Recency Effects as a Window to Generalization: Separating Decisional and Perceptual Sequential Effects in Category Learning

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Accounts of learning and generalization typically focus on factors related to lasting changes in representation (i.e., long-term memory). The authors present evidence that shorter term effects also play a critical role in determining performance and that these recency effects can be subdivided into perceptual and decisional components. Experimental results based on a probabilistic category structure show that the previous stimulus exerts a contrastive effect on the current percept (perceptual recency) and that responses are biased toward or away from the previous feedback, depending on the similarity between successive stimuli (decisional recency). A method for assessing these recency effects is presented that clarifies open questions regarding stimulus generalization and perceptual contrast effects in categorization and in other domains.

Keywords: category learning, perceptual contrast, recency effect, stimulus generalization

Sequential effects are a pervasive yet underexplored phenomenon in psychology. Although it is well established that human behavior relies heavily on long-term knowledge—including information about semantic associations, stimulus-outcome contingencies, base rates, and payoffs—short-term dependencies and recent information also have a significant effect on performance in essentially any repeated task (Bouton, 1993; Garner, 1953; Murdock, 1962; Myers, 1976; Treisman & Williams, 1984). In the majority of cognitive research, sequential effects are effectively removed from analyses by averaging response rates over many trials and ignoring the fine temporal structure of the data. However, acknowledgment and consideration of these phenomena can provide important insights into the nature of cognitive processes (Gilden, 2001). Furthermore, it has been argued that recency effects represent a functional adaptation to dynamic properties of natural environments and thus may be informative for a normative or ecological understanding of cognition (Anderson & Schooler, 1991; Real, 1991).

Two types of sequential effects have been widely observed in cognitive tasks, one based on decisional processes and another based on perceptual processes. *Decisional recency effects* involve weighting recent information more heavily, which produces a tendency to choose responses or actions that have recently been reinforced. For example, subjects in studies of probability learning

(repeated, uncued, forced-choice tasks) consistently exhibit a bias toward whichever response was correct on the previous trial (Edwards, 1961; Nicks, 1959). This tendency underlies many of the core phenomena of classical and operant conditioning (Bouton, 1993) and has also been shown to play an important role in decision making (Hogarth & Einhorn, 1992). *Perceptual recency effects* concern the dependence of the perception of a stimulus upon the values of other recently presented stimuli. Such effects are consistently found in psychophysical scaling and absolute identification tasks, where the magnitude assigned to a stimulus depends on its relationship to stimuli presented on recent trials (Garner, 1953; Jesteadt, Luce, & Green, 1977). For example, in magnitude estimation of tones of varying loudness, the same stimulus will be labeled as louder when preceded by a quiet tone than when preceded by a loud tone, once the response to the previous tone is controlled for (Jesteadt et al., 1977).

Category learning potentially involves both types of recency effect, as it involves varying stimuli as well as differential reinforcement of responses. In a typical category learning experiment, the subject is presented with a series of stimuli and asked to classify each into one of two or more categories. Following each response, feedback is given indicating the correct classification. Thus the perception of the current stimulus may be influenced by its relationship to recent stimuli (perceptual recency), whereas the tendency to assign the stimulus to a category may depend on which categories have been recently reinforced (decisional recency). These observations apply not only for experimental studies of category learning but also for most naturalistic processes whereby humans acquire new conceptual knowledge. That is, real-world semantic knowledge is likely subject to sequential effects similar to those present in categorization experiments. As is shown here, strong sequential effects persist even after performance on the task has reached asymptote, suggesting that even expert-level conceptual knowledge is subject to continuing systematic variation.

In this article, we describe a statistical approach for separately measuring decisional and perceptual recency effects in category learning. The essence of the approach is to determine the separate

effects of the previous stimulus and the previous category (i.e., feedback) upon the current response. One difficulty with studying sequential effects in category learning is that the majority of experiments use deterministic structures, in which repeated instances of the same stimulus always lie in the same category. This practice produces a confounding between previous stimuli and feedback that makes the decisional and perceptual recency effects difficult or impossible to separately identify. To break the relationship between stimulus and feedback, we adopt a probabilistic category structure, in which every stimulus has a positive probability of being in any category. This allows the effect of the previous category to be assessed while the previous stimulus is held constant, giving a measure of the decisional recency effect. Similarly, evaluating the effect of the previous stimulus while controlling for the previous category provides a measurement of the perceptual recency effect. Furthermore, the use of probabilistic tasks is more ecologically valid, as it corresponds to the graded and overlapping nature of real categories (e.g., Rosch & Mervis, 1975).

Following a review of existing evidence for decisional and perceptual recency effects, we present a mathematical model of these phenomena in category learning. The model explains how the previous stimulus and category combine with long-term knowledge of the category structure to produce categorization responses, and it shows how the sequence of stimuli, responses, and feedback can be analyzed to provide independent estimates of the contributions of each source of information (perceptual recency, decisional recency, and long-term knowledge). The model serves primarily as an analysis tool, in that fits of its parameters to empirical data allow quantitative testing of hypotheses regarding the perceptual and decisional processes underlying sequential effects. We then present an empirical investigation of sequential effects in a probabilistic category learning task. Results show clear evidence of perceptual recency effects, specifically a perceptual contrast effect whereby the previous stimulus exerts a negative effect on the representation of the current stimulus. This effect has not been previously demonstrated and is not predicted by any existing model of category learning. We also find a decisional recency effect, whose magnitude depends heavily on the similarity between successive stimuli. When the current stimulus is similar to the previous one, subjects have a strong tendency to repeat the previous feedback. However, with increasing dissimilarity this tendency weakens and eventually reverses, so that, when successive stimuli are highly dissimilar, subjects tend to respond with the opposite of the previous category. Other researchers have attempted to demonstrate negative decisional recency effects between dissimilar stimuli (Stewart & Brown, 2004; Stewart, Brown, & Chater, 2002), but as we show below, their evidence is inconclusive, because of the confounding between decisional and perceptual recency in deterministic tasks.

In the concluding section, we discuss how the distinction drawn here between perceptual and decisional recency effects can clarify important questions regarding sequential effects in category learning as well as in other domains such as absolute identification. The two most important questions we address are the nature of perceptual recency—whether it is assimilative (positive) or contrastive (negative)—and the existence of negative decisional recency—whether membership of a stimulus in a given category is used as evidence against membership of highly dissimilar stimuli in the same category. Both of these questions arise due to the confounding between previous stimuli and feedback, which leads to inconsistent or contradictory contributions from the two recency effects. Measuring these effects separately using the methods presented here resolves these contradictions and allows a clearer picture to emerge. Implications are also discussed for the relationship between decisional recency and stimulus generalization. *Stimulus generalization* is the process by which knowledge acquired about one stimulus, such as its category membership, is transferred to another stimulus, to a degree that depends on their similarity (Shepard, 1957). The dependence of decisional recency on stimulus similarity suggests that it is a by-product of generalization between successive stimuli, and hence the methods presented here for measuring decisional recency effects also provide a direct measure of stimulus generalization. This is a significant advance because generalization processes are central to many models of category learning but have not previously been directly measured in this domain. The present approach thus offers an important tool for future work investigating psychological processing during categorization, the roles of short- and long-term memory in category learning, and the nature of perceptual and category representations.

Decisional Recency Effects

One of the earliest findings in the probability learning literature is that subjects are biased to respond with whichever option was given as correct on the previous trial (e.g., Edwards, 1961; Engler, 1958; Jarvik, 1951; Nicks, 1959; Suppes & Atkinson, 1960; see Myers, 1976, for a review). For example, Engler (1958, Experiment 2, Condition H) found that in a two-choice task with equal rates of reinforcement for responses *A* and *B*, subjects' overall rate of choosing *A* was 50%, but this value was 60% on trials following reinforcement of *A* and 40% on trials following reinforcement of *B*. Jones and Sieck (2003) found an analogous effect in category learning, with subjects biased to select whichever category had been correct on the previous trial.

Category learning offers a richer domain for studying sequential effects than probability learning, because of the presence of varying cues. In particular, Jones and Sieck (2003) found in a classification task with probabilistic feedback that the magnitude of the decisional recency effect depends on the similarity between successive stimuli. Stimuli in their experiments varied on three binary-valued features. When the present stimulus matched the previous stimulus completely, the decisional recency effect was large; when these stimuli mismatched on all three dimensions, the effect was near zero. Overlap on one or two feature dimensions led to intermediate decisional recency effects. These results were based on a logistic regression analysis that accounted for the different response rates to different stimuli. However, the pattern of decisional recency effects can be illustrated by holding the present stimulus fixed and computing subjects' response rates to this stimulus as a function of the previous category and the similarity between present and previous stimuli. Regardless of the choice of present stimulus, the same pattern emerges, as exemplified in Figure 1. The overall response rate to the stimulus used for this example is about 75%, but as the figure shows, this value depends strongly on information from the previous trial. On trials when the previous stimulus is identical to the present one, there is a large bias toward repeating the previously correct category, as seen by the large difference between the two bars at distance 0. For trials on which the previous stimulus is increasingly dissimilar, this effect progressively weakens.
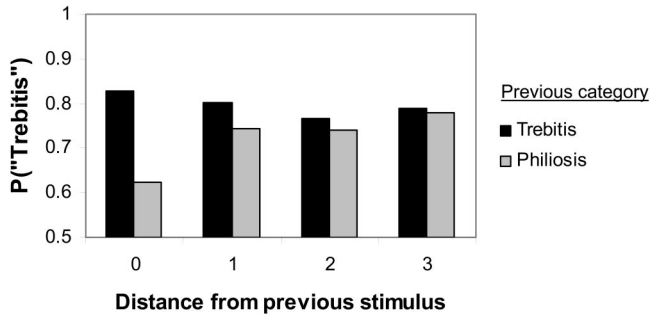
Figure 1. Effects of previous trial from Jones and Sieck (2003, Experiment 2, control condition). Shown are response rates to a single stimulus (configuration S_3 in their notation) as a function of the previously correct category and the distance between present and previous stimuli. "Distance" is defined here as the number of mismatching cue dimensions (stimuli were composed of three binary cues). All six stimuli show the same qualitative pattern as seen here. *Trebitis* and *Philiosis* are the two category labels.

The dependence of decisional recency effects on similarity between successive stimuli suggests a close relationship to stimulus generalization. Stimulus generalization, which has been studied most thoroughly in research on operant conditioning, is the process by which an individual uses knowledge about one stimulus (such as the probability that it predicts a reward) to respond to another, often novel, stimulus. The strength of generalization between stimuli is positively related to their similarity. For example, a pigeon trained to peck at a key of a certain color to obtain food will subsequently respond to a new key of a different color, but at a slower rate if the new color is very different from the trained color than if the colors are similar (Guttman & Kalish, 1956). Shepard (1957) subsequently showed that generalization strength is directly determined by the psychological (as opposed to physical) similarity between stimuli, and thus generalization allows a powerful measure of the structure of perceptual representations.

In the context of category learning, stimulus generalization amounts to classifying stimuli based on the category labels of previous, similar stimuli. This process is explicitly assumed by exemplar models of categorization (Nosofsky, 1986) and is implicitly built in to nearly all other models (Gluck, 1991; Kruschke, 1992; Love, Medin, & Gureckis, 2004; Smith & Minda, 1998). Despite this widespread acceptance of the role of generalization in category learning, direct measurement of generalization of the sort carried out in conditioning has yet to be achieved in this domain. Developing a technique for directly assessing stimulus generalization during categorization would clearly be an important methodological advance in understanding the processes involved in learning new categories. In this article, we show how elaborating the relationship between sequential effects and generalization leads to such a method.

The hypothesis adopted here is that decisional recency arises because generalization is stronger for recent stimuli than more distant ones. If this characterization is correct, then the decisional recency effect is far more sophisticated than a simple feedback echo. For example, the large, simple recency effect observed in probability learning may be due to the lack of meaningful stimulus variation, which leads the generalization gradient to be sampled only at a distance of zero, where generalization is strong but not especially complex. The variable stimuli present in category learn-

ing allow for generalization to manifest as a richer phenomenon, one that potentially plays a significant role in subjects' performance of the task. Unfortunately, binary stimuli such as those used by Jones and Sieck (2003) provide minimal additional structure; for example, they allow no measurement of the quantitative effects of continuous stimulus variation, and they leave open the possibility that the dependence of decisional recency on similarity is due primarily to special processing of identically repeated stimuli. Therefore the present study provides a focused test of the claim that decisional recency is a manifestation of stimulus generalization (biased toward recent stimuli), by using continuously varying stimuli and analyzing the functional relationship between stimulus distance and recency effects. In addition, the richer stimulus set allows a more detailed measurement of generalization behavior that should have greater applicability to more realistic learning scenarios.

Despite many appealing commonalities, there are important ways in which generalization may differ in category learning as compared with conditioning. In a categorization task, the boundaries of the stimulus space are well defined (either a priori, as with binary cues, or by experience after the subject has seen enough trials to infer the range). Further, the space is divided into logically symmetric regions corresponding to the two (or more) category labels. This contrasts with the standard interpretation of conditioning in which the stimulus space contains "consequential regions" that are finite in extent and surrounded by an unbounded region of inconsequential stimuli (Shepard, 1987). Taken together, these two properties of category learning suggest that, for a pair of stimuli that are sufficiently dissimilar (relative to the size of the stimulus space), observation of one occurring in a certain category might be taken as evidence against the other belonging to that same category (cf. Stewart & Brown, 2005). In other words, the goal of dividing a bounded stimulus space into two category regions, together with the prior expectation that these regions be roughly comparable in extent, might lead to a negative generalization effect between stimuli at opposite ends of the space. A better understanding of this potential finding should have significance for people's use of domain knowledge for learning in structured environments.

Some evidence for a negative generalization effect was found by Jones and Sieck (2003) in an analysis restricted to the second trial of the experiment. Subjects for whom the first and second stimuli in the experiment matched on at least two of the three features tended to classify the second stimulus in the same category as the feedback they had received on Trial 1. However, subjects for whom the first two stimuli mismatched on at least two dimensions showed the reverse pattern, tending to classify the second stimulus in the category opposite to that of first. This negative generalization effect is almost certainly dependent on the bounded nature of the stimulus space (e.g., if there had been seven feature dimensions then a mismatch of two would have likely led to positive generalization). The analysis of Trial 2 is particularly simple to interpret because subjects have only seen one previous stimulus and thus the effects of that trial can be trivially isolated. On the other hand, when data from the full sequence of 300 trials were analyzed, no evidence was found for negative generalization; at the maximal distance of three mismatching cues, the recency effect was almost exactly zero. Thus it is uncertain whether the negative generalization effect found by Jones and Sieck is an artifact of some strategy that is particular to early trials or whether it persists, possibly in a weaker form, later in learning.

Additional evidence for negative generalization comes from the perceptual categorization experiments of Stewart et al. (2002). The task in this study involved 10 stimuli arranged along a single dimension, divided in the middle into two deterministic categories. The primary finding was that when a borderline stimulus was preceded by an extreme stimulus, classification of the borderline stimulus was correct more often if the previous stimulus was from the opposite category. Stewart et al. termed this phenomenon the *category contrast effect*, and they interpreted it as evidence for negative generalization. That is, they assumed that on trials of this type subjects give the opposite response from whatever was correct on the previous trial because of the large difference between present and previous stimuli. Unfortunately, because Stewart et al. used deterministic categories, decisional and perceptual recency effects are confounded. Consequently, their evidence for negative generalization (or negative decisional recency) is inconclusive, because the category contrast effect may also be due to perceptual contrast, as explained in the following section.

Perceptual Recency Effects

A ubiquitous finding in studies of psychophysical scaling and perceptual identification is that the response to a given stimulus depends systematically on the stimulus that came immediately before (Garner, 1953; Holland & Lockhead, 1968; Jesteadt et al., 1977; Lockhead & King, 1983; Petrov & Anderson, 2005; Petzold, 1981; Schifferstein & Frijters, 1992; Stewart, Brown, & Chater, 2005; Ward, 1979, 1987; Ward & Lockhead, 1970, 1971). Identification is similar to category learning, except that there is a unique response assigned to each stimulus. Stimuli are generally arranged along a single continuum (e.g., loudness), and the ordering of the numerical responses corresponds to the ordering of the stimuli (e.g., 1 for quietest, 10 for loudest). In such tasks it is commonly found that responses are positively related to the previous stimulus, so that, for example, stimuli with the largest values on the dimension of variation are associated with overestimation of the stimulus on the following trial (e.g., Garner, 1953; Holland & Lockhead, 1968). Some investigators have interpreted this bias as a perceptual assimilation effect, in which the perception of the current stimulus is assumed to assimilate toward that of the previous stimulus (Lockhead & King, 1983). However, it is not clear whether the effect is due to the previous stimulus, per se, or to the feedback following that stimulus (Garner, 1953). That is, it is impossible to distinguish the explanation based on perceptual recency effects from one based on decisional recency effects, because of the perfect confounding of previous stimulus and feedback.

One approach to isolating the effect of the previous stimulus is to use tasks such as magnitude estimation that do not include feedback. In magnitude estimation the subject assigns a numerical value to each stimulus presented, with no constraint on the response and no corrective feedback. In these tasks there is still a confounding effect of the previous response (which subjects may use as a proxy for feedback; Stewart et al., 2005; Ward & Lockhead, 1970), but in this case the confounding is imperfect due to inconsistencies in responding. Jesteadt et al. (1977) analyzed the effects of recent information in a loudness estimation study, by fitting responses to a regression model with the previous stimulus and previous response as predictors. Consistent with the decisional recency interpretation (along with the assumption that previous responses are used in lieu of feedback) the previous response had a positive effect on the current response. Furthermore, with the effect of the previous response controlled for, the previous stimulus was seen to have a negative effect on the present response. Thus, with the decisional recency effect accounted for, the perceptual recency effect is seen to be negative (i.e., perceptual contrast rather than assimilation). Subsequent work by Petzold (1981; see also Schifferstein & Frijters, 1992) that does not rely on the parametric assumptions of the regression model further supports the conclusion that the previous stimulus exerts a negative effect on the present response in magnitude estimation.

The same problem of confounding between the effects of previous stimuli and feedback arises when assessing sequential effects in category learning. When the category structure is deterministic, decisional and perceptual recency effects can be indistinguishable because of the confounding between previous stimulus and category. However, a probabilistic category structure avoids this problem. In this case, the effects of the previous stimulus and feedback can be measured separately, using an approach similar to that followed in magnitude estimation (Jesteadt et al., 1977; Petzold, 1981). The details of our approach are presented below.

The importance of distinguishing between decisional and perceptual recency effects in category learning is illustrated by the category contrast effect. This phenomenon has been proposed to arise from a decisional process (i.e., negative generalization; Stewart et al., 2002), but it could also be due to perceptual processes. Specifically, a perceptual contrast effect would lead a stimulus near the category boundary to be perceived as more like a Category A stimulus when preceded by an extreme member of Category B, and vice versa. This would lead to more correct responses when the preceding extreme stimulus is from the opposite category than when it is from the same category, as illustrated in Figure 2. Although the two explanations for the category contrast effect are difficult to distinguish in a deterministic task, they make differing predictions in a probabilistic task. In a probabilistic task, an extreme stimulus will receive the same feedback value on most trials (the modal feedback for that stimulus) but will occasionally receive the opposite feedback (amodal feedback). Both the nega-
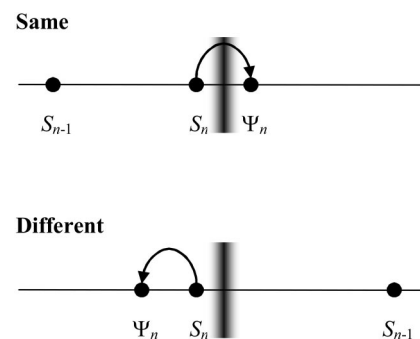

Figure 2. Perceptual explanation of the category contrast effect. In the top example, the previous stimulus (S_{n-1}) is in the same category as the present stimulus (S_n), but perceptual contrast moves the perception of the current stimulus (Ψ_n) away from S_{n-1}, across the category boundary (indicated by the blurred vertical line), leading to an incorrect response. In the bottom example, S_{n-1} is in the opposite category; in this case perceptual contrast moves Ψ_n away from the category boundary, increasing the probability of a correct response.

tive generalization and perceptual contrast explanations predict a category contrast effect when an intermediate stimulus follows an extreme stimulus with modal feedback, as this case corresponds to the deterministic version of the task. However, they make opposite predictions when the feedback for the extreme stimulus is amodal. The negative generalization explanation states that whenever an intermediate stimulus follows an extreme stimulus, the response to the second stimulus tends to be opposite the feedback given for the first. The value of the previous stimulus itself (i.e., which end of the range it lies on) has no effect; all that matters is the feedback. Thus when the feedback is amodal, the negative generalization explanation predicts the category contrast effect to reverse. The perceptual contrast explanation makes the opposite prediction. According to this explanation, the effect is due to the previous stimulus, not the previous feedback. Therefore variation in the previous feedback should have no effect, and in particular the category contrast effect is predicted to remain unchanged when the previous feedback is amodal. The predictions of the decisional and perceptual explanations, following both modal and amodal feedback, are summarized in Table 1.

Assessing Sequential Effects in Category Learning

The statistical approach presented here for measuring decisional and perceptual recency effects is based on determining the separate effects of the previous stimulus and the previous category upon the current response. Measuring the effect of the previous category (i.e., feedback) while holding the previous stimulus constant gives a measure of decisional recency or generalization from one stimulus to the next. Measuring the effect of the previous stimulus while controlling for the previous category gives a measure of perceptual recency (i.e., perceptual assimilation or contrast).

The magnitude of stimulus generalization from trial $n - 1$ to trial n is equal, by definition, to the effect of the feedback on trial $n - 1$ on the response probability on trial n. This implies that generalization effects can be determined by controlling for the stimuli S_{n-1} and S_n and calculating the effect of the feedback C_{n-1} on the response R_n. Specifically, the strength of generalization between any two stimuli, X and Y, can be determined by separately computing the response rate to Y on all trials following an instance

Table 1
Comparison of Predictions Regarding Category Contrast Effect

		Hypothesis	
Feedback	Category	Decisional	Perceptual
Modal	Same	−	−
Modal	Different	+	+
Amodal	Same	+	−
Amodal	Different	−	+

Note. All predictions are based on responses to intermediate stimuli following extreme stimuli. Cases where the response is likely to be optimal (i.e., matching the modal category) are indicated by "+"; cases where the nonoptimal (amodal) response is predicted are indicated by "−." The "Category" column indicates whether the two stimuli are from the same half of the stimulus range. The "Feedback" column refers to feedback given for the extreme stimulus. Deterministic tasks only involve the modal case (rows 1 and 2), where decisional and perceptual effects are in concert, whereas probabilistic tasks also include the amodal case, where the hypotheses make opposite predictions.

of X in Category A and the response rate to Y on all trials following an instance of X in Category B. The difference between these two values is equal to the effect of X's category membership on the response to Y (whenever Y follows X), and thus provides a measure of the generalization from X to Y. To account for ceiling effects, we consider response rates on a log-odds scale. Therefore the generalization $G(X, Y)$ from X to Y is defined as

$$G(X, Y) = \tfrac{1}{2}(L_{n|S_n=Y,S_{n-1}=X,C_{n-1}=A} - L_{n|S_n=Y,S_{n-1}=X,C_{n-1}=B}) \quad (1)$$

where L_n denotes the log-odds of the response on trial n:

$$L_n = \log\left(\frac{P[R_n = A]}{1 - P[R_n = A]}\right)$$

$$= \log(P[R_n = A]) - \log(P[R_n = B]) \quad (2)$$

and R_n is the response on trial n. The notation in the subscript of L_n in Equation 1 indicates that L_n is computed only over trials satisfying the conditions to the right of the "|" (analogous to a conditional probability). Therefore $G(X, Y)$ is given by the difference in log-odds response rates to Y attributable to the feedback for X, computed over those trials on which Y follows X. The coefficient "½" is included in the formula for G because the difference in response rates corresponds to the sum of generalization toward A on $C_{n-1} = A$ trials and generalization toward B on $C_{n-1} = B$ trials (i.e., the generalization effect is counted twice).

Assimilation or contrast effects can be measured using a complementary approach that controls for the current stimulus and previous category and determines the effect of the previous stimulus. To obtain a measure of the effect of the previous stimulus that is not affected by generalization, we average log-odds response rates over trials on which the previous category was A and those on which the previous category was B. Thus for all pairs of stimuli, X and Y, we define a conditional response measure $M(Y|X)$ giving the log-odds of responding to Y when preceded by X that corrects for generalization effects:

$$M(Y|X) = \tfrac{1}{2}(L_{n|S_n=Y,S_{n-1}=X,C_{n-1}=A} + L_{n|S_n=Y,S_{n-1}=X,C_{n-1}=B}) \quad (3)$$

This conditional response measure is equal to the log-odds response rate to Y whenever Y follows X, averaged over the two possible values of the feedback for X. It is important to note that this is different from simply computing the response log-odds over all trials on which Y follows X, as it accounts for the differential frequency with which X falls in the two categories and weights the two trial types equally. This removes the confounding between previous stimulus and previous category.

With the effect of the previous category thus controlled for, perceptual assimilation or contrast can be evaluated by considering the effect of the previous stimulus, X, on the conditional response $M(Y|X)$. Consider a task in which stimuli vary along a single dimension. When plotting $M(Y|X)$ as a function of the current stimulus, Y, assimilation or contrast effects should appear as a lateral shift between the curves for different values of X. In the case of perceptual assimilation, the perception of Y is biased toward X. Thus when the value of X is low, Y must take on a greater value to produce the same level of responding as when X is high. In other words, the curves corresponding to small values of X become shifted to the high end of the scale, and vice versa. This pattern is illustrated in Figure 3A. In the case of perceptual
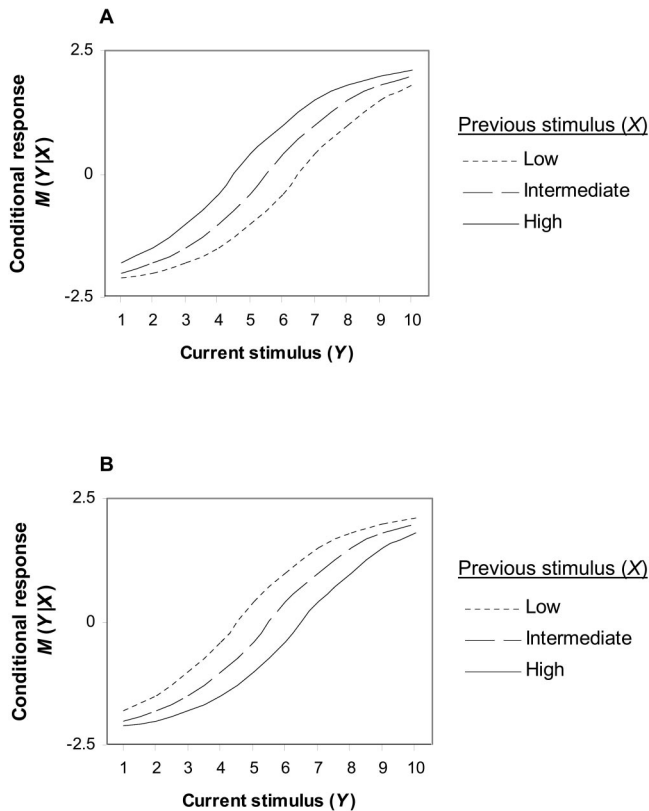
A

B

Figure 3. Illustration of perceptual assimilation and contrast effects. The vertical axis represents response rate corrected for generalization effects (see Equation 3). 3A: Predicted pattern resulting from perceptual assimilation. Response curves for low values of the previous stimulus are shifted toward the high end of the scale. 3B: Predicted pattern resulting from perceptual contrast. Response curves for low values of the previous stimulus are shifted toward the low end of the scale.

contrast, the perception of *Y* is biased away from the value of *X*, leading to the opposite pattern (Figure 3B).

A Mathematical Model of Sequential Effects in Category Learning

In this section we present a mathematical model that unifies the above discussions of decisional and perceptual recency effects in category learning. Many of the principles of this model are direct reflections of the statistical methods described in the previous section. Thus the model serves to formalize the assumptions underlying those methods as well as to make explicit certain details required for quantitative predictions. However, the model is not intended to represent a strong theory of sequential effects in itself; indeed it was formulated with the goal of remaining theoretically minimal. The main function of this model is as a data analysis tool (i.e., generalized regression) that allows separate measurement of both types of recency effects. The model also serves as a means for expressing specific hypotheses about sequential processes, such as perceptual contrast and generalization between successive stimuli. Conversely, parameter estimates from fits of the model to empirical data allow for quantitative tests of these hypotheses, as elaborated below.

The model assumes that responding is based on a combination of long-term knowledge of the category structure and generalization from recent stimuli. Our approach thus lies between models that assume subjects generalize equally from all past stimuli (e.g., Nosofsky, 1986) and models that assume responses are based only on comparison to the most recent stimulus (Stewart et al., 2002). By distinguishing between short- and long-term processes, our model also leaves open the possibility that these two sources of information are used in qualitatively different ways (following the distinction between short- and long-term memory; Atkinson & Shiffrin, 1968). For simplicity, we restrict short-term effects to the immediately preceding trial, but extending that component of the model to include dependencies over two or more trials is straightforward.

The long-term component of the model is purely descriptive, consisting of a mapping from the perceived value of the current stimulus to a response probability:

$$P[R_n = A] = f[b + w \cdot \Psi_n] \tag{4}$$

Here Ψ_n is the perception of the current stimulus, w represents the strength of association for the stimulus-category mapping, and b is a bias term. The linear form of the association between stimuli and categories (i.e., the $w \cdot \Psi_n$ term) is made for sake of simplicity, as the nature of long-term category representations is not a focus of the current study. Similarly, the value of w is assumed to be stable as we are not addressing learning effects (i.e., it is assumed that the category structure is already well-learned). Both of these assumptions are made solely for convenience and are not necessary components of our approach. The function f corresponds to response selection and is taken to be the sigmoid function commonly used in both neural networks and logistic regression:

$$f(x) = \frac{1}{1 + e^{-x}} \tag{5}$$

Again, this assumption is made largely for convenience, and our approach is compatible with other response selection functions. However, as will be seen below, the present form of the long-term component of the model appears adequate for the current study, as it corresponds closely to the empirical data.

The perception Ψ_n of the current stimulus is assumed to depend on the physical values of both the present and previous stimuli (under the simplifying assumption that sequential effects are restricted to the immediately preceding trial). Assuming a linear psychophysical function for the stimuli under investigation (as is reasonable for the stimuli used in the present empirical investigation; Wiest & Bell, 1985), the following form can be assumed for Ψ (cf. DeCarlo & Cross, 1990):

$$\Psi_n = S_n + c \cdot S_{n-1} \tag{6}$$

Here c determines the effect of the previous stimulus on the current percept. A positive value of c produces a positive dependence of the percept on the previous stimulus, corresponding to an assimilation effect. Similarly, a negative value of c corresponds to a contrast effect.

For the stimulus generalization component of the model, we adopt the standard hypothesis that generalization strength is solely a function of psychological distance between stimuli (Shepard, 1957). Again assuming a linear psychophysical function, the psychological distance is proportional to the physical distance. Thus

generalization is built into the model as a bias toward the previous category with magnitude determined by the absolute difference $|S_n - S_{n-1}|$ between present and previous stimuli. When the generalization term is included, the full form of the model becomes

$$P[R_n = \text{A}] = f[b + w \cdot \Psi_n + C_{n-1} \cdot \Gamma(|S_n - S_{n-1}|)] \qquad (7)$$

Here Γ denotes the generalization gradient, giving generalization as a function of interstimulus distance. The previous category C_{n-1} is coded as $+1$ for A and -1 for B and determines the direction of the generalization effect. Thus when Γ is positive, the response is biased toward the previous category (positive generalization), and when Γ is negative, the response is biased toward the opposite category (negative generalization). The model assumes that the generalization effect is combined with the response tendency from the long-term component of the model, and the sum is passed through the response function to generate a response probability.

Two possible forms for the generalization gradient have been proposed in the literature. The first is the exponential, which has received support in conditioning and identification studies (Shepard, 1957, 1987). The second is the Gaussian, which has been supported in category learning (Nosofsky, 1986) and which also might result from exponential generalization convolved with normally distributed perceptual noise (Ennis, 1988). In light of empirical results presented below, we focus here on the Gaussian form. In addition, to allow for the possibility of negative generalization over large distances, we include a constant term allowing the generalization gradient to have a nonzero asymptote:

$$\Gamma(d) = m + ke^{-\alpha d^2} \qquad (8)$$

Here d is the distance between successive stimuli, m is the level of asymptotic (large-distance) generalization, k determines the peak level of generalization (at $d = 0$, when successive stimuli are identical), and α determines the rate at which generalization decays with distance (i.e., the width of the generalization gradient). Both k and α are constrained to be nonnegative.

As an alternative to response probability, the model's predictions can be written in terms of response log-odds. Because the log-odds transformation is the inverse of the sigmoid response function f, the model's specification in terms of response log-odds simplifies to

$$L_n = b + w \cdot \Psi_n + C_{n-1} \cdot \Gamma(|S_n - S_{n-1}|)$$
$$= b + wS_n + cwS_{n-1} + C_{n-1} \cdot \Gamma(|S_n - S_{n-1}|) \qquad (9)$$

Thus response log-odds is expressed as a sum of four terms: the response bias or intercept term, the present stimulus, influence of the previous stimulus via perceptual assimilation or contrast, and stimulus generalization.

Formal Predictions

The model presented in the previous section allows quantitative formulation and evaluation of predictions regarding sequential effects in a categorization task. Our approach takes advantage of the close correspondence between components of the model and the methods described above for assessing decisional and perceptual recency effects. In essence, the model is "solvable" such that the implications of each of its parameters for empirical predictions

can be given explicitly (rather than implicitly), making the relation between theory and data transparent.

From Equations 1 and 9, the model predicts generalization between any pair of stimuli, X and Y, to be

$$G(X,Y) = \tfrac{1}{2}(L_{n|S_{n-1}=X,S_n=Y,C_{n-1}=\text{A}} - L_{n|S_{n-1}=X,S_n=Y,C_{n-1}=\text{B}})$$
$$= \tfrac{1}{2}[b + w \cdot \Psi_n + 1 \cdot \Gamma(|Y - X|)]$$
$$- \tfrac{1}{2}[b + w \cdot \Psi_n + (-1) \cdot \Gamma(|Y - X|)]$$
$$= \Gamma(|Y - X|). \qquad (10)$$

Therefore the generalization gradient Γ assumed by the model directly corresponds to the predicted empirical gradient G. This allows hypotheses concerning subjects' generalization behavior to be tested by evaluating fits of the model with respect to the parameters defining Γ. For example, the prediction of negative generalization between highly dissimilar stimuli can be evaluated by finding the best-fitting value of the asymptotic generalization parameter m and testing whether this value is reliably negative.

The model also allows quantitative evaluation of predictions regarding perceptual contrast or assimilation. From Equations 3, 6, and 9, the model predicts the adjusted conditional response rate to Y following X (i.e., controlling for generalization effects due to the previous category) is predicted to be

$$M(Y|X) = \tfrac{1}{2}(L_{n|S_{n-1}=X,S_n=Y,C_{n-1}=\text{A}} + L_{n|S_{n-1}=X,S_n=Y,C_{n-1}=\text{B}})$$
$$= \tfrac{1}{2}[b + w \cdot (Y + c \cdot X) + 1 \cdot \Gamma(|Y - X|)]$$
$$+ \tfrac{1}{2}[b + w \cdot (Y + c \cdot X) + (-1) \cdot \Gamma(|Y - X|)]$$
$$= b + w \cdot (Y + c \cdot X). \qquad (11)$$

Thus the conditional response profile for each value of X is shifted along the stimulus scale by a constant of $-c \cdot X$. This provides a simple relationship between the value of c and the methods described earlier for evaluating perceptual recency effects. When c is positive, Equation 11 predicts the pattern shown in Figure 3A, corresponding to perceptual assimilation. When c is negative, the opposite shift is predicted as in Figure 3B, corresponding to perceptual contrast.[1] Evaluation of the best-fitting value of c thus provides a test between the perceptual contrast and perceptual assimilation hypotheses.

Empirical Investigation

An experiment was conducted to investigate sequential effects in categorization using the methods presented above. The stimulus set comprised 10 simple geometric figures varying along a single dimension. To separately evaluate contrast and generalization effects, we used a probabilistic structure in which every stimulus had a nonzero probability of being in either category. The outcome probability followed a logistic, or sigmoid, function of stimulus value as illustrated in Figure 4, with high-valued stimuli tending to lie in Category A and low-valued stimuli in Category B (with

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[1] Note that the model predicts linear M-profiles, whereas the example in Figure 3 uses curved profiles (to emphasize the horizontal shift). This aspect of the data is not relevant to the model's central principles as it depends on the nature of the long-term stimulus-category association.

actual category labels counterbalanced across subjects). This outcome probability function was chosen to match the long-term response component of the model, so as to minimize any dependence of the results of the model-based analyses on assumptions regarding long-term category representation.

Method

Participants

Twenty students at the University of Texas at Austin participated for $6 payment or course credit. All participants were offered monetary bonuses of up to $2 for good performance.

Stimuli

Stimuli were solid gray rectangles presented on a 17-inch (43-cm) CRT monitor on a black background. Each stimulus was 1.3 inches (3.3 cm) wide and varied in height from 1.4 to 3.2 inches (3.6 to 8.1 cm) in 10 equally spaced intervals. Stimuli were centered horizontally and were aligned vertically such that the bottom edge was always 4.4 inches (11.2 cm; 43%) from the bottom of the screen. Thus all that varied was the location of the top of the rectangle.

Design

Stimuli were randomly and independently selected for each trial, with category sampled according to the logistic function $P[A] = 1/(1 + e^{-\phi(S-5.5)})$. Here S represents the current stimulus, coded as $\{1, \ldots, 10\}$. The scaling parameter ϕ was set so that outcome probabilities ranged from 10% to 90%. The outcome-probability function is displayed graphically in Figure 4. Every subject received the same category structure, up to random assignment of category labels.

Procedure

Subjects were instructed that they would be presented with a series of rectangles from two categories and that their job was to select which category each stimulus came from. No information was given regarding the category structure or whether the categories were overlapping. Each trial began with a stimulus presented in isolation on the monitor. The subject responded by pressing either *D* or *K* on a standard keyboard. These labels were mapped to the abstract categories in a random fashion for each
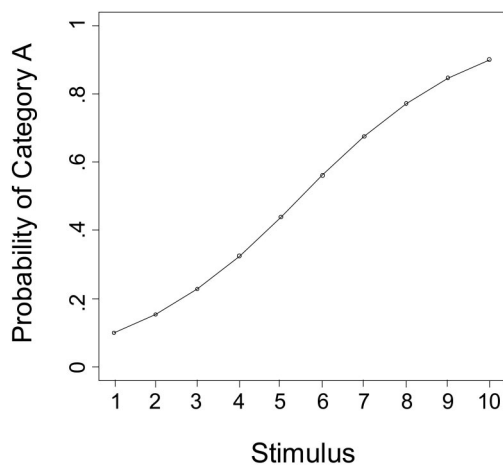

Figure 4. Category structure for the experiment. Shown is each stimulus's probability of being in Category A on any given occurrence.

Table 2
Mean Performance (%) by Block

				Block					
1	2	3	4	5	6	7	8	9	10
65.3	68.7	69.9	69.0	66.5	68.0	69.3	70.7	67.6	70.2

subject. The word *Correct* (in green) or *Wrong* (in red) appeared below the stimulus 250 ms after the response, with the sentence *That was a D* or *That was a K* (in white) one line below. All feedback was displayed in 0.33-inch (8.5-mm) font. The stimulus and feedback remained on the screen for 750 ms, after which the screen was cleared for 500 ms before the start of the next trial. Trials were grouped into blocks of 50. After each block, text appeared informing the subject of how many trials had been completed, the total number of trials in the experiment, and the proportion of correct responses in the most recent block. The experiment consisted of 10 blocks (500 trials) and lasted between 35 and 50 min.

Results and Discussion

Performance

Mean performance by block is displayed in Table 2. As can be seen from the table, subjects learned the task relatively quickly and reached asymptote at nearly 70% as compared with optimal performance of 75.1%. Because performance appears to have approached asymptote by the second block, all analyses are based on Blocks 2 through 10. Because the focus of most analyses is the effects of information from the previous trial, the first trial from each block is also omitted.

Effects of Previous Category

An initial analysis of decisional recency effects was performed by computing each subject's proportion of responses that matched the previously correct category. The overall mean repetition probability was 53.9%, which is significantly greater than chance (50%), $t(19) = 4.91$, $p < .0001$.

A more detailed pattern is revealed by examining this recency effect while controlling for the previous stimulus. Figure 5 shows the effect of the previous category on average response profiles, with separate panels for each value of the previous stimulus.[2] For example, Figure 5A shows the response profile for trials on which the previous stimulus was 1 (as indicated by the vertical gray line). In each panel, the dotted curve represents trials on which the previous category was Category A and the solid curve represents trials on which the previous category was Category B. Four aspects of this figure are important. First, for all values of the previous stimulus, the Category A curve is predominantly higher than the

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[2] In producing Figures 5–9, we took advantage of the symmetry between categories, that is, the logical invariance of the task under reversal of category labels and reflection of the stimulus continuum about its midpoint. For example, in Figure 5 the proportion of Category A responses to Stimulus *Y* following Stimulus *X* in Category A is also based on the proportion of Category B responses to Stimulus 11–*Y* on trials following Stimulus 11–*X* in Category B. Collapsing over this symmetry serves only to simplify presentation of the data and reduce the influence of statistical noise, and it has no bearing on interpretation of any of the results presented.
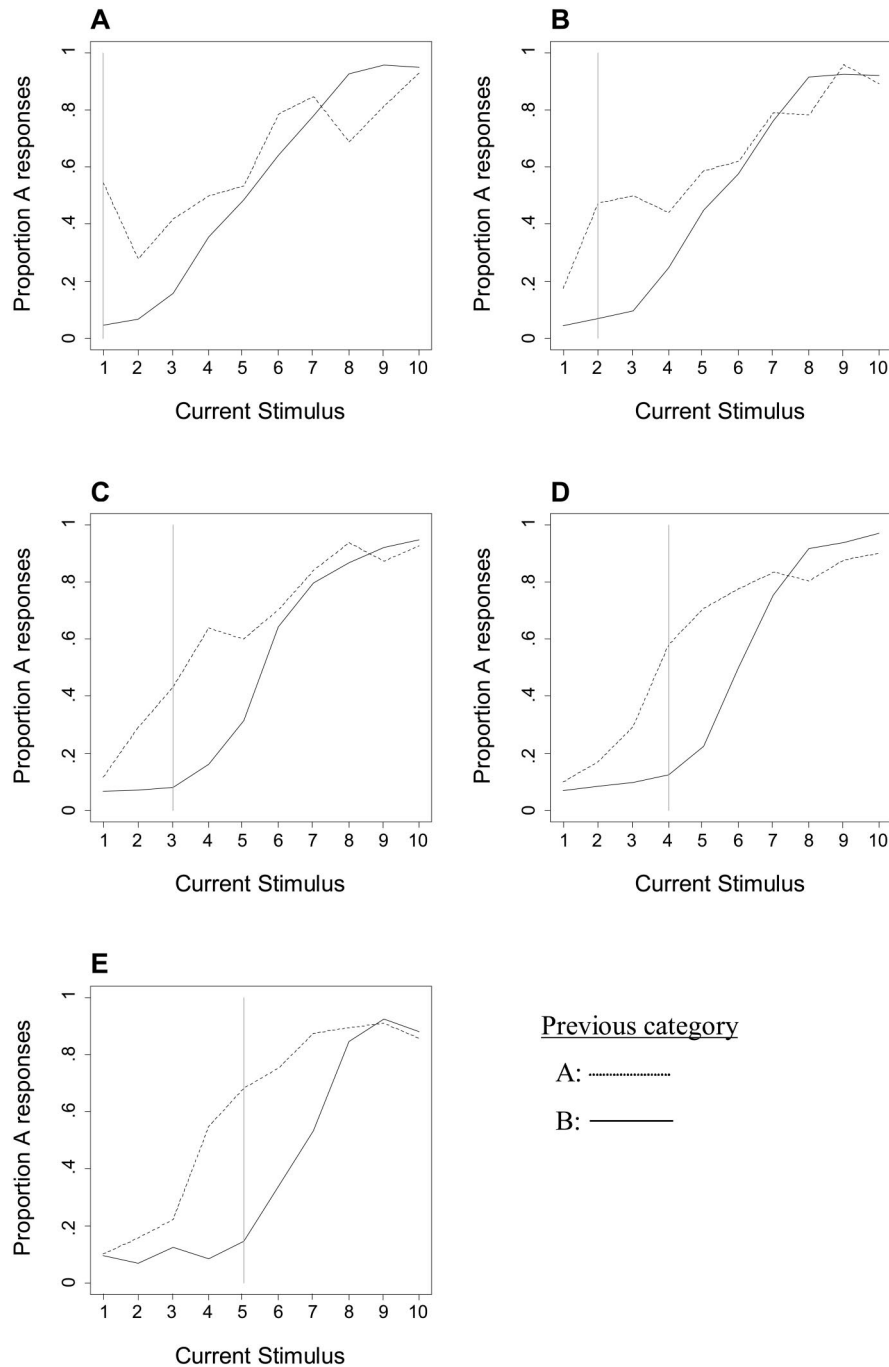
Figure 5. Effect of previous category on mean responses. 5A–5E correspond to trials on which the previous stimulus was 1 through 5, respectively. The gray bar in each graph indicates the location of the previous stimulus.

Category B curve, reflecting the overall tendency to respond with the previous category. Second, the magnitude of this effect is quite large, corresponding to a difference in response rates of up to 54%. Third, this decisional recency effect tends to be greatest when the current stimulus is similar to the previous stimulus (i.e., the separation between the curves is greatest where they intersect the gray line marking the previous stimulus). Fourth, when successive stimuli are highly dissimilar the decisional recency effect becomes slightly negative.

The data shown in Figure 5 were converted to measures of generalization using Equation 1. For each panel (i.e., each value of the previous stimulus), the response curves for the two values of the previous category were converted to log-odds and their difference was then calculated and multiplied by ½. This resulted in generalization curves $G(X, -)$ for each previous stimulus to all possible current stimuli. Figure 6 shows these generalization curves plotted against the difference between present and previous stimuli. The curves overlap closely, especially for small to mod-
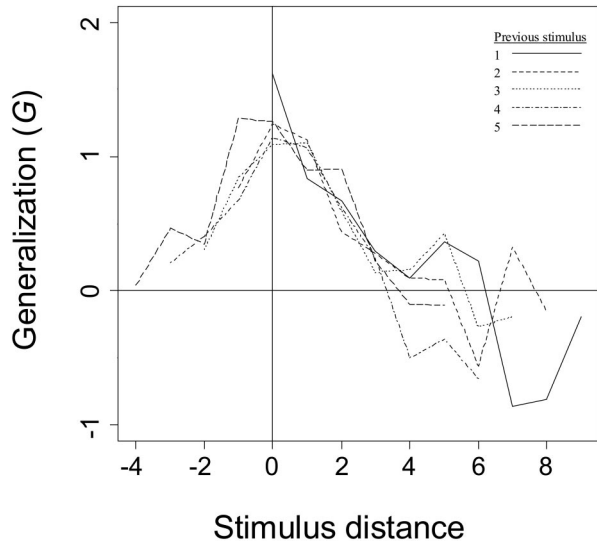
Figure 6. Empirical generalization gradients for different values of the previous stimulus. Generalization is computed according to Equation 1. Stimulus distance is the value of the current stimulus minus the value of the previous stimulus.

erate distances. This overlap shows that the magnitude of the decisional recency effect, when considered on a log-odds scale, depends only on the distance between successive stimuli. This supports the hypothesized relationship between decisional recency and stimulus generalization. Figure 6 also illustrates how the technique presented here allows direct mapping of an empirical generalization gradient. As can be seen, the gradient follows an approximately Gaussian form, although the tails appear to asymptote slightly below 0, indicating negative generalization for suffi-
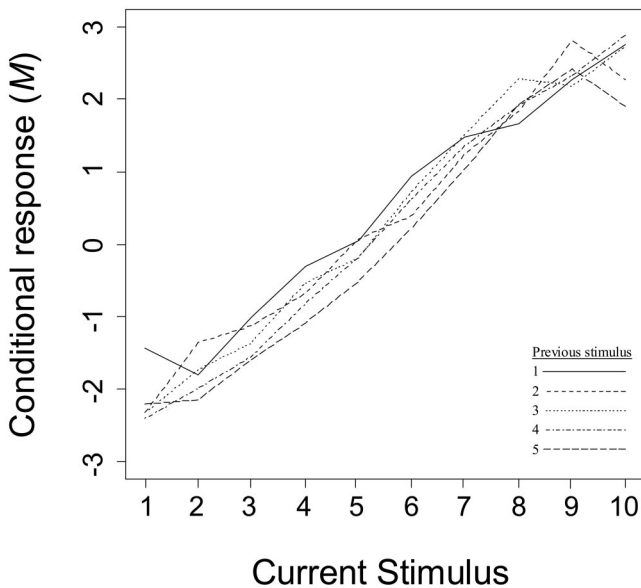

Figure 7. Log-odds response rates conditioned on the previous stimulus, calculated from Equation 3. These conditional response rates control for the previous category and hence average over generalization effects. The separation of the curves indicates a perceptual contrast effect.

Table 3
Mean Parameter Values in Model Fits

Parameter	Symbol	Average value
Intercept	b	−3.23
Long-term association	w	0.74
Assimilation/contrast	c	−0.17
Peak generalization	k	1.65
Asymptotic generalization	m	−0.18
Specificity of generalization	α	0.24

Note. Median values are given for k and m because of skewed distributions; other parameters are reported as means.

ciently dissimilar stimuli. (The present nonparametric approach does not lend itself to a reliable test of this negative generalization, but a more conclusive analysis is presented below in the modeling section.) Once again, the overall magnitude of generalization is quite large, with a peak of 1.27 (obtained by averaging over all five curves). This corresponds to an odds ratio of over 12:1 between trials when the previous category was Category A and trials when it was Category B.

Effects of Previous Stimulus

The approach proposed above for measuring perceptual assimilation or contrast effects (see Equation 3) amounts to converting each pair of curves in Figure 5 to log-odds and then computing their average. This calculation yields conditional response curves $M(-|X)$ for each value X of the previous stimulus. As explained above, these response curves control for the previous category such that contributions from generalization cancel out. The curves are displayed in Figure 7. As this figure shows, the curves are shifted laterally relative to one another, such that a greater value of S_{n-1} requires a greater value of S_n to achieve the same response probability. This pattern implies a perceptual contrast effect.

Model-Based Analyses

To obtain statistical tests of the above findings, we fit the sequential-effects model (see Equation 7) to the data for each subject (Blocks 2–10, again omitting the first trial of each block). Fits were obtained by maximum likelihood, using a general parameter search routine. Average fitted parameter values are displayed in Table 3. These fitted parameters were used to test the hypotheses of perceptual contrast, which translates to the condition $c < 0$, and negative generalization between distant stimuli, which translates to $m < 0$.

The assimilation/contrast parameter c was negative for 18 of the 20 subjects, indicating a robust perceptual contrast effect. The mean value of −.17 implies that each unit increase in the value of the previous stimulus led on average to a .17-unit decrease in the perceived value of the current stimulus. A one-sample t test shows this effect to be highly significant, $t(19) = 4.69$, $p < .001$. As a further test of the significance of the perceptual recency effect, we fit the nested model with c fixed at zero to each subject's data. This restriction led to an average reduction in log-likelihood of 2.48 per subject, $\chi^2(20) = 99.3$, $p < 10^{-11}$.

The asymptotic generalization parameter m was negative for 14 of the 20 subjects, indicating that generalization over large dis-

tances tended to be negative.[3] A Wilcoxon signed-ranks test showed the median value of m to be negative, $Z = -2.05$, $p < .05$. Fits of the nested model with m fixed at zero led to an average .91 decrease in log-likelihood per subject, $\chi^2(20) = 36.2$, $p < .05$. It is important to note, however, that the median value of m is much less, in absolute value, than that of $m + k$ (see Table 3). Thus negative generalization between dissimilar stimuli was far weaker than positive generalization between similar stimuli.

The predictions of the fitted model were used to calculate predicted generalization gradients and conditional response curves according to Equations 1 and 3. The results of these computations are shown in Figures 8 and 9. These figures can be directly compared with the empirical results in Figures 6 and 7, respectively. As can be seen, the model accurately reproduces all qualitative aspects of both generalization and perceptual contrast effects. The quantitative fit is also quite good, even though the parameters were not optimized for fitting these particular measures.

Category Contrast Effect

Stewart et al. (2002) defined the category contrast effect as better performance on intermediate stimuli when preceded by extreme stimuli from the opposite category than when preceded by extreme stimuli of the same category. Specifically, in a deterministic analogue of the category structure used here, they found better performance on Stimulus 5 following 10 and on 6 following 1 than on 5 following 1 or 6 following 10. To replicate their results in the present nondeterministic category structure, we carried out a corresponding analysis, restricted to those trials on which the previous category was the modal value for the previous stimulus (i.e., Category A for 10 and Category B for 1). Furthermore, instead of correct responses, proportions of optimal responses were calculated, where the optimal response for each stimulus is defined as its modal category (e.g., Category A for 6 and Category B for 5). The proportion of optimal responses in this analysis following "same-
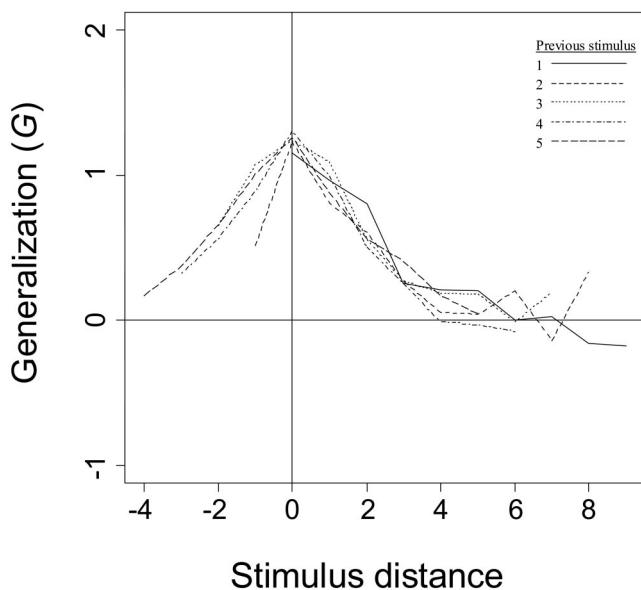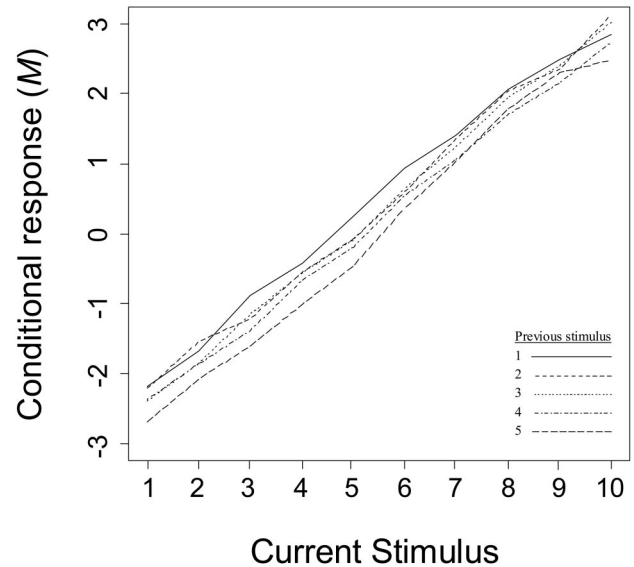

Figure 9. Predicted perceptual contrast effect from fits of the model.

category" sequences (1–5 and 10–6) was 51.3%, whereas the proportion of optimal responses following "different-category" sequences (10–5 and 1–6) was 64.1%. These are comparable to the values found by Stewart et al. (2002) for visual stimuli. The category contrast effect in this experiment is significant by paired-samples t test, $t(19) = 1.84$, $p < .05$ (one-tailed).

As discussed above, this analysis cannot discriminate between the perceptual and decisional explanations for the category contrast effect, because both hypotheses make the same prediction following modal feedback. However, they do make differing predictions following amodal feedback (see Table 1). Therefore, to evaluate the relative contributions of decisional and perceptual recency to the category contrast effect, we repeated the analysis, restricted to trials on which the previous category was the amodal value for the previous stimulus (i.e., Category A for 1 and Category B for 10). If category contrast is due to negative generalization from extreme to intermediate stimuli, then the effect should reverse under this analysis. However, to the extent that the phenomenon is due to perceptual contrast, the reversal of the previous category should have no effect. The analysis found that 46.7% of responses were optimal following 1–5 and 10–6 sequences, and 78.6% were optimal following 10–5 and 1–6 sequences. Therefore the category contrast effect was even stronger when the previous category was amodal than when it was modal. This suggests that generalization for the stimulus pairs in question was actually positive and that the category contrast effect is due to perceptual contrast that is strong enough (in the original version of the effect,

Figure 8. Predicted generalization gradients from fits of the model.

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[3] This test for negative generalization addresses a different question than the following analysis concerning the category contrast effect. There, the issue is whether generalization is negative between extreme and intermediate stimuli, that is, stimuli separated by about half the stimulus range. The analysis here addresses asymptotic generalization, that is, between stimuli separated by much larger distances. Thus the combined results of the two analyses imply that negative generalization does not occur for the distances involved in tests of the category contrast effect (at least for the present stimuli), but it does occur for larger distances.

when the previous category is modal) to overcome the influence of this positive generalization. Unfortunately, the amodal analysis does not contain enough observations (29 total over 20 subjects) to perform the proper within-subjects comparison of the two category contrast effects, but it is clear that both effects are in the same direction, contrary to the prediction of the negative generalization explanation. Combining these results with those of the analyses presented above, we can conclude that negative generalization did occur in this experiment, but only at distances greater than those involved in the category contrast effect.

General Discussion

Sequential effects have been thoroughly studied in many domains but have only recently received attention in category learning (Busemeyer & Myung, 1988; Jones & Sieck, 2003; Stewart & Brown, 2004, 2005; Stewart et al., 2002). The present study adds to these recent findings by showing that there are two types of recency effect present in categorization, one based on the effect of recent stimuli on the perception of the current stimulus (perceptual recency) and another based on the tendency to assign the current stimulus to whichever category was recently reinforced (decisional recency). These two effects, normally unidentifiable because of the confounding between previous stimuli and categories in deterministic tasks, can be separately measured when a probabilistic category structure is used.

As shown here, in a probabilistic task, perceptual recency effects can be assessed by measuring the effect of the previous stimulus while controlling for the previous category feedback, whereas decisional recency can be assessed by measuring the effect of the previous category while holding constant the previous stimulus. This approach is formalized in a mathematical model of sequential effects in categorization. The model assumes that responses are based on a combination of long-term category knowledge and generalization from recent stimuli, and that perception of the current stimulus is biased by the value of the previous stimulus. Parameter fits of the model provide quantitative measures of both perceptual and decisional recency effects as well as the dependence of decisional recency on similarity between successive stimuli. The model thus serves as a generalized regression that allows formal testing of hypotheses concerning the processes underlying sequential effects.

Application of this methodology to the present experiment led to a number of important findings. First, there was clear evidence of a contrastive perceptual recency effect, whereby the perception of the current stimulus is negatively affected by (i.e., biased away from) the previous stimulus. To our knowledge, this is the first demonstration of perceptual contrast in a categorization task, challenging standard theoretical approaches that assume perception is unaffected by previous stimuli. Second, our results also show a decisional recency effect, whereby subjects' responses are influenced by the feedback on the previous trial. When successive stimuli are similar, there is a strong tendency to respond with whichever category was previously correct. With increasing dissimilarity between present and previous stimuli, this tendency weakens and eventually reverses. Third, our results demonstrate a close relationship between the decisional recency effect and stimulus generalization. The magnitude of the decisional recency effect appears to depend only on similarity between successive stimuli, which is the hallmark characteristic of stimulus generalization

(Shepard, 1957, 1987). Thus we conclude that the decisional recency effect is a by-product of the fact that generalization is stronger from more recent stimuli. Fourth, the technique presented here allowed nonparametric mapping of the empirical generalization gradient. This provides an important check on models that assume categorization is based directly on generalization (e.g., Nosofsky, 1986), as it allows these theories to be directly grounded in data rather than implicitly tested through model fitting. Fifth, we found evidence of negative generalization between highly dissimilar stimuli. When the current stimulus is very different from the previous one, subjects tend to respond with the opposite of the previously correct category. This constitutes the first demonstration of negative generalization that is not confounded by perceptual explanations. The finding of negative generalization contrasts with most theories of categorization as well as those of conditioning (e.g., Rescorla & Wagner, 1972), which assume that reinforcement of a response will always increase the likelihood of its repetition.

One variable that was omitted in the analyses of sequential effects presented here is the previous response. Research in absolute identification has shown that responses are often used in lieu of feedback when feedback is not provided, but when feedback is given a diminished effect of the previous response is still observed. For example, Mori and Ward (1995) found that responses in an identification task without feedback were negatively dependent on the previous stimulus and positively related to the previous response. On blocks when feedback was provided, the effect of the previous stimulus (equal to the previous feedback) became strongly positive, and the effect of the previous response was reduced. To assess effects of the previous response in the present study, analyses analogous to those presented above were conducted that controlled for both the previous stimulus and feedback. These analyses revealed an effect of the previous response that was similar to, though weaker than, that found for the previous feedback. Specifically, there was a tendency for subjects to repeat their previous response, and this tendency was stronger when successive stimuli were similar. One interpretation of this result is that subjects were occasionally generalizing based on past responses rather than feedback, perhaps following trials on which the feedback was poorly encoded. Alternatively, the effect of the previous response could be a by-product of autocorrelation induced by fluctuations in attention or slow variation in long-term category representations (cf. DeCarlo & Cross, 1990; Gilden, 2001). These possibilities are interesting topics for future research. As effects of past responses are not a focus of the present study, we note here only that such effects do not alter interpretation of any of our other results. Extensions of the analyses presented above that controlled for the previous response led to the same conclusions.

The Cause of the Category Contrast Effect

Distinguishing between the two types of recency effect has important implications for the interpretation of sequential effects. Below we discuss some of these implications for identification and scaling paradigms. A more immediate example is the category contrast effect, which was previously thought to be due to negative generalization but was seen here to be a result of perceptual contrast. Evidence for negative generalization was found in the experiment, but only for distances greater than those involved in the category contrast effect (which span about half the stimulus

range). For other stimuli or experimental conditions it is possible that the crossover point between positive and negative generalization is at less than half the stimulus range, in which case negative generalization would contribute to the category contrast effect. Therefore our conclusion regarding this phenomenon is not that it is always fully due to perceptual contrast but simply that its cause cannot be isolated in a deterministic task. Thus, although the category contrast effect has been important for understanding the role of short-term relative judgment in categorization (Stewart et al., 2002), it is not diagnostic of the particular processes involved.

One other possibility that must be considered regarding the category contrast effect comes from the memory and contrast (MAC) model of Stewart et al. (2002). In addition to generalization from the previous stimulus as described earlier, MAC assumes that subjects use a direction-specific strategy in comparing successive stimuli. For example, if the current stimulus is smaller than the previous one, and the previous feedback was Category B, then the subject is assumed to use his or her knowledge of the category structure (i.e., Category A items are larger than Category B items) to infer that the current stimulus is also from Category B. This strategy has important implications for the effects of amodal feedback on the category contrast effect. Consider a situation in which Stimulus 10 is followed by Stimulus 5. If the feedback to Stimulus 10 was modal (Category A), then according to MAC negative generalization will make the subject likely (but not certain) to assign the present stimulus to Category B. If the feedback to Stimulus 10 was amodal (Category B), then the directional strategy is assumed to make the subject certain to respond Category B. Thus MAC predicts a positive effect of the previous feedback, such that the category contrast effect will become stronger following amodal feedback, just as was observed here. In other words, although our results regarding the category contrast effect show that negative generalization taken alone cannot explain the phenomenon, they do not rule out an explanation based on negative generalization plus the directional strategy (e.g., as embodied in MAC). However, other aspects of our data challenge this explanation. In particular, the analysis of MAC's predictions for the category contrast effect also applies to cases of successive extreme stimuli from opposite ends of the spectrum (e.g., 10 followed by 1). Again MAC predicts a positive (or possibly null) relationship between previous feedback and present response, but in these cases the observed effect was significantly negative. This observation is our primary evidence that negative generalization does occur between stimuli that are extremely dissimilar. In summary, the data taken as a whole are inconsistent with an explanation for the category contrast effect based on negative generalization, with or without the directional strategy. Negative generalization was seen to occur in this experiment, but only for distances larger than those involved in the category contrast effect. Furthermore, the fact that the model presented here predicts the counterintuitive finding of a negative effect of feedback following extremely dissimilar stimuli supports our assumption that stimulus generalization is directionally invariant.

Implications for Theories of Category Learning

The findings of the present empirical investigation go beyond the scope of current categorization models and suggest extensions to these models to bring them more in line with human learning. First, the perceptual contrast effect demonstrated here shows that

sequential effects must be taken into account when determining models' input representations. Such sequential effects are not anticipated by any model of which we are aware. Nearly all categorization models assume that perception of the current stimulus is veridical and thus do not allow for any variability due to recent stimuli. Those models that do assume noise in the perceptual process (Ashby & Townsend, 1986; Maddox & Ashby, 1993) assume that this noise is unbiased and independent of previous trials. The modeling approach presented here (cf. Equation 6) suggests one way to extend existing models, by elaborating their input mechanisms to depend on recent stimuli. However, future research will be required to investigate such extensions as well as to evaluate their predictions for richer, multidimensional stimuli.

Although existing models have very little to say about perceptual recency effects, many models do make predictions regarding decisional recency effects. The simplest versions of generalization-based exemplar models (Medin & Schaffer, 1978; Nosofsky, 1986) do not predict sequential effects of any sort, but they can be easily extended to do so by assuming memory decay. If more recent exemplars are more likely to be recalled, then they exert a greater influence on the present response, leading to a decisional recency effect (Nosofsky, Kruschke, & McKinley, 1992; Nosofsky & Palmeri, 1997). This recency effect is naturally dependent on the similarity between successive stimuli, as a consequence of the models' generalization-based decision processes (Sieck, 2000).

A second class of models that produce decisional recency effects is the connectionist model that learns by iterated error correction (e.g., Gluck & Bower, 1988; Kruschke, 1992; Love et al., 2004). Connection weights in these models depend most strongly on recent updates, leading recent events to exert a greater influence on responses (Estes, 1957). Thus responses that have recently been reinforced are more likely to be selected. As with the exemplar models discussed above, these models also predict the decisional recency effect to depend on successive stimulus similarity. This is because the learning following feedback to one stimulus will only affect the response to the subsequent stimulus to the extent that responses to the two stimuli rely on the same connection weights, that is, to the extent that the representations of the two stimuli overlap (Jones, 2003). Thus the similarity structure inherent in the model's representational scheme is reflected in the pattern of decisional recency effects it produces.

A more challenging aspect of our results for current models is the finding of negative generalization (i.e., a negative decisional recency effect) for highly dissimilar stimuli. Traditional models of category learning, and of learning in general, fail to predict this result because they assume that reinforcement of a response or outcome always leads to an increased expectation of its reoccurrence. One solution is suggested by network models that assume negative input activations for absent features (Gluck & Bower, 1988). Under this assumption, association of a feature to Category A leads to association of the feature's absence to Category B. This produces negative generalization between sufficiently dissimilar stimuli. The same mechanism could be extended to exemplar- or cluster-based connectionist models (Kruschke, 1992; Love et al., 2004) by assuming a negative baseline activation for hidden nodes. Such an approach may prove useful in explaining negative generalization along many-valued or continuous stimulus dimensions such as those used here. A second approach to explaining negative generalization comes from computational-level models that explicitly assume a generalization gradient with a negative asymptote,

such as the one presented here or the MAC model proposed by Stewart et al. (2002). Stewart and Brown (2005) showed how the generalized context model (Nosofsky, 1986) can also be extended in this way. This extension overpredicts negative generalization, assuming it to be as strong as positive generalization between similar stimuli (whereas the present results show the latter effect to be far stronger), but modifying the functional form of the generalization gradient should allow the model to account better for our findings without sacrificing its central principles.

Beyond the implications of the present empirical results, a key contribution of this work is the methodology introduced for separately evaluating decisional and perceptual recency effects, and in particular for relating decisional recency to stimulus generalization. As mentioned above, stimulus generalization plays a fundamental role in many models of category learning (e.g., Gluck & Bower, 1988; Kruschke, 1992; Love et al., 2004; Medin & Schaffer, 1978; Nosofsky, 1986), yet has until now eluded direct study. The idea advanced here is that generalization from the previous stimulus is measurable as the effect of the previous category on the current response (i.e., the magnitude of the decisional recency effect), for any given pair of present and previous stimuli. This effect corresponds to the subject's tendency to assign the current stimulus to the category of the previous stimulus (regardless of any long-term knowledge about the current stimulus's likely category membership), or in other words, to generalize category knowledge regarding the previous stimulus to the current one. The present empirical investigation demonstrates that this method yields reliable generalization gradients (see Figure 6) that are in good agreement with previous findings that strength of generalization depends only on interstimulus distance or similarity (Shepard, 1957, 1987).

The method for directly measuring empirical generalization gradients during category learning should prove an important tool in evaluating categorization models, as the patterns of generalization predicted by various models directly reflect their representational assumptions. For example, Jones and Sieck (2003) showed that the adaptive network model of Gluck and Bower (1988) predicts generalization in a binary-cue task to be a linear function of the number of matching cues, as a consequence of the model's feature-based input representation. Because the empirical generalization gradient was found to be nonlinear, close to an exponential (cf. Figure 1), Jones and Sieck were able to rule out this model (see Gluck, 1991, for a similar argument). The present approach also has implications for models of attentional learning (Kruschke, 1992, 2001; Love et al., 2004; Nosofsky, 1986), which predict systematic changes in generalization gradients in response to differential diagnosticity of various stimulus dimensions. By adapting the mathematical model proposed here to multidimensional stimuli, Jones, Maddox, and Love (2005) showed how learning effects on generalization can be directly measured, thus providing an important test of attentional learning models.

On the Nature of Perceptual Recency

The nature of perceptual recency effects has long been a topic of debate in the literature on identification and scaling (DeCarlo & Cross, 1990; Garner, 1953; Holland & Lockhead, 1968; Jesteadt et al., 1977; Lockhead & King, 1983; Petzold, 1981; Ward & Lockhead, 1971). These tasks are similar to category learning except

that each stimulus is assigned a unique response. As suggested above, we believe much of the confusion regarding sequential effects in this domain arises from the confounding between previous stimuli and previous feedback (or previous responses, when feedback is absent). In absolute identification with feedback, it is well established that responses are positively correlated to previous stimuli (e.g., Garner, 1953), although it is not clear whether the effect is due to the stimulus per se or to the feedback. When feedback is not present (e.g., in a magnitude estimation task) and the effect of the previous response is controlled for, the previous stimulus is seen to exert a contrastive effect on the present response (Jesteadt et al., 1977; Petzold, 1981; Schifferstein & Frijters, 1992). However, a problem arises in this type of analysis, due to autocorrelation of error. Specifically, if judgmental errors are autocorrelated, as is often found to be the case (DeCarlo & Cross, 1990; Jesteadt et al., 1977; Ward, 1979), analyses that include the previous response will misinterpret the autocorrelation as a positive effect of the previous response together with a negative effect of the previous stimulus (DeCarlo & Cross, 1990). Thus this type of evidence for perceptual contrast is not readily interpretable.

The approach proposed here for evaluating perceptual recency effects is to use a task where feedback is present but variable. In this case the effect of the previous stimulus can be measured while controlling for the previous feedback, without concerns related to autocorrelated error. The present application of this idea to a categorization task provides clear support for a negative perceptual recency effect, that is, perceptual contrast. This result suggests that a similar approach could be used in an identification task, again by using probabilistic feedback. Support for this idea comes from Experiment 2 of Stewart et al. (2005), in which identification feedback was occasionally false. This experiment showed a positive dependence of the current response on the previous feedback, supporting the feedback-based explanation for the assimilation effect in identification and suggesting that the effect of the previous stimulus is, if anything, negative. Still, the influence of the previous stimulus was not directly addressed, and thus a focused investigation is still required to determine whether the perceptual effects in identification are consistent with those found here in categorization.

Another question regarding the perceptual recency effect is the degree to which it is truly perceptual. Our use of this term is not meant to imply that the effect necessarily occurs during sensory processing but merely that it is present at the level of stimulus representation, prior to processes related to category representation or response selection. This claim is supported by the fact that the contrast effect was present after the effects of category information (i.e., decisional recency and stimulus generalization) were partialed out. This is not to say that processes associated with learning the category structure do not affect stimulus representations. Indeed there is a good deal of evidence that cognitive processes feed back to influence perception, via mechanisms such as selective attention, dimension differentiation, and feature discovery (Goldstone, 1994; Goldstone & Steyvers, 2001; Schyns, Goldstone, & Thibaut, 1998). The relationship between these perceptual learning processes and the perceptual effects found here, especially in more complex tasks where perceptual learning may play a more significant role, is an important question for future work. In addition, because both the perceptual and decisional recency effects depend on the nature of stimulus representations, the techniques presented

here may prove useful in studying changes in those representations that result from perceptual learning.

One explanation that has been advanced for the contrast effect in identification and scaling tasks is that subjects use the previous stimulus and feedback as a standard for generating the response to the current stimulus. For example, Holland and Lockhead (1968) and Stewart et al. (2005) have proposed that subjects in identification experiments use the perceived difference between present and previous stimuli as a cue for how much to adjust the response away from the previous feedback (e.g., if the current stimulus appears 2 steps greater than the previous one, and the previous feedback was 4, then respond 6). This strategy leads to a negative dependence of the current response on the previous stimulus. Luce and Green's (1974) response ratio hypothesis describes a similar process in magnitude estimation tasks. Although these explanations place the contrast effect outside of sensory processing, they are still consistent with our viewpoint, in that the locus of the effect is the representation of the current stimulus (once the previous feedback is controlled for). In this case the current stimulus is represented (partially) in terms of its relationship to the previous stimulus. The extreme version of this hypothesis, that relative information is all that is available to subjects (Stewart et al., 2005), corresponds to the extreme case of perceptual contrast—in this case, the representation of the current stimulus is entirely determined by the difference between it and the previous stimulus.

DeCarlo and Cross (1990) attempted to decompose the perceptual contrast effect found in magnitude estimation into separate contributions from pure sensory effects and the relative responding strategy described above. Unfortunately, their analysis failed to account for decisional recency effects and thus provides yet another example of the importance of considering the separate contributions of perceptual and decisional recency when interpreting sequential effects (as advocated here). DeCarlo and Cross's approach amounts to using the dependence of the current response on the previous response as an estimate of subjects' reliance on relative responding. This estimate is then used to correct the influence of the previous stimulus to obtain a measure of the pure sensory effect (i.e., the influence of the previous stimulus is assumed to be the sum of sensory effects and effects via relative responding). Application of this method to data from several studies yields a positive estimate of the sensory component of the perceptual recency effect (i.e., sensory assimilation). This is a somewhat surprising conclusion, given the broad evidence for sensory aftereffects and neural adaptation in sensory systems (e.g., Sekuler & Blake, 1994), which suggests that contrast dominates at the sensory level. The answer to this seeming contradiction may lie in decisional recency effects. By assuming the previous response exerts an effect only through the relative responding strategy, DeCarlo and Cross's analysis denies any contribution of decisional recency. Thus if a decisional recency effect is present (with the previous response used as a proxy for feedback; Ward & Lockhead, 1970), the amount of relative responding will be overestimated. This will lead to overcorrection of the effect of the previous stimulus, so that the estimate of the sensory component of the perceptual recency effect is biased toward assimilation. In short, denial of decisional recency may have led sensory contrast to be mistaken for sensory assimilation. Thus the question of sensory assimilation versus contrast cannot be answered without an independent estimate of the contribution of decisional recency to magnitude estimation.

The Functionality of Recency Effects

Recency effects have often been thought of as consequences of limited memory or by-products of error-driven learning, but they may be more sophisticated and adaptive than this characterization implies. It has been suggested in the memory literature that privileged access to recent information may be due not to architectural capacity limitations but rather to an adaptation to a dynamic environment (Anderson & Schooler, 1991; Schacter, 1999). In other words, in natural settings more recent information is more likely to be relevant and reliable, and thus a well-adapted memory system would be expected to make that information more available. A related argument has been made regarding the decisional recency effect in repeated judgment tasks: If the base rates of outcomes change over time, successive events will be autocorrelated, and thus recent outcomes are more likely to be repeated (Jones & Sieck, 2003; Real, 1991). The dependence of decisional recency on stimulus similarity may be explainable in a similar way, by assuming that category structures, in terms of cue-category correspondences, change over time. Optimal performance in such an environment cannot rely on a static and well-learned stimulus-response mapping, but instead must track the changing structure by generalizing from recent stimuli.

Another normative argument for recency effects is that they reflect adaptations to inherent limitations in representational capacity and information availability. Perceptual recency effects may be a consequence of encoding stimuli in terms of relative rather than absolute information to expand the representational range of a finite neural system (Helson, 1964). To the extent that people only have access to relative as opposed to absolute stimulus information, classifying stimuli based on their absolute values would be impossible and generalization from recent examples may be the only option (Stewart et al., 2002). Thus perceptual and decisional recency effects may be related, at a functional level. A related hypothesis regarding decisional recency is that individuals lacking long-term knowledge of the category structure, for example as a result of hippocampal amnesia, may still perform well by using a short-term strategy that amounts to similarity-dependent generalization from the preceding stimulus (Palmeri & Flanery, 2002). All of these proposals highlight the active role of short-term processes in functioning in dynamic environments with limited resources. Therefore, through further study of sequential effects in repeated judgment tasks, researchers may gain a better understanding of the manner in which perceptual stimuli are represented, the information available to decisional systems, and the statistical properties of the environments in which those systems are designed to operate.

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