K-Means Clustering

Agenda

1. Discussion Questions
2. Unsupervised Learning and Clustering
3. Common Distance Metrics
4. Scaling
5. K-Means Clustering
6. Optimal number of clusters
7. Pros & cons
8. Industry Applications

Questions to discuss

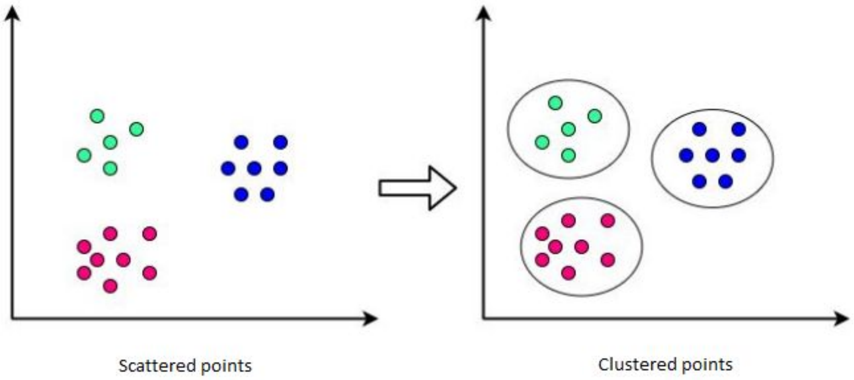
1. What is Unsupervised Learning and Clustering?
2. What is K-Means Clustering and how it works?
3. How to find the optimal number of clusters?
4. What are pros and cons of K Means Clustering?

Unsupervised Learning

- Unsupervised Learning is a class of Machine Learning techniques to find the patterns in data.
- The data given to unsupervised algorithm are not labelled, which means only the input variables(X) are given with no corresponding output variables.
- Unsupervised learning is the training an algorithm using information that is neither classified nor labelled.
- No defined dependent and independent variables.
- Patterns in the data are used to identify / group similar observations

Clustering

- It involves task of grouping a set of objects in such a way that objects in the same group are more similar to each other than to those in other groups
- Objective - to ensure that the distance between data points in a cluster is very low compared to the distance between 2 clusters.
- These kind of algorithms capture the hidden patterns in data to find the underlying structure and discover new insights.
- The similarity between data points is determined by the distance between them. Different distance can be used, like Euclidean distance, Chebyshev distance, Mahalanobis distance, etc.



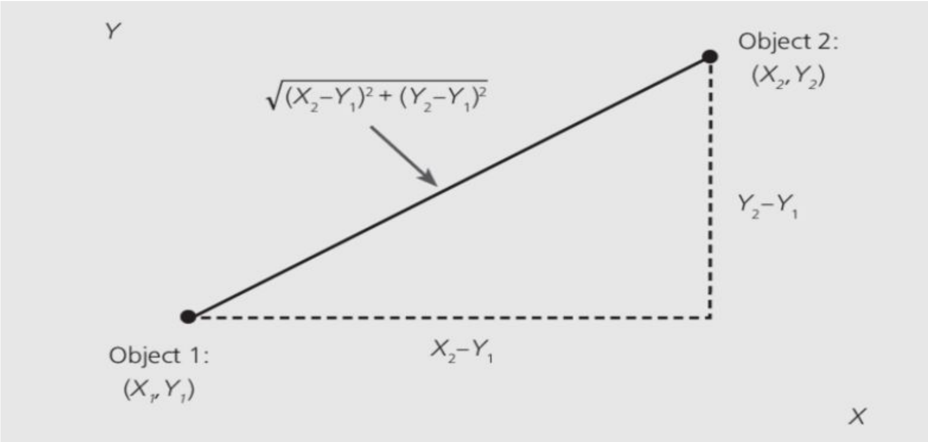
Common Distance Metrics

- Euclidean Distance Metrics

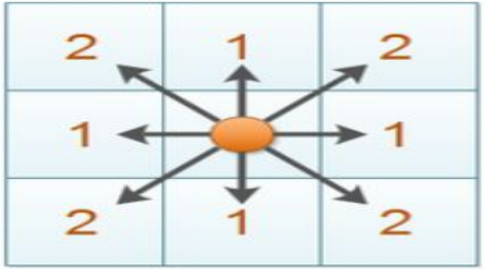
$$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

- Manhattan distances

$$\sum_{i=1}^{k}|x_i - y_i|$$



Manhattan Distance

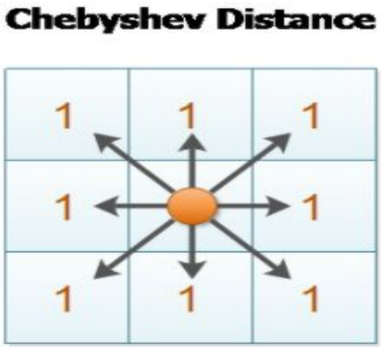


$$|x_1 - x_2| + |y_1 - y_2|$$

Common Distance Metrics

- Chebyshev distance

$$\max(|x_1 - x_2|, |y_1 - y_2|)$$



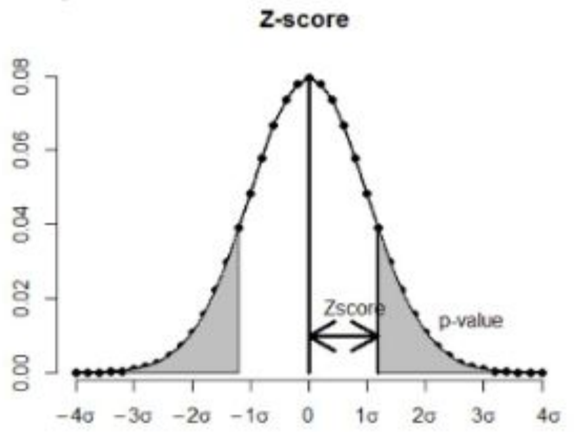
$$\max(|x_1 - x_2|, |y_1 - y_2|)$$

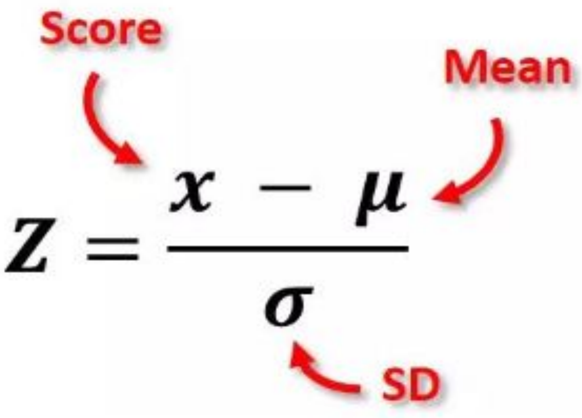
- Minkowski distance

$$\left(\sum_{i=1}^{n} |x_i - y_i|^p\right)^{\frac{1}{p}}$$

Scaling the data

- It is important to normalize the data using either Z score or standard scaler before performing K means clustering
- This ensure different attributes are of same standard values





$$Z = \frac{x - \mu}{\sigma}$$

K-Means Clustering

- K-Means is one of the most common clustering techniques.

- It is a centroid-based clustering algorithm where the objective is to find K clusters / groups.

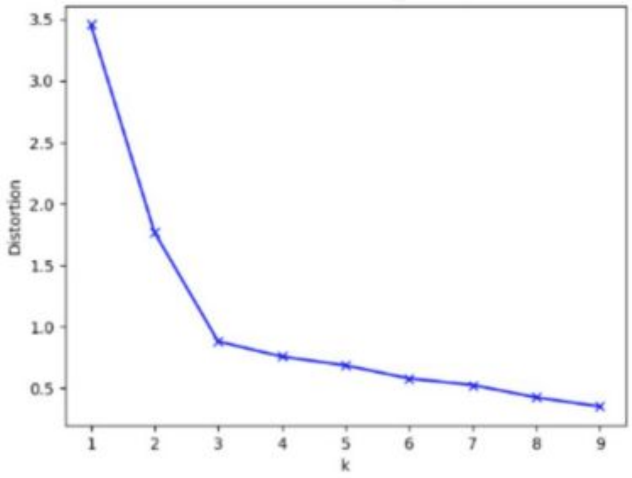
- The working of K-means clustering can be summarized as follows:

    - Step 1: Initialize the K random centroids or K points
    - Step 2: For each data point, calculate the Euclidean distance of it from randomly chosen K centroids and assign each point to a minimum distance cluster.
    - Step 3: Update the centroid by using newly assigned data points to the cluster by calculating the average of data points.
    - Step 4: Repeat the above process for a given no. of iterations or until the centroid allocation no longer changes

- Large K produces smaller groups and small K produces larger groups.

Optimal Number of Clusters: Elbow Method

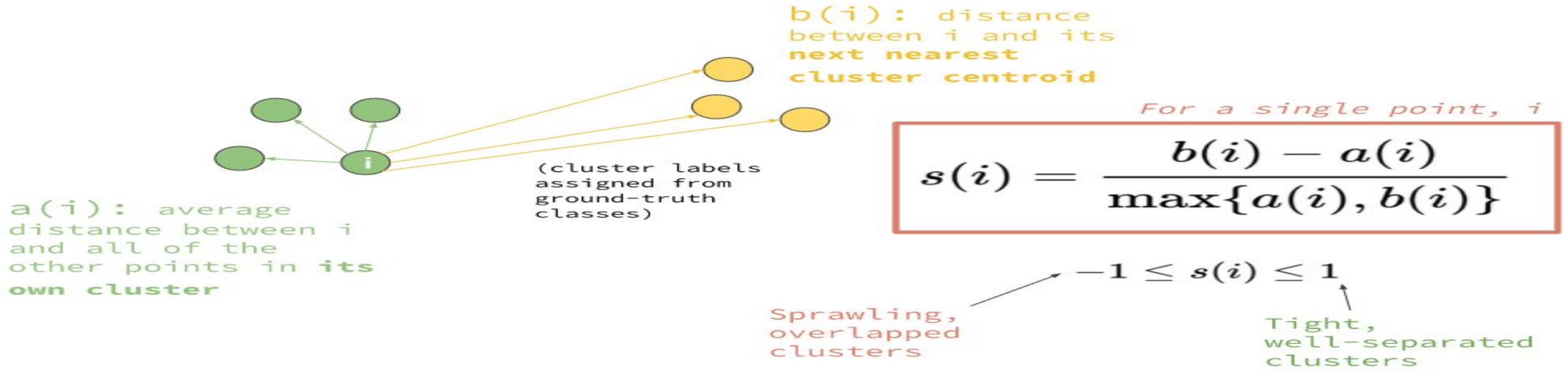
- There is no method to define the exact value of K.
- Elbow method is the most popular and well-known method to find the optimal no. of clusters.
- This method is based on plotting the value of cost function against different values of K.
- The point where the distortion declines most is said to be the elbow point and defines the optimal number of clusters for the dataset.



- In the example here, you can that the distortion decreases most at 3.
- Hence, the optimal value of k will be 3 for performing the clustering.

Optimal Number of Clusters: Silhouette Score

- The silhouette score is a metric which indicates the goodness of clustering algorithms , for especially K-means algorithms.
- It values range between -1 to +1.
- 1 indicates tight , well separated clusters, 0 indicates clusters not well separable and -1 indicates data points of a cluster is more closer to centroid of other clusters than centroid of its own clusters
- **Silhouette Score = (b-a)/max(a,b)**
- **a= average intra-cluster distance i.e the average distance between each point within a cluster.**
- **b= average inter-cluster distance i.e the average distance between all clusters.**



Pros and Cons

Pros:

- Can be implemented with ease and it is faster than other clustering algorithms
- Works great on large scale data
- Results guarantee convergence
- Easily works with new examples

Cons:

- Sensitive to outliers
- Quite difficult to determine the number of clusters
- Sensitive to initialization of cluster centers

Industry Applications of clustering

- Customer segmentation – buying patterns, income,spending behaviour, loyalty, customer lifetime value
- Anomaly detection
- Creating news feeds – cluster articles based on their similarity
- Pattern detection in medical imaging for diagnostics

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Power Ahead

Happy Learning !