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Speeded categorization: the effects of perceptual processing and decision-making time.

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Abstract

The effects of limited processing time were investigated for the binary categorization of artificial multidimensional objects. Following Lamberts and Freeman (1999), in the first stage of the experiment participants learnt to categorize 9 stimuli into two categories. In the second stage, the same stimuli were presented for categorization, and both the display time, and the time available in which to make a decision, were varied independently. It was found that each of these variables had a significant effect on accuracy of categorization, as well as response latency. Lamberts and Freeman (1999) demonstrated that restricting presentation time of a certain stimulus in their category structure caused a reversal in category assignment. We found evidence of the same reversal, but it was dependent on the time available to make a decision rather than the duration of stimulus display. Importantly, changes in accuracy due to response deadline were not explicable in terms of truncation of processing by the limited time. The study provides an empirical investigation of the intuitive notion that both perceptual processing and decision making components are time dependent.

Introduction

Our ability to assign the objects we see to the categories we know has been studied intensely over the years. One highly successful class of categorization theories is that of exemplar models, which assume that category learning involves the storage of instances in memory. Under these models, assigning a stimulus to a category involves computing its similarity to all stored exemplars. Perhaps the most influential formal model of this is Nosofsky's (1986) generalized context model (GCM), an extension of Medin and Schaffer's (1978) context model. In recent years there has been a growing interest in how the temporal characteristics of categorization could be incorporated into this model,

which in itself makes no predictions about how constituent processes occur over time. It has been acknowledged that analysis of temporal aspects could help elucidate various details of categorization in general (e.g. Lamberts, 1995). Furthermore, time constraints may be important in real-life category decisions, making understanding the time course of processing important in itself.

The GCM regards stimuli as points in multidimensional space, with each dimension corresponding to some psychological dimension in the stimulus representation. Selectively attending to a dimension stretches the space along that dimension and shrinks it along unattended ones. Assigning a stimulus i to any one category in memory involves computing its perceived similarity (an exponential function of distance in the multidimensional space) to every stored exemplar in every category. Evidence that stimulus i belongs to category A is obtained by summing its similarity to all the stored exemplars in the category A representation. The conditional probability of the item being classified into category A is given by dividing this evidence by the summed evidence for all categories.

Categorization is often assumed to comprise two distinct stages: an initial perceptual stage followed by a memory-retrieval and decision stage (e.g. Lamberts, 1998). As embodied by the GCM, in the perceptual processing stage the stimulus is processed and its perceived similarity to all exemplars is computed. In the decision-making stage, the resultant similarity information is used to make a decision about category membership. Correspondingly, there are two distinct ways in which categorization's time course has been incorporated into the GCM. Lamberts' (1995) Extended GCM (EGCM) assumes that it is perceptual processing time that varies systematically. The EGCM models this

stage as an all-or-none stochastic perceptual sampling process, with each dimension of a stimulus having an independent probabilistic function determining how quickly it is likely to be processed. When perceptual processing times are restricted, it is assumed that subsequent category decisions are carried out on the basis of whatever dimensions have been sampled by the time perceptual processing is terminated. Thus for the EGCM it is the distance in psychological space from, and hence perceived similarity to, the stored exemplars which develops over time; and this changes in discrete steps.

On the other hand it is the decision stage to which temporal components have been added in Nosofsky and Palmeri's (1997) exemplar based random walk model (EBRW). The EBRW supposes that presentation of a stimulus causes stored exemplars to be activated to varying degrees, and thus to race to be retrieved from memory and contribute to decisions regarding category membership. The degree of activation of an exemplar (and hence the rate at which each exemplar races) is proportional to its similarity to the test item, and also to its strength in memory. Immediately after an exemplar is retrieved, a new race is initiated and the next exemplar will be retrieved. Retrieved exemplars feed into a Random Walk process (e.g. Laming, 1968). For a 2-category decision, a random walk indicator moves between 2 decision barriers, one representing category A and the other category B. Each retrieved exemplar will move the counter in the direction of either category A or category B (depending on the exemplar's category membership). When the counter reaches one or other barrier, a corresponding response is initiated.

Each of these models has been able to account well for the temporal aspects of perceptual categorization data. The EBRW was designed with a view to predicting response times (Nosofsky and Palmeri, 1997). The duration of a random walk is determined both by the total number of steps required to initiate a response, and by the time taken to make each of these steps. One conceptual prediction of the model is that rapid classification decisions should be made for items that are highly similar to exemplars from one category and dissimilar to items from an alternative category. The EGCM (Lamberts, 1995; 1998; and Freeman, 1999; and Brockdorff, 1997) has been used to predict the effect on categorization performance of imposed response time limits. However, both models could conceivably be used for either purpose.

There are two important points to be made about these studies. Firstly there has been little empirical attempt to isolate either the decision-making or the perceptual processing aspects of categorization. Any aspect of processing before the response is made could be affecting response time as measured by the RT measurements. Similarly, in restricting the time

available to make a response (e.g. Lamberts 1995; 1998) it could be the restriction of time available for either or both of the putative stages which affects performance. Yet the data are interpreted in a manner which ascribes all temporal observations (whether about the effect of time constraint or the time taken to make a response) to one stage of categorization or the other. Secondly, both Lamberts (1998) and Nosofsky and Palmeri (1997) have acknowledged the potential temporal importance of "other" stages of categorization, but treat these as separate independent additions, ignoring the different ways in which they may interact. Lamberts (1998) suggests that the models may be "complementary". However, in the same paper he exemplifies a category structure designed to differentiate between the EGCM and EBRW, and applies the two models as direct competitors.

Lamberts and Freeman (1999) carried out a study manipulating the time available for *perceptual processing time* alone, imposing no restriction on the subsequent time available for a decision. After various intervals, stimuli (with 4 *binary dimensions* - after Medin and Schaffer, 1978) were replaced by pattern masks assumed to interrupt perceptual processing (e.g. Eriksen 1980). We have used and extended Lamberts' and Freeman's strategy for disambiguating the 2 stages. It was also hoped that a specific category crossover obtained by Lamberts and Freeman (1999) might be understood in more detail in terms of perceptual processing and decision making. Lamberts and Freeman's participants were taught to assign each of a set of 9 stimuli to one of two categories. The category structure (see table 1) was designed so that if a certain stimulus (stimulus 5) has been only partially processed, the EGCM predicts that it will actually be assigned to the *other* (wrong) category. However, if all the dimensions of the stimulus have been sampled, then the correct category assignment should be made. The overall purpose was to test empirically the common sense notion that both perceptual processing and decision-making are likely to be time dependent.

Method

Participants and Apparatus

32 Cambridge University undergraduates took part. The experiment was performed on an Acorn Risc PC 600 computer with a 14 inch colour monitor. Participants viewed the screen from a distance of approx. 0.6 m. Stickers marked A and B were placed respectively over the keys X and >. on the keyboard.

Stimuli

The stimuli, based on those of Lamberts and Freeman (1999) were pictures of colored table lamps consisting of 4 binary dimensions: a gold-colored base which was

either conical or composed of a stack of disks, a gold-colored stalk which was either thin or thick, a purple-colored shade which was either conical or hemispherical, and a grey-colored top which was either hemispherical or cylindrical. Each picture was approximately 55mm high and 27mm wide. The categories into which lamps were divided are shown in Table 1. There were also five pattern masks (see test phase). These were approximately 60 mm high and 32mm wide.

Design

Stimulus display time (henceforth “display time”) was a within-subjects variable with three levels of 33ms, 75ms and 150ms. The deadline (measured from stimulus onset) by which to make a category decision (“decision deadline”) was a between-subjects variable with two levels of 600ms and 1350ms.

Table 1. The category structure for the table lamp stimuli (taken from Lamberts and Freeman, 1999).

Base: 1 = conical; 0 = stacked

Stalk: 1 = thin; 0 = thick

Shade: 1 = conical; 0 = hemispherical

Top: 1 = hemispherical; 0 = conical

<i>Stimulus</i>	<i>Cate- gory</i>	<i>Base</i>	<i>Stalk</i>	<i>Shade</i>	<i>Top</i>
<u>1</u>	<u>A</u>	0	0	0	1
<u>2</u>	<u>A</u>	0	0	1	0
<u>3</u>	<u>A</u>	0	1	0	0
<u>4</u>	<u>A</u>	1	0	0	0
<u>5</u>	<u>A</u>	1	1	1	1
<u>6</u>	<u>B</u>	1	1	1	0
<u>7</u>	<u>B</u>	1	1	0	1
<u>8</u>	<u>B</u>	1	0	1	1
<u>9</u>	<u>B</u>	0	1	1	1

Procedure

The experiment consisted of two parts. In the first, the training phase, participants learnt the category membership (Table 1) of 9 lamps. In the second, the test phase, they had to categorize these lamps into the learned groups under time pressure with no feedback given. It was the results of this second phase which were of primary importance.

Training phase Participants were trained with the stimuli appearing sequentially in blocks of nine. Each lamp appeared on the screen until it was assigned to a category by pressing the “A” or “B” key. Auditory feedback was given: a short high beep indicated a correct category assignment and a long low beep indicated an incorrect one. One second after the response was made, the next stimulus appeared on the screen. Training trials were continued either until 2 consecutive blocks (i.e. 18 lamps) were correctly

categorized (in which case the participant continued with the rest of the experiment) or until 100 blocks were completed (in which case the experiment was terminated). Each stimulus was presented once in each block, and stimuli were presented in random order.

Test phase After two consecutive correct blocks, instructions for the test phase appeared on the screen. At the start of the test phase there was a practice run of 9 stimulus presentations. Each stimulus was selected from the 9 at random, with a display time randomly selected from the three possible. They were presented for categorization in the same manner as those in the test phase. Following the practice were 6 “real” blocks of 108 stimuli. Within each block of 108, each of the 9 stimuli was presented 12 times, 4 at each display time. Within these constraints the order of presentation was random. After the applicable stimulus display time, the lamp was replaced by one of the 5 pattern masks. The participant then had the remainder of the decision deadline time in which to make a category response. Assuming this response was given, the screen cleared and after one second the next trial began. No feedback was given in the test phase.

If the participant responded before the pattern mask appeared, there was a long low beep, the screen was cleared and “ANTICIPATION!” was displayed. If a response had not been made by the decision deadline, there was a long low beep, the screen cleared and “TIME OUT!” was displayed on the screen. If a key other than the designated A or B key was pressed, the screen was cleared and “INVALID KEY!” was displayed. Each of these messages remained for 2 seconds before the screen cleared. After a one second delay the cross appeared to signal the start of the next trial. Any of these errors stopped the trial and its data were discounted.

Results

Levels of significance are taken to be $p < 0.05$ unless otherwise stated, and are reported after the Huynh-Feldt correction for sphericity, where appropriate.

Lost data

Of the 32 participants commencing the training phase, 23 learnt the categories within the available 100 blocks and progressed to the test phase, 12 from the 600ms deadline condition and 11 from the 1350ms condition.

For each trial in the test phase, data could be lost in 3 ways: an invalid key press, a “timeout” or an “anticipation”. The mean and standard deviation of the data points lost by a subject (over the 648 trials) was 50.75 ± 37.07 (7.83% of all trials).

Overall, 6.82% of the 648 trials were timed out. A two-way ANOVA showed there was a significant effect of decision deadline on number of timeouts, $F(1, 21) = 5.08$, $p < 0.05$, but that the effect of perceptual processing time was not significant $F(2, 42) = 1.02$, $p > 0.1$. In the 600 ms deadline condition, 9.13% of trials were timed out and in the 1350ms condition 4.29% were timed out. Overall, 1.08% of trials were lost as anticipations. Neither the effect of display time, $F(2, 42) = 3.52$, $p > 0.05$, or decision deadline, $F(1, 21) < 0.01$, $p > 0.05$, was a significant factor in the number of anticipations observed. Only 2.01×10^{-4} % were lost as invalid key presses. The overall proportion of useable trials was 92.09%, in the 1350ms condition 96.64%, and 89.75% in the 600ms condition. Two separate analyses were performed: one including all legitimate trials, and one in which certain trials were cut out. The greatest number of time outs from any participant was 172, the greatest number of anticipations 64. Therefore, taking the anticipations to be the fastest of the participants' responses, and the timeouts the slowest, from every participant's results the fastest 64 and the slowest 172 trials were eradicated from the second analysis. This means that only 412 of each person's 648 trials were used in the restricted data set. Reported results are from the former analysis, but all the reported main effects remained significant, and reported trends were in the same directions when trials were removed.

Accuracy

There were significant effects on overall accuracy, of display time, $F(2, 42) = 15.69$, $p < 0.001$, of decision deadline, $F(1, 21) = 5.805$, $p < 0.05$, and of stimulus, $F(8, 168) = 2.14$, $p < 0.05$. There was also a significant interaction between the display and deadline variables, $F(2, 42) = 6.73$, $p < 0.01$. Mean accuracy in each of the 6 decision deadline/display time combinations is shown in Figure 2. Mean accuracy was significantly above chance (proportion correct 0.5) in both the longer, $t(10) = 3.91$, $p < 0.005$, and shorter, $t(11) = 5.395$, $p < 0.001$ (both 2-tailed tests), deadline conditions. However, the effect of display time was only significant for the longer decision deadline, $F(2, 20) = 17.72$, $p < 0.001$ (shorter deadline, $F(2, 22) = 1.16$, $p > 0.3$).

Stimulus 5 A planned contrast showed accuracy on stimulus 5 to be significantly different to accuracy on all of the other stimuli. $F(1, 21) = 10.197$, $p < 0.005$. For stimulus 5 alone, decision time was a significant factor in accuracy, $F(1, 21) = 10.09$, $p < 0.01$. However, display time was not significant: $F(2, 42) = 0.28$, $p > 0.5$. In the 1350ms condition, overall mean accuracy (0.59, s.d. 0.12) was significantly above chance, $t(10) = 2.49$, $p < 0.05$, one-tailed. For the shorter (600ms) decision deadline, mean accuracy (0.40, s.d. 0.16) was significantly below chance, and this trend approached

significance, $t(11) = 2.15$, $p < 0.05$ one-tailed. This is shown in Figure 1.

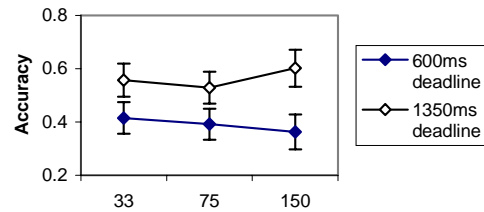


Figure 1: Stimulus 5 Accuracy

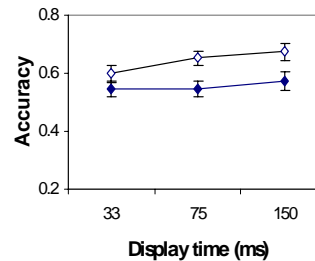


Figure 2: Accuracy for all stimuli

Response latency

There are two feasible ways of measuring response latency: from the onset and from the offset of the stimulus. When assessing the effect of decision deadline, F values are the same for both measurements, as response times measured from offset are simply calculated by adding a constant, the size of which is balanced across decision deadline conditions. However, the effect of display time in determining response latency may differ depending on which method of measurement is used. As would be expected, there is a significant effect of decision deadline on response latency (as measured from stimulus onset or offset), $F(1, 21) = 63.90$, $p < 0.001$. There is also a significant effect of display time on response latency from stimulus offset, $F(2, 42) = 95.99$, $p < 0.001$ and onset, $F(2, 42) = 5.609$, $p < 0.01$. The effect of stimulus on response time is also significant from offset and onset, $F(8, 168) = 2.95$, $p < 0.05$. There is no significant interaction between decision deadline and display time on response latency measured in either way. Mean response time (measured in both ways) in each of the display/deadline combinations is shown in figures 3 (from stimulus onset) and 4 (from stimulus offset).

Stimulus 5 Response time for stimulus 5 does not significantly differ from that for the other 8 stimuli, $F(1, 21) = 1.98, p > 0.15$.

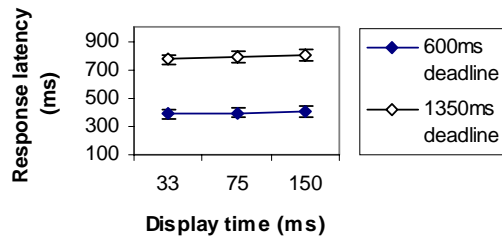


Figure 3: Response Latency from onset

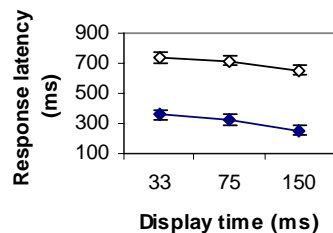


Figure 4: Response Latency from offset

Discussion

It was apparent that participants adapted their response times to meet the deadlines, and that the larger mean response time with the longer deadline was not due simply to fewer of the responses being timed out. Furthermore it was apparent that changes in accuracy for the two response deadlines were not due to the fact that longer responses were more accurate and that these tend to be timed out more in the shorter deadline condition. This consideration is an important one for procedures in which trials are discounted on the basis of responses taking too long or short a time. However, it is frequently overlooked even when a timeout procedure is in place (e.g. Lamberts and Brockdorff, 1997).

To summarize the main effects on categorization accuracy, it was discovered that both the time available to perceptually process stimuli, and the time available to make a decision, significantly affected the accuracy with which stimuli were assigned to categories, even when the effect of the other phase is controlled for. In short this supports the intuitive notion that both are markedly time dependent and that a complete temporal characterization of categorization would require consideration of both.

However, a notion requiring further consideration is that participants do not always use the full stimulus display time to perceptually process the stimulus (also suggested by Lamberts and Brockdorff, 1997). As described by the EGCM, decision processes comprise a

fixed-duration stage after completion of perceptual processing. If it is assumed that the stimulus is being processed right up until the mask appears, then such a theory would have problems accounting for our empirical effects of decision time. However, it is possible that at the shorter decision deadline, the time spent on perceptual processing is reduced in order that more time be spent on a decision, albeit based on incomplete visual information. Under this assumption it is possible that the EGCM alone could predict the effects of decision making time on accuracy. This account is also compatible with some other findings of ours. For example there was a significant interaction between decision deadline and display time in their effects on accuracy. Reference to Figure 1 indicates that the effect of increasing display time is more marked in the longer decision deadline condition. Perhaps it is only in this condition that use is made of increases in available perceptual processing time.

There was an apparent crossover in the category assignment of stimulus 5, but the circumstances responsible for this require further consideration. Lamberts and Freeman (1999) found that for shorter presentation times – i.e. when less time is available for perceptual processing – stimulus 5 was assigned to the wrong category, and for longer presentation times it was assigned correctly. This can be explained by assuming that restriction of perceptual processing time causes the decision stage of categorization to occur, in an identical fashion, but on the basis of an incomplete perceptual representation. In terms of the EGCM, if only *some* of the dimensions of stimulus 5 have been sampled, mis-categorization is likely (see table 1). However, contrary to the EGCM's basic predictions, our results indicate that it was restriction of the overall time in which to make a *decision* that caused the crossover. In fact, the time available for perceptual processing was not a significant factor in the categorization of this stimulus. Could it be that decision processes are responsible? As before, perhaps participants just cut all their *perceptual processing* times shorter for the shorter decision time than the longer one. If this is the case, then given that there was no significant effect of display time on accuracy for stimulus 5, an intriguing possibility is that processing time was cut off before 33ms for this stimulus.

Therefore our results do not rule out the possibility that decision time is constant across conditions, as assumed by the EGCM. Should it have been the case that response latencies both from stimulus onset and stimulus offset had increased as a function of display time, such an account would encounter difficulties. This result would be incompatible with the notion that at longer display times, decision processes begin before the stimulus is replaced by a mask. However, this is not the case. When measured from stimulus onset, response

latency increases as a function of display time, whereas when measured from offset, latency decreases as a function of display time.

Consider now how the EBRW could encompass the response latencies observed. Assuming that perceptual processing occupies a fixed time at the start of a trial, it would be hard to say why latency from stimulus onset significantly increases with increasing display time. If one assumes on the other hand that perceptual processing continues for as long as a stimulus is present, this means that with more information (longer perceptual processing), the random walk process takes a shorter time. This makes conceptual sense, as presumably more information means a less 'wandering' indicator in the random walk process. However, this implies that a temporal perceptual aspect needs to be added to the model as the time available to process a stimulus influences the random walk. It is also hard to see how the EBRW could predict a crossover in stimulus 5 category assignment. Nosofsky and Palmeri (1997) acknowledged that future work could address the application of the random walk model to the effects of different degrees of time restriction – to speed-accuracy trade-offs. A simple way to do this is to assume variations in the locations of response criteria. Assuming that response criteria are simply closer to the point of zero for shorter deadlines, this would make responses more haphazard, bringing overall performance closer to chance for all stimuli. This could not encompass the crossover. To do that it would have to be the case that the winners of the *earliest* races caused the counter to walk towards the *opposite* decision boundary, and that it is later walks which cancel this out and predict the correct response. However in the category structure used here, the stored exemplar activated most strongly on presentation of stimulus 5 will clearly be the memory trace of stimulus 5 itself. Conceivable modifications, such as suggesting that an exemplar becomes inhibited for a period after being retrieved, would therefore only make crossover *less* likely.

A further point for consideration is that current exemplar models' view of the relationship between perceptual processing and decision making stages is likely to be a simplification (Lamberts, 1998), and it may even be misleadingly artificial. For instance one hypothesis consistent with our crossover could be that information feeds through from the perceptual processing to the decision-making stages in a *cascaded* manner (McClelland, 1979). A cascade view would hold that perceptual information feeds continuously into the decision-making stages as it becomes available and decision-making processes work continuously on the basis of this. Perhaps at the shorter decision deadline the *decision-making* stages are basing their outcomes on incomplete stimulus representations: mis-assignment at

the shorter decision deadline suggests that some dimensions have not been taken into account. Proposing a delay between the perceptual processing of a dimension and the point the information becomes available for use by decision processes could also encompass our cross-over. Thus for the longer decision deadline, despite the same display durations, enough dimensions have been taken into account for a correct decision: during the difference between the durations in response for the two deadline conditions, additional evidence can be used by the decision components.

Existing exemplar models have provided valuable insights into how perceptual and decision-making components of categorization occur over time. Here, we have explored empirically the intuitive notion that both components have temporal aspects, and have briefly considered how the phases may be related. Our data are difficult to explain in terms of the EBRW. Certain assumptions are needed about controlling the length of perceptual processing, if the EGCM is to have much success in accommodating them; perhaps future work should concentrate on investigating the veridicality of these assumptions. Consideration should also be given to the possibility that the relationship between the two phases is likely to be non-trivial, and that addressing either individually could mask crucial intricacies.

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