$$X = \{X^{\{1\}}, X^{\{2\}}\}, \dots, X^{\{d\}}\}$$

$$X_{1}, X_{2} \longrightarrow d(X_{1}, X_{2}) = \{X_{1}, X_{2}, \dots, X^{\{d\}}\}\}$$

$$N = 100 \quad C_{1} \quad C_{2} \quad C_{3} \quad X_{1}$$

$$X_{2} \quad X_{2} \quad X_{2}$$

$$X_{3} \quad X_{400} \quad X_{100} \quad$$

$$C_{1} = \{X_{1}, X_{3}, \dots \} \Rightarrow Mean(C_{1}) \approx C_{1}$$

$$C_{2} = \{X_{2}, \dots \} \Rightarrow C_{2}$$

$$C_{3} = \{\dots, X_{100}\} \Rightarrow C_{3}$$



Lecture 07 Hierarchical Clustering

Mahdi Roozbahani Georgia Tech

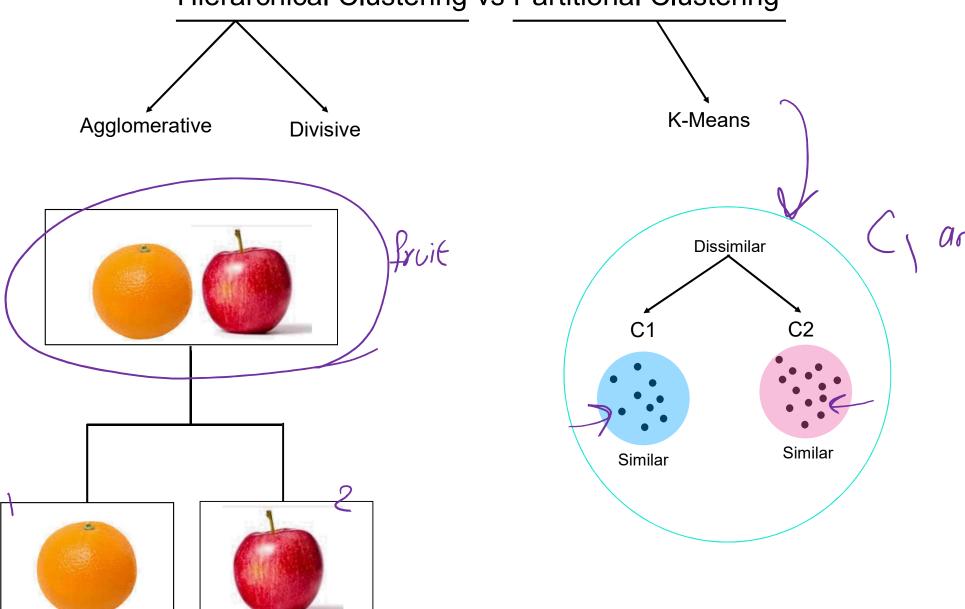
These slides are based on slides from Aarti Singh, Eric Xing, Andrew Moore, and Jiawei Han.

Outline

Overview

- Bottom-Up vs Top-Down Clustering
- Measuring Distance between Clusters

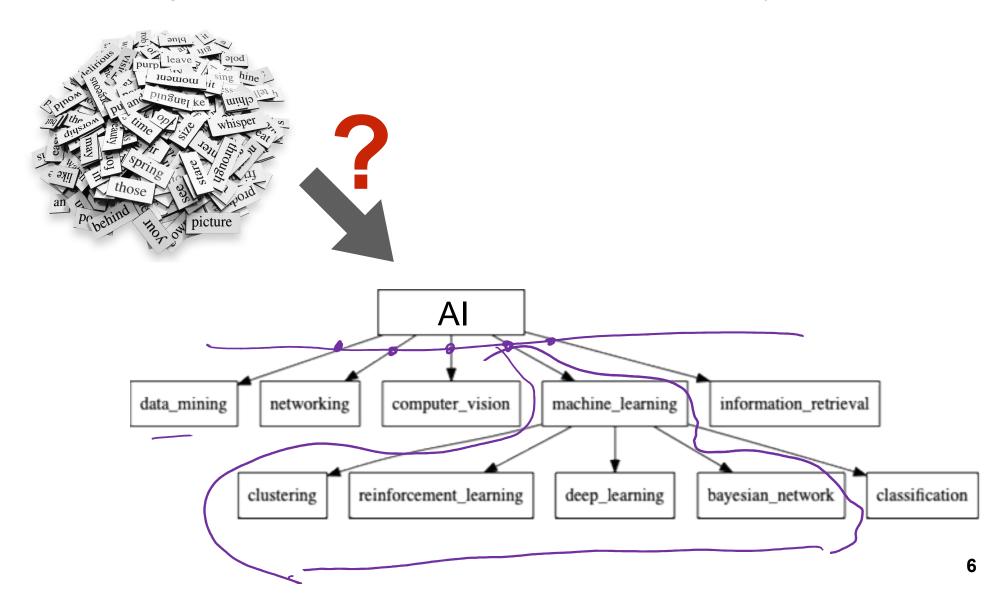
Hierarchical Clustering vs Partitional Clustering



Tree structure (parent-child relationship)

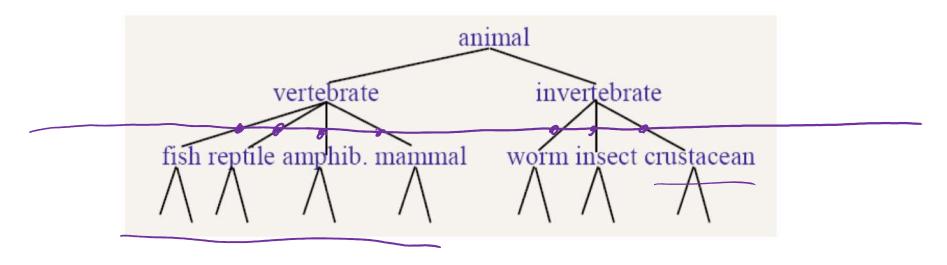
Hierarchical Clustering

• How to organize a set of CS papers into a hierarchy?



Hierarchical Clustering

 Organize objects into a tree-based hierarchical taxonomy (dendrogram)



- Many applications in the real world
 - Web pages
 - News articles
 - Scientific papers

DNA sequencing and hierarchical clustering to find the phylogenetic tree of animal evolution















Brown bear Polar bear

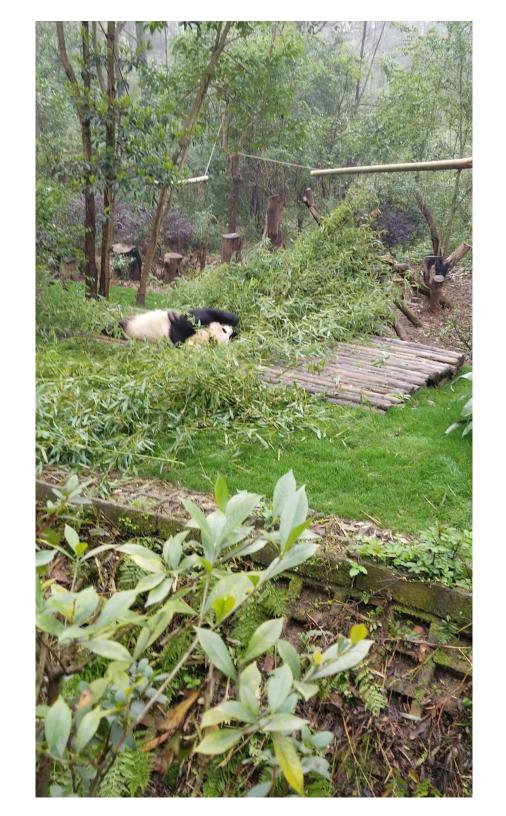
Black bear

Spectacled bear

Giant panda

Raccoon

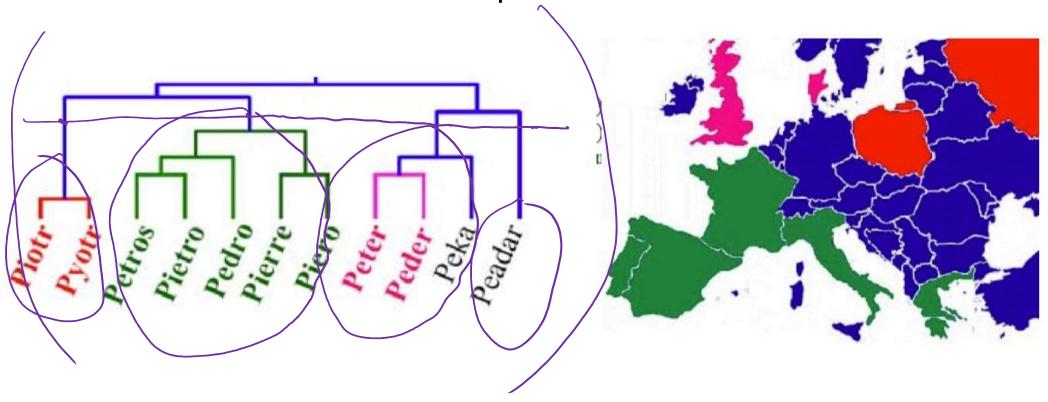
Red panda





Hierarchical Clustering

- Organizing data at multiple granularities
- Cutting the dendrogram at a desired level leads to a subcluster: each connected component forms a cluster



Outline

- Overview
- Bottom-Up vs Top-Down Clustering



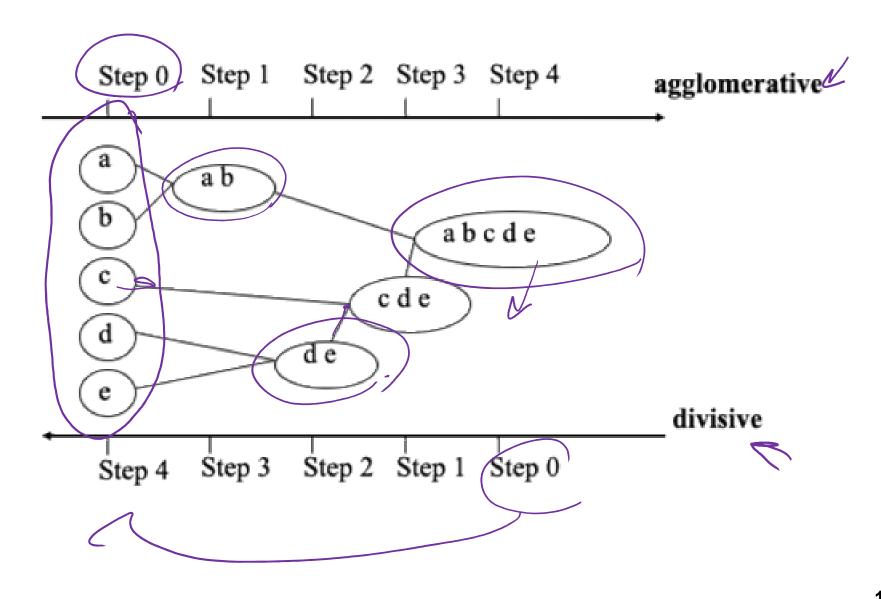
Two Paradigms for Hierarchical Clustering

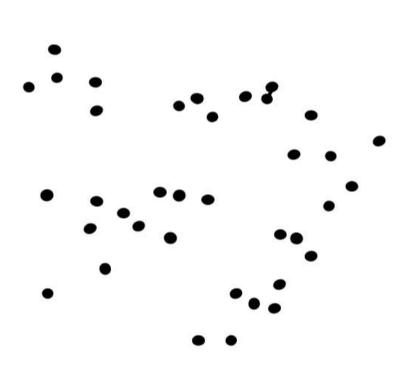
- Bottom-up Agglomerative Clustering
 - Start by considering each object as a separate cluster
 - Repeatedly join the closest pair of clusters
 - Stop when there is only one cluster left

Top-Down Divisive Clustering

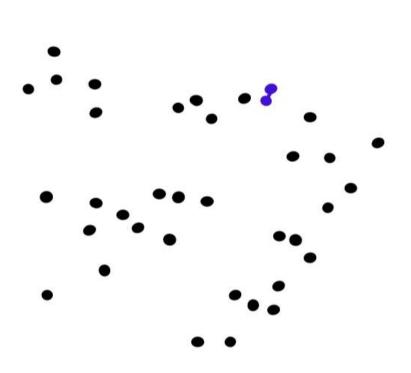
- Start by considering all objects as one large cluster
- Recursively divide each cluster into two sub-clusters
- Stop when each cluster contains only one object

Bottom-Up v.s. Top-Down



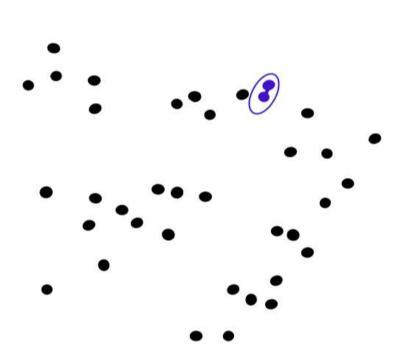


 Say "Every point is it's own cluster"



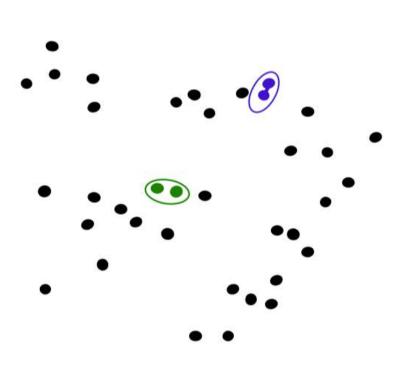
- Say "Every point is it's own cluster"
- Find "most similar" pair of clusters





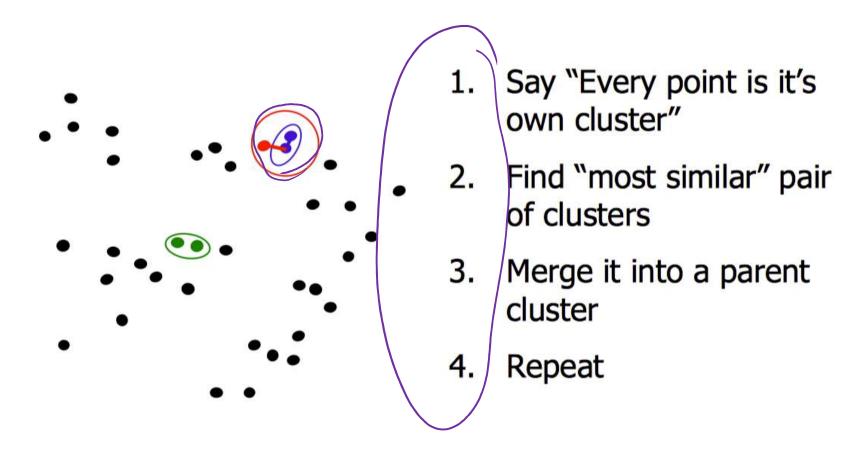
- Say "Every point is it's own cluster"
- Find "most similar" pair of clusters
- Merge it into a parent cluster

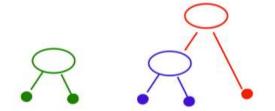




- Say "Every point is it's own cluster"
- Find "most similar" pair of clusters
- Merge it into a parent cluster
- 4. Repeat





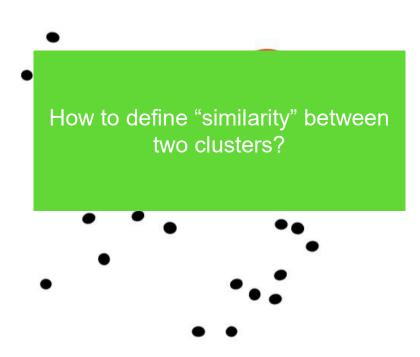


Outline

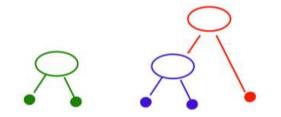
- Overview
- Bottom-Up vs Top-Down Clustering
- Measuring Distance between Clusters



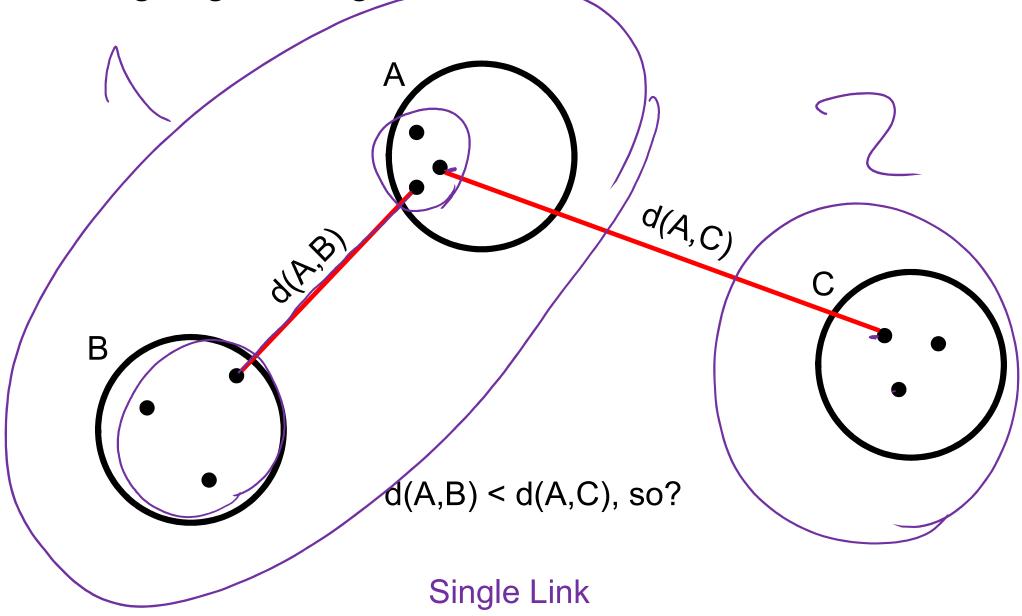
Key Question: Similarity Function



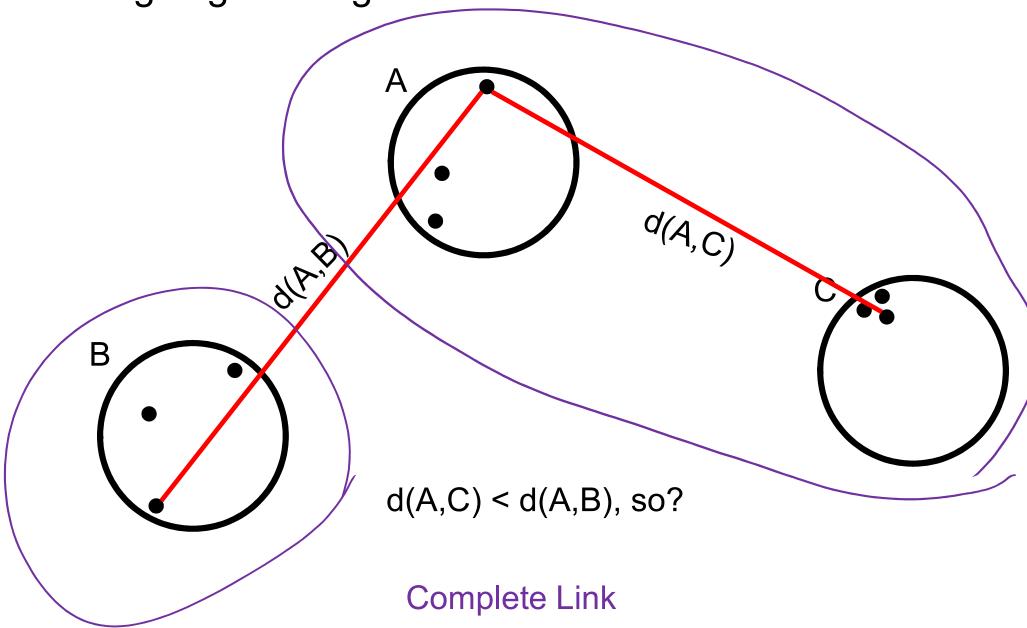
- 1. Say "Every point is it's own cluster"
- Find "most similar" pair of clusters
- Merge it into a parent cluster
- Repeat



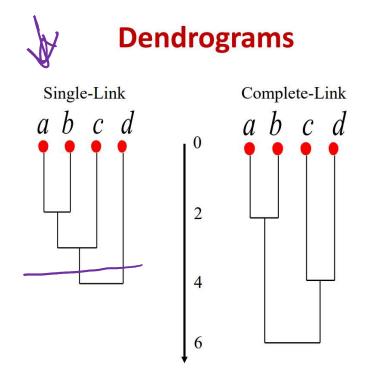
I am going to merge A with either B or C. Which one?



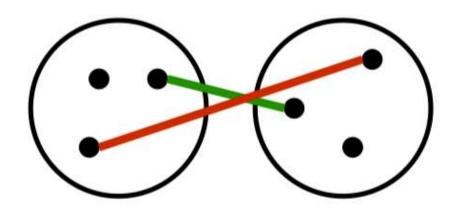
I am going to merge A with either B or C. Which one?

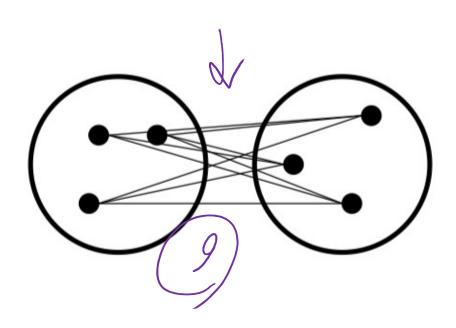


- Single link: A chain of points can be extended for long distances without regard to the overall shape of the emerging cluster. This effect is called *chaining*. It is also sensitive to outliers. It is faster in general.
- Complete link: Clusters are split into two groups of roughly equal size when we cut the dendrogram at the last merge. In general, this is a more useful organization of the data than a clustering with chains. It avoids chaining and more robust to outliers. Generally slower.
- Average link: When you don't know which one may be better for you, start it with the average link method.



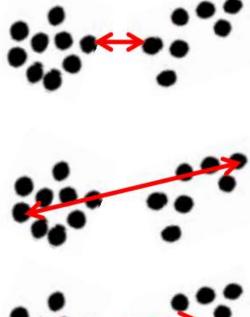
How to Define Distance Between Two Clusters?





Different algorithms differ in how the similarities are defined (and hence updated) between two clusters

- Single-Link
 - Nearest Neighbor: similarity between their closest members.
- Complete-Link
 - Furthest Neighbor: similarity between their furthest members.
- Centroid
 - Similarity between the centers of gravity
- Average-Link
 - Average similarity of all cross-cluster pairs.

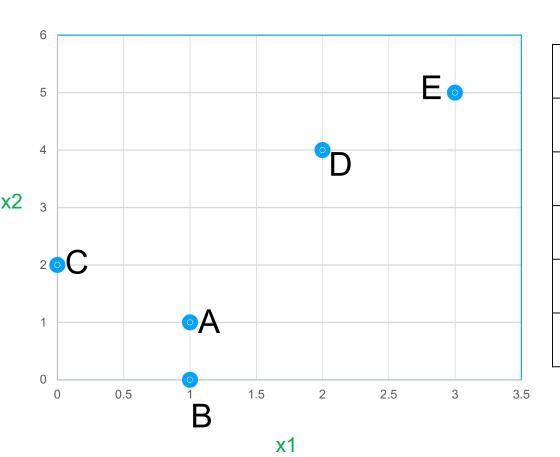




Distance Between Clusters

Different distance functions can lead to different results!

i	X1	X2
А	1	1
В	1	0
С	0	2
D	2	4
E	3	5



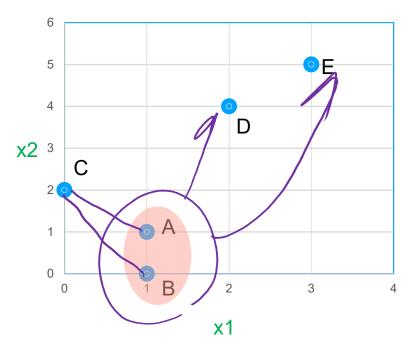
EUCLIDEAN DISTANCE

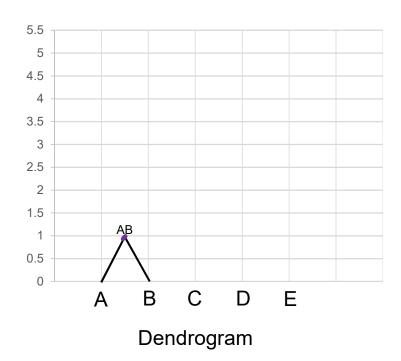
	Α	В	С	D	E
Α	0	1	1.4	3.2	4.5
В	1	0	2.2	4.1	5.4
С	1.4	2.2	0	2.8	4.2
D	3.2	4.1	2.8	0	1.4
Е	4.5	5.4	4.2	1.4	0

Distance based on Average point (Bottom-Up Clustering)

	А	В	C	9	E
Α	0	1	1.4	3.2	4.5
В	1	0	2.2	4.1	5.4
С	1.4	2.2)0	2.8	4.2
D	3.2	4.1	2.8	0	1.4
E	4.5	5.4	4.2	1.4	0

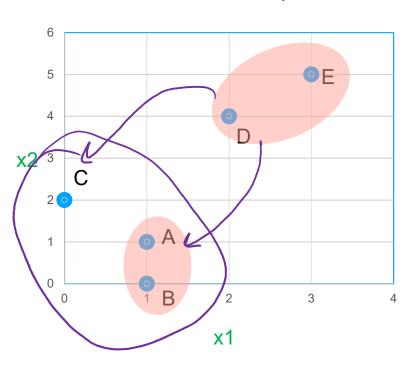
	(A,B)	С	D	Е
(A,B)	0	1.8	3.6	4.9
С	1.8	0	2.8	4.2
D	38	2.8	0	1.4
E	4.9	4.2	1.4	0



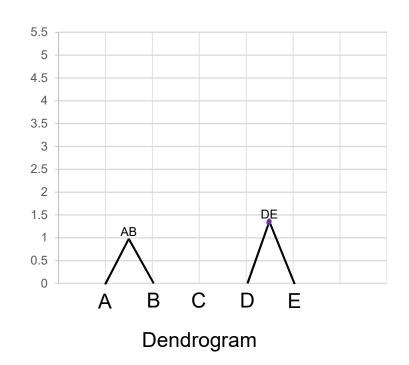


Distance based on average point (Bottom-Up Clustering)

	(A,B)	C	D	Е		
(A,B)	0	1.8	3.6	4.9		
С	1,8	0	2.8	4.2		
D	3.6	2.8	0	1.4		
E	4.9	4.2	1.4	0		
7 9						

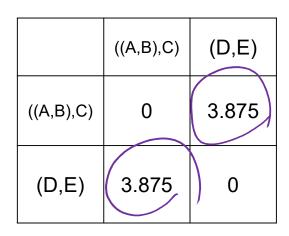


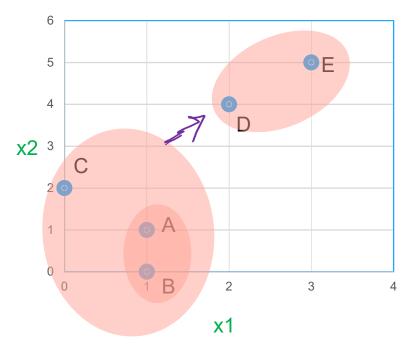
	(A,B)	С	(D,E)
(A,B)	0	1.8	4.25
С	1.8	0	3.5
(D,E)	4.25	3.5	0

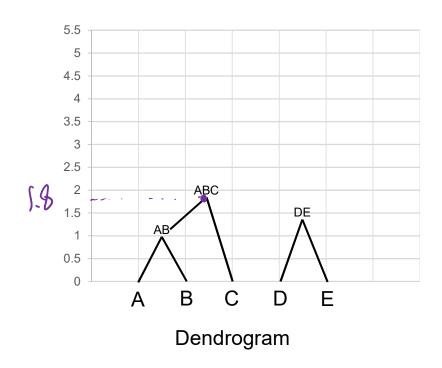


Distance based on average point (Bottom-Up Clustering)

	(A,B)	С	(D,E)
(A,B)	0	1.8	4.25
C	1.8	0	3.5
(D,E)	4.25	3.5	0



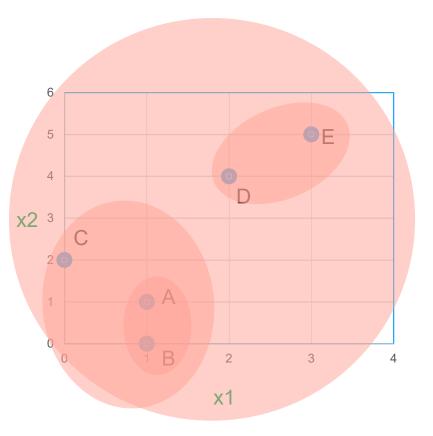


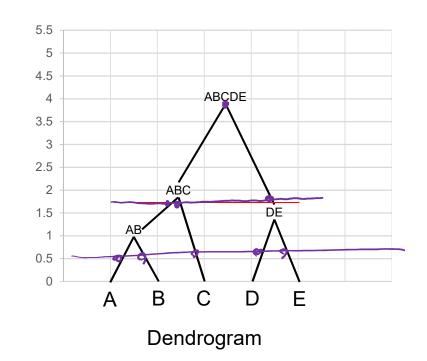


Distance based on average point (Bottom-Up Clustering)

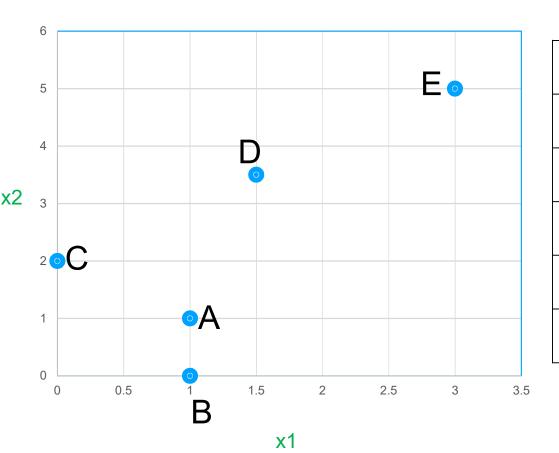
	((A,B),C)	(D,E)
((A,B),C)	0	3.875
(D,E)	3.875	0

	(((A,B),C),(D,E))
(((A,B),C),(D,E))	0





i	X1	X2
А	1	1
В	1	0
С	0	2
D	1.5	3.5
Е	3	5

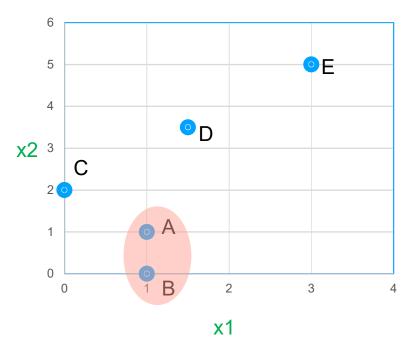


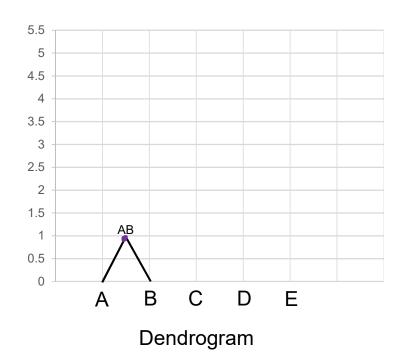
EUCLIDEAN DISTANCE

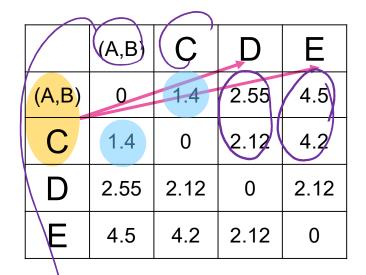
	Α	В	С	D	Е
Α	0	1	1.4	2.55	4.5
В	1	0	2.2	3.53	5.4
С	1.4	2.2	0	2.12	4.2
D	2.55	3.53	2.12	0	2.12
Е	4.5	5.4	4.2	2.12	0

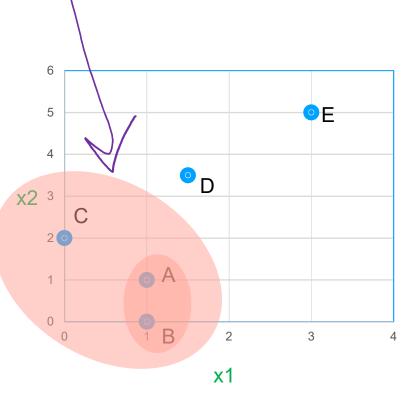
	Α	В	C	D	E/
A	0		1.4	2.55	4.5
В	1	0	2.2	3.53	5.4
С	1.4	2.2	0	2.12	4.2
D	2.55	3.53	2.12	0	2.12
Е	4.5	5.4	4.2	2.12	0

	(A,B)	C	D	E
(A,B)	0	1.4	2.55	4.5)
С	1.4	0	2.12	4.2
D	2.55	2.12	0	2.12
E	4.5	4.2	2.12	0

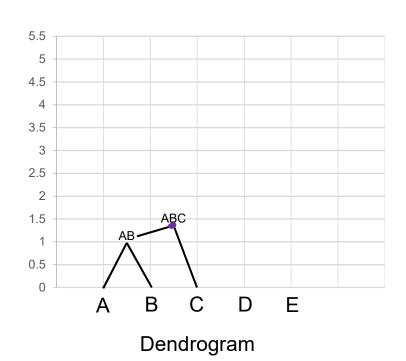


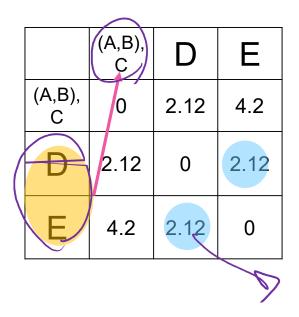




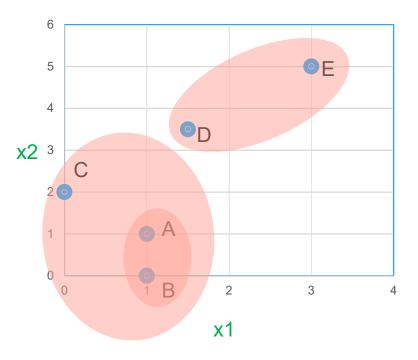


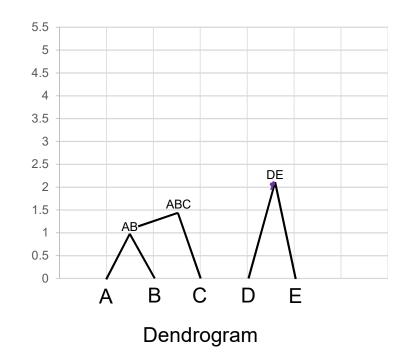
	(A,B),C	D	Е
(A,B),C	0 (2.12	4.2
D	2.12	0	2.12
Е	4.2	2.12	0





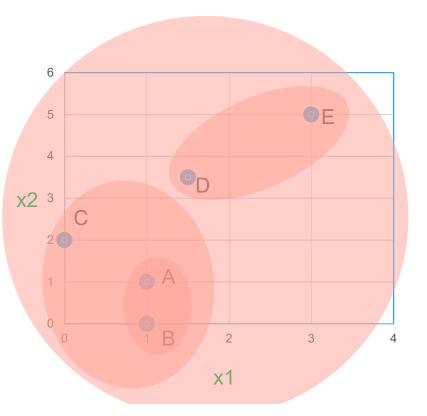
	((A,B),C)	(D,E)
((A,B),C)	0	2.12
(D,E)	2.12	0

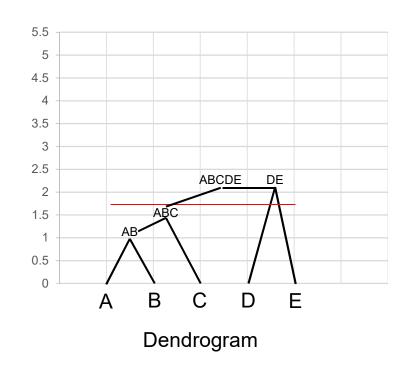




	((A,B),C)	(D,E)
((A,B),C)	0	2.12
(D,E)	2.12	0

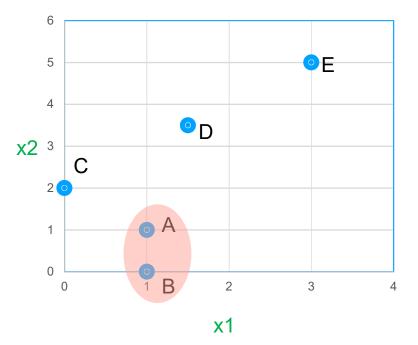
	(((A,B),C),(D,E))
(((A,B),C),(D,E))	0

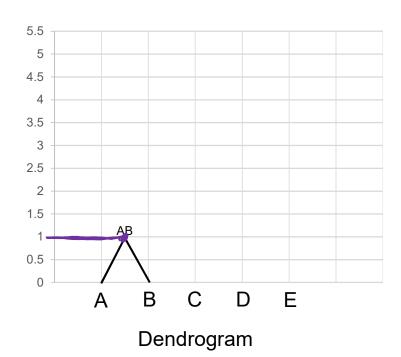




	Α	В	C	D	E
A	0		1.4	2.55	4.5
В	1	0	2.2	3.53	5.4
С	1.4	2.2) 0	2.12	4.2
D	2.55	3.53	2.12	0	2.12
E	4.5	5.4	4.2	2.12	0

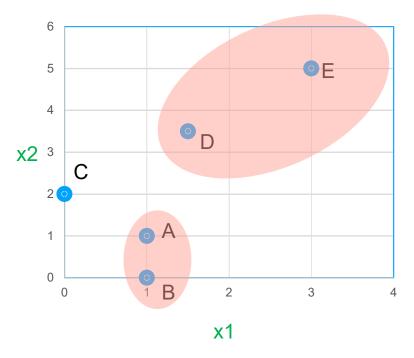
	(A,B)	С	D	Е
(A,B)	0	2.2	3.55	5.4
С	2.2	0	2.12	4.2
D	3.55	2.12	0	2.12
E	5.4	4.2	2.12	0

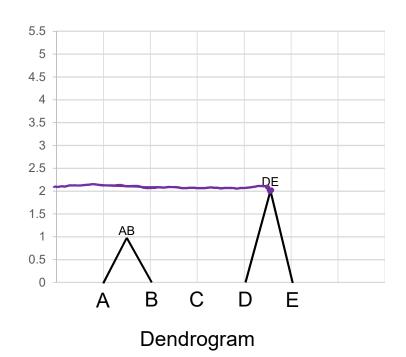




	(A,B)	Ç	D	Е
(A,B)	0	2.2	3.55	5.4
С	2.2	0	2.12	4.2
D	3.55	2.12	0	2.12
E	5.4	4.2	2.12	0

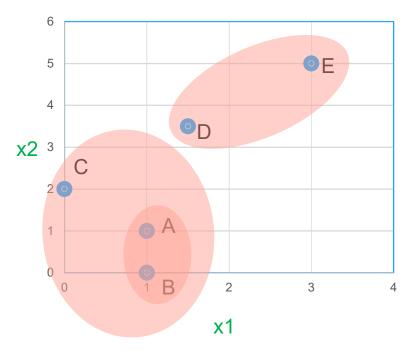
	(A,B)	С	(D,E)
(A,B)	0	2.2	5.4
С	2.2	0	4.2
(D,E)	5.4	4.2	0

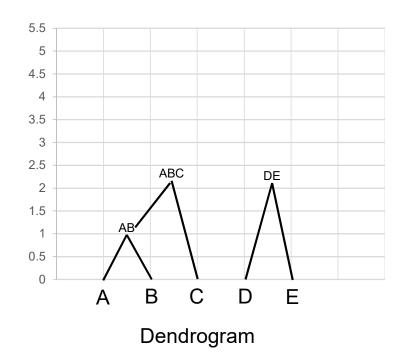




	(A,B)	С	(D,E)
(A,B)	0	2.2	5.4
C	2.2	0	4.2
(D,E)	5.4	4.2	0

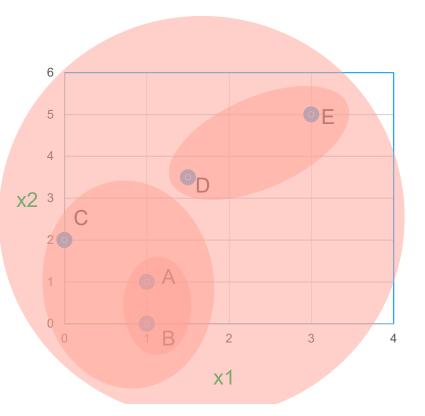
	((A,B),C)	(D,E)
((A,B),C)	0	5.4
(D,E)	5.4	0

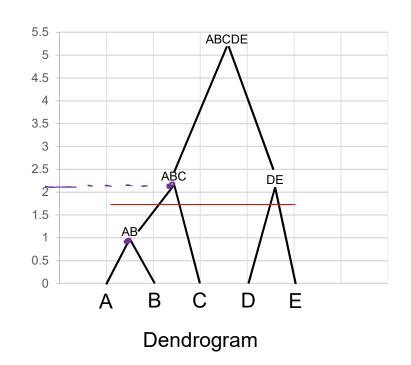


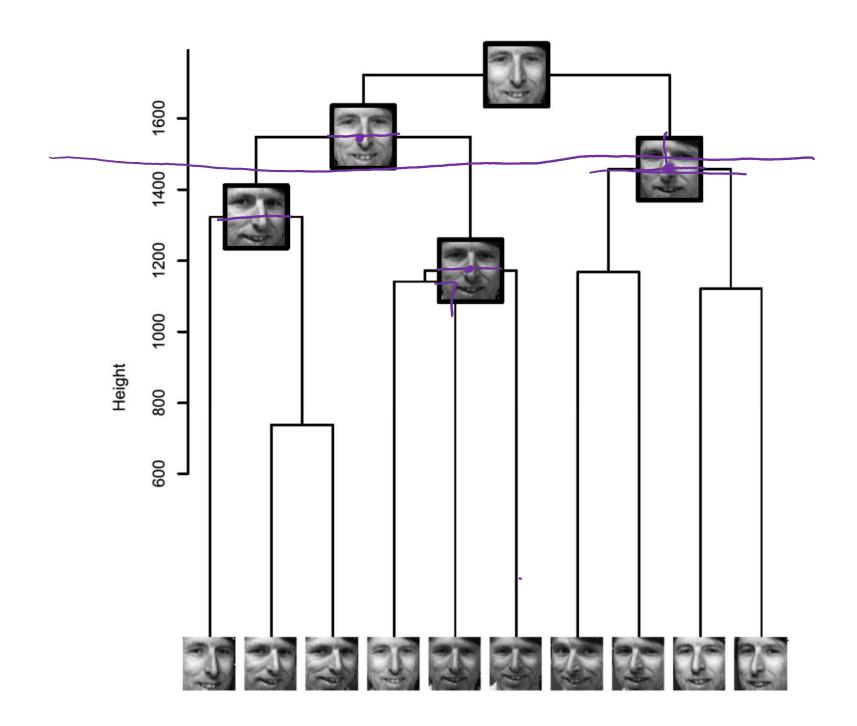


	((A,B),C)	(D,E)
((A,B),C)	0	5.4
(D,E)	5.4	0

	(((A,B),C),(D,E))
(((A,B),C),(D,E))	0

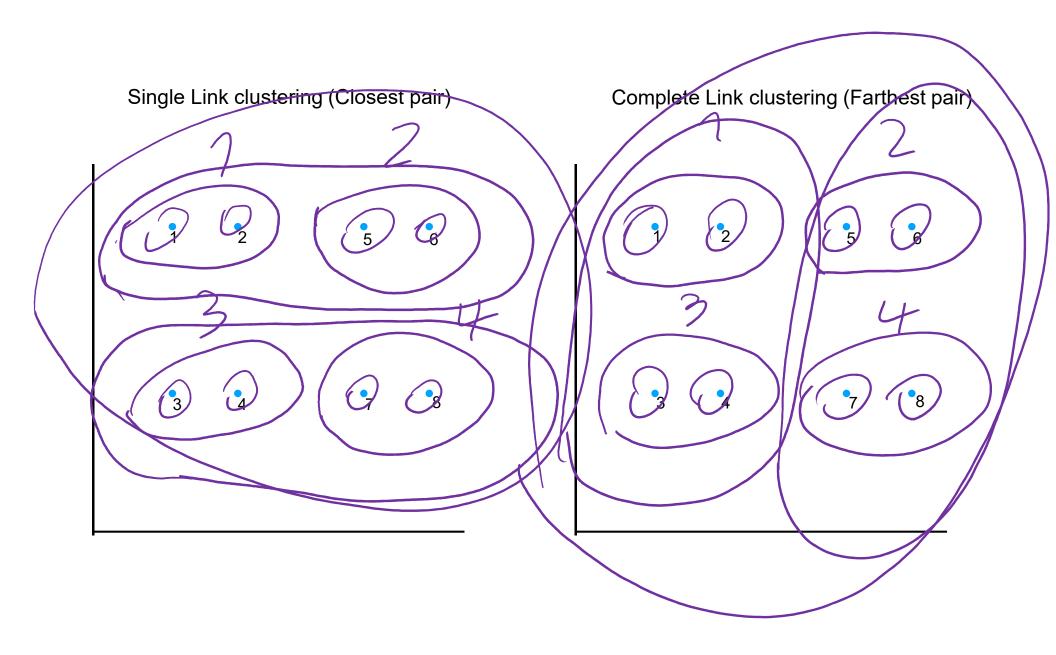




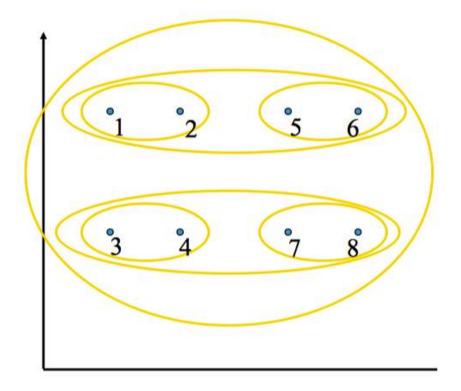


(From Bien et al. (2011))

Another Example



Closest pair (single-link clustering)



Farthest pair (complete-link clustering)

