Saliency and learning rate in concept identification

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Learning rate parameter estimates were computed for the Bower and Trabasso (1964) concept identification model on the basis of a cue saliency measure. The estimates were employed in the model to generate theoretical learning curves which were compared with curves obtained from two types of concept identification tasks.

The Bower & Trabasso (1964) model of concept identification (CI) has been fairly successful as a description of error probabilities in a two-choice task (e.g., Suppes & Ginsberg, 1963; Bower & Trabasso, 1964). Particularly the properties of stationarity and independence of presolution response probabilities are usually found in simple two-choice experiments employing binary dimensions. Stationarity and independence are interpreted as evidence of all-or-none learning.

One assumption of the Bower and Trabasso model is that the rate of learning depends on the saliency or attention value of the relevant cues as compared to the saliency of all cues. Bower & Trabasso (1964) supported this assumption by providing adequate predictions of CI rates based upon the added weights of cues. Their technique involved the estimation of the CI rate parameter, C , when certain cues were relevant and redundant from the observed rates when each of the cues alone was relevant. In other words, they estimated the saliency of cues from learning rates in order to predict learning rates. Another approach would be to measure the saliency of cues in a completely different task, and then apply this saliency measure to predict learning rate in a CI task. Testing such a measure was the main purpose of the experiment reported below.

A second purpose of the study was to determine if the model could be extended to a simple two-choice CI task with more than two levels per dimension.

Method

A total of 26 paid adult Ss were given two tasks to perform in a single experimental session. They were given a search and identification (S&I) task from which the estimates of cue saliency were taken. Next, they were given a two-choice CI task in which half of the Ss were presented with stimuli having three binary dimensions. Stimuli for the remaining Ss were described by three dimensions with four levels per dimension.

The S&I task consisted of the simultaneous presentation of all stimuli that were to be presented in the CI task. The stimuli were cards from the Wisconsin

Card Sort task with color, shape, and number dimensions. The Ss were instructed to find a particular card that the E was thinking of by asking questions that could be answered "yes" or "no" about the characteristics of the cards. Actually, there was no predetermined card but the E answered "no" until the last level of each dimension was interrogated. The levels of all dimensions were inversely ranked according to the order in which they were interrogated so that the first level interrogated received the rank with the highest numerical value. Each S solved four S&I problems and the resulting ranks were summed in a manner that provided two estimates (S_1 and S_2) of the saliency of cues. These estimates (described below) were then used to replace c in the Bower and Trabasso equation for cumulative probability of total errors, $P(T \leq k) = (1 - c)^k$. The resulting probability distributions (for S_1 , S_2 , and c) were compared with the curves obtained in the CI tasks. The Bower and Trabasso parameter c was estimated from the mean total errors in the CI task ($c = 1/\bar{T}$).

In the CI task with binary dimensions, stimulus cards that were presented simultaneously in the S&I situation were presented successively by means of a slide projector and Ss were instructed to classify each stimulus by pressing one of two buttons. Immediate feedback as to whether or not the response was correct was given. The CI task with four levels per dimension was similar to the two-level problem except that Ss were instructed to find a single relevant level and press Button 1 when it was present, Button 2 when it was not present. The number dimension was relevant for the two-level case and one particular number was relevant for the four-level problem.

The first search and identification estimate (S_1) of the saliency of relevant cues was computed differently depending on the number of levels per dimension in the problem. For the two-level problem, it was assumed that Ss attend to entire dimensions and not to specific levels of a dimension. The estimate is computed from the ranks obtained from the questions asked in the S&I task about each dimension, without ranking the levels separately. Therefore, S_1 for the two-level problem is the sum of the ranks assigned to the relevant dimension over the sum of the ranks of all dimensions.

It is assumed for the four-level problem that Ss are testing specific levels in an effort to determine the single relevant level. Therefore, the parameter estimate S_1 is the sum of the ranks assigned to the

Table 1
Salience estimates, maximum deviations and mean absolute deviations
of predicted from observed points

	Two Levels			Four Levels		
	S ₁	S ₂	C	S ₁	S ₂	C
Value	.118	.215	.173	.061	.087	.116
Max. (D)	.243	.236	.148	.311	.113	.153
Mean (D)	.124	.125	.087	.180	.086	.082

single relevant level over the sum of the ranks of all of the individual levels regardless of the dimension.

The second S&I estimate (S₂) of the salience of relevant cues is based upon a common assumption for both the two- and four-level problems. The assumption is that Ss will first test all levels of one dimension. If the relevant cue is not discovered, S will then test all levels of another dimension, and so on. Based upon these assumptions S₂ is taken as the average salience proportion of the levels on the relevant dimension. That is, a salience proportion which is the sum of ranks of a particular level over the sum of ranks of all levels is computed for each level on the relevant dimension. The average of these proportions is S₂. Therefore, S₂ is not a measure of the salience of a particular dimension or level as with S₁, but is the average salience of all levels on a single relevant dimension.

Results and Discussion

The observed and predicted cumulative probability curves, $P(T \leq k)$, for the two-level and four-level problems were computed. Table 1 presents the salience estimates used to generate the predicted probability points, the maximum absolute difference between each predicted and observed point (for each value of k), and the mean absolute difference. None of the maximum absolute differences is significant according to the Kolmogorov-Smirnov one sample test (maximum D for the four-level case, S₁ estimate, is significant at the .15 level).

The results in Table 1 indicate that in the two-level case S₁ underestimates the observed points as much as S₂ overestimates the same points. The c estimate taken from the CI data provides the best fit to the two-level problem. It is interesting to note that although Bower & Trabasso (1964) state that the model will not hold for more than two levels per dimension, the equation for the cumulative total errors provides a reasonable fit with the S₂ and c estimates of learning rate for the four-level task.

The interpretation of the results in terms of the assumptions behind the S₁ and S₂ estimates is not entirely clear. Neither the assumption that Ss attend to dimensions nor the assumption that they attend to levels is supported. Verbal reports of the Ss after

the experiment indicated that in the two-level situation four Ss tested the relevancy of dimensions by responding to both levels of each dimension until correct, four Ss responded to individual levels across dimensions, and the remaining Ss combined these strategies. The use of more than one response mode may account for the data falling between the values predicted on the basis of pure strategies (S₁ and S₂).

The results for the four-level problem indicate that the estimate based on the average salience of the levels on the relevant dimension (S₂) provides a reasonably good fit to the data. The postexperimental verbal reports of the Ss revealed that nine of the 13 Ss pressed the second button and systematically tested for relevance the levels of a single dimension before testing the levels of other dimensions. The average salience of the levels on the relevant dimension would, therefore, indicate the order of testing and those levels relative to the levels of other dimensions, and this is what the S₂ estimate measures.

Stationarity and independence analyses were performed on the presolution data using the methods described by Atkinson, Bower, & Crothers (1965). The analyses for the two-level problem supported stationarity ($\chi^2=5.56$, $df=8$, $p>.5$) and independence ($\chi^2=3.59$, $df=1$, $p>.05$). The same analyses for the four-level presolution data indicated lack of stationarity ($\chi^2=21.74$, $df=12$, $p<.05$) and lack of independence ($\chi^2=10.62$, $df=1$, $p<.005$). Therefore, the all-or-none learning hypothesis is supported by the two-level data but not the four-level data. This finding supports the limitations placed by Bower and Trabasso upon their model.

In conclusion, it would seem that the measurement of salience through the S&I task is promising but not definitive. Of course, it is quite possible that factors other than salience influence the rate of learning in a CI task. The possibility of employing strategies such as Ss reported in the four-level problem may explain some of the difficulty found when trying to apply the Bower and Trabasso model beyond the two-choice CI task with binary dimensions.

References

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Note

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