K-MEANS CLUSTERING

2143488 BIG DATA AND ARTIFICIAL INTELLIGENCE

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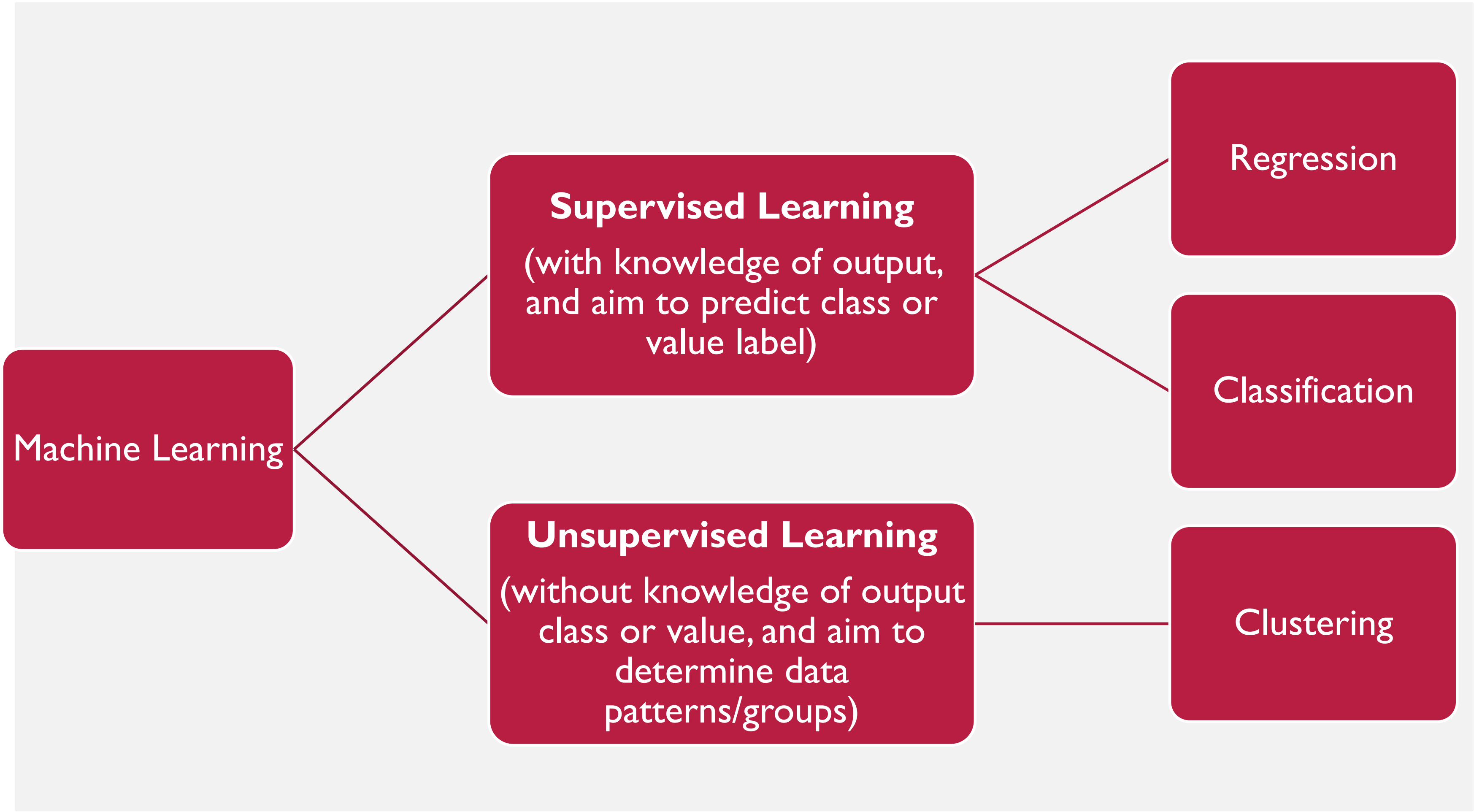
MACHINING LEARNING



K-MEANS CLUSTERING (MACQUEEN 1967)

- K-means clustering is a type of **unsupervised** learning, which is used when you have **unlabeled data** (i.e., data without defined categories or groups).
- The goal of this algorithm is to find **groups** in the data, with the number of groups represented by the variable **K**.
- The algorithm works iteratively to assign each data point to one of K groups based on the features that are provided.
- Data points are clustered based on **feature similarity**.

K-MEANS CLUSTERING

- The results of the *K*-means clustering algorithm are:
  - The **centroids** of the *K* clusters, which can be used to label new data
  - **Labels** for the training data (each data point is assigned to a single cluster)

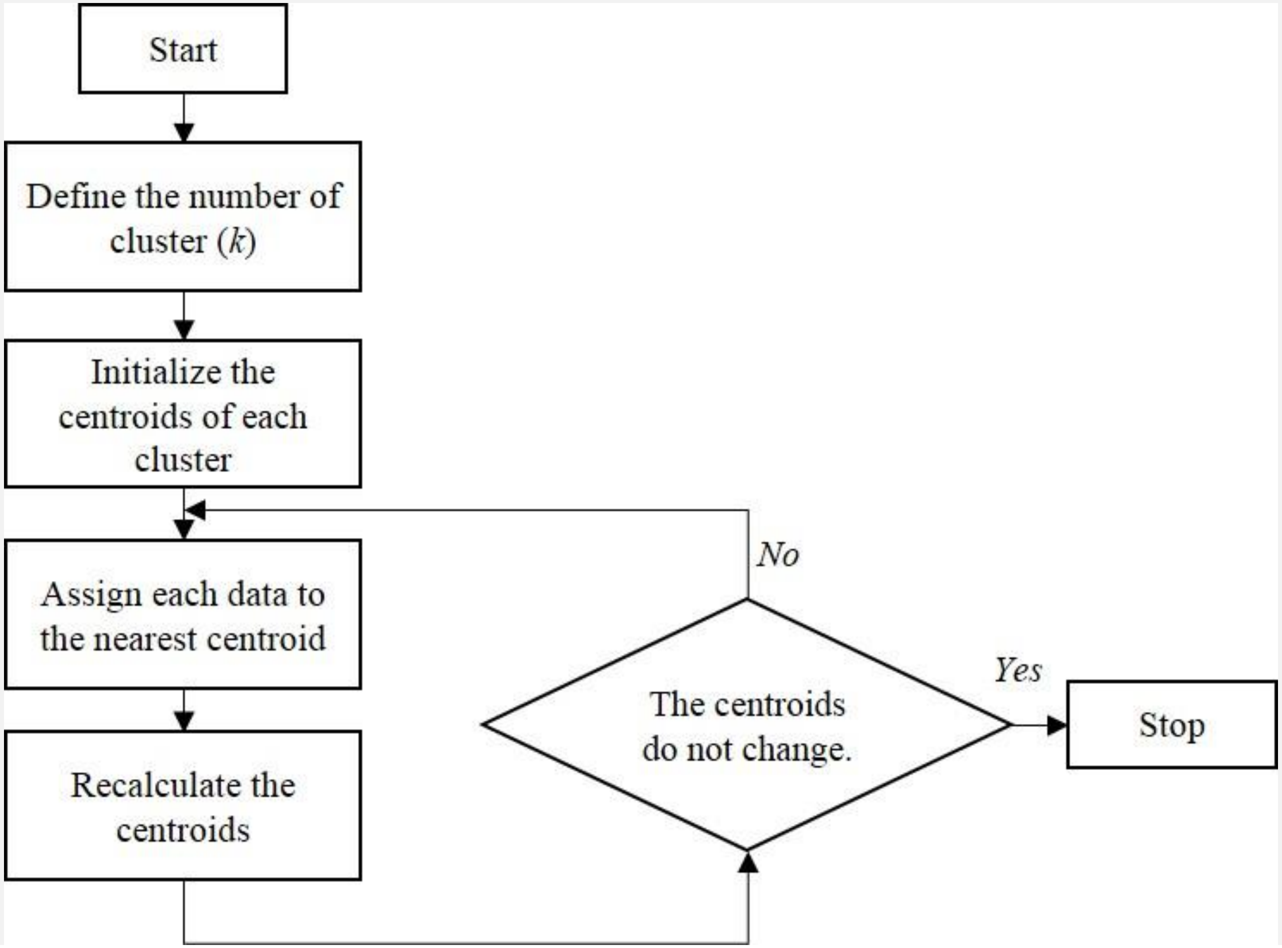
K-MEANS CLUSTERING

- **Each centroid** of a cluster is a **collection of feature values** which define the resulting groups.
- Examining the **centroid feature weights** can be used to qualitatively interpret what **kind of group** each cluster represents.

ALGORITHM

- The *K*-means clustering algorithm uses **iterative refinement** to produce a final result.
- Two inputs: the number of clusters *K* and the data set.
- The data set is a collection of features for each data point.
- The algorithms starts with **initial estimates for the *K* centroids**, which can either be randomly generated or randomly selected from the data set.

ALGORITHM


Start
Define the number of cluster (k)
Initialize the centroids of each cluster
Assign each data to the nearest centroid
Recalculate the centroids
The centroids do not change.
No
Yes
Stop

ALGORITHM

- The algorithm then iterates between two steps:

1. Data assignment step
2. Centroid update step

ALGORITHM
1. DATA ASSIGNMENT STEP:

- Each centroid defines one of the clusters.
- In this step, each data point is assigned to its nearest centroid, based on the Euclidean distance.

EUCLIDEAN DISTANCE

$$d_{ij} = \sqrt{\sum_{v=1}^{V} (x_{iv} - c_{jv})^2}$$

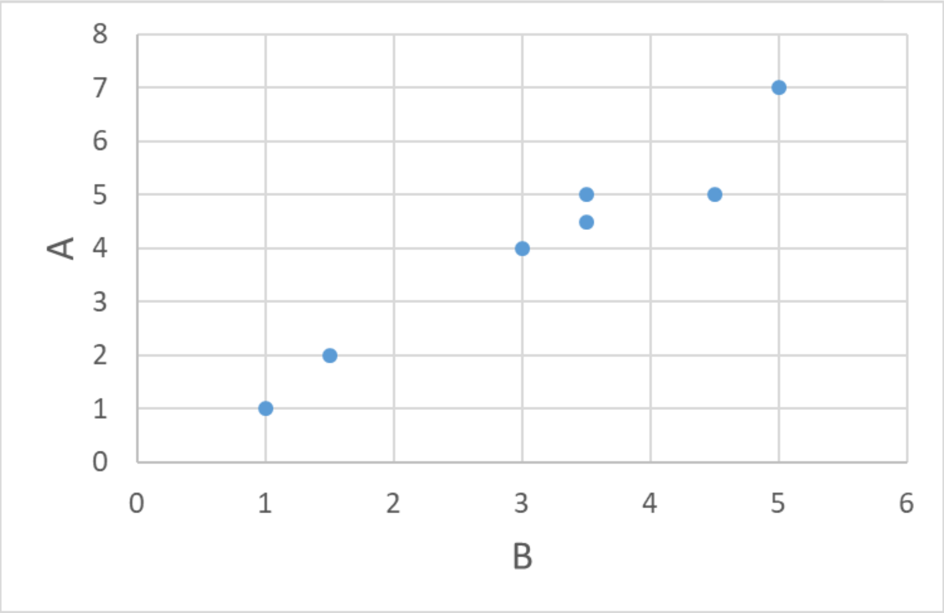
- where x_{iv} is the value of attribute v of the data i, and c_{jv} is the value of the attribute v of the centroid of the cluster j.

ALGORITHM
2. CENTROID UPDATE STEP:

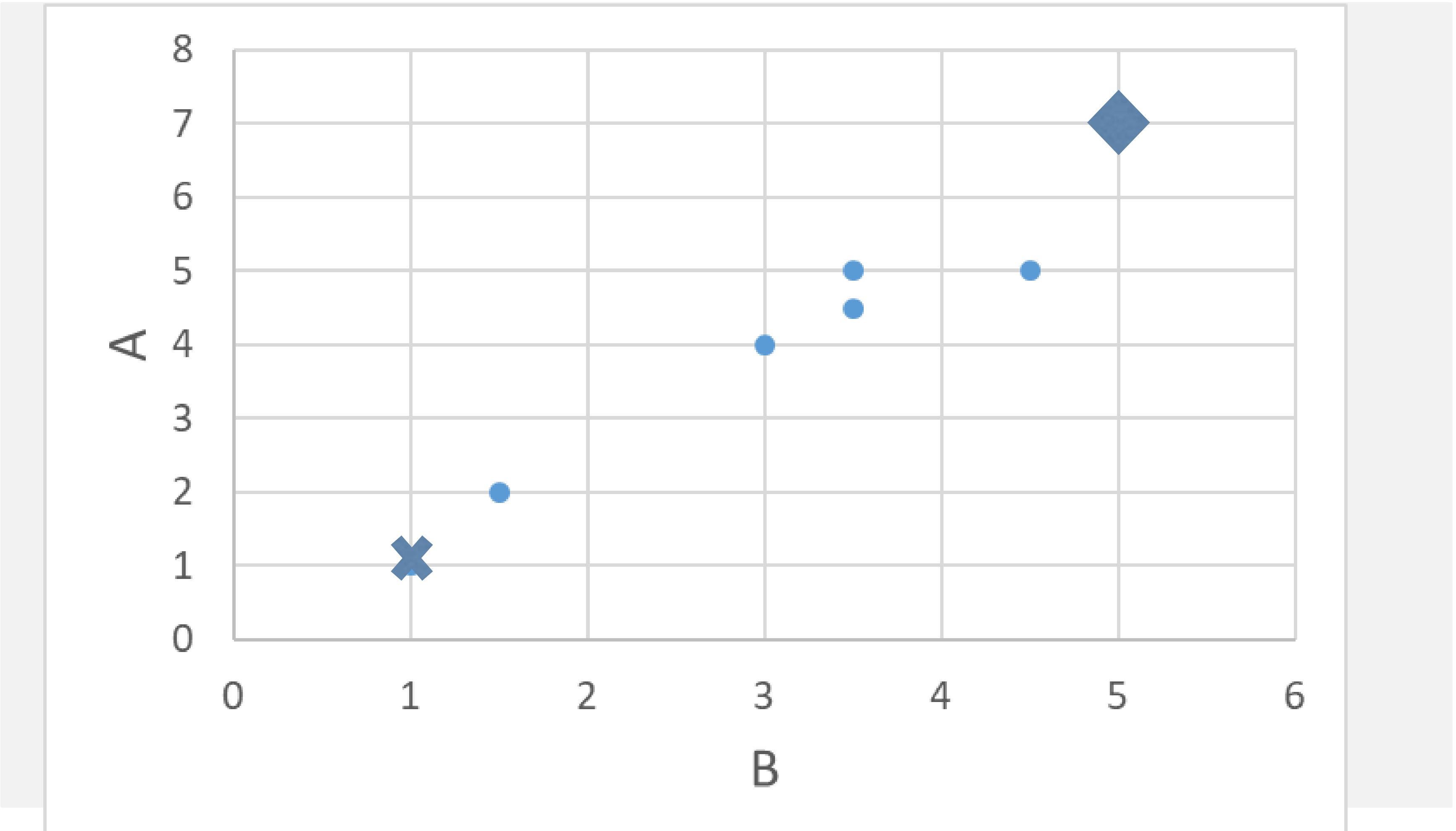
- In this step, the centroids are recomputed. This is done by taking the mean of all data points assigned to that centroid's cluster.

EXAMPLE: DATA

Subject	A	B
1	1	1
2	1.5	2
3	3	4
4	5	7
5	3.5	5
6	4.5	5
7	3.5	4.5



EXAMPLE: ITERATION 1



EXAMPLE: ITERATION 1

Iteration 1

Subject	A	B	Distance C1	Distance C2
1	1	1	0.00	7.21
2	1.5	2	1.12	6.10
3	3	4	3.61	3.61
4	5	7	7.21	0.00
5	3.5	5	4.72	2.50
6	4.5	5	5.32	2.06
7	3.5	4.5	4.30	2.92

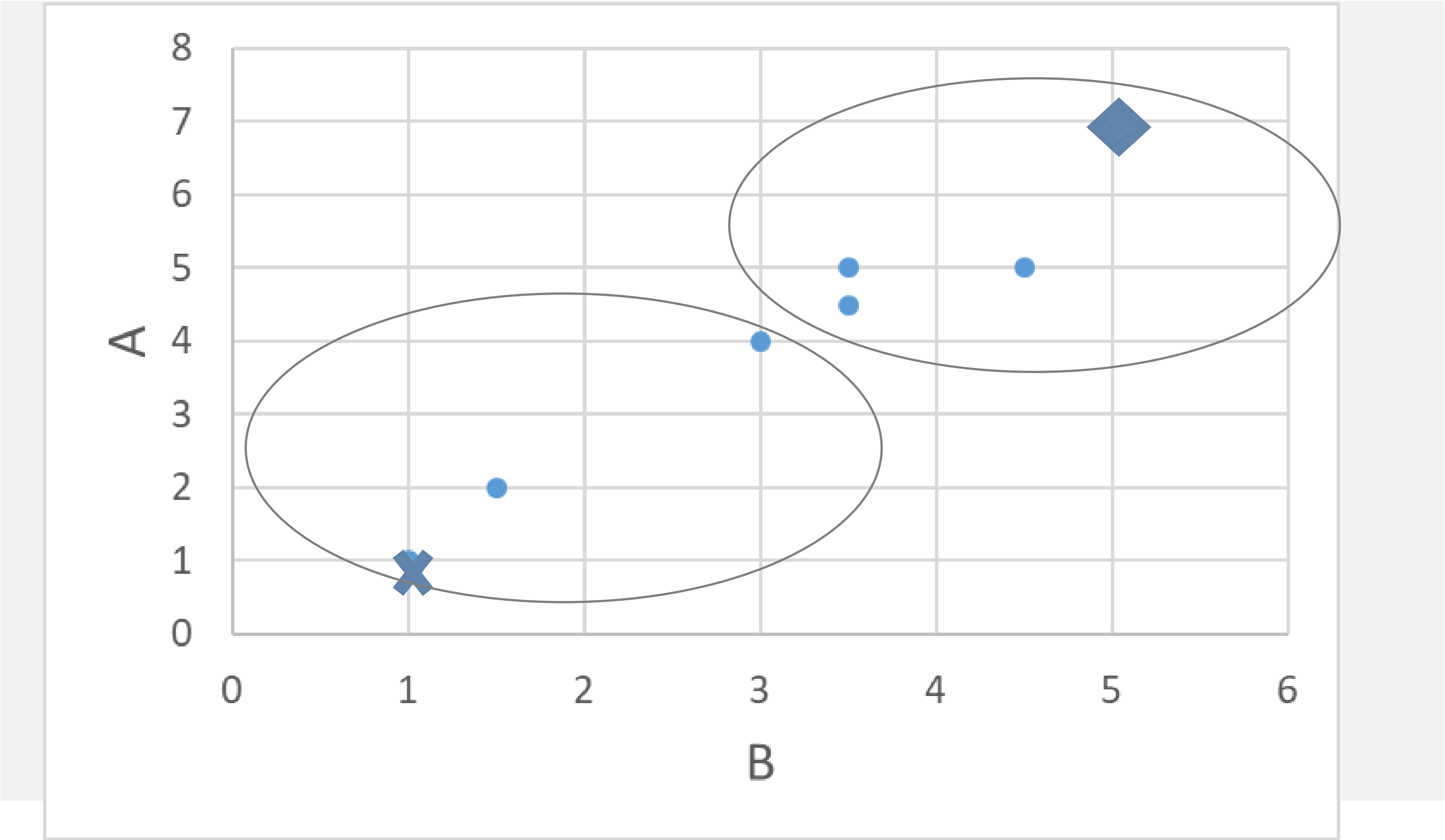
Initial centriod

	A	B
Centroid 1	1.00	1.00
Centroid 2	5.00	7.00

Re-compute centroids

	A	B
Centroid 1	1.8	2.3
Centroid 2	4.1	5.4

EXAMPLE: ITERATION 1



EXAMPLE: ITERATION 2

Iteration 2

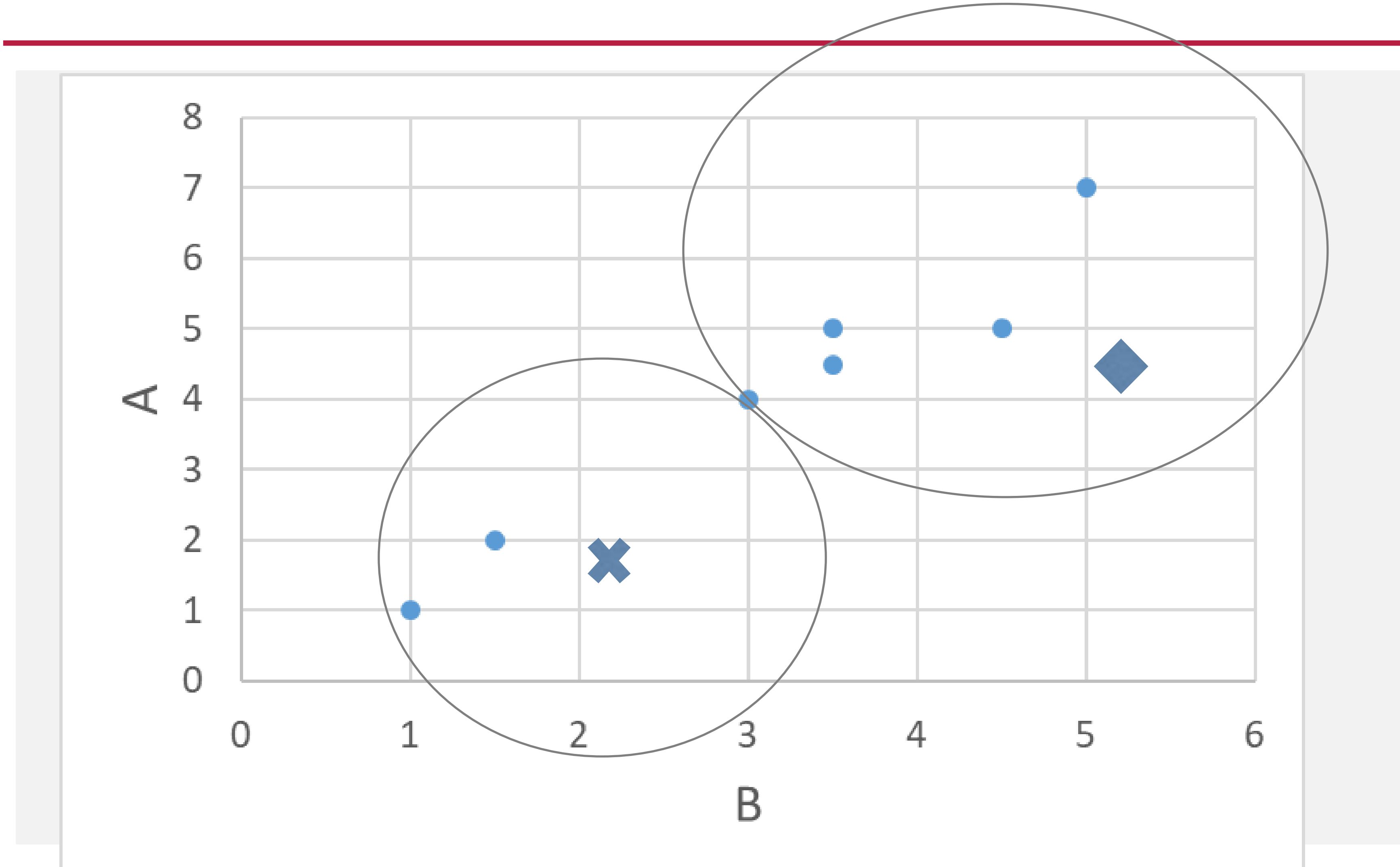
Subject	A	B	Distance C1	Distance C2
1	1	1	1.57	5.38
2	1.5	2	0.47	4.28
3	3	4	2.03	1.78
4	5	7	5.64	1.85
5	3.5	5	3.14	0.73
6	4.5	5	3.77	0.53
7	3.5	4.5	2.73	1.08

	A	B
Centroid 1	1.83	2.33
Centroid 2	4.13	5.38

Re-compute centroids

	A	B
Centroid 1	1.3	1.5
Centroid 2	3.9	5.1

EXAMPLE: ITERATION 2



EXAMPLE: ITERATION 3

Iteration 3

Subject	A	B	Distance C1	Distance C2
1	1	1	0.56	5.02
2	1.5	2	0.56	3.92
3	3	4	3.05	1.42
4	5	7	6.66	2.20
5	3.5	5	4.16	0.41
6	4.5	5	4.78	0.61
7	3.5	4.5	3.75	0.72

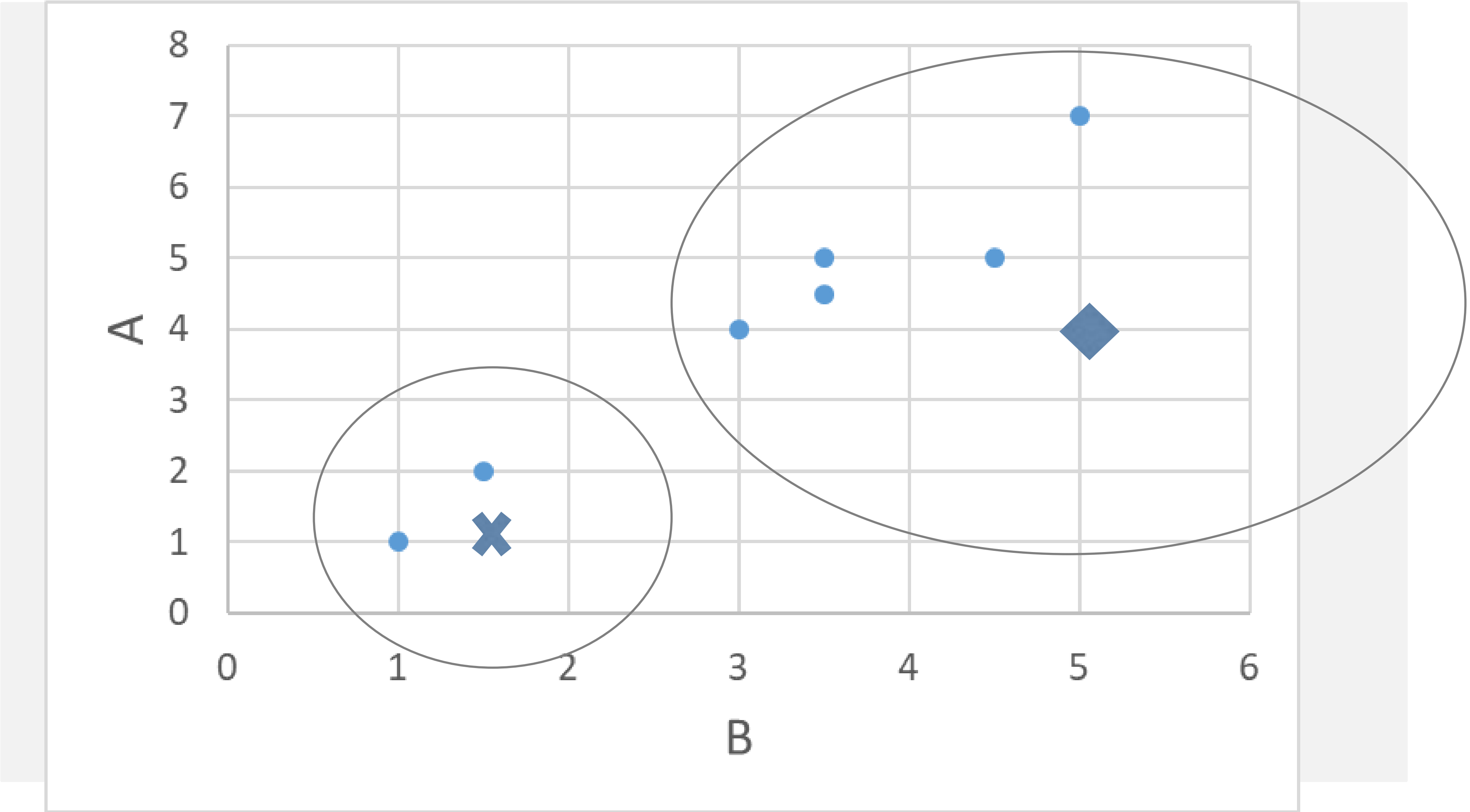
	A	B
Centroid 1	1.25	1.50
Centroid 2	3.90	5.10

Re-compute centroids

	A	B
Centroid 1	1.25	1.50
Centroid 2	3.90	5.10

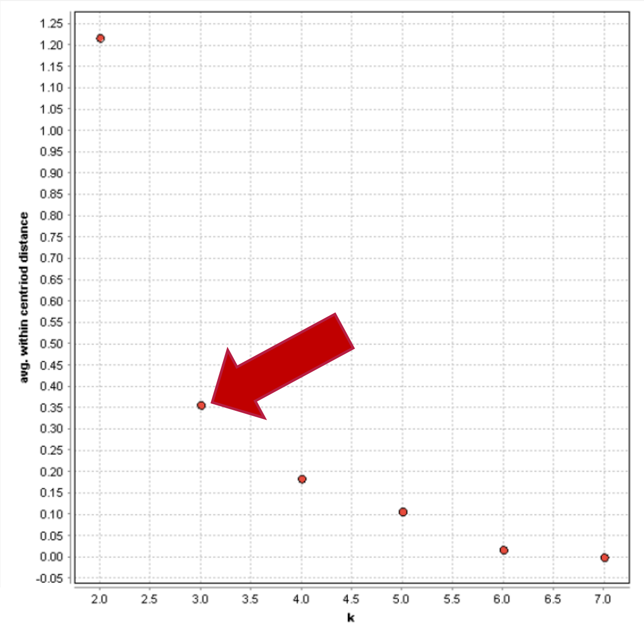
Stop

EXAMPLE: ITERATION 3



SELECT THE BEST K: ELBOW POINT

- Plot graph Within-Cluster-Sum-of Squares (OR **avg. within centroid distance**) vs. **K**
- Select the best K from **elbow point**
  - It demarks **significant drop-in** rate of increase.



SELECT THE BEST K: SILHOUETTE COEFFICIENT

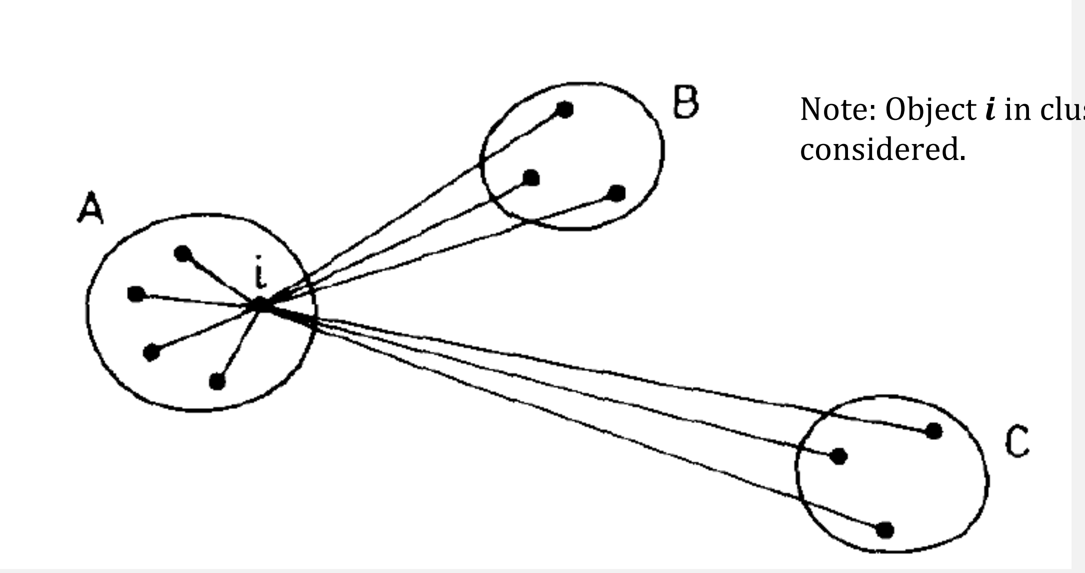
- Silhouette coefficient (Rousseeuw 1987) of observation *i* is calculated as:

$$s_i = \frac{(b_i - a_i)}{\max(a_i, b_i)}, \qquad -1 \le s_i \le 1$$

Where:
a_i: **average distance** of observation i to all other observations within same cluster
b_i: **minimum of average distance** of observation i to all other observations from all other clusters.

  - K giving the **highest average** of Silhouette (*S*) is the best K.
- It applies to any cluster, not just k-means.

SELECT THE BEST K: SILHOUETTE



Note: Object $\boldsymbol{i}$ in cluster $\boldsymbol{A}$ is being considered.

$a(i)$ = avg. dissimilarity of object $\boldsymbol{i}$ to all other objects within the **same cluster**

$d(i, O)$ = avg. dissimilarity of object $\boldsymbol{i}$ to all objects in the **other cluster $\boldsymbol{O}$**

$$b(i) = \min_{O \neq A} d(i, O)$$

SELECT THE BEST K: SILHOUETTE

- Euclidean distance

A		1	1.5	3	5	3.5	4.5	3.5
	Subject	1	2	3	4	5	6	7
1	1	0.00	0.25	4.00	16.00	6.25	12.25	6.25
1.5	2	0.25	0.00	2.25	12.25	4.00	9.00	4.00
3	3	4.00	2.25	0.00	4.00	0.25	2.25	0.25
5	4	16.00	12.25	4.00	0.00	2.25	0.25	2.25
3.5	5	6.25	4.00	0.25	2.25	0.00	1.00	0.00
4.5	6	12.25	9.00	2.25	0.25	1.00	0.00	1.00
3.5	7	6.25	4.00	0.25	2.25	0.00	1.00	0.00

B		1	2	4	7	5	5	4.5
	Subject	1	2	3	4	5	6	7
1	1	0.00	1.00	9.00	36.00	16.00	16.00	12.25
2	2	1.00	0.00	4.00	25.00	9.00	9.00	6.25
4	3	9.00	4.00	0.00	9.00	1.00	1.00	0.25
7	4	36.00	25.00	9.00	0.00	4.00	4.00	6.25
5	5	16.00	9.00	1.00	4.00	0.00	0.00	0.25
5	6	16.00	9.00	1.00	4.00	0.00	0.00	0.25
4.5	7	12.25	6.25	0.25	6.25	0.25	0.25	0.00

Euclidean								
	Subject	1	2	3	4	5	6	7
	1	0.00	1.12	3.61	7.21	4.72	5.32	4.30
	2	1.12	0.00	2.50	6.10	3.61	4.24	3.20
	3	3.61	2.50	0.00	3.61	1.12	1.80	0.71
	4	7.21	6.10	3.61	0.00	2.50	2.06	2.92
	5	4.72	3.61	1.12	2.50	0.00	1.00	0.50
	6	5.32	4.24	1.80	2.06	1.00	0.00	1.12
	7	4.30	3.20	0.71	2.92	0.50	1.12	0.00

SELECT THE BEST K: SILHOUETTE

- Compute average of Silhouette (Example: K=2)

Subject	A	B	a(i)	d(i,2)	b(i)	s(i)	Distance C1	Distance C2
1	1	1	1.12	5.03	5.03	0.78	0.56	5.02
2	1.5	2	1.12	3.93	3.93	0.72	0.56	3.92
3	3	4	1.81	3.05	3.05	0.41	3.05	1.42
4	5	7	2.77	6.66	6.66	0.58	6.66	2.20
5	3.5	5	1.28	4.16	4.16	0.69	4.16	0.41
6	4.5	5	1.50	4.78	4.78	0.69	4.78	0.61
7	3.5	4.5	1.31	3.75	3.75	0.65	3.75	0.72

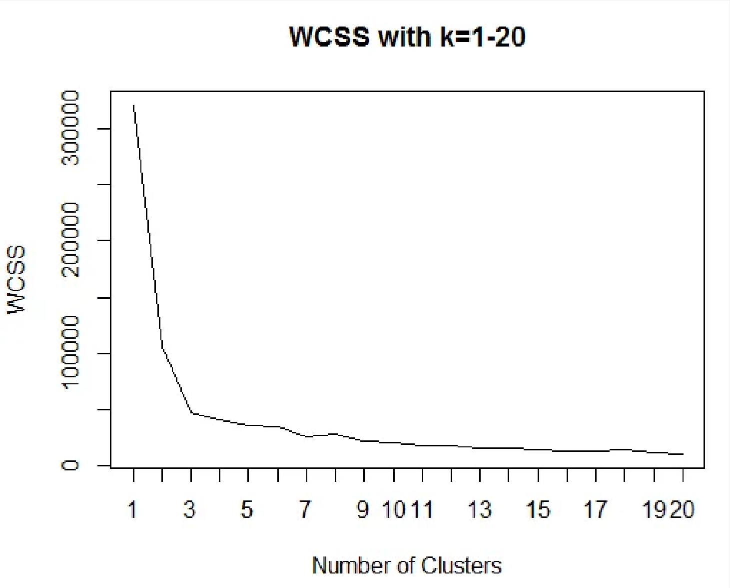
	A	B
Centroid 1	1.25	1.50
Centroid 2	3.90	5.10

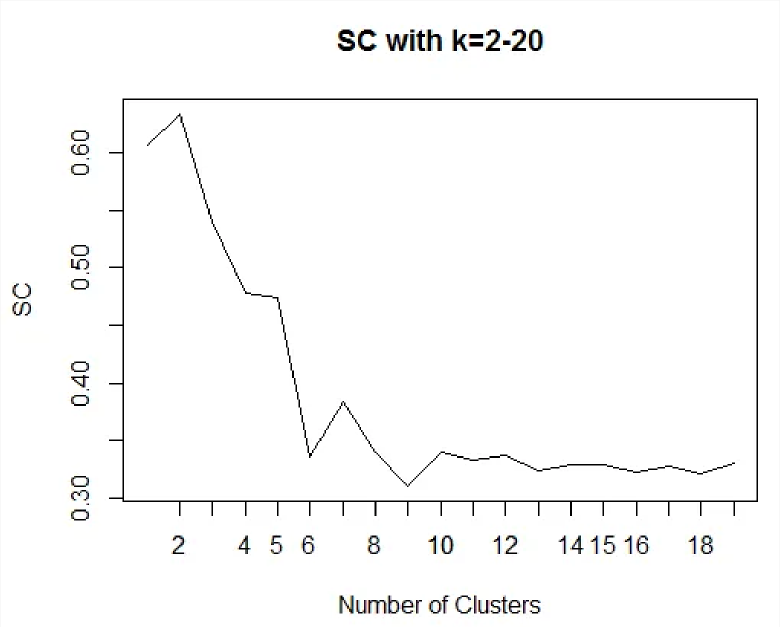
AVG of Silhouette 0.65

Re-compute centroids

	A	B
Centroid 1	1.25	1.50
Centroid 2	3.90	5.10

EXE 1: IDENTIFY K FOR K-MEANS

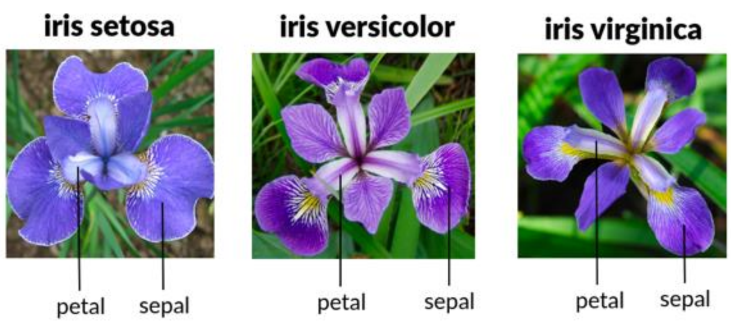


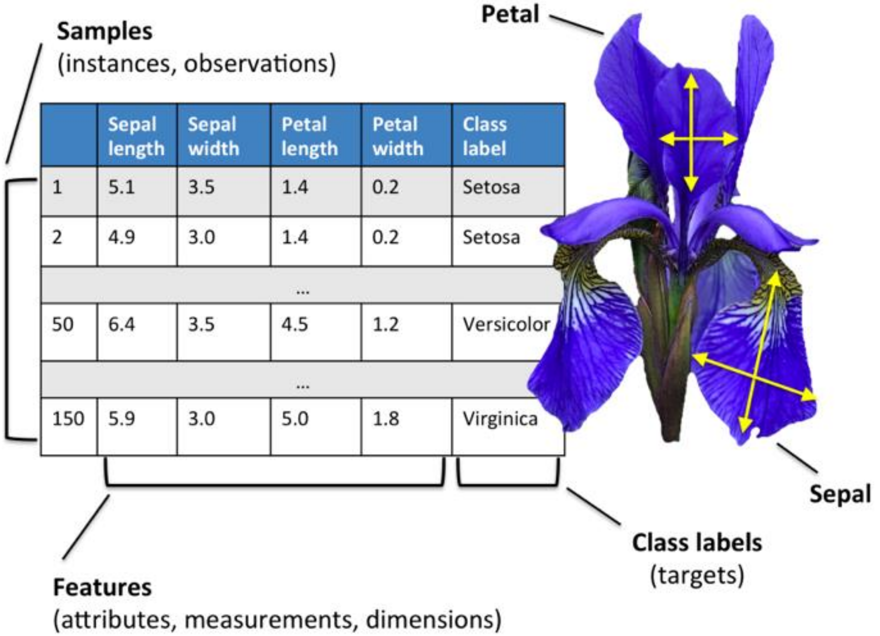


PROS AND CONS

- Pros:
  - Easy to implement
  - Low complexity $O(nkt), where\ t = \#\ of\ iterations$
- Con
  - Necessity of specifying k
  - Sensitive to noise and outlier data points
  - Sensitive to initial assignment of centroids
  - No guarantee to find a globally optimal solution

EXAMPLE: CLUSTER TYPES OF IRIS (//SAMPLES/DATA/IRIS)





	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
			...		
50	6.4	3.5	4.5	1.2	Versicolor
			...		
150	5.9	3.0	5.0	1.8	Virginica

ANALYSIS STEPS:

1. Data Preparation & Cleaning
   - Deal with missing values
   - Normalization (always do it)
2. Data Visulization & Analysis
   - Select attributes
   - Select k
3. k-means Segmentation:
   - Clusters
4. Evaluation:
   - Average within centroid distance

HW8: APPLY K-MEANS ON IMDB, AND COMPARE THE IMDB_SCORE (IMDB_1) AND CLUSTERS

- movie_title : Title of the Movie
- duration: Duration in minutes
- director_name : Name of the Director of the Movie.
- director_facebook_likes : Number of likes of the Director on his Facebook Page.
- color: Film colorization. ‘Black and White’ or ‘Color’
- genres: Film categorization like ‘Animation’, ‘Comedy’, ‘Romance’, ‘Horror’, ‘Sci-Fi’, ‘Action’, ‘Family’
- actor_1_name: Primary actor starring in the movie
- actor_1_facebook_likes : Number of likes of the Actor_1 on his/her Facebook Page.
- actor_2_name: Other actor starring in the movie
- actor_2_facebook_likes : Number of likes of the Actor_2 on his/her Facebook Page.
- actor_3_name: Other actor starring in the movie
- actor_3_facebook_likes : Number of likes of the Actor_3 on his/her Facebook Page.
- num_critic_for_reviews : Number of critical reviews on imdb
- num_voted_users: Number of people who voted for the movie
- cast_total_facebook_likes: Total number of facebook likes of the entire cast of the movie.
- language : English, Arabic, Chinese, French, German, Danish, Italian, Japanese etc
- country: Country where the movie is produced.
- gross: Gross earnings of the movie in Dollars
- budget: Budget of the movie in Dollars
- title_year: The year in which the movie is released (1916:2016)
- imdb_score: IMDB Score of the movie on IMDB
- movie_facebook_likes: Number of Facebook likes in the movie page.

H8: SOLUTION STEPS

1. Data Preparation & Cleaning
   - Select attributes
   - Deal with missing values
   - Calculate imdb_1 by **int(imdb_score)** and change it to be **ploynomial**
   - Normalized attributes
2. Data Visulization & Analysis
   - Set Label: imdb_1
   - **Select k**
3. k-means Segmentation:
   - Clusters
4. Evaluation:
   - Average within centroid distance

REFERENCES

- MacQueen, J. (1967, June). Some methods for classification and analysis of multivariate observations. In Proceedings of the fifth Berkeley symposium on mathematical statistics and probability (Vol. 1, No. 14, pp. 281-297).
- Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. Journal of computational and applied mathematics, 20, 53-65.