

Introduction to Data Science

Dr. Irfan Yousuf

Department of Computer Science (New Campus)

UET, Lahore

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Outline

- K-means

Machine Learning Algorithms

Machine Learning

Supervised learning: Train a model with known input and output data to predict future outputs to new data.

Classification

Support vector machine (SVM)

K-nearest-neighbors

Discriminant analysis

Neural Networks

Naive Bayes

Regression

Linear Regression

Assembly Methods

Decision trees

Neural Networks

Unsupervised Learning: Segment a collection of elements with the same attributes (clustering).

Clustering

K-means, k-medoids fuzzy C-means

Hidden Markov models

Neural Networks

Gaussian mixture

Clustering

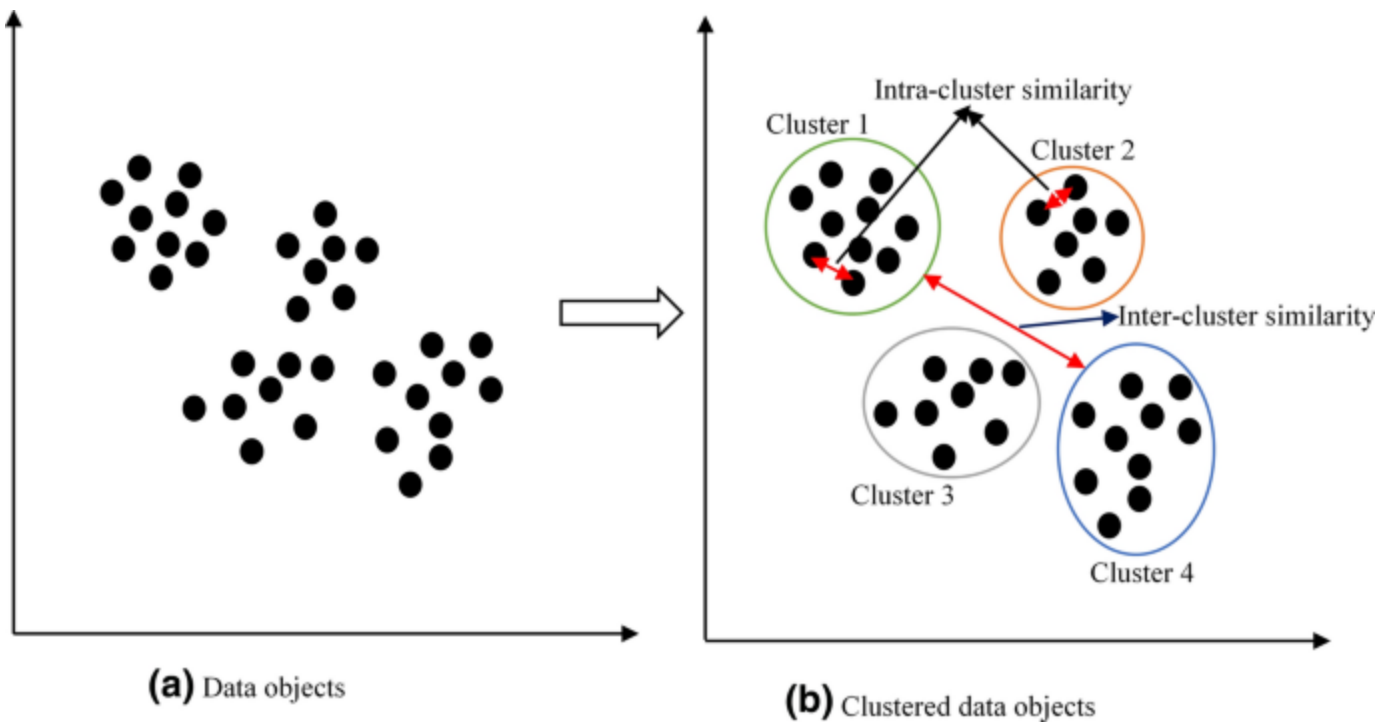
- Clustering is one of the most common exploratory data analysis technique used to get an intuition about the structure of the data.
- It can be defined as the task of identifying subgroups in the data such that data points in the same subgroup (cluster) are very similar while data points in different clusters are very different.
- we try to find homogeneous subgroups within the data such that data points in each cluster are as similar as possible according to a similarity measure such as Euclidean-based distance or correlation-based distance.

Clustering

- Clustering is considered an **unsupervised learning** method since we don't have the ground truth to compare the output of the clustering algorithm to the true labels to evaluate its performance.



Clustering



K-Means

- K-means clustering is one of the simplest and popular unsupervised machine learning algorithms.
- Unsupervised algorithms make inferences from datasets using **only input vectors** without referring to known, or labelled, outcomes.
- The objective of K-means is to group similar data points together and discover underlying patterns. To achieve this objective, K-means looks for a fixed number (k) of clusters in a dataset.
 - A cluster refers to a collection of data points aggregated together because of certain similarities.

K-Means

- We define a target number k , which refers to **the number of centroids we need in the dataset**. A centroid is the imaginary or real location representing the center of the cluster.
- Every data point is allocated to each of the clusters through reducing the **within-cluster sum of squares**.
- K-means algorithm is an **iterative algorithm** that tries to partition the dataset into K pre-defined distinct non-overlapping subgroups (clusters) where each data point belongs to only one group

K-Means Algorithm

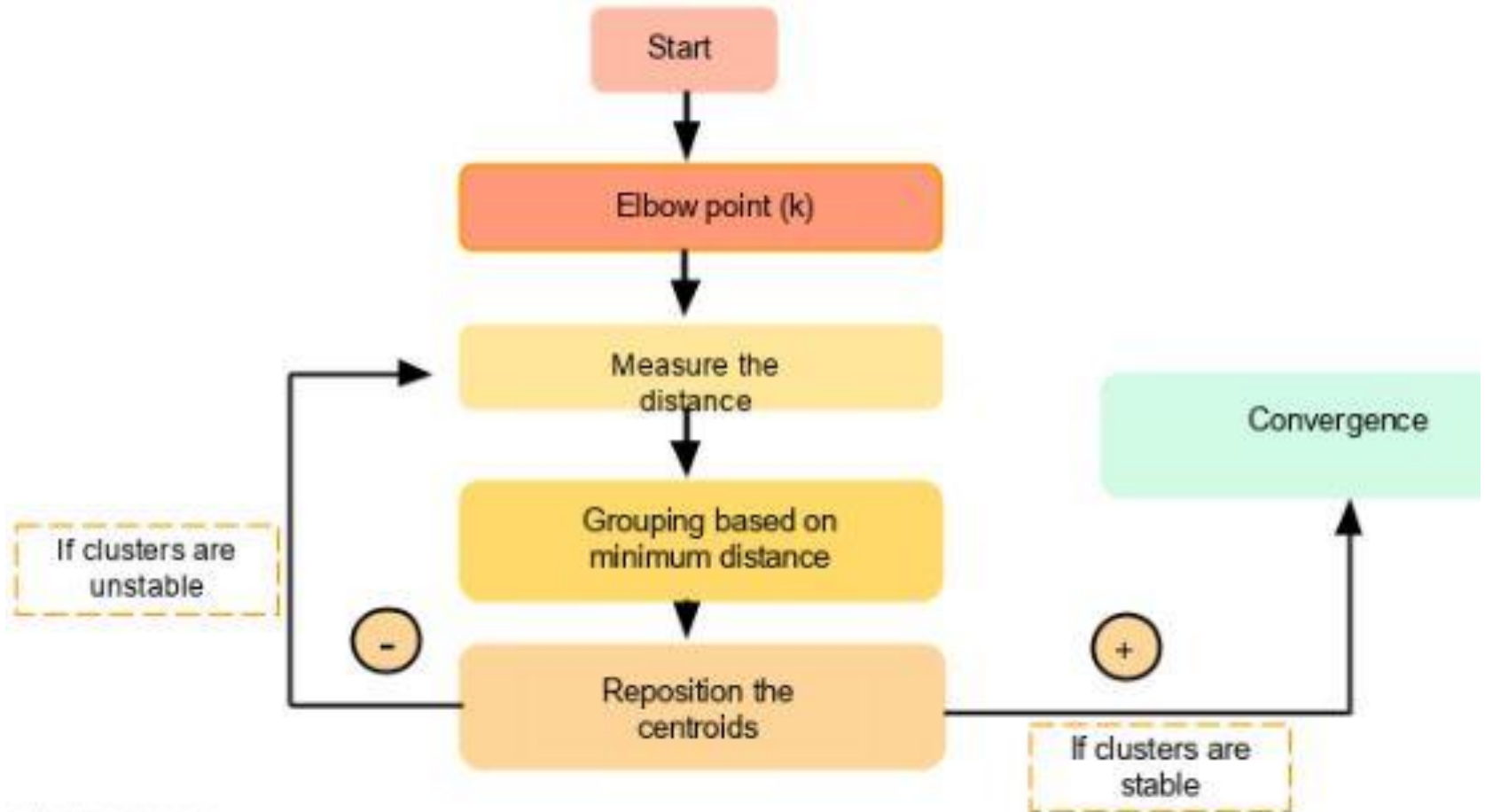
- The first step in k-means is to pick the number of clusters, K .
- Next, we randomly select the centroid for each cluster. Let's say we want to have 2 clusters, so k is equal to 2 here. We then randomly select the centroid.
- Once we have initialized the centroids, we assign each point to the closest cluster centroid:



K-Means Algorithm

- Specify number of clusters K .
- Initialize centroids by first shuffling the dataset and then randomly selecting K data points for the centroids without replacement.
- Compute the sum of the squared distance between data points and all centroids.
- Assign each data point to the closest cluster (centroid).
- Compute the centroids for the clusters by taking the average of the all-data points that belong to each cluster.
- Keep iterating until there is no change to the centroids, i.e., assignment of data points to clusters isn't changing.

K-Means Algorithm



Expectation Maximization

- The approach k-means follows to solve the problem is called **Expectation-Maximization**.
- The E-step is assigning the data points to the closest cluster. The M-step is computing the centroid of each cluster.

The diagram shows the objective function for k-means clustering, $J = \sum_{j=1}^k \sum_{i=1}^n \|x_i^{(j)} - c_j\|^2$. Annotations include: 'number of clusters' pointing to k , 'number of cases' pointing to n , 'case i ' pointing to $x_i^{(j)}$, 'centroid for cluster j ' pointing to c_j , 'Distance function' pointing to the norm $\|x_i^{(j)} - c_j\|^2$, and 'objective function' pointing to J .

$$\text{objective function} \leftarrow J = \sum_{j=1}^k \sum_{i=1}^n \underbrace{\|x_i^{(j)} - c_j\|^2}_{\text{Distance function}}$$

K-Means Example

Suppose we want to group the visitors to a website using just their age (one-dimensional space) as follows:

$$n = 19$$

15, 15, 16, 19, 19, 20, 20, 21, 22, 28, 35, 40, 41, 42, 43, 44, 60, 61, 65

Initial clusters (random centroid or average):

$$k = 2$$

$$c_1 = 16$$

$$c_2 = 22$$

$$\text{Distance 1} = |x_i - c_1|$$

$$\text{Distance 2} = |x_i - c_2|$$

Source: https://www.saedsayad.com/clustering_kmeans.htm

K-Means Example

Iteration 1:

$$c_1 = 15.33$$

$$c_2 = 36.25$$

x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	16	22	1	7	1	15.33
15	16	22	1	7	1	
16	16	22	0	6	1	
19	16	22	3	3	2	36.25
19	16	22	3	3	2	
20	16	22	4	2	2	
20	16	22	4	2	2	
21	16	22	5	1	2	
22	16	22	6	0	2	
28	16	22	12	6	2	
35	16	22	19	13	2	
40	16	22	24	18	2	
41	16	22	25	19	2	
42	16	22	26	20	2	
43	16	22	27	21	2	
44	16	22	28	22	2	
60	16	22	44	38	2	
61	16	22	45	39	2	
65	16	22	49	43	2	

K-Means Example

Iteration 2:

$$c_1 = 18.56$$

$$c_2 = 45.90$$

x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	15.33	36.25	0.33	21.25	1	18.56
15	15.33	36.25	0.33	21.25	1	
16	15.33	36.25	0.67	20.25	1	
19	15.33	36.25	3.67	17.25	1	
19	15.33	36.25	3.67	17.25	1	
20	15.33	36.25	4.67	16.25	1	
20	15.33	36.25	4.67	16.25	1	
21	15.33	36.25	5.67	15.25	1	
22	15.33	36.25	6.67	14.25	1	
28	15.33	36.25	12.67	8.25	2	45.9
35	15.33	36.25	19.67	1.25	2	
40	15.33	36.25	24.67	3.75	2	
41	15.33	36.25	25.67	4.75	2	
42	15.33	36.25	26.67	5.75	2	
43	15.33	36.25	27.67	6.75	2	
44	15.33	36.25	28.67	7.75	2	
60	15.33	36.25	44.67	23.75	2	
61	15.33	36.25	45.67	24.75	2	
65	15.33	36.25	49.67	28.75	2	

K-Means Example

Iteration 3:

$$c_1 = 19.50$$

$$c_2 = 47.89$$

x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	18.56	45.9	3.56	30.9	1	19.50
15	18.56	45.9	3.56	30.9	1	
16	18.56	45.9	2.56	29.9	1	
19	18.56	45.9	0.44	26.9	1	
19	18.56	45.9	0.44	26.9	1	
20	18.56	45.9	1.44	25.9	1	
20	18.56	45.9	1.44	25.9	1	
21	18.56	45.9	2.44	24.9	1	
22	18.56	45.9	3.44	23.9	1	
28	18.56	45.9	9.44	17.9	1	
35	18.56	45.9	16.44	10.9	2	47.89
40	18.56	45.9	21.44	5.9	2	
41	18.56	45.9	22.44	4.9	2	
42	18.56	45.9	23.44	3.9	2	
43	18.56	45.9	24.44	2.9	2	
44	18.56	45.9	25.44	1.9	2	
60	18.56	45.9	41.44	14.1	2	
61	18.56	45.9	42.44	15.1	2	
65	18.56	45.9	46.44	19.1	2	

K-Means Example

Iteration 4:

$$c_1 = 19.50$$

$$c_2 = 47.89$$

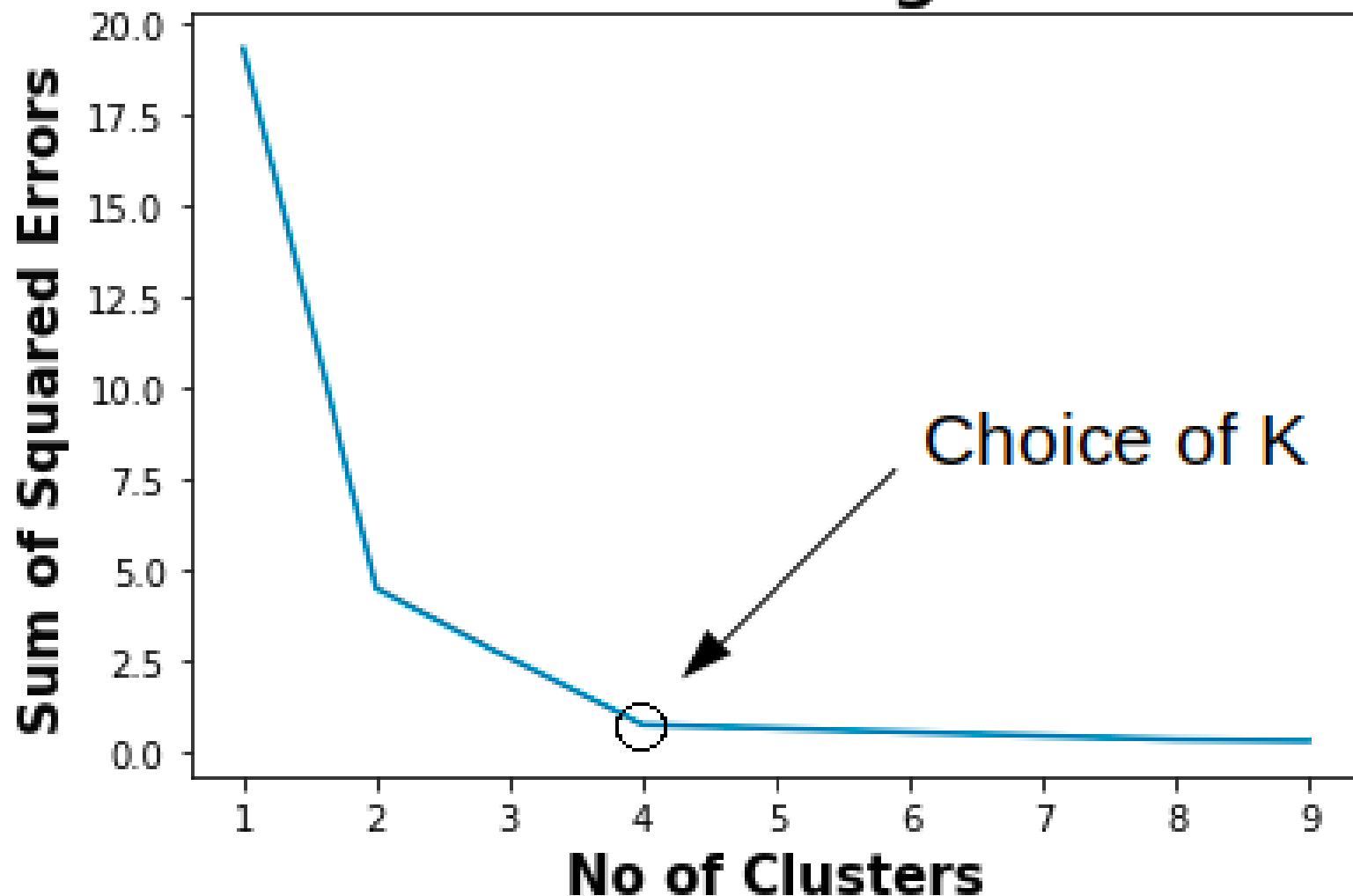
x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	19.5	47.89	4.50	32.89	1	19.50
15	19.5	47.89	4.50	32.89	1	
16	19.5	47.89	3.50	31.89	1	
19	19.5	47.89	0.50	28.89	1	
19	19.5	47.89	0.50	28.89	1	
20	19.5	47.89	0.50	27.89	1	
20	19.5	47.89	0.50	27.89	1	
21	19.5	47.89	1.50	26.89	1	
22	19.5	47.89	2.50	25.89	1	
28	19.5	47.89	8.50	19.89	1	
35	19.5	47.89	15.50	12.89	2	47.89
40	19.5	47.89	20.50	7.89	2	
41	19.5	47.89	21.50	6.89	2	
42	19.5	47.89	22.50	5.89	2	
43	19.5	47.89	23.50	4.89	2	
44	19.5	47.89	24.50	3.89	2	
60	19.5	47.89	40.50	12.11	2	
61	19.5	47.89	41.50	13.11	2	
65	19.5	47.89	45.50	17.11	2	

Elbow Method

- The elbow method runs k-means clustering on the dataset for a range of values for k (say from 1-10) and then for each value of k computes an average score for all clusters.
- We can compute Within-Cluster Sum of Squares (WCSS), the sum of square distances from each point to its assigned center.
- We then draw k vs. WCSS.

Elbow Method

Elbow Method using scikit-learn



K-Means Implementation

Implement k-Means Algorithm

Summary

- K-means