SELECTION AND ADDITIVITY OF CUES IN CONCEPT IDENTIFICATION [1]

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In concept identification (CI), cue selection may be expected since S is forced to narrow his attention to a subset of cues which are relevant to solution of a problem. In a recent CI model (Bower & Trabasso, 1964), the learning-rate parameter is defined as the probability that S selects and learns a relevant cue. In this study, we investigated selective attention by training Ss on problems with two relevant and redundant dimensions. After Ss met a criterion, they were tested on each component dimension. A relationship between the learning rate of each dimension and both the rate and which dimensions Ss learn in redundant problems was derived and tested.

In general, learning is more rapid when two dimensions, rather than one, are relevant. This facilitation has been termed "additivity of cues" (Restle, 1955) and successful rate predictions for redundant problems have been made by adding learning rates for single-dimension problems (Bourne & Restle, 1959; Bower & Trabasso, 1964; Restle, 1962; Trabasso, 1960).

If selective attention occurs, what does additivity of cues mean for the learning of an individual S? In the Restle (1955) model, the implication is that S learns something about each dimension and his probability of a correct response results from an additive combination of the two associations. If S selectively learns, he may learn either one dimension or the other or both in solving the problem. Addititivy of cues may simply mean that individual Ss learn faster with redundant problems since they have two opportunities, rather than one, to learn (cf. Sutherland & Mackintosh, 1964).

Our theoretical problem was to provide a rationale which predicted both cue additivity and selection. To do this, the Bower and Trabasso (1964) model was extended so as to allow S to select more than one cue during learning. The sampled cues are called S's "sample focus" which is formed when S makes an error. Then he tests out various hypotheses about the cues in the sample focus. On correct trials, S narrows down his focus sample to those cues which are still consistent with the stimulus-response information. If an error occurs, S resamples, with replacement, from the set of available cues until a relevant cue (or cues) is sampled and he learns. The learning rate is the likelihood that S selects a relevant dimension(s). Factors such as cue discriminability etc., which direct S's attention, are thus reflected in how fast he learns, and an estimate of rate provides us with a quantitative index of the "attention-value" of a cue.

We wish to predict whether an S learns only Cue A, Cue B, or both Cues A and B. Consider three problems. In Problem A, Dimension A is relevant and B is irrelevant; in Problem B, Dimension B is relevant and A irrelevant; in Problem A.B, both dimensions are relevant and redundant. From the model, the following set of prediction equations for which dimensions in Problem A.B are most likely learned may be derived in terms of the learning rates for Problems A and B. The probability that S solves only on Cue A is:

$$P(A) = \frac{a(1-b)^{S-1}}{a+b} \quad . \qquad [1]$$

The probability that S solves only on Cue B is:

$$P(B) = \frac{b(1-a)^{S-1}}{b+a} \quad . \qquad [2]$$

The probability that S solves on both cues is $1-P(A)-P(B)$.

The quantities a and b are the respective learning rates for Problems A and B. These parameters may also be predicted independently from learning-rate estimates for two additional groups: one group learns a problem with A relevant and B absent; a second group learns with B relevant and A absent. The rationale and equations for predicting rates for Problems A, B, and A.B are given in Trabasso (1960). The parameter S represents the size of the focus sample; it is an unknown and is arbitrarily set at some value for prediction purposes.

METHOD

Each S learned to classify cards by an anticipation method into two categories, Alpha and Beta, according to a rule. In the instructions, a complete description of the cards in terms of dimensions and values was given along with examples. The S was shown one card at a time, self-paced his responses, and then, after responding, received the correct classification. After 4 sec., a new card was presented for S's classification. Training continued until S met a criterion (see below) and then he sorted a test deck, twice, without feedback into categories. After sorting, he was questioned about his solution hypothesis.

The stimulus patterns were geometric figures drawn in crayon pencil on white 3 × 5 in. file cards. Five dimensions were used: shape (triangle or circle), location of a dot (above or below the figure), color (red or blue), position of an open side (left or right), and number of vertical lines (one or two) within the figure.

When one dimension was relevant (shape or dots), its values were consistently paired with the categories, and they varied independently of the other four

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dimensions. When two dimensions were relevant and redundant, paired values from the shape and dot dimensions were consistently reinforced with the same categories. When a dimension was irrelevant, it varied independently of the other dimensions. In all problems, the color, line, and open-side dimensions were irrelevant.

The test deck consisted of similar patterns in which either the shape or dot dimension was "removed." No dots appeared in the shape test cards and all the figures were squares in the dot test patterns. There were 16 test patterns for each relevant dimension; 8 additional patterns were included to reduce guessing of solutions during the test series.

There were five experimental groups. Group S.D learned a problem with the shape and dot dimensions relevant and redundant throughout training to a criterion of 32 consecutive correct responses and then was tested. The other four groups first learned single-dimension problems to a criterion of 10 consecutive correct and then were given 32 trials on the problem of Group S.D. After this "overtraining," they were tested.

To study the effect of adding an irrelevant cue on learning and whether this cue could be selected when made redundant during overtraining, two groups were run: Group S learned an initial problem with the shape relevant and dot irrelevant; Group D learned an initial problem with the dot relevant and shape irrelevant. Both groups were then overtrained with both dimensions relevant and redundant for 32 trials and tested.

To estimate rates for the shape and dot dimensions and see whether a novel redundant cue could be selected during overtraining, two other groups were run: Group S' learned an initial problem with shape relevant and no dots; Group D' learned with the dot relevant and shape constant (all figures were squares). Both groups were then overtrained with both dimensions relevant and redundant for 32 trials and then were tested.

The Ss were 270 introductory psychology students at the University of California, Los Angeles. There were 90 in Group S.D and 45 in each of the other groups.

RESULTS

Table 1 summarizes the main experimental and theoretical findings. Group S.D, which had two relevant dimensions, learned faster than all four single-dimension groups. All differences were significant by likelihood ratio tests on learning-rate comparisons at the .01 level. Adding an irrelevant dimension to the problems of Group S and Group D led to somewhat slower learning compared with Groups S' and D', respectively.

TABLE 1
Summary of Results

GROUP	MEAN ERRORS	LEARNING RATE	NUMBER OF Ss SOLVING ON		
			SHAPE	DOT	BOTH
S.D	4.14	.239 (.254)	31 (28)	45 (50)	13 (11)
S	10.13	.095 (.096)	43	0	0
D	5.87	.164 (.156)	0	43	0
S'	8.40	.114	37	0	6
D'	5.55	.173	0	42	1

Predictions of additivity of relevant cues for Group S.D and of irrelevant cues for Groups S and D from the estimated rates for Groups S' and D' are given in parentheses in the second column of Table 1. The predictions were quite accurate.

The right three columns of Table 1 show the number of Ss who were classified as having learned either the shape, the dot, or both dimensions. This classification was determined by S's stated solution hypothesis and his correct sorting on tests. For Group S.D, Ss who stated a solution only on shape sorted 99% correctly on the shape-test cards but only 50% (chance) on the dot tests; those who stated dots sorted 99% correct on that dimension but only 52% on shape tests; those who stated a solution on both dimensions sorted 95% correct on each. A similar pattern of solution and sorting results was obtained for each of the other four groups. Thus, the verbalized solutions and sorting-test results were in close agreement. For Group S.D, since only 13 (of the 89 who learned) solved both dimensions, the solution data clearly indicate cue selection in CI.

Two other results are of interest with respect to cue selection. In Groups S and D, no S indicated learning the irrelevant dimension which was made redundant during overtraining. Apparently, Ss do not resample irrelevant cues after solving on a relevant one, despite the fact that the previously irrelevant cue was consistently reinforced for 32 trials. Novelty effects on cue selection after learning another dimension were also slight; only seven Ss total in Groups S' and D' indicated having learned the novel relevant and redundant cue during overtraining.

Using the predicted learning rates for Groups S and D as the a and b parameter estimates in Equations 1 and 2, the number of Ss solving on the shape, dot, or both dimensions was predicted. For these predictions, the focus size, S, was set at 2 since it yielded the best fit of the data (all other integer values were significantly in error). The predicted frequencies, in parentheses in Table 1, were obtained by multiplying the values of Equations 1 and 2 by 89, the number of Ss who solved in Group S.D. The predicted values are in close agreement with the data ($X^2 = 1.18$, df = 1, $p > .05$).

These results provide strong evidence for cue selection in CI. From the data, it would also appear that whatever factors affect cue selection also affect learning rate: the rate of learning the dot dimension (Groups D and D') was one and a half times greater than that for the shape groups (S and S') and a like ratio on solvers for dots to solvers for shapes in Group S.D was also found. Defining the learning rate as the probability that S selects a relevant cue, estimates of this quantity may be used to make independent predictions of how fast redundant problems are learned and which dimensions individual Ss are most likely to learn. The results also show that additivity is a result of averaging over Ss who may learn only one or both cues, but each S has two probabilities of learning and thus learns faster.

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