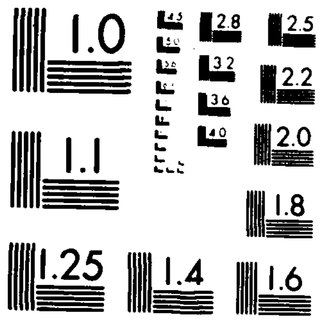
AD-A137 031 LEARNING IN A PROBABILISTIC ENVIRONMENT: A NEW APPROACH AND SOME PRELIMINARY FINDINGS(U) CHICAGO UNIV IL CENTER FOR DECISION RESEARCH J KLAYMAN MAY 83 TR-7 1/1

UNCLASSIFIED N00014-81-K-0314 F/G 5/10 NL

END
DATE
FILMED
2 84
DTIC


1.0
2.8
2.5
3.2
2.2
3.6
4.0
2.0
1.1
1.8
1.25
1.4
1.6

Cre[illegible] Vita
[illegible] exco-
[illegible] latur

12

**Learning in a Probabilistic Environment:
A New Approach, and Some
Preliminary Findings***

Joshua Klayman
University of Chicago
Graduate School of Business
Center for Decision Research

Sponsored by:
Office of Naval Research
Contract Number, N00014-81-K-0314
Work Unit Number, NR 197-071

*This work was supported by research funds from the University of Chicago, Graduate School of Business, and through the Office of Naval Research contract to Hillel Einhorn and Robin Hogarth. Thanks to Hillel Einhorn, Jay Russo and the other members of the Center for Decision Research for many comments and contributions.

Paper presented at the meeting of the Midwestern Psychological Association, Chicago, May 1983.

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER 7	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Learning in a Probabilistic Environment: A New Approach, and Some Preliminary Findings.		5. TYPE OF REPORT & PERIOD COVERED Technical Report 6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s) Joshua Klayman		8. CONTRACT OR GRANT NUMBER(s) N00014-81-K-0314
9. PERFORMING ORGANIZATION NAME AND ADDRESS Center for Decision Research, Graduate School of Business, University of Chicago, 1101 East 58th Street, Chicago, Illinois 60637		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS NR 197-071
11. CONTROLLING OFFICE NAME AND ADDRESS Office of Naval Research 800 North Quincy Street Arlington, Virginia 22217		12. REPORT DATE May 1983 13. NUMBER OF PAGES 29
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

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

Learning, prediction, feedback, experience, probability-learning, and development of expertise.

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

Many studies of "probability learning" have led to the conclusion that human learners cannot find the "rule" amidst the "noise" (Brehmer, 1980). However, It is hypothesized that under more natural conditions, learners do develop rules which are probabilistically predictive, and improve chiefly through the addition of new predictive variables. The present study → over

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

Unclassified

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

20.

represents natural learning situations by including: (a) instructions and rewards that emphasize gradual development of understanding, rather than discovery of "the right rule;" and (b) a large number of cues, which must be discovered, rather than a few cues explicitly given. Results with 12 college-student subjects indicate significant learning in a computer-displayed task, over approximately 10 hours of experience. Learning was incremental, and was accompanied by the addition of valid factors to existing rules. These results contrast with findings that people fail to utilize information effectively in probabilistic situations. Earlier studies do not, however, model situations in which learning requires the discovery and validation of predictive cues, processes critical for the development of real-world expertise.

A-1

Learning in a Probabilistic Environment: A New Approach, and Some Preliminary Findings

Planning next year's budget, deciding when to plant your corn, selecting a class of graduate students, . . . What these activities have in common is that they all require us to predict the behavior of complex, multifactor, probabilistic environments. Indeed, we face this task whenever we must deal with the economy, the weather, or almost any aspect of human behavior. Even the behavior of purely mechanical systems is effectively probabilistic to those of us with imperfect knowledge (consider the vagaries of the family car).

The research discussed here is concerned with the question of how people come to understand such systems. Specifically, how do people learn the relationships between factors in the environment when those relationships are "imperfect," that is, correlational rather than strictly lawful? Given that we must operate in a probabilistic world, this learning process is essential for the development of real-world expertise.

There is, of course, already a long history of research on this general topic, under the rubric of "probability learning" (see reviews by Brehmer, 1980; Hammond, Stewart, Brehmer, & Steinman, 1975; Slovic & Lichtenstein, 1971). There have been many variations in 30 years of this research, but there has been a common basic paradigm. The subject's task is to predict a criterion value (e.g., length of a line) based on some predictive variables ("cues"). Most often, the cue variables are given arbitrary labels (e.g., *A*, *B*, *C*), and the subject receives numerical information on each cue (e.g., "*A* = 4, *B* = 6, *C* = 1). After receiving this information, the subject makes a prediction, and subsequently is shown the true outcome (e.g., the line

associated with [4, 6, 1]). The true outcome is a lawful function of A, B, and C, plus some amount of random error. For example, several studies have used the rule

$$Y = .8\sin x_1 + .4\sin x_2 + .2\sin x_3 + \varepsilon$$

where Y is the criterion, and ε is a random number, accounting for anywhere from 12% to 75% of the variance in the criterion (Dean, Hammond, & Summers, 1972; Hammond, 1971; Hammond, Summers, & Dean, 1973; Hoffman, Earle, & Slovic, 1981).

Investigators using this paradigm are looking at people's ability to learn the relationships between cues and criterion in the presence of imperfect (i.e., probabilistic) feedback. To summarize 30 years of research very succinctly, people seem to be absolutely terrible at doing this. Consider, for example, the study by Hoffman, et al., using the three-cue function described above, with 12% random variation. Using the optimal combination of factors, subjects could in theory achieve a correlation of .94 between their predictions and the true outcomes. After 200 "stimulus-response-outcome" feedback trials, however, the average subject had achieved a correlation of .21.

In his recent review of probability-learning studies (including many of his own) Bernot Brehmer concludes:

> People do not learn optimal strategies from experience even if the they are given massive amounts of practice. . . . This is due to lack of adequate schemata for handling the probabilistic aspect of the world. (1980, pp. 233-35)

Subjects seem to be unable to separate "signal" from "noise;" they reject correct hypotheses about relationships, and frequently revive rejected hypotheses. They do seem able to apply information <u>given</u> them, e.g., if the experimenter informs the subject of the relevant cue-criterion functions

(e.g., Deane, Hammond, & Summers, 1972; Hoffman, et al., 1981). However, they seem resistant to any attempts to help them find the relationships, through instruction or through structuring of feedback information (Brehmer & Kuylenstierna, 1978, 1980; Hoffman et al., 1981).

Findings like these do not bode well for people's ability to develop any new understanding of their environments. They are also troubling, though, because they seem to contradict common everyday experiences of learning. Imagine, for example, that you ask about a colleague's whereabouts, and are told, "He usually stays home on Fridays, especially if the weather's nice, although toward the end of the term he's more likely to be around." A statement like this is not extraordinary, yet it expresses a three-factor probabilistic prediction rule. How can this be? One possibility is that we only think we have learned such rules, but they are not, in fact, valid (c.f. Einhorn & Hogarth, 1978 on "persistence of the illusion of validity"). However, it is also possible that the usual probability-learning task misses something important about human learning processes--something that does permit effective learning in natural probabilistic environments.

To explore this latter hypothesis, consider several important ways in which the laboratory learning task may differ from "real-world" learning tasks:

1. Linearity of cues. Most probability-learning tasks include cues which have a non-linear, or even non-monotic, relationship to the criterion (e.g., the three-cue function desscribed earlier). These relationships are particularly difficult to learn (Brehmer, 1980; Hammond & Summers, 1965), but it may be easy to avoid these difficulties in natural settings. A number of studies have demonstrated that complex systems can generally be well modeled with strictly linear rules. Even when the relative weights are "improper," or

the true rule contains nonlinearities, linear models can often account for a high proportion of the variance (Dawes and Corrigan, 1974; Einhorn and McCoach, 1977; Yntema and Torgeson, 1961). This is especially so if there are many, partially redundant cues in the system. Indeed, the one bright spot in the probability-learning literature is that people seem to be fairly good at learning <u>linear</u> rules, even in the presence of noise (e.g., Brehmer & Kuylenstierna, 1978, 1980; Dean et al., 1972; Naylor & Domine, 1981). Brehmer and Kuylenstierna (1978), for example, used a task with two cues each having a positive linear relationship to the criterion. The maxium attainable correlation was .80, and subjects achieved a correlation above .70 after 60 trials. Thus, even if humans thought only in terms of <u>linear</u> relationships, this would still permit a good deal of predictive ability in many situations.

2. <u>Number and explictness of cues</u>. The typical laboratory task involves only a very small number of cues (usually 1 to 3), and these are explicitly identified. In natural situations, though, there are often many possible cues, and almost always an opportunity to discover and incorporate new information. Building a model of an environment, then, involves two basic processes: finding the cues, and figuring out how to aggregate them. Probability-learning tasks eliminate the cue-finding process. Research suggests that the aggregation process is especially difficult (e.g., Dawes, 1971; Goldberg, 1970), and that finding the cues may be much more important. Leaving out a variable is more serious than misweighting it; thus Dawes' prescription that to build a good (if not "optimal") model, "the whole trick is to know what variables to look at and then know how to add" (Dawes & Corrigan, 1974, p. 105; see also Dawes, 1979; Einhorn & Hogarth, 1975).

3. <u>Instructions and rewards</u>. In the usual laboratory task, the gist of the instructions is to "find the right rule" or "best rule." There is, then,

an implied dichotomy between "right" and "wrong" rules. This is reinforced by a reward system in which the principal payoff for the subject is the discovery of "the rule." Furthermore, in many tasks, until the rule is found, little achievement is possible. Thus, there is little reason to retain hypotheses which seem less than perfect, and little opportunity to build upon partial knowledge. In contrast, in natural situations, predictive models are typically better or worse overall, in a more or less continuous way. Improvements in understanding are more likely to be gradual or incremental, and reward tends to vary continuously with predictive accuracy.

4. Time. In these tasks, the time allotted for learning has been extensive by laboratory standards (several hours), but very short in comparison with the time-span of experience usually associated with the development of real-world expertise.

The goal of the research presented here was to look at learning processes in a more natural environment, according to the four points described above. That is, the task tested here: (a) can be understood in terms of linear cue-criterion relationships; (b) provides many possible cues, not all of which are explicitly specified; (c) includes instructions which emphasize improvement, rather than ultimate solution, and payoffs that vary continuously with predictive accuracy; and (d) allows subjects adequate amounts of time for learning.

It is hypothesized that in an environment like this, significant learning will take place. Gradual improvement is expected, as learners discover and test new valid predictive cues, and add these to their rule. As the learner's rule becomes more complete, better prediction is possible. This process of addition of valid factors is hypothesized to be the major means by which predictive accuracy is improved. However, several other processes may also

contribute: Invalid factors mistakenly included in the model may be expunged; weak cues may be replaced with related cues that are more directly predictive; and a more precise understanding of the shape and magnitude of the cue-criterion relationships may be achieved. Note that only the last of these processes is tapped in the typical probability-learning task.

Methods

Subjects interact with a computer display by means of a keyboard. The screen displays geometric figures varying in size, shape, line-pattern (e.g., striped, checkered, etc.), and location. Around each figure is marked a circular "area of influence," visible to the subject. In this environment of figures, the path of a point is "traced" from a visible starting location, in a straight line in any direction (see Figure 1). Subjects are told that "were it not for the figures, the point would continue off the screen in a straight line," but that "if a trace touches the area of influence around the figure, the figure may affect the trace by causing it to stop somewhere on the screen, as shown by a little asterisk." It is then explained that

> The object of the game is to predict where the trace will stop, or if it will go off the screen. You should understand that this will be difficult, and you are not expected to be able to "solve" it exactly. Rather, you should try and figure out as much as you can about how it works, so you can make the best predictions you can.

Twelve college-student subjects participated in this study. Each subject received two types of experience with the system: learning and testing. Learning sessions were 30-minute periods in which subjects could freely design their own screens and conduct their own tests. They could draw figures of any of three sizes, three shapes, and three patterns, and place them anywhere on the screen. They could trace points starting anywhere, and going in any

direction. They were free to experiment, observe, calculate, and take notes for as much of the 30-minute period as they liked. Then, they went on to a testing phase. Here, they observed a set of 16 screens representing a random sampling of situations in which a point passes close enough to a figure to be (possibly) affected. In each test trial they were shown what event would be tried, and they made a prediction as to the outcome, indicating whether they believed the point would stop, and if so, where. After their prediction, the true outcome was observed. The testing sessions were only about one-third the length of the learning sessions and new trials proceeded quickly. Thus, most learning took place in lerning sessions, despite feedback during tests.

Learning and testing sessions were alternated, with two of each on each of seven days (about 10 hours of experience with the system). During this time, the subjects were paid according to the number of points they achieved in the testing session. Points were awarded according to the closeness of their predictions to the true observed stopping point of each test trace.

The true rule underlying the behavior of the system was a linear combination of six cues: Shape of figure; closeness of approach of trace to figure; direction of treace toward right or left; size of figure; distance from trace origin to figure; closeness of figure to center of screen. These cues were weighted such that each of the first three accounted for roughly twice as much variance as each of the last three. Note also that only two of these cues were directly specified in the display (size and shape of figure). The other four had to be discovered among the plethora of possible spatial relationships existing in the environment. Note also that one very salient cue, the line-pattern of the figure, was a false cue in this case.

The subjects were divided randomly into two conditions, six in each. In the protocol condition, subjects were asked to "think out loud" during the

procedure, and were also questioned about their thinking at various points. Those in the non-protocol condition were not asked for any verbal responses, although an experimenter was present to help operate the computer, and to handle any problems.

Results

Based on the model of learning proposed earlier, the main expectation was that learning would take place gradually. Learning should be incremental, as subjects discover and test new valid predictive cues, and add these to their predictive models.

Figure 2 shows that gradual improvement was indeed observed, at least through the sixth session. The results were analyzed using an ANOVA with one between-subjects factor (condition: protocol/no-protocol) and two within (session: one to seven; half: first test of the day/second test). The improvement with sessions was highly significant ($F[6, 60] = 8.78$, $p < .0001$), and no other effects were significant.

There are also some data about the processes through which learning was accomplished. One of the responses required of the six verbal-protocol subjects was to provide written "hints" after each day's experience. Their instructions were to provide as many clues about the system as they could, as though to a naive participant whom they wanted to help master the game. Subjects were encouraged to include any information they though might help, even if they were not yet sure.

The hints were categorized according to the nature of the predictive cues they utilized. Correct cues were those which corresponded to one of the six valid cues in the model. Partly correct cues were those which captured some, but not all, of a correct cue-criterion relationship (e.g., a cue which was

positively correlated with a correct cue). Incorrect cues were cues which had little or no predictive value in the environment. The most common example was a belief that figure-pattern mattered. Also, any postulated interactions between cues were scored as incorrect.

Figure 3 shows the changes in these categories of cues across the seven days of experience. It was hypothesized earlier that the principle mechanism of change would be the addition of new, valid cues to the model, and this is supported by the data from the helpful-hints reports. The number of partly-correct cues seems to remain constant, but this is the net result of two processes. New partially-valid cues are being discovered throughout the process, but partially-valid cues are also being replaced with stronger, correct cues. Finally, it is interesting that the role of incorrect cues is relatively small here. This is so despite the fact that cues were scored as remaining in the subject's model until explicitly discounted or until an incompatible new hypothesis was expressed. In some cases, incorrect cues persisted in subject's models, but in many cases there were a series of different incorrect cues (e.g., interactions) with only brief tenures.

The helpful-hints results are not definitive, of course, but they do proovide support for the hypothesis that addition of cues is a primary source of learning, with replacement of weak cues and removal of invalid cues as secondary processes. In their comments, subjects very seldom expressed any quantitative relationships. Expressions of rules were almost always ordinal, e.g., "the bigger it is, the sooner it stops." It was rare even for subjects to say anything about the relative importance of different cues. Thus, there is little evidence of attention to cue weights, or to the shape of the cue-criterion function.

Conclusions

This study is clearly just a beginning, but it demonstrates the need for new consideration of processes of learning in probabilistic environments. The focus should be on adding, revising, and eliminating cues rather than on pinpointing the cue-criterion function. There are a great variety of interesting question for further research along these lines. For example:

(a) Is it important that subjects be allowed to experiment, rather than just observe? Hoffman et al. (1981) found that this made no difference in a typical probability-learning task, but it might be important in discovering and validating new cues.

(b) This particular task was not deterministically predictable from the subject's point of view. There were always unknown controlling factors, but there was no explicitly random element. There are many important issues concerning what "random" means (see, e.g., Lopes, 1982). Suffice it to say here that the present experiment does not contain any factors which vary unpredictably with time. This may or may not prove to be important in the ability to learn from experience. Perhaps for learners not all unpredictability is equal.

(c) What would happen with additional learning time? Most of the subjects in the present experiment were still improving at the last session, and in all cases there was considerable room for further improvement. It is possible that different learning processes may play important roles in the longer term. For example, replacement of weak cues and attention to the shape of the cue-criterion function might be more prominent in later stages of learning.

(d) What is the effect of an initial knowledge base? In the present task, as in most learning tasks, the subject starts with very little knowledge of the workings of the system. Natural learning situations provide varying

amounts of initial knowledge from prior experience and various kinds of social transmission. How is such information applied in new learning situations? And what happens in the presence of false, misleading, or outdated initial information?

These questions, and many others of equal interest, arise from a focus on the learner's construction of a predictive model, cue by cue. It is proposed that these constructive processes are central to the ability to learn from experience in complex probabilistic environments. Certainly, much of what we know comes from learners of the past. The ability to learn from experience, though, is critical for understanding and controlling new environments, and for going beyond what is already known. In studying the construction and revision of predictive models during learning, then, we are looking into a critical element in the development of expertise.

REFERENCES

Brehmer, B. In one word: Not from experience. Acta Psychologica, 1980, 45, 223-241.

Brehmer, B. & Kuylenstierna, J. Task information and performance in probabilistic inference tasks. Organizational Behavior and Human Performance, 1978, 22, 445-464.

Brehmer, B. & Kuylenstierna, J. Content and consistency in probabilistic inference tasks. Organizational Behavior and Human Performance, 1980, 26, 54-64.

Dawes, R. M. A case study of graduate admissions: Application of three principles of human decision making. American Psychologist, 1971, 26, 180-188.

Dawes, R. M. The robust beauty of improper linear models. American Psychologist, 1979, 34, 571-582.

Dawes, R. M. & Corrigan, B. Linear models in decision making. Psychological Bulletin, 1974, 81, 95-106.

Deane, D. H., Hammond, K. R., & Summers, D. A. Acquisition and application of knowledge in complex inference tasks. Journal of Experimental Psychology, 1972, 92, 20-26.

Einhorn, H. J. & Hogarth, R. M. Unit weighting schemes for decision making. Organizational Behavior and Human Performance, 1975, 13, 171-192.

Einhorn, H. J. & Hogarth, R. M. Confidence in judgment: Persistence of the illusion of validity. Psychological Review, 1978, 85, 395-416.

Einhorn, H. J. & McCoach, W. A simple multiattribute utility procedure for evaluation. Behavioral Science, 1977, 22, 270-282.

Goldberg, L. R. Man versus model of man: A rationale, plus some evidence, for a method of improving on clinical inferences. Psychological Bulletin, 1970, 73 422-432.

Hammond, K. R. Computer graphics as an aid to learning. Science, 1971, 172, 903-908.

Hammond, K. R. & Summers, D. A. Cognitive dependence on linear and nonlinear cues. Psychological Review, 1965, 72, 215-224.

Hammond, K. R., Stewart, T. R., Brehmer, B., & Steinmann, D. Social judgment theory. In M. Kaplan & S. Schwartz (Eds.), Human Judgement and Decision Processes: Formal and Mathematical Approaches. New York: Academic Press, 1975, 271-312.

Hammond, K. R., Summers, D. A., & Dean, D. H. Negative effects of outcome feedback in multiple-cue probability learning. Organizational Behavior and Human Performance, 1973, 9, 30-34.

Hoch, S. L. & Tschirgi, J. E. Cue redundancy and extra-logical inferences in deductive reasoning. Memory and Cognition, in press.

Hoffman, P. J., Earle, T. C. & Slovic, P. Multidimensional functional learning (MFL) and some new conceptions of feedback. Organizational Behavior and Human Performance, 1981, 27, 75-102.

Lopes, L. L. Doing the impossible: A note on the induction and experience of randomness. Journal of Experimental Psychology: Learning, Memory, and Cognition, 1982, 8, 626-636.

Mynatt, C. R., Doherty, M. E. & Tweney, R. D. Consequences of confirmation and disconfirmation in a simulated research environment. Quarterly Journal of Experimental Psychology, 1978, 30, 395-406.

Naylor, J. C. & Domine, R. K. Inferences based on uncertain data: Some experiments on the role of slope magnitude, instructions, and stimulus distribution shape on the learning of contingency relationships. Organizational Behavior and Human Performance, 1981, 27, 1-31.

Slovic, P. & Lichtenstein, S. Comparison of Bayesian and regression approaches to the study of information processing in judgment. Organizational Behavior and Human Performance, 1971, 6, 649-744.

Yntema, D. B. & Torgeson, W. S. Man-computer cooperation in decisions requiring common sense. IRE Transactions of Human Factors in Electronics, 1961, 2, 20-26.

FIGURE CAPTIONS

Figure 1. Example of a display screen used in this study. A point is traced from a starting location (A). The point's behavior is affected by a geometric figure (B) if it comes within a close enough range (indicated by the circumscribed circle). In that case, it may stop before reaching the edge of the screen (C). Except for the letters A, B, C, all aspects of the display were visible to the subject. (Adapted from Mynatt, Doherty, and Tweney, 1978, with the help of Don N. Kleinmuntz.)

Figure 2. Average total test score per subject (n = 12), by days of experience. Each "day" consisted of up to one hour of learning trials, and one-half hour of test trials. Maximum possible score is approximately 750.

Figure 3. Changes in constituents of subjects' predictive models (n = 6), over days of experience. The optimal model contained six correct cues.

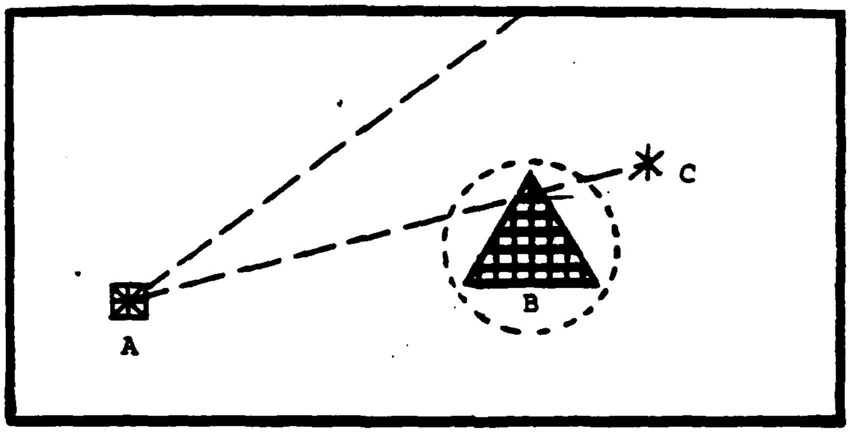


Figure 1.

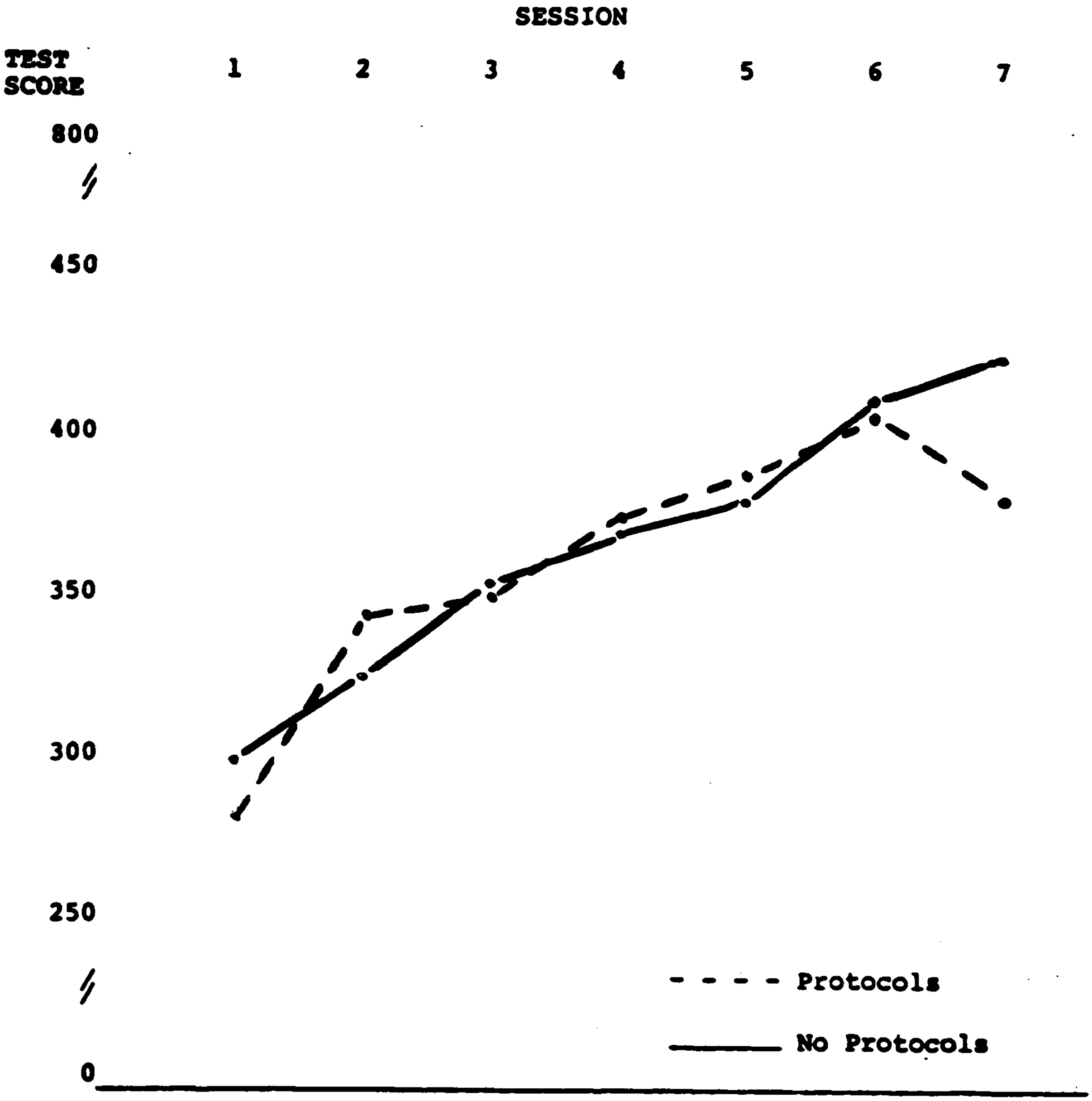

SESSION
TEST SCORE
1
2
3
4
5
6
7
800
450
400
350
300
250
0
Protocols
No Protocols

Figure 2

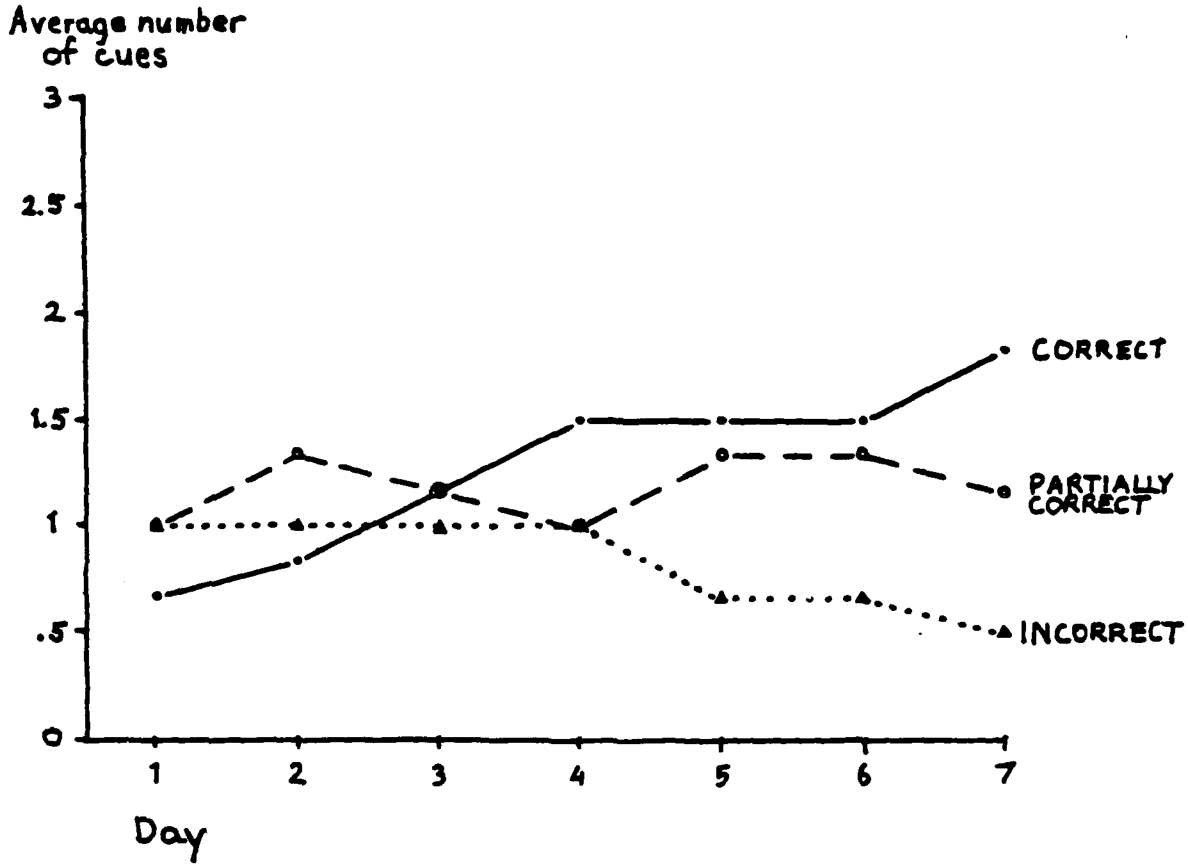

Average number of cues
3
2.5
2
1.5
1
.5
0
1
2
3
4
5
6
7
Day
CORRECT
PARTIALLY CORRECT
INCORRECT

Figure 3.

OFFICE OF NAVAL RESEARCH

Engineering Psychology Group

TECHNICAL REPORTS DISTRIBUTION LIST

OSD

CAPT Paul R. Chatelier
Office of the Deputy Under Secretary
of Defense
OUSDRE (E&LS)
Pentagon, Room 3D129
Washington, D. C. 20301

Dr. Dennis Leedom
Office of the Deputy Under Secretary
of Defense (C^3I)
Pentagon
Washington, D. C. 20301

Department of the Navy

Engineering Psychology Group
Office of Naval Research
Code 442 EP
Arlington, VA 22217 (2 cys.)

Aviation & Aerospace Technology
Programs
Code 210
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Communication & Computer Technology
Programs
Code 240
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Physiology & Neuro Biology Programs
Code 441NB
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Deparment of the Navy

Tactical Development & Evaluation
Support Programs
Code 230
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Manpower, Personnel & Training
Programs
Code 270
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Mathematics Group
Code 411-MA
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Statistics and Probability Group
Code 411-S&P
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Information Sciences Division
Code 433
Office of Naval Research
800 North Quincy Street
Arlington, VA 2217

CDR K. Hull
Code 230B
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Department of the Navy

Special Assistant for Marine Corps
Matters
Code 100M
Office of Naval Research
800 North Quincy Street
Arlington, VA 22217

Dr. J. Lester
ONR Detachment
495 Summer Street
Boston, MA 02210

Mr. R. Lawson
ONR Detachment
1030 East Green Street
Pasadena, CA 91106

CDR James Offutt, Officer-in-Charge
ONR Detachment
1030 East Green Street
Pasadena, CA 91106

Director
Naval Research Laboratory
Technical Information Division
Code 2627
Washington, D. C. 20375

Dr. Michael Melich
Communications Sciences Division
Code 7500
Naval Research Laboratory
Washington, D. C. 20375

Dr. J. S. Lawson
Naval Electronic Systems Command
NELEX-06T
Washington, D. C. 20360

Dr. Robert E. Conley
Office of Chief of Naval Operations
Command and Control
OP-094H
Washington, D. C. 20350

CDR Thomas Berghage
Naval Health Research Center
San Diego, CA 92152

Department-of the Navy

Dr. Robert G. Smith
Office of the Chief of Naval
Operations, OP987H
Personnel Logistics Plans
Washington, D. C. 20350

Dr. Andrew Rechnitzer
Office of the Chief of Naval
Operations, OP 952F
Naval Oceanography Division
Washington, D. C. 20350

Combat Control Systems Department
Code 35
Naval Underwater Systems Center
Newport, RI 02840

Human Factors Department
Code N-71
Naval Training Equipment Center
Orlando, FL 32813

Dr. Alfred F. Smode
Training Analysis and Evaluation
Group
Orlando, FL 32813

CDR Norman E. Lane
Code N-7A
Naval Training Equipment Center
Orlando, FL 32813

Dr. Gary Poock
Operations Research Department
Naval Postgraduate School
Monterey, CA 93940

Dean of Research Administration
Naval Postgraduate School
Monterey, CA 93940

Mr. H. Talkington
Ocean Engineering Department
Naval Ocean Systems Center
San Diego, CA 92152

<u>Department of the Navy</u>

Mr. Paul Heckman
Naval Ocean Systems Center
San Diego, CA 92152

Dr. Ross Pepper
Naval Ocean Systems Center
Hawaii Laboratory
P. O. Box 997
Kailua, HI 96734

Dr. A. L. Slafkosky
Scientific Advisor
Commandant of the Marine Corps
Code RD-1
Washington, D. C. 20380

Dr. L. Chmura
Naval Research Laboratory
Code 7592
Computer Sciences & Systems
Washington, D. C. 20375

HQS, U. S. Marine Corps
ATTN: CCA40 (Major Pennell)
Washington, D. C. 20380

Commanding Officer
MCTSSA
Marine Corps Base
Camp Pendleton, CA 92055

Chief, C^3 Division
Development Center
MCDEC
Quantico, VA 22134

Human Factors Technology Administrator
Office of Naval Technology
Code MAT 0722
800 N. Quincy Street
Arlington, VA 22217

Commander
Naval Air Systems Command
Human Factors Programs
NAVAIR 334A
Washington, D. C. 20361

<u>Department of the Navy</u>

Commander
Naval Air Systems Command
Crew Station Design
NAVAIR 5313
Washington, D. C. 20361

Mr. Philip Andrews
Naval Sea Systems Command
NAVSEA 03416
Washington, D. C. 20362

Commander
Naval Electronics Systems Command
Human Factors Engineering Branch
Code 81323
Washington, D. C. 20360

Larry Olmstead
Naval Surface Weapons Center
NSWC/DL
Code N-32
Dahlgren, VA 22448

Mr. Milon Essoglou
Naval Facilities Engineering Command
R&D Plans and Programs
Code 03T
Hoffman Building II
Alexandria, VA 22332

Capt. Robert Biersner
Naval Medical R&D Command
Code 44
Naval Medical Center
Bethesda, MD 20014

Dr. Arthur Bachrach
Behavioral Sciences Department
Naval Medical Research Institute
Bethesda, MD 20014

Dr. George Moeller
Human Factors Engineering Branch
Submarine Medical Research Lab
Naval Submarine Base
Groton, CT 06340

Department of the Navy

Head
Aerospace Psychology Department
Code L5
Naval Aerospace Medical Research Lab
Pensacola, FL 32508

Commanding Officer
Naval Health Research Center
San Diego, CA 92152

Commander, Naval Air Force,
U. S. Pacific Fleet
ATTN: Dr. James McGrath
Naval Air Station, North Island
San Diego, CA 92135

Navy Personnel Research and
Development Center
Planning & Appraisal Division
San Diego, CA 92152

Dr. Robert Blanchard
Navy Personnel Research and
Development Center
Command and Support Systems
San Diego, CA 92152

CDR J. Funaro
Human Factors Engineeing Division
Naval Air Development Center
Warminster, PA 18974

Mr. Stephen Merriman
Human Factors Engineering Division
Naval Air Development Center
Warminster, PA 18974

Mr. Jeffrey Grossman
Human Factors Branch
Code 3152
Naval Weapons Center
China Lake, CA 93555

Human Factors Engineering Branch
Code 1226
Pacific Missile Test Center
Point Mugu, CA 93042

Department of the Navy

Dean of the Academic Departments
U. S. Naval Academy
Annapolis, MD 21402

Dr. S. Schiflett
Human Factors Section
Systems Engineering Test
Directorate
U. S. Naval Air Test Center
Patuxent River, MD 20670

Human Factor Engineering Branch
Naval Ship Research and Development
Center, Annapolis Division
Annapolis, MD 21402

Mr. Harry Crisp
Code N 51
Combat Systems Department
Naval Surface Weapons Center
Dahlgren, VA 22448

Mr. John Quirk
Naval Coastal Systems Laboratory
Code 712
Panama City, FL 32401

CDR C. Hutchins
Code 55
Naval Postgraduate School
Monterey, CA 93940

Office of the Chief of Naval
Operations (OP-115)
Washington, D. C. 20350

Professor Douglas E. Hunter
Defense Intelligence College
Washington, D. C. 20374

Department of the Army

Mr. J. Barber
HQS, Department of the Army
DAPE-MBR
Washington, D. C. 20310

Department of the Navy

Dr. Edgar M. Johnson
Technical Director
U. S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Director, Organizations and
Systems Research Laboratory
U. S. Army Research Institute
5001 Eisenhower Avenue
Alexandria, VA 22333

Technical Director
U. S. Army Human Engineering Labs
Aberdeen Proving Ground, MD 21005

Department of the Air Force

U. S. Air Force Office of Scientific
Research
Life Sciences Directorate, NL
Bolling Air Force Base
Washington, D. C. 20332

AFHRL/LRS TDC
Attn: Susan Ewing
Wright-Patterson AFB, OH 45433

Chief, Systems Engineering Branch
Human Engineering Division
USAF AMRL/HES
Wright-Patterson AFB, OH 45433

Dr. Earl Alluisi
Chief Scientist
AFHRL/CCN
Brooks Air Force Base, TX 78235

Foreign Addressees

Dr. Daniel Kahneman
University of British Columbia
Department of Psychology
Vancouver, BC V6T 1W5
Canada

Foreign Addressees

Dr. Kenneth Gardner
Applied Psychology Unit
Admiralty Marine Technology
Establishment
Teddington, Middlesex TW11 OLN
England

Director, Human Factors Wing
Defence & Civil Institute of
Environmental Medicine
Post Office Box 2000
Downsview, Ontario M3M 3B9
Canada

Dr. A. D. Baddeley
Director, Applied Psychology Unit
Medical Research Council
15 Chaucer Road
Cambridge, CB2 2EF England

Other Government Agencies

Defense Technical Information Center
Cameron Station, Bldg. 5
Alexandria, VA 22314 (12 copies)

Dr. Craig Fields
Director, System Sciences Office
Defense Advanced Research Projects
Agency
1400 Wilson Blvd.
Arlington, VA 22209

Dr. M. Montemerlo
Human Factors & Simulation
Technology, RTE-6
NASA HQS
Washington, D. C. 20546

Dr. J. Miller
Florida Institute of Oceanography
University of South Florida
St. Petersburg, FL 33701

Other Organizations

Dr. Robert R. Mackie
Human Factors Research Division
Canyon Research Group
5775 Dawson Avenue
Goleta, CA 93017

Dr. Amos Tversky
Department of Psychology
Stanford University
Stanford, CA 94305

Dr. H. McI. Parsons
Human Resources Research Office
300 N. Washington Street
Alexandria, VA 22314

Dr. Jesse Orlansky
Institute for Defense Analyses
1801 N. Beauregard Street
Alexandria, VA 22311

Professor Howard Raiffa
Graduate School of Business Administration
Harvard University
Boston, MA 02163

Dr. T. B. Sheridan
Department of Mechanical Engineering
Massachusetts Institute of Technology
Cambridge, MA 02139

Dr. Arthur I. Siegel
Applied Psychological Services, Inc.
404 East Lancaster Street
Wayne, PA 19087

Dr. Paul Slovic
Decision Research
1201 Oak Street
Eugene, OR 97401

Dr. Harry Snyder
Department of Industrial Engineering
Virginia Polytechnic Institute and State University
Blacksburg, VA 24061

Other Organizations

Dr. Ralph Dusek
Administrative Officer
Scientific Affairs Office
American Psychological Association
1200 17th Street, N. W.
Washington, D. C. 20036

Dr. Robert T. Hennessy
NAS - National Research Council (COHF)
2101 Constitution Avenue, N. W.
Washington, D. C. 20418

Dr. Amos Freedy
Perceptronics, Inc.
6271 Variel Avenue
Woodland Hills, CA 91364

Dr. Robert C. Williges
Department of Industrial Engineering and OR
Virginia Polytechnic Institute and State University
130 Whittemore Hall
Blacksburg, VA 24061

Dr. Meredith P. Crawford
American Psychological Association
Office of Educational Affairs
1200 17th Street, N. W.
Washington, D. C. 20036

Dr. Deborah Boehm-Davis
General Electric Company
Information Systems Programs
1755 Jefferson Davis Highway
Arlington, VA 22202

Dr. Ward Edwards
Director, Social Science Research Institute
University of Southern California
Los Angeles, CA 90007

Dr. Robert Fox
Department of Psychology
Vanderbilt University
Nashville, TN 37240

Other Organizations

Dr. Charles Gettys
Department of Psychology
University of Oklahoma
455 West Lindsey
Norman, OK 73069

Dr. Kenneth Hammond
Institute of Behavioral Science
University of Colorado
Boulder, CO 80309

Dr. James H. Howard, Jr.
Department of Psychology
Catholic University
Washington, D. C. 20064

Dr. William Howell
Department of Psychology
Rice University
Houston, TX 77001

Dr. Christopher Wickens
Department of Psychology
University of Illinois
Urbana, IL 61801

Mr. Edward M. Connelly
Performance Measurement
Associates, Inc.
410 Pine Street, S. E.
Suite 300
Vienna, VA 22180

Professor Michael Athans
Room 35-406
Massachusetts Institute of
Technology
Cambridge, MA 02139

Dr. Edward R. Jones
Chief, Human Factors Engineering
McDonnell-Douglas Astronautics Co.
St. Louis Division
Box 516
St. Louis, MO 63166

Other Organizations

Dr. Babur M. Pulat
Department of Industrial Engineering
North Carolina A&T State University
Greensboro, NC 27411

Dr. Lola Lopes
Information Sciences Division
Department of Psychology
University of Wisconsin
Madison, WI 53706

Dr. A. K. Bejczy
Jet Propulsion Laboratory
California Institute of Technology
Pasadena, CA 91125

Dr. Stanley N. Roscoe
New Mexico State University
Box 5095
Las Cruces, NM 88003

Mr. Joseph G. Wohl
Alphatech, Inc.
3 New England Executive Park
Burlington, MA 01803

Dr. Marvin Cohen
Decision Science Consortium
Suite 721
7700 Leesburg Pike
Falls Church, VA 22043

Dr. Wayne Zachary
Analytics, Inc.
2500 Maryland Road
Willow Grove, PA 19090

Dr. William R. Uttal
Institute for Social Research
University of Michigan
Ann Arbor, MI 48109

Dr. William B. Rouse
School of Industrial and Systems
Engineering
Georgia Institute of Technology
Atlanta, GA 30332

Other Organizations

Dr. Richard Pew
Bolt Beranek & Newman, Inc.
50 Moulton Street
Cambridge, MA 02238

Dr. Hillel Einhorn
Graduate School of Business
University of Chicago
1101 E. 58th Street
Chicago, IL 60637

Dr. Douglas Towne
University of Southern California
Behavioral Technology Laboratory
3716 S. Hope Street
Los Angeles, CA 90007

Dr. David J. Getty
Bolt Beranek & Newman, Inc.
50 Moulton street
Cambridge, MA 02238

Dr. John Payne
Graduate School of Business
Administration
Duke University
Durham, NC 27706

Dr. Baruch Fischhoff
Decision Research
1201 Oak Street
Eugene, OR 97401

Dr. Andrew P. Sage
School of Engineering and
Applied Science
University of Virginia
Charlottesville, VA 22901

Denise Benel
Essex Corporation
333 N. Fairfax Street
Alexandria, VA 22314

ATE
LME