

Hierarchical clustering:

- Two main types:
 - Agglomerative:
 - Start with every point in its own cluster
 - At each step, merge the two closest clusters
 - Stop when every point is in the same cluster
 - Divisive:
 - Start with every point in the same cluster
 - At each step, split until every point is in its own cluster
- Agglomerative Clustering Algorithm:
 - 1. Let each point in the dataset be in its own cluster
 - 2. Compute the distance between all pairs of clusters
 - 3. Merge the two closest clusters
 - Repeat 3 & 4 until all points are in the same cluster
- Hierarchical clustering:
 - At every step, we record which clusters were merged in order to produce a dendrogram:
 - We can “cut” the dendrogram at any threshold to produce any number of clusters
 - Finding the threshold with which to cut the dendrogram requires exploration and tuning. But in general hierarchical clustering is used to expose a hierarchy in the data (ex: finding/defining species via DNA similarity).
 - To capture the difference between clusterings you can use a cost function, or methods that we will discuss later when we look at clustering aggregation.
- Distance functions:
 - Let's first define:
 - Distance between points: $d(p_1, p_2)$
 - Distance between clusters: $D(C_1, C_2)$
- single - link distance:
 - Is the **minimum** of all pairwise distances between a point from one cluster and a point from the other cluster.
 - $$D_{SL}(C_1, C_2) = \min \{d(p_1, p_2) \mid p_1 \in C_1, p_2 \in C_2\}$$
 - Can handle clusters of different sizes
 - But... Sensitive to noise points; Tends to create elongated clusters
- Complete-link distance:
 - Is the **maximum** of all pairwise distances between a point from one cluster and a point from the other cluster.
 - $$D_{CL}(C_1, C_2) = \max \{d(p_1, p_2) \mid p_1 \in C_1, p_2 \in C_2\}$$
 - Less susceptible to noise; Creates more balanced (equal diameter) clusters
 - But... Tends to split up large clusters; All clusters tend to have the same diameter
- Average-Link Distance:

- the **average** of all pairwise distances between a point from one cluster and a point from the other cluster.

$$D_{AL}(C_1, C_2) = \frac{1}{|C_1| \cdot |C_2|} \sum_{p_1 \in C_1, p_2 \in C_2} d(p_1, p_2)$$

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- Less susceptible to noise and outliers.
- But... Tends to be biased toward globular clusters

- Centroid Distance:

- The distance between the centroids of clusters.

- $D_C(C_1, C_2) = d(\mu_1, \mu_2)$

- Ward's Distance:

- difference between the spread / variance of points in the merged cluster and the unmerged clusters

$$D_{WD}(C_1, C_2) = \sum_{p \in C_{12}} d(p, \mu_{12}) - \sum_{p_1 \in C_1} d(p_1, \mu_1) - \sum_{p_2 \in C_2} d(p_2, \mu_2)$$

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