Clustering: Unsupervised Learning

IF-3270 Pembelajaran Mesin

Teknik Informatika ITB





Modul 7: Clustering



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04 Hierarchical Clustering

IF3270 - Pembelajaran Mesin (Machine Learning)



Outline

Hierarchical Clustering

Agglomerative Clustering

Divisive Clustering



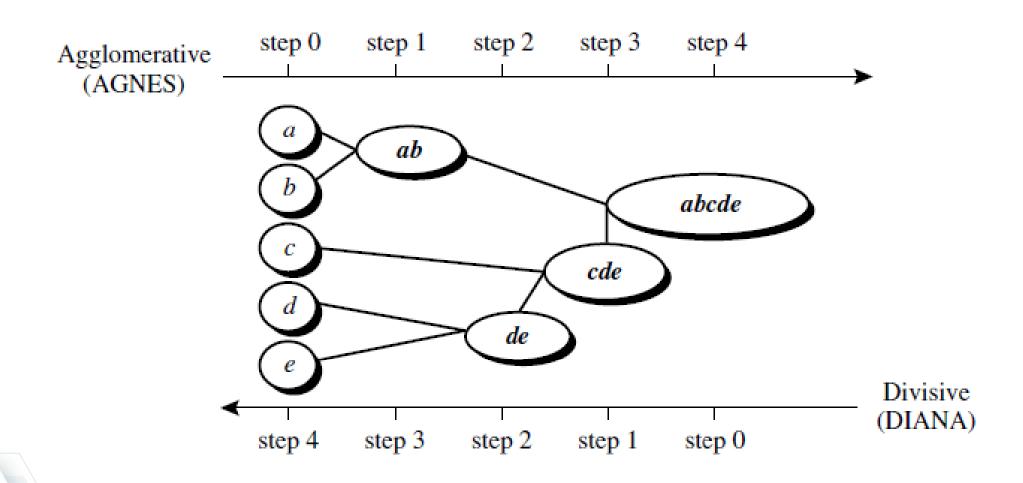
Hierarchical Clustering

A hierarchical clustering method works by grouping data objects into a hierarchy or "tree" of clusters.

- a. <u>Agglomerative hierarchical clustering</u> method uses a bottom-up strategy.
- Divisive hierarchical clustering method employs a top-down strategy.



Hierarchical Clustering



Han & Kamber (2006)



Agglomerative Clustering Algorithm

- Start with N singleton clusters. Calculate the proximity matrix for the N clusters.
- Search the minimal distance

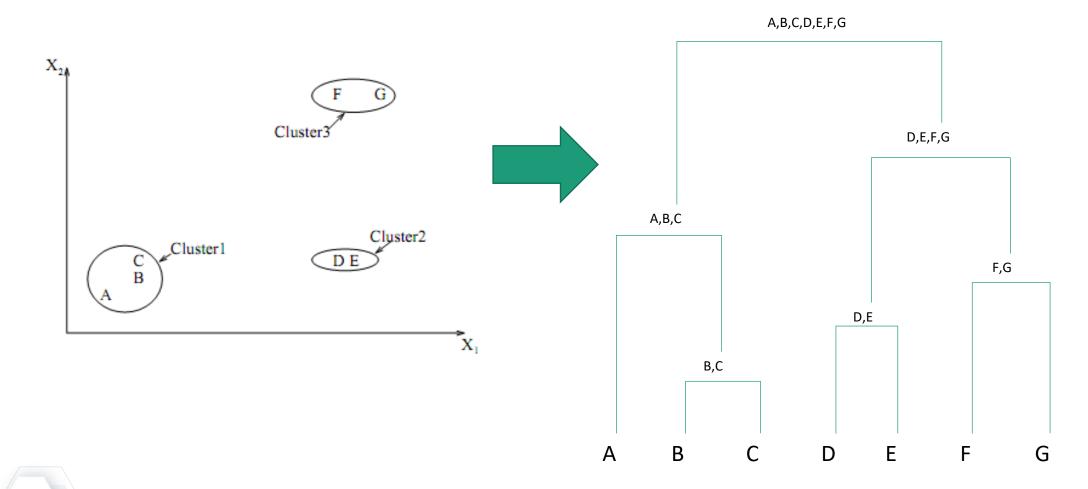
$$D(C_i, C_j) = \min_{\substack{1 \le m, l \le N \\ m \ne l}} D(C_m, C_l)$$

where D(*,*) is the distance function discussed before, in the proximity matrix, and combine cluster C_i and C_j to form a new cluster.

- Update the proximity matrix by computing the distances between the new cluster and the other clusters.
- Repeat steps 2)-3) until all objects are in the same cluster.



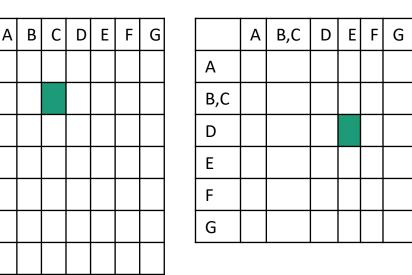
Ilustrasi Agglomerative HC





Cluster3 Cluster3 Cluster2 DE

Ilustrasi Agglomerative HC (lanj)



	Α	В,С	D,E	F	G
Α					
В,С					
D,E					
F					
G					

	Α	В,С	D,E	F,G
Α				
В,С				
D,E				
F,G				

• Iterasi 0: (A),(B),(C),(D),(E),(F),(G)

В

D

- Iterasi 1: (A),(B,C),(D),(E),(F),(G)
- Iterasi 2 : (A),(B,C),(D,E),(F),(G)
- Iterasi 3 : (A),(B,C),(D,E),(F,G)
- Iterasi 4 : (A,(B,C)),(D,E),(F,G)
- Iterasi 5 : (A,(B,C)),((D,E),(F,G))
- Iterasi 6 : ((A,(B,C)),((D,E),(F,G)))

	A, (B,C)	D,E	F,G
A, (B,C)			
D,E			
F,G			

	A, (B,C)	(D,E), (F,G)
A, (B,C)		
(D,E), (F,G)		



Dendogram

Iterasi 0: (A),(B),(C),(D),(E),(F),(G)

Iterasi 1: (A),(B,C),(D),(E),(F),(G)

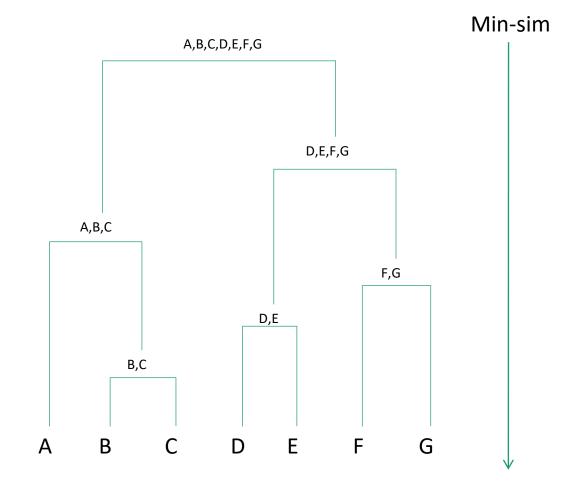
Iterasi 2 : (A),(B,C),(D,E),(F),(G)

Iterasi 3: (A),(B,C),(D,E),(F,G)

Iterasi 4: (A,(B,C)),(D,E),(F,G)

Iterasi 5 : (A,(B,C)),((D,E),(F,G))

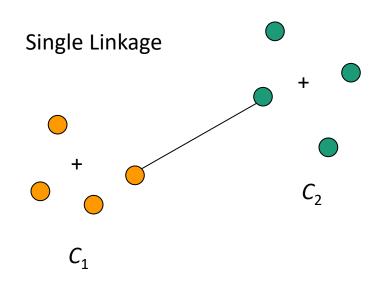
Iterasi 6 : ((A,(B,C)),((D,E),(F,G)))



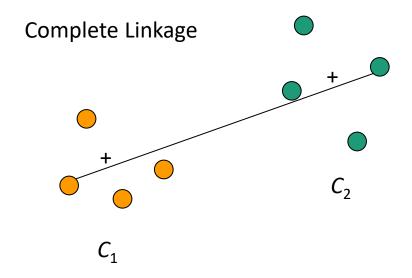
Max-sim



Linkage: Single, Complete, Average, Average Group



Dissimilarity between two clusters = Minimum dissimilarity between the members of two clusters

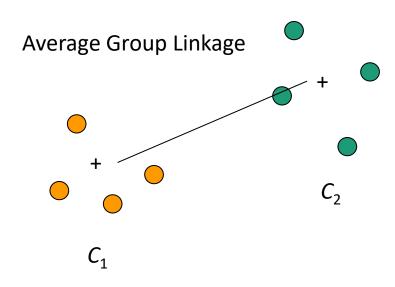


Dissimilarity between two clusters = Maximum dissimilarity between the members of two clusters

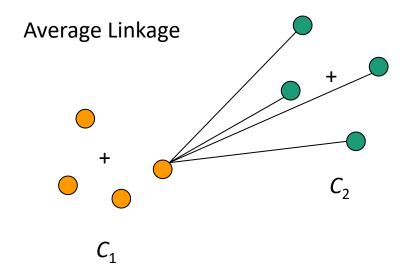




Linkage: Single, Complete, Average, Average Group (lanjutan)



Dissimilarity between two clusters = Distance between two cluster means.



Dissimilarity between two clusters = Averaged distances of all pairs of objects (one from each cluster).





Single vs Complete-Link

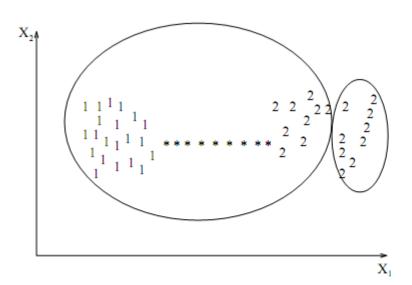


Figure 12. A single-link clustering of a pattern set containing two classes (1 and 2) connected by a chain of noisy patterns (*).

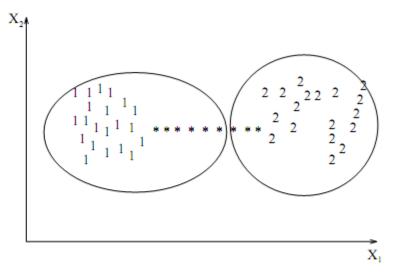


Figure 13. A complete-link clustering of a pattern set containing two classes (1 and 2) connected by a chain of noisy patterns (*).

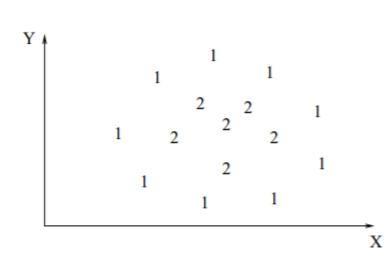


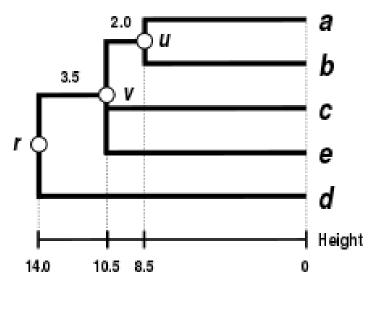
Figure 11. Two concentric clusters.

- Single link clustering suffers from a chaining effect.
- From a pragmatic viewpoint, it has been observed that the completelink algorithm produces more useful hierarchies in many applications that single-link alg.

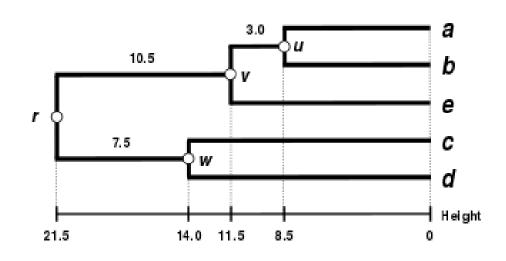
Sumber: Jain dkk (1999)



Single vs Complete-Link







Complete-link



Divisive Clustering

- In the beginning, the entire data set belongs to a cluster and a procedure successively divides it until all clusters are singleton clusters.
- Divisive clustering is not commonly used in practice:
 - For a cluster with N objects, there are 2^{N-1} -1 possible two-subset divisions, which is very expensive in computation (Xu & Wunsch, 2005).





05 Cluster Evaluation

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