

EFFECTS OF STIMULUS COMPLEXITY ON IDENTIFICATION AND CATEGORIZATION

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ABSTRACT: Data are presented showing that humans and non-humans are severely limited in their ability to identify stimuli that vary along a single dimension. Increasing the dimensionality of spatially undifferentiated stimuli improves performance. However, this improvement is trivial compared to that observed when spatially complex stimuli, such as pictures, are presented for identification. The theoretical account of memory and decision processes presented here suggests that, while the number of items that can be held in working memory varies among species, the number of items that can be identified depends more upon the characteristics of the stimuli than upon the organism making the identification.

There are remarkable similarities in the way human and non-human animals discriminate among, identify, and categorize sources of stimulation. For example, both humans and other animals are severely limited in their ability to identify stimuli that vary along a single dimension, such as the intensity of a light, yet they easily identify vast numbers of complex stimuli, such as pictures. We shall provide a theoretical account of identification performance based on the premise that the behavioral similarities described reflect similarities in the underlying decision processes.

Our account of identification performance assumes that a stimulus is identified only when it roughly matches a record of a past event held in *working memory*. Differences in the number of items that can be identified correctly depend upon the capacity of this working memory and the type of stimuli to be identified. We will present preliminary data that suggest that three species—pigeons, monkeys and humans—differ in the number of records of past events that can be held in working memory. We will also suggest that increases in stimulus complexity activate a process of retrieving repeated samples

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of information from long-term memory which, in turn, results in an increase in the number of stimuli that can be identified.

MEMORY SAMPLING MODEL OF DECISION MAKING

Although our model for the learning and decision process was originally developed to account for the behavior of pigeons, it also applies in some interesting ways to identification and categorization behavior in other species. The structure of the model and its parameters are described briefly here. For more detailed treatments see Heinemann, (1983a,b), Chase, (1983), Heinemann and Chase, (1990), Chase and Heinemann, (1991, in press).

An experiment of Heinemann, Avin, Sullivan and Chase (1969) illustrates the type of experiment for which our model was first developed. Pigeons were trained to identify, by pecks on the appropriate response key, two sounds that differed only in intensity. They were rewarded with food for making one response, R_1 , when presented with the softer sound, and an alternative response, R_2 , when presented with the louder sound. For one group the two sounds differed by 2.3 dB, for a second by 7 dB, and for a third by 29 dB.

The course of acquisition was typical of that observed in many experiments of this sort. At the beginning of training, there was a period during which there was no evidence of discrimination, the *pre-resolution period* (PSP). The length of this PSP (number of trials) was inversely related to the difference between the two sound intensities. The PSP was followed by a gradual improvement in the accuracy of the discrimination. After the accuracy of the discrimination appeared to have attained an asymptotic level, the birds were given a generalization test during which they were presented with 11 sound intensities in addition to those used in training. Figure 1 shows the generalization test data for the three groups of birds. Note that the proportion of R_2 responses rises gradually with increasing sound intensity, following a curve that is similar to the psychometric function one would obtain from humans tested for intensity discrimination with the method of single stimuli. The birds acted as though they had learned the "rule": make R_1 for soft sounds and R_2 for loud sounds.

Our theoretical account of these data assumes that, during the PSP, the subject learns to "attend" to those sensory channels that provide information predictive of the outcome of its choice behavior. In the experiment we are discussing, for example, the bird learns that of all the stimuli present in the experimental chamber only the intensity of the sound predicts which key choice will lead to reward. Only information arriving over those sensory channels that were found to

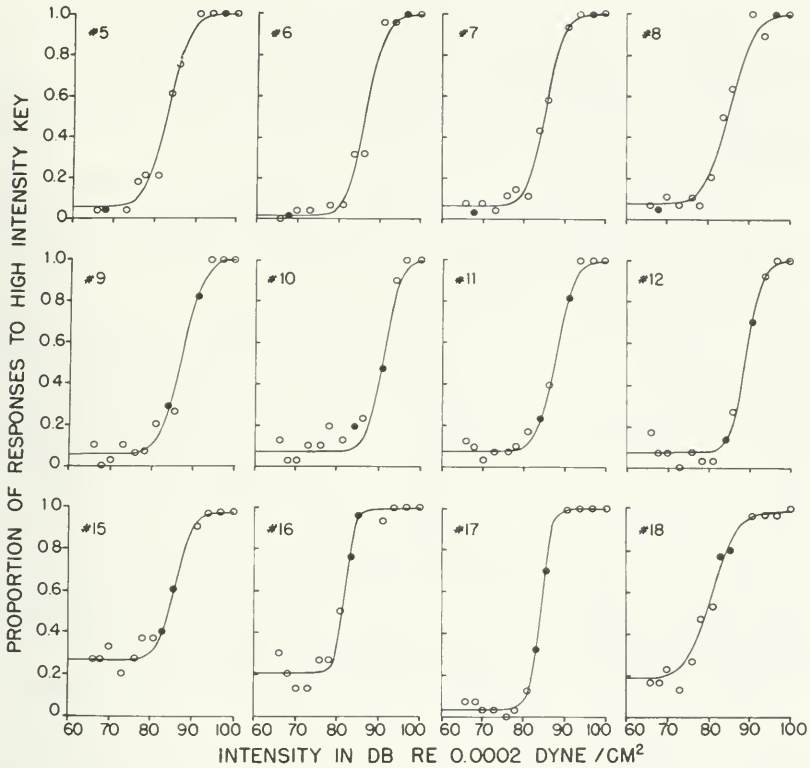


FIGURE 1. Distribution of choices obtained during generalization test following training to discriminate between levels of white noise differing by 29 dB (top row), 7 dB (middle row), and 2.3 dB (bottom row). Each panel shows the results for one pigeon. (From Heinemann, Avin, Sullivan, & Chase, 1969).

transmit information relevant to the discrimination are processed during the second stage of learning.

The second stage of learning involves a memory that has a large but not unlimited storage capacity. This memory will be referred to simply as the *long-term memory* (LTM). On each trial of an experiment the subject is assumed to deposit in the LTM a record that contains:

(a) A representation of the stimulus information that the analysis done during the PSP has shown to provide useful cues. In the example under consideration, the particular loudness experienced when the choice was made is represented as a point on a loudness continuum. The physical differences in the acoustic stimuli determine the separations between the corresponding points along the loudness continuum.

(b) A representation of the response made. For the analysis described here this is represented by a label, e.g. R_1 or R_2 .¹

(c) A representation of the reward received. For the analysis described here the records are labeled as positive if food was delivered; negative if it was not.

Each record is said to occupy a *storage location* in LTM. The location to which each record is sent is selected randomly and any record occupying a storage location will be destroyed ("overwritten") when a new record is entered at that location.²

It is assumed that during each trial the subject retrieves from the LTM one or more small random samples of positive records (records showing that a reward was received). Each sample contains from 3 to 18 records. The only information that is used in the response selection process is the information contained in the last sample of records the subject retrieves. After having retrieved a sample, the subject retrieves another sample if, and only if, the sample in hand provides no information about the consequences of past behavior in the presence of sensations reasonably similar to the one currently experienced. Our estimates suggest that, if approximately ten attempts to retrieve useful information have failed, the subject simply chooses the response associated with the largest expected value of reward.

When useable information has been retrieved from LTM, the choice of response is based on a comparison of the information retrieved from the LTM to the sensation induced by activity in the sensory channels to which the subject is attending. This sensation will be called the *current input*. It is assumed that the records of previous sensory experiences are distorted by Gaussian noise while residing in the LTM.³ After a record has been retrieved, and is being held in working memory, the sensation represented on that record fluctuates rapidly over time, momentary values falling into a Gaussian distribution whose mean represents the value retrieved from the LTM. Four such records are shown in Figure 2.

The response the subject selects is the one that the retrieved information indicates is most likely to earn a reward. To find this re-

¹To describe behavior in situations in which response confusion occurs, e.g. when the response keys are closely spaced, responses are represented in memory by stimulation (visual and kinesthetic) received when a particular key was pecked. In such cases key position is represented as varying along a sensation continuum monotonic with key position (see, Chase, 1983).

²While this treatment of the LTM is sufficient for the present purposes it is unlikely that the LTM is without organization. As the model develops we plan to consider various sources of organization—temporal, motivational, contextual—and consider how these may interact in the decision processes in which retrieval remains random within the relevant subset of memory.

³Without this source of noise all the records in the sample represented by the same response label would be identical. Under these circumstances accuracy of identification would be limited only by sensory overlap.

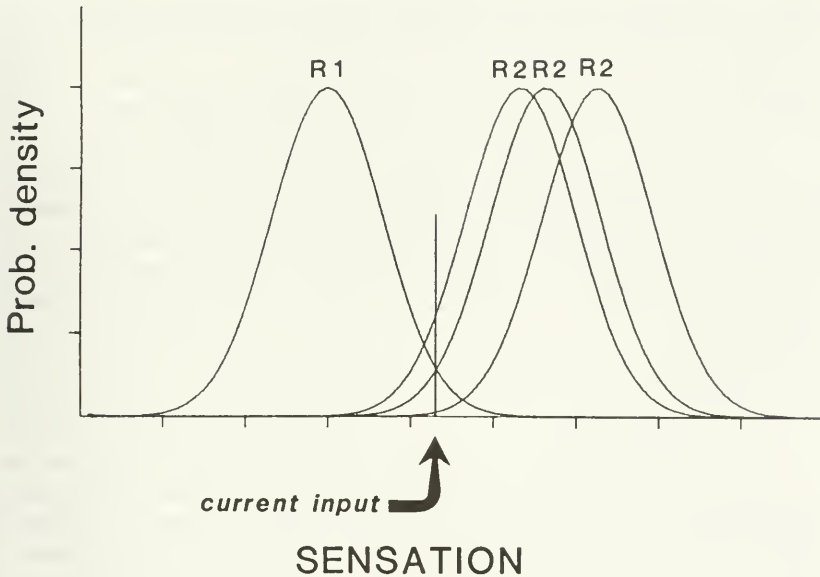


FIGURE 2. A sample of four records retrieved from LTM. The choice of response is based on the probability densities at the point labeled "current input."

sponse the subject gets the sum of the probability densities for each response at the current input, and selects the response for which the sum of the densities is the greatest. The process is illustrated in Figure 2, which shows four distributions of remembered sensations, each of which was represented on a single record. Three of the records show that R_2 was rewarded and one shows that R_1 was rewarded. The process amounts to summing the heights of the R_2 curves above the point representing the current input, doing the same for the R_1 curves, and then determining which sum is the larger. The response made is the one for which the probability density is the highest. If the probability density at the current input is below some very small threshold value, a new sample is drawn.

Accuracy is affected by the number of records in the sample that carry the same response label. A correct response cannot be made unless the sample contains at least one record with the required response label. Errors will also be made when the probability density at the current input is highest for an incorrect response. Chase and Heinemann (1991, in press) have shown that, as the number of records associated with each of two responses increases, the effects of the noise added during storage and retrieval from LTM decrease, becoming negligible for sample sizes greater than 32. With a sufficiently

large sample, the only significant source of error remaining is "sensory noise." This is determined by the spacing of the stimuli and may be described as arising from the rapid fluctuation in the sensation represented on that record while it is in working memory.⁴

This model is expressed in the form of a computer program. Precise quantitative predictions are made through presenting the computer with problems and conditions analogous to those presented to our subjects. Computer-simulated performance is compared to the data produced by our subjects. In fitting the data described in this paper all parameters were fixed except (1) sample size and (2) stimulus spacing.

Theoretical Treatment of Generalization

Our model provides the following explanation for the generalization data shown in Figure 1: After training, the LTM is filled with records showing that R_1 was rewarded in the presence of a sensation that was induced by training-stimulus S_1 , and R_2 was rewarded in the presence of a sensation induced by training-stimulus S_2 . On the average, sensations induced by S_2 will be remembered as more intense than sensations induced by S_1 , but the distributions of remembered intensities overlap. Because random samples retrieved from LTM reflect the distribution of records in LTM, it will be true of the sample also that the records showing remembered R_1 s will be associated with remembered sensations that are less intense than those associated with remembered R_2 s.

As illustrated in Figure 2, the decision rule specifies that the response made is the one for which the probability density at the current input is greatest. Probability densities for R_1 and R_2 tend towards identity at the "category boundary," the point bisecting the distance between the two training stimuli. As the distance from the category boundary increases, the difference in probability densities for the two alternatives increases. As a result, one response is made much more frequently than the other. If this were the only factor operating, the generalization curves would be monotonic and their lower and upper ends would approach asymptotes of 0 and 1.0. However, several experiments have shown that test stimuli that produce current inputs which are far removed from the category boundary may yield response proportions near 0.5, the chance level. According to our model this reflects "guessing", which will occur when repeated sampling has failed to produce useful stimulus information (i.e. a

⁴The stimuli are represented as points on an axis scaled in standard units. The fluctuations described here as momentary changes in sensation are simply the probability densities defined by the normal distribution.

sample yielding an above-threshold probability density at the current input.)⁵

Effects of Stimulus Complexity

In the Heinemann et al. (1969) experiment the stimuli were sounds that differed in only a single dimension, intensity. The stimuli used in investigations of identification and categorization have ranged from such unidimensional stimuli through multidimensional stimuli and photographs of objects, to the actual objects. In the paragraphs that follow we shall show how the type of stimuli presented influences performance, compare data from a number of different species, and provide a theoretical account of the effects of stimulus complexity on the number of items that can be correctly identified or categorized.

In experiments on identification each stimulus requires a unique response; in categorization the number of stimuli exceeds the number of responses permitted, so that the same response is made for several stimuli. This distinction is not sharp however, because, in practice, it is impossible to present exactly the same stimulus on repeated trials.

The Heinemann et al. (1969) experiment is an example of a two-stimulus identification experiment. During the generalization test novel stimuli were presented for categorization but the subject was not informed whether the category to which any stimulus was assigned was the "correct" one. As shown above, under these conditions the new stimuli appear to be categorized according to the same rule used during identification training. The model treats categorization exactly as it does identification, except that in categorization-training the same response label may be associated with stimuli that differ markedly from each other.

(a) *Unidimensional stimuli.* While a very large number of complex stimuli can be identified without error, humans and other animals are severely limited in their ability to identify stimuli that vary along only a single dimension. In absolute identification situations, stimuli that can be identified perfectly when they are presented in pairs are often confused when they are presented as members of a larger set of stimuli. This rather surprising finding was highlighted in 1956 by George Miller, who pointed out that humans can identify only about "7 plus or minus 2" unidimensional stimuli with perfect accuracy. Much more recently Chase (1983), and Chase, Murofushi,

⁵In the Heinemann et al. paper (1969) the generalization test data were described using the concepts of signal detection theory. While this theoretical description provides a reasonable first approximation to the data, it requires that the gradients be monotonic. The relationship of the model presented here to signal detection theory is described in Chase and Heinemann (1991, in press).

and Asano (1985) have reported a similar limit in non-human animals.

Figure 3 is an adaptation of the graphical representation Miller (1956) used to show the relationship between information transmitted (number of items correctly identified, expressed as a power of two) and input information (number of equally probable items in the set to be identified). The data shown were obtained from pigeons, humans, and monkeys trained to identify luminance levels that would rarely be confused if they were presented in pairs. The pigeons and monkeys were trained to identify 3, 7 or 9 luminance values, covering a range of 3.0 and 3.8 log units for separate groups of pigeons, and 3.2 log units for the monkeys. Also shown is the performance of humans required to identify the 9 luminances used in the monkey experiment. Note that both the monkeys and the pigeons were able to identify three luminance levels virtually without error. As the number of stimuli was increased from 3 to 5 and finally to 9, information trans-

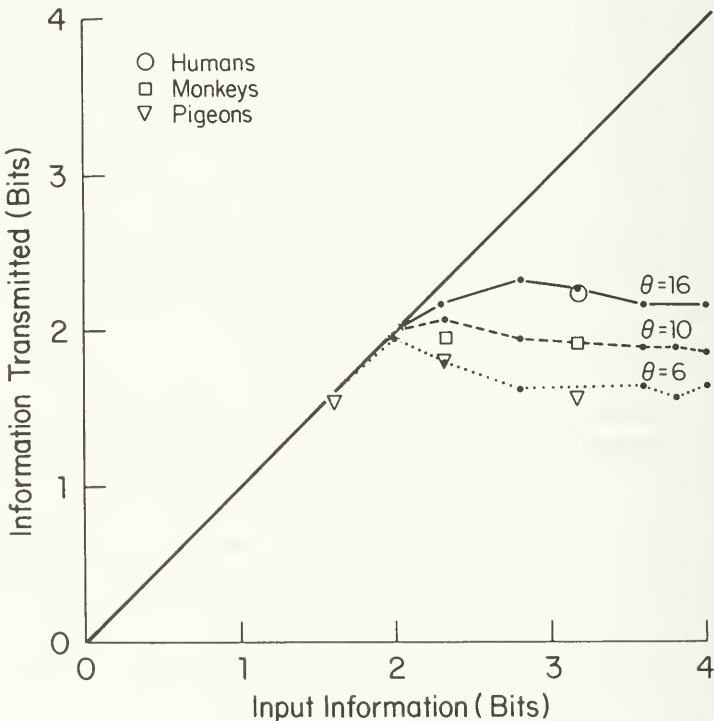


FIGURE 3. Transmitted information as a function of input information. The theoretical curves differ in sample size, θ . Perfect performance is shown by the diagonal line.

mitted remained virtually unchanged for the pigeons. The value was 1.7 bits which is the equivalent of 3.2 items identified without error. Monkeys performed slightly better. For them information transmitted was 2.0 bits, equivalent to 4 items. Information transmitted for the human subjects trained with 9 choices was 2.6 bits, a value close to that suggested by Miller. The lines connecting the dots in Figure 3 are functions predicted by our model.

In order to increase input-information, and thus the potential for correctly identifying more stimuli, additional stimuli must be added to the set. Increasing the number of stimuli within a fixed range decreases the separation between adjacent stimuli. Because most errors involve confusions between adjacent stimuli, it is not surprising that more errors are made as the number of stimuli is increased in this fashion.

However, it might seem reasonable to expect that more stimuli could be identified if the additional stimuli were added at the ends of the range, so that the separation between adjacent stimuli is not decreased. It turns out that increasing the range in this way, or increasing it by increasing the separation between adjacent stimuli, does not solve the problems because the improvement in performance that results from increasing stimulus spacing quickly levels off. This phenomenon, the *range effect*, was first reported for human observers by Pollack (1953) who found little improvement in absolute identification of tones differing in frequency with a 20-fold increase in stimulus spacing. Braida and Durlach (1972) examined performance of human observers in an absolute identification task that involved 10 intensities (equally spaced on a logarithmic scale) of a 1000 Hz tone. As the range of stimulus intensities was increased from .225 to 3.6 log units, performance improved but a further increase in the range from 3.6 to 5.4 log units had little effect on performance.

Similar parametric data do not exist for non-humans. However, Chase (1983) found no differences in information transmitted for pigeons in absolute identification tasks that involved luminance ranges of 3.0 and 3.8 log units. In this experiment separate groups of pigeons were trained with either five or nine stimuli distributed over one of the two ranges. Evidence that pigeons show a range effect was also obtained under different experimental conditions by Richter (1977) and by Hinson and Lockhead (1986).

According to our model, both the range effect and the limit on the number of undimensional stimuli that can be identified without error result from the small number of records held in working memory when the decision is made. Because the size of the sample retrieved from LTM is fixed, each response will be represented by progressively fewer records in the sample as the number of stimuli to be identified increases. For illustrative purposes let us assume that, on each trial

of an absolute identification experiment in which presentation probabilities are equal, a sample of eight records is drawn randomly from the LTM. In a two-choice situation there will then be, on the average, four records that provide stimulus information for each of the two responses. If four responses are possible then each response will be represented by only two records, on the average. In a situation in which eight stimuli are to be identified each response will be represented, on the average, by only a single record. As the number of responses increases, the amount of stimulus information relevant to each response decreases. In addition, it becomes increasingly likely that the correct response will not be represented at all in the sample. In that situation, increasing the separation between adjacent stimuli cannot produce any increase in accuracy. Thus, according to our model, the factor that is responsible for the range effect and the limit on the number of stimuli that can be accurately identified is the limited number of records available when the response decision is made.

The deleterious effects of retrieving only a sample of the information available in LTM would be diminished if the subject were to retrieve more than one sample. However, for resampling to occur the stimulus to be identified must be very dissimilar from any stimulus represented in the sample (so that the probability density at the current input will be below threshold). This rarely occurs when the experiment is done with stimuli that vary along a single dimension.

In order to obtain the theoretical curves shown in Figure 3, our computer program made absolute identifications of 3, 5 and 9 items. In these simulations, the sensations induced by the stimuli were equally spaced within a fixed range, as was true for the living subjects whose results are shown in Figure 3.⁶ The only parameter varied was sample size. These simulations suggest that pigeons, monkeys, and humans differ in the size of the sample on which the response-decision is based. Our simulations yield an estimated sample size of 6 for pigeons, 10 for monkeys, and 16 for humans.

(b) *Multidimensional stimuli.* The number of stimuli that can be identified without error is larger than seven if these stimuli differ from each other in more than one dimension. For example, Pollack and Ficks (1954) found that human subjects could identify without error as many of 128 auditory stimuli that varied along eight dimensions, such as intensity, frequency, duration, etc. Another example comes from experiments by Lockhead (1970) who studied identification performance of humans in several situations. In one situation stimuli from two dimensions were presented separately for identifica-

⁶The stimuli used in training were approximately equally spaced in terms of discriminability. In our computer simulation the extreme stimuli of the set were separated by 24 standard units.

tion. In two other situations the stimuli presented for identification were binary compounds created by pairing values from the two dimensions in linear or sawtooth fashion. Lockhead found that the compound stimuli were identified more accurately than their unidimensional components, and, more specifically, that accuracy varied directly with the Euclidean distance between pairs of adjacent stimuli. Chase and Heinemann (1972) published data showing that this was true for pigeons as well.

We use the Euclidean metric in our theoretical treatment of identification of multidimensional stimuli. We assume that each sensation is represented by a point in n -dimensional space and the distributions representing remembered sensation are n -variate Gaussian ones. Increasing the dimensionality of the stimuli increases the Euclidean distance between remembered sensations. In addition to improved discrimination, this results in an increase in the number of trials on which resampling occurs. Both factors appear to be responsible for the improvement in accuracy as the dimensionality of the stimuli increases. For example, in our simulations of the Pollack and Ficks (1954) experiment, the current input corresponding to each eight-dimensional space, and each remembered value of such a current input is represented by an eight-dimensional Gaussian distribution. Under these conditions a larger number of stimuli can be identified without error because of the geometric fact that the distance between the peaks of distributions that represent remembered values of the stimuli increases with the dimensionality of the space. The greater geometric distance among stimuli results in substantial resampling because, in the eight dimensional space, the sum of the probability densities is quite frequently below threshold at the current input. The results yielded by the computer program are identical to the empirical results of Pollack and Ficks.

(c) *Patterned stimuli.* The improvements in performance that result, empirically and in theory, from increasing the number of redundant cues on which identification is based is relatively small when one considers the fact that many thousands of complex stimuli such as faces, pictures, spoken words, and Chinese characters can be identified virtually without error by humans. As noted by Lockhead (1970) "the judging of multidimensional aspects of a complex stimulus is not sufficient to account for the large number of objects we can identify in the world." (p. 8) He showed that even simple patterns, 20 face-like patterns composed of four lines within a circle, could be identified without error.

According to our model the increase in the number of complex stimuli that can be identified without error results primarily from resampling.

In situations in which spatial information is irrelevant, as is true

for sounds or an evenly illuminated surface, we treated sensory information as though it arrived over a single "sensory channel." In extending our model to visual pattern recognition we assume that at any moment in time the continuum of sensations induced by a pattern of stimulation may be represented by a sample of evenly spaced "sensory channels." That is, in representing visual patterns the internal representation of the visual field is partitioned into finite-sized cells called pixels. Each pixel is characterized by its two spatial coordinates and its hue, saturation, and brightness. Any particular visual experience can be represented in memory by the spatial coordinates of the relevant channels, and codes for the brightness, hue, and saturation at each channel.

In our simulations of pattern recognition we have so far considered only dot-matrix patterns made up of two gray-levels, e.g. black points on a uniform white background. This simplification makes it unnecessary to represent the non-spatial dimensions. It is assumed that while a record of a visual pattern resides in LTM, the values of the X and Y coordinates of each point vary randomly and independently over time, the distributions of momentary values being Gaussian. A record of this type is illustrated in Figure 4. The concentric circles represent the bivariate density functions representing the remembered letter A. The x's represent the current input points produced by the dot matrix letter A.

According to our model, a subject trained to recognize a number of different dot matrix letters when shown a particular letter for identification, retrieves a few records from LTM and compares the current input pattern to each of the patterns represented on the retrieved records in order to find the best match. We assume that response selection is based on a decision quantity D , computed as follows: At each point on the current input calculate the mean probability density contributed by each point on the memory record. (A mean density that falls below the threshold is assigned a value of zero.) This will yield as many means as there are current input points. The decision quantity, D , is equal to the product of these means. If two or more records in the sample represent the same response, the value of D associated with that response is the sum of the individual D values. The decision rule is: Make the response associated with the largest value of D . If no record is associated with a value of D that is greater than zero, draw a new sample. Finally, if k successive samples fail to yield a non-zero value of D for any record, then choose the response associated with the greatest probability of reward in the past. This rather complicated-sounding procedure is simply an extension of the decision rule described earlier for the treatment of unidimensional stimuli. It is a type of "fuzzy template" matching scheme in which the current input (a pattern) is compared to remembered patterns. The

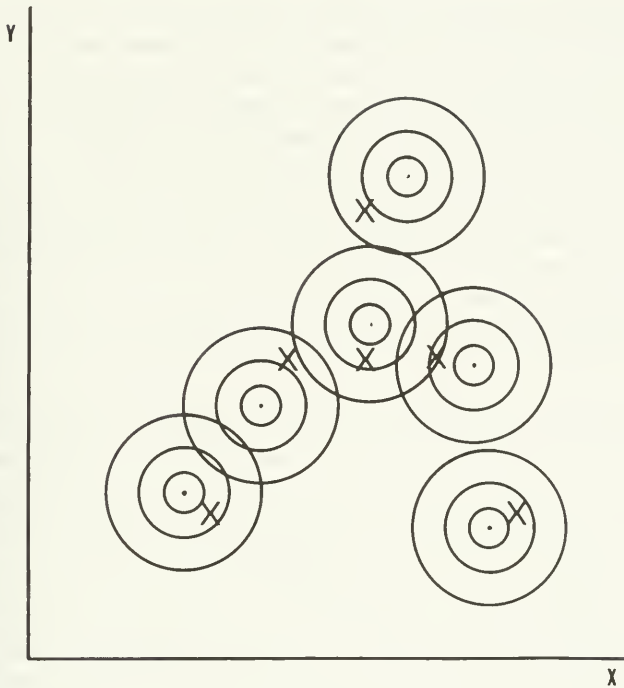


FIGURE 4. Remembered group of points representing the letter A as shown on a single record retrieved from LTM. The concentric circles represent contours of constant probability density on the bivariate distributions for the spatial coordinates of each point. The x's represent points on the current input.

response made is the one associated with the greatest probability of being correct.

The model was used to simulate choice behavior in a pattern recognition experiment involving the 26 letters of the alphabet. The confusion matrix generated showed that certain errors, e.g., confusions between E and F will occur frequently while others, e.g., A and T rarely occur. The simulated matrix compared quite well with one published by Blough (1985) which was based on confusions made by pigeons presented with the same stimuli in a three-choice discrimination task (Heinemann & Chase, 1990). The model-generated confusion matrix also correlated well with one based on confusions made by a chimpanzee who identified the letters by pressing a key on a console (Matsuzawa, personal communication), and with matrices based on human reaction times and similarity ratings (Podgorny and Garner, 1979).

It was pointed out earlier that humans can identify a vast num-

ber of patterned stimuli. The ability to identify large numbers of complex stimuli is clearly not uniquely human. Pepperberg's (1981) parrot made a different vocal response to each of more than 50 objects. Terrace (1979), following the earlier work of Gardner and Gardner (1978), trained a chimpanzee to express over 125 words in American Sign Language. Other researchers (e.g. Asano, Kojima, Matsuzawa, Kubota & Murofushi, 1982; Premack, 1976; Savage-Rumbaugh, 1984) trained chimpanzees to identify objects by touching or manipulating forms that represented these objects. Although, it is beyond the scope of this paper to consider whether the behavior observed in these animals is evidence of linguistic abilities, these studies do provide evidence that non-humans are capable of identifying many stimuli.

Although pigeons can be trained to choose among as many as nine response keys (Chase, 1983), most research on pigeons' memory for complex stimuli has examined categorization rather than identification. The ability of pigeons to categorize an amazingly large number of colored photographs on the basis of rote memory was first demonstrated by Greene (1983) and Vaughan and Greene (1984). For example, Vaughan and Greene (1984) trained pigeons to memorize, by rote, more than 300 scenes projected in full color. In this experiment pecking on some randomly selected photographs was rewarded, pecking on others delayed the end of the trial. Pigeons learned this task readily and showed excellent retention when tested later. In a related experiment, Heinemann, Ionescu, Stevens, and Neiderbach, (in preparation) showed pigeons slides of natural scenes projected on a small screen located between two choice keys. The pigeons were rewarded for pecking either the left or right choice key. Half of all pictures shown were randomly assigned for reward if the right key was pecked, the other half for reward if the left key was pecked. During the course of the experiment the number of pictures presented was increased in rather large steps from 80 to 640, at which point the pigeons were performing at a level of about 85 percent correct. Although the experiment was terminated at that point, there was no evidence that the pigeons were approaching a limit on the number of slides they could categorize.

CONCLUSION

The data presented here suggest that the processes underlying identification and categorization are similar in humans and non-humans. Preliminary work suggests that the number of remembered items that can be held in working memory varies among species. However, the number of stimuli that can be identified or categorized appears to depend much more upon the characteristics of the stimuli

than upon the organism making the identification. Both humans and non-humans are severely limited in their ability to identify stimuli that vary along a single dimension. Increasing the dimensionality of spatially undifferentiated stimuli (e.g., evenly illuminated areas of constant shape) improves performance. However, this improvement is trivial compared to that observed when spatially complex stimuli, such as pictures, are presented for identification.

In dealing with visual patterns our model represents the spatial aspects of the visual sensations as sensory channels or pixels whose spatial coordinates can be defined in a two-dimensional space. The basic processes involved in the identification of such complex stimuli are assumed to be the same as those involved in identification of uni-dimensional ones: A small sample of records is drawn from long-term memory. The pattern of stimulation represented on each of these records is compared to the current pattern of stimulation. If a reasonable match is obtained, that is, if the joint probability density associated with the current input (D) is above threshold for at least one of the records, then a response is made. If none of the comparisons yields a value of D that is above threshold then a new sample is drawn. Additional samples are drawn until a match (or a guess if sampling fails to retrieve useful information) is made.

This description of identification and categorization is, of course, based on a variety of simplifying assumptions. For example, in its present state of development our model treats visual patterns as "snapshots", whereas living organisms looking at real objects are almost invariably exposed to patterns of stimulation that are continuously changing because of movement of the object that is being inspected, or of the inspecting organism. Further development of our model will depend in part on the removal of some of these simplifying assumptions. Much additional work, both theoretical and empirical, is needed before the fine differences and similarities among species are understood. Many alternative theoretical approaches to the problems that have been discussed are obviously possible, but very few have been developed in quantitative detail. If the heavy theoretical emphasis of this paper needs any justification, it is that any comparative analysis of psychological *processes* is necessarily bound to theory.

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