
**Main point:** The authors present an overview of minimum spanning trees (MST’s) and single linkage analysis, discussing the applications of minimum spanning tree-finding algorithms and single linkage clustering algorithms briefly. They show how to derive a single linkage clustering dendrogram by using a minimum spanning tree, and state some advantages and disadvantages of single linkage clustering versus methods which “generally define clusters by maximizing some simple function of average interset distance and so tend to give fairly compact, roughly spherical clusters.”

The minimum spanning tree problem is presented and several works are cited which have independently solved this problem using similar or even identical approaches. In the first approach to finding a minimum spanning tree, the shortest edge between a vertex currently outside the minimum spanning tree and a vertex in the spanning tree is found, and this edge and its adjacent vertex are added to the MST. An alternative algorithm (Prim’s) starts at a random vertex, and in a breadth-first search manner, explores the the neighbors of the vertices currently in the MST to find the minimum-weight edge and adjacent vertex to add to the MST, until all vertices have been explored.

Single linkage cluster analysis (SLCA) is discussed next, and the authors point out that the clusters resulting from applying a cut-off edge weight (or distance) value to a single linkage dendrogram can also be obtained by first finding the minimum spanning tree of the graph containing \( n \) vertices, and then cutting all edges in the tree that are of higher weight (distance) than the threshold applied to the single linkage dendrogram. This is because by definition, the MST contains the \( n-1 \) smallest-weight edges which would, in order from smallest to greatest edge value, cause vertices to join together to form clusters at each step of an agglomerative single-linkage clustering algorithm in each of at most \( n-1 \) steps (the number of steps depends on the distance intervals or levels in a single linkage dendrogram). The authors point out that clusters discovered by an agglomerative algorithm are equivalent to those discovered by a divisive hierarchical algorithm which repeatedly divides clusters by removing edges from greatest to smallest edge weight.

One application of SCLA is briefly discussed, showing that an MST on a two-dimensional embedding of 9 dimensional data produces results that are fairly accurate, revealing the data points that are close to each other in terms of generalized distances between the “canonical variate means” of the samples forming each data point. The authors argue that this makes MST a useful “ancillary technique” when the data set is large and it becomes too expensive to compute a complete distance matrix.