Scope. The primary purpose of the journal is the advancement of quantitative research in anthropology. The journal will provide a forum for scientific research, methodological developments, computer applications, and other subjects of interest to anthropologists in the traditional subdisciplines of biological/physical anthropology, archeology, and social/cultural anthropology, including linguistic anthropology. Although traditional in subdisciplinary breadth, the journal will highlight new developments in quantitative methods and modeling and computer applications in anthropology. Of particular interest will be articles that introduce new mathematical and statistical methods, empirical research applying new or innovative quantitative or systematic approaches, articles that are of both theoretical and methodological quantitative interest, and articles involving computer simulations and modeling. We also welcome articles providing qualitative discussions of fundamental analytical problems and theoretical issues, especially if these cross the subdisciplinary boundaries in new and interesting ways.

Journal of Quantitative Anthropology is published quarterly.
Subscription prices, per volume: Institutions USD 183.00, Individuals USD 97.50.
Second-class postage paid at Rahway, N.J.
U.S. Mailing Agent: Mercury Airfreight International Ltd., 2323 Randolph Ave., Avenel, NJ 07001.
Published by Kluwer Academic Publishers, Spuiboulevard 50, P.O. Box 17, 3300 AA Dordrecht, The Netherlands, and 101 Philip Drive, Norwell, MA 02061, U.S.A.
Postmaster: Please send all address corrections to: *Journal of Quantitative Anthropology*, c/o Mercury Airfreight International Ltd., 2323 Randolph Ave., Avenel, NJ 07001, U.S.A.

The Relation between Typicality and Semantic Similarity Structure

A. KIMBALL ROMNEY, DEVON D. BREWER and WILLIAM H. BATCHELDER

School of Social Sciences
University of California, Irvine
Irvine, CA 92717, USA

ABSTRACT: Rosch and Mervis (1975) indirectly showed a strong positive relationship between a lexical item's typicality and its similarity to all other items in a natural semantic domain. Thus the most typical items in a domain should be found in the center of a judged similarity scaling representation. We examine this model, and three additional models, of the relation between typicality and semantic similarity in two different word lists drawn from each of six natural semantic domains. The distribution of typicality is not well accounted for by any of the four structural models, which suggests caution in the application of the concept of typicality if any assumptions about relations to semantic similarity are involved.

The concept of typicality introduced in the 1970's by Rosch and her colleagues (Rosch 1973, 1975; Rosch and Mervis 1975; Rosch, Simpson, and Miller 1976) has stimulated a large body of productive research and is now well established in the literature. It has been repeatedly observed that some exemplars of a semantic domain are considered more representative or typical of that domain than other exemplars. For instance, subjects reliably judge a truck to be a better example of a vehicle than a wheelbarrow and an orange as a better example of fruit than an olive. Typicality ratings for words in natural semantic domains also have been shown to predict categorical judgment time (McFarland, Duncan, and Kellas 1978; Rosch 1973; Smith, Shoben, and Rips 1974), frequency of mention in production/free listing tasks (Dahlgren 1985; Hampton and Gardiner 1983; Mervis, Catlin, and Rosch 1976; Rosch 1973), and order in which items are learned developmentally (Anglin 1976).

Since Rosch and Mervis (1975), the gradient of typicality in a semantic domain has generally been thought to map closely onto the semantic similarity structure of that domain. For six natural semantic domains, Rosch and Mervis (1975) indirectly showed that the more similar an item was to all other items in a domain, as measured by the centrality or distance from the origin in a multidimensional scaling of judged similarities of those items, the more typical the item was. This demonstration was indirect because they correlated typicality with "family resemblance" (an index based on number of shared features with other members of the domain) and family resemblance with distance from the origin in the scaling solutions, but they did not correlate typicality with distance from the origin in the scaling solutions. Nonetheless the correlations they reported were remarkably high (Spearman rhos from 0.84 to 0.95).

There are also other theoretical possibilities of how typicality might relate to the semantic similarity structure of lexical items in natural semantic domains. Boster (1988) suggested that the most typical members should be found in the subregion(s) of the semantic similarity space that is most densely populated. Drawing on Krumhansl's (1978) notions of a density-dependent geometric similarity model, Boster (1988) noted that distinctions are more difficult to make among items in dense subregions of the similarity space than in relatively sparse subregions. By implication, items in dense subregions would be more interchangeable, in a semantic sense, with other items in the domain, and thus be more representative and typical of the domain, than items in sparse subregions.

Another related idea is that the location of the most typical items in the semantic similarity space of a domain cannot be reliably predicted *a priori*, but that they should be similar to each other and therefore cluster together (i.e., be close to each other relative to other items) somewhere in the space. An additional logical possibility is a vector model in which items range in typicality along a vector through the space, i.e., the typicality of the items diminishes regularly in a linear sweep from one edge of the semantic similarity space to another.

The significance of relating typicality to semantic similarity structure lies in the fact that spatial representations of the internal structure of homogeneous domains are known to relate to a number of cognitive functions. For example, distances from such models have been shown to predict categorical judgment time (Caramazza et al. 1976; Rips, Shoben, and Smith 1973; Shoben 1976), completion of analogies (Rips et al. 1973; Rumelhart and Abrahamson 1973), clustering in free recall (Romney, Brewer, and Batchelder 1993), reaction time to solve triadic comparison problems (Hutchison and Lockhead 1977; Romney 1989), and simple inductive judgments (Rips 1975). As Nosofsky (1992: 26) observes, "the beauty of deriving a similarity scaling representation by modeling performance in a given task is that the derived representation can then be used to predict performance in independent tasks involving the same objects and stimulus conditions." Since typicality also relates to several cognitive functions, it stands to reason that the two should have some determinate relation.

In this paper we examine the centrality, density, cluster, and vector models of the relation between typicality and semantic similarity in two different word lists drawn from each of six natural semantic domains. Within each of the six domains we chose one word list consisting of high typicality words and one word list of both high and low typicality words (see details below). The semantic similarity structure for each of the 12 lists was represented

as a three dimensional Euclidean space obtained from correspondence analysis (Gifi 1990; Greenacre 1984; Weller and Romney 1990) of judged similarity data from a triads task (Weller and Romney 1988). As a kind of comparison and control, we also examine each model substituting frequency of mention from Battig and Montague (1969) for typicality.

METHOD

Subjects

Two hundred eighty-nine undergraduates at the University of California, Irvine participated in this study. Each subject responded to only one word list. The number of subjects responding to a word list ranged from 20 to 28, with a mean of 24.1. Some subjects received course credit for participation, while others participated as part of a class exercise.

Stimuli

Twelve different word lists were drawn from six semantic domains. Lists 1-1 to 1-6, hereafter called greatest typicality lists, consisted of the 21 most typical items from Rosch's (1975) *fruit, vegetable, furniture, vehicle, weapon*, and *clothing* domains, respectively. Lists 2-1 to 2-6, hereafter called high variance typicality lists, were composed of twenty items (of widely varying typicality) from Rosch and Mervis' (1975) fruit, vegetable, furniture, vehicle, weapon, and clothing domains, respectively, and one additional item of the greatest typicality per domain from Rosch (1975) not already included in Rosch and Mervis' (1975) twenty items. Thus, greatest typicality lists have items with higher overall typicality but less variance in typicality than high variance typicality lists.

Procedure

Similarity judgments were collected on the 21 items for each word list with a triads test (Weller and Romney 1988). Subjects were presented with sets of three items and asked to circle the item most different from the other two. Each triads test was individually randomized with the program ANTHROPAC (see note 1) using a lamda-one balanced, incomplete block design (Burton and Nerlove 1976). This design produces 70 triadic comparisons for the test, where each pair of items occurs exactly once and each of the 21 items occurs 10 times.

The triads tests were printed on 8 1/2 × 11 in. paper and were four pages long, with one page of instructions, two pages with 24 triads each and one page with 22 triads. On the first page, the following written instructions were given: "Thank you for participating in this study. On the next page, you will find a set of three words on each line. For each set, please circle the word which is most different in meaning from the other two. For example, for the set *house woman building* you would circle *woman*, since it is the word most different in meaning. Here is another example: *dog cat rock*. In this case, you would circle *rock*. Please give an answer for every set of three, even if you are not sure of the answer. Do not skip any sets: if you don't know the answer, just guess. Thank you." Subjects responded in groups ranging in size from 10 to 200 subjects and were given twenty minutes to complete the task.

RESULTS

For each word list the triads data were transformed into a 21 by 21 proximity matrix, with one unit of similarity scored for the two items in each triad that were not circled by a subject (Weller and Romney 1988). A single aggregated proximity matrix was formed by adding the scores for all subjects. A three-dimensional Euclidean representation of the similarity of items for each word list was obtained through correspondence analysis (Gifi 1990; Greenacre 1984; Weller and Romney 1990). A three-dimensional Euclidean representation was chosen, in part, on the findings of Tversky, Rinot, and Newman (1983) that data with a value around two on their statistic C can be well represented in low dimensional Euclidean space. The mean value of C for our 12 lists was 2.06.

The representation depicts the judged similarity structure of each word list in terms of Euclidean distances, where more similar items are closer to each other than less similar items. For the 12 word lists the average correlation between the raw proximities and the three-dimensional Euclidean distance was 0.73. This compares to correlations of 0.68 for birds (12 items) and 0.65 for mammals (12 items) reported by Rips et al. (1973: 10) for 12 subjects. For all of the analyses, items in a word list were ranked from 1 to 21 on typicality and frequency and, following Rosch and Mervis (1975: 581), these rankings were used in all subsequent analyses.

Centrality model

In each word list, the distance from the origin of the three dimensional Euclidean representation, or centrality, was calculated for each item. The pairwise Pearsonian, and corresponding partial, correlations among these distances, typicality, and frequency appear in Table I.

Given expectations from Rosch and Mervis (1975), the correlations between typicality and centrality were low. The overall results from Spearman rank correlations were virtually the same. The correlations

TABLE I

For each word the number of subjects (N) and correlations among typicality (T), centrality (C), and frequency (F) with the partial correlations between each pair of variables, holding the third constant, shown in parentheses

Word List[a]	N	r_{TxC}	r_{FxC}	r_{TxF}
1-1. fruit1	25	0.01 (0.06)	–0.04 (–0.07)	0.77*** (0.77)
1-2. vegetable1	23	–0.08 (0.06)	–0.22 (–0.21)	0.59** (0.59)
1-3. furniture1	24	0.37 (0.16)	0.52* (0.49)	0.48* (0.37)
1-4. vehicle1	25	0.73*** (0.80)	–0.39 (–0.60)	0.15 (0.50)
1-5. weapon1	25	0.21 (0.24)	–0.14 (–0.18)	0.17 (0.20)
1-6. clothing1	28	0.27 (0.30)	0.09 (–0.15)	0.70*** (0.70)
Mean r		0.28** (0.27)	–0.02 (–0.12)	0.51*** (0.52)
2-1. fruit2	25	0.67*** (0.39)	0.59** (0.07)	0.85*** (0.75)
2-2. vegetable2	28	0.52* (0.40)	0.37 (0.06)	0.64** (0.56)
2-3. furniture2	23	0.48* (0.08)	0.51* (0.19)	0.89*** (0.85)
2-4. vehicle2	22	0.76*** (0.47)	0.70*** (0.21)	0.20 (0.60)
2-5. weapon2	21	0.55* (0.48)	0.36 (–0.22)	0.85*** (0.83)
2-6. clothing2	20	0.54* (0.25)	0.54* (0.24)	0.75*** (0.64)
Mean r		0.60*** (0.35)	0.52*** (0.09)	0.75*** (0.71)

NOTE: Mean correlations calculated by using Fisher's (1948) z transformations. Significance tests for means based on Stouffer's method of aggregating z scores (Mosteller and Bush 1954). Partial correlations are reported without significance tests and group mean partial correlations are simple averages.

[a] Word lists 1-1 to 1-6 were the 21 most typical items from the domain. Word lists 2-1 to 2-6 included items of high variance typicality (see text for details).

* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

between all pairs of the three variables were higher for high variance typicality lists than for greatest typicality lists, which seems reasonable since high variance typicality lists have more variance in both typicality and frequency. In general, centrality was not as strongly associated with typicality or frequency as typicality and frequency were with each other. Centrality bore a modest relationship with typicality in greatest typicality lists, while frequency was unrelated to centrality for greatest typicality lists. In 9 of the 12 lists, the correlations between typicality and centrality were larger than those between frequency and centrality, and the typicality-centrality relationship was consistently positive, with only one word list showing a negative correlation (list 1-2, vegetable1, $r = -0.08$). Overall, however, the relationship between typicality and centrality was only marginally stronger than the association between frequency and centrality.

An examination of the partial correlations between each pair of variables, holding the third constant, reveals two appreciable modifications to the zero order effects in the high variance typicality lists. The mean observed correlation of 0.60 between typicality and centrality drops to 0.35 when the effects of frequency are partialled out. Similarly, the mean observed correlation of 0.52 between frequency and centrality drops to 0.09 when the effects of typicality are partialled out.

Density model

For every word list, the local densities of each point were calculated. Local density was defined as the average distance between a particular point and its n nearest neighbors in the three dimensional Euclidean representation from correspondence analysis, with n ranging from 1 to 20. Thus, twenty different local density values (one for each number of nearest neighbors) were computed for each item in a word list. In each word list, typicality and frequency were correlated with local density for each number of nearest neighbors.

Table II presents the Pearsonian correlations between local density for six nearest neighbors and typicality and frequency. Table II also includes the minimum and maximum correlations between local density and typicality and frequency from all 20 numbers of nearest neighbors. Local density

TABLE II
Correlations between local density in the three dimensional Euclidean distance representation and typicality and frequency

Word List[a]	r Local Density [6 nearest neigh.] × Typicality (min., max. r)	r Local Density [6 nearest neigh.] × Frequency (min., max. r)
1-1. fruit1	−0.44* (−0.59, −0.08)	−0.29 (−0.49, −0.07)
1-2. vegetable1	0.19 (0.00, 0.36)	−0.09 (−0.29, −0.08)
1-3. furniture1	0.57** (0.43, 0.61)	0.12 (0.11, 0.48)
1-4. vehicle1	0.71*** (0.33, 0.73)	−0.45* (−0.48, −0.37)
1-5. weapon1	0.16 (0.10, 0.22)	−0.30 (−0.40, −0.17)
1-6. clothing1	−0.40 (−0.52, 0.10)	−0.24 (−0.26, 0.01)
Mean r	0.17*	−0.22*
2-1. fruit2	0.69** (0.65, 0.76)	0.60** (0.57, 0.67)
2-2. vegetable2	0.59** (0.52, 0.66)	0.31 (0.31, 0.38)
2-3. furniture2	0.18 (0.14, 0.38)	0.22 (0.16, 0.42)
2-4. vehicle2	0.74*** (0.64), 0.76)	0.64** (0.49, 0.68)
2-5. weapon2	0.50* (0.43, 0.53)	0.33 (0.27, 0.36)
2-6. clothing2	0.57** (0.28, 0.57)	0.53* (0.33, 0.53)
Mean r	0.57***	0.45***

NOTE: Mean r values calculated using Fisher's (1948) z transformations. Significance tests for means based on Stouffer's method of aggregating z-scores (Mosteller and Bush 1954).
[a] Labeling same as in Table I.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

and typicality were only mildly correlated for greatest typicality lists, although there was a wide range in the strength of these associations across these six lists, including two negative correlations. For the high variance typicality lists, local density and typicality were more strongly correlated, although still only moderately. Local density and frequency were moderately related in high variance typicality lists and not associated at all in greatest typicality lists. In 9 of the 12 lists, typicality was more strongly related to local density than frequency, although not by a large degree.

Cluster model

To examine the cluster model, we tested the hypothesis that the seven most typical or frequent items were clustered, i.e., were closer to each other than would be expected by chance, in the three dimensional Euclidean semantic space. The Quadratic Assignment Procedure (QAP) (Hubert and Schultz 1976; Nakao and Romney 1984) was employed to test this hypothesis. The QAP generates the equivalent of a permutation distribution for random rearrangements of a proximity or distance matrix and can compare the degree of proximity or distance within and between comparison groups. In our case, the data matrix was the matrix of the three dimensional Euclidean distances among items for a particular word list. For each word list, the structure matrix modeled the seven most typical (frequent) items as one group to be compared with all other items. All QAP analyses reported in this paper were done with 10,000 Monte Carlo permutations. QAP z-scores index the difference between observed distances among the seven most typical (frequent) items and the expected mean distances among seven items obtained from the permutation distribution. Monte Carlo nonparametric probability values for the likelihood that the observed distance among the seven most typical (frequent) items would occur by chance were obtained by noting the proportion of 10,000 permutations in which the distances among seven randomly selected items were at least as large as observed.

Table III shows the QAP clustering results, with positive z-scores indicating clustering and asterisks representing the Monte Carlo probability values. The most typical items in each of the high variance typicality lists were significantly and moderately clustered, while the most typical items were only weakly clustered in the greatest typicality lists. The most frequent items also tended to be significantly clustered in the high variance typicality lists, but were not clustered at all in the greatest typicality lists. For all 12 lists, the most typical items were more strongly clustered than the most frequent items, but in most cases these differences were not dramatic.

TABLE III
Z-scores from OAP for clustering of seven most typical and seven most frequent items in the three dimensional Euclidean distance representation

Word List[a]	Typicality QAP Clustering z	Frequency QAP Clustering z
1-1. fruit1	1.72*	–0.42
1-2. vegetable1	–0.63	–1.03
1-3. furniture1	2.13*	0.99
1-4. vehicle1	2.51*	–0.57
1-5. weapon1	0.90	–1.07
1-6. clothing1	2.83**	1.97*
Cumulative Z	3.86***	–0.05
2-1. fruit2	3.01***	2.61***
2-2. vegetable2	1.57*	0.18
2-3. furniture2	2.51***	2.42***
2-4. vehicle2	4.54***	3.20***
2-5. weapon2	1.64*	1.24
2-6. clothing2	2.92***	1.73*
Cumulative Z	6.61***	4.65***

NOTE: For individual lists, stars represent nonparametric probability values based on proportions as large from 10,000 permutations (see text). Cumulative Z scores obtained from Stouffer's method of aggregation (Mosteller and Bush 1954). Corresponding probabilities are from normal distribution.
[a] Labeling same as in Table I.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

Vector model

The vector model was investigated by regressing, separately, the typicality and frequency rank orders onto the three dimensional Euclidean distance coordinates for the 21 items in a word list. The resulting multiple correlation measures the degree of association for the best linear typicality (frequency) gradient through the semantic similarity space. This procedure is known as property fitting or PROFIT (Carroll and Chang 1970).

The vector model results appear in Table IV. Moderate to strong typicality vectors occurred in the high variance typicality lists, while somewhat weaker typicality vectors were found in greatest typicality lists. Frequency vectors of moderate strength were observed in both greatest and varying typicality lists. Typicality multiple correlations were higher than frequency multiple correlations in 11 of the 12 lists, and the degree of association (in terms of variance explained) tended to be about twice as great for typicality than for frequency. In comparing the vector model results to those from the other models, however, interpretations of the apparent greater strength of association of these multiple correlations should be tempered by consideration of the corresponding probability values.

TABLE IV
Multiple correlations for typicality and frequency vectors regressed onto items' coordinates in three dimensional Euclidean distance representation

Word List[a]	Typicality Vector Multiple R	Frequency Vector Multiple R
1-1. fruit1	0.75**	0.59
1-2. vegetable1	0.25	0.47
1-3. furniture1	0.67*	0.15
1-4. vehicle1	0.72**	0.64*
1-5. weapon1	0.57	0.41
1-6. clothing1	0.79***	0.57
Mean R	0.65	0.49
2-1. fruit2	0.87***	0.64*
2-2. vegetable2	0.74**	0.28
2-3. furniture2	0.68*	0.54
2-4. vehicle2	0.79***	0.58
2-5. weapon2	0.56	0.46
2-6. clothing2	0.80***	0.47
Mean R	0.76	0.50

NOTE: Mean R values calculated using Fisher's (1948) z transformations.
[a] Labeling same as in Table I.
* $p < 0.05$. ** $p < 0.01$. *** $p < 0.001$.

DISCUSSION

Our results demonstrate that earlier assumptions about the structural basis of typicality in natural semantic domains require modification. Even though Rosch and Mervis (1975) never directly reported the correlations between typicality and centrality in the judged similarity scaling, the implication was that the correlations were quite high. Our results in Table I indicate much weaker associations and the zero-order correlations for our high variance typicality lists are in the same range as those reported by Barsalou (1985) between typicality and central tendency (the average judged similarity rating involving an item from complete paired comparisons) and frequency and central tendency in nine natural semantic domains, mean $r = 0.63$ and 0.55 (compared to our 0.60 and 0.52), respectively. Clearly, a large portion of typicality is left unexplained by measures of centrality and central tendency. Moreover, none of the other three models fare any better in accounting for typicality.

Typicality tended to have slightly stronger relations to judged similarity than did frequency in all four models, but, in general, typicality and frequency were more strongly related to each other than either was to judged similarity. Thus, in structural terms, typicality and frequency were only somewhat distinct from each other.

Another prominent characteristic of the results is the unexpected extent to which the four models (centrality, density, clustering, and vector) are not independent of one another. There is a moderate tendency for the models to fit at about the same level for a given word list. This may be seen by examining the relationship between typicality and the judged similarity structure for the "best" fit and the "worst" fit word lists, namely, vehicle2 and vegetable1. Figure 1 shows a two-dimensional representation of the judged similarity structure of vehicle2 (word list 2-4) with the typicality ranking proportional to the size of the symbols, where the largest symbol represents the item judged most typical. The most typical (largest) items are clustered near the center in the upper-left quadrant of the figure. This arrangement of items produces a relatively close fit to each of the four models. Typicality correlates 0.76 with centrality (the highest of any word list), correlates 0.74 with density (the highest of any word list), has a QAP z score of 4.5 on clustering (the highest of any word list), and a multiple correlation of 0.79 on the vector model (the third highest of any word list).

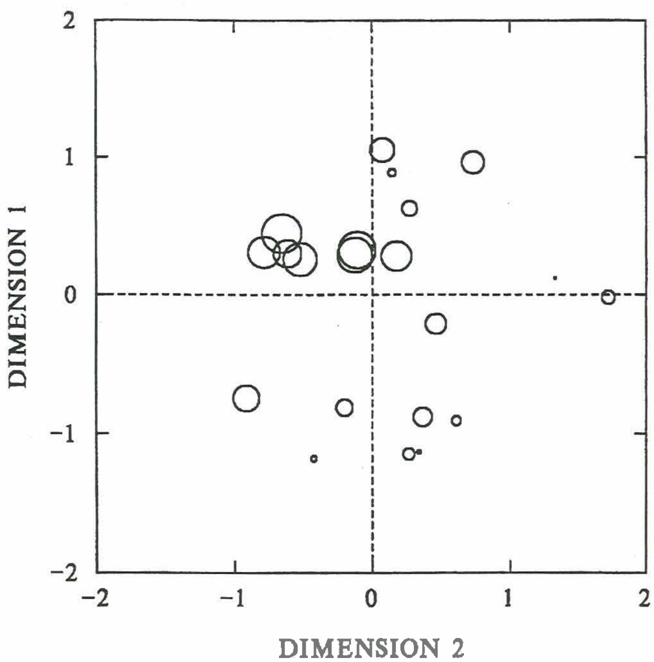

Fig. 1. Two dimensional Euclidean representation from correspondence analysis of Vehicle2 word list with items' typicality proportional to symbol size.

The relationship between typicality and the judged similarity structure of vehicle2 (word list 2-4) in Figure 1 comes closest to the pattern we would expect on the basis of *a priori* theory from Rosch and Mervis (1975). As implied in their article, the most typical items would be placed together in the central area of the judged similarity structure. An implicit assumption is that the judged similarity distances are consistent with the number of shared features among items (as Rosch and Mervis (1975) demonstrated). Given this theoretical pattern it becomes clear that our four models are not mutually exclusive. If high typicality items are near the center, they may

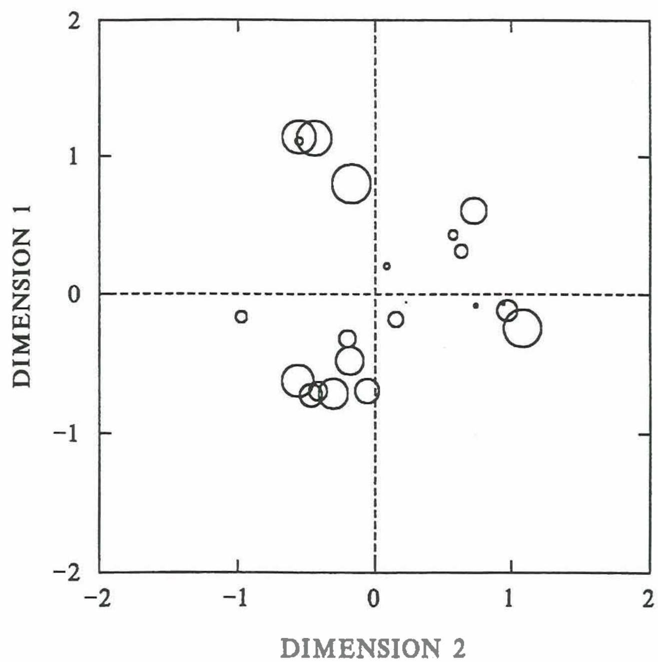

Fig. 2. Two dimensional Euclidean representation from correspondence analysis of Vegetable1 word list with items' typicality proportional to symbol size.

also be in a dense area and clustered (in this scenario the vector model would not work very well). If the high typicality items cluster on one side of the picture, as they do in Figure 1, then the density and vector models should both fit well. Thus for the vehicle2 word list the fit to all four models is fairly good.

Figure 2 shows a representation of vegetable1 (word list 1-2), again with the typicality ranking proportional to the size of the symbols. In this case none of the four models fits at all well. The high typicality items do not cluster in any one area of the similarity representation and these items display no tendency to be close to the center of the picture. For whatever reasons. The concept of typicality, as based on the idea of shared features, does not seem to work in this word list.

Figures 1 and 2 illustrate the "best" and "worst" fits between typicality and judged similarity structure among all 12 word lists. In general, the word lists of high variance typicality tended towards the "best" pattern, while the word lists of greatest typicality tended towards the "worst" patterns. This shows that the selection of items from a semantic domain is critical when typicality is a variable of interest. More importantly, while there were statistically significant findings for each model, the effects were relatively weak and inconsistent. This general result suggests caution in the application of the concept of typicality if any assumptions about relations to judged similarity are involved.

NOTE

[1] We thank William H. Batchelder for comments on earlier drafts of this paper. This research was supported by NSF Grant No. SES-9210009 to A. K. Romney and W. H. Batchelder. The second author was supported during this research by a Chancellors Fellowship from the University of California, Irvine and an Air Force Laboratory Graduate Fellowship from the Air Force Office of Scientific Research. Correspondence regarding this paper and requests for reprints should be addressed to: A. Kimball Romney, School of Social Science, University of California, Irvine, Irvine, CA 92697.

REFERENCES

Anglin, J. 1976 Les premiers termes de reference de l'enfant. In La memorie semantique. S. Ehrlich and E. Tulving, eds. Paris: Bulletin de Psycholgie.
Barsalou, L. W. 1985 Ideals, Central Tendency, and Frequency of Instantiation as Determinants of Graded Structure in Categories. Journal of Experimental Psychology: Learning, Memory, and Cognition 11: 629–654.
Battig, W. F. and W. E. Montague 1969 Category Norms of Verbal Items in 56 Categories: A Replication and Extension of the Connecticut Category Norms. Journal of Experimental Psychology Monographs 80(3, Pt. 2).
Boster, J. S. 1988 Natural Sources of Internal Category Structure: Typicality, Familiarity, and Similarity of Birds. Memory and Cognition 16: 258–270.

Burton, M. L. and S. B. Nerlove 1976 Balanced Designs for Triads Tests: Two Examples from English. Social Science Research 5: 247–267.
Caramazza, A., H. Hersh and W. S. Torgerson 1976 Subjective Structures and Operations in Semantic Memory. Journal of Verbal Learning and Verbal Behavior 15: 103–117.
Chang, J. J. and J. D. Carroll 1968 How to Use PROFIT, a Computer Program for Property Fitting by Optimizing Nonlinear or Linear Correlation. Murray Hill, NJ: Bell Telephone Laboratories.
Dahlgren, K. 1985 The Cognitive Structure of Social Categories. Cognitive Science 9: 379–398.
Fisher, R. A. 1948 Statistical Methods for Research Workers. New York: Jafner Publishing Co., Inc.
Gifi, A. 1990 Nonlinear Multivariate Analysis. Chichester: John Wiley & Sons.
Greenacre, M. J. 1984 Theory and Application of Correspondence Analysis. New York: Academic Press.
Hampton, J. A. and M. M. Gardiner 1983 Measures of Internal Category Structure: A Correlational Analysis of Normative Data. British Journal of Psychology 74: 491–516.
Hubert, L. J. and J. Schultz 1976 Quadratic Assignment as a General Data Analysis Strategy. British Journal of Mathematical and Statistical Psychology 29: 190–241.
Hutchison, J. W. and G. R. Lockhead 1977 Similarity as Distance: A Structural Principle for Semantic Memory. Journal of Experimental Psychology: Human Learning and Memory 3: 660–678.
Krumhansl, C. L. 1978 Concerning the Applicability of Geometric Models to Similarity Data: The Interrelationship between Similarity and Spatial Density. Psychological Review 85: 445–463.
McFarland, C. E., Jr., E. M. Duncan and G. Kellas 1978 Isolating the Typicality Effect in Semantic Memory. Quarterly Journal of Experimental Psychology 30: 251–262.
Mervis, C. B., J. Catlin and E. Rosch 1976 Relationships Among Goodness-of-Example, Category Norms, and Word Frequency. Bulletin of the Psychonomic Society 7: 283–284.
Mosteller, F. and R. R. Bush 1954. Selected Quantitative Techniques. In Handbook of Social Psychology. G. Lindzey, ed. Pp. 289–344. Cambridge, MA: Addison-Wesley.
Nakao, K. and A. K. Romney 1984 A Method for Testing Alternative Theories: An Example from English Kinship. American Anthropologist 86: 668–673.
Nosofsky, R. M. 1992. Similarity Scaling and Cognitive Process Models. In M. R. Rosenzweig and L. W. Porter (eds.) Annual Review of Psychology 43: 25–53.
Rips, L. J. 1975. Inductive Judgments about Natural Categories. Journal of Verbal Learning and Verbal Behavior 14: 665–681.
Rips, L. J., E. J. Shoben and E. E. Smith 1973 Semantic Distance and the Verification of Semantic Relations. Journal of Verbal Learning and Verbal Behavior 12: 1–20.
Romney, A. K. 1989 Quantitative Models, Science, and Cumulative Knowledge. Journal of Quantitative Anthropology 1: 153–223.
Romney, A. K., D. D. Brewer and W. H. Batchelder 1993 Predicting Clustering from Semantic Structure. Psychological Science 4: 28–34.
Rosch, E. H. 1973 On the Internal Structure of Perceptual and Semantic Categories. In Cognitive Development and the Acquisition of Language, T. E. Moore, ed. Pp. 111–144. New York: Academic Press.
Rosch, E. 1975 Cognitive Representations of Semantic Categories. Journal of Experimental Psychology: General 104: 192–233.
Rosch, E. and C. B. Mervis 1975 Family Resemblances: Studies in the Internal Structure of Categories. Cognitive Psychology 7: 573–605.
Rosch, E., C. Simpson and R. Miller 1976 Structural Bases of Typicality Effects. Journal of Experimental Psychology: Human Perception and Performance 2: 491–502.
Rumelhart, D. L. and A. A. Abrahamson 1973. Toward a Theory of Analogical Reasoning. Cognitive Psychology 5: 1–28.

Shoben, E. J. 1976 The Verification of Semantic Relations in a Same-Different Paradigm: An Asymmetry in Semantic Memory. Journal of Verbal Learning and Verbal Behavior 15: 365–379.
Smith, E. E., J. Shoben and L. J. Rips 1974 Structure and Process in Semantic Memory: A Featural Model for Semantic Decisions. Psychological Review 81: 214–241.
Tversky, A., Y. Rinot and C. M. Newman 1983 Nearest Neighbor Analysis of Point Processes: Applications to Multidimensional Scaling. Journal of Mathematical Psychology 27: 235–250.
Weller, S. C. and A. K. Romney 1988 Systematic Data Collection. Newbury Park, CA: Sage.
Weller, S. C. and A. K. Romney 1990 Metric Scaling: Correspondence Analysis. Newbury Park, CA: Sage.

Methods for Analyzing Three-Way Cognitive Network Data[1]

ECE KUMBASAR

School of Social Sciences
University of California, Irvine
Irvine, CA 92697
USA

ABSTRACT: A generalized three-way data paradigm for cognitive social networks is introduced. The paradigm requires each actor to report on a given network relation, for every ordered pair embedded in the network. In this way, each actor 'describes' the entire network from an ego-based perspective. The richness of information obtained makes it possible to compare individual perceptions with each other and with respect to a global aggregate view of the structure. Correspondence analysis is discussed as a descriptive multidimensional scaling method to achieve these goals. It is also possible to investigate each actor's perception of the social structure in terms of structural properties like centrality, reciprocity, and transitivity. Tests are developed for the null hypotheses that centrality ranks, reciprocity, and transitivity are at chance levels, controlling for tie density. Some examples of current statistical models for three-way data are also discussed.

KEY WORDS: three-way data, cognitive bias, social networks, correspondence analysis, centrality, reciprocity, transitivity

1. INTRODUCTION

Within the general area of social networks, there have been several studies questioning the validity of cognitive data in research, claiming that people have extremely poor recall when asked about the frequency and patterning of their social interactions with others in their network (e.g., Bernard and Killworth 1977; Bernard, Killworth and Sailer 1980, 1982). Others, re-analyzing some of the data sets from these same studies, showed that people in fact have a remarkable ability to recall their social interactions, and that the methodology used in analyzing specific data types plays a crucial role in uncovering the similarities between cognitive and observed data from a given network (Romney and Faust 1982; Romney and Weller 1984). Yet, there are also extensive studies pointing out individual differences in perception of social as well as non-social objects (e.g., Freeman, Romney, and Freeman 1987; Tversky and Kahneman 1973, 1974). Consequently, the global network representation inferred from individual reports may vary depending upon such factors as the data-type, whether it is ego-based (two-way) or network-based (three-way), the scale-type used for individual