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DISCRIMINATION LEARNING IN A VERBAL CONDITIONING SITUATION $\frac{1}{2}$

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This study deals with an analysis of discrimination learning in a modified verbal conditioning situation (1,7). Two stimuli, designated T_1 and T_2 , are employed, and two responses A_1 and A_2 are available to the subject. Each trial begins with the presentation of either T_1 or T_2 , the probability of a T_1 trial is β and the probability of a T_2 trial is 1- β . Following the T_1 stimulus, an A_1 response is correct with probability π_1 , and an A_2 response is correct with probability $1-\pi_1$. Following the T_2 stimulus, an A_1 response is correct with probability π_2 , and an A_2 response is correct with probability $1-\pi_2$. The subject is instructed to maximize the number of trials on which his response is correct.

The primary aim of the study is to evaluate the adequacy of the Burke and Estes <u>Component Model for Stimulus Variables in Discrimination Learning</u> (2) in the type of experimental situation described above. The theory is presented in detail elsewhere (2, 5, 6), and only the salient features will be reviewed here. The principle assumption is that the two stimuli T_1 and T_2 are to be conceptually represented as two sets of stimulus elements which are designated S_1 and S_2 respectively. On T_1 trials the organism's response is determined by a sample of stimulus elements from S_1 ; on T_2 trials, by a sample of stimulus elements from S_2 . In addition, a set S_c is designated which represents those stimulus elements common to both sets S_1 and S_2 ($S_c = S_1 \cap S_2$); that is, stimulus events common to the presentation of either T_1 or T_2 . One can think of the size of the S_c set as providing an <u>index of similarity</u> between T_1 and T_2 , the larger the relative size of S_c with respect to S_1 and S_2 the greater the similarity between the stimuli (3).

Given the above stimulus representation and rules for conditioning (2,4) one can derive an expression for the probability of an A_1 or A_2 response on trial n. For our purposes we will be concerned with the long run probability of response behavior and, consequently, will present only asymptotic predictions. Namely,

(1)
$$p_{\infty}(A_{1}|T_{1}) = \pi_{1}(1-\omega_{1}) + \pi_{c}\omega_{1}$$

(2)
$$p_{\infty}(A_1|T_2) = \pi_2(1-\omega_2) + \pi_c\omega_2$$

where $p_{\infty}(A_1|T_i)$ is the expected asymptotic probability of an A_1 response on a T_i (i=1 or 2) type trial, and $\pi_c = \beta \pi_1 + (1-\beta) \pi_2 \cdot \frac{2}{2}$

The quantity ω_1 is a theoretical parameter and essentially represents a ratio of the number of elements in S_c to the number of elements in S_i . Consequently $0 \le \omega_i \le 1$ and is independent of experimental parameters π_1 , π_2 , and β . In our situation T_1 and T_2 are symmetric, and it is natural to assume $\omega_1 = \omega_2 = \omega$. The closer ω is to unity, the greater the similarity between T_1 and T_2 ; the closer ω is to zero, the greater the dissimilarity between T_1 and T_2 .

Method

Subjects.-- The Ss were 205 undergraduates obtained from introductory

courses in psychology at Stanford University. They were run in 20 subgroups, with from 8 to 14 Ss per subgroup.

<u>Procedure</u>.-- Each <u>S</u> received a sheet of paper on which numbers from 1 to 320 were printed, following each number were the letters A and B. <u>Ss</u> were also provided with two blank sheets of heavy white paper. The instructions began as follows:

" I want to see how well you can do in a rather unusual problem situation. At the beginning of each trial, I will announce the number of the trial, and then I will say one of these two nonsense words: MEF or ZIL. About 4 seconds later I will say either A or B. Immediately after I have said ZIL or MEF on each trial, you are to guess whether I will say A or B on that trial by circling either A or B in the appropriate place on your answer sheet. If you expect an A, circle A; if you expect a B, circle B. Guess on every trial even if you are very unsure - your guesses or hunches may turn out to be right, and it is important to have a complete record of your learning. Try to improve as you go along and make as many correct choices as possible.

"I want you to make each choice without seeing any of your previous choices. Therefore, please take the small strip of heavy white paper and slide it down the answer sheet, covering each choice as soon as you have made it. When you have completed a column, use the big piece of paper to cover that whole column, and again use the small strip to slide down the next column." The remainder of the instructions involved repetition of the main points. The E stood at the back of the room where it was possible to watch

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<u>Ss</u> to be sure they were following instructions. The number of each trial was announced; one second later \underline{E} said either MEF or ZIL, 4 seconds after that either A or B, and 2 seconds later the number of the next trial was announced.

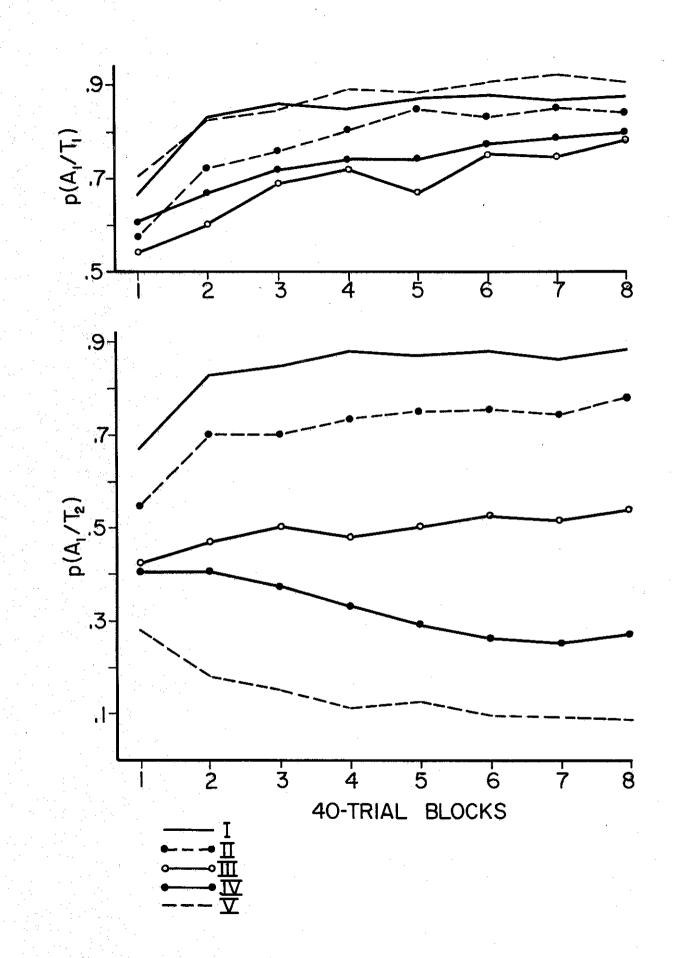
After the fourth trial \underline{E} interrupted the sequence to ask whether \underline{Ss} had any questions. Questions were answered by rephrasing appropriate parts of the instructions. The remaining 316 trials were run without interruption. The complete procedure took 45 to 50 minutes for each subgroup.

MEF and ZIL were selected from the list of nonsense syllables with zero association value given by Glaze (8). They met the criteria of being clearly distinguishable, having an unambiguous correct pronounciation, and sounding unlike either A or B.

<u>Design</u>.-- There were five experimental conditions. For all experimental groups π_1 was .85 and β was .50. The groups differed with respect to the π_2 parameter; the values of π_2 were .85 (Group I), .70 (Group II), .50 (Group III), .30 (Group IV) and .15 (Group V). Within each of the five experimental groups there were four subgroups distinguished as follows: (1) $T_1 = \text{MEF}(T_2 = \text{ZIL})$ and $A_1 = A(A_2 = B)$, (2) $T_1 = \text{ZIL}$ and $A_1 = A$, (3) $T_1 = \text{MEF}$ and $A_1 = B$, and (4) $T_1 = \text{ZIL}$ and $A_1 = B$.

For each of the 20 subgroups a different random sequence of events was generated in accordance with the assigned values of π_1 and π_2 with the following restrictions imposed on the randomization: (i) Each successive block of 40 trials included 20 T₁ trials and 20 T₂ trials, (ii) Of the 20 T₁ trials in a 40 trial block, an A₁ response was correct on exactly π_1 (20) of the trials and an A₂ was correct on the remaining $(1-\pi_1)$ (20)

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trials, and (iii) of the 20 T₂ trials in a 40-trial block, an A₁ response was correct on exactly $\pi_2(20)$ of the trials and an A₂ was correct on $(1-\pi_2)(20)$ trials.

Groups I, II, IV and V consisted of 40 Ss each; there were 45 Ss in Group III.

Results and Discussion

Figure 1 presents the mean group response behavior over all trials of the experiment. In this figure (i) the proportion of A_1 responses given a T_1 trial and (ii) the proportion of A_1 responses given a T_2 trial are plotted in successive blocks of 40 trials. In each block of 40 trials there are 20 T_1 's and 20 T_2 's, therefore the proportion computed for an individual S is based on 20 observations.

An inspection of this figure indicates that response curves are fairly stable over the last 120 trials, and it appears reasonable to assume that a constant level of responding has been reached. Consequently, proportions computed over the last 120 trials were used as estimates of $p_{\infty}(A_1|T_1)$ and $p_{\infty}(A_1|T_2)$.

A simple analysis of variance was run for each experimental group to test for differences between the four subgroups with respect to the total number of A_1 responses in the last 120 trials. None of the five analyses were significant at the .05 level, and for subsequent analyses the subgroup distinctions within an experimental group were not considered.

Table 1 presents the observed mean proportions for the last 120 trials and the standard deviations associated with the means. Entries for Groups I, II, IV and V are based on N=40; entries for Group III are based on N=45. TABLE 1. Observed values of $p_{\infty}(A_1|T_1)$ and $p_{\infty}(A_1|T_2)$ computed over the last block of 120 trials.

· · · · · · · · · · · · · · · · · · ·	$\mathbb{P}_{\infty}(\mathbf{A}_{1} \mathbf{T}_{1})$		$p_{\omega}(A_1 T_2)$	
	mean	S	mean	S
I	.871	.098	870	.092
II	.838	.099	.766	.105
III	•757	.119	.515	. 157
IV	.785	.139	.262	.172
V	.910	.085	.088	.087

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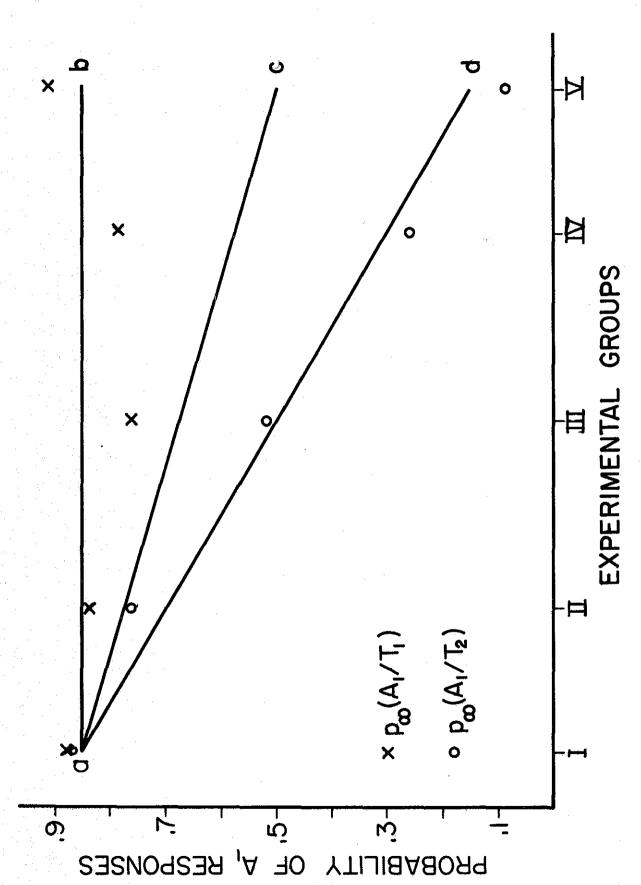










Figure 2 presents a schematic representation of the theoretical predictions as well as the observed asymptotic values given in Table 1. By substituting appropriate parameter values in Equations (1) and (2) we establish the following results: (1) If $\omega=0$, then (for the group designation on the abscissa) $p_{\infty}(A_1|T_1)$ falls on the straight line ab and $p_{\infty}(A_1|T_2)$ falls on the straight line ad. (2) If $\omega=1$, then both $p_{\infty}(A_1|T_1)$ and $p_{\infty}(A_1|T_2)$ falls on the straight line ac. (3) If $0 < \omega < 1$, then (i) $p_{\infty}(A_1|T_1)$ falls on a straight line with origin at point a and bounded between lines ab and ac and (ii) $p_{\infty}(A_1|T_2)$ falls on a straight line with origin at point a and bounded between lines ac and ad. Further, the amount of displacement of $p_{\infty}(A_1|T_1)$ from the line ab is the same as the displacement of $p_{\infty}(A_1|T_2)$ from the line ad and is a function of the value of ω .

An inspection of Figure 2 suggests certain analyses of the data. In particular, the expected values of $p_{\infty}(A_1|T_1)$ for the various groups should lie on or between the lines ab and ac. However, the observed values for both Groups I and V are above the ab line. To establish whether these observed points are significantly above the maximum value of .85, \underline{t} tests were run employing the observed standard deviations of the mean as the error term. The obtained values of \underline{t} were 1.36 and 4.46 for Groups I and V respectively. With 39 d.f. the Group I result is not significant at the .10 level, while the Group V result is significant beyond the .01 level. Thus, for Group V the observed value of $p_{\infty}(A_1|T_1)$ was significantly greater than the maximum value predicted by the theory.

Similarly the expected values of $p_{\infty}(A_1|T_2)$ for the various groups should lie on or between the lines ac and ad. Yet for Group I the

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observed value is above .85 and for Groups IV and V the observed values are below .30 and .15 respectively. To establish whether the observed results were significantly different from these values, \underline{t} tests were again run. The obtained values of \underline{t} were 1.37, 1.40 and 4.58 for Groups I, IV, and V respectively. Thus, for Group V the observed value of $p_{\infty}(A_1|T_1)$ is significantly smaller than the minimum value predicted by the theory.

A more stringent requirement of the theory is that (i) the expected values of $p_{\infty}(A_1|T_1)$ fall on a straight line bounded between the lines ab and ac and (ii) the expected values of $p_{\infty}(A_1|T_2)$ fall on a straight line bounded between the lines ac and ad. Inspection of Figure 2 clearly indicates, at least for $p_{\infty}(A_1|T_1)$, that this is not the case. The observed values of $p_{\infty}(A_1|T_1)$ decrease from Groups I to III but instead of continuing in this trend, show a marked increase for Groups IV and V. Thus we find a convex rather than a linear relationship between $p_{\infty}(A_1|T_1)$ and the groups when ordered from I to V.

An experiment employing a procedure similar to the one used in this study was reported by Estes and Burke (5). They had two experimental conditions, in both of which $\pi_1 = 1.00$ and $\pi_2 = .50$. The results qualitatively resemble our observations for Groups II and III in that their observed values of $p_{\infty}(A_1|T_1)$ are below π_1 and their observed values of $p_{\infty}(A_1|T_2)$ are slightly above π_2 .

In conclusion, the results of the present study indicate substantial disagreement between theoretical predictions and observed values. If one were dealing only with the data of Groups I-III or with the Estes-Burke data (5), a fairly strong case could be made for the model. However the results on Groups IV and V leave little doubt that the formalization is not

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adequate in its present form to account for this type of discrimination situation.

It should be noted that, in one sense, this study cannot be viewed as a satisfactory test of the theory. It may be that the relationship of asymptotic response behavior to π_1 and π_2 obtained in the present experiment are artifacts of the massed trial procedure employed. In the derivation of Equations (1) and (2) it was assumed by Burke and Estes that either S_1 or S_2 was sampled <u>independently</u> on each trial. If, however, the trials occur in close temporal succession, then the stimulus complex affecting the subject on any trial may include traces of the stimulation associated with the responses and reinforcing events of one or more preceding trials. Therefore a more acceptable test of the theory, in the form presented by Burke and Estes, would require a situation where experimental techniques are employed to reduce the carry-over of trace stimulation from one trial to the next (9).

Summary

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The study deals with an analysis of discrimination learning. Two stimuli designated T_1 and T_2 are employed and two responses A_1 and A_2 are available. Each trial begins with the presentation of either T_1 or T_2 , the probability of T_1 and of T_2 each being $\frac{1}{2}$. Following T_1 , an A_1 is correct with probability π_1 and an A_2 is correct with probability $1-\pi_1$. Following T_2 , an A_1 is correct with probability π_2 and an A_2 with probability $1-\pi_2$. \underline{S} is instructed to maximize the number of trials on which his response is correct.

Five groups were run. For all groups $\pi_1 = .85$, the groups differed with respect to π_2 parameter which assumed the values .85, .70, .50, .30 and .15. Analysis of the data was in terms of a theoretical model for discrimination learning proposed by Burke and Estes (2). Discrepancies between predicted and observed outcomes were examined. However it was pointed out that the highly massed trial procedure employed in the study did not provide an optimal test of the theory.

Footnotes

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 $\frac{2}{}$ These results, in slightly modified form, are present in Equations 18 and 19 of the Burke-Estes article.

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