

# Clustering Algorithms: k-Means and k-Medoids

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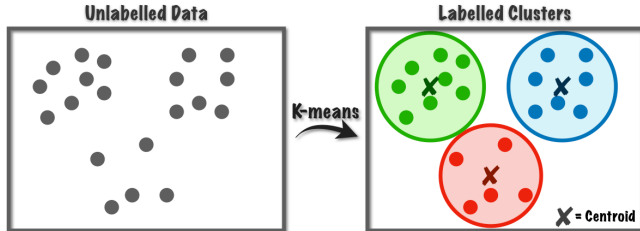


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# k-Means

- k-Means is a widely used clustering algorithm due to its efficiency.
- Time complexity:  $O(Nmq)$ , where  $q$  is the number of iterations, and  $m$  is number of clusters.
- Suitable for large datasets.



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# Advantages of k-Means

- Fast and computationally efficient.
- Simple to implement and interpret.
- Can be extended for different clustering problems.



# Drawbacks of k-Means

- Sensitive to outliers and noise.
- Struggles with non-spherical clusters.
- Generally applicable to data sets with continuous valued feature vectors



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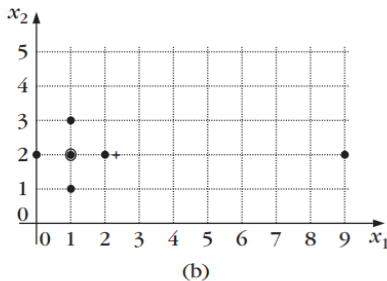
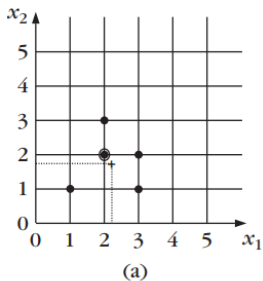
# Introduction to k-Medoids

- In the k-medoids methods, each cluster is represented by a vector selected among the elements of  $X$ , and we will refer to it as the **medoid**
- More robust to **outliers**.
- Works for both continuous and discrete datasets.





# K-mean Vs K-Medoids



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## Partitioning Around Medoids (PAM)

- Used to determine the set of the  $m$  medoids that best represent the data set
- Iteratively swaps medoids with non-medoids to minimize cost.
- Time Complexity:  $O(m(N - m)^2)$ .



# PAM Algorithm: Optimization Approach

- PAM minimizes  $J(\mathcal{M}, U)$ , where  $\mathcal{M}$  is the set of medoids.
- Constraints: Medoids are actual elements from dataset  $X$ .
- Two sets of medoids  $\mathcal{M}$  and  $\mathcal{M}'$  are **neighbors** if they share  $m - 1$  elements.
- A neighbor  $\mathcal{M}_{ij}$  results from replacing  $x_i$  with  $x_j$ .



# PAM Algorithm: Iterative Improvement

- Start with a random set  $\mathcal{M}$  of  $m$  medoids.
- For each neighbor  $\mathcal{M}_{ij}$ , compute:

$$\Delta J_{ij} = J(\mathcal{M}_{ij}, U_{ij}) - J(\mathcal{M}, U)$$

- If  $\Delta J_{qr} = \min(\Delta J_{ij}) < 0$ , replace  $\mathcal{M}$  with  $\mathcal{M}_{qr}$ .
- Repeat until no further improvement.



# Computation of $\Delta J_{ij}$

- $\Delta J_{ij}$  is computed by summing individual point contributions:

$$\Delta J_{ij} = \sum_{h \in X \setminus \mathcal{M}} C_{hij}$$

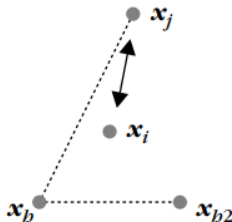
- Four cases determine  $C_{hij}$ , depending on:
  - Whether  $x_h$  belongs to the cluster of  $x_i$ .
  - Whether  $x_j$  is closer than the second nearest medoid.



## Case 1: Retains Second Closest Medoid

- $x_h$  belongs to the cluster of  $x_i$ .
- After replacing  $x_i$  with  $x_j$ ,  $x_h$  is now represented by the second closest medoid  $x_{h2}$ .
- The cost change is:

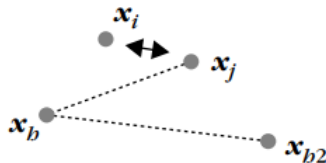
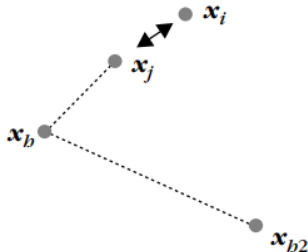
$$C_{hij} = d(x_h, x_{h2}) - d(x_h, x_i) \geq 0$$



## Case 2: Switches to New Medoid

- $x_h$  was initially assigned to  $x_i$ .
- After replacing  $x_i$  with  $x_j$ ,  $x_h$  now moves to  $x_j$ .
- The cost change is:

$$C_{hij} = d(x_h, x_j) - d(x_h, x_i)$$

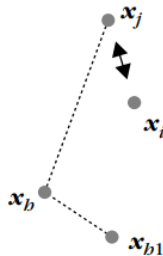




## Case 3: Remains in the Same Cluster

- $x_h$  is not assigned to  $x_i$ , and the replacement does not affect its assignment.
- Thus, there is no change in cost:

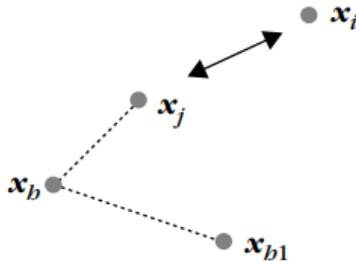
$$C_{hij} = 0$$



## Case 4: Moves from a Different Medoid

- $x_h$  was initially assigned to a different medoid  $x_{h1}$ .
- After the replacement,  $x_h$  is now assigned to  $x_j$ .
- The cost change is:

$$C_{hij} = d(x_h, x_j) - d(x_h, x_{h1}) \geq 0$$



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# CLARA and CLARANS

- **CLARA:** Draw randomly a sample  $X'$  of size  $N'$  from the entire data set,  $X$  and to determine the set of the medoids  $M'$  that best represents  $X'$  using the PAM algorithm
- **CLARANS:** PAM is applied on the entire data set  $X$ , but with a slight modification. At each iteration, not all neighbors of the current set of medoids are considered. Instead, only a randomly selected fraction

$$q < m(N - m)$$

of them is utilized.



# CLARA and CLARANS

- CLARANS is more accurate but computationally expensive.
- In some cases CLARA runs significantly faster than CLARANS. It must be pointed out that CLARANS retains its quadratic computational nature and is thus not appropriate for very large data sets.



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# Conclusion

- **k-Means:** Simple and efficient but sensitive to initialization.
- **k-Medoids:** More robust but computationally heavier.
- **CLARA and CLARANS:** Trade-off between speed and accuracy.
- **Suggested numbers in CLARA:** Experimental studies suggest that five  $X'$  and  $N' = 40 + 2m$  lead to satisfactory results.
- **Suggested numbers in CLARANS:** Experimental studies suggest that  $q$  can be chosen as the maximum between  $0.12m$  ( $N - m$ ) and 250.

