


# CLUSTERING

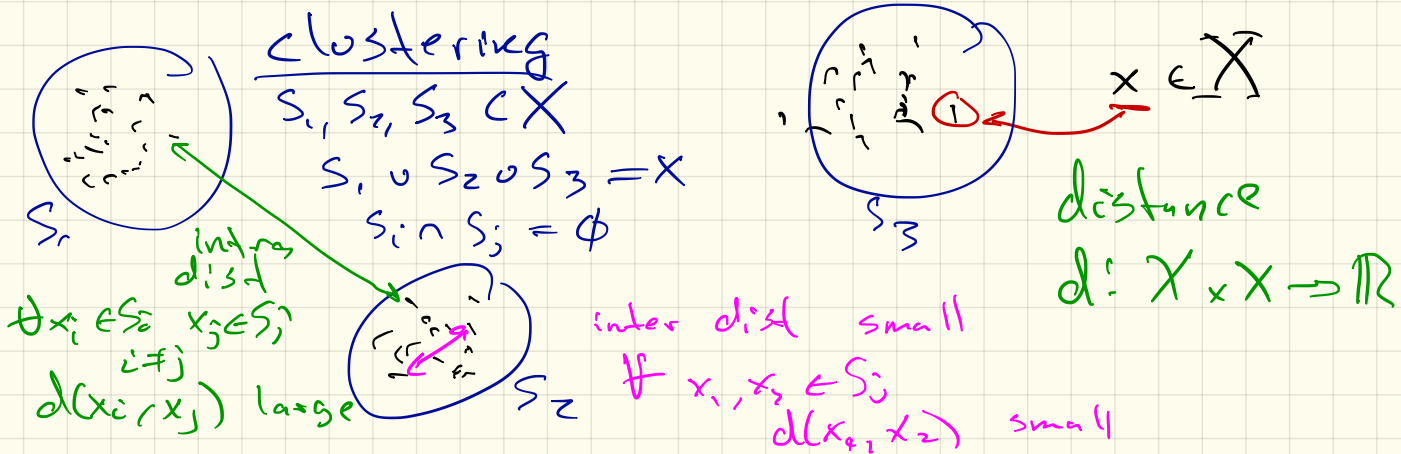
## Hierarchical Agglomerative Clustering

1000s of types of clustering!

- HAC 
- Assignment-based clustering
- Spectral

"When data is easily clusterable, most clustering algorithms work quickly and well."

When data is not easily clusterable, then no algorithm can find good clusters."



# Common data

Handwritten notes on grid paper, consisting of several lines of illegible scribbles and symbols.

Hier      Agg      Clust

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Input  $X$ , dist  $d$ ,  $d: X \times X \rightarrow \mathbb{R}$

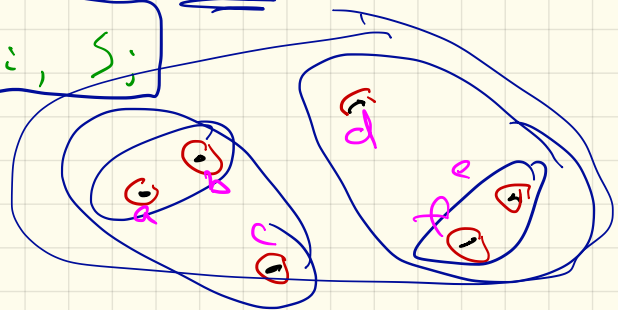
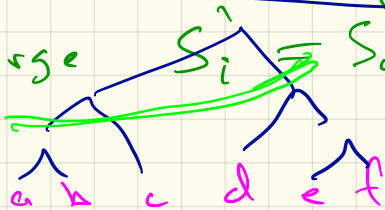
Algo: If two points (or clusters) are close enough, put them in the same cluster. Repeat.

0. Each  $x_i \in X \rightarrow$  put in separate cluster  $S_i$

1. While (two clusters are close enough)

1a. Find closest pair  $S_i, S_j$

1b. Merge  $S_i \rightarrow S_i \cup S_j$



# Distance between pair clusters $S_1, S_2$

- find "center"  $c_1$  of  $S_1$ ,  $c_2$  of  $S_2$

$$D(S_1, S_2) = d(c_1, c_2)$$

- $c_i = \text{average}(S_i)$
- $c_i = \text{random}(S_i)$

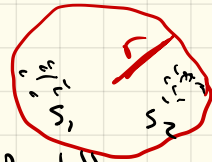
- $c_i = \arg \min_{x \in S_i} \|x\|$

- $c_i = \text{median}(S_i) = \arg \min_{c \in S_i} \sum_{x \in S_i} d(x, c)$

- $D(S_1, S_2) = \text{radius}(\text{min enclosing ball}(S_1 \cup S_2))$

- $D(S_1, S_2) = \min_{x_1 \in S_1, x_2 \in S_2} d(x_1, x_2)$

average      max



"single link"

- Build generative model  
compare likelihoods  $L(S_1), L(S_2), L(S_1 \cup S_2)$



two means

# Which Variant?

- gives proper clustering; "smallest error"

↳ Dist D linked  
to error eval.

• Computational Complexity

1.  $O(n^2)$  pairwise dist.

2.  $O(n)$  nodes in hierarchy.

$O(n^3) \rightarrow O(n^2 \log n)$  (w/ PG)

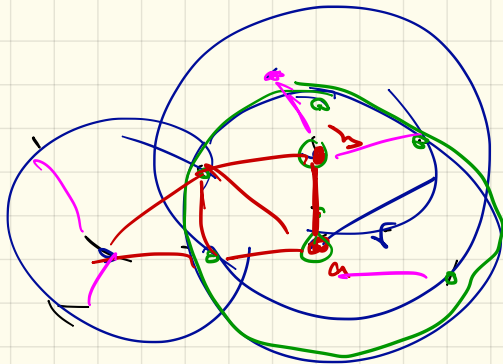
2.  $O(n \log n)$  or  $O(nk)$

# DB Scan

$O(n \log n)$ ?

$X, d,$  param:  $r$   
radius

$T$   
threshold density



each  $B_r(x)$   
 $|B_r(x) \cap X| \geq T$   
if  $\geq T$   
 $x \rightarrow$  "core point"

link core points  
 $d(x, x') < r$   
 $\rightarrow$  cluster.

# K-Center Cluster Gonzalez Algo.

$O(nk)$

In  $X, d, k$  any d metric

Out:  $c_1, c_2, \dots, c_k \leftarrow$  centers of clusters,

$c_1 \leftarrow$  arbitrarily ( $x$ )

for  $j=2$  to  $k$

$$c_j = \arg \max_{x \in X} \left( \min_{c \in \{c_1, \dots, c_{j-1}\}} \|x - c\| \right)$$

