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Current Problems and Resolutions

Under this heading are brief reports of studies that increase our understanding of compelling social problems, bring us somewhat closer to a solution, and show promise of transcending their own origin in the zeitgeist. These Notes consist of a summary of the study's procedure and as many details about the results as space allows. Additional details concerning the results can be obtained by communicating directly with the author.

Preparing Card Sort Data for Multidimensional Scaling Analysis in Social Psychological Research: A Methodological Approach

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ABSTRACT. Card sorting is a popular data-gathering technique. Although multidimensional scaling (MDS) is a statistical analogue of the technique, researchers rarely apply it to this type of data. The authors' contention is that a barrier to applying MDS to card sorting data is the lack of guidance in the literature about how to organize and prepare the data for analysis. The authors describe a method that gives guidance to researchers in the field of social psychology who want to analyze card sort data using MDS, which can be used to confirm or validate hypotheses about specific social psychological structures hidden in data.

Keywords: card sorting, data analysis, multidimensional scaling analysis

CARD SORTING IS A POPULAR data-gathering technique. This popularity is because of its numerous advantages, including ease of administration, low susceptibility to experimental demand characteristics, economy in handling large numbers of objects or stimuli, grounding in a theoretical framework such as Kelly's personal construct theory, and utility with different types of objects or stimuli (e.g., pictures, personality traits, colors; Fincher & Tenenberg, 2005; Green & Manzi, 2002; Johnston, 1995; Rosenberg & Kim, 1975; Rosenberg, Nelson, & Vivekananthan, 1968; Rugg & McGeorge, 2005; Russell & Bullock, 1985). "In a typical application of the sorting method, the respondent is asked to partition a set of inter-related objects or terms into different groups on the basis of their 'similarity,' 'relatedness,' or 'co-occurrence'—depending on the particular application" (Rosenberg & Kim, p. 489).

When card sorting presents challenges to researchers, it is not in administration, but in analysis or how the researcher makes sense of the data (Fincher & Tenenberg, 2005). Giguere (2006) made a distinction between free sorting and card sorting. In fact, both techniques are card sorting, but one applies a free format and the other uses a fixed format. The free format does not restrict the number of groups or piles that can be generated during the card sorting. In the present article, card sorting will always refer to the free format. Efforts to make sense of card sort data follow a two-step process: The first step is to prepare the data for the analytic technique of choice, and the second step is to apply the actual technique.

Multidimensional scaling (MDS) is one statistical technique that historically has been used to analyze card sort data. MDS refers to a class of statistical techniques that convert a matrix of proximities (i.e., numerical values indicating the degree of dissimilarity among stimuli such as Euclidean distance measures) into a geometric configuration or map of points in n-dimensional space (Kruskal, 1964; Kruskal & Wish, 1978; Takane, Young, & de Leeuw, 1976). Rosenberg and Kim (1975) pointed out that MDS is suitable for analyzing card sort data because of its function to uncover underlying dimensions in respondents' judgments uncontaminated by the researcher's preconceptions.

Other researchers have asserted that card sorting is a more preferable method of data collection for MDS analyses because it is more natural, interesting, and comprehensible than techniques such as pairwise ratings of similarity between stimuli (Giles, Llado, McKirnan, & Taylor, 1979). Nevertheless, pairwise ratings of similarity between stimuli have also been used to derive data for MDS analyses (Forsyth & Pope, 1984; Isenberg & Ennis, 1981). MDS can be used to confirm or validate hypotheses about specific social-psychological structures hidden in data (Giguere, 2006). In this way, MDS is the statistical analogue of the card sorting technique. Moreover, despite the compatibility of MDS with card sorting and its application in past studies (Giles et al.; Green & Manzi, 2002; Johnston, 1995; Lickel et al., 2000; Rosenberg & Kim, 1975; Rosenberg et al., 1968; Russell & Bullock, 1985), researchers have devoted little attention to the subject matter.

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Recent discussions in the literature of card sorting do not mention MDS as an appropriate analytic method. Rugg and McGeorge (2005) asserted, “Relatively few types of statistics can be applied to sorts” (p. 103). Researchers recognize the fact that cluster analytic approaches can represent relations among stimuli of co-occurrence matrixes, similarity, or relatedness in the form of dendrograms (Diebel, Anderson, & Anderson, 2005; Fincher & Tenenberg, 2005). It is important to note that cluster analysis is similar to MDS in that both techniques use proximity data for analysis. However, a recent article by Giguere (2006) providing a tutorial on MDS did point out that card sorting data is appropriate for MDS. There are also studies involving the application of MDS to card sorting data (Giles et al., 1979). However, neither these studies nor tutorials on card sorting or MDS illuminate the specific steps from data collection to data preparation for MDS analyses.

Our contention is that one barrier to applying MDS to card sorting data is the lack of guidance in the literature about how to organize and prepare the data for analysis. Thus, the purpose of this article is to describe a method for organizing card sort data for MDS. After failing to find instructions in the literature about how to prepare the data, we figured it out ourselves. In this article, we aim to share that information with other researchers so that they can avoid the same difficulties.

First, we conduct a review of card sorting and MDS in social psychology research to illustrate both the utility of the statistical method and the lack of detail about data preparation. Second, we describe the research project for which the data were gathered to provide a context. Third, we provide an overview to illustrate how the study data were (a) derived from the participants’ card sort activities, (b) constructed into variables and coded, and (c) organized in a spreadsheet to permit the transformation of participants’ card sort data into proximity matrixes, which was required before these data could be subjected to MDS analysis. Last, we give a brief summary of how to interpret MDS analyses and conclude with some limitations of our application of MDS.

Card Sorting and MDS Analyses in Social Psychological Research

Several studies using MDS analyses in social psychological research were published over the past 3 decades (Forsyth & Pope, 1984; Giles et al., 1979; Green & Manzi, 2002; Isenberg & Ennis, 1981; Johnston, 1995; Lickel et al., 2000; Rosenberg & Kim, 1975; Rosenberg et al., 1968; Russell & Bullock, 1985). The present review was not meant to be exhaustive but, rather, a brief overview of the social psychology literature in which MDS was the method of data analysis. This overview of the application of MDS in actual experiments shows the heuristic value of the technique for social psychology. Select experiments are highlighted, particularly the ones that used a sorting task.

One of the advantages of MDS is that the dimensional solutions can be compared across different groups. For example, the methodology can be used with individuals of different ages, levels of development (Giles et al., 1979; Russell & Bullock, 1985), or cultures (Lickel et al., 2000). Russell and Bullock compared the classification of pictures of emotional facial expression by preschoolers and adults by examining the stimulus coordinate values of the dimensions from the respective MDS solutions. With the inclusion of preschoolers who do not have the vocabulary to describe emotions, they were able to learn whether language mediated emotion classification and determine how early in human development different emotions can be recognized. They derived proximity data from the sorts of the pictures of facial emotional expressions into piles reflecting similar affect. The frequency of co-occurrence of pictures in a pile was the measure of similarity, but Russell and Bullock did not delineate how this data was organized.

Another advantage of MDS is that it can analyze data with different levels of measurement. Metric MDS is used with interval level data, and nonmetric MDS is applied to ordinal and nominal level data (Kruskal & Wish, 1978). Metric and nonmetric MDS differ in that the former uses a linear function to transform dissimilarities into disparities, whereas the latter uses a positive monotonic function (Guigere, 2006; Kruskal & Wish). In other words, an iterative search procedure is used instead of linear factoring to extract dimensions in nonmetric MDS (Powell & Juhnke, 1983). Thus, the nonmetric function is less precise than the metric function in ascertaining the final MDS solution. Consistent with this assertion, Powell and Juhnke analyzed trait ratings as both interval and ordinal data in MDS and found the metric function to yield greater accuracy than the nonmetric function.

Johnston (1995) used nonmetric MDS to uncover the underlying structure of the Rokeach Value Survey (RVS) because factor analytic studies have failed to identify a stable structure. He deduced, “Very likely the difficulties encountered identifying this structure are the result of the ordinal, ipsative nature of RVS data, which are not suited for factor analysis” (p. 584). He subjected the 18 instrumental values and 18 terminal values to separate card sorting tasks. For each of his 76 participants, he derived similarity matrixes from the data and submitted them to MDS. However, Johnston did not provide readers with information on how the data matrixes were formed. The MDS analyses revealed a consistent two-dimensional solution of individualism and collectivism, underlying both instrumental and terminal values. Despite the problems of precision, nonmetric MDS may be more useful than other methods when the data is not interval level.

Studies have compared MDS to other methodologies. Green and Manzi (2002) found MDS revealed more complex racial stereotypes about subgroups of Blacks than did discriminant function analysis. Isenberg and Ennis (1981) found that MDS converged with Bales’s systematic multiple level observation of groups in terms of the dimensions underlying the internal structure of small groups. Lickel et al. (2000) found that MDS of sorting data yield similar dimensions as subjects’ ratings of the select properties of different types of groups. Overall, with the exception of Powell and Juhnke’s (1983) study, MDS rivals other methodologies in social psychological research. Thus, it follows that greater use of MDS in social psychology would yield quality research with the added benefit of the unobtrusive assessment of study participants' thinking or decision-making processes.

Card sorting has also been compared to other forms of data collection for MDS analyses. Green and Manzi (2002) compared card sorting to attribute listing in the study of racial stereotype subgroups of Blacks. They converted both types of data to dissimilarity data and subjected them to MDS. The card sorting task yielded more differentiation among the subgroups and global category of Black than did attribute listing, which Green and Manzi considered a more heuristic outcome. Russell and Bullock (1985) compared MDS results from a sorting task involving pictures of facial affect with earlier results from a study of emotion-related words. They found that the same dimensional structure of emotions emerged in both instances. Taken together, these studies suggest that card sorting may be superior to or, at minimum, equally effective as other methods of data collection for MDS.

Description of the Research Project

The purpose of the study was to explore the utility of MDS in the exploration of cultural competence at the organizational level (Whaley & Longoria, 2008). Specifically, the goal of the research project was to derive dimensions of cultural competence from narratives provided by community mental health centers in Texas that applied for grant funding through a statewide Special Mental Health Initiative (SMHI) sponsored by the Hogg Foundation for Mental Health. In all, 30 proposals were randomly selected from the SMHI population of 156 applicants. We deconstructed the narrative section of these 30 proposals into statements that described the provision of culturally competent mental health services. We identified 99 statements with discrete descriptions of organizational cultural competence and printed each of the statements on a separate 3×5-inch note card.

Ten individuals with master or doctorate-level degrees in the behavioral and social sciences agreed to participate in the card sort activity. We instructed them to categorize (or sort) the cards by creating mutually exclusive piles comprised of conceptually similar statements. Thus, statements in the same pile were more conceptually similar to each other compared with those that made up the other piles. The number of cards in a pile could range from 1 to 99. We asked the participants to bind the cards with paper clips to ensure that we knew which ones were placed in specific piles.

Overview of the Data Preparation Procedure

In this section, we use the data from several of the aforementioned participants to illustrate how we prepared it to be entered on a database and for subsequent MDS analyses. Figure 1 shows card-sort data collected from 2 participants in this study. Participant 1 (P1) and Participant 2 (P2) sorted 99 statements into seven and three piles, respectively. For example, of the seven piles created by P1, one pile contained 15 cards (again, a unique statement was printed on a separate card), a second contained 16 cards, and another separate pile contained 19 cards. As follows, Figure 1 shows the number of cards that made up each of the remaining separate four piles created by P1 (i.e., 14, 18, 3, and 14). Figure 1 also shows that P2 created one pile that contained 37 cards, another that contained 26 cards, and a third that contained 36 cards. In sorted and bound piles, each participant returned 99 cards to us as per the instructions.

Table 1 shows a spreadsheet that contains a portion of the card sort data illustrated in Figure 1. In this study, we entered data into a SPSS 13.0 Data Editor spreadsheet as shown in Table 1. We constructed independent variables to systematically quantify (a) each participant (participant), (b) separate piles created by the participants (pile), and (c) the presence or absence of a unique statement in a specific pile (e.g., Statements 1–99). We then placed these variables in the columns of the database.

An examination of the independent variables labeled participant and pile in Table 1 shows that P1 and P2 created seven and three separate piles of cards, respectively. We organized each pile created by the participants as a row in the spreadsheet (i.e., a case) and coded the 99 unique statements as binary variables (i.e., 1 or 0) in the remaining columns (see Table 1). For example, we coded statements that were placed in a specific pile (i.e., a row) by a study participant as 1. Conversely, we coded statements that were not placed in a specific pile by a study participant as 0. Because the statements were placed in mutually exclusive piles, the data were at the nominal level of measurement. Table 1 also illustrates the outcome of the data-coding entry used in this methodological protocol. It shows a complex pattern of unique statements that participants did (and did not) place in the same pile.

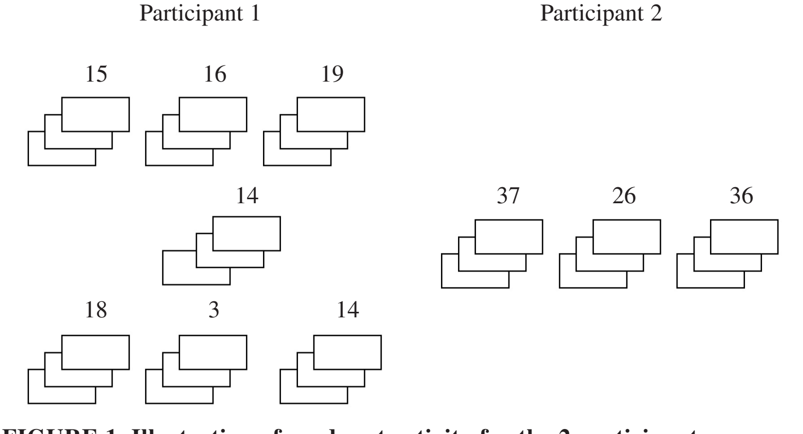

FIGURE 1. Illustration of card sort activity for the 2 participants.

TABLE 1. Data Coding of Card Sort Activity for the 2 Participants

Participant	Pile	Cards	Statement 1	→	→	Statement 99
1	1	15	0	0	0	0
1	2	16	0	0	0	0
1	3	19	0	1	0	0
1	4	14	1	0	0	0
1	5	18	0	0	1	0
1	6	3	0	0	0	1
1	7	14	0	0	0	0
2	1	37	0	0	1	1
2	2	26	0	1	0	0
2	3	36	1	0	0	0

We then converted the study participants' card sort data into proximity matrixes using SPSS 13.0 (Norusis, 2005). Thus, we did not use the shape of the original rectangular data matrix in MDS analyses. We used the frequency of the co-occurrence of statements in the same pile across participants and number of piles to estimate the distance between cases in a 99 × 99 matrix. In other words, the proximity data matrix used in the actual MDS analyses was a symmetrical square. The matrix of proximities was numerical values (i.e., Euclidean distance measures that indicated the degree of dissimilarity among stimuli). It is important to note the proximity data values could have been ascertained by creating matrixes for groups defined by demographic or other characteristics (e.g., level of cultural competence). We did not use this option in this study because of the large number of stimuli, or statements.

The stimuli were the statements printed on cards and sorted by the study participants. We used MDS to convert a matrix of proximities into a geometric configuration (or map of points) in *n*-dimensional space and uncover meaningful categories encompassing the semantic relations in the proximity data (i.e., the participants' card sorts). In sum, we converted the participants' card sort data into proximity matrixes on the basis of the Euclidean distance formula and then analyzed them using the alternating least squares approach to scaling (ALSCAL) method of MDS in SPSS 13.0 (Takane et al., 1976). To see how MDS results were interpreted and discussed, see Whaley and Longoria (2008). For a detailed discussion of the use of MDS in SPSS, see Giguere (2006). However, the subsequent section gives a brief description of how MDS output was interpreted.

Interpreting MDS Analyses

Using SPSS for Windows, we selected the "Analyze" option, then "Scale" and "Multidimensional Scaling." Next, the box for MDS popped up with additional options. We submitted the variables of Statements 1–99 in the blank space in the "Variables" box. Continuing to the "Options" in the "Multidimensional Scaling" box, we selected "Model and options summary" for the "Display" for the SPSS output. We also chose additional options that are subsequently presented. Last, when all the commands were entered, we hit "OK" to run the analyses. The appendix presents the summary of the selected options.

The SPSS output contains the iteration history along with Young's S-stress formula, fit indexes of R^2 and Kruskal's stress formula, as well as stimulus coordinate values for each MDS solution in two to six dimensions. The iteration history is automatically generated and has little to do with the selection of the final n-dimensional solution. R^2 and Kruskal's stress formula are more significant in the choice of the final MDS solution. R^2 is a measure of goodness of fit similar to its use in regression models. R^2 values represent the amount of variance explained in the matrix of scaled data (i.e., disparities) by their corresponding distances in multidimensional space, with higher values indicating better fit. Similarly, the Kruskal stress index is a badness-of-fit measure, reflecting the degree of correspondence between the proximity matrix and the spatial configuration in n dimensions. Higher stress values indicate poorer fit, which is why it is labeled *badness of fit*. The selection of the final MDS solution in terms of number of dimensions is based on the absolute value of fit measures, the change in the fit measures from n dimensions to $n - 1$ dimensions, and interpretability of dimensions.

A stress value less than or equal to .10 can be construed as indicating a good fit of a particular n-dimensional solution (Kruskal & Wish, 1978). To refine the choice of MDS solutions, another approach is to examine the amount change in the stress value from n dimensions to $n - 1$ dimensions. The best MDS solution is when the change becomes negligible, because the additional dimension does not add any significant information. A common method of making this judgment is to plot the stress values on the y axis and the number of dimensions in descending order on the x axis. The point at which there is an elbow in the graph, signaling the leveling off or negligible change in stress values from n dimensions to $n - 1$ dimensions, is the optimal MDS solution. This method is analogous to using the Cattell's scree test of eigenvalues in selecting number of factors or dimensions for factor analysis.

Last, the researcher can inspect the stimulus coordinate values of the dimensions in the best candidate solutions to determine their interpretability. In our study (Whaley & Longoria, 2008), the large number of stimuli made a study of each variable impractical, so we examined the five statements with the highest positive stimulus values and the five with the highest negative stimulus coordinate values to interpret a given dimension. Studies that use a smaller number of stimuli often require subjects to rate each of them on a set of conceptually relevant items and then correlate those item ratings with stimulus coordinate values for the corresponding stimuli to define each dimension (Forsyth & Pope, 1984; Green & Manzi, 2002; Isenberg & Ennis, 1981; Lickel et al., 2000). The meaningfulness of the dimension is a final criterion to use in selecting the best MDS solution.

Conclusion

The method described in this article is meant to give guidance to researchers who want to analyze card sort data using MDS. The compatibility between card sorting and MDS compelled us to share our approach with other researchers. Moreover, our brief review of the literature suggested that both the data collection method (cart sorting) and the analytic technique (MDS) are the best approaches to a variety of social psychological phenomena. However, there are some limitations to this procedure, as we have developed and implemented it, that should be noted. First, our method assumes that the number of cards in a pile does not influence the probability of statements co-occurring in the same pile. This assumption can be checked since the number of cards in each pile is known. Giles et al. (1979) actually used the number and size of the piles as a reciprocal value in judging the similarity between two stimuli.

Second, variability in card sorting because of individual differences in raters is not taken into consideration. However, subject weights can be computed from ALSCAL to determine whether individual differences among raters are related to the MDS solutions (Takane et al., 1976). Other researchers have examined individual differences by grouping the participants according to characteristics of interest and performing separate MDS analyses for the different groups (e.g., Giles et al., 1979; Forsyth & Pope, 1984; Johnston, 1995; Russell & Bullock, 1985). The stimulus coordinate values are compared across groups to examine individual differences. Another approach to individual differences in card sorting is to conduct between-group comparisons on the number of piles generated, internal consistency of ratings or judging behavior, and the comparability of fit indices across multiple MDS solutions. In fact, we used this latter strategy to address the issue in the context of our broader study (Whaley & Longoria, 2008) and found no rater effects.

Last, we limited our approach to a single-sort procedure during the sorting task. There may be instances when it is appropriate to allow multiple sorts. In fact, Rosenberg and Kim (1975) found that a multiple-sort procedure was superior to a single-sort procedure for certain stimulus domains. Future researchers who choose to adopt this basic method of preparing card sort data for MDS can address these issues.

AUTHOR NOTES

Arthur L. Whaley is a research scientist at the Institute for Social Research, University of Michigan. His research interests include racial disparities in mental health care, social–cognitive biases in clinical decision making, African American mental health, and the development and implementation of evaluation programs. **Richard A. Longoria** received his doctorate in social work from the University of Texas at Austin and was a post-doctoral research fellow at the Hogg Foundation for Mental Health at the time the study (Whaley & Longoria, 2008) was completed. His research interests include culturally competent social-service delivery systems, interorganizational relationships, and the well-being of grandparents raising grandchildren.

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APPENDIX
Summary of ALSCAL Procedure for Multidimensional Scaling Analysis from SPSS Output

ALSCAL procedure options

Data options

Number of rows (observations or matrix)	99
Number of columns (variables)	99
Number of matrixes	1
Measurement level	Ordinal
Data matrix shape	Symmetric
Type	Dissimilarity
Approach to ties	Leave tied
Conditionality	Matrix
Data cutoff at	.000000

Model options

Model	Euclid
Maximum dimensionality	6
Minimum dimensionality	2
Negative weights	Not permitted

Output options

Job option header	Printed
Data matrixes	Not printed
Configurations and transformations	Not plotted
Output dataset	Not created
Initial stimulus coordinates	Computed

Algorithmic options

Maximum iterations	30
Convergence criterion	.00100
Minimum S-stress	.00500
Missing data estimated by	Ulbounds
Tiestore	1000

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