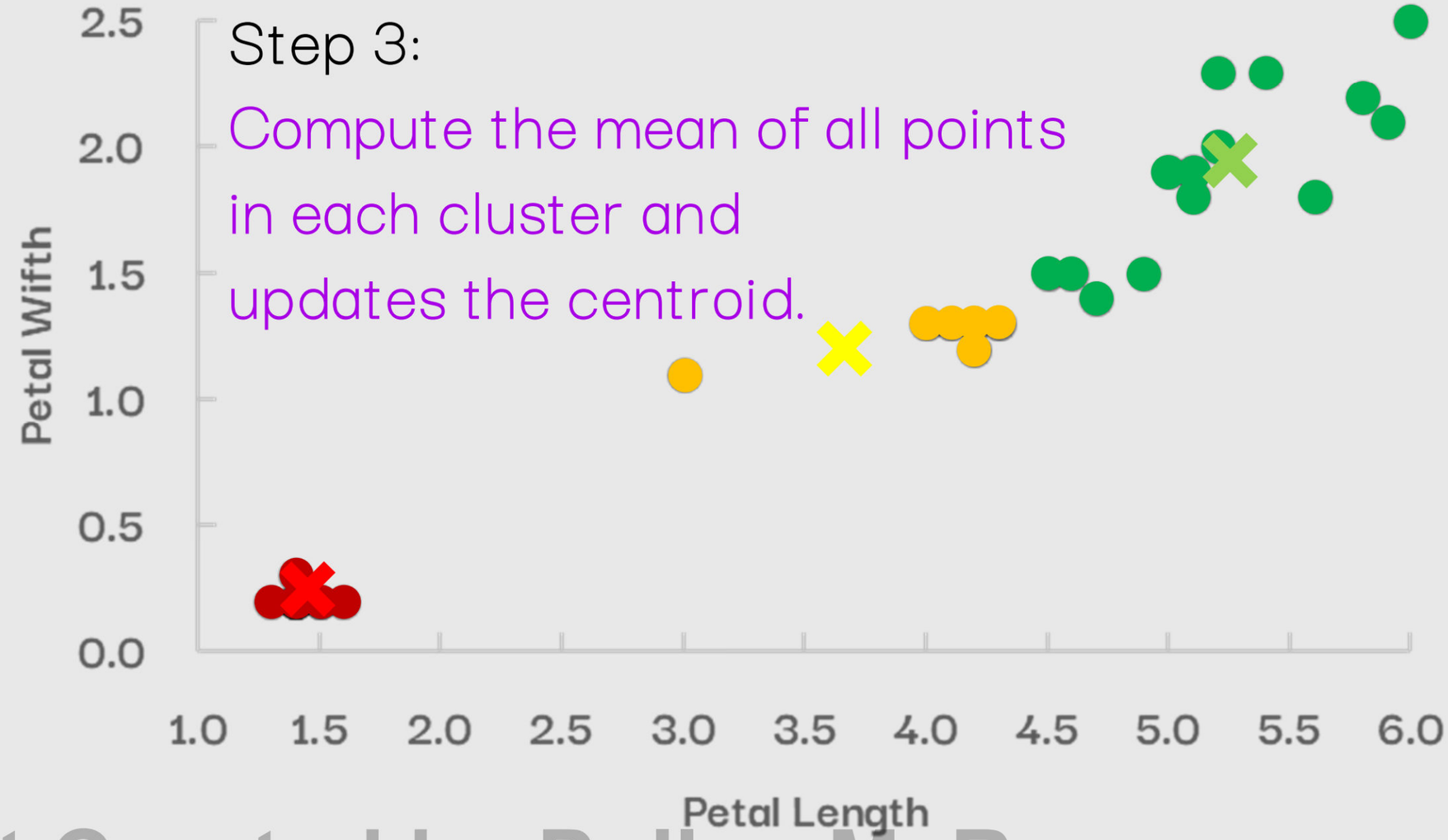
K-Means Clustering



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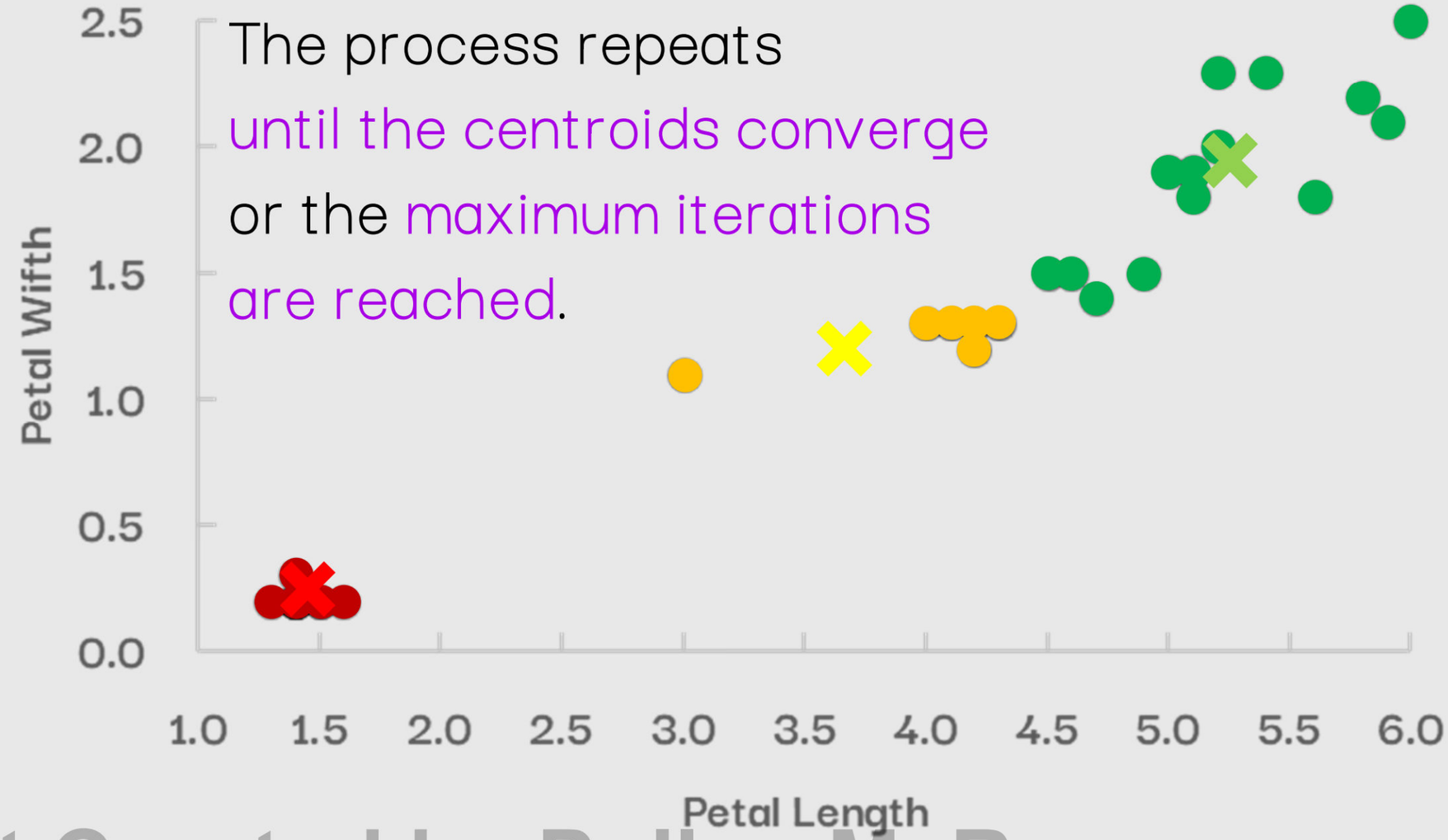
K-Means Clustering

The process repeats
until the centroids converge
or the maximum iterations
are reached.



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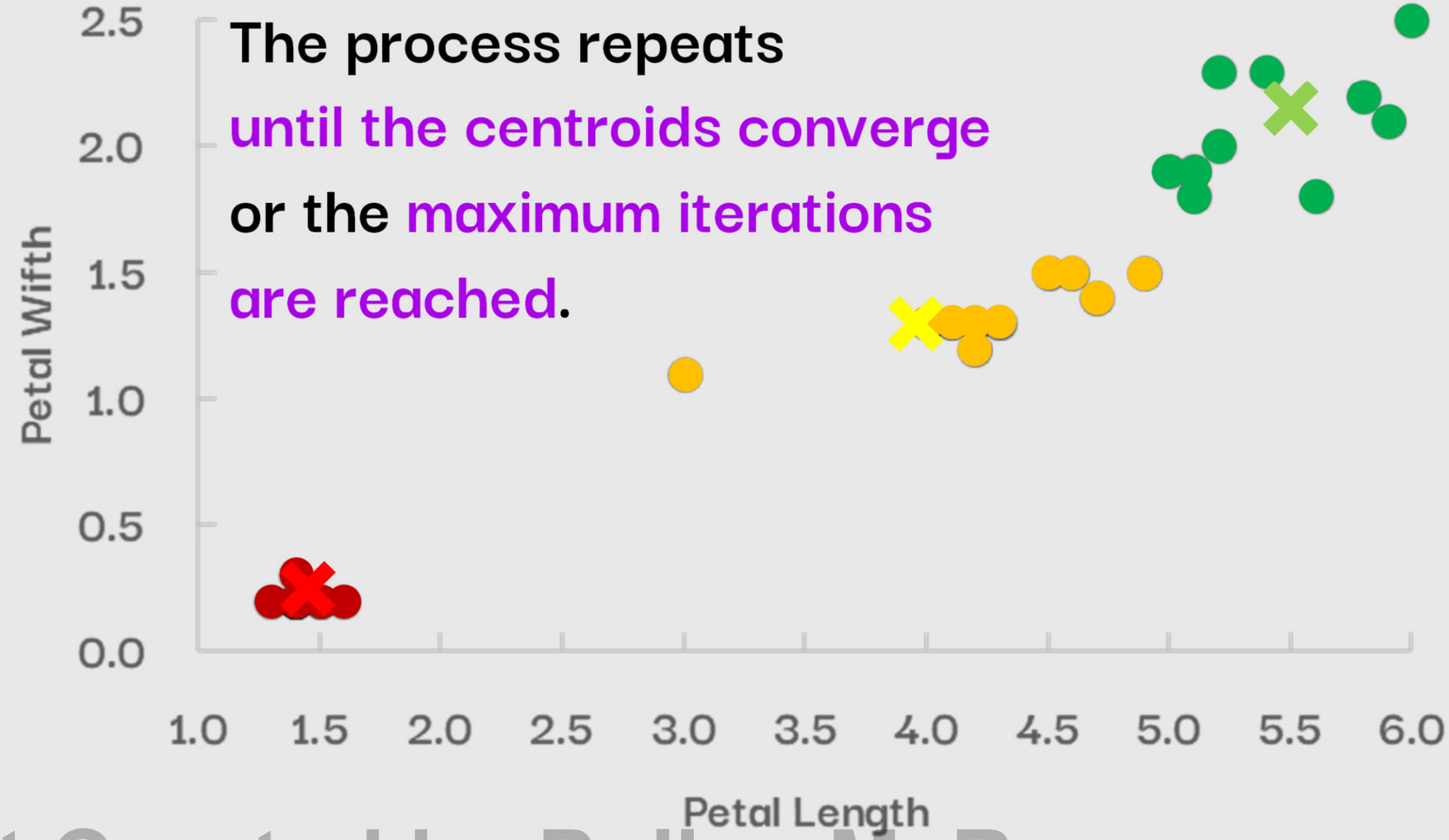
K-Means Clustering



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K-Means Clustering

K-means clustering is simple yet sensitive to initial conditions and outliers.

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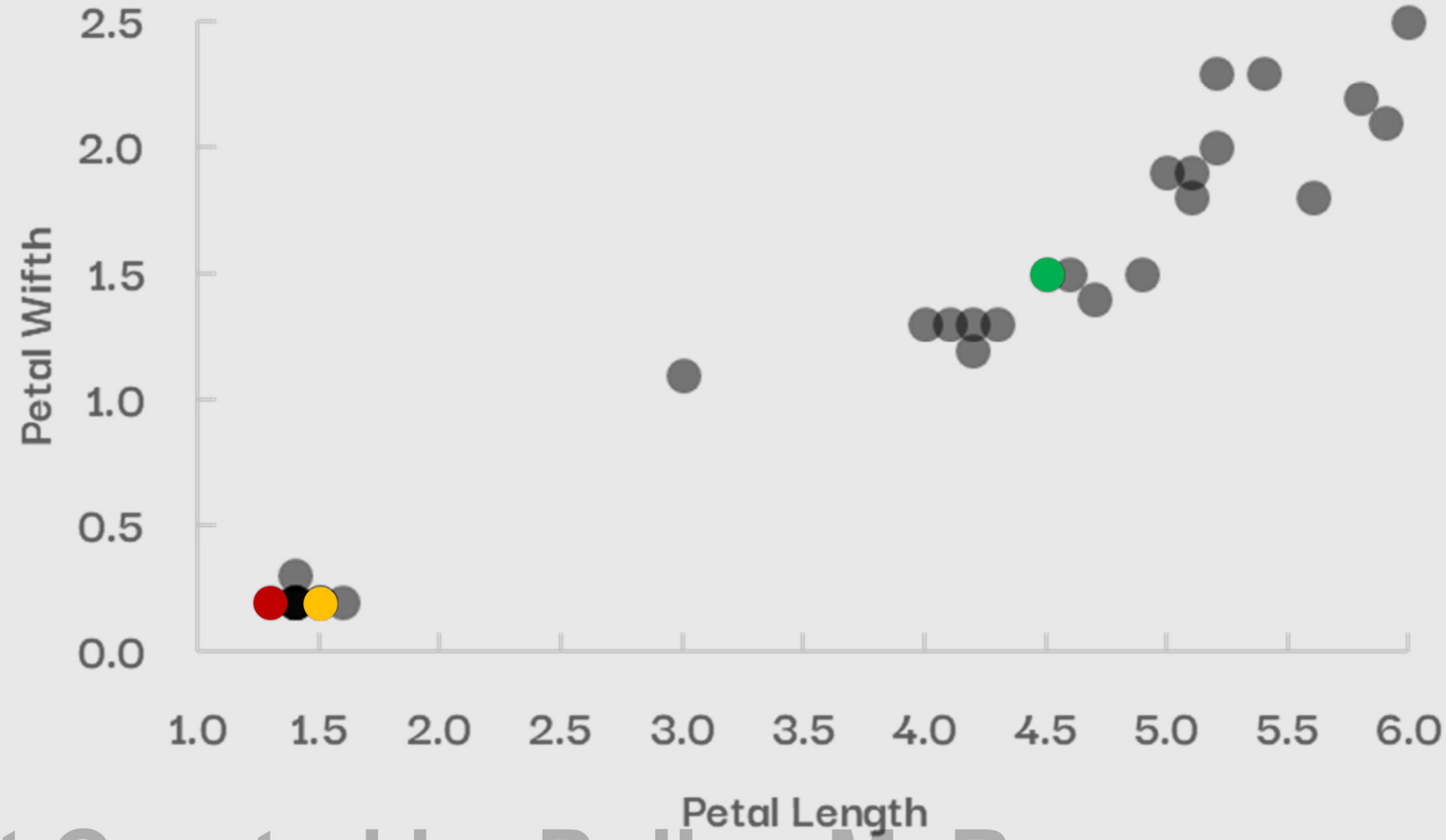
K-Means Clustering



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K-Means Clustering

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K-Means Clustering

It is important to optimize the centroid initialization and the number of clusters *k*, to achieve the most meaningful clusters.

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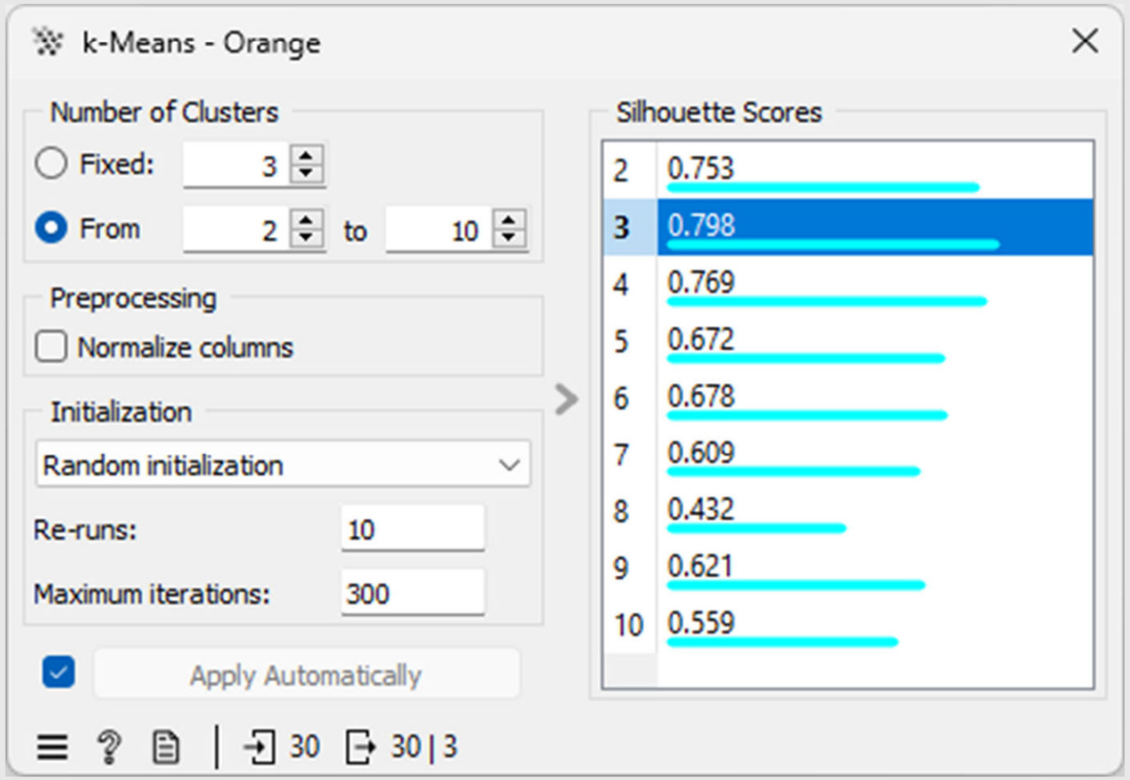
K-Means Clustering



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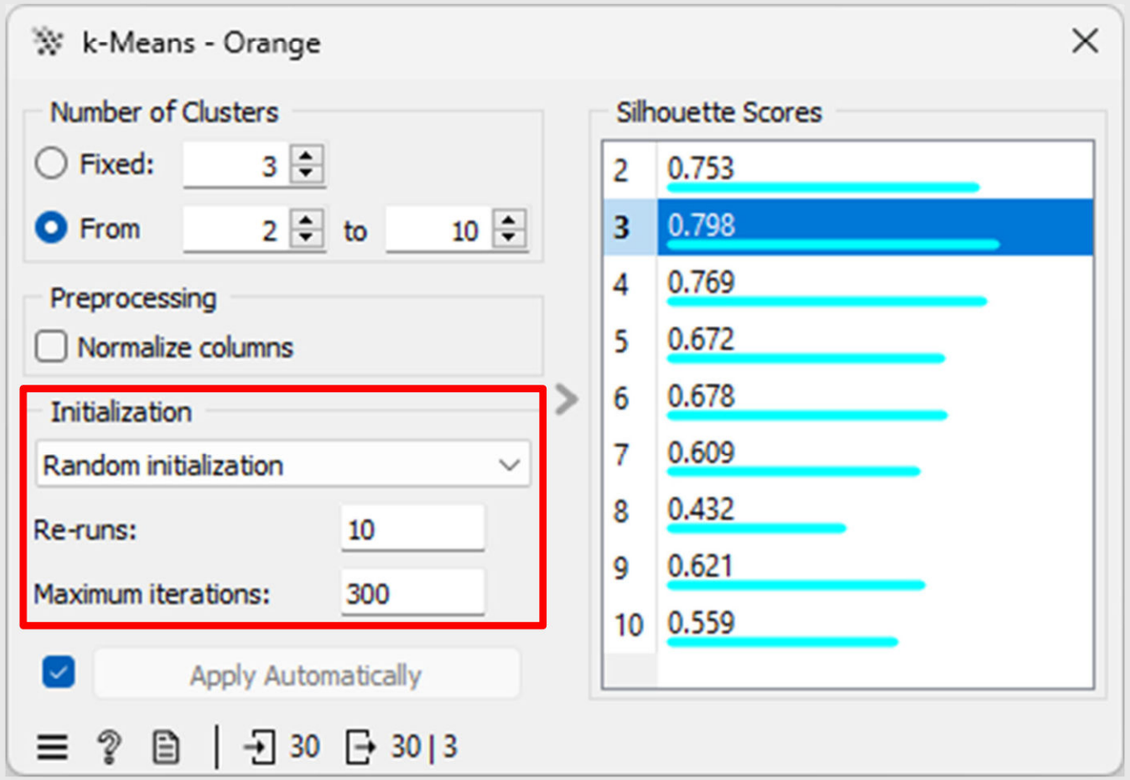
K-Means Clustering



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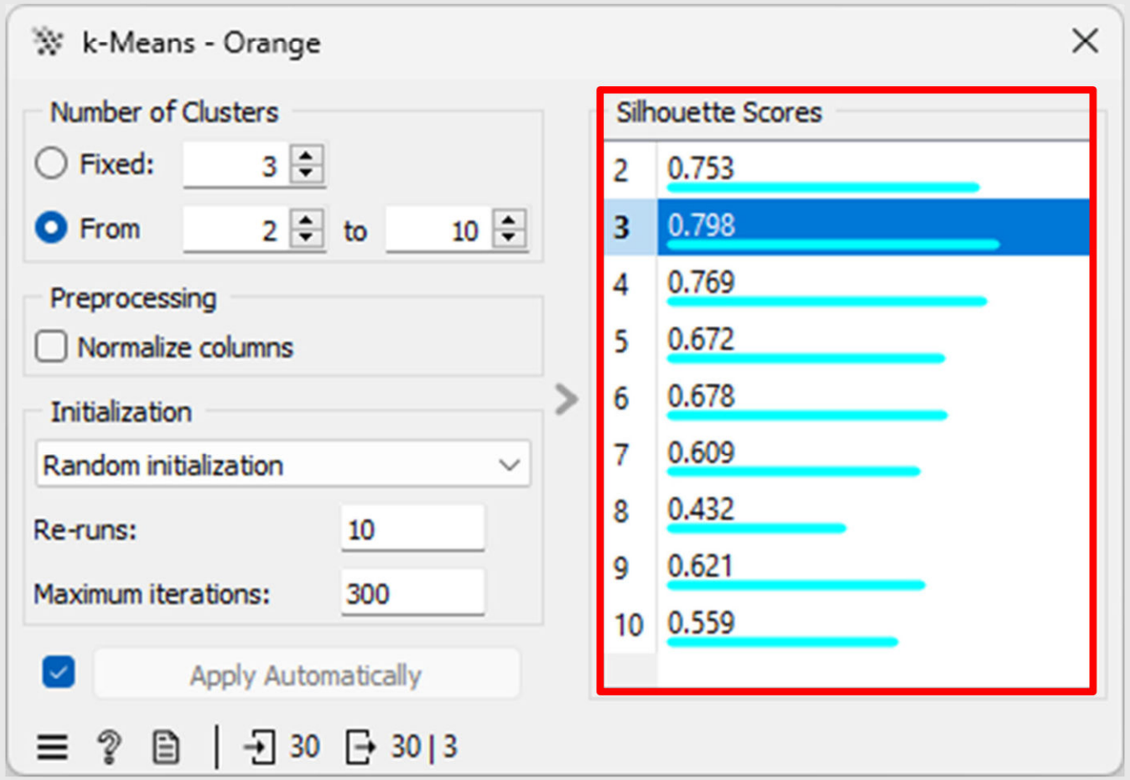
K-Means Clustering



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K-Means Clustering

StatQuest!

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https://www.youtube.com/watch?v=4b5d3muPQmA

HOW TO CHOOSE THE OPTIMAL NUMBER OF CLUSTERS?

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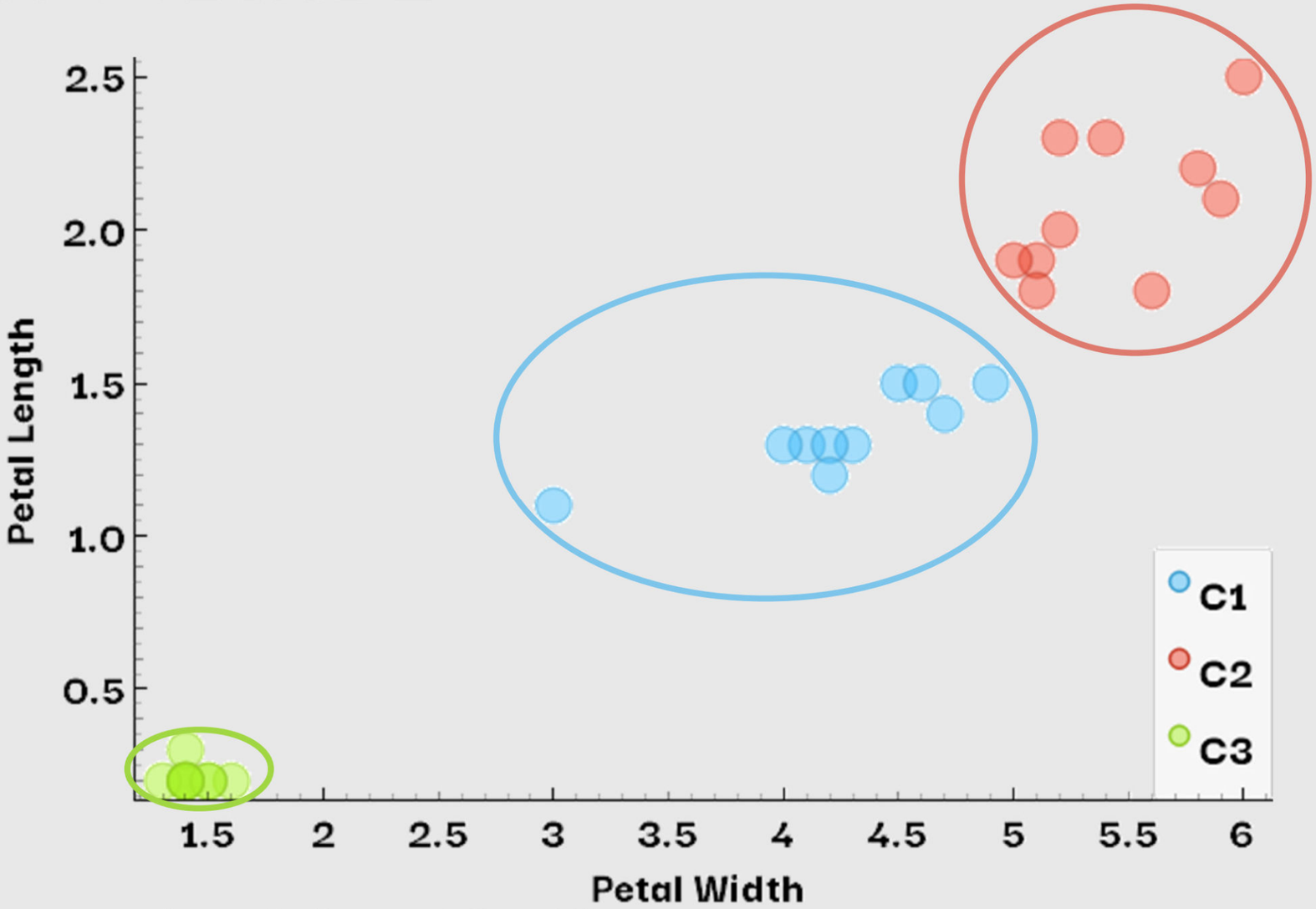
Elbow Method



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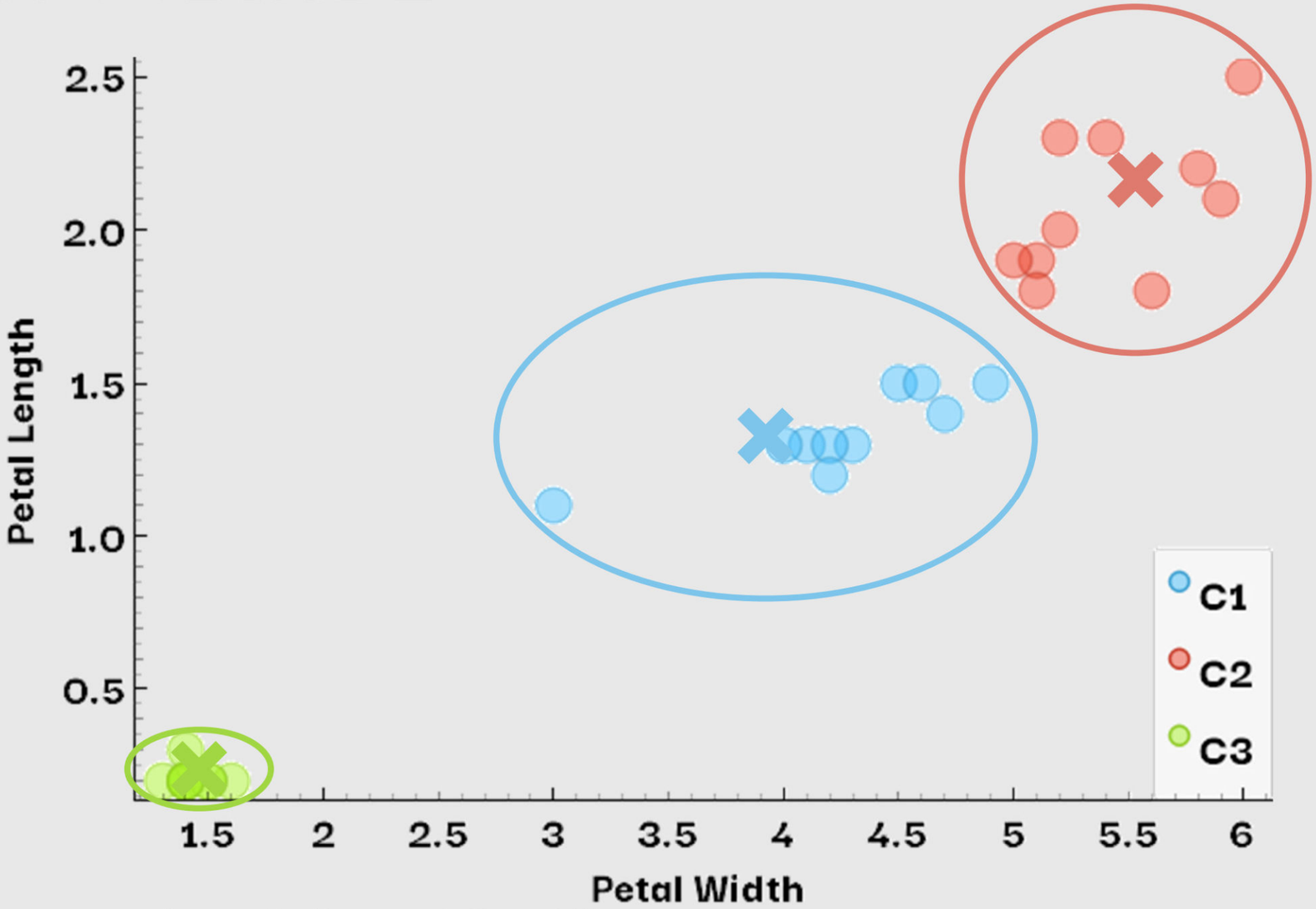
Elbow Method



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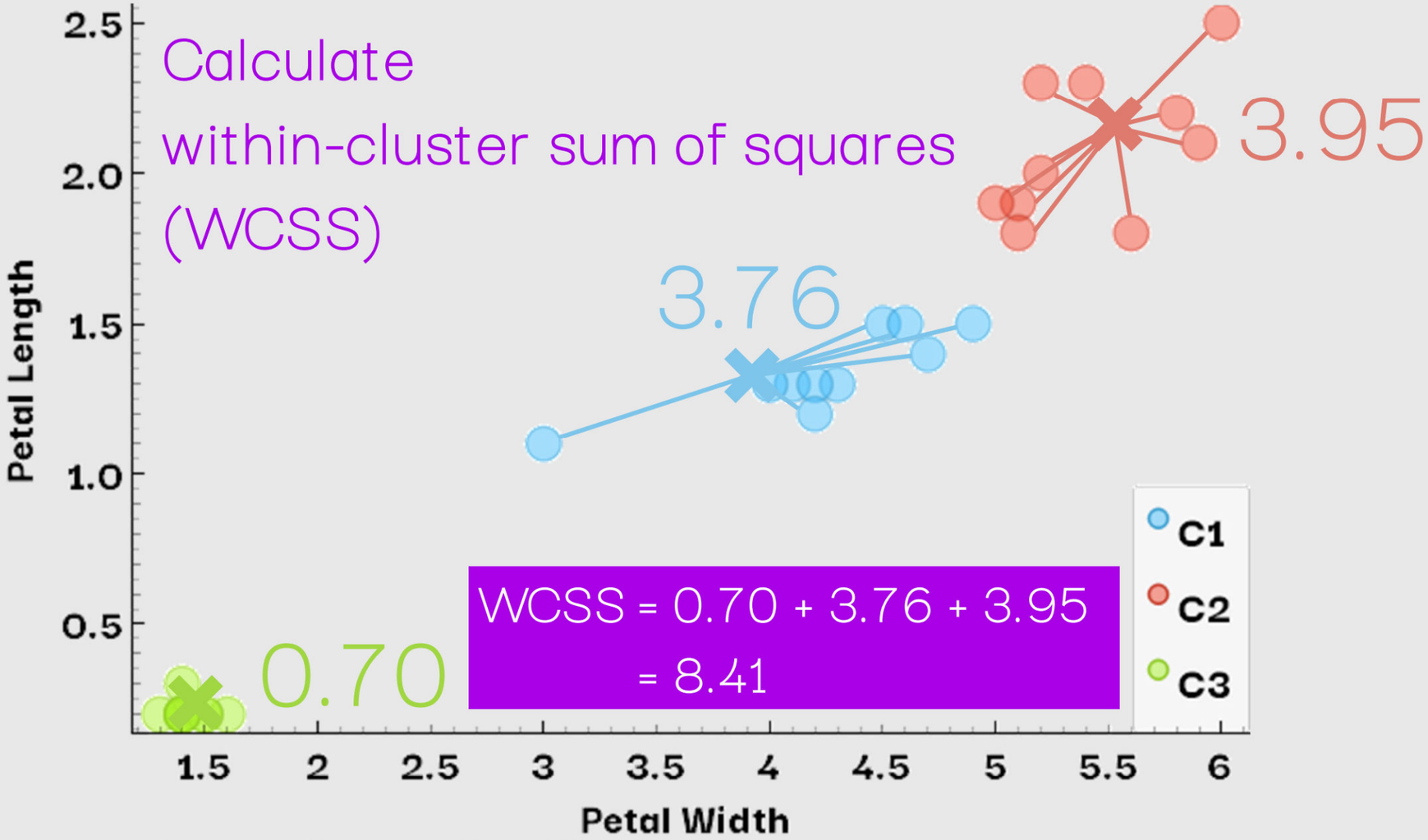
Elbow Method

Calculate
within-cluster sum of squares
(WCSS)



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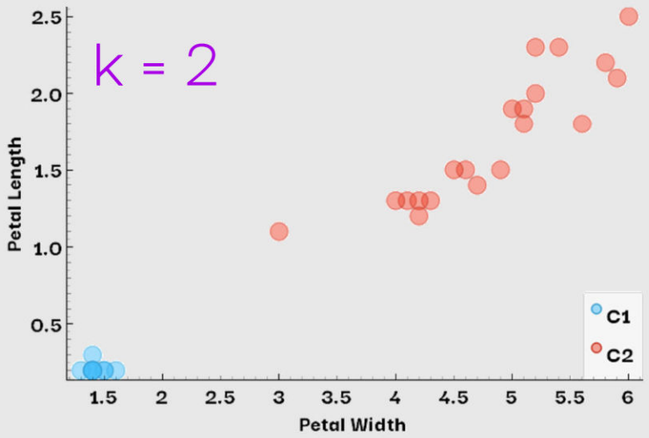
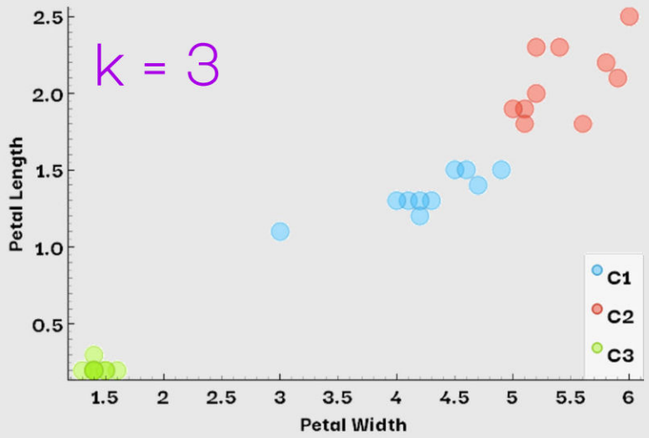
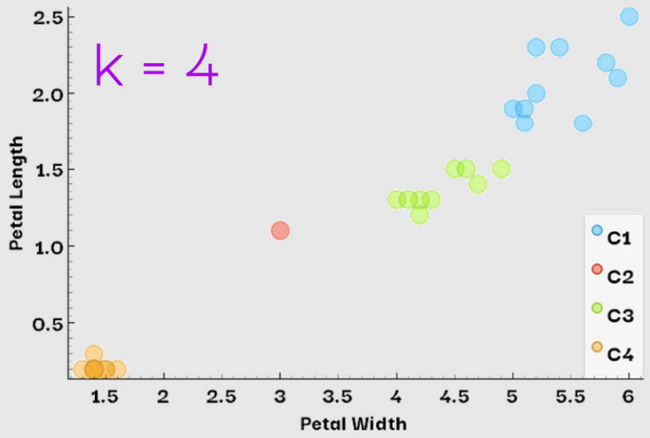
Elbow Method



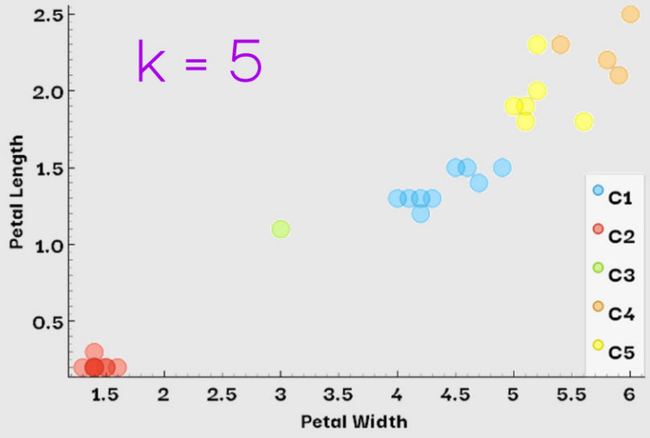
WCSS: 15.77



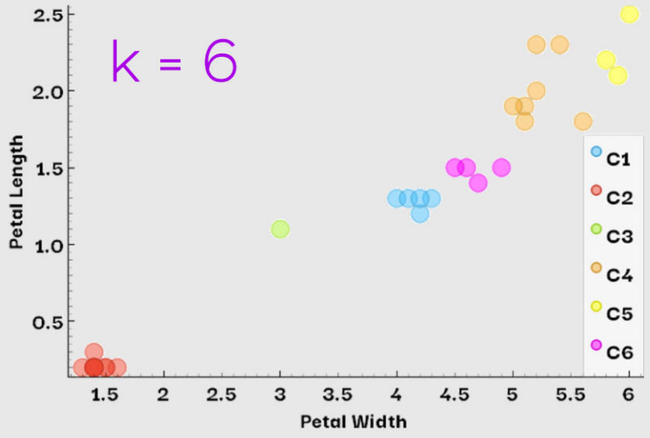
WCSS: 8.41



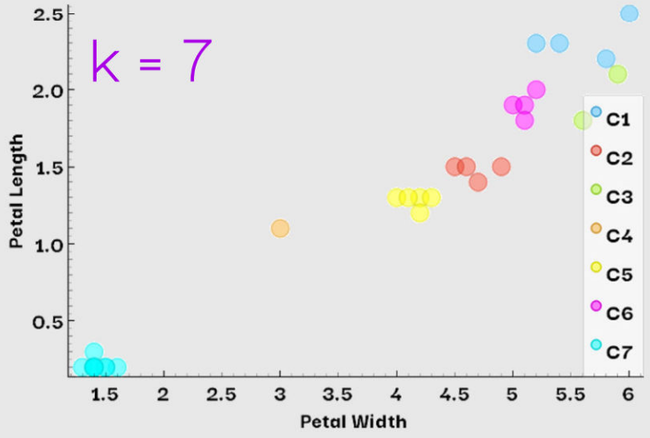
WCSS: 7.17



WCSS: 5.48



WCSS: 3.99



WCSS: 5.19

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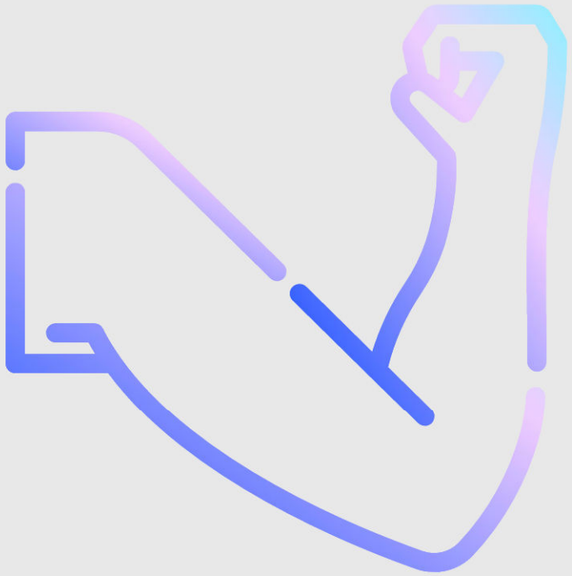
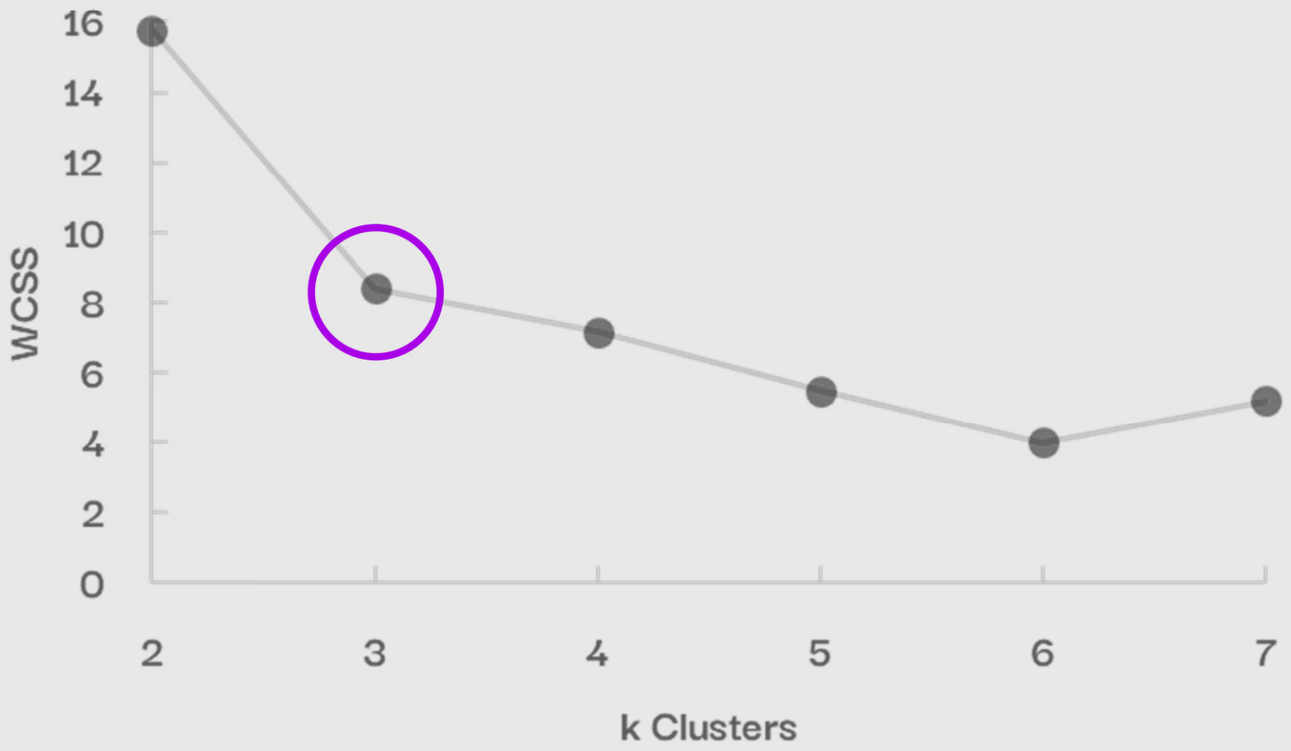
Elbow Method





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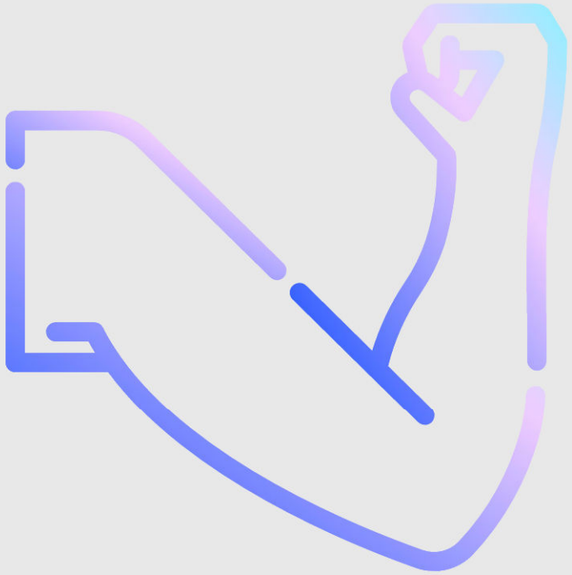
Elbow Method



The optimal number of clusters is 3.

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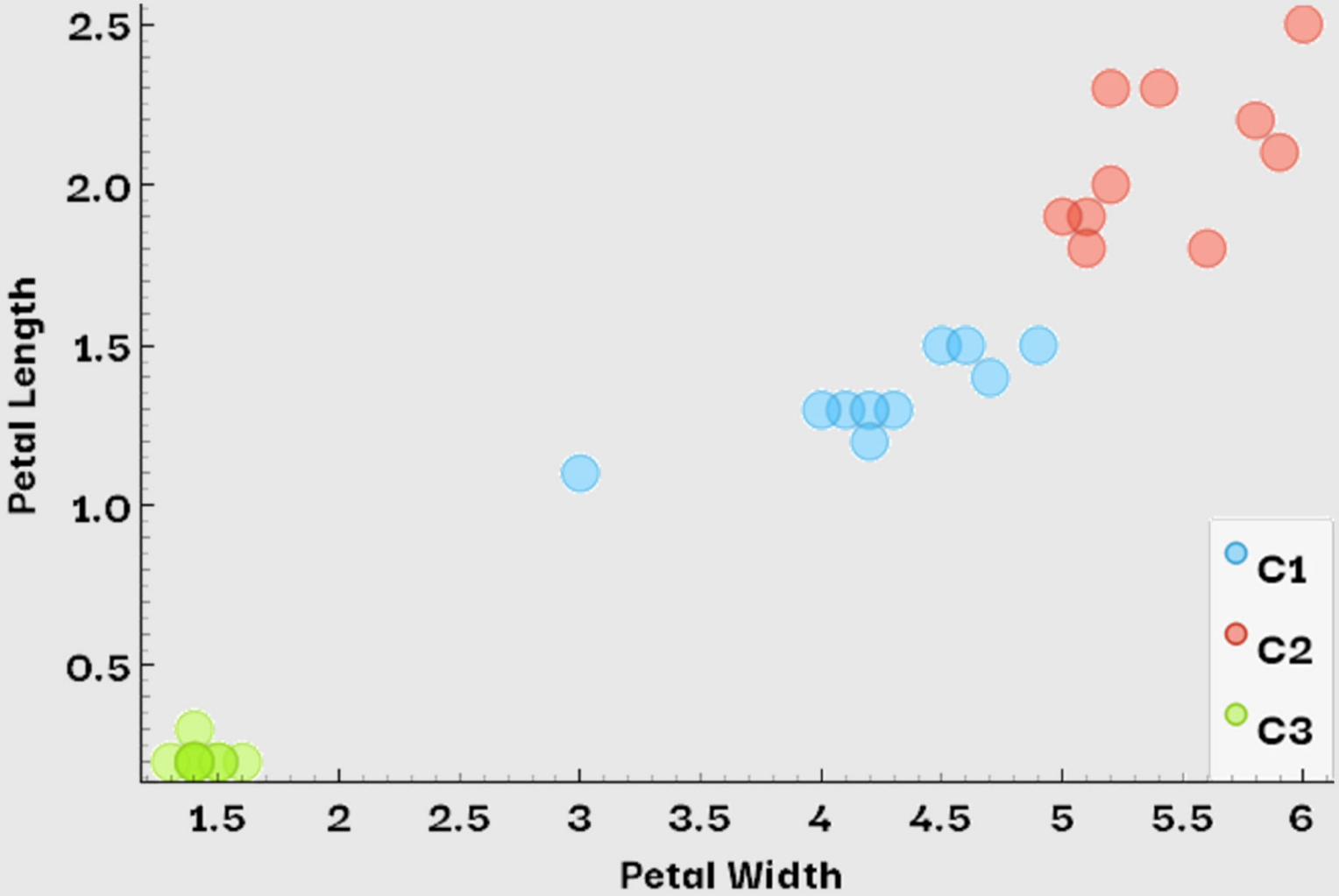
Silhouette Score



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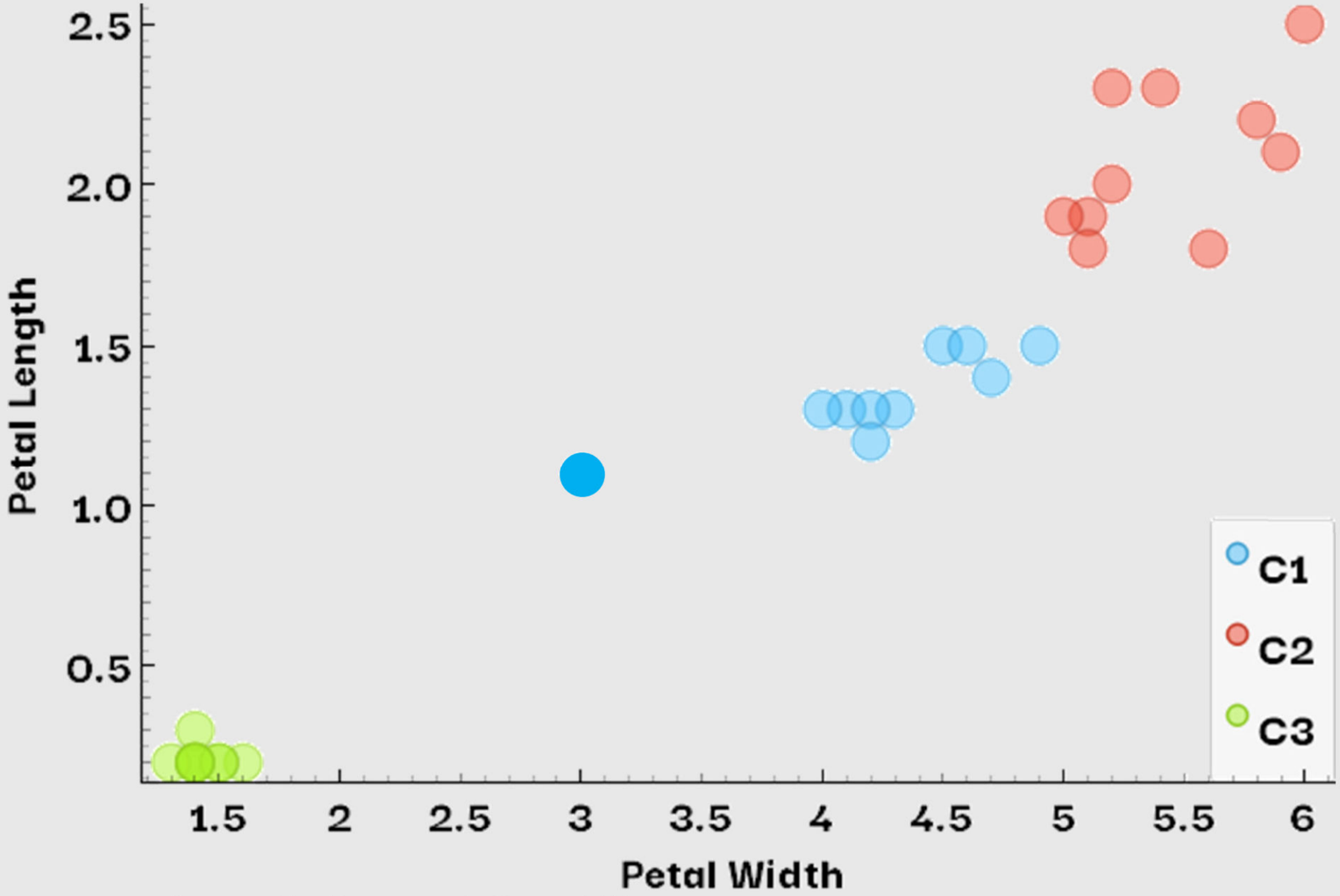
https://campus.datacamp.com/courses/cluster-analysis-in-r/k-means-clustering

Silhouette Score



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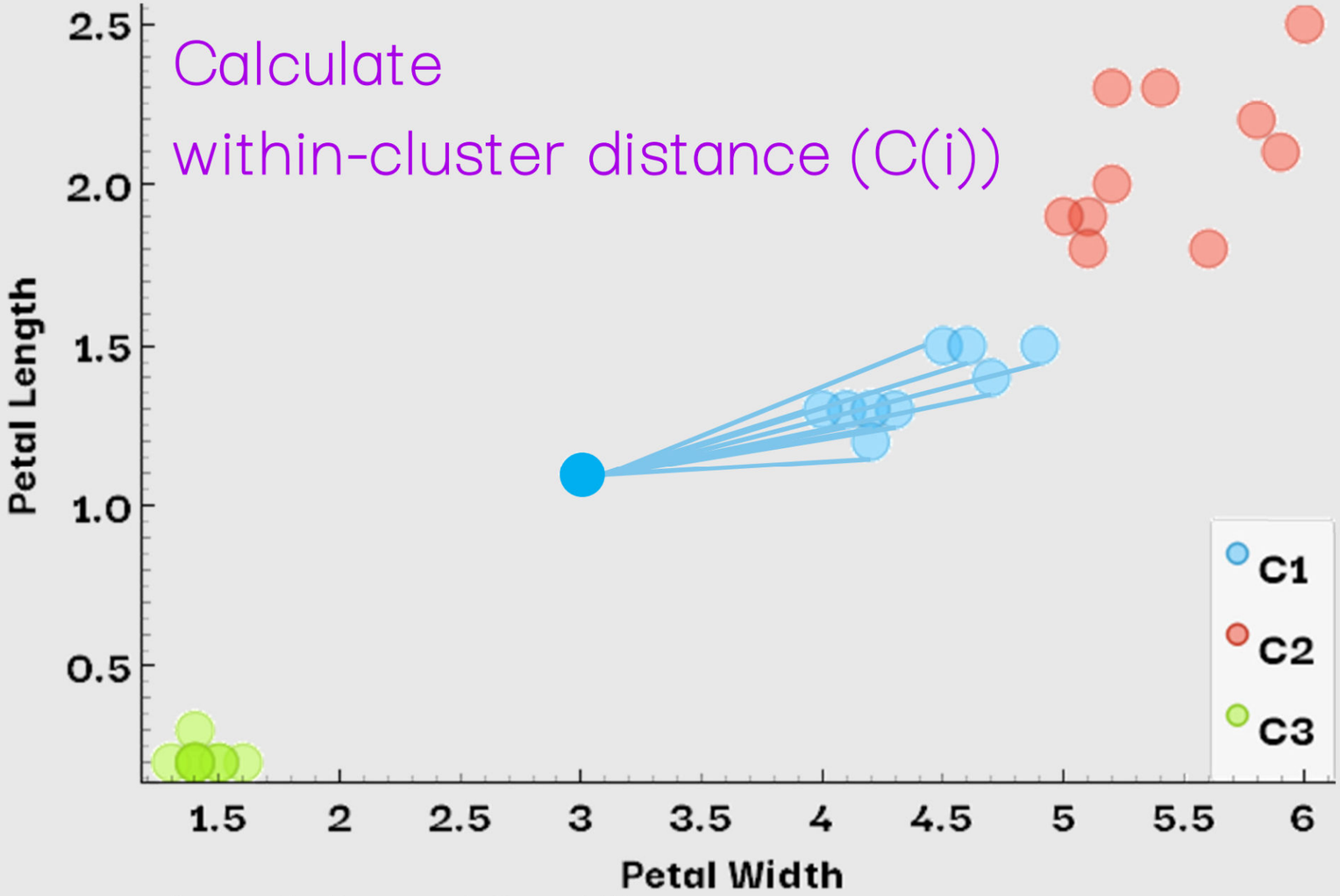
https://campus.datacamp.com/courses/cluster-analysis-in-r/k-means-clustering

Silhouette Score

Calculate

within-cluster distance (C(i))



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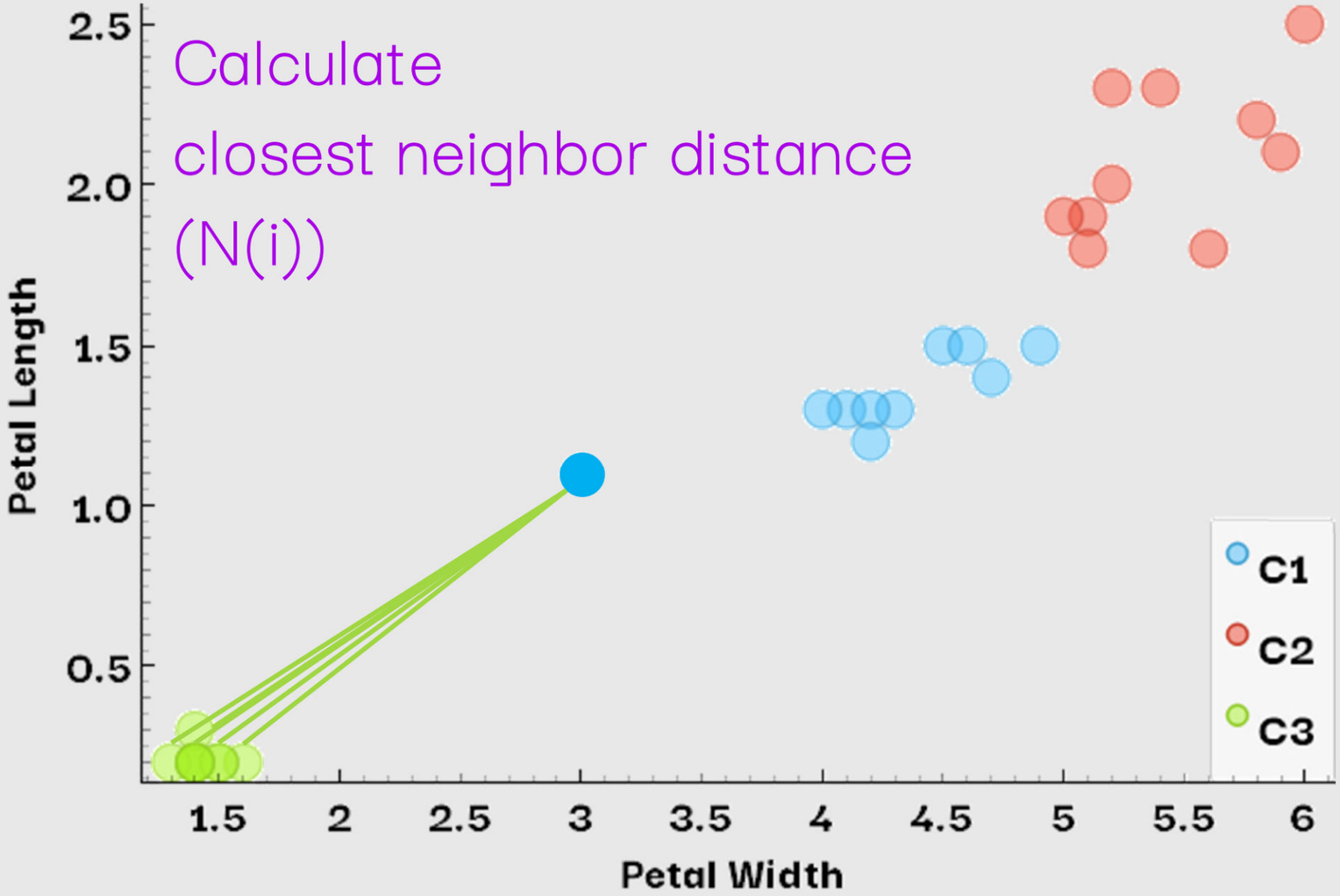
https://campus.datacamp.com/courses/cluster-analysis-in-r/k-means-clustering

Silhouette Score

Calculate
closest neighbor distance
(N(i))



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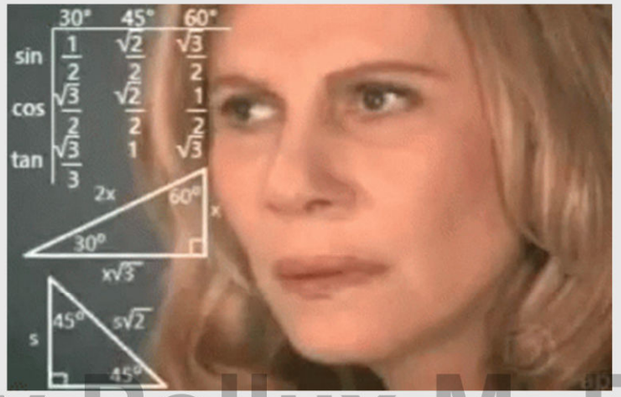
https://campus.datacamp.com/courses/cluster-analysis-in-r/k-means-clustering

Silhouette Score

$$s(i) = \begin{cases} 1 - \dfrac{C(i)}{N(i)} & \text{if } C(i) < N(i) \\ 0 & \text{if } C(i) = N(i) \\ \dfrac{N(i)}{C(i)} - 1 & \text{if } C(i) > N(i) \end{cases}$$



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Silhouette Score

Silhouette Score	Interpretation
1	Observations are well matched to the assigned cluster.
0	Observations are on the border between two clusters.
-1	Observations may be assigned to the wrong cluster.

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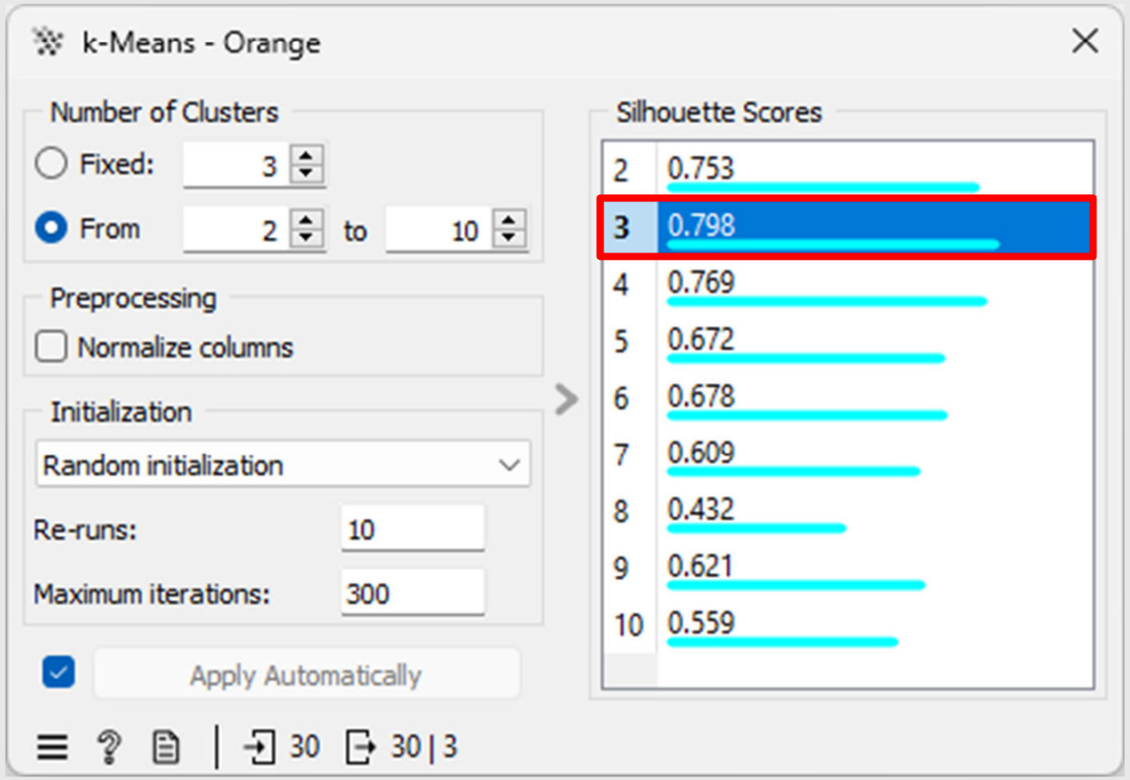
Silhouette Score



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Silhouette Score

Silhouette analysis: observation level performance

CLUSTER ANALYSIS IN R

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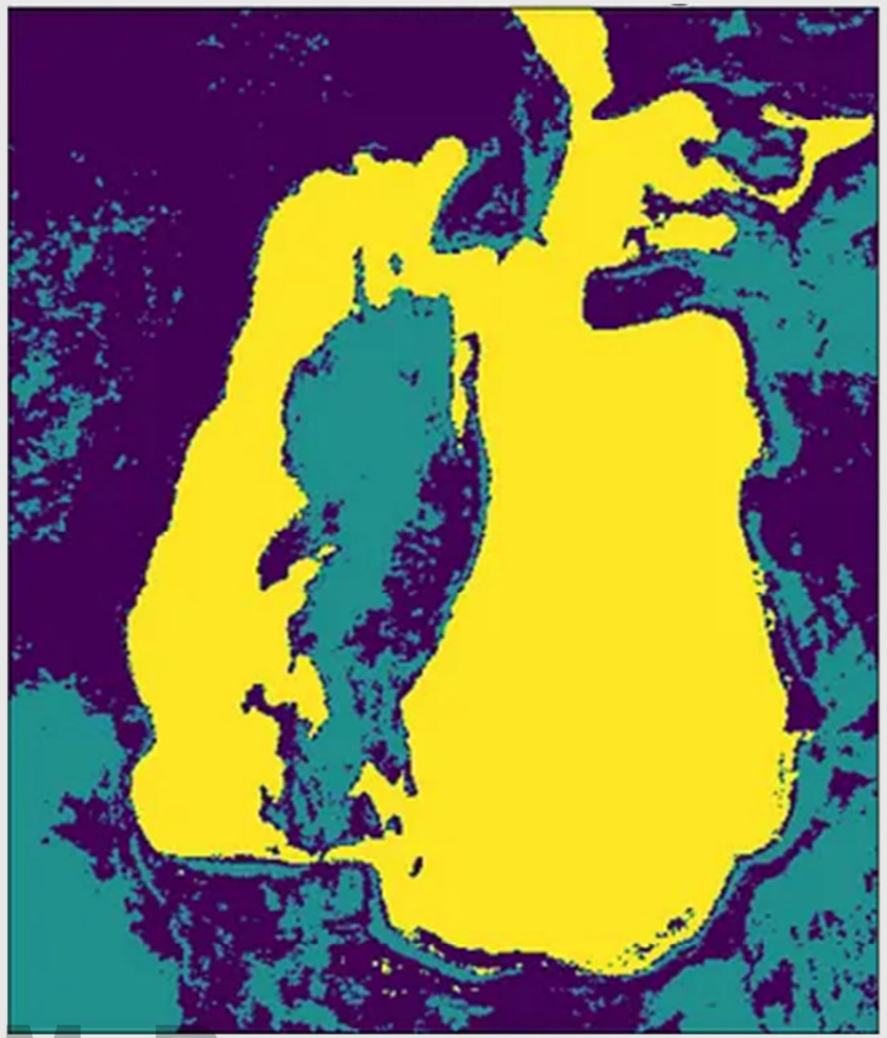
https://campus.datacamp.com/courses/cluster-analysis-in-r/k-means-clustering

K-Means Clustering **Applications**



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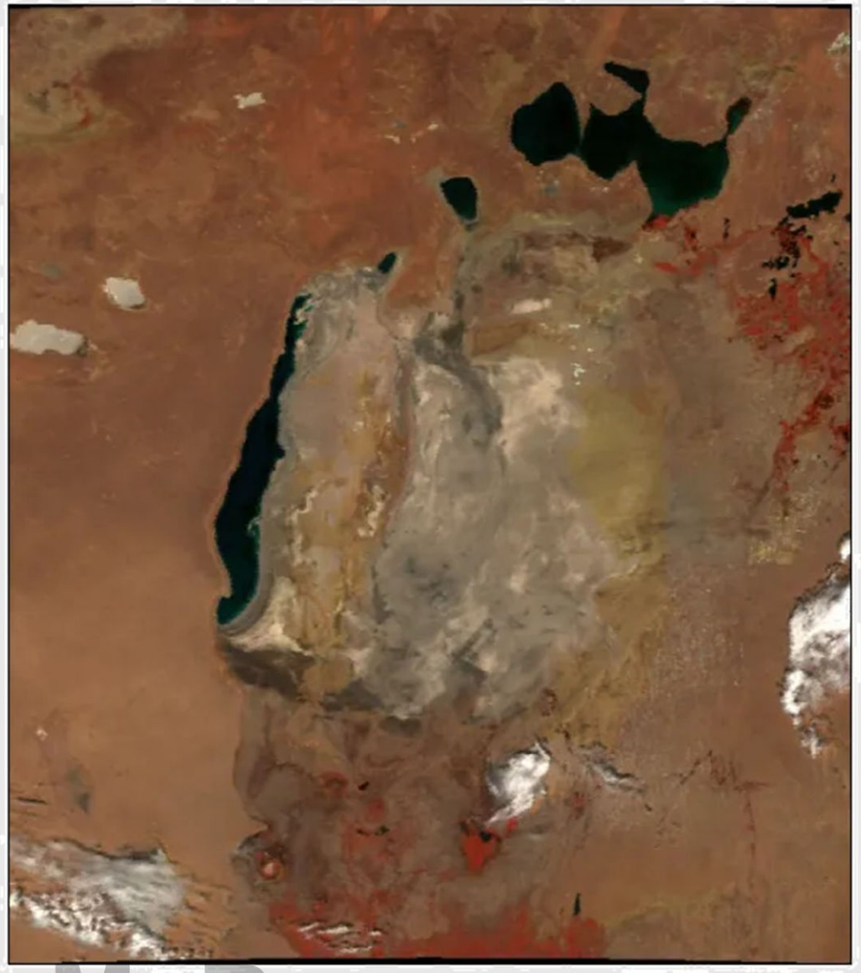
https://towardsdatascience.com/semantic-segmentation-of-remote-sensing-imagery-using-k-means-e4c165d9218e

K-Means Clustering Applications

2000-08-01

2023-08-01



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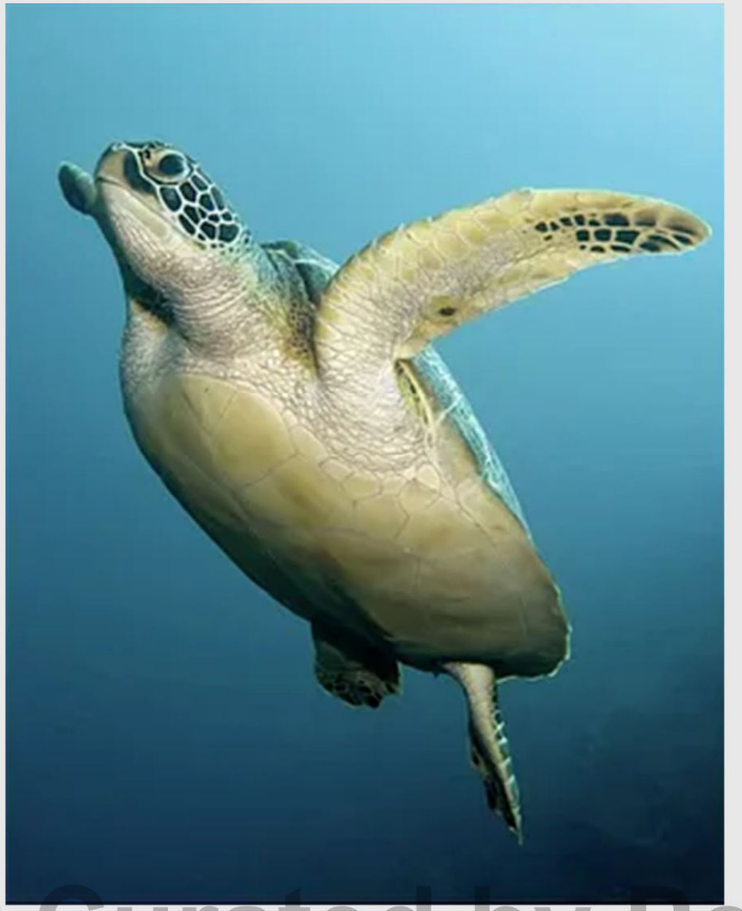
K-Means Clustering **Applications**

Initial Image



Compressed Image

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https://towardsdatascience.com/clear-and-visual-explanation-of-the-k-means-algorithm-applied-to-image-compression-b7fdc547e410

K-Means Clustering Applications

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https://www.youtube.com/watch?v=yR7k19YBqiw

THANK YOU!

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