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# Recall and Measures of Memory Organization

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The relations between recall performance and specific network and spatial representations of memory were investigated in serial and free recall paradigms. The structural representations were derived from relatedness ratings by using the alternating least squares scaling (ALSCAL), Kruskal-Young-Shepard-Torgerson (KYST; Kruskal & Wish, 1978), and Kruskal multidimensional scaling algorithms and the Pathfinder network scaling algorithm. In the serial recall task, list organization defined by the network yielded faster learning than organization defined by multidimensional space, although both types of organizations yielded increases in the number of items recalled. In free recall, the network representations were predictive of recall order even with the original ratings partialed out. The spatial representations, however, were not independently predictive of recall. The results suggest that Pathfinder networks better capture the relations important for recall than do spatial representations. Also, Pathfinder networks provide information about memory organization that is not directly available in pairwise ratings.

The nature of memory organization is of importance to researchers interested in the learning and comprehension of recently experienced events as well as those interested in the representation and use of knowledge. The ability to recall information is related to the organization of that information. Experimenter-imposed organization facilitates recall, whether that organization is categorical (Bousfield, 1953; Bousfield, Cohen, & Whitmarsh, 1958; Bower, 1972; Cofer, Bruce, & Reicher, 1966) or associative (Jenkins, Mink, & Russell, 1958; Jenkins & Russell, 1952). Even without imposed organization, subjects develop their own organization, and the degree of that organization relates to the level of recall (Tulving, 1962).

Experimenter-imposed organization is usually determined by using nomothetic norms with the assumption that public agreement is manifested in each individual's knowledge structure and affects each person's recall. Research on subjective organization has shown a tendency for recall protocols to be consistent across individuals, suggesting again the role of the organization of knowledge (Tulving, 1962). The idea of separate but interdependent semantic and episodic memory systems reflects this view (Tulving, 1983). The organization of semantic memory presumably affects the learning and comprehension of episodes.

Further support for the relation between knowledge organization and organization in recall has been provided by studies comparing similarity ratings of pairs of concepts to the order in which the concepts are recalled. In general, it has been assumed that similarity ratings reflect the proximity between concepts in semantic memory. Schwartz and Humphreys (1973) found a significant correlation between similarity ratings of concept pairs and the number of times the pairs were recalled adjacently in free recall: Pairs rated as most similar were most frequently recalled together. Similarly, Caramazza, Hersh, and Torgerson (1976) found a correspondence between similarity ratings and interitem proximity in recall. Thus, recall organization was influenced by the same underlying organization of knowledge that was reflected in similarity ratings. In this study, these relations were explored further and the analyses were extended to structural representations of knowledge.

## Structural Representations of Knowledge

Theorists assuming a featural model of semantic memory have made use of sophisticated scaling algorithms, such as multidimensional scaling (MDS), to aid in defining semantic features (Rips, Shoben, & Smith, 1973). Empirical evidence has supported the psychological validity of MDS representations. Several studies have indicated that distances derived from MDS solutions are predictive of categorical judgement time (Caramazza et al., 1976; Rips et al., 1973; Shoben, 1976), analogy completions (Rips et al., 1973; Rumelhart & Abrahamsen, 1973) and organization in free recall (Caramazza et al., 1976). MDS has also been applied to areas such as music perception and cognitive development in order to reveal underlying cognitive structure (Shoben, 1983).

A considerable amount of theoretical work on semantic memory has made use of network representations of stored concepts. The actual networks, however, often have been based largely on logical, hierarchical relations and the intuitions of

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the theorists (e.g., Collins & Loftus, 1975; Collins & Quillian, 1969). Although theoretical networks have been used to explain empirical findings (Collins & Loftus, 1975; Schvaneveldt & Meyer, 1973), the absence of a scaling method to produce networks has precluded network studies analogous to the MDS studies that relate empirical representations to underlying cognitive structure and processes. However, some researchers have used various methods to define network structures empirically (Chi & Koeske, 1983; Fillenbaum & Rapaport, 1971; Friendly, 1977; Hutchinson, 1981; Schvaneveldt & Durso, 1981). Friendly (1977), for example, obtained proximities from recall orders and used the proximities to derive structural representations of the organization in recall.

Recently, scaling procedures have been developed that produce network structures from empirical proximity data (i.e., dissimilarities) of the type used by MDS. The research reported here made use of Pathfinder, an algorithm that yields network structures given estimates of pairwise proximities for a set of entities. Because both the Pathfinder network scaling algorithm (Schvaneveldt & Durso, 1981; Schvaneveldt, Durso, & Dearholt, 1985[1]; Schvaneveldt, Durso, Goldsmith et al., 1985) and the MDS algorithm (e.g., Kruskal, 1977; Kruskal & Wish, 1978; Shepard, 1962a, 1962b) have been described elsewhere, we describe them here only briefly.

Both MDS and Pathfinder require estimates of psychological proximity. Commonly, subjects assign a rating reflecting a judgement of relatedness to all possible pairs of $N$ concepts. These proximity estimates are then analyzed by the algorithms. MDS positions each concept in a $K$-dimensional space, where the distance between points reflects the psychological proximity of the corresponding concepts. Pathfinder produces a network with concepts represented as nodes and relations between concepts represented as links connecting some of the nodes. Links may be either directed (allowing traversal in only one direction) or undirected (allowing traversal in either direction). Thus, distances between concepts may be either symmetrical or asymmetrical. Of course, with symmetrical proximity estimates, only undirected links can be included in the network representation.

The definition of Pathfinder networks is quite simple. Each network consists of a group of concepts in which each concept is represented by a node and each node is connected by a link to each other node for which we have proximity estimates. The weight or the cost of the link connecting two nodes is the proximity estimate for the pair of concepts corresponding to those nodes. Thus, low proximity-estimates will result in low link weights and high proximity-estimates will result in high link weights. With a complete set of proximity estimates, this network will correspond to a complete graph. After applying the Pathfinder algorithm, a link remains in the network if and only if that link is a minimum-length path between the two concepts. A path consists of a sequence of nodes and the connecting links. The length of a path is a function of the weights associated with the links in the path. Different functions for computing path length yield different networks. In particular, the number of links in the resulting network decreases systematically with decreases in the computed lengths of multilink paths in the network.

Two methods have been used to define path length. One method, which subsumes several special cases, uses the Minkowski r-metric to compute path length. This metric was originally developed as a generalized distance measure in multidimensional space (Dunn-Rankin, 1983) and can be stated as follows. Let $X_{ai}$ be the value of the coordinate for point $a$ along dimension $i$ in an $n$ dimensional space ($i$ runs from 1 to $n$) and let $X_{bi}$ be the value of the coordinate for point $b$ along dimension $i$ in that same space, then the distance between points $a$ and $b$ for a given value of $r$, $d_{ab(r)}$, is

$$d_{ab(r)} = (\sum_{i=1}^{n} |X_{ai} - X_{bi}|^r)^{1/r},\ 1 \le r \le \infty. \qquad (1)$$

Thus, when $r = 1$ the formula defines the city block metric and when $r = 2$ the formula specifies Euclidean distance.

Similarly, the Minkowski r-metric can provide a general definition of the length of a path in a network. Let $l_i$ be the weight associated with link $i$ in a path. The set of all weights in a path with $n$ links is given by $l_i$, $i = 1, 2, \ldots, n$. The length of the path, L(P), is given by

$$\mathrm{L(P)} = (\sum_{i=1}^{n} l_i^r)^{1/r},\ 1 \le r \le \infty. \qquad (2)$$

As the value of $r$ varies over the allowable range, the number of links in the resulting networks varies systematically. In particular, as $r$ decreases, additional links are added, but all links in networks with larger values of $r$ are still included. With $r = \infty$, Pathfinder produces a network which is the union of the minimal spanning trees for the network defined by the data (a complete graph if all pair-wise proximity estimates are available). The minimal spanning tree is unique, unless certain patterns of ties occur in the data. With $r = 1$, Pathfinder simply uses the sum of the link weights to determine the length of a path in the network. Intermediate values of $r$ produce networks with intermediate numbers of links.

A second method for computing path lengths follows from the theory of spreading activation in network structures. This method computes the length of a path by summing the link weights in both directions, starting from the nodes at each end of the path. The path length is taken as the maximum sum to the node where the two summations intersect. This method is analogous to measuring the maximum distance to the intersecting node when the path is traversed simultaneously from both ends. This node would be the point where spreading activation from the two end nodes would meet, and the length would be the maximum distance traveled by the activation. This method for computing distance is called the parallel method because the distances are traversed in parallel from both ends of the path. The parallel method yields networks with an intermediate number of links compared to the Minkowski method with $r = \infty$ and $r = 1$.

A family of Pathfinder networks can be generated by varying both the function that defines path length and the maximum number of links in paths. The number of links in a particular network varies systematically as a function of the values of these

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[1] Copies of the Schvaneveldt, Durso, and Dearholt (1985) manuscript can be obtained by requesting manuscript no. MCCS-85-9 from the Computing Research Laboratory, Memoranda Series, Box 3CRL, NMSU, Las Cruces, New Mexico 88003, U.S.A.

two parameters. Schvaneveldt et al. (1985) provided additional details.

Both MDS and Pathfinder reduce a large amount of data in the form of pairwise estimates to a smaller set of parameters, but they tend to highlight different aspects of the underlying structure. Pathfinder focuses on the local relations among concepts, whereas MDS provides a more global understanding of the dimensionalized concept space.

## Construction of the Structures

In this study, 24 subjects judged the relatedness of all possible pairs of 25 concepts taken from Schvaneveldt and Durso (1981) on a scale from 0 to 9. In selecting these concepts, Schvaneveldt and Durso attempted to create a reasonably coherent domain that contained a number of logical and intuitive relations. In particular, both logical property and categorical relations existed, as well as properties that were related to diverse concepts in the domain (e.g., red) and properties that were more restricted (e.g., feathers). The relatedness judgments were converted to distances by subtraction from 9, averaged over subjects, and analyzed by the alternating least squares scaling (ALSCAL; Young, Takane, & Lewyckyj, 1978) program and the Pathfinder program. The converted relatedness judgments are referred to in this article as *ratings*.

### *The Pathfinder Solution*

The parallel option of Pathfinder (see Schvaneveldt et al., 1985) was chosen for these data. This option defines the network by assuming that spreading activation occurs between the two concepts being judged. The parallel option tends to produce networks of moderate complexity, with sufficient links to allow construction of lists for the serial recall task. This network appears in Figure 1. The nodes were located on the page according to presumed hierarchial relations among the concepts in order to contrast the Pathfinder solution with the logical hierarchy.

### *The MDS Solution*

The ratings were analyzed with the ordinal option of the ALSCAL program. The choice of optimal dimensionality was influenced by a number of considerations: Stress and $r^2$ tended to "elbow" at two or three dimensions, the third dimension allowed easier interpretation of dimensions one and two (Kruskal & Wish, 1978), and the Isaac and Poor (1974) procedure suggested three dimensions. Thus, the "true" dimensionality of the space appeared to be closer to three than two. The value of $r^2$ for the three-dimensional space was .76 and this solution appears in Figure 2. The Euclidean distances for pairs of concepts in this particular solution ranged from 2 to 38 in arbitrary units.

As mentioned previously, similarity ratings and distance in multidimensional space have both been shown to be predictive of organization in free recall (Caramazza et al., 1976; Schwartz & Humphreys, 1973). Likewise, the development of the Pathfinder algorithm has provided a means of investigating the predictive ability of networks and comparing empirically derived networks to spatial solutions. Consequently, in this article we investigated the extent to which Pathfinder and MDS capture latent structure in the rating data that could be of use in recall.

Given that more organized lists of words tend to yield faster learning than less organized lists, it should be the case that a series of close concepts in multidimensional space should yield performance superior to a list of distant concepts, and a list of linked concepts in the network should yield performance superior to unlinked concepts. In addition, if the multidimensional scaling procedure is better able to capture relations useful in recall, a list organized according to MDS distances should yield better performance than a network list. Alternatively, if Pathfinder is better at extracting the relevant relations, subjects should learn a network list faster than an MDS list. Therefore, serial recall performance was used in Experiment 1 as an index of the psychological validity of MDS and Pathfinder structures.

## Experiment 1A

### *Method*

*Subjects.* In this experiment, 83 introductory psychology students from New Mexico State University volunteered in partial fulfillment of a research familarization requirement.

*Materials.* There were four conditions that differed only in the stimulus list that was presented to the subject. Four lists were constructed to correspond to the four experimental conditions: (a) network organized, (b) network control, (c) MDS organized, and (d) MDS control. All stimuli were taken from the set of 25 natural concepts.

Pairs of the concepts were classified into four categories based on their relations in the network and spatial representations. Related–both pairs were highly related according to both ALSCAL and Pathfinder and, consequently, were close in the MDS solution and linked in the network. An example of such a pair is BIRD–ROBIN. A second category, unrelated–both pairs, included those pairs that were distant in the MDS solution and not linked in the network such as HOOVES–ROSE. Thus, unrelated–both pairs were considered unrelated by both solutions. There also existed pairs that were related in one solution, but unrelated in the other. The pair MAMMAL–DEER is an example of a related–MDS pair that was close in the ALSCAL solution and not directly linked in the Pathfinder network. On the other hand, FROG and GREEN were linked in the Pathfinder network, but distant in the ALSCAL solution. This is an instance of a related–network pair. Thus, the last two categories (related–MDS and related–network) consisted of pairs that were considered related by either the ALSCAL algorithm or the Pathfinder algorithm, but not both. Related–MDS pairs and related–network pairs made up the MDS-organized and network-organized lists, respectively. The control conditions consisted of unrelated–both pairs. Related–both pairs were not included in the lists.

Each list consisted of 13 items. The constraints of the network-organized condition required that successive items in the list be linked in the network but distant in multidimensional space. Thus, this list consisted of related–network pairs. An optimal network list was created by finding a list of 13 items that satisfied the linking criterion and had the greatest average MDS distance between pairs. The network control list was constructed by rearranging the 13 items from the network-organized list in such a way that all successive items in the list were not linked in the network and were distant in MDS (i.e., unrelated–both pairs). Thus, the network-organized list was made up of linked but distant items, whereas the control list contained the same items, but was organized so that successive pairs were both distant and not linked.

Similarily, the MDS-organized list was constructed by ordering a list of 13 items such that successive items were close in the spatial solution, but not linked in the Pathfinder network. Thus, successive items in this list consisted of related–MDS pairs. The optimal MDS-organized list was obtained by selecting the list with the minimum average MDS distance that did not include any linked pairs. The MDS control list was constructed by scrambling the items in the MDS-organized list so that for successive pairs, distance was maximized and no links were present (i.e., unrelated–both pairs). Therefore, the MDS-organized list was made up of items that were close in space but not linked, whereas the MDS control list contained the identical items rearranged so that they were both distant and not linked.

The average MDS distance was 21.9 for the network-organized list and was 29.2 for the network control list. The MDS-organized list had an average MDS distance of 9.3 and the MDS control list had an average distance of 28.7. It should be noted that the average distance of the MDS-organized list (9.3), which excluded linked pairs, compared favorably with the distance that could be obtained without the link restriction (7.0). Also, the pairs in the MDS-organized list were closer in MDS distance than any pair in the network-organized list.

The four lists appear in Table 1. One can determine some of the differences between the Pathfinder solution and the three-dimensional MDS solution by contrasting pairs across the network-organized and the MDS-organized lists. These lists contain successive pairs that were scaled as related by the Pathfinder and ALSCAL algorithms, respectively. Inspection of the table shows that the pairs in the organized lists exhibit several relations, whereas the control lists show few if any such pair-wise relations. The two organized lists contain both paradigmatic and syntagmatic relations. Intuitively, the relations of the MDS list appear to be more abstract than those of the Pathfinder list, as one might expect from a procedure that produces global information about structure.

*Procedure.* Subjects were randomly assigned to one of the four conditions. Each subject was seated in front of a terminal and presented with instructions. The instructions stated that a list of 13 items would be presented one at a time and the task was to recall the list out loud in the order of presentation. The subjects were told that recall trials would continue until they correctly recalled the entire list in order. A brief (500-ms) tone signaled the presentation of the list and another 500-ms tone signaled the end of the list and the beginning of the response phase. The list was presented in the same order for each trial. Each item remained on the screen for 1.5 s.

Subjects recalled the list until they indicated that they wanted another exposure to the acquisition list. Responses were recorded for each trial during the recall phase by an experimenter who was seated behind a partition. The experimenter also controlled the presentation of additional trials to the subject and repeated trials until the subject reached criterion or until an upper limit of 20 trials was exceeded. For each subject the number of trials to the first perfect recall was recorded.

## Results and Discussion

Data for 80 of the 83 subjects were analyzed. Data from 3 subjects were discarded because they failed to achieve perfect

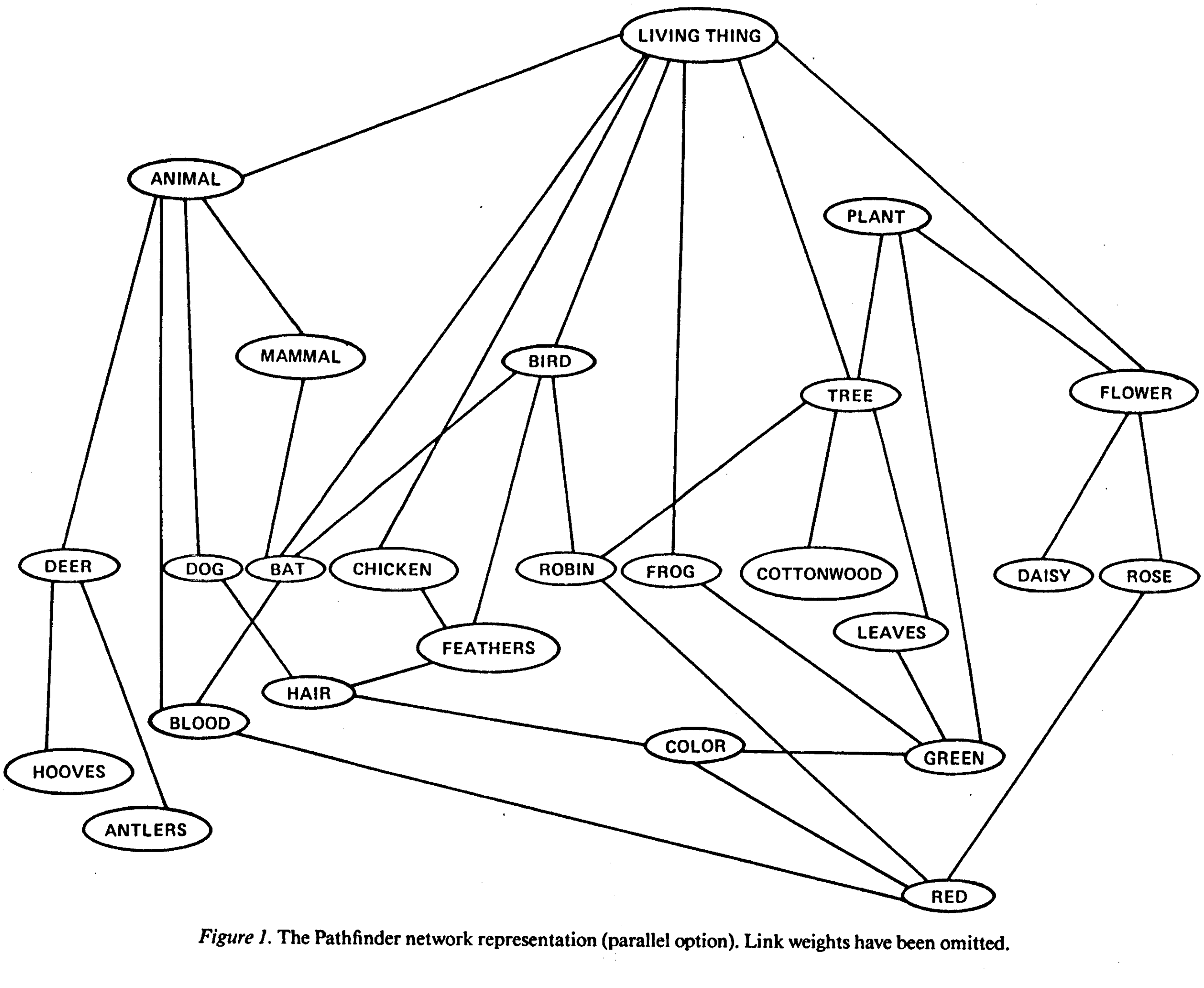

*Figure 1.* The Pathfinder network representation (parallel option). Link weights have been omitted.

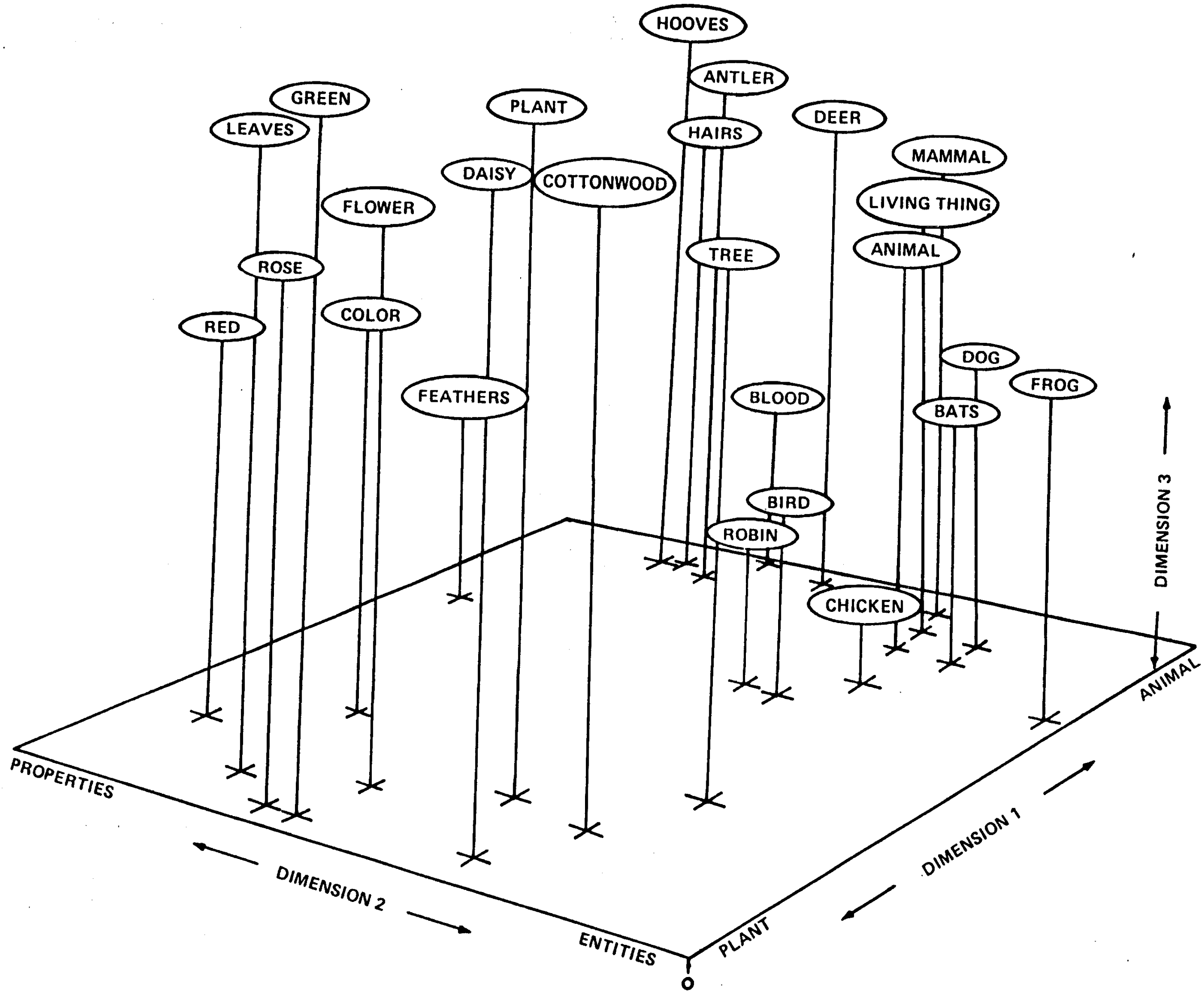

*Figure 2.* The ALSCAL three-dimensional spatial representation. Labels along the first and second dimensions indicate the author's interpretation of those dimensions.

recall in 20 presentations of the list. Of the 3 subjects, 2 were in the MDS control group and one was in the MDS-organized group. The analysis consisted of planned comparisons (Keppel, 1973). Because of the extensive literature on organization effects in recall, directional tests were used when comparing an organized list to an unorganized list; the tests comparing organized MDS and network lists were nondirectional.

Mean number of trials to criterion for the network-organized group was 4.7, compared with 7.9 for the MDS-organized group. Network and MDS control groups averaged 8.1 and 9.2 trials, respectively. Contrasts revealed that the network-organized list yielded faster learning than did its matched control, $t(38) = 4.12$, $SE = .84$, $p < .001$, but the MDS-organized list was not statistically better than its matched control. In addition, the network-organized list was learned in fewer trials than MDS-organized list, $t(38) = 3.77$, $SE = .86$, $p < .001$, whereas there was no difference between the two controls.

In order to investigate more specific acquisition differences among the four conditions, the numbers of items recalled by subjects in each of 18 trials were analyzed. Because it did not take each subject 18 trials to reach criterion, it was assumed that 13 items were recalled on any trials occurring after a subject had successfully learned the list. Learning curves for each condition are presented in Figure 3. For each of the four planned comparisons noted in the previous analysis, an analysis of variance was performed on number of items recalled with list as a between-subjects factor and trials as a within-subjects factor. The main effect of trials was significant in all four cases, suggesting that as expected, subjects' recall performance improved over trials. The main effect of list was significant in all cases except for the comparison between the two control lists. More items were recalled from the network-organized list than from the network control list, $F(1, 38) = 15.68$, $MS_e = 9.47$, $p < .001$, and more items were recalled from the MDS-organized list than from the MDS control list, $F(1, 38) = 6.19$, $MS_e = 19.78$, $p < .05$. Also, more items were recalled from the

Table 1
*Word Lists and MDS Distances for Experiments 1A and 1B*

| Experiment 1A | | | | Experiment 1B |
|---|---|---|---|---|
| MDS organized | MDS control | NET organized | NET control | MDS organized |
| Mammal | Tree | Frog | Leaves | Hairs |
| 3 | 23 | 31 | 31 | 17 |
| Deer | Color | Green | Blood | Blood |
| 12 | 21 | 20 | 17 | 21 |
| Dog | Daisy | Color | Hairs | Living thing |
| 4 | 26 | 26 | 29 | 19 |
| Bats | Frog | Hairs | Chicken | Leaves |
| 10 | 30 | 22 | 37 | 18 |
| Frog | Rose | Feathers | Green | Red |
| 16 | 32 | 22 | 36 | 13 |
| Tree | Dog | Chicken | Bats | Feathers |
| 10 | 31 | 21 | 35 | 14 |
| Daisy | Flower | Living thing | Red | Color |
| 5 | 32 | 17 | 36 | 16 |
| Plant | Bats | Bats | Frog | Robin |
| 7 | 36 | 21 | 30 | 9 |
| Cottonwood | Green | Blood | Color | Chicken |
| 13 | 33 | 23 | 23 | 14 |
| Flower | Mammal | Red | Tree | Bats |
| 7 | 28 | 21 | 34 | 10 |
| Green | Cottonwood | Robin | Feathers | Frog |
| 13 | 26 | 21 | 25 | 16 |
| Rose | Deer | Tree | Living thing | Tree |
| 11 | 26 | 18 | 17 | 16 |
| Color | Plant | Leaves | Robin | Green |
| $M = 9.25$ | $M = 28.67$ | $M = 21.92$ | $M = 29.17$ | $M = 15.25$ |

*Note.* MDS = ALSCAL multidimensional scaling and NET = Pathfinder network.

network-organized list than from the MDS-organized list, $F(1, 38) = 6.63$, $MS_e = 5.23$, $p < .05$. Because the network-organized list was learned faster than its control list and faster than the MDS-organized list, the finding that more items were recalled from the network-orgaized list than from the other two lists is not too surprising. However, the fact that more items were recalled from the MDS-organized list than from its control, when there was no difference between the two lists in trials to criterion, is of interest. These results suggest that the MDS organization facilitated recall of the items making up the list, although it did not facilitate serial recall of the items. The interaction of trial and list was significant in both the network-organized versus network-control comparison, $F(17, 646) = 4.9$, $MS_e = 2.45$, $p < .001$, and the network-organized versus MDS-organized comparison, $F(17, 646) = 1.77$, $MS_e = 1.77$, $p < .05$. Both of these interactions were due to the fact that the effect of list was greatest for the first five trials.

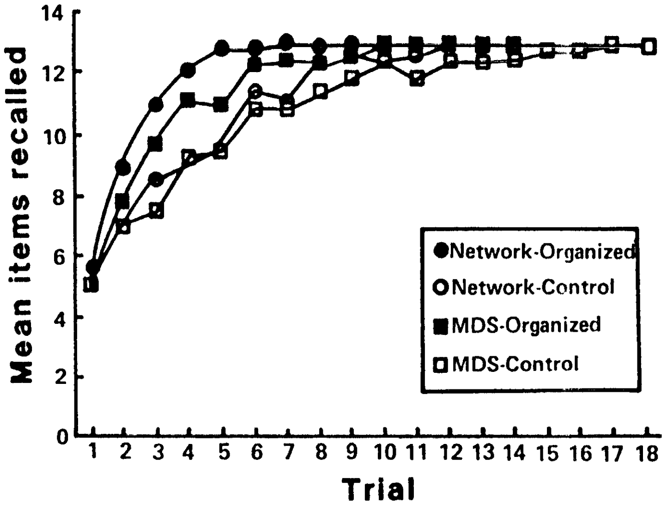

*Figure 3.* Learning curves for each condition in Experiment 1A.

Differences among the four conditions were also analyzed for serial position effects. An analysis of variance was performed on the proportion of items recalled in each of four positions (list positions 1–3, 4–6, 7–10, and 11–13, respectively) over the first three trials. List was a between-subjects factor, and position and trial were within-subjects factors. As expected, for each of the comparisons the effects of trial, position, and trial by position were statistically significant. However, because no significant interactions between list and serial position occurred, these data are not presented or discussed in detail.

In general, the results of Experiment 1A indicate that subjects learned the network-organized list faster than the MDS-organized list and the network control list, whereas the MDS-organized list was not learned faster than its control. However, a more detailed trial-by-trial analysis revealed that even though subjects learned the MDS-organized list and the MDS control list in the same number of trials, more items were recalled by subjects in the MDS-organized condition than those in the MDS control condition. Thus, it appears that the network organization facilitated serial recall of the list, whereas the MDS organization facilitated the recall of items, but not in the correct order. Martin and Noreen (1974) argued that serial learning is accomplished by learning sub-sequences or chunks of a list first and then by learning how the sub-sequences are arranged. Thus, a list can be represented as a hierarchy of chunks. Perhaps the MDS organization enabled subjects to recall easily chunks of related items, but was of no help in ordering items within or between chunks. On the other hand, the network organization facilitated both chunking and ordering processes in serial recall. Therefore, the disadvantage of MDS organization in this experiment might be due to the specific requirements of serial recall. In Experiment 2 a free-recall paradigm was used in order to address this issue.

The advantage of the network-organized list over the MDS-organized list suggests that organization defined by Pathfinder is more appropriate for serial recall than is organization defined by MDS. The lack of a difference between the two controls suggests that any differences among the items used in the MDS lists and the Pathfinder lists cannot be the sole contributor to the advantage of the network representation. In the next study, we controlled any possible difference in materials that may have contributed to the advantage of the network organization over the spatial organization.

## Experiment 1B

This experiment was designed to determine if the network advantage in list acquisition time would hold when organized MDS and network lists were constructed from identical items. Two lists were used that differed only in the ordering of the items.

### *Method*

*Subjects.* Forty introductory psychology students from the same pool as the first experiment participated. They were randomly assigned to either the network or spatial conditions.

*Materials.* Two lists were constructed from the set of 13 items used in the network-organized list of Experiment 1A. Unfortunately, it was impossible to create a network list from the items that yielded the MDS-organized list in Experiment 1A (compare Figure 1 with Table 1).

The order of the items within the lists was determined as before. One list was organized according to the network representation and the other according to the spatial representation. The network-organized list was identical to the list used in Experiment 1A and contained pairs of items that were linked, but distant in MDS (i.e., related–network pairs). The new MDS-organized list was obtained by rearranging the items in the network list until the list contained pairs that were not linked in the network, but which were close in the spatial representation (i.e., related–MDS pairs). The order that minimized MDS distance while maintaining the "not linked" criterion was selected as optimal. This new MDS list is presented in the last column of Table 1. The average distance for the new MDS list was 15.3. Although this distance was greater than the average distance for the MDS-organized list used in Experiment 1A (9.3), it was the minimum distance that could be achieved with the restricted set of items and was still less than the mean distance (21.9) for the network list. Thus, the resulting list was the optimal MDS list for this set of items.

*Procedure.* Except for the change in conditions, all procedures were identical to Experiment 1A.

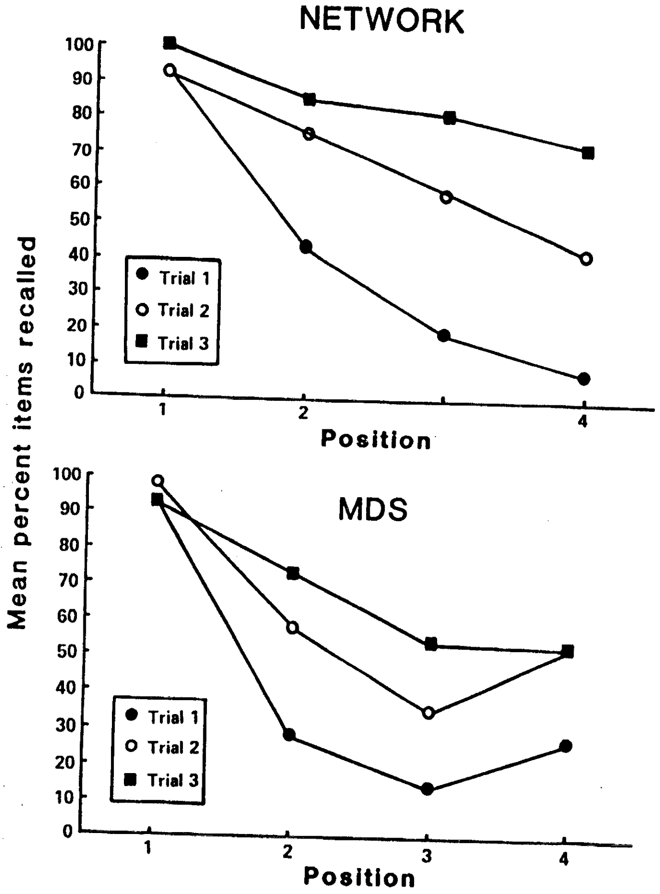

*Figure 4.* Serial position curves for the network-organized and MDS-organized conditions in Experiment 1B.

### *Results and Discussion*

The number of trials to the first perfect recall was analyzed. Mean number of trials to criterion was 4.7 for the network group and 8.0 for the MDS group, $t(38) = 3.51$, $SE = .96$, $p < .001$. Even when materials were held constant, the superiority of the network organization over the MDS organization in terms of acquisition time persisted.

As in Experiment 1A, an analysis of variance was performed on number of items recalled over 18 trials for each of the two lists. Again, the main effect of trials was significant as was the main effect of list, $F(1, 38) = 5.31$, $MS_e = 7.73$, $p < .05$, and the trial by list interaction, $F(17, 646) = 2.1$, $MS_e = 1.83$, $p < .05$. In general, subjects' recall performance improved over trials, subjects in the network condition recalled more items than subjects in the MDS condition, and list effects were greatest in the first few trials.

Analysis of serial position effects over the first three trials revealed significant effects of trial, position, and trial by position. However, the position by list interaction, $F(3, 114) = 3.28$, $MS_e = .11$, $p < .05$, and the position by list by trial interaction, $F(6, 228) = 2.16$, $MS_e = .05$, $p < .05$, were also statistically significant. Serial position curves for the network and MDS lists are presented in Figure 4. The position by list interaction was caused by a greater advantage of the network list over the MDS list in the middle positions than in the beginning and end positions. The three-way interaction was due to the fact that the position effect (i.e., primacy) tended to dissipate over trials in the network condition much faster than it did in the MDS condition. Consequently, by the third trial, items in all four positions were recalled almost equally well by those in the network condition, whereas there was still a large primacy effect in the MDS condition. These results support earlier conclusions that the MDS disadvantage is caused by problems in chaining the items or chunks of items together in serial order.

## Experiment 2

It is possible that the advantage of the network list organization over the MDS organization was due to the serial recall required of the subjects. Perhaps the local relations inherent in the network structure lend themselves well to serial recall. Although the functional "stimulus" for serial learning is not merely the preceding word (e.g., Young, 1961), requiring the subjects to learn the list in order may increase the likelihood that local relations will prove effective in generating the next word to be recalled. On the other hand, although spatial representations, which emphasize global relations, did not appear to benefit ordered recall, they did appear to facilitate chunking and might yield large benefits when a subject is free to recall a list in any order.

If the network structure generated by Pathfinder captures underlying organization in memory, then not only should a network organization facilitate serial recall, but in addition, the network structure should be revealed in free-recall organization. That is, we should be able to predict organization in free recall from the network organization of the concepts. Techniques have been developed to derive memory representations from free-recall order (Friendly, 1977; Reitman & Rueter, 1980). Thus, the network and MDS representations can be compared to the structure obtained from free-recall order. It is also of interest to compare the performance of the MDS and network solutions in predicting recall organization to the predictive performance of the original ratings from which they were derived. Are the representations derived from the ratings more accurate in predicting recall order than are the original ratings?

In Experiment 2 subjects were presented with random presentations of a list of 13 items and were allowed to recall the list in any order. Proximities derived from the subjects' recall organization were then compared to the ratings and derived MDS and network representations.

### *Method*

*Subjects.* In Experiment 2, 60 introductory psychology students from New Mexico State University volunteered in partial fulfillment of a research familiarization requirement.

*Materials.* Stimuli were the same 13 items used to construct the lists in Experiment 1B. Instead of constructing ordered lists as in the previous experiments, the 13 items were randomly ordered on each trial.

*Procedure.* All 60 subjects were presented with the same set of 13 items in a free-recall task. The instructions stated that a list of 13 items would be presented one at a time and that the task was to recall the items out loud in any order. The subjects were told that recall trials would continue until they had recalled all 13 items correctly at least one time. The presented list was randomized for each trial. The experimenter recorded the order in which the subject recalled the items on each trial. Other than these changes, procedures were identical to those of Experiment 1A.

### *Results and Discussion*

*Proximity analysis of free recall.* In order to compare the subjects' free-recall organization to the organization revealed in ratings, networks, and MDS solutions, comparable representations of these factors were required. Friendly (1977) and Reitman and Rueter (1980) both described techniques for deriving structural representations of memory from recall order. Reitman and Rueter derived a tree structure from multiple recall orders. This technique required multiple perfect recall trials, some of which were initially cued with one of the items. In addition to being constrained by specific recall procedures, the Reitman and Rueter technique generated a specific type of tree structure.

Friendly (1977) described a more general procedure which generated proximities from free-recall order. These proximities are similar to the original rating proximities used to derive the spatial and network structures in this study. A variation of Friendly's technique was applied to the free-recall data in this experiment. The recall proximities were the number of other items intervening between the members of pairs of items in the recalled list. For example, if a four-item list was recalled in the order a–b–c–d, then the proximity of a and b would be 0, a and c = 1, a and d = 2, b and c = 0, b and d = 1, and c and d = 0. A set of proximities of this type was generated for each subject from the recall order on the first perfect trial. Whereas Friendly averaged proximities over several trials for each subject, in this study the proximities were averaged over subjects to obtain a single set of proximities that represented average recall organization.

*MDS and network proximities.* Sets of proximities comparable to the recall proximities and original rating proximities were also derived from the spatial and network representations. The spatial proximities were obtained by calculating all pairwise Euclidean distances in the solution space. Thus, each MDS proximity corresponded to the distance between members of a specific pair in the MDS solution. In Experiments 1A and 1B the ALSCAL program was used to generate a three-dimensional MDS solution. In this experiment six different MDS solutions were generated in order to generalize the results to several different cases. The solutions differed from each other in the specific algorithm used to generate the solution (ALSCAL, Kruskal-Young-Shepard-Torgerson (KYST; Kruskal & Wish, 1978), or Kruskal) and in the dimensionality of that solution (three or four).

Three different network structures were also generated from the rating data. They differed in the complexity of the network (minimal, optimal, or parallel) which was determined by the way in which path length was computed. The minimal network was the simplest network produced by Pathfinder and resulted from computing path length with Minkowski $r = \infty$ and the maximum number of links in a path = 24. Because there was one tie in the data, this network consisted of 25 links. The optimal network was a network consisting of 30 links that resulted when Minkowski $r = 5$ and maximum number of links in a path = 3. This network was labeled "optimal" simply because it accounted for 65% of the variance in the empirical judgments and better fits required many more links. In contrast, networks with fewer links fit the data much more poorly (see Schvaneveldt et al., 1985). The parallel network was the same network that was used in the first two experiments. This network was derived by using the parallel method (described earlier) of defining path length as opposed to the Minkowski r-metric. The parallel network had 37 links.

The network proximities for these three networks were obtained by either an additive method or a parallel method. According to the additive method, proximities were equal to the length of the minimum-length path connecting each pair of nodes in the network. The path lengths were computed by summing the weights (the original pair-wise ratings) of the links in the path. The parallel method for computing proximities is related to the parallel method for defining path length. For each pair of items the proximity was equal to the shortest parallel path length between the corresponding nodes, where parallel path length was determined as previously discussed (i.e., the maximum summed distance to a node on the path). Thus, there were six network solutions, three structures by two proximity transformations.

There were 78 (13 taken two at a time) proximities derived from free recall because the list to be recalled consisted of 13 items. The subset of 78 proximities corresponding to these 13 items was extracted from each of the rating, MDS, and network proximities. Therefore, the following analyses were performed on 14 sets of 78 proximities derived from free recall, ratings, the six network solutions, and the six MDS solutions.

*Relation between recall organization and memory representations.* An examination of scatter plots of each of the independent variables: ratings, network proximities, and MDS proximities against recall proximities revealed no obvious nonlinear relations between any of the independent variables and recall. Thus, linear correlations should provide information about the relations between recall organization and the various measures of organization. The mean correlations that are reported were derived by first performing a Fisher's $Z$ transformation on the individual correlations, calculating a weighted average of the $Z$s, and transforming the result back to an $r$ (McNemar, 1962). Correlations among recall, ratings, networks, and MDS proximities are presented in Table 2.

All of the correlations reported in this matrix were significant at the .05 level with 76 degrees of freedom, except the four underlined correlations. It should be noted that each of the nonsignificant correlations was between particular network and MDS solutions. In addition, correlations between the ratings and the various network and spatial solutions provided an estimate of goodness of fit to the original data for that particular solution.

Of particular interest were the correlations of the network and spatial solutions with recall. The highest correlation ($r$ = .58) was between recall and the optimal network with parallel proximities and the lowest correlation was between recall and the three-dimensional KYST MDS solution ($r$ = .35). It should be noted that even the highest recall–MDS correlation ($r$ = .50) was slightly lower than the lowest recall–network correlation ($r$ = .53). Although ratings, network proximities, and MDS proximities each correlated significantly with recall, they were also correlated with each other. The independent contributions of these measures of organization were examined with partial correlations.

Because ratings were used to derive the network representations, it was not surprising that each of the sets of network proximities was significantly correlated with the ratings, mean $r(76)$ = .592, range = .397 to .759. These correlations, coupled with the significant correlation between ratings and recall, $r(76)$ = .555, might account for the significant correlations between the various networks and recall, mean $r(76)$ = .551, range = .526 to .583. However, even when the effect of ratings was removed from the network–recall correlations, the six partial correlations between network and recall proximities were all statistically significant, mean $r$ network, recall/ratings (75) = .345, $p < .01$, range = .260 (parallel network with additive proximities) to .401 (minimal network with parallel proximities). This result suggests that the network proximities contained information relevant to recall organization that was not directly available in the original ratings.

Like the network representations, the MDS representations were also derived from ratings and thus, were significantly correlated with the original ratings, mean $r(76)$ = .811 range = .742 to .859. When the effect of ratings was removed from the six MDS–recall correlations, the resulting partial correlations were close to zero, mean $r$ MDS, recall/ratings (75) = −.004, range = −.119 to .048. Thus, in contrast to the network proximities, the MDS proximities were not independently predictive of recall. These low partial correlations could be attributed to the fact that the MDS solutions all correlated relatively well with ratings and thus, were greatly affected by removal of the ratings. In general, the proximities derived by MDS were predictive of recall to the extent that they conveyed the same information as the ratings. On the other hand, the network proximities contained predictive information about recall organization that was not shared with the ratings.

Because the MDS and Pathfinder procedures highlight different aspects of the rating data, it is reasonable to assume that the proximities derived from the two procedures would differ. To determine whether the network and MDS representations shared common features other than the original ratings, the rating effect was partialed out of the 36 different MDS–network correlations. The resulting mean partial correlation, $r$ MDS, network/ratings (75) = .02, was not significant suggesting that the MDS and Pathfinder procedures did indeed generate distinct structures. It should be noted, however, that 7 of the 36 partial correlations were significant at the .05 level, range of $r$ MDS, network/ratings (75) = −.248 to .375. Interestingly, four of these correlations involved the three-dimensional Kruskal MDS solution suggesting that this solution was most like the network representations. On the other hand, the fact that this particular MDS solution shared some features with the network did not improve its correlation with the recall data, $r$ Kruskal 3-D, recall/ratings (75) = .018, $p > .05$. In general, these results indicate that most relations between the two types of structures can be attributed to the shared ratings.

On the basis of the above results, it appears that the networks had properties that were predictive of recall. At least some of these properties were not shared by the ratings, and thus were not shared by MDS (because most MDS solutions had only the ratings in common with the networks and for the few MDS solutions that had more in common with the networks, the shared

Table 2
*Intercorrelations of Recall, Rating, Network, and MDS Proximities*

| | Rating | Network | | | | | | MDS | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Proximities | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 |
| 1. Recall | .56 | .53 | .53 | .54 | .58 | .56 | .58 | .41 | .50 | .35 | .49 | .42 | .48 |
| 2. Rating | — | .44 | .40 | .69 | .60 | .76 | .60 | .75 | .86 | .75 | .86 | .74 | .86 |
| Network | | | | | | | | | | | | | |
| 3. MA | | — | .98 | .70 | .74 | .64 | .74 | .19 | .39 | .18 | .40 | .38 | .36 |
| 4. MP | | | — | .66 | .75 | .60 | .75 | .19 | .37 | .17 | .37 | .37 | .33 |
| 5. OA | | | | — | .95 | .88 | .90 | .43 | .60 | .42 | .59 | .69 | .60 |
| 6. OP | | | | | — | .82 | .96 | .40 | .56 | .37 | .55 | .64 | .55 |
| 7. PA | | | | | | — | .85 | .47 | .66 | .48 | .66 | .70 | .66 |
| 8. PP | | | | | | | — | .43 | .58 | .41 | .57 | .64 | .58 |
| MDS | | | | | | | | | | | | | |
| 9. A3 | | | | | | | | — | .89 | .97 | .87 | .60 | .87 |
| 10. A4 | | | | | | | | | — | .90 | .97 | .77 | .97 |
| 11. K3 | | | | | | | | | | — | .91 | .60 | .90 |
| 12. K4 | | | | | | | | | | | — | .72 | .98 |
| 13. R3 | | | | | | | | | | | | — | .73 |
| 14. R4 | | | | | | | | | | | | | — |

*Note.* Underlined correlations failed to reach significance at the .05 level. For the six networks, the first letter corresponds to the particular type of network structure (M = minimal, O = optimal, P = parallel) and the second letter refers to the method used to derive proximities (A = additive, P = parallel). For the six MDS solutions, the first letter indicates the MDS algorithm that was used (A = ALSCAL, K = KYST, R = Kruskal) and the number following it refers to the number of dimensions chosen for that solution (3 = three dimensions, 4 = four dimensions).

features did not appear relevant to recall). Proximities derived from MDS had no predictive properties that were not shared by the ratings.

It was of interest to determine whether the ratings accounted for variance in recall organization that was not accounted for by the networks or MDS solutions. For instance, a network might contain all of the predictive information contained in the ratings along with its independent information. However, when the effects of all six networks were partialed out of the rating–recall correlation, the partial correlation was significant, $r$ rating, recall/all networks (70) = .33, $p < .01$, suggesting that there was predictive information in the ratings not accounted for by the network. Similarly, MDS might contain all of the predictive information that is contained in the ratings. Again, the partial correlation between ratings and recall with the MDS effects eliminated suggested that this was not true, $r$ ratings, recall/all MDS solutions (70) = .203, $p < .05$. Thus, the ratings contained information about recall that was not completely accounted for by either the network solutions or the MDS solutions.

## General Discussion

This study supplies additional evidence for the role of organization in recall. Although all of the lists used in the serial recall experiments, including the control lists, were composed of concepts from a coherent domain, when (network) organization was imposed on these "related" concepts by the experimenter, learning was facilitated. Thus, "fine-grained" organization imposed on a list of items from a coherent domain can aid acquisition. In addition, this fine-grained organization was apparent in a free-recall paradigm. The organization imposed on the items by subjects corresponded to the organization revealed by the network.

More important, these experiments suggest that perceived relatedness between members of the list contains information useful in recall, provided the appropriate scaling algorithm is used to extract that information. The network captured more of the information useful in recall than did MDS. Lists derived from network solutions were learned more rapidly than a control list and more rapidly than a list derived from a spatial solution for the same rating data. The list derived from a spatial solution was not learned more rapidly than the control list, although overall more items were recalled in the spatial list than in the control list, suggesting that subjects had problems ordering the items in the spatial list. However, the advantage of the network-organized lists cannot solely be attributed to the serial nature of the task. In a free-recall paradigm, proximity of concept pairs in networks was a better predictor of free recall organization than MDS proximities. Furthermore, this result was replicated in a total of six different MDS solutions and six different networks, suggesting that the predictive success of networks was not merely due to idiosyncratic features of particular MDS solutions or networks.

The finding that MDS proximities were not by themselves good predictors of recall seems to be somewhat at odds with findings discussed earlier in this paper. Caramazza et al., (1976) obtained significant correlations between similarity ratings and recall organization. They also indicated that correlations of MDS proximities and recall were of similar magnitude. These results are comparable to the correlations obtained in Experiment 2 of this study between ratings and recall and between the various MDS solutions and recall. All of these correlations were statistically significant. On the other hand, eliminating effects of the ratings greatly reduced the MDS–recall correlation. Consequently, the results of the present study replicated those of Caramazza et al. in finding significant correlations between both ratings and recall and MDS and recall. In addition, the present study extended these findings to include a comparison of ratings and MDS with the network. Furthermore, when the influence of the ratings was eliminated from the correlations of MDS and network proximities with recall organization, only the network correlated significantly with recall.

The finding that the network proximities were predictive of recall organization independently of the original ratings merits some discussion. Whereas one purpose of scaling techniques such as ALSCAL and Pathfinder is to represent complex conceptual relations in a simpler fashion (rather than a set of ratings), another goal of such techniques is to extract psychologically valid information about the structure of memory that is not present in the original data. In other words, the general goal is to reduce the data by highlighting the most critical information. The Pathfinder algorithm appears to be successful in accomplishing both goals. It generated networks that represented complex data and it extracted information related to recall organization. The spatial solution simplified the complex rating data, but there was no evidence that any additional information was contained in the location of concepts in multidimensional space.

It is possible that the advantage of lists organized according to the network in the first experiment was due to the extra information that was present in the network that was not present in MDS. It is interesting to speculate about the content of this additional information. The network proximities were derived from combinations of ratings between related pairs of items and consequently, judgments about related pairs of items were emphasized over judgments about less related pairs. Perhaps subjects produce more accurate estimates of proximity for related items than for unrelated items and thus, the focus on the ratings of related pairs is psychologically meaningful. Therefore, the extra network information may be the result of this meaningful focus on information from related pairs of items.

The correlations between recall and the various representations not only suggested general differences between network and spatial representations, but they also pointed to specific differences among various types of networks and various types of spatial solutions. For instance, it is surprising that the network with the highest partial correlation with recall removing the ratings effect (the minimal network with parallel proximities) was also the simplest of the three types of networks generated. The fact that this particular network was correlated least with ratings and was thus, least affected by removal of the ratings, could account for the size of the partial correlation. In addition, across all three types of networks, this same partial correlation was greater with parallel proximities than with additive proximities. This latter result supports a spreading activation notion of semantic distance.

The results of this study also suggest advantages in combining information from a variety of representational techniques. There was information in the original ratings that was relevant to recall organization that was not revealed by the MDS representation or the network representation. On the basis of the partial correlations obtained in the second experiment, it appears that maximum prediction of free recall organization could be achieved with a combination of information from the network proximities and ratings.

Possible extensions of this research involve the comparison of structural representations using evidence from other tasks such as semantic priming, completion of analogies, and categorization judgments. Tasks such as categorization judgments and analogy completion seem to require a more global analysis of the concepts than does recall. Perhaps MDS represents relations among concepts that are predictive of tasks other than recall. As mentioned before, several studies have found significant correlations between MDS and tasks involving category judgments or analogy completions. The extent to which the network representation can account for performance in these tasks is an issue for future research. At any rate, a representation of memory should reveal information that is useful in a variety of tasks involving memory organization.

In conclusion, the Pathfinder algorithm provides a useful alternative to spatial models of organization, without restricting the results to strictly hierarchical structures. Our data provide evidence for the value of the resultant network structures, and suggest, at least for the tasks considered here, that these structures are capable of extracting information important for recall. Organization as defined by a network proved to be more effective in facilitating learning than organization defined by a spatial configuration. Also, organization as defined by a network more closely resembled subjects' organization in free recall than organization defined by MDS.

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