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A COMPUTER CONTROLLED EXPERIMENT ON RECENCY IN PROBABILITY LEARNING[1]

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Both theroretical work and research results have been somewhat equivocal on the subject of recency in the two-choice probability learning task. The present paper describes a computer controlled experiment designed to investigate the consequences of reinforcement of negative recency on its occurrence. Results are examined in terms of both the methodology of computer controlled experimentation and the substance of Estes' pattern model of such learning.

INTRODUCTION

THE study reported in the present paper had two aims: The primary concern involved an empirical examination of first order conditional response probabilities in a two-choice noncontingent probability learning situation; the secondary concern was with the effects of a design employing full computer control of this standard verbal learning task.

The two-choice noncontingent probability learning experiment is a reasonably standard procedure. The basic design stems from Humphreys' (1939) early work. Two events E_1 and E_2 are defined by the experimenter. On each of a series of trials S is required to predict which of these events will occur next. Thus, he may display response A_1 if his prediction is that E_1 will occur, or A_2 if he thinks E_2 will occur. Following his choice either E_1 or E_2 occurs according to a random schedule with some fixed probability, Π, of E_1. Thus, after each prediction, S is informed as to the correctness of that choice.

Experimental apparatus varies from time to time and experimenter to experimenter. So does the wording of instructions for S and the level of Π. But the basic form of the experiment is reasonably standard. The results, too, are reasonably standard. Most Ss match their probabilities of predicting event E_1 to the objective probability of that event (Π) over a considerable range of variation in experimental conditions (Estes, 1962a; 1964).

A good many attempts to develop a theory of this type of probability learning have been made (Bush & Estes, 1959). At this moment, the most generally satisfactory theoretical effort seems to be provided by the N-element pattern model of Estes' stimulus sampling theory (Estes, 1959). This model is derived within the general framework of stimulus sampling theory; it provides convincingly accurate predictions of both asymptotic response probabilities and learning rates. Moreover, the pattern model yields predictions of response probabilities conditional upon both responses and reinforcements on previous trials.

These predicted conditional probabilities do, however, provide a basis for controversy. The prediction is that given the occurrence of event E_1 on trial n, the probability of response A_1 (prediction of E_1) on trial $n + 1$ will be greater than it would have been if E_2 occurred on trial n. This is called positive recency.

On the other hand, a number of investigators have observed that some Ss display the opposite tendency—negative recency (Anderson, 1960; Feldman, 1959; Nicks, 1959). For these Ss the occurrence of E_1 on n is occasion for the reduction of their likelihood of responding with A_1 on $n + 1$. Such Ss seem to assume the maturation of probabilities; they display the gambler's fallacy.

Estes (1962b, p. 133) has characterized such behavior as pre-experimental bias car-

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ried over from gambling and other real life situations. Although this particular example suggests that Estes may have been victimized by rigged games of chance, the basic idea is not unreasonable. It indicates, in fact, the importance of examining probability learning in natural settings in an attempt to uncover the bases upon which such a strategy might rest.

In any case, Estes (1962b) has argued from theoretical grounds that, once they have been exposed to the probability learning task, subjects should exhibit, not negative, but positive recency. Only when negative recency is reinforced, he has suggested, should it be exhibited.

Empirical evidence on recency is not unequivocal. On one hand the studies cited above show negative recency. In contrast, Estes (1962b) has cited a series of studies where *Ss* were trained to exhibit positive recency. However, only a relatively small number of studies have explicitly set out to control the reinforcement of recency (Hake & Hyman, 1953; Engler, 1958; Anderson, 1960). The results of these studies suggest that *Ss* do respond to differing reinforcement schedules, but the patterns of such response are not entirely clear. Moreover, theoretical work on this aspect of probability learning is sketchy. More data are needed before convincing models can be developed.

A review of the general literature on the two-choice probability learning experiment, however, reveals that more data on recency are available than we might at first suspect. Experiments of two distinct types have been conducted that differ in their reinforcement of negative recency. These two types of experiments have been confused perhaps because both result in probability matching. It is, however, a reasonable conjecture that they arrive at this result through quite different psychological mechanisms.

In both of these experiments subjects are required to predict the occurrence of alternative events. In both, one event, E_1 occurs with some probability, Π ($\Pi \geqq .5$). The alternative, E_2, occurs, of course, with probability $1 - \Pi$. In experiments of the first type, which I shall term strict random, all trials are strictly independent (Friedman, Burke, Cole, Keller, Millward, & Estes, 1964). Thus, the probability of an event, say E_1 on trial $n + 1$ is equal to Π regardless of the event occurring on trial n:

$$Pr(E_{1,n+1} \mid E_{1,n}) = Pr(E_{1,n+1} \mid E_{2,n}) = Pr(E_1) = \Pi;$$

and no recency at all—neither positive nor negative—is reinforced.

Experiments of the second type, however, are characterized by certain constraints on independence of trials. Typically, a series of k trials is defined such that within the series there are exactly Πk events of type E_1 and $(1 - \Pi)k$ events of type E_2 (Siegel, 1961). Since these events are randomly ordered, I shall refer to experiments of this kind as random permutations. Note that here the probability of an event, E_1, on trial $n + 1$ is dependent upon the event on trial n. In general,

$$Pr(E_{1,n+1} \mid E_{1,n}) < Pr(E_{1,n+1} \mid E_{2,n}).$$

Thus, the random permutation experiment puts a constraint on the length of runs. Probabilities do mature within each series of k trials, and as a result, negative recency is reinforced.

The present study, then, is an explicit attempt systematically to compare the conditional probabilities of response, notably the display of recency, under these two established forms of the two-choice experiment.

METHOD

Subjects

Ss were 60 volunteers from the student body of the University of Hawaii. Thirty-eight were females and eight were graduate students. None had previous experience with experiments in verbal learning.

Equipment and procedure

E for this experiment was an IBM 1130 computer. *Ss* were ushered into a room containing the computer and invited to sit at the console. They were told that to start the experiment they should strike the key marked RETURN. When they did so, the machine took over. It typed the following instructions:

HELLO.

I AM A COMPUTER AND I AM WORKING AS A PSYCHOLOGIST. TO TALK TO ME YOU MUST TYPE. BUT FOR THIS EXPERIMENT YOU WILL ONLY HAVE TO TYPE NUMBERS. NOTE THAT THE NUMBERS ARE PRINTED IN WHITE ABOVE THE LETTERS ON THE RIGHT SIDE OF THE KEYBOARD. ZERO IS IN THE TOP LINE AND THE OTHERS ARE BELOW.

LET'S TRY THE KEYBOARD. YOU TYPE THE NUMBER ZERO.

If the subject typed any character other than 0 the computer responded,

NO, TRY IT AGAIN. LOOK FOR 0 AT THE TOP OF THE KEYS.

If zero was typed the response was:

VERY GOOD. NOW WE ARE GOING TO TRY A LEARNING EXPERIMENT. I WILL TYPE A SERIES OF NUMBERS ONE AT A TIME. EACH WILL BE EITHER 0 OR 1. YOUR JOB IS TO TRY TO PREDICT CORRECTLY WHICH NUMBER I WILL TYPE ON EACH TRIAL. WHEN I AM READY I WILL TYPE A STAR (*). IF YOUR PREDICTION IS THAT I WILL TYPE A 0, YOU TYPE THE NUMBER 0. IF YOUR PREDICTION IS 1, YOU TYPE 1. LET'S TRY A SAMPLE RUN.

Here an asterisk was presented. If S typed 0 or 1 he was reinforced; if any other character was typed, he was asked to try again. Once a correct response was made, the machine continued:

NOW LET'S GO AHEAD. THERE WILL BE 200 TRIALS. WHEN I TYPE A *, MAKE YOUR PREDICTION. IN EACH CASE I WILL TYPE OUT THE ACTUAL NUMBER SO YOU CAN SEE WHETHER YOU WERE RIGHT OR WRONG. DO YOUR BEST TO PREDICT EACH TRIAL CORRECTLY. SO, HERE WE GO....

The computer then generated a (pseudo) random number and assigned S to either a schedule of strict random reinforcement or one of random permutation with $k = 4$. Π in both cases was .75. Another random number was used to determine whether 0 or 1 would be E_1. The human experimenter, though sometimes present, was unaware of the experimental conditions for any S.

The responses of each S were recorded automatically by the computer and were printed on the printer and written on the disk in groups of 20 at the end of the 200 trials. On demand, E could obtain a summary of the performance of all Ss at any time, along with estimates of the parameters of Estes' pattern theory. In short, the computer was used for the entire experimental procedure: (1) instructing Ss, (2) conducting a practice trial, (3) randomly assigning each S to the experimental or control group, (4) randomly choosing E_1, (5) presenting 200 stimuli, (6) recording 200 responses, (7) presenting 200 reinforcements, (8) refining and storing the data for each S, (9) summarizing data over all Ss, (10) estimating pattern theory parameters, and (11) generating tables to permit the comparison of theoretical and observed learning behavior.

RESULTS AND DISCUSSION

Methodological

It is apparent that the fact that a computer was the research instrument in this study might be critical for the results obtained. There is nothing in principle about computer based experiments that limits their effectiveness or generality. In this experiment, however, use of the particular computer system available did necessitate at least three departures from standard experimental form.

First, the main console was used as the input-output device. The console panel includes a complicated array of flashing lights above the keyboard. These lights might be assumed to be stimuli by S, or at least might serve as distractions. This potential problem could be eliminated by the use of one of the standard remote typewriter or cathode ray tube consoles available for time-shared computer systems.

Second, since this computer system provided no programmed access to the internal clock, control of the time between the presentation of the stimulus and the occurrence of the event was not possible. Instead, for each trial, the occurrence of E_1 or E_2 had to await the response by S. This too, of course, is not a necessary limitation of a computer based experiment. The more developed computer systems permit programmed access to the clock and thereby allow the display of events at any specified interval after the stimulus has been presented.

Third, this system required the use of a typewriter for both input and output. Thus, a permanent copy of the history of his trials was present and available to each S. It was noted that some Ss referred frequently to this record, and one or two studied it at length. Clearly, the presence of such a record departs from the traditional experimental form and potentially contaminates the learning process. Use of a cathode ray tube for display would, of course, eliminate this problem.

In any case, it seemed advisable to examine the possibility that the computer process introduced significant instrument effects in the two-choice learning experiment.

The results shown in Table 1 are relevant to this hypothesis. Both groups display the typical negatively accelerated increasing functions that close-in on the phenomenon of probability matching. The last 80 responses for both groups were judged to be reasonably stable, so they were used to determine the degree to which probability matching was revealed. The probability of choosing the more frequent alternative for the last 80 responses of the strict random group was .753, while that for the random permutations group was .754. These results are consistent with previous findings where probability matching was displayed. For the combined group, the probability of an A_1 response is .753. This is based on 4800 observations, and it is quite close to the expected value of $\Pi = .75$. It seems, therefore, that use of this computer system, even with its anticipated limitations, did not seriously distort the results of the two-choice experiment.

TABLE 1

PROPORTIONS OF RESPONSES PREDICTING THE MORE FREQUENT ALTERNATIVE (A_1) IN BLOCKS OF 20 TRIALS

Trial Block	*Proportion of A_1 Responses*		
	Strict Random	*Random Permutation*	*Combined Group*
1–20	.606	.565	.585
21–40	.676	.675	.675
41–60	.768	.730	.749
61–80	.738	.745	.741
81–100	.793	.710	.751
101–120	.788	.775	.781
121–140	.736	.746	.741
141–160	.768	.736	.752
161–180	.778	.761	.769
181–200	.730	.771	.750
Number of Ss	30	30	60

Substantive

Our concern here is with differences in the sequence of choices under conditions of strict randomness and random permutation. A choice on any trial may depend upon the event (E_1 or E_2) or the choice (A_1 or A_2) on the previous trial, or a combination of both. The sequential statistics are shown in Tables 2 and 3 for the final 80 responses for the two groups.

Marked sequential effects are displayed for each group. The range is from .484 to .853 for the strict random group, and from .518 to .849 for the random permutation group. Moreover, it is apparent that the conditional probabilities of an A_1 response under these several conditions differ for the two groups. They differ not only in magnitude but in relative order.

Sequential statistics displayed by the strict random group follow the order defined by the n-element pattern model of stimulus sampling theory. In this case, the parameters for the pattern model were estimated according to the procedure suggested by Atkinson, Bower and Crothers (1965). Thus, using the observations with the largest number of degrees of freedom, we can let

$$P = Pr(A_{1,n+1} \mid A_{1,n}, E_{1,n})$$

and

$$Q = Pr(A_{1,n+1} \mid A_{1,n}, E_{2,n}).$$

Then,

$$\mathbf{N} = \frac{1}{4(P - \Pi)} = 2.424$$

and

$$\mathbf{c} = 1 - \mathbf{N}(Q - (\Pi(1 - \mathbf{N}^{-1}))) = .512.$$

TABLE 2

SEQUENTIAL STATISTICS FOR THE FINAL 80 RESPONSES OF THE STRICT RANDOM SERIES

Condition on Trial n	*Number of A_1 on Trial $n+1$*	*Total*	*Prob. of A_1 on $n+1$*
A_1, E_1	1150	1348	0.853
A_1, E_2	294	458	0.641
A_2, E_1	288	437	0.659
A_2, E_2	76	157	0.484
A_1	1444	1806	0.799
A_2	364	594	0.612
E_1	1438	1785	0.805
E_2	370	615	0.601
Total	1808	2400	

On the basis of these estimates the theoretical values of the sequential statistics were generated. They are shown in Table 4 along with the corresponding observed values.

Inspection of Table 4 shows that in every case the theoretical estimates of conditional probabilities are quite good. In interpreting this correspondence, however, it must be remembered that there are only two independent entries in Table 4. Two entries were used in estimating the parameters N and c, and four of the entries may be calculated from the remaining four, so the results must be interpreted with caution. Nonetheless, the results do demonstrate general consistancy between the pattern model and these observations.

For the strict random group, positive recency is displayed. The probability of an A_1 response following an E_1 trial is .805 and following an E_2 trial only .601. Thus the occurrence of an event increases the likelihood that it will be predicted on the next trial.

TABLE 3

SEQUENTIAL STATISTICS FOR THE FINAL 80 RESPONSES OF THE RANDOM PERMUTATION SERIES

Condition on Trial n	*Number of A_1 on Trial $n+1$*	*Total*	*Prob. of A_1 on $n+1$*
A_1, E_1	1132	1412	0.801
A_1, E_2	309	400	0.722
A_2, E_1	205	395	0.518
A_2, E_2	164	193	0.849
A_1	1441	1812	0.795
A_2	369	588	0.627
E_1	1337	1807	0.739
E_2	473	593	0.797
Total	1810	2400	

TABLE 4

PREDICTED AND OBSERVED VALUES OF SEQUENTIAL STATISTICS FOR THE FINAL 80 RESPONSES OF THE STRICT RANDOM GROUP

Asymptotic Quantity	*Predicted*	*Observed*
$Pr(A_1 \mid A_1E_1)$	.853	.853
$Pr(A_1 \mid A_1E_2)$	.641	.641
$Pr(A_1 \mid A_2E_1)$	.651	.659
$Pr(A_1 \mid A_2E_2)$	.440	.484
$Pr(A_1 \mid A_1)$	.800	.799
$Pr(A_1 \mid A_2)$	.599	.612
$Pr(A_1 \mid E_1)$	.802	.805
$Pr(A_1 \mid E_2)$	.591	.601

On the other hand, the order of conditional probabilities for the random permutation group displays negative recency. Note that the conditional probability of an A_1 response following an E_1 trial is .739 and that following an E_2 trial is .797. Here, *Ss* show a tendency to alternate; given the occurrence of an event, they will predict the alternative with greater likelihood.

This result provides evidence for the conjecture by Estes (1964) that reinforcement of negative recency will result in its display. In the random permutation experiment the sampling function of events is not independent of previous events. Thus, since it assumes independence, the usual pattern model interpretation is not appropriate in this case. On the face of it, a different learning model appears to be required in order to account for the case of random permutations.

A clue to the direction in which to seek such a model can be found in Table 5. Although between-group comparisons showed negative recency for the random permutation group, comparing conditional response and event probabilities within groups reveals that both exhibit a tendency to overpredict

TABLE 5

CONDITIONAL RESPONSE AND REINFORCEMENT SCHEDULES FOR BOTH GROUPS

Condition	*Strict Random*	*Random Permutation*
$Pr\ (E_{1,n+1} \mid E_{1,n})$	.750	.6875
$Pr\ (A_{1,n+1} \mid E_{1,n})$	.805	.739
Difference	+.055	+.0515
$Pr\ (E_{1,n+1} \mid E_{2,n})$	.750	.9375
$Pr\ (A_{1,n+1} \mid E_{2,n})$	.601	.797
Difference	−.149	−.1405

the occurrence of E_1 event pairs and to underpredict E_2, E_1 event pairs. Moreover, this tendency is displayed to just about the same degree by *S*s in both strict random and random permutation groups.

This result suggests that *S*s do in fact discriminate stimuli in terms of event sequences. Both, we might suppose, do attempt to follow conditional event probabilities. In the strict random experiment, the independence of events permits *S*s to behave as if their sampling function were independent of event sequences. In general, it could be assumed that in every case, *S*s sample stimuli conditionally upon event sequences and only when those event sequences themselves are independent does *S*'s sampling appear to be independent of event sequence.

In any case, it is clear that the two traditional forms of the two-choice noncontingent probability learning experiment do yield differing results in terms of conditional response probabilities. Some theoretical modification or extension is needed to account for this fact.

REFERENCES

Anderson, N. H. Effect of first-order conditional probability in a two-choice learning situation. *J. exp. Psychol.*, 1960, 59, 73–93.

Atkinson, R. C., Bower, G. H., & Crothers, E. J. *An introduction to mathematical learning theory*. New York: John Wiley and Sons, 1965.

Bush, R. R., & Estes, W. K. (Eds.). *Studies in mathematical learning theory*. Stanford: Stanford Univ. Press, 1959.

Engler, J. Marginal and conditional stimulus and response probabilities in verbal conditioning. *J. exp. Psychol.*, 1958, 55, 303–307.

Estes, W. K. A descriptive approach to the dynamics of choice behavior. In E. Nagel, P. Suppes, & A. Tarski (Eds.), *Logic, methodology and philosophy of science: Proceedings of the 1960 international congress*. Stanford: Stanford Univ. Press, 1962, Pp. 424–433. (a)

Estes, W. K. Learning theory. *Annu. rev. Psychol.*, 1962, 12, 107–144. (b)

Estes, W. K. Probability Learning. In A. W. Melton (Ed.), *Categories of human learning*. New York: Academic Press, 1964.

Estes, W. K., & Suppes, P. Foundations of statistical learning theory, II. The stimulus sampling model for simple learning. Tech. Rep. No. 26, Institute for Mathematical Studies in the Social Sciences, Stanford University, 1959.

Feldman, J. On the negative recency hypothesis in the prediction of a series of binary symbols. *Amer. J. Psychol.*, 1959, 72, 597–599.

Friedman, M. P., Burke, C. J., Cole, M., Keller, L., Millward, R. B., & Estes, W. K. Two-choice behavior under extended training with shifting probabilities of reinforcement. In R. C. Atkinson (Ed.), *Studies in mathematical psychology*. Stanford: Stanford Univ. Press, 1964, Pp. 250–316.

Hake, H. W., & Hyman, R. Perception of the statistical structure of a random series of binary symbols. *J. exp. Psychol.*, 1953, 45, 67–74.

Humphreys, L. G. Acquisition and extinction of verbal expectations in a situation analogous to conditioning. *J. exp. Psychol.*, 1939, 25, 294–301.

Nicks, D. C. Prediction of sequential two-choice decisions from event runs. *J. exp. Psychol.*, 1959, 57, 105–114.

Siegel, S. Decision-making and learning under varying conditions of reinforcement, *Ann. N. Y. Acad. Sci.*, 1961, 89, 766–782.

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. . . the species of the things of the world are not immediately suited for themselves to bring to completion an action on the eye because of the nobility of the latter. Therefore these species must be assisted and excited by the species of the eye, which proceeds through the space occupied by the visual pyramid, altering and ennobling the medium and rendering it commensurate with sight. Thus the species of the eye prepares for the approach of the species of the visible object and, moreover, ennobles the species of the object so that it is wholly conformable to and commensurate with the nobility of the animate body (i.e. the eye).

ROGER BACON, *Opus Majus*