DOCUMENT RESUME

ED 189 171 TM 800 348

AUTHOR Sternberg, Robert J.; Gardner, Michael K.

TITLE Unities in Inductive Reasoning. Technical Report No. 18.

INSTITUTION Yale Univ., New Haven, Conn. Dept. of Psychology.
SPONS AGENCY Office of Naval Research, Arlington, Va. Personnel and Training Research Programs Office.
PUB DATE Oct 79
CONTRACT N0001478C0025
NOTE 66p.: Portions of this paper were presented at the Annual Meeting of the Society for Mathematical Psychology (Providence, RI, August, 1979).

EDRS PRICE MF01/PC03 Plus Postage.
DESCRIPTORS Classification: Cognitive Measurement: *Cognitive Processes: Correlation: Higher Education: *Induction: *Intelligence: Models: Response Style (Tests)
IDENTIFIERS Analogy Test Items: Series Completion

ABSTRACT

Two experiments were performed to study inductive reasoning as a set of thought processes that operates on the structure, as opposed to the content, of organized memory. The content of the reasoning consisted of inductions concerning the names of mammals, assumed to occupy a Euclidean space of three dimensions (size, ferocity, and humanness) in organized memory. Problems used in the experiments were analogies, series, and classifications. They were presented in unrestricted-time form by paper and pencil for-choice items and tachistoscopically as two choice items. Time required in the tachistoscopic form was assumed to be an additive combination of five stages: selection of components of the problem, of strategy, of internal representations for the information, of a speed-accuracy trade off, and the monitoring of solutions. Results partially confirmed the vector model of memory space for names of mammals. Response latencies confirmed the prediction that analogies required one more processing step than did series, which in turn required one more step than did classifications. The significance of these findings for the explanation of general intelligence is discussed. (Author/CTM)

Unities in Inductive Reasoning

Robert J. Sternberg and Michael K. Gardner

Department of Psychology
Yale University
New Haven, Connecticut 06520

Technical Report No. 18
October, 1979

This research was sponsored by the Personnel and Training Research Programs, Psychological Sciences Division, Office of Naval Research, under Contract No. N0001478C0025, Contract Authority Identification Number NR 150-412.

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER Technical Report No. 18	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) "Unities in Inductive Reasoning"		5. TYPE OF REPORT & PERIOD COVERED Periodic Technical Report (1 Jul 79 - 30 Sep 79) 6. PERFORMING ORG. REPORT NUMBER Research Report No. 4-79
7. AUTHOR(s) Robert J. Sternberg and Michael K. Gardner		8. CONTRACT OR GRANT NUMBER(s) N0001478C0025
9. PERFORMING ORGANIZATION NAME AND ADDRESS Department of Psychology Yale University New Haven, Connecticut 06520		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS 61153N; RR 042-04; RR 042-04-01; NR 150-412
11. CONTROLLING OFFICE NAME AND ADDRESS Personnel and Training Research Programs Office of Naval Research (Code 458) Arlington, Virginia 22217		12. REPORT DATE 1 Oct 79 13. NUMBER OF PAGES 46
14. MONITORING AGENCY NAME & ADDRESS(if different from Controlling Office)		15. SECURITY CLASS. (of this report) Unclassified 15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

Portions of this paper were presented at the Annual Meeting of the Society for Mathematical Psychology, Providence, August, 1979.

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

Inductive reasoning, component, analogies, series completions, classifications

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Two experiments sought to discover sources of communalities in performance on three inductive reasoning tasks: analogies, series completions, and classifications. In Experiment 1, 30 subjects completed an untimed pencil-and-paper test in which they were asked to solve 90 induction items, equally divided among the three kinds of induction items noted above. The subjects' task was to rank-order four response options in terms of their goodness of fit as completions for each particular item. Data sets for the three tasks

DD FORM 1 JAN 73 1473 EDITION OF 1 NOV 65 IS OBSOLETE
S/N 0102-LF-014-6601

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered) were highly correlated, suggesting the possibility of a common model of response choice across tasks. Moreover, a single exponential model of response choice provided a good fit to each data set. The single parameter estimate for this model was roughly comparable across tasks. In Experiment 2, 36 subjects completed a timed tachistoscopic test in which they, too, were asked to solve 90 induction items, equally divided among the three kinds of induction items noted above. The subjects' task was to choose the better of two response options as a completion for each particular item. Data sets for the three tasks were again highly intercorrelated, suggesting the possibility of a common model of real-time information processing across tasks. Moreover, a single linear model of response times provided a good fit to each data set. Three of four parameter estimates were roughly comparable across tasks. It was concluded that a common model of response choice and of information processing can account for at least some of the previously observed relationships in performance across induction tasks. The implications of these findings for psychometric and information-processing accounts of induction and intelligence are discussed.

Unities in Inductive Reasoning

Robert J. Sternberg and Michael K. Gardner

Yale University

Running head: Unities in Inductive Reasoning

Send proofs to Robert J. Sternberg
Department of Psychology
Yale University
Box 11A Yale Station
New Haven, Connecticut 06520

Abstract

Two experiments sought to discover sources of communalities in performance on three inductive reasoning tasks: analogies, series completions, and classifications. In Experiment 1, 30 subjects completed an untimed pencil-and-paper test in which they were asked to solve 90 induction items, equally divided among the three kinds of induction items noted above. The subjects' task was to rank-order four response options in terms of their goodness of fit as completions for each particular item. Data sets for the three tasks were highly intercorrelated, suggesting the possibility of a common model of response choice across tasks. Moreover, a single exponential model of response choice provided a good fit to each data set. The single parameter estimate for this model was roughly comparable across tasks. In Experiment 2, 36 subjects completed a timed tachistoscopic test in which they, too, were asked to solve 90 induction items, equally divided among the three kinds of induction items noted above. The subjects' task was to choose the better of two response options as a completion for each particular item. Data sets for the three tasks were again highly intercorrelated, suggesting the possibility of a common model of real-time information processing across tasks. Moreover, a single linear model of response times provided a good fit to each data set. Three of four parameter estimates for this model were roughly comparable across tasks. It was concluded that a common model of response choice and of information processing can account for at least some of the previously observed relationships in performance across induction tasks. The implications of these findings for psychometric and information-processing accounts of induction and intelligence are discussed.

Unities in Inductive Reasoning

Inductive reasoning requires an individual to reason from part to whole, or from particular to general (Webster's New Collegiate Dictionary, 1976). Inductive reasoning problems can be of various kinds. One of the most interesting kinds is that which Greeno (1978) refers to as problems of inducing structure. Problems of this kind include analogies (e.g., LAWYER is to CLIENT as DOCTOR is to (a) PATIENT, (b) MEDICINE), series completions (e.g., Which word should come next in the following series? PENNY, NICKEL, DIME, (a) COIN, (b) QUARTER), and classifications (e.g., Which of the two words at the right fits better with the three words at the left? CAT, MOUSE, LION, (a) SQUIRREL, (b) EAGLE). These problems are of particular interest because they have played a key role in both the psychometric and information-processing literatures on reasoning and intelligence, as well as in the recent literature attempting to integrate the psychometric and information-processing approaches.

In the psychometric literature, problems of inducing structure have been considered important because they provide particularly good measures of general intelligence, or _g_. Factor analyses of multiple ability tests often yield a "general factor," or single source of individual differences, that permeates the entire range of tests (Spearman, 1927). Even when this general factor does not appear from an immediate factoring of the tests (Thurstone, 1938), it often appears when factors that do not include a general factor are themselves factored (Humphreys, 1962). When correlations are computed between individual tests and the general factor, problems of inducing structure usually show some of the highest correlations. Moreover, scores on these problems are highly correlated among themselves (see Cattell, 1971; Horn, 1968).

These results suggest that some common source of individual differences underlies performance on these various kinds of problems. The importance of this common source of individual differences to psychometric theory is shown by the fact that the concept of g has played a prominent part in several major psychometric theories of intelligence (e.g., Burt, 1940; Horn & Cattell, 1966; Humphreys, 1962; Spearman, 1927; Vernon, 1971), and by the fact that the problems of inducing structure are such good measures of g that they are found on an overwhelming majority of psychometric intelligence tests.

In the information-processing literature, problems of inducing structure have been considered important because the underlying processes involved in solving these problems seem to be so basic to human cognition, both in laboratory and real-world settings. These problems have served as the bases for a number of task analyses. Several computer programs, for example, have been devoted exclusively to the solution of analogies (Evans, 1968; Reitman, 1965) or series completions (Simon & Kotovsky, 1963), and other computer problems have dealt with analogies or series completions, among other kinds of problems (Williams, 1972; Winston, 1974). Analogy problems have been studied experimentally in a number of investigations with human subjects (e.g., Mulholland, Pellegrino, & Glaser, in press; Sternberg, 1977a, 1977b; Whitely & Barnes, 1979), as have series completions (e.g., Holzman, Glaser, & Pellegrino, 1976; Kotovsky & Simon, 1973). We are unaware of any previously published information-processing analyses of the classification task, although Pellegrino and his colleagues are currently studying this task (Pellegrino, Note 1), and the literature on concepts and thei attainment can be viewed as indirectly studying this sort of task (e.g., Bruner, Goodnow, & Austin, 1956; Rosch, 1978).

Several information-processing psychologists have claimed that the high intercorrelations obtained between subjects' performances on various kinds of problems of inducing structure are attributable to communalities in information processing across the various problem types (e.g., Greeno, 1978; Pellegrino & Glaser, 1979, in press; Sternberg, 1977b, 1979). The investigations reported here represent what we believe is a first attempt to demonstrate these communalities in information processing experimentally. To the extent that the investigations are successful, they offer the promise of illuminating at least some sources of the mysterious _g_ factor that has been obtained in numerous psychometric inquiries into the nature of human intelligence.

Two experiments were conducted. The first experiment sought to demonstrate that a common model could account for response choices in the solution of analogies, series completions, and classifications. The second experiment sought to demonstrate that a common model could account for real-time information processing in the solution of these three kinds of problems.

EXPERIMENT 1

Our proposed model of response choice in inductive reasoning of the sort required by analogies, series completions, and classifications, is an extension of the Rumelhart-Abrahamson (1973) model of response choice in analogical reasoning. Rumelhart and Abrahamson defined reasoning as the set of thought processes in information retrieval that operates upon the structure, as opposed to the content, of organized memory. If information retrieval depends upon specific content stored in memory, then retrieval is referred to as "remembering." If, however, information retrieval depends upon the form of one or more relationships among words, then it is referred to as "reasoning."

Pursuing this definition of reasoning, Rumelhart and Abrahamson claimed that probably the simplest possible reasoning task is the judgment of the similarity or dissimilarity between concepts. They assumed that the degree of similarity between concepts is not directly stored as such, but is instead derived from previously existing memory structures. Judged similarity between concepts is a simple function of the "psychological distance" between these concepts in the memory structure. The nature of this function and of the memory structure upon which it operates is clarified by their assumptions (after Henley, 1969) that (a) the memory structure may be represented as a multidimensional Euclidean space and that (b) judged similarity is inversely related to distance in this space.

On this view, analogical reasoning may be considered a kind of similarity judgment between concepts, one in which not only the magnitude of the distance but also the direction is of importance. For example, we would ordinarily interpret the analogy problem, A : B :: C : X_i, as stating that A is similar to B in exactly the same way that C is similar to X_i. According to the assumptions outlined above, we might reinterpret this analogy as saying that the directed or vector distance between $\underline{A}$ and $\underline{B}$ is exactly the same as the vector distance between $\underline{C}$ and $\underline{X}_i$. The analogy is imprecise to the extent to which the two vector distances are not equal.

Rumelhart and Abrahamson formalized the assumptions of their model by stating that given an analogy problem of the form A : B :: C : (X_1, X_2, ..., $X_{\underline{n}}$), it is assumed that

A1. Corresponding to each element of the analogy problem there is a point in an m-dimensional space....

A2. For any analogy problem of the form A : B :: C : ?, there exists a concept I such that A : B :: C : I and an ideal analogy point, denoted $\underline{I}$ such that $\underline{I}$ is located the same vector distance from $\underline{C}$ as $\underline{B}$ is from $\underline{A}$. The coordinates of $\underline{I}$ are given by the ordered sequence $\{\underline{c}_j + \underline{b}_j - \underline{a}_j\}$, $\underline{j}$ = 1, m.

A3. The probability that any given alternative $X_{\underline{i}}$ is chosen as the best analogy solution from the set of alternatives $X_{\underline{1}}$, ..., $X_{\underline{n}}$ is a monotonic decreasing function of the absolute value of the distance between the point $\underline{X}_i$

and the point $\underline{I}$, denoted $|\underline{X}_i - \underline{I}|$. (p. 4)

The first assumption simply states that the concepts corresponding to the elements of the analogy exist and are locatable within the $\underline{m}$-dimensional space representing the memory structure. The second assumption states that an ideal solution point also exists within the memory structure, and that this point also represents a concept; it is quite likely that no real-world concept will correspond to this ideal point, so that the ideal point may not have a named concept in the English (or any other) language. The third assumption states that the selection of a correct answer option is governed by the distance between the various answer options and the ideal point, such that less distant answer options are selected more often than are more distant answer options.

These assumptions permit ordinal predictions about the goodness of the various answer options, but do not permit quantitative predictions. In order to make quantitative predictions of response choices, Rumelhart and Abrahamson made assumption 3 more specific, and added two more assumptions:

> 3'. The probability that any given alternative X_i is chosen from the set of alternatives $X_1,\ldots,X_n$ is given by $Pr(X_i|X_1,\ldots,X_n) = \underline{p}_i = v(d_i)/[\sum_j^n v(d_j)]$, where $d_i = |\underline{X}_i - \underline{I}|$ denotes the absolute value of the distance between $\underline{X}_i$ and I, and v( ) is a monotonically decreasing function of its argument.
>
> 4. $v(X) = \exp(-\alpha X)$, where X and α are positive numbers.
>
> 5. We assume that the subjects rank a set of alternatives by first choosing the Rank 1 element according to 3' and, then, of the remaining alternatives, deciding which is superior by application of 3' to the remaining set and assigning that Rank 2. This procedure is assumed to continue until all alternatives are ranked. (pp. 8-9)

The more specific version of assumption 3 (labeled 3') is an adaptation of Luce's (1959) choice rule to the choice situation in the analogy. Assumption 4 further specifies that the monotone decrease in the likelihood of choosing a particular answer option as best follows an exponential decay function with increasing distance from the ideal point. The model of response choice therefore requires a single parameter, α, representing the slope of the function. Rumelhart and Abrahamson actually had their subjects rank-order answer options. The investigators predicted the full set of rank orderings by assuming (in assumption 5) that once subjects had ranked one or more options, they would rank the remaining options in exactly the same way that they had ranked the previous options, except that they would ignore the previously ranked options in making their further rankings.

Rumelhart and Abrahamson (1973) carried out three ingenious experiments to test their model of analogical reasoning, using Henley's (1969) mammal-name space of three dimensions (size, ferocity, humanness) as a basis for representing informatior about the mammals. The first experiment set out to show that subjects rank-order options in accordance with the assumptions outlined above. Subjects rank-ordered options in 30 analogy problems using mammal names as analogy terms. The second experiment set out to show that the response distribution should depend upon the ideal solution point and upon the alternative set, but not upon the terms of the particular analc gy problem. Twelve analogy pairs were constructed that had the same ideal points withi a tolerance of .12 scaled units (roughly the distance between a lion and a tiger), and in which the ith closest alternative for one set was at about the same distance from tl ideal point as the ith closest alternative for the other set. There were no overlappi analogy terms across paired items, however. The third experiment set out to show that if the ideal point of an analogy is given a name corresponding to an imaginary mammal, subjects will use the newly named mammal in the same way in solving analogies that they use the names of actual mammals. Subjects were taught the meanings of three imaginary mammals, and were then asked to perform some tasks that tested their understanding of the properties of these imaginary mammals. The experiments were generally supportive of the Rumelhart-Abrahamson model, and the results led the authors to conclude that at least for those portions of semantic memory that are representable as multidimensional semantic spaces, the proposed model of analogical reasoning provides a good account of response choices.

We propose a modest extension of the Rumelhart-Abrahamson model so that it can account for response choices in series completion and classification problems as well as in analogy problems. Figure 1 shows how the extended model accounts for response choices in each of the three types of problems.

Insert Figure 1 about here

Consider an analogy problem of the form, A : B :: C : (D_1, D_2, D_3, D_4), e.g., TIGER : CHIMPANZEE :: WOLF : (1. RACCOON, 2. CAMEL, 3. MONKEY, 4. LEOPARD), where the subject's task is to rank-order the answer options in terms of how well their relation to WOLF is parallel to that between CHIMPANZEE and TIGER. In an analogy problem such as this one, the subject must find an ideal point, $\underline{I}$, that is the same vector distance from WOLF as CHIMPANZEE is from TIGER. Having found this point, the subject rank-orders answer options according to their overall Euclidean distance from the ideal point. The probability of selecting any one answer option as best is assumed to follow an exponential decay function, with probability decreasing as distance from the ideal point increases. The same selection rule is applied in rank-ordering successive options, with previously selected options removed from consideration.

Consider next a series completion problem of the form, A : B : (C_1, C_2, C_3, C_4), e.g., SQUIRREL : CHIPMUNK : (1. RACCOON, 2. HORSE, 3. DOG, 4. CAMEL), where the subject's task is to rank-order the answer options in terms of how well they complete the series carried from SQUIRREL to CHIPMUNK. Here, the subject must find an ideal point, $\underline{I}$, that is the same vector distance from CHIPMUNK as CHIPMUNK is from SQUIRREL. Note that the difference between a series completion problem and an analogy is that whereas the terms of an analogy form a parallelogram (or its $\underline{m}$-dimensional analogue) in the multidimensional space, the terms of a series completion form a line segment (or its $\underline{m}$-dimensional analogue) in the space. The same principle would apply, regardless of the number of terms in the item stem. Having found the ideal point, the subject rank-orders answer options with respect to the ideal point in just the same way that he or she would in an analogy problem.

Consider finally a classification problem of the form, A, B, C, (D_1, D_2, D_3, D_4), e.g., ZEBRA, GIRAFFE, GOAT, (1. DOG, 2. COW, 3. MOUSE, 4. DEER), where the subject's task is to rank-order the answer options in terms of how well they fit with the three terms in the item stem. In this type of problem, the subject must find an ideal point, I, that represents the centroid in multidimensional space of ZEBRA, GIRAFFE, and GOAT. Having found this point, the subject rank-orders the answer options according to their overall Euclidean distance from the ideal point, in just the same was as he or she would for analogies or series completions. Again, the same basic principle applies without regard to the number of terms in the item stem. The centroid of the points is theorized always to serve as the ideal point.

In Experiment 1, subjects were presented 30 analogies, 30 series completions, and 30 classifications (in an order counterbalanced across subjects). The subjects' task was to rank-order the goodness of four alternative answer options in terms of their appropriateness as completions to the problem stems. The task was untimed.

Method

Subjects

Thirty college-age adults from the New Haven area--19 women and 11 men--participated in the experiment. Subjects received either pay at the rate of $2.50 per hour, credit toward fulfillment of an introductory psychology course requirement at Yale, or some combination of the two.

Materials

Problems of all three types--analogies, series completions, classifications--were composed of mammal names from the set multidimensionally scaled by Henley (1969). There were 30 problems of each type, and each drew upon the set of 30 names in the following ways.

Analogies were taken from Experiment 1 of Rumelhart and Abrahamson (1973).[1]

All 30 analogy problems were of the form, A : B :: C : (D_1, D_2, D_3, D_4), for example, TIGER : CHIMPANZEE :: WOLF : (1. RACCOON, 2. CAMEL, 3. MONKEY, 4. LEOPARD).[2] Rumelhart and Abrahamson constructed their analogy stems (A : B :: C) by sampling without replacement from the pool of 30 mammal names until all of the terms were exhausted, and then by replacing the entire pool. The first term sampled became the A term of the first problem; the second term became the B term of the first problem; the third term became the C term of the first problem; the fourth term became the A term of the second problem; etc. This selection procedure continued until 30 unique analogy stems were formed. At this point, answer options were selected with the following constraints: (a) one option was within .5 scaled units of distance from the ideal point; (b) a second option was between .5 and 1.0 scaled units from the ideal point; (c) a third option was between 1.0 and 1.5 scaled units from the ideal point; (d) a fourth option was more than 1.5 scaled units from the ideal point; additionally, answer options were not permitted to overlap with mammal names in the analogy stem. If any of these constraints could not be satisfied, a new unique stem was formed, and the constraints were again applied to the new analogy. This process was repeated until 30 acceptable analogies had been constructed.

Series completion problems were of the form, A : B : (C_1, C_2, C_3, C_4), for example, SQUIRREL : CHIPMUNK : (1. RACCOON, 2. HORSE, 3. DOG, 4. CAMEL).[3] The series completion problems were generated in a manner that was similar to that used for the analogy problems. All possible combinations of two of the mammal terms were produced, and an ideal point for each of these pairs of terms was calculated. This procedure yielded a total of 870 possible series completion problems. Problems were selected from this set at random until 30 acceptable items were produced. The constraints for acceptability were that (a) the ideal point lie within the (arbitrary) boundaries of the multidimensional space produced by Henley's (1969) scaling and that (b) four suitable answer options could be selected according to the constraints used for the production of answer options in the analogy problems.

Classification problems were of the form, A, B, C, (D_1, D_2, D_3, D_4), for example, ZEBRA, GIRAFFE, GOAT, (1. DOG, 2. COW, 3. MOUSE, 4. DEER).[4] Classification problem stems were sampled from all possible triplets of mammal names with geometric perimeters of greater than 1.5 scaled units of distance, but less than 2.0 scaled units. The perimeter of the "triangle" of terms in the multidimensional space was constrained in this way so that problems would be neither too easy nor too difficult: Very small perimeters (as would be obtained for TIGER, LION, LEOPARD) led to problems that were exceedingly easy, whereas very large perimeters (as would be obtained for GORILLA, SQUIRREL, CAMEL) led to problems that were exceedingly difficult. The permissible range for acceptable triples was rather small, and forced modification of the constraints used in selecting answer options so that a sufficient number of acceptable items could be produced. The new constraints were that (a) one answer option be within .4 scaled units of distance from the ideal point; (b) a second answer option be between .4 and .8 scaled units from the ideal point; (c) a third answer option be between .8 and 1.2 scaled units from the ideal point; and (d) a fourth answer option be at greater than 1.2 scaled units from the ideal point; answer options were not allowed to overlap in content with stem terms. Two hundred eighty-two classification problems satisfied all of the above constraints. These were sampled from randomly without replacement to produce 30 classification problems for the experiment.

A standardized test of general intelligence, Forms A and B of the Culture Fair Test of g, Level 3 (Cattell & Cattell, 1963), was also administered to all subjects. The test contained four types of inductive-reasoning problems--figural series completions, figural classifications, figural matrix problems, and figural topological reasoning problems.

Procedure

Subjects were tested in groups of from one to nine members. After signing consent forms, subjects read instructions silently for the three tasks combined while the experimenter read them aloud. Instructions made clear the natures of the three different tasks, and no subject expressed any questions about how each of the three tasks operated, or about how they differed from one another. Subjects then solved the 90 test problems, which were presented in paper-and-pencil format. The subjects' task was to rank-order the answer options from best to worst. Subjects were allowed as much time as they needed to finish; this time period never exceeded 1½ hours. Subjects who finished before others in their group were given an irrelevant filler task. When all subjects had completed the test items, they received the standardized intelligence test. After the test was completed (in roughly 45 minutes), subjects were debriefed and compensated for their participation.

Design

The main dependent variable was proportion of subjects choosing each possible response as first, second, third, and fourth best. The independent variable used to predict these proportions was distance of each option from the ideal point. One parameter, α, was estimated for the predicted negative exponential function. Problems were blocked into sets of 30 analogies, 30 series completions, and 30 classifications, presented in counterbalanced order across subjects such that five subjects received each of the six possible orders. Items within a block were presented in a different random order to each subject, and answer options within each item were also presented in a different random order to each subject. The standardized intelligence test was scored for number of items completed correctly.

Results

Basic Data Sets

The basic data sets for the present experiment, as well as for Experiment 1 of Rumelhart and Abrahamson (1973), are shown in Table 1. This table shows

---

Insert Table 1 about here

---

the proportions of subjects ranking each answer option as first, second, third, or fourth best, as a function of that option's distance from the ideal point. First, it is worth noting that the pattern of response choices in the 16 cells for the present analogy data closely replicate those in the 16 cells for the Rumelhart-Abrahamson analogy data, $r = .99+$, RMSD (root-mean-square deviation) $= .02$. Second, the patterns of response choices across the three tasks in the present experiment are highly similar: For analogies and series completions, $r = .99$, RMSD $= .03$; for analogies and classifications, $r = .97$, RMSD $= .05$; for series completions and classifications, $r = .98$, RMSD $= .04$. These high levels of similarity in response choices are consistent with the notion that a single model of response choice is used in all three tasks. Further analysis is needed, however, to test our proposal for what this model is.

Tests of Model of Response Choice

The value of α was estimated as 2.52 for the analogies, 2.56 for the series completions, and 2.98 for the classifications. Although these values differ significantly from each other, $\underline{F}(2,48) = 3.73$, $\underline{p} < .05$, they are certainly in the same ballpark, and the most extreme value corresponds roughly to that obtained by Rumelhart and Abrahamson for their analogies, 2.91. The somewhat discrepant value, that for classifications, was obtained in the task for which slightly different constraints were set on the distances of answer options from the ideal point, which, conceivably, might have been partly responsible for the discrepancy.

We believe that the three values are close enough to suggest that the decision rules used for rank-ordering options in each of the three tasks are extremely similar, if not identical.

The fits of the exponential model to the three data sets of the present experiment plus that of Rumelhart and Abrahamson (1973, Experiment 1) are shown in Figure 2, which compares predicted response choices to observed response choices. For analogies, r = .97, RMSD = .05; for series completions, r = .98,

Insert Figure 2 about here

RMSD = .04; for classifications, r = .99, RMSD = .03. Although the residual variance was small in each case, at least part of it was highly systematic. Residuals were correlated across task: The product-moment correlations were .83 between predicted minus observed values for analogies and series completions, .80 between residuals for analogies and classifications, and .95 between residuals for series completions and classifications. A visual inspection of the residuals revealed to us at least some of the systematic trends. Prediction of first-choice data tended to be best, as expected, since α was estimated on the basis of the first-choice data. Also, the proportion of subjects predicted to choose the best option as second best was overestimated in all three tasks, while the proportion of subjects predicted to choose the best option as third or fourth best was underestimated in each case. Responses to the best option were thus more spread out than was predicted by the model, perhaps because individual differences in perceptions of distance increase as distance increases.

Individual Differences

Analyses of individual differences were disappointing: Values of α were not significantly correlated with each other across tasks, nor were they significantly correlated with scores on the Cattell Culture Fair Test of g. Several other indices of overall performance on the three kinds of inductive reasoning tasks were also computed, but these did not correlate with each other or with the ability test. The low correlations presumably reflect the low reliability of the inductive-reasoning task scores for individual subjects, which for proportions of items answered correctly were .24 for analogies, .59 for series completions, and .30 for classifications.

Discussion

The results of this experiment suggest that one communality in performance across analogies, series completions, and classifications is in the model of response choice subjects use in rank-ordering the goodness of alternative answer options. The same model seemed to be used in each of these three tasks, and even the value of the exponential response-choice parameter seemed to be about the same in each experiment, and in close agreement with that obtained by Rumelhart and Abrahamson (1973) in their study of response choice in analogical reasoning. Although the proposed model of response choice provided a good fit to the response-choice data, the residual variance was largely systematic, suggesting that the proposed model did not capture all systematic features of the subjects' decision rule. The model also, of course, does not explain how subjects got to the point where they could rank-order the answer options. The information-processing model described below seeks to provide such an explanation.

EXPERIMENT 2

Our proposed model of real-time information processing in inductive reasoning of the sort required by analogies, series completions, and classifications, is an extension of the Sternberg (1977a, 1977b) model of information processing in reasoning by analogy. In this model, reasoning is viewed as involving (a) selection and execution of a set of components for solving reasoning problems, (b) selection and execution of a strategy for combining these components, (c) selection and utilization of an internal representation for information upon which the components and strategy act, (d) selection and maintenance of a speed-accuracy tradeoff whereby components are executed at a rate that produces an acceptable level of accuracy in performance, and (e) monitoring of one's decisions and solution processes to assure that information processing is leading toward an acceptable solution to the problem at hand.

Response time in reasoning is hypothesized to equal the sum of the amounts of time spent on the various information-processing components used in problem solution. Hence, a simple linear model predicts response time to be the sum across the different components of the number of times each component operation is performed (as an independent variable) multiplied by the duration of that component operation (as an estimated parameter). Proportion of response errors is hypothesized to equal the (appropriately scaled) sum of the difficulties encountered in executing each component operation. A simple linear model predicts proportion of errors to be the sum across the different component operations of the number of times each component operation is performed (as an independent variable) multiplied by the difficulty of that component operation (as an estimated parameter). This additive combination rule is based upon the assumption that each subject has a limit on processing capacity (or space; see Osherson, 1974). Each execution of an operation uses up capacity. Until the limit is exceeded, performance is flawless except for constant sources of error (such as motor confusion, carelessness, momentary distractions, etc.). Once the limit is exceeded, however, performance is at a chance level (Sternberg, 1977a).

Consider as an example the analogy, TIGER : CHIMPANZEE :: WOLF : (1. CAMEL, 2. MONKEY). According to the theory, a subject encodes each term of the analogy, retrieving from semantic memory and placing in working memory the locations in semantic space of the terms of the problem; next, the subject infers the relation between TIGER and CHIMPANZEE, recognizing the vector distance between these first two terms of the analogy; then, the subject maps the higher-order relation between the first and second halves of the analogy, here recognizing the vector distance from the term heading the first half (TIGER) to the term heading the second half (WOLF); next, the subject applies the relation inferred between the first two terms from the third analogy term, here, WOLF, to form an ideal point representing the ideal solution to the analogy; then, the subject compares answer options, seeking the ideal solution from among the answers presented;[5] if none of the answer options corresponds to the ideal point, the subject must justify one of the answer options as preferable to the other(s), in that it is closest to the ideal point (MONKEY is closer than CAMEL); finally, the subject responds with the chosen answer, MONKEY.

How does the information-processing model described above interface with the model of response-choice described earlier? Essentially, the exponential response-choice parameter of the response-choice model quantifies the decision rule used during justification of one response as superior to the others: It represents an end-product of the series of reasoning components. In a rank-ordering task, the subject applies justification repeatedly, successively assigning rank i to the alternative that is ith closest to the ideal point. Errors within and between subjects in the calculation of distances between the ideal point and the various answer options, as well as differences in placements of points in the mammal-name space, lead to intra- and inter-individual differences in assignments of ranks in accordance with the exponential function.

The same basic model can be extended to series completion problems. Consider, for example, the series completion, SQUIRREL : CHIPMUNK : (1. RACCOON, 2. HORSE). The subject must encode each term of the series completion. Next, he or she infers the relation of succession between SQUIRREL AND CHIPMUNK. Mapping is not necessary in this and other series problems, because there is no distinction geneous domain: Geometrically, there is no realignment of vectors from one area of the space (<u>A</u>:<u>B</u>) to another (<u>C</u>:<u>I</u>). The subject must, however, <u>apply</u> the relation inferred between SQUIRREL and CHIPMUNK from CHIPMUNK to an ideal point. Next, the subject <u>compares</u> the answer options, seeking the one corresponding to the ideal point. If neither option (or in the case of more than two options, none of the options) corresponds to the ideal point, the subject <u>justifies</u> one option as closer or closest to the ideal point. In the present example, RACCOON is closer to the ideal point than is HORSE. Finally, the subject <u>responds</u> with the chosen answer. As in the case of analogies, the rank-ordering task would require multiple justifications to determine which option is closest to the ideal point, of those options not yet ranked.

The model can also be extended to classification problems. Consider, for example, the problem, ZEBRA, GIRAFFE, GOAT, (1. COW, 2. DOG). The subject must <u>encode</u> the terms of the problem. Next, the subject must <u>infer</u> what is common to ZEBRA, GIRAFFE, and GOAT, in essence seeking a prototype or centroid that abstracts what is common to the three terms; as was the case in the series-completion problems, the subject need not map any higher-order relation, since all of the terms of the problem are from a single, homogeneous domain. In classification problems, application is also unnecessary, because the inferred centroid <u>is</u> the ideal point: The subject need not extrapolate in any way to seek some further point in the multidimensional semantic space. Next, the subject <u>compares</u> the answer options, seeking the ideal solution. If none is present, the subject <u>justifies</u> one option as closer to the ideal point than the other(s). Finally, the subject <u>responds</u>. As in the case of analogies and series completions, rank-ordering the options requires multiple executions of the <u>justification</u> component. Ranking in these problems and in the series completions proceeds according to the decision rule described in Experiment 1.

Whereas the same single parameter of response choice applies in all three inductive reasoning tasks, the parameters of information processing in the three tasks are slightly different: The analogies task requires the full set of seven information-processing parameters; the series completion task requires a subset of six of the seven parameters in the analogies task; the classification task requires a subset of five of the six parameters in the series completion task. Thus, one would expect that for problems with terms of equal difficulty, analogies would be slightly more difficult than series completion problems, and series completion problems would be slightly more difficult than classification problems.

In Experiment 2, subjects were presented with 30 analogies, 30 series completions, and 30 classifications (in an order counterbalanced across subjects). The subjects' task was to select the better of two alternative answer options in terms of its appropriateness as a completion to the problem stem. The subjects were timed as they solved each item.

Method

Subjects

Thirty-six college-age adults from the New Haven area--17 women and 19 men--participated in the experiment. Subjects received pay at the rate of $2.50 for their participation in the experiment.

Materials

The 30 analogies, 30 series completions, and 30 classifications had the same stems as the items in Experiment 1. They differed from the items in Experiment 1, however, in having two rather than four answer options. The two options in each problem were randomly chosen with the constraint that each possible pairing of options (best with second best, best with third best, best with worst, second best with third best, second best with worst, third best with worst) be equally represented. Since there were six possible kinds of pairings, five items of each of the three problem types contained one of the kinds of pairings.

Three standardized ability tests were used in this experiment. Like the test in the first experiment, the items required inductive reasoning of the kind required for solution of the items in the main part of the experiment. The tests were figural classifications and figural analogies from Form 1 of the Cognitive Abilities Test, Level H (Thorndike & Hagen, 1971), and figural analogies from Form T of the Differential Aptitude Test (Bennett, Seashore, & Wesman, 1972).

Procedure

Subjects were tested individually. Stimulus items were presented tachistoscopically, and response latencies were timed via an attached millisecond clock. The stimuli were presented via the method of precueing (Sternberg, 1977b, 1978), whereby each stimulus trial is divided into two parts. In the first part of the trial, the subject received some amount of precueing; the subject was told to take as long as he or she needed to process the advance information fully, but no longer. In the second part of the trial, the subject received the full stimulus item; the subject was told to solve the item as quickly as possible, using whatever information may have been gleaned from the first part of the trial, without making an error. There were two conditions of precueing: In an uncued condition, the first part of the trial consisted merely of a lighted, blank field; in a cued condition, the first part of the trial consisted of either the first two terms of the item (analogies and series completions) or the first three terms of the item (classifications). The second part of the trial was always presented one second after the subject indicated by pressing a button that he or she had completed processing of the first part of the trial. The purpose of the precueing was to facilitate separation of parameters that would otherwise have been confounded: The data of primary interest were those from the second part of the trial, in which the full item was presented.

Each item was presented twice, once in the uncued condition and once in the cued condition. Items were presented in 12 blocks of 15 items each. Each block contained a single type of item (analogies, series completions, or classifications) in a single condition of precueing (uncued or cued). Item types alternated across successive blocks such that subjects always received one of the six possible permutations of analogies, series completions, and classifications in three adjacent blocks. The same permutation was used repeatedly (four times) for a given subject, but permutations were varied across subjects. Precueing conditions alternated across successive blocks such that a cued block always followed an uncued block (or vice versa) until the full set of items had been exhausted after six blocks. At this point, each item had been presented in one or the other condition of precueing. Then the items were re-presented according to the same scheme, except that each item was presented in the precueing condition in which it had not yet appeared. Testing on the stimulus items consumed roughly 2½ hours.

The ability tests were administered in pencil-and-paper format in fixed order (figural classifications, then figural analogies, then figural series completions) upon completion of the tachistoscopic testing. Ability testing took about ½ hour, and was conducted in a separate session.

Design

The main dependent variable was response latency to solution in the second part of the trial. Error rate served as a subsidiary dependent variable. It was assumed that subjects used prior information presented in the cued condition to reduce as much as possible the information processing required in the second part of the trial. For example, when presented with the first two terms of an analogy in the first part of the trial, subjects were assumed to encode these terms and to infer the relation between them so that they would not have to perform these operations in the second part of the trial. The independent variables used to predict response latencies and error rates in the second part of the trial for cued items thus took into account information processing in the first part of the trial. The independent variables (for both cued and uncued items) were (a) the number of terms to be encoded; (b) spatial distance between A and B (for analogies and series completions) or the maximum of the three distances between A and B, A and C, and B and C (for classifications), used to estimate inference time and difficulty; (c) spatial distance between A and C (for analogies), used to estimate mapping time and difficulty; (d) spatial distance between C and I (for analogies) or between B and I (for series completions), used to estimate application time and difficulty; (e) spatial distance between D_1 and D_2 (for analogies and classifications) or between C_1 and C_2 (for series completions), used to estimate comparison time and difficulty; (f) spatial distance between I and D_{Keyed} (for analogies and classifications) or between I and C_{Keyed} (for series completions), used to estimate justification time and difficulty. Motor response time and difficulty were estimated as regression constan

Subjects were crossed with precueing conditions and with items such that each subject received each item in each condition of precueing. Items within a block were presented in a different random order to each subject. Ability tests were scored for number of items completed correctly.

Results

Basic Statistics

Table 2 presents mean response latencies for all items (correctly answered and incorrectly answered combined) and for correctly answered items only.

Insert Table 2 about here

Recall that according to the proposed information-processing model, errors can result when an overflow occurs in the processing capacity or space allocated to a given item. When an overflow occurs, some items are answered correctly by chance; others are answered incorrectly. An incorrect answer guarantees that an overflow has occurred, although a correct answer does not guarantee that one has not occurred, since the answer may have been correct by chance. But the same information-processing model applies in any of these events. Hence, modeling was performed upon all data points. In fact, modeling correct latencies only would have had little differential effect, since, as can be seen in the table, the mean values for the two data sets were very close to each other, and since the correlations across item types between the two data sets were very high (.95 for analogies, .93 for series completions, and .97 for classifications).[6]

A two-way analysis of variance on all solution latencies revealed a significant effect of task, $F(2,70) = 30.12$, $p < .01$, and of precueing, $F(1,35) = 145.51$ $p < .01$. The interaction was not significant, $F(2,70) = .74$, $p > .10$. A two-way analysis of variance on error rates also revealed a significant effect of task, $F(2,70) = 6.64$, $p < .01$, but a nonsignificant effect of precueing condition, $F(1,35) = 1.52$, $p > .10$. The interaction was nonsignificant, $F(2,70) = .29$, $p > .10$.

It is of interest to note that analogies were solved most slowly, series completions next most slowly, and classifications most rapidly. This is the rank order of processing time predicted by the model, according to which analogies require one more component than do series completions, which in turn require one more component than do classifications. The error rates did not show this pattern: Although classifications had a lower mean error rate than did analogies, series completions had the highest error rate. We are uncertain as to how to account for this finding.

Task Intercorrelations and Factor Structure

Intercorrelations across subjects were computed between mean response latencies for each pair of data sets: The correlations were .85 between analogies and series completions, .86 between analogies and classifications, and .88 between series completions and classifications. A principal-components factor analysis of the three sets of latencies revealed a strong general factor in the first, unrotated principal component, accounting for 91% of the variance in the individual-differences data. Had the tests shown no overlap in individual differences variation (zero intercorrelations), this factor would have accounted for only 33% of the individual-differences variation. The data are thus consistent with the notion that a single real-time information-processing model might apply across tasks.

A comparable set of analyses was performed on the ability-test scores: Here, the correlations were .72 between analogies and series completions, .45 between analogies and classifications, and .65 between series completions and classifications. A principal-components factor analysis of the three sets of test scores (numbers correct) revealed an unrotated, general first factor accounting for 74% of the variance in the individual-differences data. Again, such a factor would have accounted for only 33% of the individual-differences variation if the intertask correlation had been 0. These results, too, are consistent with the notion of common processes across tasks. Indeed, high correlations and the resulting strong general factor resulting from sets of ability tests like these were the first psychometric clue we had, historically, that common processes were involved across inductive reasoning tasks found on intelligence tests.

Finally, intercorrelations were computed between task scores across the two forms of task presentation (tachistoscopic, leading to response latencies, and pencil-and-paper, leading to numbers correct). Correlations across task format were lowe. than those within format, as would be expected if there were at least some medium-specific variance that were not shared across task formats. Such medium-specific variance might result from differences across task formats in speed-accuracy tradeoffs, in attentional allocations for items presented singly (as in a tachistoscopic task) and for items presented as a group (as in a pencil-and-paper task), in kinds of strategy or other planning required, or in what is measured by latency and accuracy scores. Most probably, some combination of these and other factors was involved. The correlations ranged from -.21 to -.41, with a median for the nine intertask correlations of -.35 ($p < .05$). Correlations of tasks with their analogues across formats (e.g., tachistoscopic analogies with pencil-and-paper analogies) were only trivially higher than correlations of nonanalogous tasks across formats (e.g., tachistoscopic analogies with pencil-and-paper series completions): The median correlation for analogous tasks was -.35 ($p < .05$), whereas the median correlation for nonanalogous tasks was -.30 ($p < .05$). A factor analysis of the six tasks (three tachistoscopic and three pencil-and-paper) yielded a first, unrotated principal component accounting for 57% of the variance in the data. If tests were uncorrelated, a value of 17% would have been obtained. The response latencies all loaded in the .80s on this factor, whereas the number-correct measures all loaded in the .60s on the factor. The higher loadings of the response-latencies would be expected on the basis of their higher intercorrelations with each other. As expected, the second unrotated principal component, accounting for 26% of the variance in the data, was a bipolar factor distinguishing pencil-and-paper tasks from response-latency ones. The general factor unifying the various kinds of tasks was thus about twice as strong as the medium-specific factor differentiating the two task formats. Subsequent factors were of little interest.

<u>Tests of Model of Information Processing</u>

<u>Response latencies</u>. The proposed model of information processing was fit to the response latencies for uncued and cued conditions combined (60 data points) in each of the three tasks. Four parameters--encoding, comparison, justification, and response--could be estimated reliably in each of the three tasks, and hence final models were based only upon these four parameters. Other parameters could be estimated reliably in some tasks but not others, but since our interest was in unities in information processing, these parameters were deleted from the final common model. It is impossible to say whether the failure to estimate these other parameters reliably was due to insufficient stability of the data or to failure of the full model to account for information processing in one or more tasks. Further analyses will be based only upon the common parameters.

Table 3 shows parameter estimates for each parameter in each task. If the

---

Insert Table 3 about here

---

tasks truly involve the same components, then the parameter estimates should be equal within a margin of error of estimation across tasks.[7] A one-way analysis of variance was conducted across tasks upon each of the four parameter estimates of interest. For encoding, $\underline{F}(2,70) = 2.81$, $.05 < \underline{p} < .10$; for comparison, $\underline{F}(2,70) = .46$, $\underline{p} > .10$; for justification, $\underline{F}(2,70) = 9.88$, $\underline{p} < .001$; for response, $\underline{F}(2,70) = 2.48$, $.05 < \underline{p} < .10$. Only one of the parameters--justification--showed a clearly significant difference in value across the three tasks; two others showed marginally significant differences, and one showed no difference at all. These results are interpreted as at least modestly supportive of process equivalence or near-equivalence across tasks, with the exception of the result for justification.

The fits of the model to the three sets of data were assessed by correlating predicted with observed values and by calculating the root-mean-square deviation

(RMSD) of observed from predicted values. For analogies, r = .88, RMSD = 1.10 seconds; for series completions, r = .82, RMSD = .92 seconds; for classifications, r = .78, RMSD = 1.09 seconds. The maximum possible values of the correlations according to classical test theory are the square roots of the reliabilities of the data sets, which were .96 for analogies, .92 for series completions, and .93 for classifications. Thus, most but not all of the systematic variance in the data was accounted for by the model. Residuals of observed from predicted values were correlated for random halves of the subjects, and corrected by the Spearman-Brown formula. All correlations were statistically significant (.61 for analogies, .64 for series completions, .75 for classifications), indicating that the residual variance was indeed quite reliable. At least some of this unaccounted for variance was probably attributable to parameters that were not statistically reliable for all three tasks, and hence were not included in the final model fitting for any of the tasks. Further unexplained variance probably resulted from attributes of mammals that are not captured by the three-dimensional spatial representation into which the mammals were placed.

Error rates. Similar modeling was done for error rates, although parameter estimates for individuals were extremely unstable, and could not be compared across tasks. Fits were assessed by the correlation between predicted and observed values and by root-mean-square deviation. For analogies, r = .43, RMSD = .16; for series completions, r = .61, RMSD = .15; for classifications, r = .39, RMSD = .16. The respective square roots of the reliability coefficients were .92, .92, and .93.

Correlations of Latency Parameters across Tasks

Correlations were computed across pairs of latency parameters for individual tasks. These correlations were generally positive but statistically nonsignificant, perhaps in part because each individual parameter estimate was computed on the basis of only a single observation for each of 60 data points (30 uncued and 30 precued).

Discussion

The results of this experiment suggest that one communality in performance across analogies, series completions, and classifications is in the model of information processing subjects use in solving the induction problems. The same model seemed to be used in each of the three tasks, and the values of the real-time information processing parameters were generally comparable across tasks, with the notable exception of justification. Because previous tests of the proposed model on analogy problems were conducted upon problems with very different types of content, it was not possible to compare parameter estimates obtained in this experiment to those obtained in previous work (e.g., Sternberg, 1977b). Although the proposed model of information processing provided a good fit to the latency data and a fairly good fit to the less reliable error data, the residual variance was systematic at least in part, suggesting that the proposed model did not capture all systematic features of the subjects' information processing. The model does not, of course, explain how subjects actually decide upon their response choices: This function is served by the previously described model of response choice, which fills in the decisions that take place during execution of the justification component.

GENERAL DISCUSSION

The two experiments reported in this article, taken together, suggest that the high intercorrelations found in the past across subjects' performance on three inductive reasoning tasks commonly found in intelligence-testing batteries were probably due at least in part to communalities in models of response choice and information processing used in the three tasks. Results of the first experiment indicated that the Rumelhart-Abrahamson (1973) model of response choice in analogical reasoning could be extended to series completions and classifications as well;

results of the second experiment indicated that the Sternberg (1977a, 1977b) model of information processing in analogical reasoning could be similarly extended.

The unities identified in this experiment have been demonstrated only for reasoning problems using a single type of content--mammal names. In order to build a strong case for a unified account of inductive reasoning in the three tasks studied here, one would want to demonstrate communalities across contents as well as within a single content. One of us is currently engaged in analyzing data from such research (Sternberg, Note 2), where the three tasks considered in this experiment are crossed with three different types of content--schematic-picture, verbal, and geometric.

The implementations of the models described in this research assumed a multidimensional representation for information in the data base upon which information processing took place. This assumption limits the content domains to which the theories as implemented here can be expeditiously applied, since only semantic fields seem to yield clean, interpretable, and replicable dimensions.[8] Previous research has shown that theory testing can be carried quite far through the use of semantic fields (e.g., Rips, Shoben, & Smith, 1973; Rumelhart & Abrahamson, 1973; Shepard, 1964; Shepard, Kilpatric, & Cunningham, 1975; Smith, Shoben, & Rips, 1974; Sternberg, Tourangeau, & Nigro, 1979; Tourangeau & Sternberg, in press). Nevertheless, the constraint of using a semantic field must be seen as limiting the generality of the results. It must be emphasized that this constraint is a practical one rather than a theoretical one, in the sense that a spatial representation might apply to items not falling into semantic fields, but merely be difficult to reproduce through the experimental and scaling techniques presently available to us. We agree with Hutchinson and Lockhead (1977) that a spatial representation provides a rather general form of representation for a variety of purposes, and with Hollan (1975) that spatial and network models are mathematically interchangeable. Rips, Smith, and Shoben (1975) have noted that the choice of representation serves a largely heuristic function, and in the present research, the spatial representation seems to have served this function reasonably well. Although we believe that subjects use a spatial representation in solving these problems, we also believe that other representations are available to subjects as they solve these (and other) problems, and that subjects make use of these alternative representations as needed. To illustrate, modeling of error rates in the first experiment reported here (and in a previously reported experiment, Sternberg, 1977b) reveals that an overlapping clustering model (Shepard & Arabie, 1979) fits the error data quite well for analogies and classifications. In classifying three animals such as a LION, TIGER, and LEOPARD as similar, for example, it seems quite likely that subjects would cluster them as "ferocious jungle beasts" as well as identifying them according to their size, ferocity, and humanness in a spatial representation. The cluster representation does not work well for series completions, where, logically as well as psychologically, it would seem inappropriate. As mentioned earlier, some of the systematic unexplained variance in the modeling of the data in these experiments was probably due to alternative encodings of the mammal names that are not captured in the first three dimensions of a spatial model of representation.

Another simplification in the present research is the assumption that an additive, serial model of information processing describes the sequencing of information processing in the execution of strategy for solving induction items. In fact, it seems unlikely that subjects process information strictly in this manner. Grudin (in press) has presented evidence suggesting that in analogy solution, subjects sometimes infer the relation between A and C and map the relation between A and B, rather than the other way around. Whitely and Barnes (1979) have presented evidence suggesting that there are at least some individual differences in the order in which subjects process information in analogy solution. The work of Simon and Kotovsky (1963) also suggests forms that individual differences might take in the solution of series completions. The approximation proposed in this article seems like a reasonable start toward understanding reasoning in induction problems, although there is certainly a long way to go in this quest.

The present research goes far enough to suggest that there are important communalities in the rules for response choice and the strategies for information processing used in three induction tasks, but it does not go far enough to suggest just what psychological mechanisms underlie these communalities. Processes such as "encoding" and "inference" need to be unpacked in order to determine not just what is done, but how it is done.

We have concentrated upon communalities across induction tasks in the performance component of information processing, but we believe that another major source of communalities across these and other tasks is to be found at the "metacomponential" level of information processing (Sternberg, 1979, Note 3), where plans and decisions are made regarding what performance components will be used in information processing. The problem of isolating the metacomponents of information processing from composite task performance is currently being pursued by one of us (R.J.S.) in collaboration with Bill Salter.

One of the most widely replicated findings in the literature on human intelligence is that of a general factor of intelligence, whereby people who tend to perform well (or poorly) on one set of tasks also tend to perform well (or poorly) on other sets of tasks. Although the finding of a general factor can scarcely be disputed at this point in time, the psychological explanation for this finding has been a source of considerable debate (Hunt, 1978; Spearman, 1927; Thomson, 1939; Thorndike, Bregman, Cobb, & Woodyard, 1928; Sternberg, 1979; Hunt, Note 4; Jensen, Note 5; Sternberg, Note 3). The present article suggests some possible sources of generality in an important subset of intelligent behavior, that of inducing structure.

In one respect, the major objective of the present research is consistent with that of traditional factor-analytic research: Both kinds of research seek to understand sources of communalities in performance on different complex information-processing tasks. In another respect, however, the objective is quite different: The present research seeks these sources of communality in dynamic information-processing constructs rather than in static factorial ones. In this respect, the research is similar in its major objective to the research of Carroll (1976), Hunt, Lunneborg, and Lewis (1975), and Sternberg (1977b). Factors are viewed as interpretable in information processing terms, and hence as reducible to more elementary sources of individual differences. But just as it was necessary to understand factors in terms of the more basic information-processing components that constitute them, so is it now necessary to understand the psychological mechanisms that are used to effectuate these performance components. Research on metacomponents may prove to be a start in this direction, although it is too early to tell. To a large extent, this research, like factor-analytic research, will be successful to the degree that it stimulates the level of theorizing that will eventually subsume it as a special case.

Reference Notes

1. Pellegrino, J. W. Personal communication, November, 1978.

2. Sternberg, R. J. Components of inductive reasoning. Research in progress, October, 1979.

3. Sternberg, R. J. Components of human intelligence. (NR 150-412 ONR Technical Report No. 19.) New Haven: Department of Psychology, Yale University, 1979.

4. Hunt, E. Intelligence as an information-processing construct. (NR 154-398 ONR Technical Report No. 5.) Seattle: Department of Psychology, University of Washington, 1979.

5. Jensen, A. R. g: Outmoded theory or unconquered frontier. Invited address presented to the American Psychological Association, Toronto, 1978.

References

Bennett, G. K., Seashore, H. G., & Wesman, A. G. Differential aptitude tests. New York: The Psychological Corporation, 1972.

Bruner, J. S., Goodnow, J. J., & Austin, G. A. A study of thinking. New York: Wiley, 1956.

Burt, C. The factors of the mind. London: University of London Press, 1940.

Carroll, J. B. Psychometric tests as cognitive tasks: A new "structure of intellect." In L. B. Resnick (Ed.), The nature of intelligence. Hillsdale, N.J.: Erlbaum, 1976.

Cattell, R. B. Abilities: Their structure, growth, and action. Boston: Houghton-Mifflin, 1971.

Cattell, R. B., & Cattell, A. K. S. Test of g: Culture fair, Scale 3. Champaign, Illinois: Institute for Personality and Ability Testing, 1963.

Evans, T. G. A program for the solution of geometric-analogy intelligence test questions. In M. Minsky (Ed.), Semantic information processing. Cambridge, Massachusetts: M.I.T. Press, 1968.

Greeno, J. G. Natures of problem-solving abilities. In W. K. Estes (Ed.), Handbook of learning and cognitive processes (Vol. 5: Human information processing). Hillsdale, N.J.: Erlbaum, 1978.

Grudin, J. Processes in verbal analogy solution. Journal of Experimental Psychology: Human Perception and Performance, in press.

Henley, N. M. A psychological study of the semantics of animal terms. Journal of Verbal Learning and Verbal Behavior, 1969, 8, 176-184.

Hollan, J. D. Features and semantic memory: Set-theoretic or network model? Psychological Review, 1975, 82, 154-155.

Holzman, T. G., Glaser, R., & Pellegrino, J. W. Process training derived from a computer simulation theory. Memory and Cognition, 1976, 4, 349-356.

Horn, J. L. Organization of abilities and the development of intelligence. Psychological Review, 1968, 75, 242-259.

Horn, J. L., & Cattell, R. B. Refinement and test of the theory of fluid and crystallized ability intelligences. Journal of Educational Psychology, 1966, 57, 253-270.

Humphreys, L. G. The organization of human abilities. American Psychologist, 1962, 17, 475-483.

Hunt, E. B. Mechanics of verbal ability. Psychological Review, 1978, 85, 109-130.

Hunt, E. B., Lunneborg, C., & Lewis, J. What does it mean to be high verbal? Cognitive Psychology, 1975, 7, 194-227.

Hutchinson, J. W., & Lockhead, G. R. Similarity as distance: A structural principle for semantic memory. Journal of Experimental Psychology: Human Learning and Memory, 1977, 3, 660-678.

Kotovsky, K., & Simon, H. A. Empirical tests of a theory of human acquisition of concepts for sequential events. Cognitive Psychology, 1973, 4, 399-424.

Luce, R. D. Individual choice behavior. New York: Wiley, 1959.

Mulholland, T. M., Pellegrino, J. W., & Glaser, R. Components of geometric analogy solution. Cognitive Psychology, in press.

Osherson, D. N. Logical abilities in children (Vol. 2): Logical inference: Underlying operations . Hillsdale, N.J.: Erlbaum, 1974.

Pellegrino, J. W., & Glaser, R. Cognitive correlates and components in the analysis of individual differences. In R. Sternberg & D. Detterman (Eds.), Human intelligence: Perspectives on its theory and measurement. Norwood, N.J.: Ablex, 1979.

Pellegrino, J. W., & Glaser, R. Components of inductive reasoning. In R. E. Snow, P.-A. Federico, & W. E. Montague (Eds.), Aptitude, learning, and instruction: Cognitive process analysis (Vol. 1). Hillsdale, N.J.: Erlbaum, in press.

Reitman, W. Cognition and thought. New York: Wiley, 1965.

Rips, L. J., Shoben, E. J., & Smith, E. E. Semantic distance and the verification of semantic relations. Journal of Verbal Learning and Verbal Behavior, 1973, 12, 1-20.

Rips, L. J., Smith, E. E., & Shoben, E. J. Set-theoretic and network models reconsidered: A comment on Hollan's "Features and semantic memory." Psychological Review, 1975, 82, 156-157.

Rosch, E. R. Human categorization. In N. Warren (Ed.), Studies in cross-cultural psychology. London: Academic Press, 1978.

Rumelhart, D. E., & Abrahamson, A. A. A model for analogical reasoning. Cognitive Psychology, 1973, 5, 1-28.

Shepard, R. N. Attention and the metric structure of the stimulus space. Journal of Mathematical Psychology, 1964, 1, 54-87.

Shepard, R. N., & Arabie, P. Additive clustering: Representation of similarities as combinations of discrete overlapping properties. Psychological Review, 1979, 86, 87-123.

Shepard, R. N., Kilpatric, D. W., & Cunningham, J. P. The internal representation of numbers. Cognitive Psychology, 1975, 7, 82-138.

Simon, H. A., & Kotovsky, K. Human acquisition of concepts for sequential patterns. Psychological Review, 1963, 70, 534-546.

Smith, E. E., Shoben, E. J., & Rips, L. J. Structure and process in semantic memory: A feature model for semantic decisions. Psychological Review, 1974, 81, 214-241.

Spearman, C. The abilities of man. New York: Macmillan, 1927.

Sternberg, R. J. Component processes in analogical reasoning. Psychological Review, 1977, 84, 353-378. (a)

Sternberg, R. J. Intelligence, information processing, and analogical reasoning: The componential analysis of human abilities. Hillsdale, N.J.: Erlbaum, 1977. (b)

Sternberg, R. J. Isolating the components of intelligence. Intelligence, 1978, 2, 117-128.

Sternberg, R. J. The nature of mental abilities. American Psychologist, 1979, 34, 214-230.

Sternberg, R. J., Tourangeau, R., & Nigro, G. Metaphor, induction, and social policy: The convergence of macroscopic and microscopic views. In A. Ortony (Ed.), Metaphor and thought. New York: Cambridge University Press, 1979.

Thomson, G. H. The factorial analysis of human ability. London: University of London Press, 1939.

Thorndike, E. L., Bregman, E. O., Cobb, M. V., & Woodyard, E. I. The measurement of intelligence. New York: Teachers College, 1928.

Thorndike, R. L., & Hagen, E. Cognitive Abilities Test, Form 1. Boston: Houghton-Mifflin, 1971.

Thurstone, L. L. Primary mental abilities. Chicago: University of Chicago Press, 1938.

Tourangeau, R., & Sternberg, R. J. Aptness in metaphor. Cognitive Psychology, in press.

Vernon, P. E. The structure of human abilities. London: Methuen, 1971.

Webster's new collegiate dictionary. Springfield, Mass.: G. & C. Merriam, 1975.

Whitely, S. E., & Barnes, G. M. The implications of processing event sequences for theories of analogical reasoning. Memory and Cognition, 1979, 7, 323-331.

Williams, D. S. Computer program organization induced from problem examples. In H. A. Simon & L. Siklossy, Representation and meaning: Experiments with information processing systems. Englewood Cliffs, N.J.: Prentice-Hall, 1972.

Winston, P. H. Learning structural descriptions from examples. In P. H. Winston (Ed.), The psychology of computer vision. New York: McGraw-Hill, 1974.

Footnotes

This research was supported by Contract N0001478C0025 from the Office of Naval Research to Robert J. Sternberg. We are grateful to members of Robert Sternberg's research group at Yale for valuable comments on an earlier version of the manuscript. Portions of this paper were presented at the annual meeting of the Society for Mathematical Psychology, Providence, August, 1979. Requests for reprints should be addressed to Robert J. Sternberg, Department of Psychology, Yale University, Box 11A Yale Station, New Haven, Connecticut 06520.

[1]We are grateful to Adele Abrahamson for supplying the analogies used in Experiment 1 of Rumelhart and Abrahamson (1973). The analogies were formed from Henley's (1969) scaling of 30 mammal names in a three-dimensional space. This multidimensional scaling resulted in three interpretable dimensions--size, ferocity, and humanness--and Euclidean distances within the space were computed on the basis of distances between coordinates on these three dimensions.

[2]The "correct" rank order, based upon distance from the ideal point, is 1. MONKEY, 2. RACCOON, 3. LEOPARD, 4. CAMEL.

[3]The "correct" rank order is 1. RACCOON, 2. DOG, 3. HORSE, 4. CAMEL.

[4]The "correct" rank order is 1. DEER, 2. COW, 3. DOG, 4. MOUSE.

[5]The comparison component did not appear in the theory of analogical reasoning as originally presented (Sternberg, 1977a, 1977b). The model separating comparison from application was tested in one experiment (Sternberg, 1977b, Chapter 7), but was found not to perform as well as the model in which this separation did not occur. Hence, the model with the additional parameter was rejected. Whitely and Barnes (1979) have recently suggested that the separation should have been maintained. The present data are consistent with their data in suggesting the utility of the separation, and hence it is now introduced into the model, as suggested by Whitely

and Barnes, who refer to the component as "confirmation."

[6]We initially performed modeling on both sets of data, but because the only differences that were obtained were minor and seemingly due to the lessened reliability of the "corrects only" data set (from which error latencies had been removed), we discontinued this duplication of effort.

[7]In order for the expectation of the parameter estimates to be the same in all three tasks, it is also necessary that the same content and representation of information apply across tasks. The content obviously was the same. There is some evidence of possible minor differences in representations (as discussed in the General Discussion of the paper).

[8]By "semantic field," we mean a set of terms that all fall into a single, clearly definable, semantic category, such as mammal names, bird names, presidents of the United States, brand names of automobiles, etc.

Table 1

Subjects' Rankings as a Function of Alternative Distance and Task

Rank distance of the Alternative from I	Subject-assigned ranks 1	2	3	4	Task
1	.709	.180	.069	.046	Rumelhart and Abrahamson's Analogies
2	.177	.546	.137	.129	
3	.086	.160	.526	.226	
4	.043	.111	.243	.600	
	1	2	3	4	
1	.659	.204	.089	.048	Analogies
2	.211	.521	.139	.129	
3	.080	.149	.543	.228	
4	.050	.126	.229	.596	
	1	2	3	4	
1	.686	.181	.076	.058	Series Problems
2	.221	.556	.161	.062	
3	.050	.181	.527	.242	
4	.043	.082	.237	.638	
	1	2	3	4	
1	.599	.268	.094	.039	Classifications
2	.284	.478	.177	.061	
3	.091	.186	.508	.216	
4	.026	.069	.221	.684	

Note: Tabled values represent proportions of subjects assigning each rank to each answer option. Each proportion is based upon 900 observations (30 subjects x 30 items).

Table 2

Mean Solution Latencies and Error Rates for Each Condition of Precueing

Response Latencies

Item Type	All Items		Items Correctly Answered	
	Uncued	Cued	Uncued	Cued
Analogies	8.51	6.06	8.28	5.95
Series Completions	7.08	5.08	6.74	4.99
Classifications	6.65	4.29	6.45	4.05

Error Rates

Item Type	Uncued	Cued
Analogies	.23	.22
Series Completions	.26	.24
Classifications	.18	.18

Note: Response latencies are expressed in seconds.

Table 3

Parameter Estimates for Each Information-Processing Component in Each Task

Parameter	Task	Parameter Estimate
Encoding	Analogies	1.22
	Series Completions	1.00
	Classifications	.79
Comparison	Analogies	.13
	Series Completions	.14
	Classifications	.14
Justification	Analogies	.36
	Series Completions	.18
	Classifications	.24
Response+[a]	Analogies	1.36
	Series Completions	3.36
	Classifications	2.93

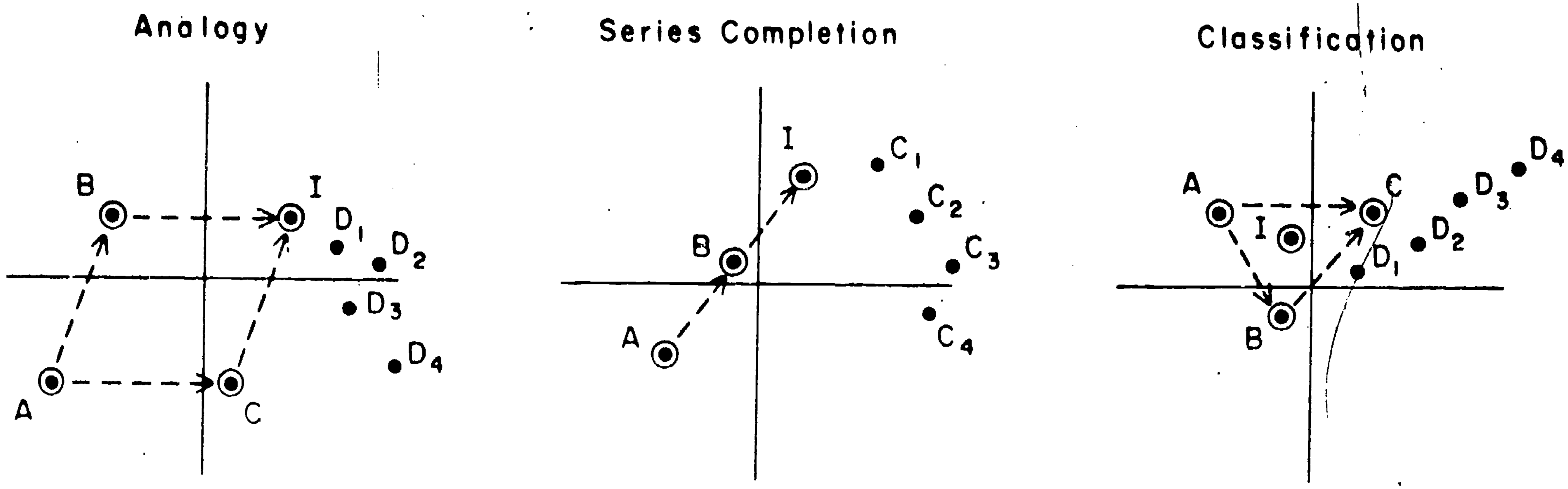
Note: Parameter estimates, expressed in seconds, are unstandardized linear regression coefficients. Comparison was estimated as a "time savings" for greater distance, but is expressed here in unsigned form. All coefficients are statistically significant at the 5% level or better.

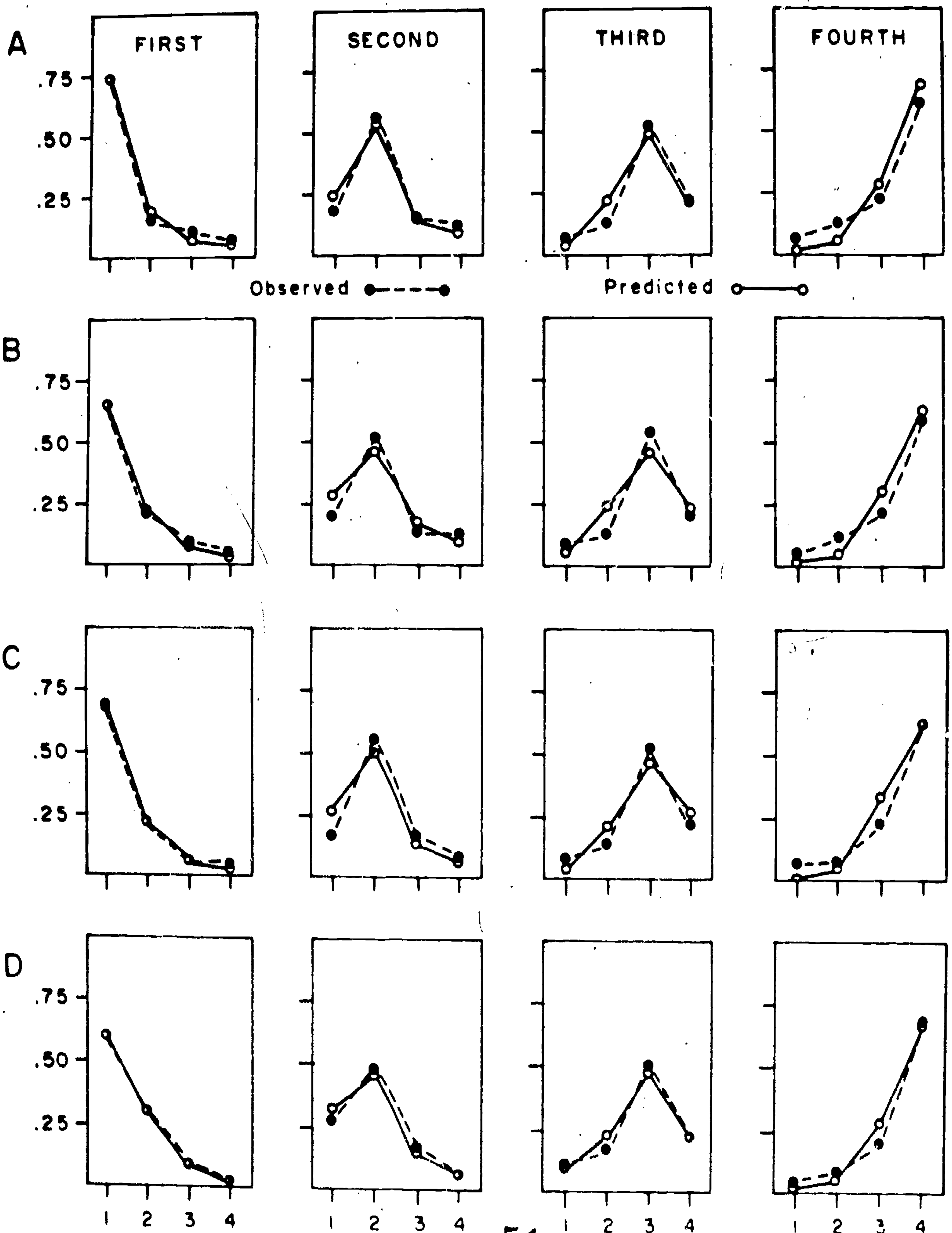
[a]The estimation of this parameter includes the response component latency plus any other latency constant across all item types.

Figure Captions

Figure 1. Schematic diagrams showing rules for arriving at ideal point, _I_, in each of three induction tasks. In analogies, _I_ is located as the fourth vertex in a parallelogram having _A_, _B_, and _C_ as three given vertices. In series completions, _I_ is located as the completion of a line segment that is at the same vector distance from _B_ that _B_ is from _A_. In classifications, _I_ is the centroid of the triangle with _A_, _B_, and _C_ as vertices. The rules can be extended to _n_ dimensions by assuming _n_-dimensional analogues to the two-dimensional figures depicted. In each type of problem, four answer options are presented at successively greater Euclidean distances from the ideal point.

Figure 2. Predicted versus observed proportions of subjects ranking each of the four answer options as first, second, third, and fourth choice. Columns 1, 2, 3, and 4 correspond to the first-, second-, third-, and fourth-choice data, respectively. Panel A is for Rumelhart and Abrahamson's (1973) analogy data; panel B is for the analogy data in the current experiment; panel C is for the series completion data in the present experiment; panel D is for the classification data in the present experiment. The abscissa of each graph is the rank distance of each answer option from the ideal point; the ordinate is the proportion of subjects choosing each option. Predicted data are represented by solid lines, and observed data are represented by broken lines.


Analogy
A
B
C
I
D1
D2
D3
D4
Series Completion
A
B
I
C1
C2
C3
C4
Classification
A
B
C
I
D1
D2
D3
D4


A
B
C
D
FIRST
SECOND
THIRD
FOURTH
.75
.50
.25
Observed
Predicted
1
2
3
4

Technical Reports Presently in this Series

NR 150-412, ONR Contract N0001478C0025

#1. Sternberg, R. J. Intelligence research at the interface between differential and cognitive psychology: Prospects and proposals. January, 1978.

#2. Sternberg, R. J. Isolating the components of intelligence. January, 1978.

#3. Sternberg, R. J., Guyote, M. J., & Turner, M. E. Deductive reasoning. January, 1978.

#4. Sternberg, R. J. Toward a unified componential theory of human reasoning. April, 1978.

#5. Guyote, M. J., & Sternberg, R. J. A transitive-chain theory of syllogistic reasoning. April, 1978.

#6. Sternberg, R. J., & Turner, M. E. Components of syllogistic reasoning. April, 1978.

#7. Sternberg, R. J., Tourangeau, R., & Nigro, G. Metaphor, induction, and social policy: The convergence of macroscopic and microscopic views. April, 1978.

#8. Sternberg, R. J. A proposed resolution of curious conflicts in the literature on linear syllogistic reasoning. June, 1978.

#9. Sternberg, R. J. The nature of mental abilities. June, 1978.

#10. Sternberg, R. J. Psychometrics, mathematical psychology, and cognition: Confessions of a closet psychometrician. June, 1978.

#11. Tourangeau, R., & Sternberg, R. J. Understanding and appreciating metaphors. June, 1978.

#12. Sternberg, R. J. Representation and process in transitive inference. October, 1978.

#13. Tourangeau, R., & Sternberg, R. J. Aptness in metaphor. October, 1978.

#14. Sternberg, R. J. Contrasting conceptions of intelligence and their educational implications. November, 1978.

#15. Sternberg, R. J., & Weil, E. M. An aptitude-strategy interaction in linear syllogistic reasoning. April, 1979.

#16. Sternberg, R. J. Intelligence tests in the year 2000: What forms will they take and what purposes will they serve? April, 1979.

#17. Sternberg, R. J. New views on IQs: A silent revolution of the 70s. April, 1979.

Technical Reports Presently in this Series

NR 150-412, ONR Contract N0001478C0025

#18. Sternberg, R. J., & Gardner, M. K. Unities in inductive reasoning. October, 1979.

#19. Sternberg, R. J. Components of human intelligence. October, 1979.

#20. Sternberg, R. J. The construct validity of aptitude tests: An information-processing assessment. October, 1979.

#21. Schustack, M. W., & Sternberg, R. J. Evaluation of evidence in causal inference. October, 1979.

Navy

1 Dr. Ed Aiken
Navy Personnel R&D Center
San Diego, CA 92152

1 Dr. Jack R. Borsting
Provost & Academic Dean
U.S. Naval Postgraduate School
Monterey, CA 93940

1 Dr. Robert Breaux
Code N-71
NAVTRAEQUIPCEN
Orlando, FL 32813

1 MR. MAURICE CALLAHAN
Pers 23a
Bureau of Naval Personnel
Washington, DC 20370

1 Dr. Richard Elster
Department of Administrative Sciences
Naval Postgraduate School
Monterey, CA 93940

1 DR. PAT FEDERICO
NAVY PERSONNEL R&D CENTER
SAN DIEGO, CA 92152

1 CDR John Ferguson, MSC, USN
Naval Medical R&D Command (Code 44)
National Naval Medical Center
Bethesda, MD 20014

1 Dr. John Ford
Navy Personnel R&D Center
San Diego, CA 92152

1 CAPT. D.M. GRAGG, MC, USN
HEAD, SECTION ON MEDICAL EDUCATION
UNIFORMED SERVICES UNIV. OF THE
HEALTH SCIENCES
6917 ARLINGTON ROAD
BETHESDA, MD 20014

1 LT Steven D. Harris, MSC, USN
Code 6021
Naval Air Development Center
Warminster, Pennsylvania 18974

Navy

1 CDR Robert S. Kennedy
Naval Aerospace Medical and
Research Lab
Box 29407
New Orleans, LA 70189

1 Dr. Norman J. Kerr
Chief of Naval Technical Training
Naval Air Station Memphis (75)
Millington, TN 38054

1 Dr. Leonard Kroeker
Navy Personnel R&D Center
San Diego, CA 92152

1 CHAIRMAN, LEADERSHIP & LAW DEPT.
DIV. OF PROFESSIONAL DEVELOPMMENT
U.S. NAVAL ACADEMYY
ANNAPOLIS, MD 21402

1 Dr. William L. Maloy
Principal Civilian Advisor for
Education and Training
Naval Training Command, Code 00A
Pensacola, FL 32508

1 CAPT Richard L. Martin
USS Francis Marion (LPA-249)
FPO New York, NY 09501

1 Dr. James McBride
Code 301
Navy Personnel R&D Center
San Diego, CA 92152

2 Dr. James McGrath
Navy Personnel R&D Center
Code 306
San Diego, CA 92152

1 DR. WILLIAM MONTAGUE
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

Navy

1 Commanding Officer
Naval Health Research
Center
Attn: Library
San Diego, CA 92152

1 Naval Medical R&D Command
Code 44
National Naval Medical Center
Bethesda, MD 20014

1 CAPT Paul Nelson, USN
Chief, Medical Service Corps
Code 7
Bureau of Medicine & Surgery
U. S. Department of the Navy
Washington, DC 20372

1 Library
Navy Personnel R&D Center
San Diego, CA 92152

6 Commanding Officer
Naval Research Laboratory
Code 2627
Washington, DC 20390

1 JOHN OLSEN
CHIEF OF NAVAL EDUCATION &
TRAINING SUPPORT
PENSACOLA, FL 32509

1 Psychologist
ONR Branch Office
495 Summer Street
Boston, MA 02210

1 Psychologist
ONR Branch Office
536 S. Clark Street
Chicago, IL 60605

1 Office of Naval Research
Code 437
800 N. Quincy SStreet
Arlington, VA 22217

Navy

1 Office of Naval Research
Code 441
800 N. Quincy Street
Arlington, VA 22217

5 Personnel & Training Research Programs
(Code 458)
Office of Naval Research
Arlington, VA 22217

1 Psychologist
OFFICE OF NAVAL RESEARCH BRANCH
223 OLD MARYLEBONE ROAD
LONDON, NW, 15TH ENGLAND

1 Psychologist
ONR Branch Office
1030 East Green Street
Pasadena, CA 91101

1 Scientific Director
Office of Naval Research
Scientific Liaison Group/Tokyo
American Embassy
APO San Francisco, CA 96503

1 Office of the Chief of Naval Operations
Research, Development, and Studies Branc
(OP-102)
Washington, DC 20350

1 Scientific Advisor to the Chief of
Naval Personnel (Pers-Or)
Naval Bureau of Personnel
Room 4410, Arlington Annex
Washington, DC 20370

1 LT Frank C. Petho, MSC, USNR (Ph.D)
Code L51
Naval Aerospace Medical Research Laborat
Pensacola, FL 32508

1 DR. RICHARD A. POLLAK
ACADEMIC COMPUTING CENTER
U.S. NAVAL ACADEMY
ANNAPOLIS, MD 21402

Navy

1 Roger W. Remington, Ph.D
Code L52
NAMRL
Pensacola, FL 32508

1 Dr. Bernard Rimland
Navy Personnel R&D Center
San Diego, CA 92152

1 Mr. Arnold Rubenstein
Naval Personnel Support Technology
Naval Material Command (08T244)
Room 1044, Crystal Plaza #5
2221 Jefferson Davis Highway
Arlington, VA 20360

1 Dr. Worth Scanland
Chief of Naval Education and Training
Code N-5
NAS, Pensacola, FL 32508

1 A. A. SJOHOLM
TECH. SUPPORT, CODE 201
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

1 Mr. Robert Smith
Office of Chief of Naval Operations
OP-987E
Washington, DC 20350

1 Dr. Alfred F. Smode
Training Analysis & Evaluation Group (TAEG)
Dept. of the Navy
Orlando, FL 32813

1 CDR Charles J. Theisen, JR. MSC, USN
Head Human Factors Engineering Div.
Naval Air Development Center
Warminster, PA 18974

1 W. Gary Thomson
Naval Ocean Systems Center
Code 7132
San Diego, CA 92152

Navy

1 Dr. Ronald Weitzman
Department of Administrative Sciences
U. S. Naval Postgraduate School
Monterey, CA 93940

1 DR. MARTIN F. WISKOFF
NAVY PERSONNEL R& D CENTER
SAN DIEGO, CA 92152

Army

1 Technical Director
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 HQ USAREUE & 7th Army
ODCSOPS
USAAREUE Director of GED
APO New York 09403

1 DR. RALPH DUSEK
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Dr. Myron Fischl
U.S. Army Research Institute for the
Social and Behavioral Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Ed Johnson
Army Research Institute
5001 Eisenhower Blvd.
Alexandria, VA 22333

1 Dr. Michael Kaplan
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Dr. Milton S. Katz
Individual Training & Skill
Evaluation Technical Area
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Beatrice J. Farr
Army Research Institute (PERI-OK)
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Milt Maier
U.S. ARMY RESEARCH INSTITUTE
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

Army

1 Dr. Harold F. O'Neil, Jr.
ATTN: PERI-OK
5001 EISENHOWER AVENUE
ALEXANDRIA, VA 22333

1 Dr. Robert Sasmor
U. S. Army Research Institute for the
Behavioral and Social Sciences
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Frederick Steinheiser
U. S. Army Reserch Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

1 Dr. Joseph Ward
U.S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Air Force

1 Air Force Human Resources Lab
AFHRL/PED
Brooks AFB, TX 78235

1 Air University Library
AUL/LSE 76/443
Maxwell AFB, AL 36112

1 Dr. Philip De Leo
AFHRL/TT
Lowry AFB, CO 80230

1 Dr. Genevieve Haddad
Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

1 CDR. MERCER
CNET LIAISON OFFICER
AFHRL/FLYING TRAINING DIV.
WILLIAMS AFB, AZ 85224

1 Dr. Ross L. Morgan (AFHRL/ASR)
Wright -Patterson AFB
Ohio 45433

1 Dr. Roger Pennell
AFHRL/TT
Lowry AFB, CO 80230

1 Personnel Analysis Division
HQ USAF/DPXXA
Washington, DC 20330

1 Research Branch
AFMPC/DPMYP
Randolph AFB, TX 78148

1 Dr. Malcolm Ree
AFHRL/PED
Brooks AFB, TX 78235

1 Dr. Marty Rockway (AFHRL/TT)
Lowry AFB
Colorado 80230

Air Force

1 Jack A. Thorpe, Capt, USAF
Program Manager
Life Sciences Directorate
AFOSR
Bolling AFB, DC 20332

1 Brian K. Waters, LCOL, USAF
Air University
Maxwell AFB
Montgomery, AL 36112

Marines

1 H. William Greenup
Education Advisor (E031)
Education Center, MCDEC
Quantico, VA 22134

1 DR. A.L. SLAFKOSKY
SCIENTIFIC ADVISOR (CODE RD-1)
HQ, U.S. MARINE CORPS
WASHINGTON, DC 20380

CoastGuard

1 Mr. Richard Lanterman
PSYCHOLOGICAL RESEARCH (G-P-1/62)
U.S. COAST GUARD HQ
WASHINGTON, DC 20590

1 Dr. Thomas Warm
U. S. Coast Guard Institute
P. O. Substation 18
Oklahoma City, OK 73169

Other DoD

1 Dr. Stephen Andriole
ADVANCED RESEARCH PROJECTS AGENCY
1400 WILSON BLVD.
ARLINGTON, VA 22209

12 Defense Documentation Center
Cameron Station, Bldg. 5
Alexandria, VA 22314
Attn: TC

1 Dr. Dexter Fletcher
ADVANCED RESEARCH PROJECTS AGENCY
1400 WILSON BLVD.
ARLINGTON, VA 22209

1 Dr. William Graham
Testing Directorate
MEPCOM
Ft. Sheridan, IL 60037

1 Military Assistant for Training and Personnel Technology
Office of the Under Secretary of Defense for Research & Engineering
Room 3D129, The Pentagon
Washington, DC 20301

1 MAJOR Wayne Sellman, USAF
Office of the Assistant Secretary of Defense (MRA&L)
3B930 The Pentagon
Washington, DC 20301

Civil Govt

1 Dr. Susan Chipman
Basic Skills Program
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. William Gorham, Director
Personnel R&D Center
Office of Personnel Managment
1900 E Street NW
Washington, DC 20415

1 Dr. Joseph I. Lipson
Division of Science Education
Room W-638
National Science Foundation
Washington, DC 20550

1 Dr. Joseph Markowitz
Office of Research and Development
Central Intelligence Agency
Washington, DC 20205

1 Dr. John Mays
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Arthur Melmed
National Intitute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Andrew R. Molnar
Science Education Dev. and Research
National Science Foundation
Washington, DC 20550

1 Dr. Jeffrey Schiller
National Institute of Education
1200 19th St. NW
Washington, DC 20208

Civil Govt

1 Dr. H. Wallace Sinaiko
Program Director
Manpower Research and Advisory Services
Smithsonian Institution
801 North Pitt Street
Alexandria, VA 22314

1 Dr. Thomas G. Sticht
Basic Skills Program
National Institute of Education
1200 19th Street NW
Washington, DC 20208

1 Dr. Frank Withrow
U. S. Office of Education
400 6th Street SW
Washington, DC 20202

1 Dr. Joseph L. Young, Director
Memory & Cognitive Processes
National Science Foundation
Washington, DC 20550

Non Govt

1 Dr. Earl A. Alluisi
HQ, AFHRL (AFSC)
Brooks AFB, TX 78235

1 Dr. John R. Anderson
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

1 Dr. John Annett
Department of Psychology
University of Warwick
Coventry CV4 7AL
ENGLAND

1 DR. MICHAEL ATWOOD
SCIENCE APPLICATIONS INSTITUTE
40 DENVER TECH. CENTER WEST
7935 E. PRENTICE AVENUE
ENGLEWOOD, CO 80110

1 1 psychological research unit
Dept. of Defense (Army Office)
Campbell Park Offices
Canberra ACT 2600, Australia

1 Dr. Alan Baddeley
Medical Research Council
Applied Psychology Unit
15 Chaucer Road
Cambridge CB2 2EF
ENGLAND

1 Dr. Patricia Baggett
Department of Psychology
University of Denver
University Park
Denver, CO 80208

1 Dr. Jackson Beatty
Department of Psychology
University of California
Los Angeles, CA 90024

1 Dr. Isaac Bejar
Educational Testing Service
Princeton, NJ 08450

Non Govt

1 Dr. Nicholas A. Bond
Dept. of Psychology
Sacramento State College
600 Jay Street
Sacramento, CA 95819

1 Dr. Lyle Bourne
Department of Psychology
University of Colorado
Boulder, CO 80302

1 Dr. Robert Brennan
American College Testing Programs
P. O. Box 168
Iowa City, IA 52240

1 Dr. John S. Brown
XEROX Palo Alto Research Center
3333 Coyote Road
Palo Alto, CA 94304

1 DR. C. VICTOR BUNDERSON
WICAT INC.
UNIVERSITY PLAZA, SUITE 10
[illegible] STATE ST.
[illegible], UT [illegible]

1 Dr. John B. Carroll
Psychometric Lab
Univ. of No. Carolina
Davie Hall 013A
Chapel Hill, NC 27514

1 Dr. William Chase
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

1 Dr. Micheline Chi
Learning R & D Center
University of Pittsburgh
3939 O'Hara Street
Pittsburgh, PA 15213

1 Dr. John Chiorini
Litton-Mellonics
Box 1286
Springfield, VA 22151

Non Govt

1 Dr. Kenneth E. Clark
College of Arts & Sciences
University of Rochester
River Campus Station
Rochester, NY 14627

1 Dr. Norman Cliff
Dept. of Psychology
Univ. of So. California
University Park
Los Angeles, CA 90007

1 Dr. Allan M. Collins
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, Ma 02138

1 Dr. Meredith Crawford
Department of Engineering Administration
George Washington University
Suite 305
2101 L Street N. W.
Washington, DC 20037

1 Dr. Ruth Day
Center for Advanced Study
in Behavioral Sciences
202 Junipero Serra Blvd.
Stanford, CA 94305

1 Dr. Emmanuel Donchin
Department of Psychology
University of Illinois
Champaign, IL 61820

1 Dr. Hubert Dreyfus
Department of Philosophy
University of California
Berkely, CA 94720

1 Dr. Marvin D. Dunnette
N492 Elliott Hall
Dept. of Psychology
Univ. of Minnesota
Minneapolis, MN 55455

1 ERIC Facility-Acquisitions
4833 Rugby Avenue
Bethesda, MD 20014

Non Govt

1 MAJOR I. N. EVONIC
CANADIAN FORCES PERS. APPLIED RESEARCH
1107 AVENUE ROAD
TORONTO, ONTARIO, CANADA

1 Dr. Ed Feigenbaum
Department of Computer Science
Stanford University
Stanford, CA 94305

1 Dr. Richard L. Ferguson
The American College Testing Program
P.O. Box 168
Iowa City, IA 52240

1 Dr. Victor Fields
Dept. of Psychology
Montgomery College
Rockville, MD 20850

1 Dr. Edwin A. Fleishman
Advanced Research Resources Organ.
Suite 900
4330 East West Highway
Washington, DC 20014

1 Dr. John R. Frederiksen
Bolt Beranek & Newman
50 Moulton Street
Cambridge, MA 02138

1 Dr. Alinda Friedman
Department of Psychology
University of Alberta
Edmonton, Alberta
CANADA T6G 2J9

1 Dr. R. Edward Geiselman
Department of Psychology
University of California
Los Angeles, CA 90024

1 DR. ROBERT GLASER
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

Non Govt

1 Dr. Ira Goldstein
XEROX Palo Alto Research Center
3333 Coyote Road
Palo Alto, CA 94304

1 DR. JAMES G. GREENO
LRDC
UNIVERSITY OF PITTSBURGH
3939 O'HARA STREET
PITTSBURGH, PA 15213

1 Dr. Ron Hambleton
School of Education
University of Massechusetts
Amherst, MA 01002

1 Dr. Harold Hawkins
Department of Psychology
University of Oregon
Eugene OR 97403

1 Dr. Barbara Hayes-Roth
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406

1 Dr. Frederick Hayes-Roth
The Rand Corporation
1700 Main Street
Santa Monica, CA 90406

1 Dr. James R. Hoffman
Department of Psychology
University of Delaware
Newark, DE 19711

1 Dr. Lloyd Humphreys
Department of Psychology
University of Illinois
Champaign, IL 61820

1 Library
HumRRO/Western Division
27857 Berwick Drive
Carmel, CA 93921

Non Govt

1 Dr. Earl Hunt
Dept. of Psychology
University of Washington
Seattle, WA 98105

1 Mr. Gary Irving
Data Sciences Division
Technology Services Corporation
2811 Wilshire Blvd.
Santa Monica CA 90403

1 Dr. Steven W. Keele
Dept. of Psychology
University of Oregon
Eugene, OR 97403

1 Dr. Walter Kintsch
Department of Psychology
University of Colorado
Boulder, CO 80302

1 Dr. David Kieras
Department of Psychology
University of Arizona
Tuscon, AZ 85721

1 Dr. Stephen Kosslyn
Harvard University
Department of Psychology
33 Kirkland Street
Cambridge, MA 02138

1 Mr. Marlin Kroger
1117 Via Goleta
Palos Verdes Estates, CA 90274

1 LCOL. C.R.J. LAFLEUR
PERSONNEL APPLIED RESEARCH
NATIONAL DEFENSE HQS
101 COLONEL BY DRIVE
OTTAWA, CANADA K1A OK2

1 Dr. Jill Larkin
Department of Psychology
Carnegie Mellon University
Pittsburgh, PA 15213

Non Govt

1 Dr. Alan Lesgold
Learning R&D Center
University of Pittsburgh
Pittsburgh, PA 15260

1 Dr. Robert Linn
College of Education
University of Illinois
Urbana, IL 61801

1 Dr. Frederick M. Lord
Educational Testing Service
Princeton, NJ 08540

1 Dr. Richard B. Millward
Dept. of Psychology
Hunter Lab.
Brown University
Providence, RI 82912

1 Dr. Allen Munro
Univ. of So. California
Behavioral Technology Labs
3717 South Hope Street
Los Angeles, CA 90007

1 Dr. Donald A Norman
Dept. of Psychology C-009
Univ. of California, San Diego
La Jolla, CA 92093

1 Dr. Melvin R. Novick
Iowa Testing Programs
University of Iowa
Iowa City, IA 52242

1 Dr. Jesse Orlansky
Institute for Defense Analysis
400 Army Navy Drive
Arlington, VA 22202

1 Dr. Robert Pachella
Department of Psychology
Human Performance Center
330 Packard Road
Ann Arbor, MI 48104

Non Govt

1 Dr. Seymour A. Papert
Massachusetts Institute of Technology
Artificial Intelligence Lab
545 Technology Square
Cambridge, MA 02139

1 Dr. James A. Paulson
Portland State University
P.O. Box 751
Portland, OR 97207

1 MR. LUIGI PETRULLO
2431 N. EDGEWOOD STREET
ARLINGTON, VA 22207

1 DR. STEVEN M. PINE
4950 Douglas Avenue
Golden Valley, MN 55416

1 Dr. Martha Polson
Department of Psychology
University of Colorado
Boulder, CO 80302

1 DR. PETER POLSON
DEPT. OF PSYCHOLOGY
UNIVERSITY OF COLORADO
BOULDER, CO 80302

1 DR. DIANE M. RAMSEY-KLEE
R-K RESEARCH & SYSTEM DESIGN
3947 RIDGEMONT DRIVE
MALIBU, CA 90265

1 MIN. RET. M. RAUCH
P II 4
BUNDESMINISTERIUM DER VERTEIDIGUNG
POSTFACH 161
53 BONN 1, GERMANY

1 Dr. Peter B. Read
Social Science Research Council
605 Third Avenue
New York, NY 10016

Non Govt

1 Dr. Mark D. Reckase
Educational Psychology Dept.
University of Missouri-Columbia
12 Hill Hall
Columbia, MO 65201

1 Dr. Fred Reif
SESAME
c/o Physics Department
University of California
Berkely, CA 94720

1 Dr. Andrew M. Rose
American Institutes for Research
1055 Thomas Jefferson St. NW
Washington, DC 20007

1 Dr. Leonard L. Rosenbaum, Chairman
Department of Psychology
Montgomery College
Rockville, MD 20850

1 Dr. Ernst Z. Rothkopf
Bell Laboratories
600 Mountain Avenue
Murray Hill, NJ 07974

1 Dr. David Rumelhart
Center for Human Information Processing
Univ. of California, San Diego
La Jolla, CA 92093

1 PROF. FUMIKO SAMEJIMA
DEPT. OF PSYCHOLOGY
UNIVERSITY OF TENNESSEE
KNOXVILLE, TN 37916

1 Dr. Irwin Sarason
Department of Psychology
University of Washington
Seattle, WA 98195

1 DR. WALTER SCHNEIDER
DEPT. OF PSYCHOLOGY
UNIVERSITY OF ILLINOIS
CHAMPAIGN, IL 61820

Non Govt

1 Dr. Richard Snow
School of Education
Stanford University
Ctanford, CA 94305

1 DR. ALBERT STEVENS
BOLT BERANEK & NEWMAN, INC.
50 MOULTON STREET
CAMBRIDGE, MA 02138

1 DR. PATRICK SUPPES
INSTITUTE FOR MATHEMATICAL STUDIES IN THE SOCIAL SCIENCES
STANFORD UNIVERSITY
STANFORD, CA 94305

1 Dr. Hariharan Swaminathan
Laboratory of Psychometric and Evaluation Research
School of Education
University of Massachusetts
Amherst, MA 01003

1 Dr. Brad Sympson
Office of Data Analysis Research
Educational Testing Service
Princeton, NJ 08541

1 Dr. Kikumi Tatsuoka
Computer Based Education Research Laboratory
252 Engineering Research Laboratory
University of Illinois
Urbana, IL 61801

1 Dr. David Thissen
Department of Psychology
University of Kansas
Lawrence, KS 66044

1 Dr. John Thomas
IBM Thomas J. Watson Research Center
P.O. Box 218
Yorktown Heights, NY 10598

1 DR. PERRY THORNDYKE
THE RAND CORPORATION
1700 MAIN STREET
SANTA MONICA, CA 90406

Non Govt

1 Dr. J. Uhlaner
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364

1 Dr. Benton J. Underwood
Dept. of Psychology
Northwestern University
Evanston, IL 60201

1 Dr. Howard Wainer
Bureau of Social SCience Research
1990 M Street, N. W.
Washington, DC 20036

1 Dr. Phyllis Weaver
Graduate School of Education
Harvard University
200 Larsen Hall, Appian Way
Cambridge, MA 02138

1 Dr. David J. Weiss
N660 Elliott Hall
University of Minnesota
75 E. River Road
Minneapolis, MN 55455

1 DR. SUSAN E. WHITELY
PSYCHOLOGY DEPARTMENT
UNIVERSITY OF KANSAS
LAWRENCE, KANSAS 66044

1 Dr. J. Arthur Woodward
Department of Psychology
University o California
Los Angeles, CA 90024

1 Dr. Karl Zinn
Center for research on Learning and Teaching
University of Michigan
Ann Arbor, MI 48104