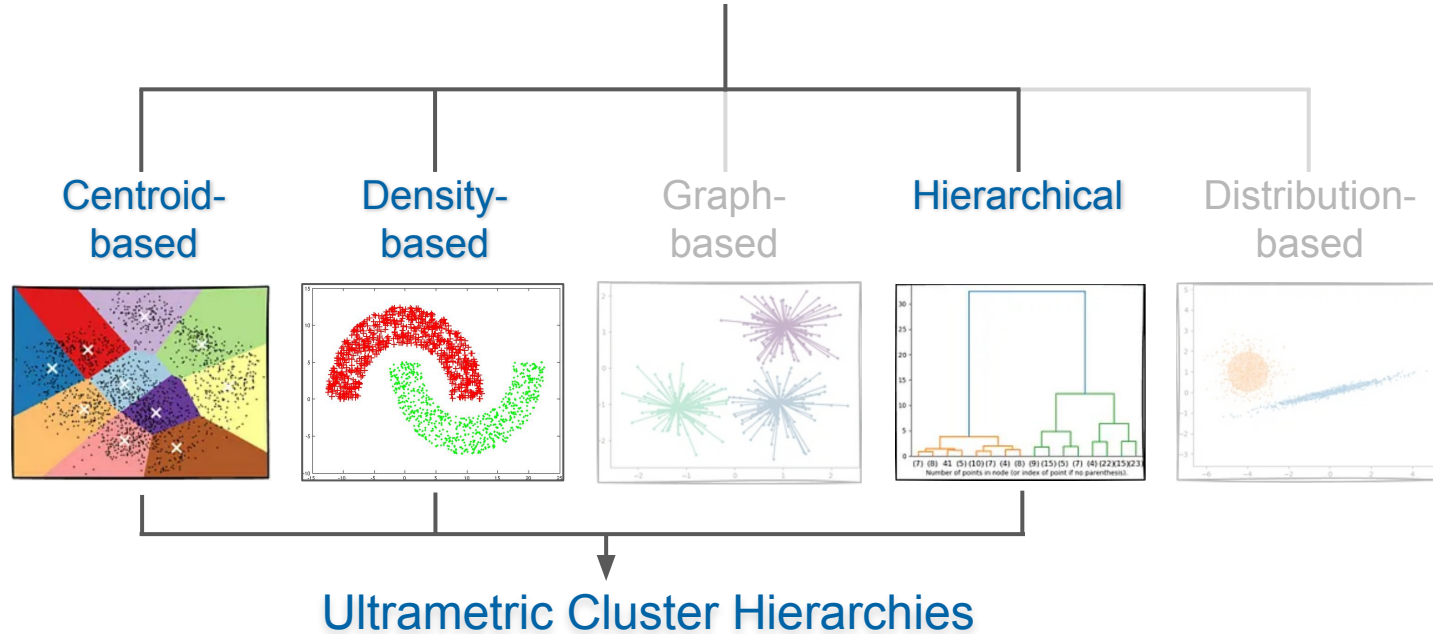


# Ultrametric Cluster Hierarchies: I Want 'em All!

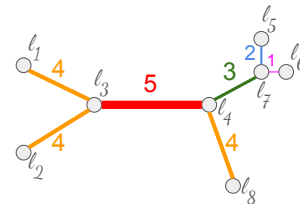
*Andrew Draganov\*, **Pascal Weber**\*,  
Rasmus Jørgensen, Anna Beer, Claudia Plant, Ira Assent*

December 3rd, 2025: 11 a.m. – 2 p.m.  
Exhibit Hall C,D,E

# Different Clustering Algorithm Types

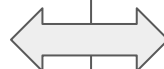


# All ultrametrics are hierarchical

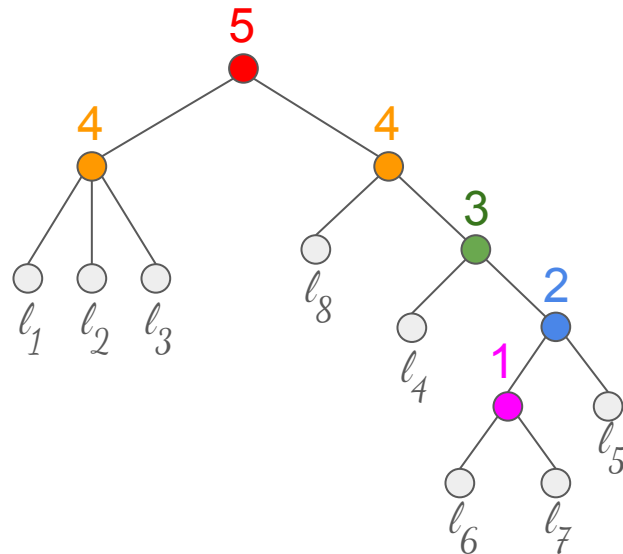


$$d(x, z) \leq \max \{d(x, y), d(y, z)\}$$

	$l_1$	$l_2$	$l_3$	$l_4$	$l_5$	$l_6$	$l_7$	$l_8$
$l_1$	0	4	4	5	5	5	5	5
$l_2$	4	0	4	5	5	5	5	5
$l_3$	4	4	0	5	5	5	5	5
$l_4$	5	5	5	0	3	3	3	4
$l_5$	5	5	5	3	0	2	2	4
$l_6$	5	5	5	3	2	0	1	4
$l_7$	5	5	5	3	2	1	0	4
$l_8$	5	5	5	4	4	4	4	0

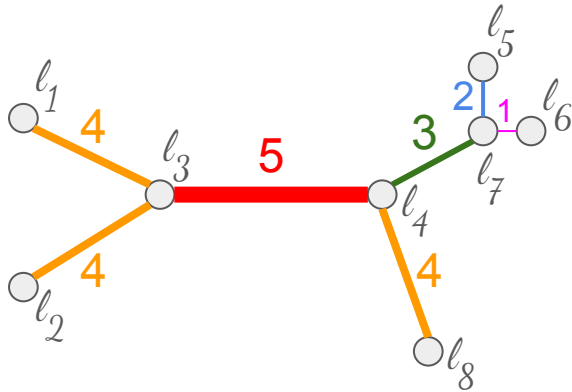


Distance between two leaves is the value in their lowest common ancestor (LCA):

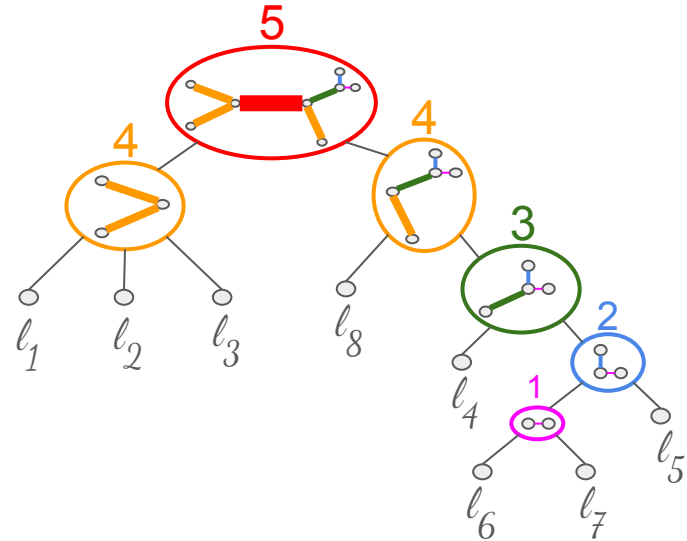


# All ultrametrics are hierarchical

Minimax distance is the largest step in the minimax path between two nodes, which is always on a minimum spanning tree (MST)



Distance between two leaves is the value in their lowest common ancestor (LCA):

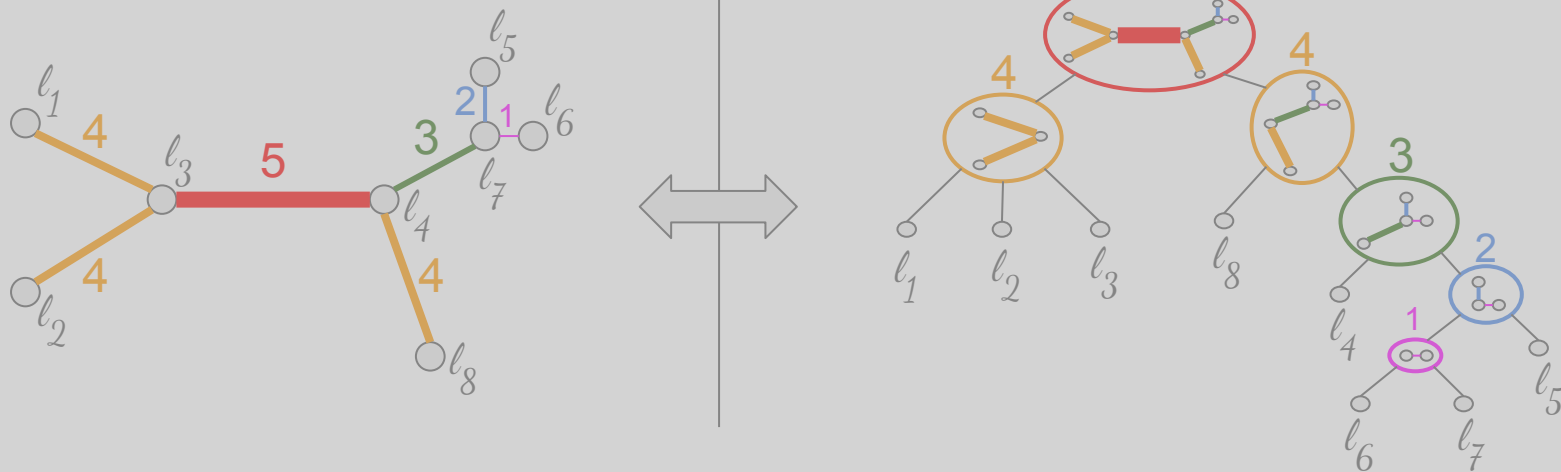


# All ultrametrics are hierarchical

Minimax distance is the value of the  
minimax path between two nodes, which is  
always on a minimum spanning tree (MST)

**Density-based clustering**  
corresponds to thresholding an **ultrametric**

is the value of the  
lowest common ancestor (LCA):

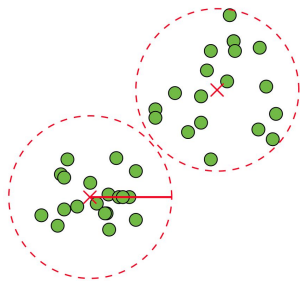


# What happens if we do centroid-based clustering in ultrametrics?

- The following are NP-hard in standard metric spaces but can be **solved optimally in ultrametrics**:

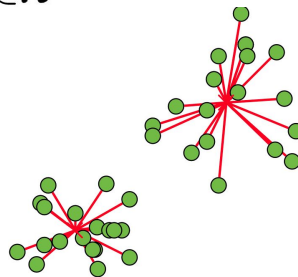
$k$ -center

$$\max_{x \in \mathcal{X}} \min_{c \in C} d(x, c)$$



$k$ -means

$$\sum_{x \in \mathcal{X}} \min_{c \in C} d(x, c)^2$$

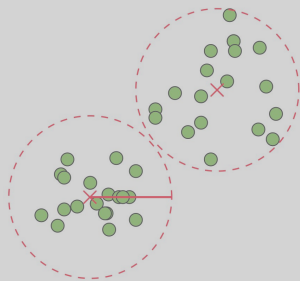


# What happens if we do centroid-based clustering in ultrametrics?

- The following theorem states that it takes **Sort(n) time** to find the optimal  $k$ -means solutions for **all** values of  $k$  in an **ultrametric**

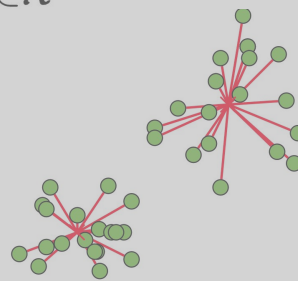
$k$ -center

$$\max_{x \in \mathcal{X}} \min_{c \in C} d(x, c)$$



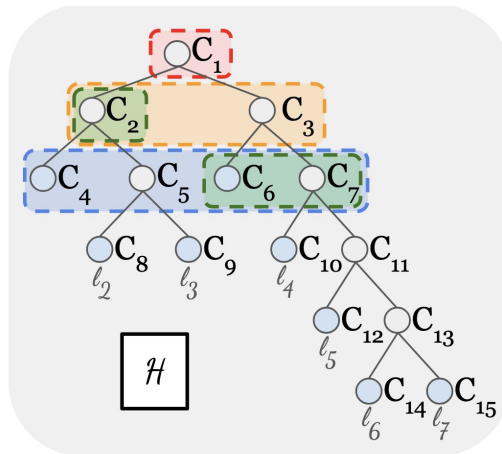
$k$ -means

$$\sum_{x \in \mathcal{X}} \min_{c \in C} d(x, c)^2$$



# The optimal $k$ -means solutions are *themselves* hierarchical

The optimal  $k$ -means solution and the optimal  $(k+1)$ -means solution in an ultrametric are identical except that a single cluster was split in two



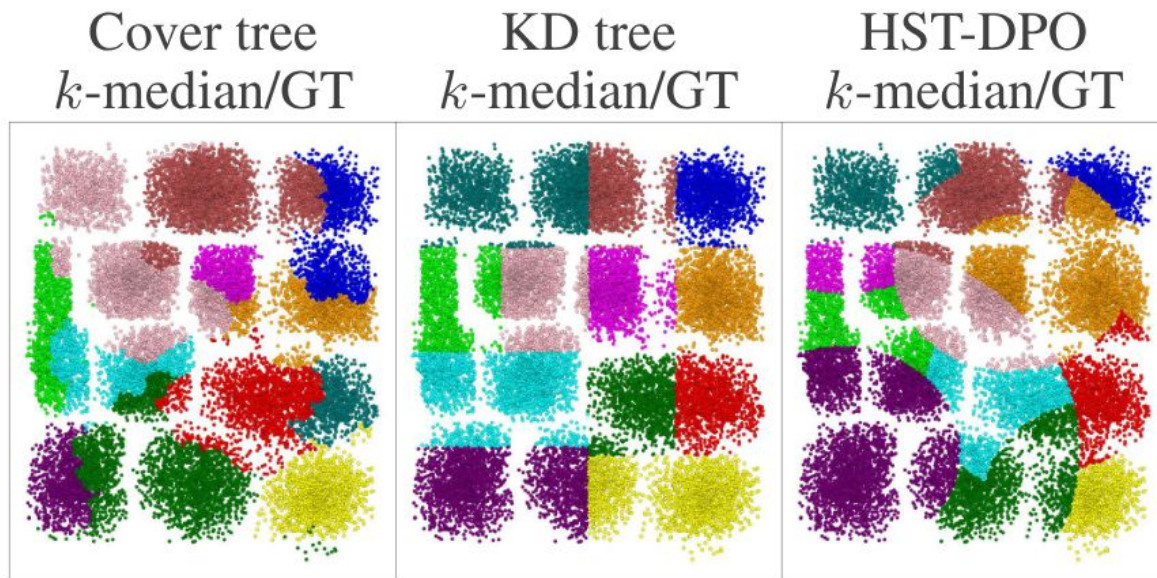
$$\begin{aligned} \mathcal{P}_1 &= \{C_1\} & k=1 \\ \mathcal{P}_2 &= \{C_2, C_3\} & k=2 \\ \mathcal{P}_3 &= \{C_2, C_6, C_7\} & k=3 \\ \mathcal{P}_4 &= \{C_4, C_5, C_6, C_7\} & k=4 \\ &\vdots & \vdots \end{aligned}$$



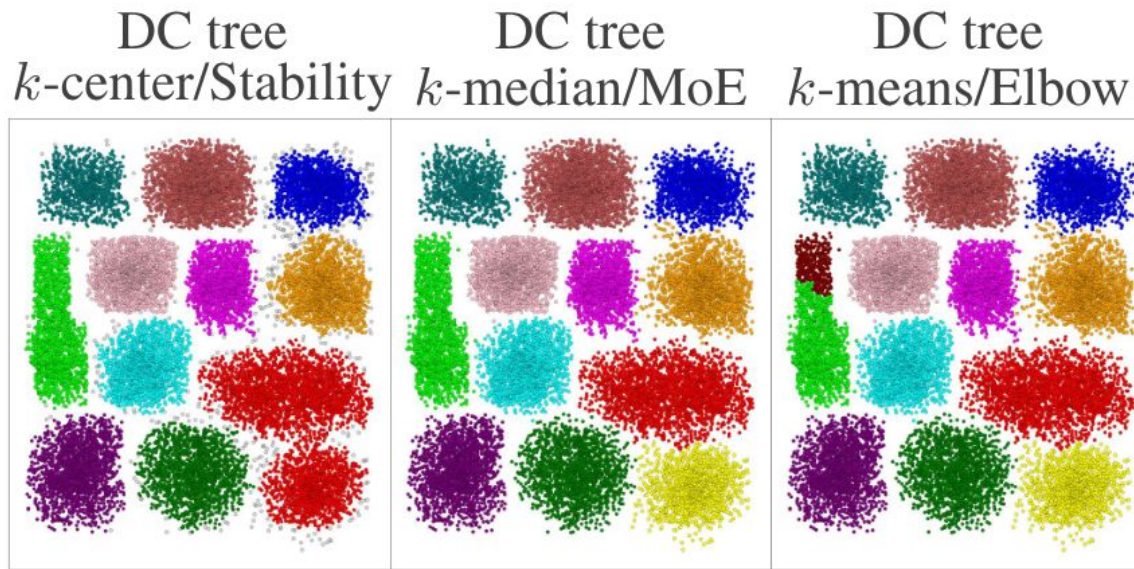
# Implications

1. Solve *any* center-based clustering task in *any* ultrametric *optimally* in  $\text{Sort}(n)$  time
  - a. Takes this time for *all* values of  $k$
  - b. These solutions are hierarchical
2. One can pick any clustering from this hierarchy extremely quickly (in  $O(n)$  time)
  - a. Threshold the values in the tree (DBSCAN)
  - b. Pick the “best” clustering by a function (HDBSCAN)
  - c. Optimal clustering for a user-specified value of  $k$
  - d. Elbow method

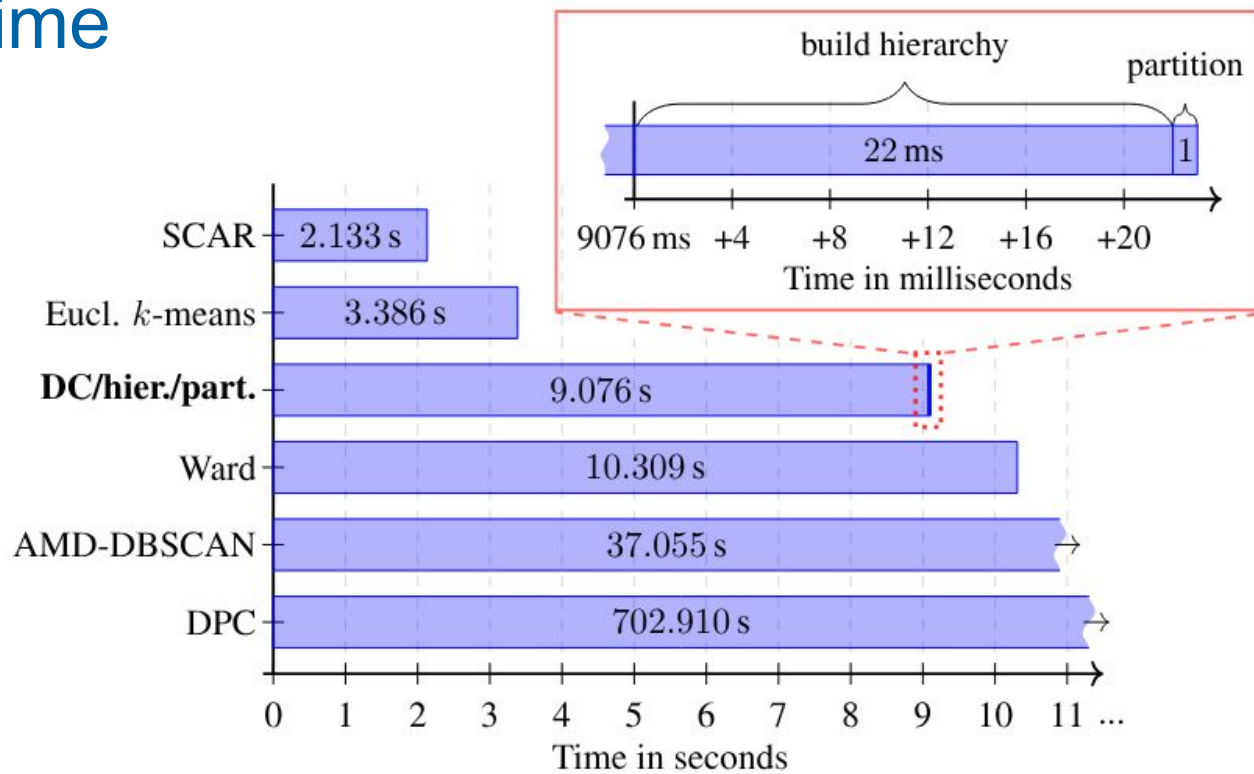
# Different Ultrametrics



# Different Hierarchies



# Runtime



# Summary

- It takes **Sort(n) time** to find the optimal  $k$ -means solutions for **all** values of  $k$  **in an ultrametric**
- Outperforms other clustering algorithms in clustering accuracy
- Ultrametric Cluster Hierarchies – Implementation:  
Similarity **H**ierarchy **P**artitioning Framework (SHiP framework)

Github Repo



pip package

