

Week 15– Unsupervised Learning Clustering

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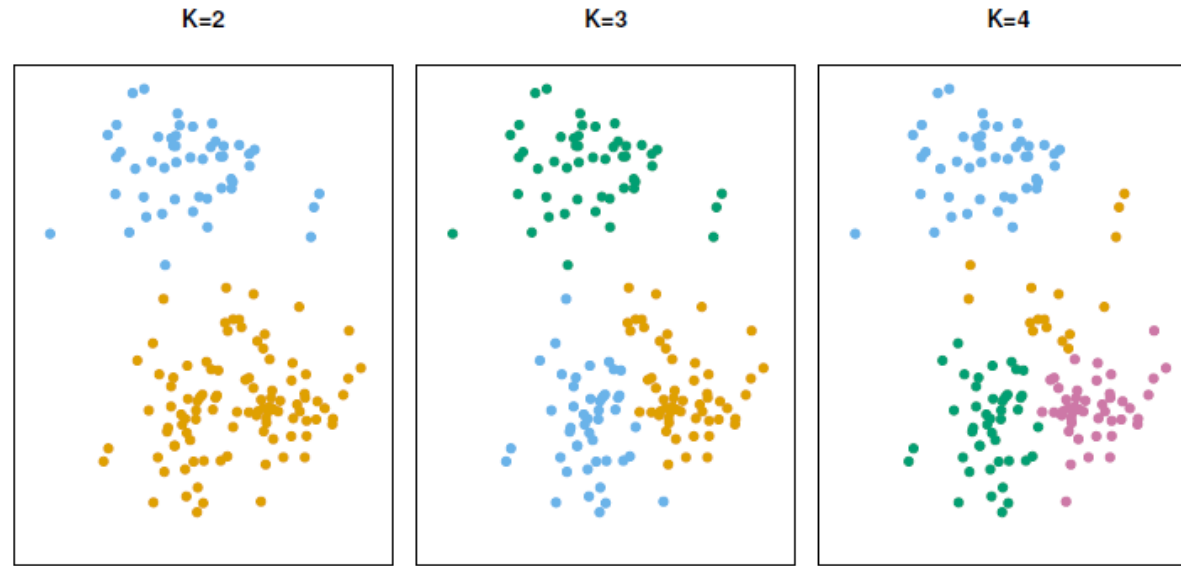
PCA vs Clustering

- PCA looks for a low-dimensional representation of the observations that explains a good fraction of the variance.
- Clustering looks for homogeneous subgroups among the observations.

Clustering Methods

- In *K-means clustering*, we seek to partition the observations into a pre-specified number of clusters.
- In *hierarchical clustering*, we do not know in advance how many clusters we want; in fact, we end up with a tree-like visual representation of the observations, called a *dendrogram*, that allows us to view at once the clusterings obtained for each possible number of clusters, from 1 to n .

K-Means Clustering



A simulated data set with 150 observations in 2-dimensional space. Panels show the results of applying K -means clustering with different values of K , the number of clusters. The color of each observation indicates the cluster to which it was assigned using the K -means clustering algorithm. Note that there is no ordering of the clusters, so the cluster coloring is arbitrary. These cluster labels were not used in clustering; instead, they are the outputs of the clustering procedure.

K-Means clustering (details)

Let C_1, \dots, C_K denote sets containing the indices of the observations in each cluster. These sets satisfy two properties:

1. $C_1 \cup C_2 \cup \dots \cup C_K = \{1, \dots, n\}$. In other words, each observation belongs to **at least one** of the K clusters.
2. $C_k \cap C_{k'} = \emptyset$ for all $k \neq k'$. In other words, the clusters are **non-overlapping**: no observation belongs to **more than one** cluster.

For instance, if the i th observation is in the k th cluster, then $i \in C_k$.

K-Means clustering (details)

- The idea behind K -means clustering is that a *good* clustering is one for which the *within-cluster variation* is as small as possible.
- The **within-cluster variation** for cluster C_k is a measure $WCV(C_k)$ of the amount by which the observations within a cluster differ from each other.
- Hence we want to solve the problem

$$\underset{C_1, \dots, C_K}{\text{minimize}} \left\{ \sum_{k=1}^K WCV(C_k) \right\}. \quad (2)$$

- In words, this formula says that we want to partition the observations into K clusters such that the total within-cluster variation, summed over all K clusters, is as small as possible.

Defining WCV

- Typically we use Euclidean distance

$$\text{WCV}(C_k) = \frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^p (x_{ij} - x_{i'j})^2, \quad (3)$$

where $|C_k|$ denotes the number of observations in the k th cluster.

- Combining (2) and (3) gives the optimization problem that defines K -means clustering,

$$\underset{C_1, \dots, C_K}{\text{minimize}} \left\{ \sum_{k=1}^K \frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^p (x_{ij} - x_{i'j})^2 \right\}. \quad (4)$$

K-Means Clustering Algorithm

1. Randomly assign a number, from 1 to K , to each of the observations. These serve as initial cluster assignments for the observations.
2. Iterate until the cluster assignments stop changing:
 - 2.1 For each of the K clusters, compute the cluster *centroid*.
The k th cluster centroid is the vector of the p feature means for the observations in the k th cluster.
 - 2.2 Assign each observation to the cluster whose centroid is closest (where *closest* is defined using Euclidean distance).

Properties of K-Means Clustering

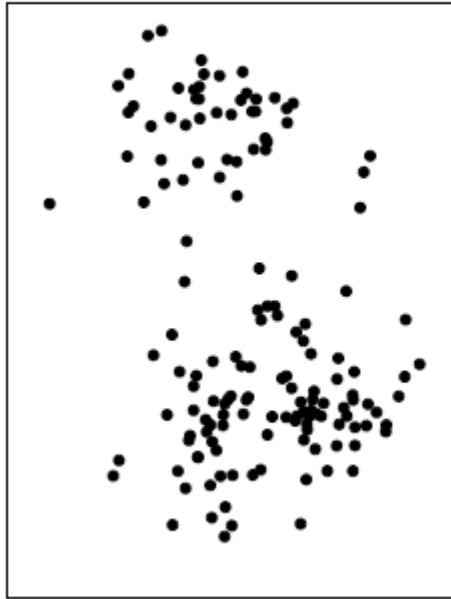
- This algorithm is guaranteed to decrease the value of the objective (4) at each step. *Why?* Note that

$$\frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^p (x_{ij} - x_{i'j})^2 = 2 \sum_{i \in C_k} \sum_{j=1}^p (x_{ij} - \bar{x}_{kj})^2,$$

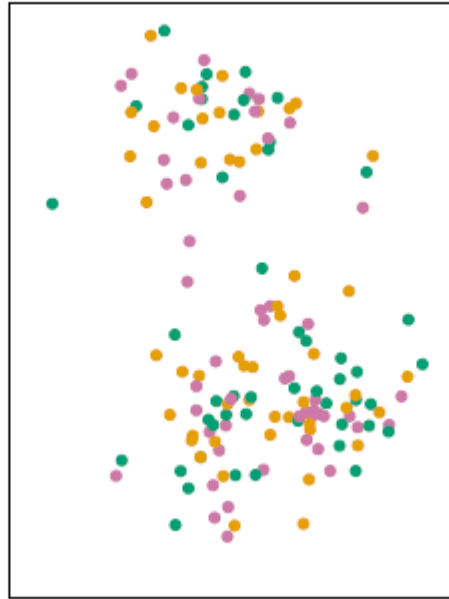
where $\bar{x}_{kj} = \frac{1}{|C_k|} \sum_{i \in C_k} x_{ij}$ is the mean for feature j in cluster C_k .

- however it is not guaranteed to give the global minimum.
Why not?

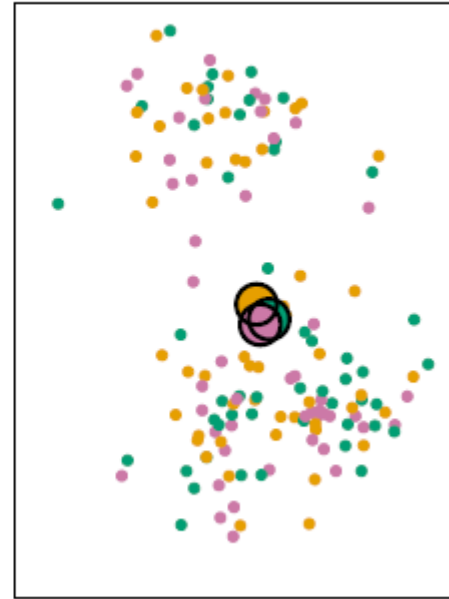
Data



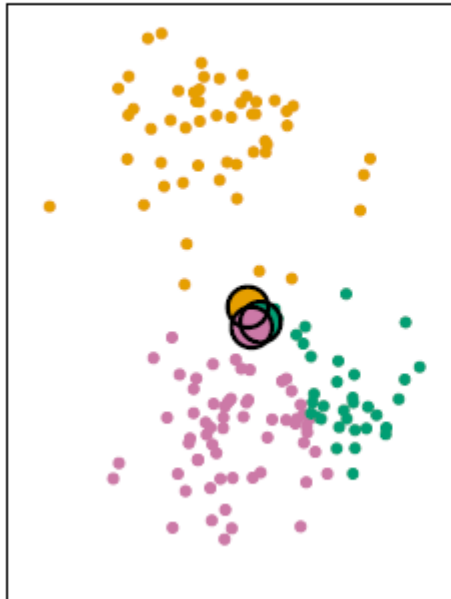
Step 1



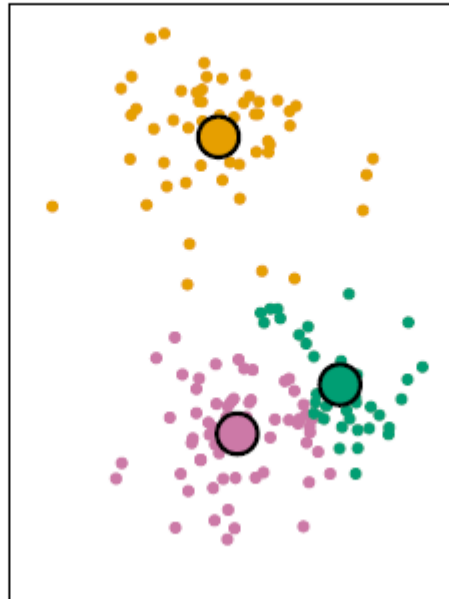
Iteration 1, Step 2a



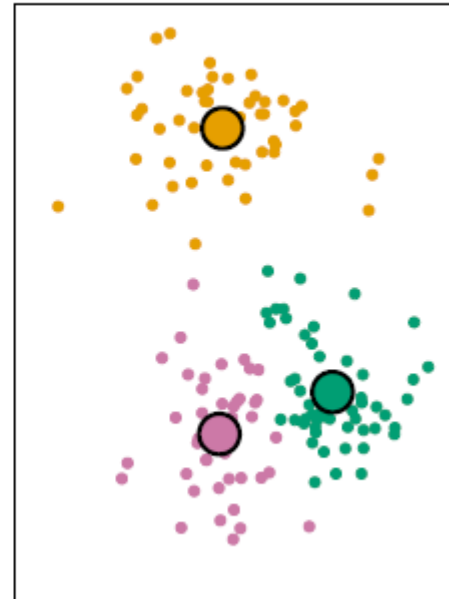
Iteration 1, Step 2b



Iteration 2, Step 2a

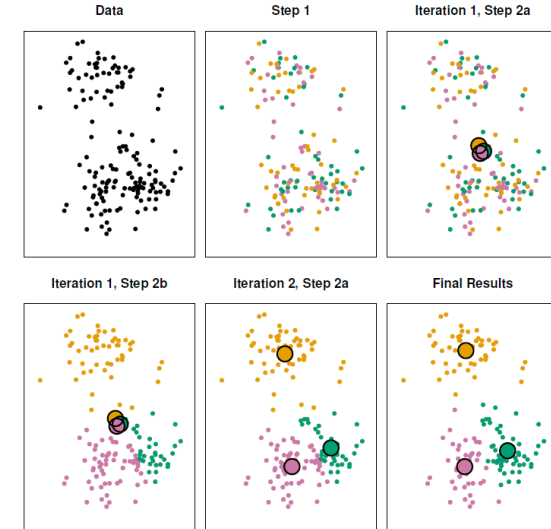


Final Results



The progress of the K-means algorithm with $K=3$.

- *Top left:* The observations are shown.
- *Top center:* In Step 1 of the algorithm, each observation is randomly assigned to a cluster.
- *Top right:* In Step 2(a), the cluster centroids are computed. These are shown as large colored disks. Initially the centroids are almost completely overlapping because the initial cluster assignments were chosen at random.
- *Bottom left:* In Step 2(b), each observation is assigned to the nearest centroid.
- *Bottom center:* Step 2(a) is once again performed, leading to new cluster centroids.
- *Bottom right:* The results obtained after 10 iterations.



Example: different starting values

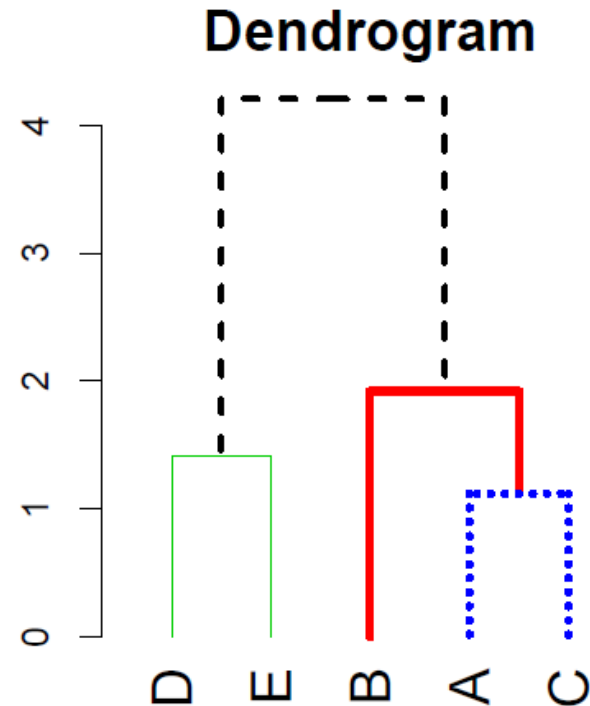
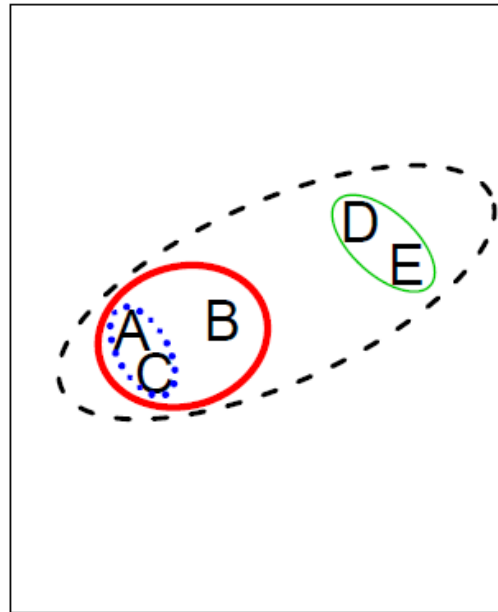


Hierarchical Clustering

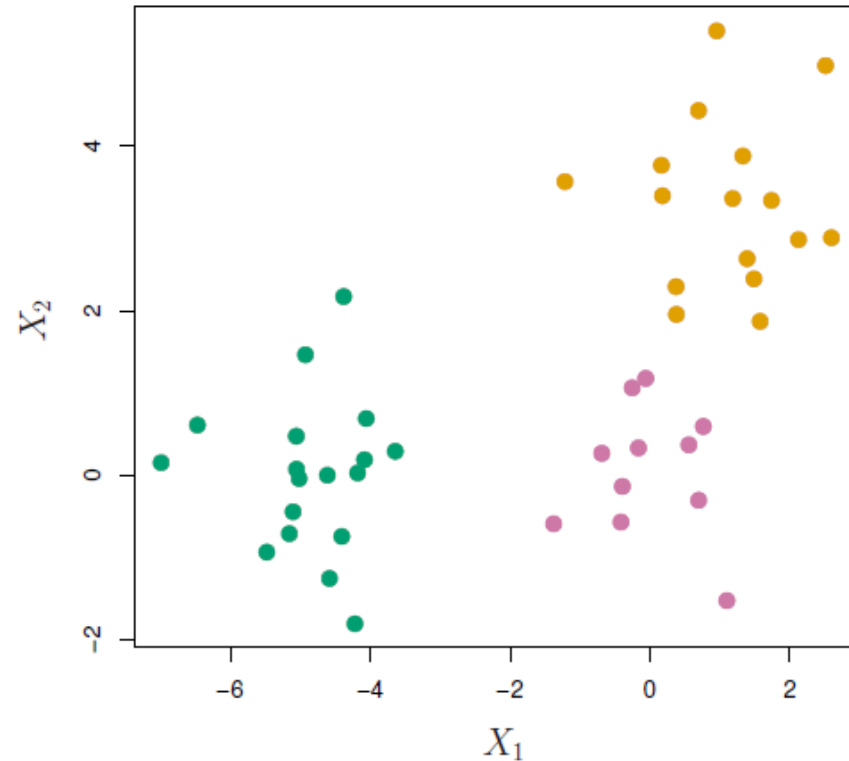
- K -means clustering requires us to pre-specify the number of clusters K . This can be a disadvantage (later we discuss strategies for choosing K)
- *Hierarchical clustering* is an alternative approach which does not require that we commit to a particular choice of K .
- In this section, we describe *bottom-up* or *agglomerative* clustering. This is the most common type of hierarchical clustering, and refers to the fact that a dendrogram is built starting from the leaves and combining clusters up to the trunk.

Hierarchical Clustering Algorithm

- Start with each point in its own cluster.
- Identify the **closest** two clusters and merge them.
- Repeat.
- Ends when all points are in a single cluster.

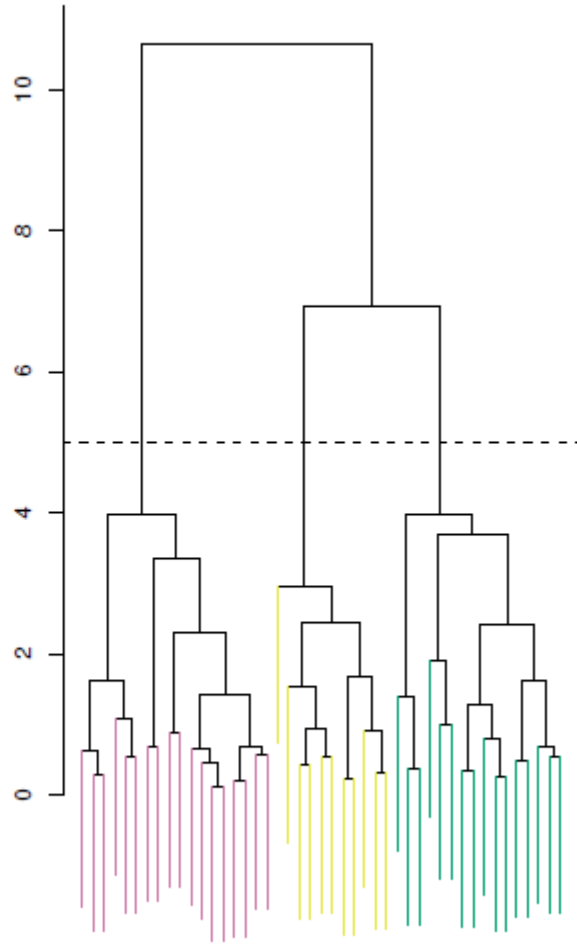
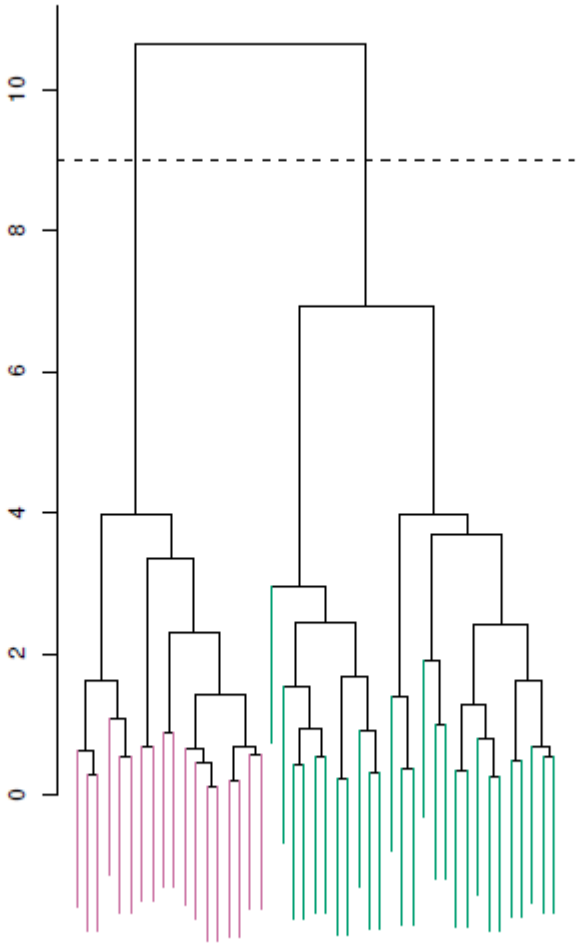
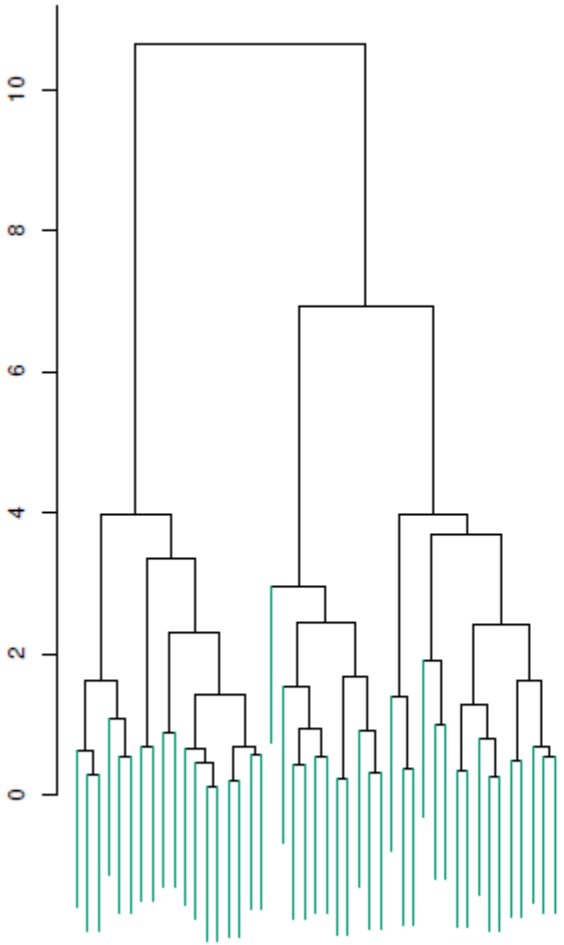
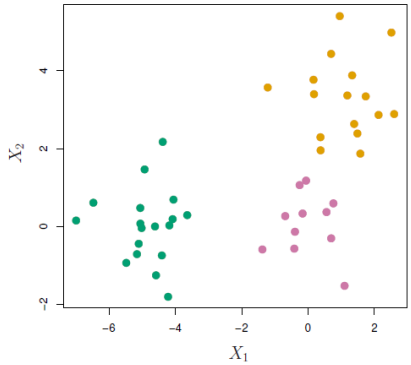


Example



45 observations generated in 2-dimensional space. In reality there are three distinct classes, shown in separate colors. However, we will treat these class labels as unknown and will seek to cluster the observations in order to discover the classes from the data.

Application of Hierarchical Clustering

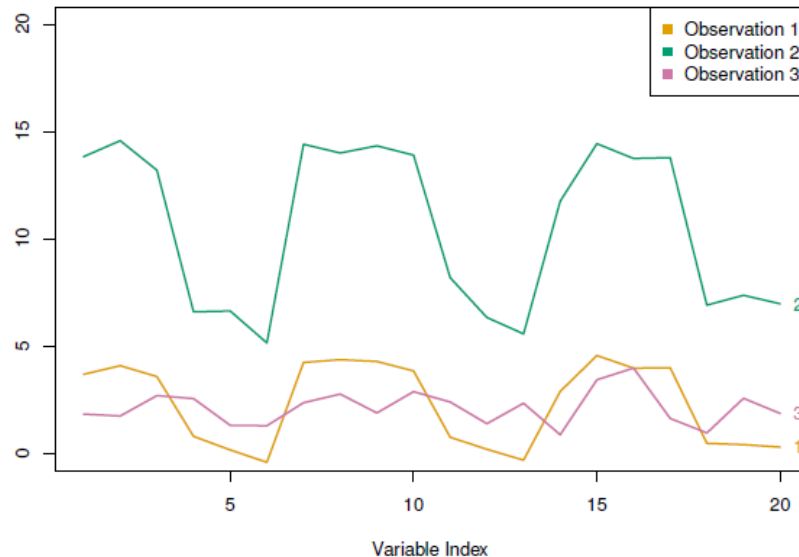


Types of Linkage

<i>Linkage</i>	<i>Description</i>
Complete	Maximal inter-cluster dissimilarity. Compute all pairwise dissimilarities between the observations in cluster A and the observations in cluster B, and record the <i>largest</i> of these dissimilarities.
Single	Minimal inter-cluster dissimilarity. Compute all pairwise dissimilarities between the observations in cluster A and the observations in cluster B, and record the <i>smallest</i> of these dissimilarities.
Average	Mean inter-cluster dissimilarity. Compute all pairwise dissimilarities between the observations in cluster A and the observations in cluster B, and record the <i>average</i> of these dissimilarities.
Centroid	Dissimilarity between the centroid for cluster A (a mean vector of length p) and the centroid for cluster B. Centroid linkage can result in undesirable <i>inversions</i> .

Choice of Dissimilarity Measure

- So far have used Euclidean distance.
- An alternative is *correlation-based distance* which considers two observations to be similar if their features are highly correlated.
- This is an unusual use of correlation, which is normally computed between variables; here it is computed between the observation profiles for each pair of observations.



Practical Issues

- *Scaling of the variables matters!*. Should the observations or features first be standardized in some way? For instance, maybe the variables should be centered to have mean zero and scaled to have standard deviation one.
- In the case of hierarchical clustering,
 - What dissimilarity measure should be used?
 - What type of linkage should be used?
- How many clusters to choose? (in both K -means or hierarchical clustering). Difficult problem. No agreed-upon method. See Elements of Statistical Learning, chapter 13 for more details.
- Which features should we use to drive the clustering?

Conclusion

- *Unsupervised learning* is important for understanding the variation and grouping structure of a set of unlabeled data, and can be a useful pre-processor for supervised learning
- It is intrinsically more difficult than *supervised learning* because there is no gold standard (like an outcome variable) and no single objective (like test set accuracy).
- It is an active field of research, with many recently developed tools such as *self-organizing maps*, *independent components analysis* and *spectral clustering*.
See *The Elements of Statistical Learning*, chapter 14.