**TOP: Data Clustering 076/091** 

Instructor: Sayan Bandyapadhyay
Portland State University

### Outline

1 Introduction

2 Algorithms

3 Quality

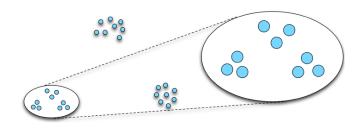
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Hierarchical clustering is an example of the latter formulation



Views at different scales

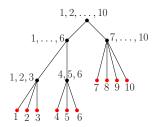
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- Partition based clustering: depends on the cost
- Hierarchical: both are right
  - Multi-scale clustering
  - Effective in exploratory setting
  - One of the popular methods

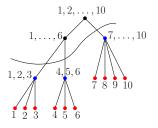
### Representation

- A clustering is still a partition of X
- Multi-scale clustering is represented by a rooted tree
- Each node v corresponds to  $S(v) \subseteq X$ 
  - Root *r* is associated with X; S(r) = X
  - If v is a child of u,  $S(v) \subset S(u)$
  - If a node u has children  $v_1, v_2, \ldots, v_m$ ,  $\{S(v_1), S(v_2), \ldots, S(v_m)\}$  is a partition of S(u)



### A Single Clustering

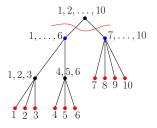
- A set of nodes  $V_1, V_2, ..., V_k$  of the tree
  - $\blacksquare$  no two  $V_i$  have an ancestor descendant relationship
  - $\blacksquare$  any path from r to a leaf intersects exactly one  $V_i$



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### Two Approaches

- Top-down: Divisive
- Bottom-up: Agglomerative

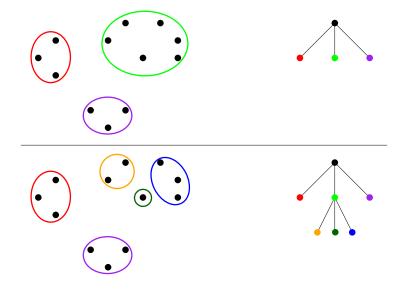
### Divisive Hierarchical Clustering (DHC)

#### **Algorithm DHC**

**Require:** Set of points X, root node r, a constant c

- 1:  $S(r) \leftarrow X$
- 2: **if**  $|X| \le c$  **then** return r
- 3: end if
- 4: Partition X into c pieces  $X_1, \ldots, X_c$  using any c-clustering algorithm
- 5: Create nodes  $v_1, \ldots, v_c$ .  $S(v_i) \leftarrow X_i$  for  $1 \le i \le c$ . Set r as the parent of each  $v_i$
- 6: Recursively call DHC on each  $(X_i, v_i, c)$
- 7: Return the tree rooted at r, and all S(v)

# An Example with c = 3



### Hierarchical Agglomerative Clustering (HAC)

#### **Algorithm** Template for HAC

#### **Require:** Set of points *X*

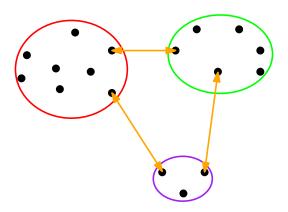
- 1:  $S \leftarrow \{(\mathbf{x}, \{\mathbf{x}\}) \mid \mathbf{x} \in \mathbf{X}\}$
- 2:  $\mathcal{G} \leftarrow \mathcal{S}$
- 3: **while**  $|\mathcal{G}| > 1$  **do**
- 4: Find  $(\mathbf{V}, \mathbf{C})$  and  $(\mathbf{V}', \mathbf{C}')$  in  $\mathcal{C}$  that are the closest
- 5: Create node r and cluster  $\hat{C} = C \cup C'$ . Set  $S(r) = \hat{C}$
- 6: Assign r as the parents of v and v'
- 7: Insert  $(r, \hat{C})$  and remove (v, C) and (v', C') from  $\mathcal{C}$
- 8: Insert  $(r, \hat{C})$  into S
- 9: end while

### Distance between Two Clusters

- Single-Linkage
- Complete-Linkage
- Average-Linkage

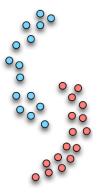
## Single-Linkage

Distance between C and C' is  $\min_{x \in C, x' \in C'} d(x, x')$ 



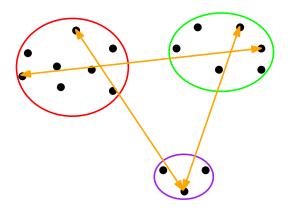
# Single-Linkage

Retrieves clusters that are not convex



# Complete-Linkage

Distance between C and C' is  $\max_{x \in C, x' \in C'} d(x, x')$ 



## Average-Linkage

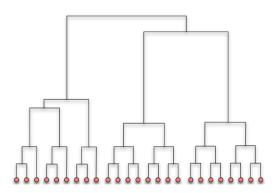
 A compromise between Single-Linkage and Complete-Linkage

### Average-Linkage

 A compromise between Single-Linkage and Complete-Linkage

■ Distance between C and C' is  $\frac{1}{|C||C'|}\sum_{x \in C, x' \in C'} d(x, x')$ 

### Dendograms



- A tree/hierarchical structure to represent HACs
- Vertical edge lengths represent the distance between two clusters

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- $\blacksquare$   $\mathcal{C}_k$ : merge until k clusters
- Compare with *k*-clustering, e.g., *k*-center
- Single-Linkage  $\mathcal{G}_k$  is k factor worse than optimal k-center
- Complete-Linkage and Average-Linkage  $G_k$  is  $\log k$  factor worse than optimal k-center



■ Distance between points  $x_j$  and  $x_{j+1}$  is  $1 - j\epsilon$ 



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$$G_k = \{\{x_1\}, \{x_2\}, \ldots, \{x_{k-1}\}, \{x_k, \ldots, x_n\}\}$$



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Cost (or radius) of the supercluster:  $\sum_{j=k}^{n-1} (1-j\epsilon)/2 \ge (n-k-\epsilon\binom{n}{2})/2 \approx (n-k-1)/2$ 



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- k-center OPT:  $\approx n/2k$