

Unsupervised ML

- No labels / output given
- Model finds pattern by itself
- Main task clustering

Clustering

↳ grouping similar data points together.

Same group \rightarrow more similar data points.

different group \rightarrow less similar.

K-means Clustering Algorithm

It is an unsupervised ML algo that divided dataset into K distinct clusters.

Each cluster is represented by centroid (mean).

Each data point belongs to nearest cluster.

Goal \rightarrow group similar data together without labels.

Working cycle

Step 1 \rightarrow choose K , you have to tell algo don't find it
 But to know what will be the best K for your cluster algorithm.

★ Elbow method is used to find best K .

\rightarrow Plot K vs WCSS, Look for elbow point.

WCSS (within cluster sum of squares).

WCSS needs to be minimum

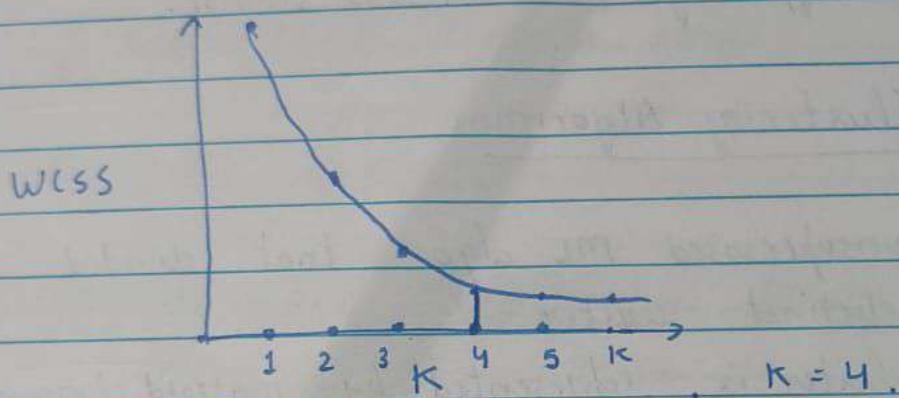
Small wcss \rightarrow points are closed to centroid (good cluster)

Large wcss \rightarrow points far from centroid (Bad cluster)

Core idea of Elbow Method

As K increase WCSS decreases, but after a point improvement becomes very small. That point is elbow best K value to use.

Why Elbow \rightarrow algo. don't finds K . we have to tell. if we given K and it will be wrong K (bad clustering) so finds optimal K by elbow method & use.



Step 2 \rightarrow Initialize centroids

Randomly select K points as initial centroid

Many times K-means select centroid randomly so chances are there it can initialize centroids very closely. which lead to form bad clusters.

So $(K++)$ algo comes in picture, id is same as K-means, slight change. it initialize centroids not randomly but based on distance & Probabilistic which helps in best centroid selection.

Step 3 Compute distance of points to all centroid using euclidean Distance formula.
then assign point to nearest centroid.

Step 4 → Update centroid, calculate mean of all points & update centroid.

Step 5 → Repeat (convergence).

ex → Points, $(1,1)$ $(2,1)$ $(4,3)$ $(5,4)$, $K=2$

initial centroid

$C_1 (1,1)$ $C_2 (5,4)$

Assignment after distance calculate

$[C_1 (1,1), (2,1)]$ $[C_2 (5,4), (4,3)]$

↓ updation ↓

$(1 (1.5, 1))$ $(2 (4.5, 3.5))$

②

Hierarchical clustering

It is an unsupervised clustering algo that builds a hierarchy of clusters in the form of tree structures (Dendrogram).

↳ Types

↳ Agglomerative (Bottom up) (commonly used).

↳ Divisive (Top down) (Rarely used).
Computationally expensive.

Agglomerative HC \rightarrow intuition

Step 1 \rightarrow Start with individual clusters
if there n points, initially n clusters.

Step 2 \rightarrow Compute distance Matrix
calculate distance b/w every pair of clusters / points
with euclidean distance.

Step 3 \rightarrow Merge Closest clusters
find two nearest clusters, merge them
into one.

Step 4 \rightarrow Update Distance Matrix
recalculate distances

Step 5 \rightarrow Repeat until one cluster
or continue till points are in single cluster.

Final clusters

Draw a horizontal line at max distance height
no. of vertical lines cut = no. of clusters.

Adv

No need to specify K .

Dendrogram given full picture

Works well with small datasets

Disadv

Computationally expensive

Not for large datasets

Sensitive to outliers

ex → to visualize

A (1,1) B (2,1) C (4,3) D (5,4).

| | A | B | C | D |
|---|------|------|------|------|
| A | 0 | 1 | 3.61 | 5 |
| B | 1 | 0 | 2.83 | 4.24 |
| C | 3.61 | 2.83 | 0 | 1.41 |
| D | 5 | 4.24 | 1.41 | 0 |

First merge, min distance = 1 b/w A & B

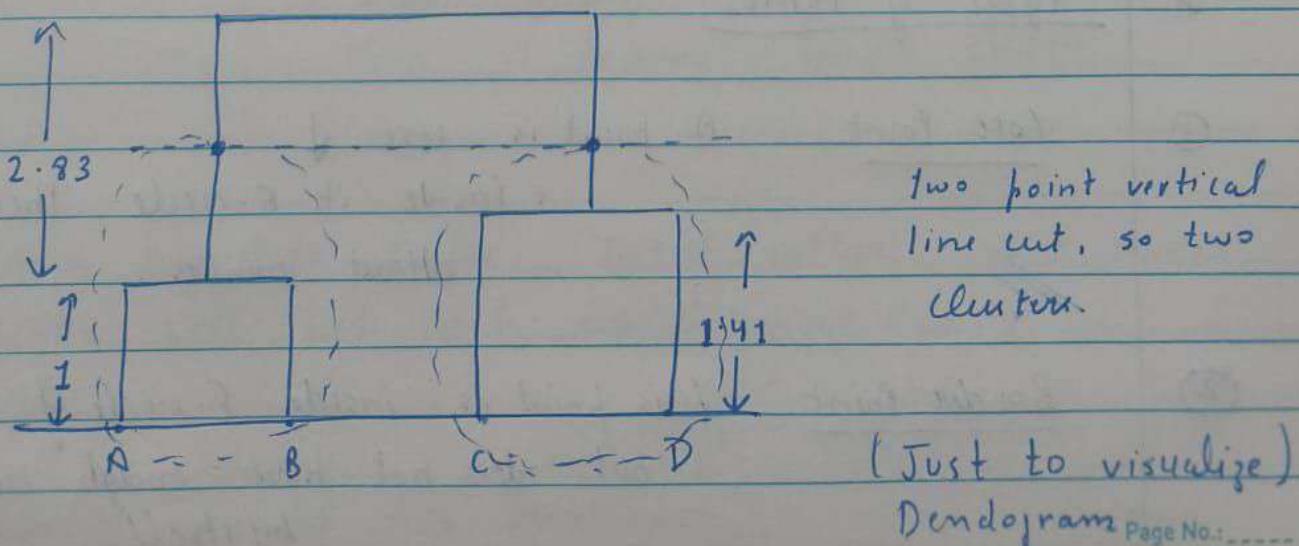
| | AB | C | D |
|----|------|------|------|
| AB | 0 | 2.83 | 4.24 |
| C | 2.83 | 0 | 1.41 |
| D | 4.24 | 1.41 | 0 |

Second merge, min distance = 1.41 b/w C & D

{AB}, {C, D}

Distance b/w AB & CD = min (2.83, 4.24) = 2.83

Final merge → {ABC,D}



③ DBSCAN clustering algo

Full Form → Density Based spatial clustering Algorithm with Noise

It is an unsupervised, density based clustering algorithm that groups based on density of data points, and automatically detect noise / outliers.

Places where many points are close together → cluster
lonely points far away → noise (outliers)

→ ① ϵ (epsilon)

A radius / circle size

Radius of neighbourhood

Too small → many outliers / noise - no cluster formed

Too large → all point move in one cluster.

→ ② min pts

Minimum no. of points required to form a dense region includes the point itself.

or

min no. of points find inside circle to form a cluster.

* Types of Points

① Core Point A point is core if

- inside its ϵ -circle there are at least min pts.

② Border Point This point is inside ϵ -circle of core point but does not have enough neighbours by itself.

(3) Noise Point

↳ Not, Not
Core Border

not in any core & circle area and also
self no minpts neighbour available in E-circle.

* Working DBSCAN

Step 1- Choose E & Minpts (hyperparameter tuning).

Step 2- Pick any point

↳ Draw E-circle around it & count point inside
including that point also.

Step 3 - if points \geq Minpts \rightarrow Core
Else \rightarrow Noise (For now).

Step 4 \rightarrow If point is core,

Make a new cluster, add all nearby
point, if nearby points is also core
expand it.

Step 5 \rightarrow Repeat for all points.

- Every point is visited once
- Noise stays noise unless it touch a
E-circle of any core point if it does
then it becomes border point.

Adv

- Finding any shape cluster, Detect outliers, no K needed.
- works well with real world noisy data

Disadv

Hard to choose E

High dimensional data problem.