

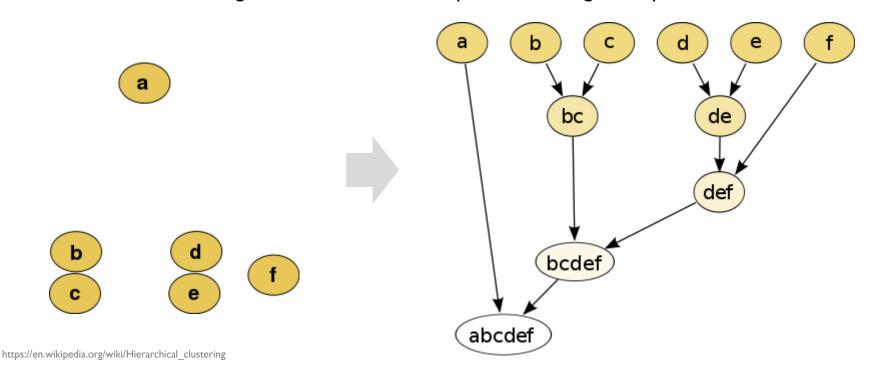
Lecture 9: Clustering

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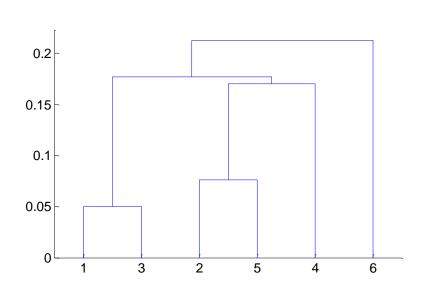
AGENDA

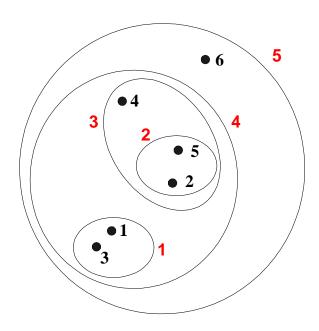
01	Clustering: Overview
02	K-Means Clustering
03	Hierarchical Clustering
04	Density-based Clustering: DBSCAN
04	R Exercise

- Hierarchical clustering
 - √ Produces a set of nested clusters organized as a hierarchical tree
 - ✓ Can be visualized as a dendrogram
 - A tree like diagram that records the sequences of merges or splits



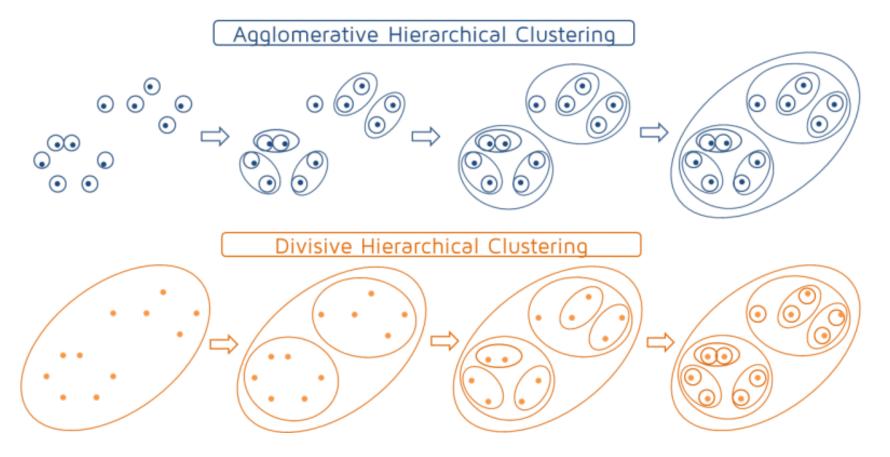
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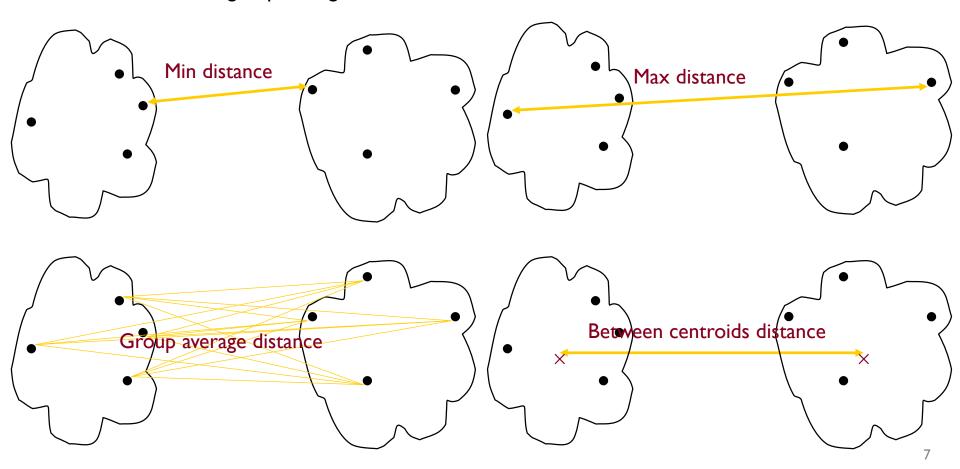


- Strengths of Hierarchical clustering
 - ✓ Do not have to assume any particular number of clusters
 - Any desired number of clusters can be obtained by 'cutting' the dendrogram at the proper level
 - ✓ May correspond to meaningful taxonomies
- Two main types of hierarchical clustering
 - √ Agglomerative clustering
 - Start with the points as individual clusters
 - At each step, merge the closest pair of clusters until only one cluster left
 - ✓ Divisive clustering
 - Start with one, all-inclusive cluster
 - At each step, split a cluster until each cluster contains a point

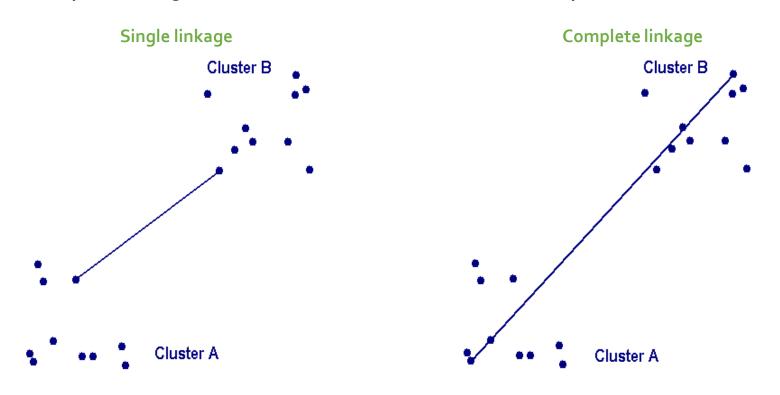
- Strengths of Hierarchical clustering
 - √ Agglomerative clustering vs. Divisive clustering



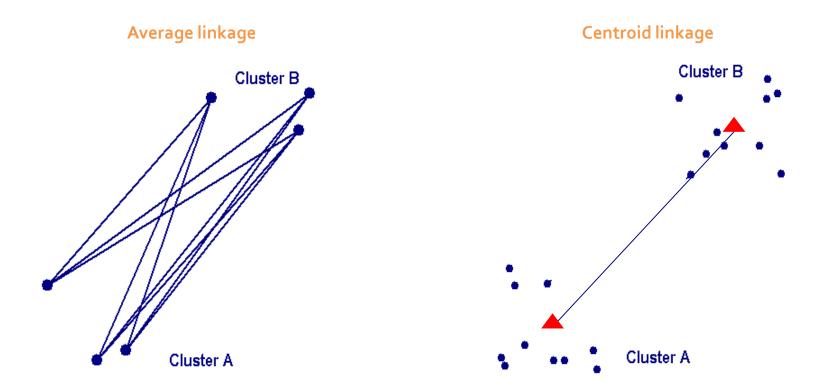
- Agglomerative clustering algorithm
 - √ Key operation: computation of the proximity of two clusters
 - Min, max, group average, between centroid, etc.



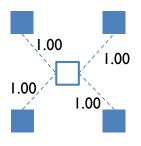
- Agglomerative clustering algorithm
 - ✓ Single linkage: minimum distance between two data points in different clusters
 - ✓ Complete linkage: maximum distance between two data points in different clusters

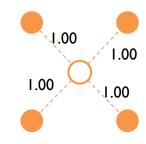


- Agglomerative clustering algorithm
 - ✓ Average linkage: mean distance between two data points in different clusters
 - ✓ Centroid linkage: distance between centroids in different clusters

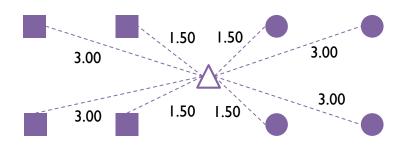


- Agglomerative clustering algorithm
 - √ Ward method: Compare the sum of squared error (SSE) before and after the merge
 - SSE before merge: $1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 1^2 = 8$





• SSE after merge: $4 \times 1.5^2 + 4 \times 3^2 = 45$



■ Ward distance: 45-8 = 37

- Agglomerative Clustering Procedure
 - ✓ Step 1:Assume that each data point is an individual cluster, compute the cluster distance
 - ✓ Step 2: Repeat the following procedure
 - Step 2-1: Merge the two closest clusters
 - Step 2-2: Update the cluster distance matrix
 - √ When all data points are merged as a single cluster, stop

• Example

Initial Data Items

Distance Matrix

Dist	A	В	С	П
A		20	7	2
В			10	25
С				3
D				







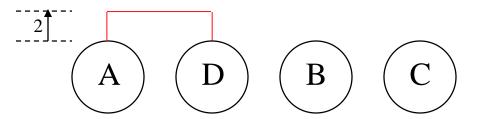


• Example

Current Clusters

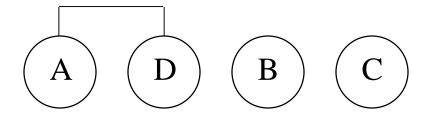
Dist	Α	В	С	

Dist	A	В	С	П
А		20	7	2
В			10	25
С				3
D				



• Example

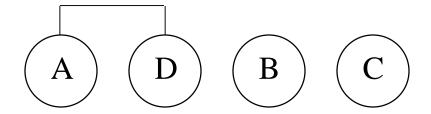
Current Clusters



Dist	AD	В	С	
AD		20	3	
В			10	
С				

• Example

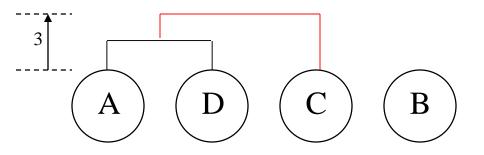
Current Clusters



Dist	AD	В	С	
AD		20	3	
В			10	
С				

• Example

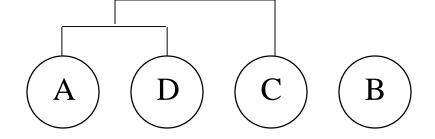




Dist	AD	В	С	
AD		20	3	
В			10	
С				

• Example

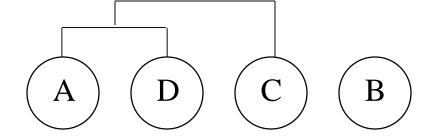
Current Clusters



Dist	AD C	В	
AD C		10	
В			

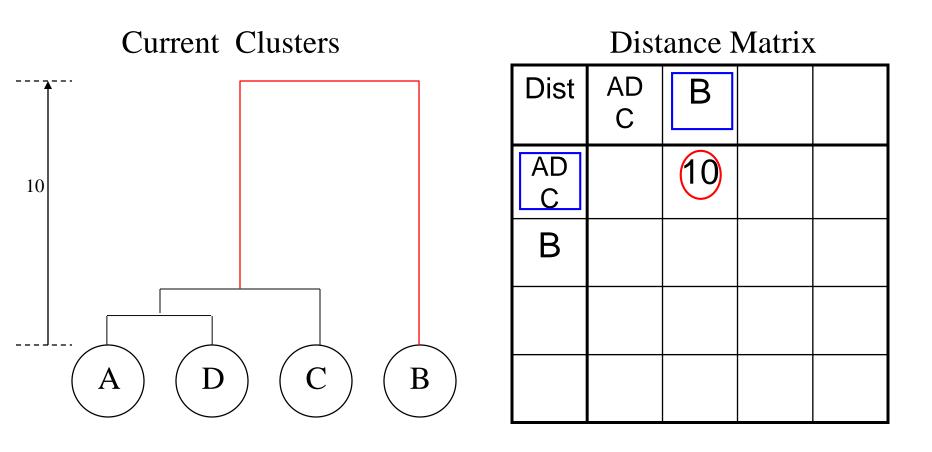
• Example

Current Clusters

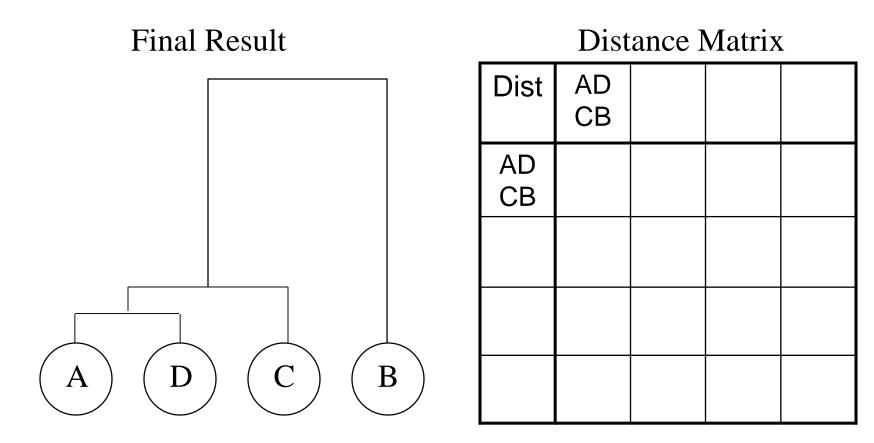


Dist	AD C	В	
AD C		10	
В			

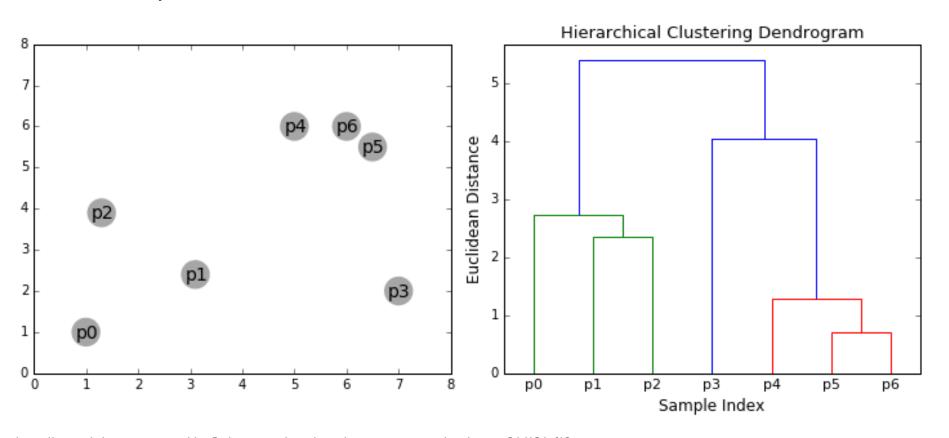
• Example



• Example



HC example



https://towards datascience.com/the-5-clustering-algorithms-data-scientists-need-to-know-a 36d I 36ef 68-clustering-algorithms-data-scientists-need-to-know-a 36ef 68-clustering-algorithms-data-a 36ef 68-clustering-algorithms-data-a 36ef 68-clustering-algorithms-data-a 36ef 68-clustering-algorithms-data-a 36ef 68-clustering-algorithms-data-a 36ef 68-clustering-algorithms-data-a 36ef 68-clustering-algorithms-d

- Clustering top 100 film synopses (http://brandonrose.org/clustering)
 - √ Tokenizing and stemming each synopsis
 - √ Transforming the corpus into vector space using tf-idf
 - ✓ Calculating cosine distance between each document as a measure of similarity
 - ✓ Clustering the documents using the <u>k-means algorithm</u>
 - ✓ Using multidimensional scaling to reduce dimensionality within the corpus
 - ✓ Plotting the clustering output using matplotlib and mpld3
 - ✓ Conducting a hierarchical clustering on the corpus using <u>Ward clustering</u>.
 - ✓ Plotting a Ward dendrogram
 - √ Topic modeling using <u>Latent Dirichlet Allocation (LDA)</u>

MDS result

