Concept mapping: A look at what's underneath

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1. Concept mapping background

Concept mapping is a six step process, as summarized by Kane and Trochim (2007): (1) *preparation*, which includes selection of participants and a brainstorming focus statement, (b) *generation* of focus response statements via brainstorming, (c) *structuring* of statements via sorting and rating, (d) *representation* of statements by computing a concept map, (e) *interpretation* of maps and (f) *utilization* of maps.

2. Context

To create an outcomes map, twenty-one grassroots community leaders participated in a concept mapping process. They generated responses to the following focus statement: "Think about yourself, your family, your child's school, your church and your neighborhood. When [our organization] does community organizing, this is what happens: _________." After structuring and representing the statements on a map, several leaders reviewed the map and interpreted it by choosing appropriate names for five groupings of the eighty-nine responses. Final results from the study are available in the *Journal of Community Psychology* (Orsi, 2014). This presentation discusses the statistical analysis conducted using the 'cluster' package (Maechler, 2011) in the R statistical software environment (R Development Core Team, 2011).

3. Analysis assumptions & alternatives

A. Multidimensional scaling solution

Multidimensional scaling (MDS) places the response statements on a map in a way that reflects the relative conceptual proximity of the statements. Statements which were frequently sorted together are close together; statements which were infrequently sorted together are further apart. Although multidimensional scaling can produce a map in many dimensions, Kane and Trochim (2007) recommend a two-dimensional map because it is easy to interpret and generally useful for the purposes of research or evaluation. For the community organizing data, we calculated a goodness-of-fit metric for the MDS solution called the *stress*, which is always greater than or equal to zero. Kruskal and Wish (1978) offer the rough guideline that if stress is greater than 0.10, then the number of dimensions chosen for the MDS solution may not be correct. For our data, the stress measure for the two dimensional solution was 0.24 and the stress measure for a three dimensional solution was 0.17 – a 29% reduction. The question is, of course, how could we display the three-dimensional solution in a way that could be clustered and that community leaders could meaningfully interpret?

B. Cluster analysis

We used cluster analysis to group the mapped response statements into clusters (Kane and Trochim, 2007). Clusters are mathematically-based groupings of the response statements and are closely related to how often each pair of statements was sorted together by participants. There are several types of cluster analysis algorithms, including hierarchical methods (agglomerative and divisive) and also non-hierarchical partitioning algorithms. Johnson and Wichern (2007) suggest trying multiple clustering methods for an analysis, as do Kaufman and Rousseeuw (1990). For this study, four types of clustering discussed by Kaufman and Rousseeuw (1990) were used: partitioning around medoids (PAM), fuzzy analysis (FANNY), agglomerative nesting (AGNES) and divisive analysis (DIANA). PAM and FANNY are non-hierarchical partitioning methods. AGNES is a hierarchical agglomerative method and DIANA is a hierarchical divisive method. All of the maps produced using these methods are available in Orsi (2011).

Each map was clustered into 4, 5, 6 and 7 groups. The AGNES algorithm provides an agglomerative coefficient which quantifies whether or not there is a natural cluster structure in the data. The agglomerative coefficient ranges between 0 and 1 with higher values indicating a clear clustering structure (Kaufman & Rousseeuw, 1990, p. 213). For the AGNES solutions, the agglomerative coefficient was very high (0.98). The DIANA algorithm produces a similar measure ranging between 0 and 1. Its value for these data was 0.93. Kaufmann and Rousseeuw note, however, that both the agglomerative and divisive coefficients can be influenced by even one outlier. Based on a visual inspection of the maps, a tight clustering structure is not evident. Therefore, high values for these coefficients may be due to outliers rather than a clear clustering structure. The FANNY algorithm calculates a normalized version of Dunn's partition coefficient (Dunn, 1976) to assess the clarity of its cluster structures (Kaufman & Rousseeuw, 1990). This measure ranges from 0 to 1 where 1 indicates a completely well-partitioned (i.e. non-fuzzy) cluster solution. The normalized partition coefficients for the FANNY cluster solutions ranged from 0.133 to 0.214, indicating a set of rather poorly-partitioned cluster solutions. Poor partitioning measures were validated by visual inspection. With the exception of a well-defined cluster at the left side, the rest of the clusters were not well-differentiated. The PAM algorithm does not offer a numeric measure of the goodness of the clustering solution.

After running sixteen clustered solutions, the next step was to narrow the set to a reasonable number of maps which could be interpreted by the participants. To begin, note that FANNY did not produce a 7-group solution; its "7-group" solution contained only six clusters (almost identical to the 6-cluster solution). Also, two of the 7-group solutions (DIANA and AGNES) had one cluster which was very small (two to four statements). Since not all of the 7-cluster solutions were viable, they were eliminated from consideration. Next, the remaining DIANA solutions were eliminated. The 4-group DIANA solution poorly differentiated a visually obvious cluster on the left side of the map. The 5- and 6-group DIANA solutions also displayed one cluster with only two members. Eliminating the 7-group solutions and DIANA narrowed the field from sixteen maps to nine.

The remaining nine cluster solutions displayed a great deal of similarity. Each of them had clusters arranged in a more-or-less oval-shaped pattern around a relatively empty area slightly to the upper left of the center of the map. To compare the nine remaining maps, two cluster validation indices were calculated: Dunn and Davies-Bouldin (Davies & Bouldin, 1979; Dunn, 1974; Halkidi, Batistakis & Vazirgiannis, n.d.). Both assess the separation of clusters. These indices can be calculated in the R statistical environment using a number of different intracluster diameter and intercluster distance measures. Because the MDS map appears to contain both outliers and overlapping points, average intracluster diameter and intercluster distance measures were used to calculate the indices. Average intracluster diameter is the average of all distances between the point pairs in a cluster (Nieweglowski, 2009). Average intercluster distance is the average distance between all possible point pairs formed by taking one member of the point pair from one cluster and the other member of the point pair from another cluster (Johnson and Wichern, 2007, p. 681; Nieweglowski, 2009). Other options are complete linkage (for both intracluster diameter and intercluster distance) and single linkage (for intercluster distance). These measurements are based on the furthest apart and closest together point pairs, and so may be unduly influenced by outliers or overlap. Therefore, average linkage distances were used for both measures so as to be more representative of the entire cluster.

Dunn's index is a measure of dissimilarity between clusters. Thus, we looked for the cluster solution with the highest value for Dunn's index. For the nine remaining solutions, the values of Dunn's index ranged from 1.54 to 3.04. The solution with the highest index (3.04) was the PAM 4-cluster solution. However, the index for the AGNES 5-cluster solution was virtually identical at 3.00. The Davies-Bouldin index is a measure of similarity between clusters. Thus, we looked for the cluster solution with the lowest value for the Davies-Bouldin index. The values of Davies-Bouldin ranged from 0.47 to 0.56. The solution with the lowest index was the AGNES 4-cluster solution. These results allowed us to narrow down the selection of cluster maps presented to the community leaders for interpretation, namely, the AGNES 4- and 5-cluster solutions. It was also helpful that three of the cluster groups were identical between the AGNES 4- and 5-cluster solutions. The 5-cluster solution broke the least cohesive cluster from the 4-cluster solution in two. The AGNES 5-cluster solution was the final result used to disseminate this study.

4. References

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