PATTERN RECOGNITION OVER DISTORTIONS, BY HUMAN SUBJECTS AND BY A COMPUTER SIMULATION OF A MODEL FOR HUMAN FORM PERCEPTION

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The recognition of single randomly generated, "meaningless" patterns has been studied during the past few years by a number of investigators (Attneave, 1957; Crook, Gray, Hanson, & Weisz, 1959; Vanderplas & Garvin, 1959b). Several experiments have further examined the abilities of human Ss in recognizing such patterns over certain simple variations, such as random noise (Crook et al., 1959; Hillix, 1960), contour noise (Fitts & Leonard, 1957), and systematically continued transformations (LaBerge & Lawrence, 1957). But no experiments have been reported in which Ss were asked to learn sets of variants of a pattern through experience with individual examples of these sets. Yet this is the typical procedure for computer "pattern recognition" simulation programs (Selfridge & Neisser, 1960; Uhr, 1962). It also presents a good experimental paradigm for the learning of patterns by human beings. Given N patterns and n variants of each pattern, S is presented with each of the nN particular pattern instances, asked to give it the correct name of the N names, and then told the correct name. This, in more systematic form, is what the child experiences during the natural experiments of his day-by-day learning. That is, the child is given particular instances of such things as "chair," "dog," the letter "A," or his mother's face; and he learns to build up general concepts, or pattern classes.

This sort of experiment, then, should serve as a convenient method for studying concept formation and perceptual learning of patterns in human Ss. It should also give a convenient framework within which to examine the predictive fit of pattern recognition simulations by computer programs, when they purport to be embodiments of theoretical models of human form perception. The use of meaningless patterns for stimulus sets reduces the wealth of information that the human can bring to bear. It also allows for control and systematic variation of the parameters of the stimulus sets.

The main experiment examined the learning of pattern sets as a function of (a) interrelations between patterns, (b) practice, and (c) individual differences between Ss (including the simulated model as an S). Subsidiary experiments examined the effects of different (a) durations of stimulus presentation, (b) size of pattern set, and (c) complexity of pattern.

In addition, three form perception
experiments were replicated using the computer as S. These were those of Attneave (1957) and Vanderplas and Garvin (1959b), who examined Ss' abilities to make fine discriminations between individual patterns, and Fitts and Leonard (1957), who examined Ss' abilities to generalize from individual patterns to variants.

The computer program is the first version of a model for form perception and concept formation. The program does not appear to take advantage of such trivially superior abilities of a digital computer as perfect rote memory or extreme arithmetic precision. Nor does it have built-in imprecision to simulate so-called imprecisions in human Ss, such as memory decay. Finally, it should be noted that this is not a trivial test for computer programs of this sort, at the present stage of their development. In fact, relatively few programs are capable of even attempting to handle arbitrary new pattern arrays, and it is not known whether any would do appreciably better than the present program (Highleyman, 1961; Uhr, 1962).

**METHOD**

*Main Experiment*

**Subjects and design.**—Human Ss were tested in groups of 6 to 10, approximately half men and half women. For the analyses of variance, 3 men and 3 women were chosen randomly from each group. The Ss were all paid volunteer college students. Each S was tested on two stimulus sets; half were given the "unrelated" stimulus set first, the other half were given the "interrelated" stimulus set first. A test on a stimulus set consisted of five learning trials through the entire set of 25 stimuli, i.e., five variants of each of the five patterns. The order of presentation was determined by using a random number table, with ordering different for each of the five trials.

**Apparatus and stimuli.**—Two sets of patterns were chosen that would be sufficiently difficult so that Ss could not learn them immediately, but sufficiently learnable so that reasonably interesting learning curves would be generated. These stimulus sets are reproduced in Fig. 1. Each set consisted of five pattern types, each pattern type with five variants. One set was chosen from Crook's eight-sided patterns (Fig. 1a). This was the "easy," "unrelated" set. The second set was chosen from LaBerge and Lawrence's

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1. We would like to thank M. N. Crook, of Tufts University, and D. H. Lawrence, of Stanford University, for their kindness in supplying us with usable copies of their original stimuli.
(1957) systematically varied patterns, in which the five different pattern types are actually related to one another (Fig. 1b). This was the interrelated or hard set. The "distance" as measured in an objective manner among members of the same pattern type (and more or less confirmed by the subjective judgments collected by LaBerge and Lawrence) is in certain cases greater than the distance between members of different pattern types.

Stimuli were projected, one at a time, by means of a reflector projector, onto a screen approximately 5 to 8 ft. in front of Ss. Stimulus size was approximately 3 in. square, which subtended roughly a 5° to 1° arc at the retina. These distances were chosen to give optimal viewing conditions and still be comparable to the computer's resolving power. Pretesting was used to determine the most favorable lighting and viewing conditions, ones that would result in maximal learning for human Ss. Each stimulus was presented for 5 sec. Ten to 15 sec. after its removal, Ss were told what the correct name or type was. The following stimulus appeared 3 to 7 sec. after that.

Several subsidiary experiments were run as checks on some of these control conditions.

(a) One subsidiary control group was given the same stimulus set under the same conditions, except for a 2-sec. presentation period.

(b) An additional group of Ss was given a set of seven patterns, including the five that had been used for the "easy" set, in order to see to what extent short-term memory for too large a number of different pattern sets might be serving as a limiting factor for learning.

(c) The effects of different complexities of stimuli were examined with a third group of Ss, who were given four-sided patterns. (Complexity was defined by the number of sides to the randomly generated stimulus.) In each of these subsidiary experiments, all other conditions were held constant. Results are presented as comparisons between the two pertinent groups involved.

Finally, a computer program designed to recognize patterns across their variants in a manner suggested by psychological and physiological data (Uhr & Vossler, 1961, 1962) was also tested on these same input patterns. Inputs were presented to the computer in the same order that they had been presented to Ss. The resolution of the inputs was also the same. Although there was no possibility of making a meaningful equation between computer program and Ss for such matters as duration of presentation of stimuli, illumination, and other viewing conditions, an effort was made to give Ss the best possible viewing conditions.

Briefly, the pattern recognition program works as follows: Unknown patterns are presented to the computer in discrete form, as a 20 X 20 matrix of zeros and ones. The program randomly generates measuring operators that simulate local neuron nets, by one of several random methods, and uses this set of operators to transform the unknown input matrix into a list of four 3-bit characteristics. These characteristics are then compared with lists of characteristics in memory, one for each type of pattern previously processed. As a result of similarity tests, the name of the list most similar to the list of characteristics just computed is chosen as the name of the input pattern. The characteristics are then examined by the program and depending on whether they individually contributed to success or failure in identifying the input, amplifiers for each of these characteristics are then turned up or down. This adjustment of amplifiers leads eventually to discarding operators which produce poor characteristics, as indicated by low amplifier settings, and to their replacement by newly generated operators.

Replications

All replication experiments used only the computer as S. Here again an attempt was made to equate computer and human conditions wherever possible. Attneave (1957) asked Ss to discriminate among members of a set of eight randomly produced variants of a prototype. The computer was tested on one of the several sets which Attneave found essentially equivalent. Vanderplas and Garvin (1959b) asked Ss to learn a set of eight low-association-value patterns in a paired-associate procedure, in which the other member of the association was a nonsense syllable. Fitts and Leonard (1957) had Ss learn 12 different prototype patterns during three 6 to 10 min. self-study periods. The 70% who passed the criterion of three out of four correct test trials were then tested

The authors are grateful to F. Attneave for supplying us with his original stimuli.

Fitts and Leonard (1957, p. 30) have presented results of their experiment in this mode, and P. Fitts has kindly supplied the authors with the original stimulus, along with details (Leonard & Fitts, unpublished manuscript) of their experiment.
FIG. 2. Mean percentage errors for human Ss (from 6 to 10 Ss per point) compared with percentage errors for computer simulation program, on the easy and on the hard sets of stimuli (first presentation).

RESULTS

Main Experiment

Figure 2 presents mean errors on successive trials ("passes") for Ss and for the computer simulation program. Table 1 presents results from the analysis of variance on these data. The two pattern sets, and their two presentations, have been analyzed as a single dimension of four "conditions," because of limitations in available computer programs. The program's performance can probably most meaningfully be compared with the human performance in learning the first of the two sets learned, since the program does not accumulate broad general abilities and facility for new problems through experience in any way comparable to the human being. Therefore, it did not appear worthwhile to run a "second set" experiment using the program as S. Instead, Set 1 results were used as best estimates of what performance would have been on Set 2. (This would appear to be a conservative estimate, since it is saying in effect that no learning will occur, although, in fact, the program is capable of self-modification, and actually "learns" to recognize patterns originally through a process of this sort.) Differences between "conditions," between "passes," and between Ss were all significant beyond the .001 level.

TABLE 1

ANALYSIS OF VARIANCE OF ERRORS AS A FUNCTION OF PATTERN SETS, TRIALS, AND Ss

<table>
<thead>
<tr>
<th>Source</th>
<th>Simulation Program as Contrasted with Mean Human Performance</th>
<th>Simulation Program as One of 7 Ss, along with Individual Human Ss</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>df</td>
<td>MS</td>
</tr>
<tr>
<td>Between Ss</td>
<td>1</td>
<td>1265.63</td>
</tr>
<tr>
<td>Trials (T)</td>
<td>4</td>
<td>1163.21</td>
</tr>
<tr>
<td>Conditions (C)</td>
<td>3</td>
<td>1562.63</td>
</tr>
<tr>
<td>Ss × T</td>
<td>4</td>
<td>36.31</td>
</tr>
<tr>
<td>Ss × C</td>
<td>3</td>
<td>207.42</td>
</tr>
<tr>
<td>T × C</td>
<td>12</td>
<td>36.81</td>
</tr>
<tr>
<td>Ss × T × C</td>
<td>12</td>
<td>77.11</td>
</tr>
<tr>
<td>Total</td>
<td>39</td>
<td></td>
</tr>
</tbody>
</table>

Note.—The computer simulation program is included as an S.

* P = .05.
** P = .005.
*** P = .001.
In particular, the difference between the simulation program and the mean human performance was significant beyond the .005 level, the simulation's performance being consistently better.

Figure 3 presents results, for the unrelated pattern set, for the best of the individual Ss, and for the computer program. On this set of patterns, some of the human Ss when they had already had the experience provided by the other set of patterns, outperformed the simulation program. Figure 4 presents results, for the interrelated pattern set, for the best of the individual Ss, and for the program. On this more difficult set of patterns, the best human performances do not exceed the performance of the program. Nor, in fact, does the best human performance appear to improve very markedly as a result of the additional experience afforded Ss doing this task as their second task. That is, most of the improvement in the overall group performance appears to result from the improvement of the poorer members of the group.

Figures 5, 6, and 7 present results, for human Ss alone, for (a) different durations of presentation of stimuli— for 2-sec. and 5-sec. durations; (b) different size of pattern sets—for five and for seven patterns; and (c) different pattern complexities—four-sided and eight-sided patterns. There were no significant effects attributable to either number of pattern sets or duration of stimulus presentation (as varied in this experiment). Complexity of patterns did, however, tend to affect recognition, as indicated by the interaction effect (significant at the .05 level) between complexity and Ss.

Table 2 presents results of the
Fig. 5. Effects of duration of stimulus presentation. (Dotted line presents results—10 Ss—in learning when patterns were presented for a 2-sec. period. Solid line presents results—9 Ss—when patterns were presented for a 5-sec. period, all other conditions comparable.)

replications. For a more accurate comparison of Vanderplas and Garvin's (1959a, 1959b) results with ours, the error due to Ss' learning nonsense syllables would have to be excluded since the computer program dealt only with the visual patterns. But, since the program made no errors at all on its second pass through the set, we have not bothered to make such an adjustment. On the Fitts and Leonard (1957) set, the program learned the prototypes to a 75% level after its first experience, and to a 100% level after its second. It gen-

Fig. 6. Effects of size of pattern set. (Dotted line presents results—mean scores for 10 Ss—in learning seven sets of patterns. Solid line presents results—9 Ss—for five sets of patterns, all other conditions comparable.)

TABLE 2

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Mean Performance for Human Ss</th>
<th>Performance of Simulated Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Attneave (1957)</td>
<td>29.75</td>
<td>3.00</td>
</tr>
<tr>
<td>(cumulative errors to learning)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Vanderplas &amp; Garvin (1959b)</td>
<td>3%</td>
<td>100%</td>
</tr>
<tr>
<td>(2nd trial correct)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fitts &amp; Leonard (1957)</td>
<td>62%</td>
<td>100%</td>
</tr>
<tr>
<td>(1st exposure percentage correct)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fig. 7. Effects of number of sides to a pattern. (Dotted line presents results—8 Ss—in learning four-sided patterns. Solid line presents results—6 Ss—for eight-sided patterns, all other conditions comparable.)
eralized with 76% accuracy after the first experience, and with 100% accuracy after the second, as contrasted with human Ss, who generalized with 62% accuracy after 1 hr. of learning.

**Discussion**

These results suggest that the simulation program may well be performing at a higher level as a "pattern recognizer" than can be achieved by the human S when he is divested of some of his advantages based upon past experience and contextual information. This, of course, is a very narrow test of the program's abilities, nor is it known to what population of patterns these results might be generalized. However, the program was not designed with these pattern sets in mind, or even with this general type of pattern set in mind. At this stage of experimentation, it would seem reasonable to simply continue to test such programs out on as wide a range of stimuli as possible.

The fact that the program performs better than human Ss in this experiment should not be taken very seriously. The simulation is capable of coping with only a part of the perceptual problem. It would not be at all unlikely, or uninteresting, to find that, as the program's generality increases, its abilities at any particular task decreases as a direct and intrinsic function of its greater powers in other directions.

Further experiments of this sort should serve at least two purposes. First, by varying such things as the number of patterns, the number of variants of each pattern, the distance between these variants, the way the individual stimuli sample the pattern's total population, and the distance between patterns, a rather rich domain of behavior closely related to what we have traditionally named "perceptual learning" and "concept formation" should be thrown open to assessment. By testing performance on new variants, different from those originally learned, generalization of classes and concepts can be studied. Second, by comparing the simulation program's performance with human performance as a function of such variations, a beginning can be made in attempting to fit some of the details of the curves generated by the simulated model to the curves generated by human Ss.

**Summary**

Human Ss, and a computer simulation program of a model for form perception, were examined for their behavior in learning to respond with the proper name for a pattern type over variant examples of the pattern. In the main experiment, five pattern types of five variants each were presented to all Ss (including the simulation program). Four "conditions" were examined: (a) unrelated patterns, (b) interrelated patterns; each presented as the first, and as the second, set. Differences between Ss, and between "passes" through the set (learning trials) were also examined. All of the above variables showed differences significant beyond the .001 level. In particular, the simulation of the model performed at a significantly lower error rate (beyond the .005 level) than did the group of human Ss.

The effects, on human Ss, or varying (a) duration of stimulus presentation, (b) size of the set of patterns, and (c) complexity of patterns were also examined. Only complexity of pattern affected performance significantly.

In addition, three experiments by other investigators who tested human Ss were replicated, to test the computer model. The model outperformed human Ss in all cases.

**References**


FITTS, P. M., & LEONARD, A. J. Stimulus correlates of visual pattern recognition: A probability approach. Laboratory of Aviation Psychology, Ohio State University, 1957.


VANDERPLAS, J. M., & GARVIN, E. A. Complexity, association value, and practice as factors in shape recognition following paired-associate training. *J. exp. Psychol.*, 1959, 57, 155–163. (b)

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