# K-means clustering

is a popular unsupervised machine learning algorithm used for clustering data points into groups or clusters based on their similarity. The algorithm aims to minimize the sum of squared distances between the data points and their corresponding cluster centroids.

Here's a step-by-step overview of the K-means clustering algorithm:

1. Choose the number of clusters (K) you want to create.

2. Initialize K centroids randomly or by selecting K data points as centroids.

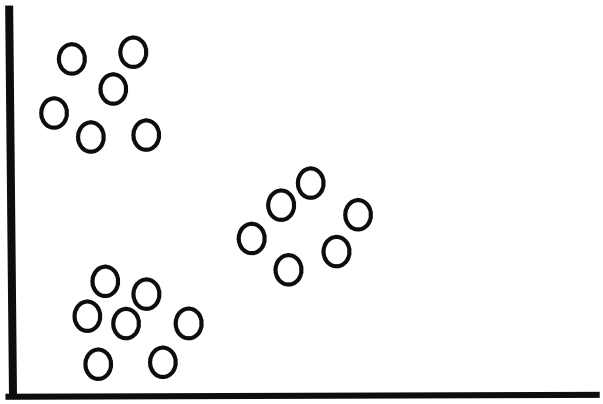
3. Assign each data point to the nearest centroid based on the Euclidean distance or other distance metrics.

4. Recalculate the centroids of each cluster by taking the mean of all the data points assigned to that cluster.

5. Repeat steps 3 and 4 until convergence or until a maximum number of iterations is reached.

6. Once convergence is reached, the algorithm has successfully formed K clusters. Each data point belongs to the cluster whose centroid it is closest to.

K-means clustering has several applications, such as customer segmentation, image compression, document clustering, and anomaly detection. However, it is worth noting that the algorithm's effectiveness can depend on the nature of the data and the appropriate choice of K.



# Elbow curve

The Within-Cluster Sum of Squares (WCSS) is a metric used in the elbow curve method to evaluate the quality of clustering results, specifically in K-means clustering. It quantifies the compactness or tightness of the clusters obtained by measuring the sum of squared distances between each data point and its corresponding cluster centroid.

To create an elbow curve using WCSS, you can follow these steps:

1. Run the K-means algorithm on your dataset for a range of values of K, typically starting from 1 and increasing incrementally.

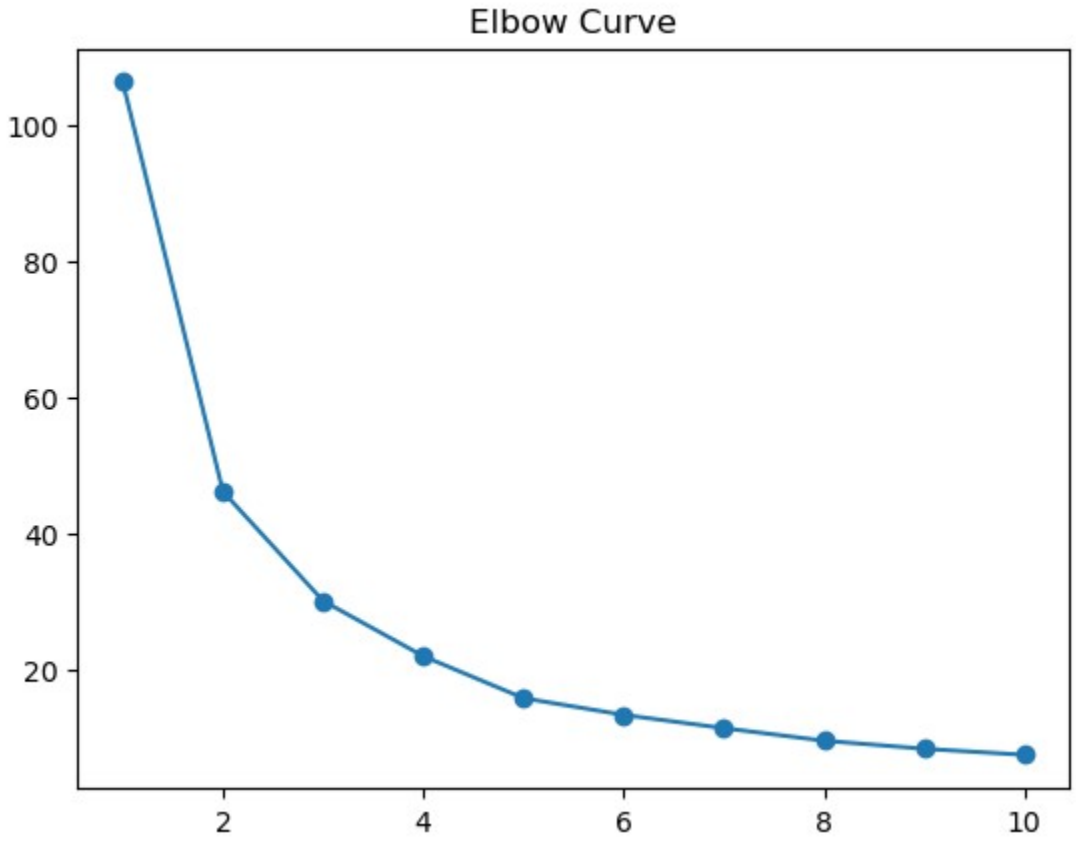
2. For each value of K, calculate the sum of squared distances between each data point and its assigned centroid. Sum these values to obtain the total WCSS for that particular value of K.

3. Plot the WCSS values against the corresponding K values on a line graph.

4. Examine the plot and look for the "elbow point," which is the point where the decrease in WCSS starts to flatten out. This is often represented by a significant change in the slope of the curve, resembling an elbow. The elbow point indicates the value of K at which the clustering performance starts to plateau.

5. Choose the value of K at the elbow point as the optimal number of clusters for your dataset.

The idea behind using WCSS for the elbow curve is that as you increase the number of clusters, the WCSS tends to decrease. However, adding more clusters will eventually result in diminishing improvements in clustering quality. The elbow point helps in finding the balance between the number of clusters and the compactness of the clusters.




Total within cluster Sum of Squares (WCSS)

$$\sum_{i=}^{k_i} \sum_{i=1}^{X_i} (X_i - \overline{X_k})^2$$

## Silhouette method

The silhouette method is a popular technique for evaluating the quality of clustering results, including K-means clustering. It provides a measure of how well each data point fits into its assigned cluster and can help determine the optimal number of clusters.

The silhouette method calculates a silhouette coefficient for each data point, which ranges from -1 to 1. The coefficient quantifies the cohesion within the cluster (how close the data point is to other points in its cluster) and the separation between clusters (how far the data point is from points in other clusters). The higher the silhouette coefficient, the better the clustering result.

Here's how you can use the silhouette method to evaluate clustering results:

1. Run the K-means algorithm on your dataset for a range of values of K.

2. For each value of K, calculate the silhouette coefficient for each data point. The formula for the silhouette coefficient of a data point "i" is as follows:

$$\textbf{silhouette\_coefficient(i)} = \frac{(\boldsymbol{b_i} - \boldsymbol{a_i})}{\mathbf{max}(\boldsymbol{a_i}, \boldsymbol{b_i})}$$

- "a(i)" represents the average distance between data point "i" and other points within the same cluster.

- "b(i)" represents the average distance between data point "i" and points in the nearest neighboring cluster.

3. Calculate the average silhouette coefficient across all data points for each value of K.

4. Plot the average silhouette coefficients against the corresponding K values on a line graph.

5. Examine the plot and look for the highest average silhouette coefficient. This indicates the number of clusters that provides the best separation and cohesion among the data points.

The silhouette method helps in identifying the optimal number of clusters by selecting the value of K that maximizes the average silhouette coefficient. A high average silhouette

coefficient suggests that the clustering result is well-defined and distinct, while a low value indicates that the clusters are overlapping or poorly separated.