

→ K-Means Clustering

- What is K-means

K-means is an unsupervised clustering algorithm that partitions data into K clusters, where each data point belongs to the cluster with the nearest centroid.

- Purpose (When)

To group similar data points together based on distance, minimizing intra-cluster variance.

- Why it is used

- Simple and fast
- Scales well to large datasets
- Easy to implement and interpret
- Effective when clusters are spherical

- How it works (Algo.)

- Choose number of clusters K
- Randomly initialize K centroids
- Assign each data point to nearest centroid
- Recompute centroids as cluster mean
- Repeat until convergence

- Formula

Within cluster sum of squares:
$$J = \sum_{i=1}^K \sum_{x \in C_i} \|x - \mu_i\|^2$$

C_i = cluster

μ_i = centroid

- Technical Details
 - Distance metric: Euclidean
 - Convergence when centroids stop moving
 - Sensitive to initialization
- Parameters
 - $n_clusters (K)$: no. of clusters
 - init: centroid initialization
 - max_iter: maximum iterations
 - tol: convergence threshold
- Pros
 - Fast and scalable
 - Easy to understand
 - Efficient for large datasets
- Cons
 - Must choose K beforehand
 - Sensitive to outliers
 - Fails on non-spherical clusters
 - Sensitive to initialization
- Real-world Applications
 - Customer segmentation
 - Image compression
 - Market basket analysis
 - Document clustering

→ Hierarchical clustering

- What is hierarchical clustering

Hierarchical clustering builds a tree-like structure (dendrogram) that represents nested clusters without requiring K beforehand.

- Purpose (When)

To discover natural grouping structures and cluster hierarchy in data.

- Why it is used

- No need to predefine number of clusters
- Produces interpretable dendrogram
- Works well for small datasets

- How it works

• Agglomerative (Bottom-up)

- Start with each point as its own cluster
- Merge closest clusters
- Repeat until one cluster remains
- Cut dendrogram at desired level

• Divise (Top-Down)

- Start with all points as one cluster
- Divide most apart clusters

- Distance Linkage methods

- Single: Min distance
- Complete: Max distance
- Average: Avg distance
- Ward: Variance minimization

- Formula (Ward's method)

$$\Delta ESS = \frac{n_1 n_2}{n_1 + n_2} \| \mu_1 - \mu_2 \|^2$$

- Technical Details

- Time complexity: $O(n^3)$ (naive)
- Memory intensive
- Distance matrix required

- Parameters

linkage: merge criterion

metric: distance measure

n_clusters: optional

- Pros

- No K required initially
- Interpretable hierarchy
- Deterministic results

- Cons

- Not scalable
- Sensitive to noise
- Cannot undo merges

- Real World Applications

- Biological Taxonomy
- Document classification
- Gene expression analysis

→ DBSCAN (Density-based Spatial Clustering)

- What is DBSCAN
DBSCAN is a density-based clustering algorithm that groups points in high-density regions and labels sparse points as outliers.
- Purpose (When)
To identify arbitrarily shaped clusters and detect noise automatically.
- Why it is used
 - No need to specify number of clusters
 - Handles noise naturally
 - Detects non-spherical clusters
- How it works
 - Select parameters ϵ (epsilon) and MinPts
 - Identify core points
 - Expand clusters from core points
 - Label non-reachable points as noise
- Definitions
 - Core Point: \geq MinPts within ϵ radius
 - Border Point: reachable but not core
 - Noise Point: not reachable.
- Technical Details
 - Distance based density estimation
 - Sensitive to ϵ choice
 - Struggles with varying densities

- Parameters
 - ϵ (ϵ): Neighborhood radius
 - min_samples: min points for core
 - metric: distance measure
- Pros
 - No K required
 - Detects noise / outliers
 - Finds complex shapes
- Cons
 - Poor with varying densities
 - Parameter tuning is hard
 - Struggles in high dimensions
- Real-world applications
 - Anomaly detection
 - GPS location clustering
 - Image segmentation
 - Fraud detection