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Presolution Dimensional Shifts in Concept Identification: A Test of the Sampling with Replacement Axiom in All-or-None Models[1]

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The experiment tests an all-or-none theory for concept learning. The assumption tested is that the subject tries out cues (hypotheses) randomly without utilizing information from the past sequence to limit his search. The test condition run involved multiple shifts in relevancy of two cues during the course of learning. Contrary to prediction, this procedure retarded learning. A proposed revision assumes that the subject eliminates inconsistent cues but after awhile forgets that they had been eliminated. Quantitative assumptions to this effect accurately fit the present results. Related research is discussed which also is consistent with the revised sampling rule.

The basic postulate of all-or-none learning models (e.g. Bower, 1961; Restle, 1961, 1962; Bower and Trabasso, 1964a) is that the subject's performance changes in discrete, discontinuous steps. In those situations where only a single unit is to be learned, the learning sequence of an individual subject may be characterized by a Markov chain with two states, one of which is absorbing. Each subject begins in the non-absorbing (unlearned) state wherein he responds correctly with probability p. On some one trial, an effective learning event occurs whereby the subject enters the absorbing (learned) state and responds correctly with probability 1. The important Markov chain assumptions are that the probability of making the transition from the initial to the learned state is independent of the previous history of the subject and is constant over trials.

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The present paper is concerned with a test of these latter assumptions. Specifically, we shall consider the learning of a two-category concept identification problem. In concept identification problems of this type, the subject learns by the conventional anticipation method a binary rule to classify a series of complex stimuli which vary in n binary dimensions. A dimension is either relevant and always leads to correct responses or it is irrelevant and leads to correct and incorrect responses on half of the trials. The models of Restle (1962) and Bower and Trabasso (1964a) commonly suppose that on an *error* trial the subject samples either hypotheses or cues based upon the dimensions and proceeds to test the relevance of the sampled hypotheses. If the subject is correct, he retains the hypotheses for another trial; if he makes an error, the subject *resamples with replacement* from the population of available hypotheses, H. The probability of learning on an error trial, c, is assumed to equal the probability that the subject samples a relevant hypothesis (i.e., the proportion of relevant hypotheses in H.)

In this model the constancy of the learning parameter follows from the assumption of resampling with replacement. In effect, the theory assumes that the subject has no memory for what previous hypotheses have been tried and rejected. If hypotheses have been rejected from H as they were sampled, tested and found to be inconsistent with the stimulus-response assignments, and if no new hypotheses were added to the initial pool, then the proportion of relevant hypotheses, c, would increase with each error. The question of what kind of resampling occurs is unanswered. If memory is operative, as other data indicate (e.g. Trabasso and Bower, 1964a), then the model would have to be modified to take account of this variable in the sampling process and learning rate.

The present test involves what has been called "additivity of cues" (Restle, 1962). Suppose a weight, w_j, is assigned to cue j and represents its salience. The probability of sampling cue j after an error is called c_j and is

$$c_j = \frac{w_j}{\sum_k w_k} . \tag{1}$$

The summation in the denominator is over all cues in the available pool. If cue j is the only relevant cue, then c_j is the probability that after an error, the subject solves the problem by selecting cue j, which ensures that he will make no further errors. If the pool of cues and their weights remain fixed, then c_j remains fixed over trials. This entails a geometric distribution of errors before solution with mean of $1/c_j$.

The standard additivity design (Restle, 1962) involves three conditions with a constant pool of cues but varying the set of relevant cues. Letting w_i summarize the combined weight of a constant pool of irrelevant cues, the three conditions and their respective learning rates are as follows:

$$\text{Condition 1: Cue 1 relevant: } c_1 = \frac{w_1}{w_1 + w_2 + w_i} .$$

Condition 2: Cue 2 relevant: $c_2 = \dfrac{w_2}{w_1 + w_2 + w_i}$.

Condition 1.2: Cues 1 and 2 relevant and redundant: $c_{1\cdot 2} = \dfrac{w_1 + w_2}{w_1 + w_2 + w_i}$.

Thus, $c_{1.2} = c_1 + c_2$. The learning rate for Condition 1.2 may be predicted from the error scores (which estimate c) in Conditions 1 and 2.

The present test involves a procedure which theoretically should produce the same additivity result, although the prediction is arrived at in a different way. The procedure, called a Dimensional Shift (*DS*) condition, has the subject begin with Cue 1 relevant and Cues 2 and *i* irrelevant. On the second error of a series (if the subject made a second error), the subject was told "correct" and the classifications were shifted by the experimenter so that Cue 2 was now relevant while Cues 1 and *i* were irrelevant. The new classification was that which would be correct according to the subject's response on the shift trial. To illustrate, suppose Cue 1 is the location of a dot (above or below the central figure), Cue 2 is the shape of the central figure (circle or triangle) and the categories are called "*A*" and "*B*." Starting with the dot relevant, suppose the second error occurred when a circle was presented and the subject said "*A*." Then he was told "correct" and the classification rule was shifted (without the subject's knowledge) to the shape as relevant with the rule: circle-*A* and triangle-*B*. After the shift, the subject's responses were reinforced according to the new assignments. If the subject made a second error on this new series, he was told "correct" on that trial and the rule was shifted back to the dot as relevant and shape irrelevant, again with the specific response assignments determined by the subject's response on the shift trial. By this procedure, the classification rule could be shifted back and forth repeatedly over the course of learning. A subject was considered to have solved the problem if he responded correctly on ten consecutive trials following a shift or following an informed error. The statistic of interest is the mean number of *informed* errors since the theory supposes that opportunities for resampling and solving the problem occur only when the subject is told that he is wrong.

Despite the complexity of the DS procedure, in theory it should be an easy problem for the subject. He is expected to solve on that informed error trial when he samples *either* Cue 1 or Cue 2 to test. Thus, the observed mean informed errors in the *DS* condition should be equal to that in Condition 1.2 and be less than those in Conditions 1 and 2. To illustrate the reasoning here, suppose an informed error occurs while Cue 1 is relevant. If, on that trial, the subject samples Cue 1, he will solve without any more errors. If, at the informed error trial, the subject samples Cue 2, which is currently irrelevant, he will eventually make another "incorrect" response (without being told so) but on that trial, the experimenter will shift the correct answers into correspondence with the hypothesis that the subject is using. In this case, the subject will be told "correct" and he will make no further errors. In either event, the total probability that any informed error is the last one is the probability that the subject samples Cue 1 or Cue 2 on that trial.

In an earlier experiment (Trabasso and Bower, 1964b), a *DS* condition was compared with the mean of Conditions 1 and 2. Although learning in the *DS* condition was slightly faster, the difference was not statistically significant. Our subsequent analysis given above, instigated a replication of the experiment with the addition of Condition 1.2 as a proper control group.

METHOD

Procedure. The same instructions were read to all subjects. The subject's task was to learn to classify cards into two classes, called Alpha and Beta. The subject was told that the cards could be classified correctly according to a rule and he was given a detailed description of the stimulus dimensions and their values.

Cards were presented one at a time on a holder. The subject self-paced his verbal responses and the experimenter showed the correct classification after the subject responded to each card. The subject had 4 sec. to view the pattern after reinforcement. A different order of presentation was given each subject by shuffling cards at the end of every 32 trials if the subject had not reached the criterion of 10 successive correct responses. Since the probability of an *informed* error was lower (1/4 vs. 1/2) for the *DS* condition compared with the other conditions, an equal opportunity for informed errors was achieved by terminating the experiment at 152 trials for the subjects in the *DS* condition and at 76 trials for all other subjects when the subject failed to learn.

Stimulus materials. The stimuli were geometric figures drawn in crayon pencil from templates on white 3 × 5-inch file cards. There were five binary dimensions: shape (circle or triangle); position of a 1/4-inch dot (above or below the figure); color of the figure and dot (red or blue); number of lines within a figure (one or two) and position of an open side on the figure (right or left). There were $2^5 = 32$ patterns for conditions 1, 2 and *DS*; condition 1.2 had 16 patterns since the shape and dot were relevant and redundant.

Experimental conditions. Four groups were run in the experiment.

Group *DS* had a problem where one of two dimensions (shape or dot) was initially relevant. As outlined above, on every second error, the subject's response was called correct in accord with an instantaneous shift of the response assignments to the other relevant dimension.

Group 1.2 has a problem both the shape and dot dimensions were relevant and redundant throughout.

Group 1 had a problem with the shape relevant and the dot position irrelevant.

Group 2 had a problem with the dot position relevant and the shape irrelevant.

In all problems, the color, line, and open-side dimensions varied independently and were always irrelevant. Within each condition, the four stimulus-response assignments were counterbalanced across subjects.

Subjects. The subjects were 220 volunteers recruited from introductory psychology classes at the University of California, Los Angeles. Participation in experiments was a course requirement. The first forty subjects in each group were randomly assigned to their condition. Additional subjects were run in Groups 1.2, 1, and 2 for different experimental purposes and their data are also included. The subjects were thus distributed: 40 in Group *DS*; 90 in Group 1.2; 45 each in Groups 1 and 2.

RESULTS AND DISCUSSION

Additivity of cues. Statistical comparisons between learning rates were made by using maximum-likelihood estimates. Taking into account those subjects who failed to learn, the equation for these estimates (from Bower and Trabasso, 1964a) is

$$\hat{c} = \frac{P}{E[T] - (1 - P)} . \tag{2}$$

In Eq. 2, $\hat{c}$ is the estimate of the learning parameter, P is the proportion of subjects who solved the problem, and $E(T)$ is the mean number of *informed* errors for all subjects. Comparisons of the estimate for Group 1.2 with the others was made by likelihood-ratio tests (c.f. Restle, 1961) and the results are summarized in Table 1.

TABLE 1

SUMMARY OF EXPERIMENTAL RESULTS

Group	Proportion of solvers	Mean informed errors	Learning rate	Chi-square
1.2	.99	4.14	.239	—
DS	.90	6.75	.135	11.02[a]
1	.96	5.87	.164	5.46[a]
2	.96	10.13	.095	31.29[a]

[a] $df = 1$, $p < .05$.

In Table 1, it can be seen that the shape and dot cues were additive but that Group *DS* learned more slowly that Group 1.2. The relevant cues were additive in that Group 1.2 learned faster than either Group 1 or 2, respectively. The predicted rate for Group 1.2 is the sum of the rates of groups 1 and 2, or .095 + .164 = .259, which was not significantly different from the observed value of .239 ($\chi^2(1) = 0.62$, $p > .50$). Converting to mean errors, the predicted value is 3.86, compared with 4.15 observed. The mean number of informed errors for group *DS* was nearly equal to the average of Groups 1 and 2, a result which replicates the prior finding (Trabasso and Bower, 1964b). However, the significant difference between the learning rates of Groups *DS* and 1.2 disconfirms the main prediction under test. Accordingly, we are led to consider some modification in the theory's assumption. The critical assumption would appear to be that regarding the subject's memory.

A revision Involving Resampling without Replacement for a Fixed Number of Trials

As pointed out above, resampling with replacement amounts to the assumption that the subject can not remember what events have occurred in the past information sequence. If we wish to alter this postulate by imputing some memory to our model subject, there appears to be at least two ways to proceed. One approach is to suppose that the subject remembers specific stimulus-response information from the trials of the recent past. An alternative approach is to suppose that he remembers some hypotheses that he has tried and rejected. For various reasons, the former approach seems more facile in handling the present data of the *DS* condition. Adopting the former approach—memory for specific past stimulus-response information—there still are several alternative ways to introduce this factor in the theory. We have tried several notions, and we report here the one which appears most promising.

As before, it is assumed that information processing (sampling) goes on only on a trial when the subject is told that his response is wrong. Let us call this trial n for a reference. We make three assumptions. First, assume that the subject remembers the specific stimulus pattern and correct response from trial $n - 1$. Second, assume that after the error on trial n, he compares the stimulus-response information on trial n to that which he remembers from trial $n - 1$. This comparison is a consistency check on each attribute of the stimulus. He temporarily sets aside (eliminates from consideration on this trial) any attribute which has inconsistent response assignments on trials n and $n - 1$. For example, if both patterns are red but are given different responses or if the colors differ but are given the same response, then the color attribute has inconsistent assignments on those two trials and hence would be set aside. Third, assume that once an attribute is found to be inconsistent and is set aside, it remains set aside (eliminated) for the next k informed error trials. The number k could be considered to be a random variable; for our purposes here, it makes no material difference if we assume that k is some constant. Translating the sense of the assumptions into other words: we suppose that the subject discovers that certain attributes are not relevant, but that he eventually forgets this information as other events intervene; when he forgets it, that attribute again becomes an available candidate for sampling. We have thus postulated two means by which a cue could be set aside for the sampling that takes place on error trial n: (a) the cue fails to pass the consistency check in the trial n *vs.* $n - 1$ comparison, or (b) it failed on an earlier consistency check and has not yet been revived. At the end of this process, the subject may be conceived to have two lists: those attributes that are still effective candidates for being the relevant cue and those that have been temporarily set aside. It is assumed that he then selects a cue from the pool of effective cues (the first list), with the sampling probability of a cue determined by its weight or salience.[2]

[2] This mode of exposition makes it appear that the subject is engaging in an exhausting series of cognitive operations. A simpler description is to say that after the error the subject samples cues randomly one at a time, and stops with the first cue that passes its consistency checks (is not eliminated by information in memory). This process achieves the same end result as the exhaustive one elaborated in the text.

A few implications of this revised sampling rule may be noted in passing. First, the rule will never eliminate a relevant cue that has had fixed response assignments throughout training. Second, an irrelevant cue has a probability of 1/2 of being set aside at each error trial. The net effect of the rule in the standard problem is simply to reduce the average weight of the irrelevant cues (which is unknown in any event). Third, of importance to us, this rule is the only one we have been able to devise which is consistent with the results of our prior experiments on presolution reversals (Bower and Trabasso, 1964b). In Experiments I and II of that earlier report, the *S-R* assignments were reversed if a subject errored after 10 (or 5) trials on the initial assignments; yet such reversed subjects solved their problem with about the same number of errors as did controls whose answers were not reversed. In Experiment III of that report the subject was told "correct," and the *S-R* assignments were reversed on every second error that he made; yet the average number of informed errors before solution was the same as for controls trained with fixed *S-R* assignments.

The reversal results fit easily into the altered sampling rule. The important point to be noted is that the relevant cue would never be eliminated by our rule in those experiments. The assignments for the relevant cue on an informed error pattern and the one preceding were always consistent. The only occasions for an inconsistency was on a reversal shift trial, but on that trial the subject's response was called "correct," hence he would not carry out a consistency check. Thus, the altered sampling rule would expect no interference in learning the reversal problem, as was found.

Sampling Rule Applied to Cue-Additivity and DS Conditions

We now interpret the results of the present experiment in terms of this revised sampling rule. We consider first the results on cue additivity. It may be seen that the general effect of the altered sampling rule is to reduce the weight of the irrelevant cues by some average amount; let b be this average fractional reduction. In these terms, the three groups in the additivity paradigm would have the following average learning rates:

Group 1: Cue 1 relevant, Cues 2 and i irrelevant

$$c_1 = \frac{w_1}{w_1 + b(w_2 + w_i)} . \tag{3a}$$

Group 2: Cue 2 relevant, Cues 2 and i irrelevant

$$c_2 = \frac{w_2}{w_2 + b(w_1 + w_i)} . \tag{3b}$$

Group 3: Cues 1 and 2 relevant, Cue i irrelevant

$$c_{1\cdot 2} = \frac{w_1 + w_2}{w_1 + w_2 + bw_i} . \tag{3c}$$

It is clear enough that $c_{1.2}$ is larger than either c_1 or c_2 so, in this qualitative sense, cue additivity still follows from the new sampling rule. However, Eqs. 3a and 3b involve more unknowns (3) than we have relations, so $c_{1.2}$ is determined only up to a function of the known estimates, c_1 and c_2, and the unknown, b. Hence, no parameter-free prediction of $c_{1.2}$ is possible in this case.

Nonetheless, a slight variant of Conditions 1 and 2 does permit a parameter-free prediction of $c_{1.2}$. The variant is to run a condition (call it 1′) similar to Group 1 except that Cue 2 is absent; similarly, Condition 2′ is similar to Group 2 except that Cue 1 is absent. Let c_1' and c_2' be the estimated learning rates under these new conditions. c_1' is given by Eq. 3a with $w_2 = 0$, and c_2' is given by Eq. 3b with $w_1 = 0$. For this case, the following relation may be derived:

$$c_{1\cdot 2} = \frac{c_1'(1 - c_2') + c_2'(1 - c_1')}{1 - c_1'c_2'}. \tag{4}$$

Fortunately for this analysis, conditions 1′ and 2′ had been run in the experiment (with 45 subjects each) for different purposes. The estimates obtained by Eq. 2 from their data were $c_1' = .114$ and $c_2' = .173$. We note that these estimates are larger than c_1 and c_2 (see Table 1), as the model expects (Eqs. 3a, 3b). When these values of c_1' and c_2' are substituted into Eq. 4, the value of $c_{1.2}$ predicted is .252. This accords tolerably well with the observed estimate of .239 in Table 1.

The analysis above demonstrates that the revised sampling rule is consistent with cue-additivity results. However, this is not a very exacting validity check; almost any sampling axiom will do fairly well in this regard.

Application of the revised sampling rule to the Dimensional Shift (*DS*) conditions encounters analytic difficulties. The problem is that sometimes the sampling probability for Cue 1 is c_1 (when both cues are effective), sometimes it is c_1' (when Cue 2 has been temporarily set aside), and sometimes it is 0 (when it has been set aside). Thc same holds for Cue 2. To deal with this complexity, we have simulated the *DS* experiment with 40 Monte Carlo runs of the model. The main features of the Monte Carlo runs were as follows:

(a) 20 stat-subjects began with Cue 1 relevant and 20 with Cue 2 relevant.

(b) Prior to learning, the probability of a correct response was 1/2 (ignoring shift trials when told "correct" instead of "error").

(c) When both cues were effective, the sampling probabilities were $c_1 = .095$ and $c_2 = .164$.

(d) if Cue 2 were set aside, the sampling probability on cue 1 was $c_1' = .114$; if Cue 1 were set aside, the sampling probability of cue 2 was $c_2' = .173$.

(e) if the currently relevant cue were sampled on an error trial, the subject solved the problem with no more errors.

(f) if the currently irrelevant cue were sampled on an error trial, then with probability 1/2 it was presumed inconsistent with the prior trial information and was set aside for k subsequent informed error trials. With probability 1/2 it was presumed consistent with the prior trial information; in this case, the subject retained that cue as his hypothesis, made a second (uninformed) error, and solved when the answers were shifted into line with his hypothesis.

Four different set of 40 Monte Carlos each were run with k taking on the constant values 1, 2, 3, 4. Recall that k is the number of subsequent error trials for which an inconsistent cue is set aside. Table 2 compares some summary statistics of Group *DS* with those of the four Monte Carlo runs.

TABLE 2

SUMMARY STATISTICS COMPARING GROUPS *DS* AND MONTE CARLO DATA

		Error trials before replacement (k)			
Statistic	Group *DS*	1	2	3	4
Mean informed errors	6.75	5.18	6.10	6.42	7.28
Standard deviation	8.78	4.15	5.82	7.23	7.78
Mean shifts	6.25	4.52	5.55	5.75	6.62
Mean trial of last error	25.85	19.22	21.15	22.62	26.80
Standard deviation	36.60	17.74	21.20	25.06	31.18
Average success probability	.516	.550	.470	.478	.500
Number of subjects solving on					
Shape	13	18	17	14	16
Dot	23	22	23	26	24
Number of inconsistencies		13	16	15	14
Number of subjects switched into criterion	15	14	18	13	14

In Table 2, as k is increased, the data of Group *DS* are more closely approximated. The approximation improves particularly for average informed errors, average trial of last error, and average shifts as well as their variances. For these data, the best value of k would be between 3 and 4. The larger observed variance in informed errors and trial of last error resulted from four subjects who did not solve in Group *DS*, whereas all Monte Carlo subjects solved. The close approximation of the success probabilities before learning supports the assumption that percentage correct responses in this task is near 1/2.

The number of *DS* subjects solving on the shape or the dot dimensions should be proportional to the sampling probabilities of these two dimensions; that is, the expected proportion of subjects solving on the shape cue is approximately $c_1/(c_1 + c_2)$, or $.195/.259 = .366$. For Group *DS*, omitting the nonsolvers, the prediction is that $36 \times .366 = 13.2$ subjects will solve on the shape cue; 13 did so. For the Monte Carlo groups, $40 \times .366 = 14.6$ subjects were expected to solve on shape; averaging the four runs, 16.25 subjects did so. The average number of subjects who were shifted into solution for the Monte Carlo groups is 14.75, whereas 15 did so in Group *DS*. Additionally, the error distribution of Group *DS* was compared with that generated by the Monte Carlos for each value of k. The generated distribution tended to be geometric in form and none differed significantly from that of Group *DS* by Kolmogorov-Smirnov two-sample tests. Putting together these various comparisons of data with model predictions, we seem to have definite support for the revised sampling rule.

Stationarity of Presolution Responses

Since subjects learned the *DS* problem under conditions where the stimulus-response assignments were continually shifting and since the average probability of a correct response was near the chance level of one-half, the learning of this problem would appear discrete. Similarly, the learning of Problems 1, 2, and 1.2 were examined for their correspondence to assumptions of the all-or-none models. In theory, the presolution responses may be represented as a stationary and independent Bernoulli process. The data prior to the last error for subjects in Groups 1.2, 1 and 2 were combined since presolution responding should be the same for these groups. Backward learning curves over ten trials prior to solution for these groups showed a slightly positive but nonsignificant trend (tau $= .378, p > .05$), with the average probability of a success at .524, significantly higher than the *a priori* one-half ($X^2(1) = 5.77$, $p < .05$). Successive correct and incorrect responses prior to the last error were statistically independent. ($X^2(1) = 2.65$, $p > .05$). Thus, the basic assumption of discrete learning in these problems would appear to be supported by the presolution data of all four groups.

Random Reinforcement

We have shown that the revised sampling rule explains the present *DS* result and also the presolution reversal results reported previously. We mention one other set of results which were not explainable by the former "no memory" assumption but which seem consistent with the revised sampling rule. In experiments by Levine (1962) and Holstein and Premack (1965), the subject was first exposed to a trial block of random reinforcement (no cue relevant) followed by consistent reinforcement of a particular cue. Both experiments found that rate of learning the consistent problem was retarded relative to control subjects who had no prior series of random reinforcement. Moreover, the learning rate deficit was constant and independent of the number of trials in the random series (Levine used from 4 to 60 trials). The interference produced by random reinforcement is expected by the revised rule because an inconsistent reinforcement on the to-be-relevant cue during the random series would set it aside for some trials carrying over into the consistent problem. Moreover, the number of carry-over trials that it is set aside depends only upon the last inconsistent trial on the to-be-relevant cue before the problem shift, and the number of prior inconsistent trials is irrelevant. Hence, the interfering effect of the random series should be relatively independent of its length, as was found.

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