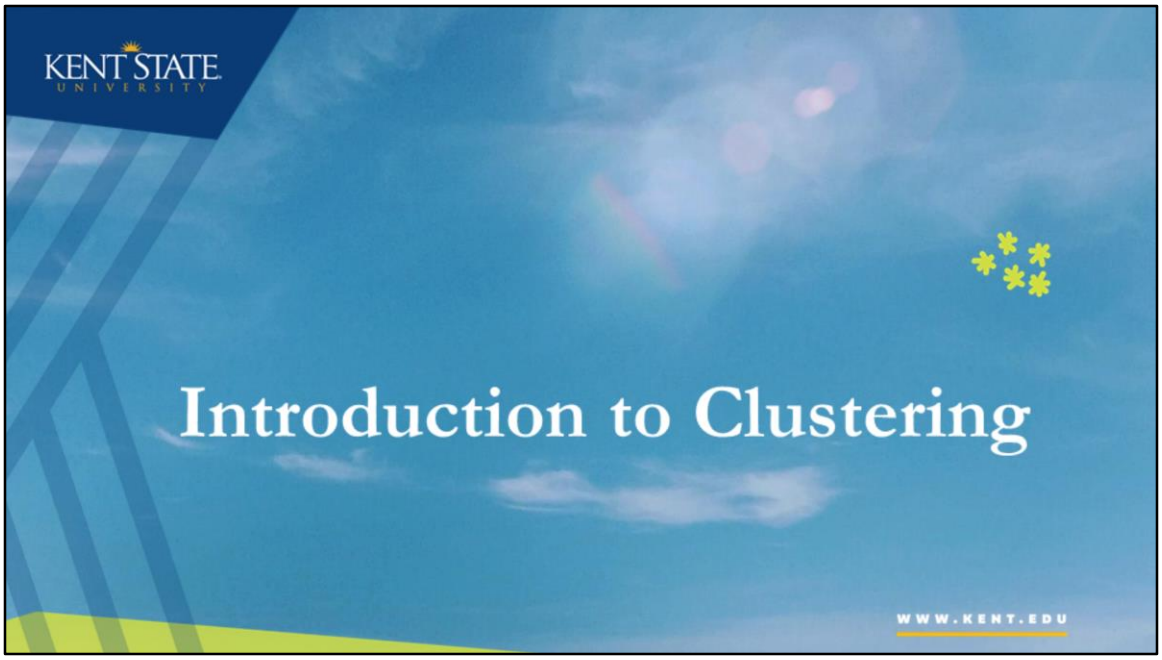
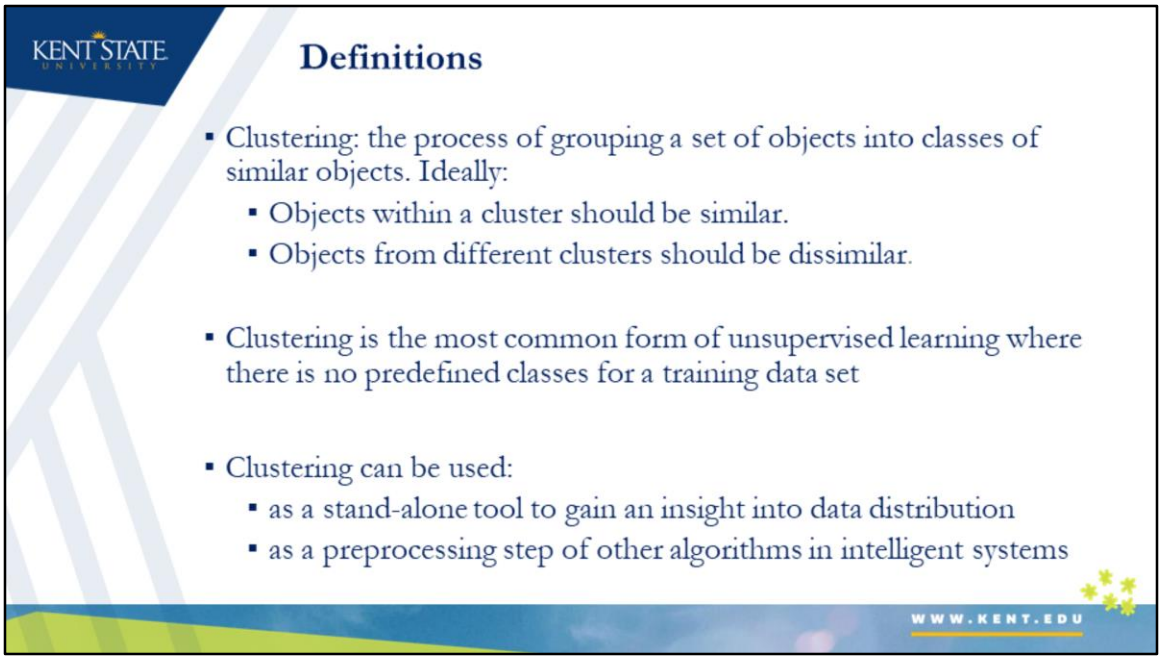
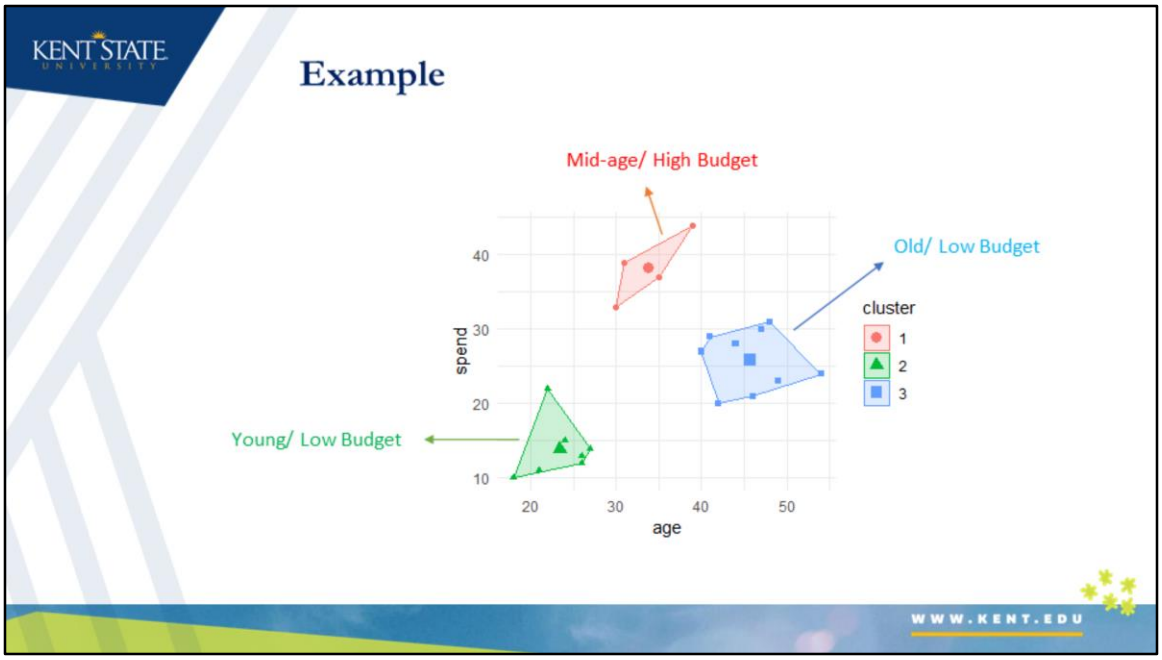


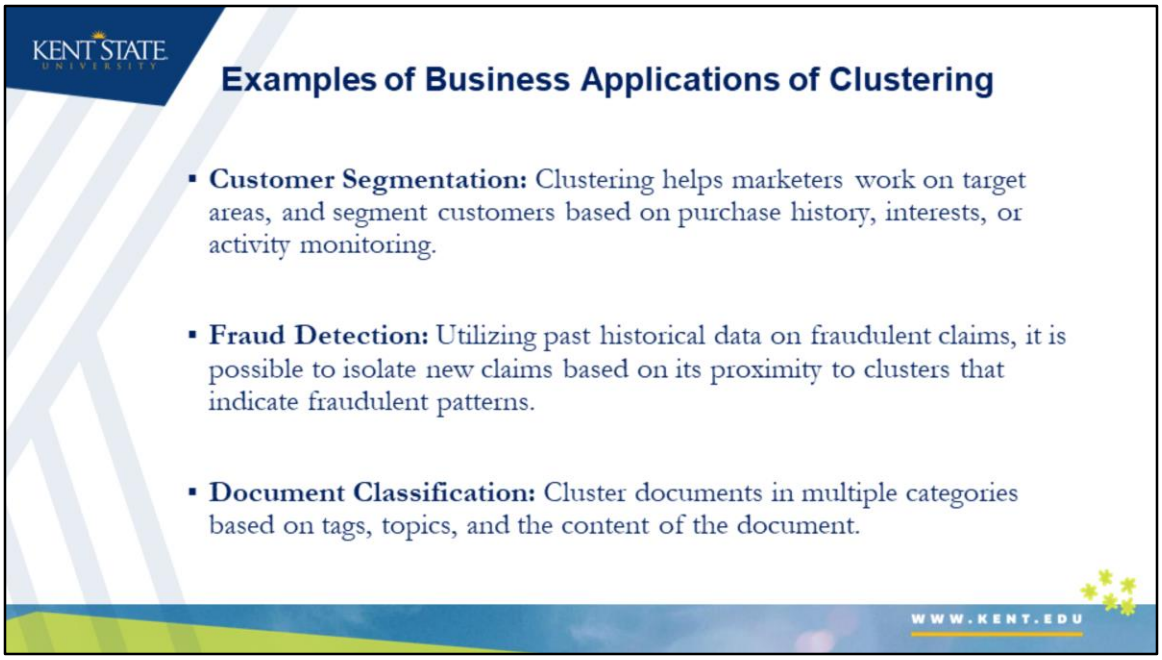
Here, we discuss a popular unsupervised learning method called clustering.



The goal of clustering is to segment the data into a set of homogeneous clusters of records for the purpose of generating insight. Separating a dataset into clusters of homogeneous records is also useful for improving performance of supervised methods, by modeling each cluster separately rather than the entire, heterogeneous dataset. Clustering is used in a vast variety of business applications, from customized marketing to industry analysis.



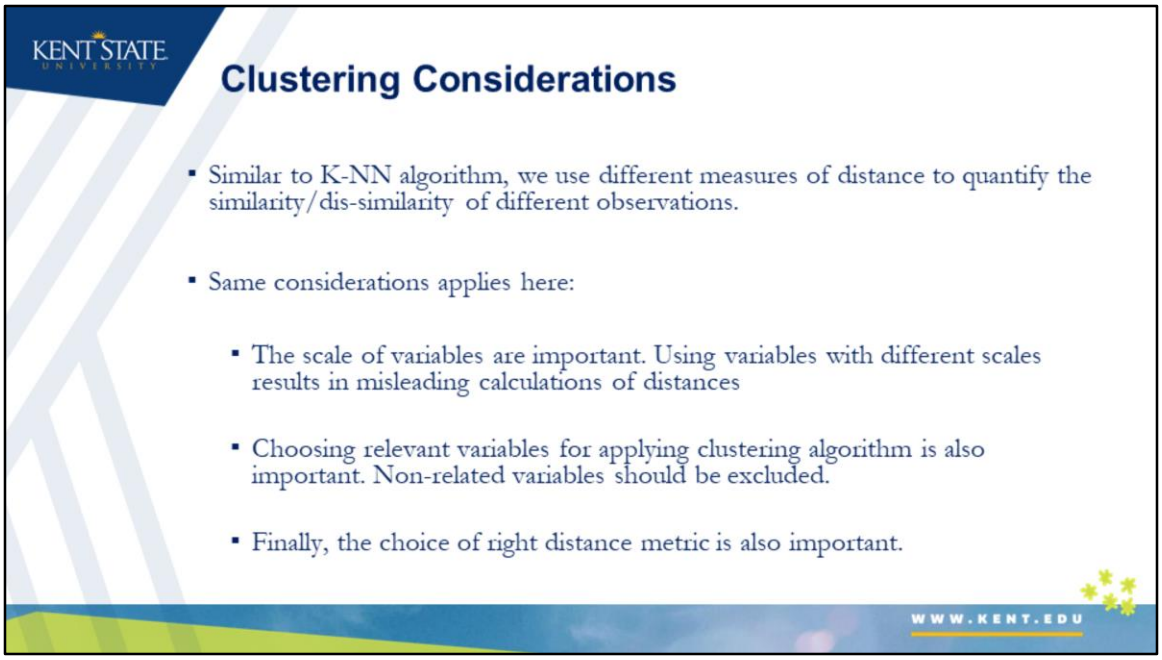
This is an example of clustering. Note the separation of items based on Age and Spending. Any number of independent variables can be used, though one should ask "how do you form the clusters, and how many should there be?"



Cluster analysis is used to form groups or clusters of similar records based on several measurements made on these records. The key idea is to characterize the clusters in ways that would be useful for the aims of the analysis. This idea has been applied in many areas. Biologists, for example, have made extensive use of classes and subclasses to organize species. A spectacular success of the clustering idea in chemistry was Mendeleev's periodic table of the elements.

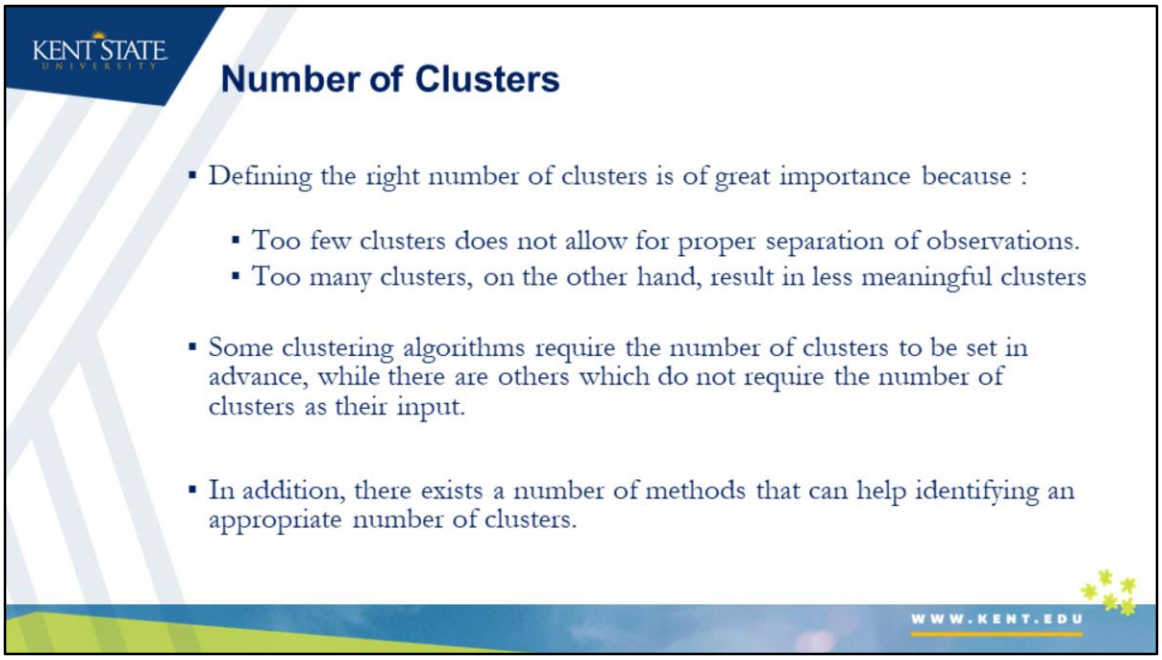
One popular use of cluster analysis in marketing is for market segmentation: customers are segmented based on demographic and transaction history information, and a marketing strategy is tailored for each segment. In countries such as India, where customer diversity is extremely location-sensitive, chain stores often perform market segmentation at the store level, rather than chain-wide (called "micro segmentation").

In finance, cluster analysis can be used for creating balanced portfolios: Given data on a variety of investment opportunities (e.g., stocks), one may find clusters based on financial performance variables such as return (daily, weekly, or monthly), volatility, beta, and other characteristics, such as industry and market capitalization.



Cluster analysis can be thought of as an algorithm that measures the distance between records, and according to these distances, forms clusters. This is similar to the k-NN algorithms, which also use distance measures to identify neighbors.

As distance values, especially for numeric variables, are affected by scale, it is important that we *normalize* values before computing distances. As with other methods, only relevant variables should be included in your analysis.



In general, there are two types of clustering algorithms for a dataset of n records: hierarchical and non-hierarchical clustering.

Hierarchical methods can be either agglomerative or divisive. Agglomerative methods begin with n clusters and sequentially merge similar clusters until a single cluster is obtained. Divisive methods work in the opposite direction, starting with one cluster that includes all records. Hierarchical methods are especially useful when the goal is to arrange the clusters into a natural hierarchy.

Non-hierarchical methods, such as k-means, use a prespecified number of clusters. These methods are generally less computationally intensive and are therefore preferred with very large datasets. As we primarily study k-means in this module, one issue is in specifying the number of clusters beforehand. We will see approaches to address this issue.

And, those of you paying attention will realize that marketing is now at the individual level, or a cluster of size 1.