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Recent studies involving nonlinear discrimination problems suggest that stimuli in human associative learning are represented configurally with narrow generalization, such that presentation of stimuli that are even slightly dissimilar to stored configurations weakly activate these configurations. The authors note that another well-known set of findings in human associative learning, cue-interaction phenomena, suggest relatively broad generalization. Three experiments show that current models of human associative learning, which try to model both nonlinear discrimination and cue interaction as the result of a process, fail because they cannot simultaneously account for narrow and broad generalization. Results suggest that human associative learning involves (a) an exemplar-based process with configural stimulus representation and narrow generalization and (b) an adaptive learning process characterized by broad generalization and cue interaction.

Nonlinear discrimination and cue interaction are two important characteristics of human associative learning. Current models of associative learning (e.g., Kruschke, 1992; Pearce, 1994) explain nonlinear discrimination by assuming that people store stimulus information configurally. These configural models can also explain cue interaction but only to the extent that they allow for broad generalization between stimuli. However, recent research on nonlinear discrimination problems suggests that human associative learning is sometimes characterized by relatively narrow generalization (e.g., Shanks, Darby, & Charles 1998). These results cannot be explained by Pearce’s (1994) popular configural model, which has a fixed intermediate level of generalization. Kruschke’s (1992) ALCOVE model can accommodate both the broad generalization and the narrow generalization, but it does not predict a priori when generalization will be narrow or broad.

In this article, we explore factors that influence the extent of generalization in summation and patterning designs and argue that the data are best accounted for by two processes. First, there is an exemplar-based process characterized by configural stimulus representation with narrow generalization. Second, there is an adaptive process characterized by broad generalization and cue interaction. Moreover, we claim that exemplar-based learning is the default process and that adaptive learning becomes active when there is a predictive focus during training. In addition, even after adaptive learning, exemplar-based learning can drive responses at test when task constraints encourage participants to retrieve exemplars they have experienced in the past.

Historically, human associative learning has been described by adaptive learning models using an elemental representation of stimuli and a delta learning rule (e.g., Gluck & Bower, 1988; Rescorla & Wagner, 1972). Elemental representation implies that the learning system decomposes stimuli into their constituent elements and only represents the elements in memory. The delta learning rule describes a process in which the learning system (a) receives information about cues, (b) makes a prediction about an outcome on the basis of the summed association strengths between the representations of the cues and the outcome, (c) acts on this prediction, (d) receives feedback on the realized outcome, and (e) updates the association strengths. Elemental representation and delta-rule learning have been especially successful at explaining cue-interaction phenomena such as blocking (e.g., Dickinson, Shanks, & Evenden, 1984; Kamin, 1969), unblocking or feature-negative discrimination (e.g., Rescorla & Wagner, 1972; Shanks, 1991), conditioned inhibition or feature-positive discrimination (e.g., Chapman & Robbins, 1990; Pavlov, 1927/1960), and the relative validity effect (e.g., Baker, Mercier, Vallée-Tourangeau, Frank, & Pan, 1993; Wagner, Logan, Haberlandt, & Price, 1968). Figure 1A illustrates the most basic network structure for an elemental model.

Assuming that cues are represented elementally and that they combine linearly to determine a response to a compound cue is inconsistent with experiments that involve nonlinear discrimination problems (e.g., Edgell & Castellan, 1973; Mellers, 1980). For example, humans routinely learn to solve negative patterning discriminations in which two single-element stimuli, A and B, are followed by an outcome but the combined stimulus, AB, is not (e.g., Shanks, Charles, Darby, & Azmi, 1998; Shanks, Darby, & Charles, 1998; Young, Wasserman, Johnson, & Jones, 2000). These findings are informative because no linear combination of independent associations from elements A and B to the outcome can explain both the separate (A → O, B → O) and combined (AB → no O) results. Thus, negative patterning discrimination is not
easy to explain when cues are represented solely in terms of their elements.

Configural Representation

Adaptive models of associative learning can account for nonlinear discrimination results if the elemental representation assumption is replaced by an assumption of configural representation. For example, Pearce’s (1994) configural model and Kruschke’s (1992) ALCOVE model assume that each stimulus, whether single-element or compound, is represented as a configuration. The advantage of configural representation is that single-element stimuli in a negative patterning scenario (e.g., A, B) can be represented separately from the compound stimulus (e.g., AB), allowing single elements to form strong positive associations to outcomes while the compound does not. Figure 1 illustrates the most basic network structure for a configural model (Panel B).

Adaptive learning models that assume delta-rule learning and configural stimulus representation can explain nonlinear discriminations, but an additional assumption about generalization must be made for these models to adequately account for cue interaction. In configural models, generalization occurs when the presentation of a stimulus leads to activation of similar configural representations that, in turn, activate the outcome. Generalization can account for cue-interaction effects because it predicts that a compound stimulus (e.g., AB) can activate the representations of elements of that compound stimulus (e.g., A). For example, blocking occurs when presentation of the AB compound stimulus activates the previously reinforced single-element configuration (A). Activation of the A configuration in memory leads to activation of the outcome, reduces the discrepancy between actual and desired outcome activations, and reduces the updating of the association strength between the AB configuration and the outcome.

Different configural adaptive models make different assumptions about generalization. For example, Pearce’s (1994) configural adaptive model has a fixed and intermediate level of generalization that is broad enough to predict moderately sized cue-interaction effects. Recent findings, however, have proven problematic. First, unless side assumptions are made about contextual cues, Pearce’s model assumes too narrow a level of generalization to account for summation effects (see Pearce, George, & Aydin, 2002; Rescorla, 1997, for examples in the animal learning literature). In summation paradigms, participants first encounter reinforced single-element stimuli (e.g., A → O and B → O) and at least one reinforced compound stimulus (e.g., CD → O). When participants are then tested with two compound stimuli, one made up of two elements encountered as separate stimuli during learning (e.g., AB) and one made up of two elements encountered in the same compound during learning (e.g., CD), they often respond more strongly to the former (AB) than the latter test stimulus (CD). Such a summation effect can only occur when presentation of a compound test stimulus (AB) strongly activates the configural nodes representing the single-element stimuli whose element it shares (A and B). Thus, summation requires broader generalization than Pearce’s model seems to allow.

There is also recent evidence that suggests Pearce’s (1994) level of generalization is too broad (e.g., Baeyens, Vansteenwegen, Hermans, Vervliet, & Eelen, 2001; Shanks, Charles, et al., 1998; Shanks, Darby, & Charles, 1998). For example, participants in a study by Shanks, Darby, and Charles received AB → Outcome 1 (O1), CD → no O, EF → O2, and GH → no O trials in a first learning phase followed by A → no O, B → no O, C → O3, and D → O2 trials in a second learning phase before being tested with AB, CD, EF, and GH. Pearce’s configural model predicts sufficiently broad generalization from the compound test stimuli to the corresponding single-element configurations (encountered in the second learning phase) that responding to the AB test stimulus should be weaker than responding to the CD test stimulus. However, the results showed the opposite effect. There are additional experiments that show no significant interference, hence, no evidence of generalization at all (Baeyens et al., 2001; Shanks, Charles, et al., 1998; Shanks, Darby, & Charles, 1998).

In summary, findings of both broader and narrower generalization than Pearce’s (1994) model allows suggest that generalization in associative learning is not constant and that models of associative learning should allow more than one level of generalization. Kruschke’s (1992) ALCOVE model and its descendants (e.g., Kruschke & Johansen, 1999) address this problem by including a freely estimable generalization or specificity parameter. However, Kruschke’s theory does not tell us when generalization will be broad or narrow.

Adaptive Versus Exemplar-Based Process

Configural representation with a free generalization parameter is one possible way to account for broad and narrow generalization.
Predictive Focus During Learning

We have assumed that the adaptive learning system relies on a delta-learning rule and is characterized by cue interaction and broad generalization. Although not necessarily meant to describe a process as such, the delta rule seems to reflect an inherently predictive psychological process. In its most basic form (e.g., Gluck & Bower, 1988), the delta rule holds that updating of the strength of an association (or weight of a connection, \( w_{ij} \)) between the representation of a cue or configuration \( i \) and an outcome \( j \) is a function of the discrepancy between a predicted outcome level \( o_j \) and a teaching signal representing the actual outcome level \( d_j \). More precisely:

\[
\Delta w_{ij} = \beta (d_j - o_j) a_i, \tag{1}
\]

where \( a_i \) is the activation of the cue representation \( i \), \( \beta \) is a learning-rate parameter, and the predicted outcome level \( o_j \) is equal to

\[
o_j = \sum_{i=1 \to n} w_{ij} a_i. \tag{2}
\]

Thus, delta-rule learning seems to rely on a prediction \( (o_j) \), followed by feedback about the accuracy of the prediction \( (d_j) \), which in turn is used to update connections in memory. If adaptive learning follows the delta-learning rule and delta-rule learning requires participants to make predictions during learning, adaptive learning, and hence, broad generalization, may depend on a predictive focus during learning.

This predictive focus could be promoted in several ways. First, participants may be more likely to focus on predicting an outcome when they are instructed to learn how to predict a specific outcome. Second, although not a necessary condition (see Price & Yates, 1993, Experiment 4), participants should be more likely to adopt a predictive focus when they are asked to make trial-by-trial predictions. The idea that adaptive processing with broad generalization is more likely to occur when participants are instructed to learn to predict or explain a specific outcome and when participants have to make trial-by-trial predictions is consistent with the fact that most findings of strong cue-interaction effects involve just such situations (e.g., Chapman, 1991; Chapman & Robbins, 1990; Dickinson et al., 1984; Price & Yates, 1993, 1995; Shanks, 1991).

When participants do not focus on predicting an outcome during learning, participants should be less likely to engage in an adaptive learning process and test responses should be dominated by the exemplar-based process. There is indirect evidence for this assumption. First, Hendrickx and De Houwer (1997) did not observe cue interaction in implicit learning situations. In their critical study, participants were presented with a row of letters and asked to decide if the central letter was part of a predetermined set of target letters. In a blocking condition, a preexposure phase presented a letter from a flanker set to one side of the central letter every time a target letter was present. Participants in the control condition were not exposed to this flanker set. In Learning Phase 2, three letters were presented on each trial. The presentation of letters from the preexposure flanker set and a new flanker set were perfectly correlated with the presentation of a target letter in the central location of the letter triplet. During the subsequent test phase, only the target and second flanker sets were presented. The second flanker set was no longer correlated with the outcome. Surprisingly, the second flanker set influenced response times equally in blocking and control conditions. That is, no evidence for blocking was found.

Second, participants often perform better at nonlinear discriminations when participants are not actively trying to explain or predict an outcome (e.g., Johnstone & Shanks, 1999; Reber, 1989). For example, Reber (1976) presented participants with strings of letters that were designed according to specific and complex nonlinear rules and then asked participants to judge whether new letter strings were well-formed according to the rules inherent in the original stimuli. A group asked to merely remember the letter strings during training performed better than a group asked to discover the rules during training, which suggests that nonlinear, configural tasks are solved best by a more passive system geared at storing and recalling exemplars.

Third, findings by Williams, Sagness, and McPhee (1994) suggest that elemental (adaptive) processing is less likely to occur as unambiguous elemental solutions become more difficult to achieve. Although other researchers have found cue-interaction effects in similar situations, Williams et al. showed a lack of cue interaction unless participants receive a pretreatment that could easily and unambiguously be solved on the basis of individual

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1 Although memory representation in this system could be configural, it is more parsimonious to assume it represents information elementally. This assumption is consistent with other authors’ arguments about the existence of separate exemplar-based and elemental or cue abstraction–based learning systems (e.g., Baker, Murphy, & Vallée-Tourangeau, 1996; Justlin, Olsson, & Olsson, 2003).
elements’ predictive values. If adaptive processing is more effortful, it is entirely possible that an inability to find an unambiguous solution will encourage people to stop expending effort on this seemingly fruitless way of processing and rely on a default, exemplar-based process instead.

**Orientation at Test**

An adaptive process of prediction–feedback–updating is essentially forward-looking, in the sense that the process makes predictions about the future and that the learning is focused on reducing error on the next trial. It is also forward-looking because such a process does not require storage of exemplars and their retrospective retrieval at test (e.g., Baker, Murphy, & Vallée-Tourangeau, 1996). Accurate prediction can often be achieved by adjusting the association strengths between cue elements and outcomes, with no evidence of individual exemplars or episodes remaining beyond their influence on the association strengths. In contrast, an exemplar-based process of storing exemplars and later retrieving those exemplars at test is essentially backward-looking. During learning, exemplars are stored. At test, an exemplar-based system looks back and tries to retrieve the exemplars participants have experienced in the past learning phase. The predictive or causal judgment about the test stimulus is then based on its similarity to the retrieved exemplars. Thus, the exemplar-based system is more likely to drive test responses when participants have a backward orientation at test.

Several researchers have found results that are consistent with our hypothesis about temporal orientation. For example, Price and Yates (1995) and Matute, Arcediano, and Miller (1996) have shown that cue interaction is obtained only when questions are asked in a forward-looking manner. For example, cue interaction is obtained for questions estimating the probability of an outcome given the presence of a set of cues and for judgments of a cue’s causality for an outcome. However, cue interaction is not obtained for judgments of frequencies, judgments of the probability of cues given outcomes, or questions about co-occurrences. These results are consistent with the idea that adaptive associations are unidirectional and independent of exemplar-memory traces. When questions are directionally consistent with forward-looking, cue-to-outcome associations, the adaptive process governs responses and generates cue interaction. All other questions should be answerable only by the exemplar-based process and, hence, not generate cue interaction.

**Learning Cue–Test Cue Similarity**

Another factor that should influence responding at test is the extent to which the test stimuli match the exemplars encountered during learning. If each system’s impact on test responses depends on the strength of their relative outcome activations, increased similarity between a test item and a specific exemplar stored in memory should lead to more exemplar-system–driven responding. In the exemplar-based system, characterized by narrow generalization and increasing marginal response to similarity, test stimuli that are more similar to specific configurations stored in memory should activate the representations of those configurations much more strongly and lead to much stronger responses. In the adaptive system, increased similarity to specific exemplars might also lead to stronger responses, but the effect of similarity should be weaker because of broader generalization.

There is evidence consistent with our predictions about the influence of altering the similarity between test stimuli and exemplars encountered during learning. Shanks and his colleagues (Shanks, Charles, et al., 1998; Shanks, Darby, & Charles, 1998) and Baeyens et al. (2001, Experiment 3) found that responding to stimuli that were identical to stimuli encountered during learning was only weakly affected by interference from other stimuli that shared some, but not all, of their elements. For example, in a predictive learning task with trial-by-trial prediction, Shanks, Charles, et al. (Experiment 3) first exposed participants to trials in which two compound stimuli, AB and DE, were not followed by an outcome, one each of their constituting elements, A and D, were followed by the outcome, and compounds AC and DF were also followed by the outcome. In a second phase, DE was again presented without the outcome and B was presented followed by the outcome. Unless generalization is narrow, the latter stimulus presentation should lead to interference in responses to an AB test stimulus. However, perhaps because the AB test stimulus was identical to the previously encountered AB learning stimulus, no interference was found, as evidenced by equally mooted responses to AB and DE test stimuli. Thus, these results are consistent with the idea that as similarity between test stimuli and previously encountered stimulus configurations becomes very high, the exemplar-based system more strongly influences responding at test. In fact, Shanks, Darby, and Charles explicitly suggested the possibility that episodic memory (i.e., the storage and retrieval of exemplars) may have played a role in their results.

**Summary**

In summary, there is reason to believe that humans can use both exemplar-based processes and adaptive processes to predict outcomes and judge causality. In the following sections, we describe three experiments showing both narrow and broad generalization in human associative learning. We argue that the results are consistent with an explanation in terms of two different processes or systems: one backward-looking, exemplar-based system, characterized by configural representation with narrow generalization and a lack of cue interaction and one forward-looking, adaptive system characterized by broad generalization and cue interaction.

**Experiment 1**

In the previous section, we hypothesized that the adaptive learning process is characterized by relatively broad generalization and cue interaction, whereas the exemplar-based learning process is configural with narrow generalization and no cue interaction. We also hypothesized that the exemplar-based process was the default process and that an adaptive learning process required a focus on predicting a particular outcome. In Experiment 1 we explored these hypotheses by manipulating the learning task in a basic

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2 The assumption of increasing marginal response to similarity in the exemplar-based process is a standard assumption (Shepard, 1987) that is consistent with well-known configurial models, both of the connectionist (e.g., Kruschke’s, 1992, ALCOVE model) and memory-array (e.g., Hintzman’s, 1984, MINERVA2 model) varieties.
summation design (e.g., A → O, B → O, CD → O; see Table 1 for the full design of this and following experiments). The predict condition asked participants to learn to predict an outcome by making trial-by-trial predictions with feedback. The choose condition asked participants to screen stimuli consisting of cues and outcomes and select the three that were most attractive. The critical test was a contrast between the predictions for a compound composed of previously encountered, single-element cues (AB) and the previously encountered compound (CD).

Predictions

The difference in responding between AB and CD should be more positive when participants are asked to learn to predict than when they are asked to choose attractive alternatives. When people engage in adaptive processing, the single-element cues (e.g., A and B) will form stronger associations with an outcome than the elements of a compound cue (e.g., C and D) because joint presentation of elements in a compound cue leads each element to compete for the association strength needed to activate the outcome. Thus, Elements C and D will have weaker associations with the outcome than Elements A and B. Responses that are based on an exemplar-based system will show a smaller difference between responses to the AB and CD test stimulus, eventually turning negative as generalization becomes more narrow. Although the A and B cues will each have association strengths to the outcome that are equivalent to the CD configural cue, the impact of A and B’s associations on responses to the AB test cue will be limited by narrow generalization in an exemplar-based system. Whereas the CD test cue will strongly activate the CD configural representation because of their similarity, the AB test cue will activate the A and B configural representations only weakly.

Method

Participants. The participants were 73 undergraduate students who volunteered in exchange for course credit. The entire experiment was presented on personal computers.

Stimuli. Participants were asked to review cue and outcome information about 40 bottles of wine. Participants viewed six trials for each of the following stimuli: A → O+, B → O+, CD → O+, E → O–, F → O–, GH → O–. There were also two presentations each of the filler stimuli, I and J. The A, C, E, and G stimuli were the producing regions California, France, Australia, and South Africa. California and France were counterbalanced as the A/C stimuli and Australia and South Africa were counterbalanced as the E/G stimuli. The B and F stimuli were “wooded (Oak)” or “unwooded” fermentation. The D and H stimuli were “boutique” or “estate” vineyards. The B/D and F/H stimuli were also counterbalanced. Outcomes were quality ratings on a 5-star scale. The O+ trials had a high quality rating of four stars and the O– trials had a low quality rating of two stars. The I and J filler stimuli were also wine-producing regions. I had a 1-star rating and J had a 5-star rating. Negative and filler stimuli were added to create variation on the outcome dimension, which enhances learning about the positive A, B, and CD stimuli at the expense of the context. The 40 trials were presented in random order.

Procedure. Experiment 1 had two conditions in a two-cell, between-participants design. The participants were provided with one of the following sets of instructions:

Predict condition. In this study, we are going to ask you to become an expert at predicting the quality of Chardonnay wines. On each of the following 40 screens, you will see the name of a bottle of wine and some information about the wine. You will then be asked to predict the quality of the wine. Immediately afterwards, you will receive feedback on your prediction. By the end of the experiment, you should be able to differentiate high quality wines from low quality wines.

Choose condition. In this study, we are going to ask you to review 40 bottles of Chardonnay wine. As you review these bottles of wine, we want you to try to select three bottles you would be willing to purchase. You can assume that all bottles are comparably priced. If you do not drink wine, please assume that you plan to buy the wine as a gift.

Participants were then presented with information about each bottle of wine. On four separate lines, participants were told the brand name, the producing region, fermentation, and the type of vineyard information was absent on a trial, the space for this information was left blank. For each wine, participants in the predict condition were first presented with cue information and asked to predict the outcome (quality level on a 5-star scale). Next, they were given feedback by presenting cue information and asked to predict the outcome (quality level on a 5-star scale). The 40 trials were presented in random order.

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Table 1

<table>
<thead>
<tr>
<th>Training</th>
<th>Test</th>
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<tr>
<td>Experiments 1 and 2</td>
<td></td>
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<tr>
<td>A → O+</td>
<td>A</td>
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<tr>
<td>B → O+</td>
<td>E</td>
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<tr>
<td>CD → O+</td>
<td>AB</td>
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<td>E → O–</td>
<td>EF</td>
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<td>F → O–</td>
<td>GH</td>
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<td>GH → O–</td>
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<tr>
<td>I → O+</td>
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<td>J → O–</td>
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<td>Experiment 3: Phase 1</td>
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<tr>
<td>A → O+</td>
<td>AB</td>
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<tr>
<td>B → O+</td>
<td>CD</td>
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<tr>
<td>CD → O+</td>
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<td>E → O–</td>
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<td>Experiment 3: Phase 2</td>
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<tr>
<td>AB → O–</td>
<td>AB</td>
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<td>C → O–</td>
<td>CD</td>
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<td>D → O–</td>
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<tr>
<td>F → O+</td>
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Note. A–J are product features; O+ indicates high quality; O– indicates low quality.
At test, all participants were asked to judge the quality of eight new wines that had the characteristics A, C, E, G, AB, CD, EF, and GH using a 101-point rating scale. The 0 to 100 rating scale had a single star at the left endpoint, two stars at the lower quartile, three stars at the midpoint, four stars at the upper quartile, and five stars at the right endpoint. Note that each compound consisted of a producing region and a fermentation container or a vineyard type. Also note that the EF and GH test responses replicated the AB and CD test responses using negative outcomes.

Results

Cues paired with positive outcomes. The results are shown in Figure 2. The Processing Task × Test Stimulus interaction was statistically significant, $F(1, 71) = 9.15$, $p < .05$, indicating that the difference between AB and CD was indeed more positive in the predict condition than in the choose condition. In the predict condition, the quality of the AB compound ($M_{AB} = 82.1, SE = 2.01$) was rated higher than the quality of the CD compound ($M_{CD} = 73.9, SE = 2.43$), $F(1, 71) = 4.13, p < .05$. In the choose condition, the quality of the previously encountered CD compound ($M_{CD} = 70.7, SE = 2.25$) was rated higher than the quality of the AB compound ($M_{AB} = 62.2, SE = 3.36$), $F(1, 71) = 5.09, p < .05$.

Cues paired with negative outcomes. The Processing Task × Test Stimulus interaction was statistically significant, $F(1, 71) = 7.03, p < .05$. In the predict condition, responding to the previously encountered compound ($M_{GH} = 26.6, SE = 2.29$) did not differ significantly from responding to the compound of which the elements had only been encountered separately ($M_{EF} = 25.1, SE = 2.44$), $F(1, 71) = 0.15$. In the choose condition, the quality of the previously encountered GH compound ($M_{GH} = 28.7, SE = 2.17$) was rated lower (i.e., more extreme) than the quality of the EF compound of which the elements had only been encountered separately ($M_{EF} = 40.9, SE = 3.70$), $F(1, 71) = 12.01, p < .05$.

Discussion

Consistent with our dual process view, the results in Experiment 1 support the hypothesis that a predictive focus influences the extent of stimulus generalization in human associative learning. More specifically, when participants were asked to make trial-by-trial predictions and to learn how to predict the outcome, an adaptive learning process was active and led to stronger responding to test stimuli composed of previously encountered elements (e.g., AB) than test stimuli consisting of previously encountered compounds (e.g., CD). This difference can be attributed to the broad generalization of the adaptive learning system. When participants were asked to merely attend to the stimuli and choose some favorites, they engaged a configural process with narrow generalization, leading to stronger responding to the previously encountered compound stimulus (CD) than the previously encountered elemental stimuli (e.g., AB). As discussed before, Pearce’s (1994) configural model predicts that both test compounds in this design should encourage equivalent responses. Kruschke’s (1992) ALCOVE model can explain these results post hoc because it has a freely estimable generalization parameter but would not predict the difference between the conditions a priori.

Whereas adaptive processing should be more likely to occur when instructions ask participants to learn to predict and participants have to make trial-by-trial predictions, we should note that even under such conditions, broad generalization characteristic of

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4 Predictions for the test stimuli that were paired with the low-quality outcome (i.e., EF and GH) depend on the psychological interpretation of this quality level. If this quality level is experienced as neutral (i.e., a zero outcome), no learning should take place on E, F, and GH trials in either condition. If low quality is experienced as a positive level on the quality dimension, the effects should be in the same direction as the results for the AB and CD test items, but attenuated. If low quality is experienced as a negative outcome or as a different outcome dimension, the effect should be the inverse of the results for the AB and CD test items. Thus, the results for the EF and GH test stimuli are theoretically nondiagnostic. It seems natural, however, to assume that low quality is not encoded as a positive or neutral level on the quality dimension. We return to this issue in the General Discussion section.

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Figure 2. Experiment 1: Mean quality ratings for test compounds paired with positive (Panel A) and negative (Panel B) outcomes.
elemental adaptive processing may not be universal. Despite predictive instructions and trial-by-trial prediction, Williams et al. (1994) found little evidence of cue interaction in blocking–unblocking and conditioned inhibition designs unless participants received a pretreatment that could easily be solved on the basis of individual elements’ predictive values. A lack of cue interaction, of course, could be due not only to narrow stimulus generalization but also to a noninteractive learning rule combined with broad generalization. Nevertheless, a caveat seems in place about the universality of adaptive processing in situations with predictive learning instructions and trial-by-trial prediction.

Experiment 2

In addition to the predictive versus nonpredictive nature of the learning process, a second potential difference between the adaptive process and the exemplar-based process is the former is inherently forward-looking whereas the latter is inherently backward-looking. We hypothesized that in predictive learning situations, both systems are likely to be active during learning and can be used to make predictions at test. To the extent that such directionality can be manipulated, we expect that instructions to look back at test can increase the impact of the exemplar-based process on predictions at test. To the extent that such directionality can be manipulated, we expect that instructions to look back at test can increase the impact of the exemplar-based process on predictions at test. In Experiment 2, all participants made trial-by-trial predictions and were asked to learn to predict an outcome. At test, half the participants were asked to make predictions, whereas the other half were asked to think back to what they saw during learning before making predictions. We expected that the former group would exhibit broader generalization in their responses than the latter group.

Method

Participants. The participants were 95 undergraduate students who volunteered in exchange for course credit.

Procedure. Experiment 2 had two conditions in a two-cell, between-participants design. The forward-looking condition in Experiment 2 was identical to the predict condition of Experiment 1. The backward-looking condition was also identical to the predict condition of Experiment 1 except for one change. Right before the test stimuli were presented, participants in the backward-looking condition were asked to think back to the stimuli they had seen during the learning phase using the following instruction:

We want you to reflect back on the types of wines you saw. You saw six different types of wines. These wines varied by the area of production, the type of fermentation, and the type of vineyard. Some wines listed only one of these attributes whereas other wines listed combinations of the attributes. Please try to list the six different types of wines you saw.

Except for this change, the test phase was identical to the test phase in the forward-looking condition. Hence, unlike in the experiments by Price and Yates (1995) and Matute et al. (1996), the test question remained predictive across conditions.

We predicted that participants in the forward-looking condition would be more likely to use the adaptive system to respond, leading to broader generalization, relative to participants in the backward-looking condition. Thus, the difference between AB and CD should be more positive in the forward-looking condition than in the backward-looking condition. One could similarly predict that the difference between the EF and GH test responses would be more negative in the forward-looking condition than in the backward-looking condition.

Results

Cues paired with positive outcomes. The results are shown in Figure 3. The Test Instruction × Test Stimulus interaction was significant, \( F(1, 93) = 8.39, p < .05 \). In the forward-looking condition, the compound composed of cues that were previously encountered only as elements (\( M_{AB} = 83.5, SE = 1.50 \)) led to a more positive response than the previously encountered compound (\( M_{CD} = 77.6, SE = 2.20 \)), \( F(1, 93) = 5.18, p < .05 \). This result replicated the predict condition of Experiment 1. In the backward-looking condition, the novel compound (\( M_{AB} = 78.2, SE = 2.21 \)) led to a less positive response than the previously encountered compound (\( M_{CD} = 82.9, SE = 1.47 \)), \( F(1, 93) = 3.31, p = .07 \).

Cues paired with negative outcomes. The Test Instruction × Test Stimulus interaction was marginally significant, \( F(1, 93) = 2.87, p < .10 \). In the forward-looking condition, both compounds

![Figure 3. Experiment 2: Mean quality ratings for test compounds paired with positive (Panel A) and negative (Panel B) outcomes.](image-url)
yielded similar responses ($M_{EF} = 23.5, SE = 2.01$; $M_{GH} = 23.4, SE = 1.60$), $F(1, 93) = 0$. In the backward-looking condition, the previously encountered compound ($M_{GH} = 20.0, SE = 1.47$) yielded a more negative response than the novel compound ($M_{EF} = 25.7, SE = 1.97$), $F(1, 93) = 5.99, p < .05$.

**Discussion**

The results in Experiment 2 support the hypothesis that the directionality of processing at test influences the extent of stimulus generalization in human associative learning. The results are consistent with a dual process view on human associative learning. More specifically, when participants were asked to make trial-by-trial predictions and to learn how to predict the outcome, both processes were active and available for subsequent responses. When no explicit instructions were given at test, relatively broad generalization indicative of the adaptive process was found. However, when participants were instructed to look back and retrieve exemplars at test, outputs of the exemplar-based process became more dominant and generalization became more narrow.

The results of Experiment 2 are difficult to explain for existing single-process theories of human associative learning that strive to explain both cue interaction and configurality because the learning phase in both conditions was identical. The results are also problematic for explanations that argue that participants can learn using either an elemental learning strategy or a configural learning strategy but not both at the same time (e.g., Williams et al., 1994), also because the identical learning phase should lead to the same pattern of responses in both conditions. However, if two different learning systems were simultaneously active during learning, manipulations at test can impact the influence of each learning system’s output on responding at test.

We cannot exclude the possibility that the retrieval of exemplars in the backward-looking condition led to extra adaptive learning involving rehearsal of retrieved exemplars. Note, however, that extra learning of the type that yielded a positive difference between the AB and CD test stimuli in the forward-looking condition should lead to an even larger positive difference between the AB and CD test stimuli in this condition, which is the opposite of what we found. In addition, one might argue that retrieving and writing down exemplars might encourage a causal reasoning process (Cheng, 1997). Interestingly, such a process should also lead to the opposite result of the one we obtained, as the causal power of the C and D elements should be discounted.

**Experiment 3**

A third potential difference between the adaptive process and the exemplar-based process is the exemplar-based process should be more sensitive to stimulus similarity. In Experiment 3 we tested the hypothesis that, even in forward-looking, predictive learning situations, the exemplar-based process is likely to have a stronger influence on responses to test stimuli that are more similar to stimuli encountered during the learning phase. In Experiment 3 we also used a within-subject design to control for concerns that the backward-looking condition of Experiment 2 encouraged extra adaptive learning involving the rehearsal of exemplars.

In Experiment 3, we not only kept the learning phase identical between conditions, we also kept the test phase identical. We created a single-cell design in which the two-process theory predicts that some test stimuli will exhibit broad and narrow generalization in different stages of the experiment whereas other test stimuli will exhibit narrow generalization throughout the experiment. This implies different levels of generalization for different combinations of stimuli and times in the learning process, a result that is inconsistent with assumptions of either constant generalization over the course of an experiment or constant generalization across stimuli.

The experiment consisted of two phases of predictive learning trials. Each phase consisted of five blocks of four trials. In the first learning phase, participants encountered the following stimulus types: A $\rightarrow$ O+, B $\rightarrow$ O+, CD $\rightarrow$ O+, E $\rightarrow$ O-. In the second learning phase, participants encountered AB $\rightarrow$ O-, C $\rightarrow$ O-, D $\rightarrow$ O-, and F $\rightarrow$ O+. The test stimuli were AB and CD, with the first test being the last trial of the first learning phase (a CD trial) and the first trial of the second learning phase (an AB trial). The second test came after the second learning phase.

Our two-process model predicts different processes will be used to make judgments for different stimuli in different phases, because it assumes that both learning systems tend to be active in predictive learning situations. The exemplar-based system is likely to have a stronger effect on judgments to the extent that the cue configurations used to make a prediction are highly similar to previously encountered cue configurations. At the end of Phase 1, participants should be likely to use the adaptive system to make judgments about novel stimulus AB and the exemplar-based system to make judgments about previously encountered compound CD. As a result, AB should lead to a more positive outcome prediction than CD, as happened in Experiments 1 and 2. After Phase 2, participants should be more likely to use the exemplar-based system to make judgments about both AB and CD, because both are highly similar to stimuli that have been encountered previously. In exemplar-based judgments with narrow generalization, CD might lead to a more positive quality prediction than AB because the compound-cue CD was directly paired with the high-quality outcome, whereas the compound-cue AB was paired with the low-quality outcome. Thus, we expect the positive difference between responses to the AB versus CD test stimuli to decrease going from the first to the second tests.

**Method**

**Participants.** The participants were 33 undergraduate students who volunteered in exchange for course credit.

**Procedure.** The processing task was identical to the predict condition in Experiment 1. Participants were asked to review information about 40 bottles of wine. In Phase 1, all participants viewed five blocks of the four trials A $\rightarrow$ O+, B $\rightarrow$ O+, CD $\rightarrow$ O+, E $\rightarrow$ O-. In Phase 2, all participants viewed five blocks of the four trials AB $\rightarrow$ O-, C $\rightarrow$ O-, D $\rightarrow$ O-, and F $\rightarrow$ O+. The A, C, E, and F stimuli were the producing regions California, France, Australia, and South Africa. California and France were counterbalanced. The B and D stimuli were boutique or estate vineyards and were also counterbalanced. Presentation of the Phase 1 and Phase 2 trials were in a fixed semi-random order so that the last trial of Phase 1 was a CD trial and the first trial of Phase 2 was an AB trial. There was no break between the learning phases and participants were not made aware of the existence of two different learning phases.
Results and Discussion

The results are shown in Figure 4. The Testing Phase × Test Compound interaction was significant, \( F(1, 29) = 9.67, p < .05 \). When the compound stimuli were tested at the end of Phase 1, participants predicted AB to be higher quality (\( M_{AB} = 4.79, SE = 0.07 \)) than CD (\( M_{CD} = 4.48, SE = 0.09 \)), \( F(1, 29) = 7.47, p < .05 \). When the compound stimuli were tested at the end of Phase 2, participants predicted AB to be lower quality (\( M_{AB} = 57.7, SE = 4.15 \)) than CD (\( M_{CD} = 71.1, SE = 3.77 \)), \( F(1, 29) = 9.02, p < .05 \).

The data are consistent with the predictions of the two-process model. It is again difficult to see how a one-process model could account for these results. To do so, a one-process model would have to assume that generalization changes over time and across stimuli. Indexing the generalization parameter by the combination of test stimulus and stage in the experiment would allow one-process models to fit the data post hoc. However, these one-process models would still not predict when and for which test stimuli generalization would be broader or narrower.

In addition to the exemplar-based system’s greater sensitivity to similarity, another mechanism may have contributed to the effects found in Experiment 3. The second learning phase may also have encouraged a reduction in adaptive processing. Research by Williams et al. (1994) showed there is a lack of cue interaction unless participants receive a pretreatment that can easily and unambiguously be solved on the basis of individual elements’ predictive values. These results may be taken to suggest that elemental processing is less likely when it is difficult to quickly and consistently achieve zero-discrepancy prediction using an elemental process. Thus, it is possible that the change in outcome patterns, and accompanying changes in prediction discrepancies, between the first to the second learning phase made participants stop processing adaptively in the second learning phase, leading to more exemplar-based responses at test after the second learning phase. A decrease in adaptive processing that was due to prediction difficulty is consistent with our two-process theory in which adaptive processing is described as error-driven, effortful, and “not always on”.

General Discussion

Several authors have argued that human learning relies on an exemplar-based system as well as an elemental system that connects individual elements with outcomes (e.g., Baker et al., 1996; Erickson & Kruschke, 1998; Juslin, Olsson, & Olsson, 2003; Shanks & St. John, 1994; Sutherland & Rudy, 1989). We concur and propose there is an adaptive system with broad generalization and cue interaction and an exemplar-based system with configural representation and narrow generalization. In three experiments, we documented the simultaneous existence of broad and narrow generalization and introduced three factors that influenced the extent of stimulus generalization. We found that test responses reflect more narrow generalization when participants merely evaluate stimuli consisting of cue and outcome information than when they make trial-by-trial predictions. We also found that test responses suggest more narrow generalization when participants in a predictive learning situation are asked to retrieve previously seen stimuli before making their test judgments. Finally, we found that responses suggest narrower generalization for test stimuli that are more similar to the stimuli encountered during learning.

Adaptive and Exemplar-Based Processes

Representation and learning rules. Whereas it is difficult to explain our results without the assumptions that the adaptive system is characterized by broad generalization and a delta-learning rule and that the exemplar-based system is configural with narrow generalization, the data leave open several possibilities regarding representation in the adaptive system and the learning rule in the exemplar-based system. Before exploring these possibilities, it is important to discuss what the adaptive and exemplar-based processes are not. First, it is not the case that both processes rely on elemental representation of stimulus information but differ in terms of their learning rule. That is, the exemplar-based process is not just an elemental system with a simple Hebbian rule that strengthens associations whenever cues and outcomes occur to-
gether without generating cue interaction. Under elemental representation, presenting a compound cue at test fully activates all its elements, regardless of whether they were encountered in the same or different combinations before test. When, in addition, the associations between individual elements only depend on how often and consistently these elements are paired with an outcome, all four elements in a summation design (e.g., A, B, C, D) should have equally strong outcome associations. Thus, at test all elements should be activated equally strongly in memory and feed activation to the outcome over equal strength associations. As a result, both test compounds (e.g., AB and CD) should lead to the same response. This was clearly not the case in our experiments. In other words, the exemplar-based process has to represent cues configurally.

Second, it is also not the case that both processes rely on configural representation of stimulus information but differ in terms of their learning rule. Under configural representation, cue interaction should not be an issue in the summation design. That is, there are no instances in the learning phase in which learning about a compound stimulus can be affected by generalization to other stimuli that share some of the compound’s elements—the CD, A, and B stimuli have no elements in common. In summary, our results are not driven exclusively by a difference in learning rule between the two processes. There is an essential difference in generalization.

The fact that the two processes differ in terms of generalization does not negate the possibility that representation and learning rule do not differ. First, whereas the data support the configurality of representation in the exemplar-based system, they are not diagnostic with respect to representation in the adaptive system. As long as generalization is broad enough to generate the summation effect (AB > CD), it is possible that the adaptive system represents information configurally. Second, whereas many demonstrations of cue interaction phenomena in predictive learning tasks support the existence of delta-rule learning in the adaptive system, our results are not diagnostic with respect to the learning rule in the exemplar-based system. As we argued earlier, broad generalization is needed for cue interaction to occur. When generalization is very narrow, strong cue-interaction effects cannot be obtained, even when learning follows the delta-learning rule. This conclusion is consistent with evidence showing the absence of strong cue-interaction effects in situations favoring the exemplar-based system (van Osseelaer & Janiszewski, 2001).

Interaction between processes. Thus far, we have made few claims about how adaptive and exemplar-based systems combine to determine responses at test. We have merely investigated factors that make one system’s output stronger or more influential relative to the other. Dual processes can potentially combine in many different ways that are difficult to identify and separate empirically (Gilbert, 1999). The results in our experiments, however, suggest that, unless special factors in the environment make participants think back, and unless stimuli are very similar to stimuli encountered before, the adaptive system will often dominate responses when adaptive processing has taken place during learning. It would not be surprising that a system that is more effortful and not “always on” tends to dominate responding.

Low-quality outcome. Although the interaction effects between test stimulus and experimental condition for stimuli paired with the low-quality outcome mirrored those for the high-quality outcome in Experiments 1 and 2, the results for the low-quality outcome need to be interpreted with caution. It was not clear a priori how participants would encode low-quality outcomes, and different ways of encoding should lead models of associative learning to generate different predictions (see footnote 4). Thus, results with respect to the low-quality outcome in Experiments 1 and 2 are not perfectly diagnostic with respect to process and model selection. However, the specific pattern of results is consistent with our explanation.

If low quality was encoded as a negative level on the quality dimension or as a dimension separate from the high-quality outcome, exemplar-based learning (with configural representation and narrow generalization) should have led to the following pattern. Quality for the GH test stimulus, which was presented as a compound in the learning phase, would be predicted lower (i.e., more extreme) than for the EF test stimulus, whose elements were presented separately during the learning phase. This is what we found in the choose and backward-looking conditions. Pure adaptive learning (with elemental representation and delta-rule learning) should have led to lower quality predictions for the EF test stimulus than the GH test stimulus. We did not find this result in the predict and forward-looking conditions of Experiments 1 and 2. Instead, responding to both test stimuli was not significantly different. This is not difficult to explain. If adaptive learning is indeed not the default system and requires more effort and motivation than the exemplar-based system, it would not be surprising that participants would be less motivated to learn about unattractive outcomes (i.e., low quality in wines), as reflected in lower adaptive learning rates. In fact, Rescorla and Wagner (1972) explicitly included an outcome-dependent, learning-rate parameter in their elemental adaptive model to reflect lower learning rates for less intense outcomes and nonevents. To the extent that responding is influenced by both the adaptive system and the default exemplar-based system, these lower adaptive learning rates could generate a pattern of responses in the predict and forward-looking conditions in which no significant difference is found between the EF and GH stimuli.

Implications for Existing Theories of Associative Learning

Single-process models. It is difficult for single-process models of human associative learning to explain our results. Using a simple summation design (i.e., A → O, B → O, CD → O) we find some situations in which responding to AB is stronger than to CD and other situations in which the reverse happens. Pearce’s (1994, 2002) popular configural model with a fixed level of generalization predicts that responding to our test compounds (AB and CD) would be identical, unless side assumptions are made about context cues.6 Configural models with a single, freely estimable generalization parameter, such as the most basic versions of the

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6 When a constant context cue is assumed, Pearce’s model predicts a summation effect such that responding to AB is stronger than to CD. When different context cues are assumed in learning and test phase, the model predicts that responding to CD is stronger than to AB. Thus, for Pearce’s model to explain our results, the learning and test phase would have to be coded as having the same context in some conditions but as having different contexts in other conditions, which seems difficult to justify. In addition, one would have to assume that the predictive learning phase and forward-looking test phase in Experiments 1 and 2 were encoded as the same context but that the predictive learning phases and forward-looking test phase of Experiment 3 were encoded as different contexts. Given the similarity between these experiments, it does not seem credible that learning and test phases were encoded as the same context in the predictive and forward-looking conditions of Experiments 1 and 2 but were encoded as different contexts in Experiment 3.
trials will lead both a 1 and a 2 to develop associations whose

will activate half of each single cue

Elements d 1 and d 2 , presenting the CD compound during learning

is represented by Elements c 1 and c 2 , and Cue D is represented by

Vogel, & Wagner, 2000; Wagner, 2003) introduced two elemental

models of Pavlovian conditioning that represent each (single and

compound) cue by multiple elemental nodes. The inhibited ele-

ments model is an elemental version of Pearce’s (1994) model.

According to this model, each single cue has a unique set of

 elemental nodes that represent it. If two cues appear together, some

of their elemental nodes are inhibited so that the total number of

activated elemental nodes remains the same regardless of how

many cues are presented. Learning of associations between the

 elemental nodes and the outcome is according to the delta rule.

Thus, when Cue A is represented by elements a 1 and a 2, A → O+

trials will lead both a 1 and a 2 to develop associations whose

strength equals half the desired activation of the outcome node

(i.e., λ in the Rescorla–Wagner model or d j in Equation 1). The

same is true for Cue B, represented by Elements b 1 and b 2 , and B

→ O+ trials. At test, Compound Cue AB leads to activation of

half of A’s elements (e.g., a 1 ) and half of B’s elements (e.g., b 2 )

whereas the other half of the elements are inhibited. As a result,

total outcome activation will be equal to λ at asymptote. If Cue C

is represented by Elements c 1 and c 2 , and Cue D is represented by

Elements d 1 and d 2 , presenting the CD compound during learning

will activate half of each single cue’s elements (e.g., c 1 and d 2 ) and

the rest will be inhibited. The activated elements will form asso-
ciations with the outcome that sum up to λ. Thus, total outcome

activation at test will also be equal to λ at asymptote. In summary,

the inhibited elements model predicts that both test compounds

(AB and CD) in our experiments should show identical levels of

outcome activation.

Wagner and Brandon (Brandon et al., 2000; Wagner, 2003;

Wagner & Brandon, 2001) also described a replaced elements

model, in which single cues are again represented by several

elements but in which compound cues are also represented by

compound-specific elements. When compounds are presented,

the number of activated elements is equal to the sum of the number of

elements representing each of its constituting cues separately.

Thus, unlike the inhibited elements model, presenting a compound

cue leads to the activation of more elements than presenting a

singular cue. Another important difference is that in the replaced

elements model, one or more of the elements representing each

single cue are inhibited during presentation of a compound cue and

replaced by activating a compound-specific element. Depending

on the proportion of compound- versus element-specific elements,

responses to the AB test stimulus can be more, equally, or less

positive than to the CD test stimulus in a summation design.

Although earlier versions of the theory used one compound-

specific element, leading to the prediction that responses to the AB

test stimulus would be at least as positive as to the CD test stimulus

(Brandon et al., 2000; Wagner & Brandon, 2001), a later version

has loosened this assumption (Wagner, 2003). Such a model with

varying proportions of compound-specific elements essentially has

a free-generalization parameter, similar to configural models such

as ALCOVE (Kruschke, 1992) and could fit the data in Experi-

ment 1. However, just like ALCOVE, this account would be

entirely post hoc unless proportions of compound-specific ele-

ments can be predicted. In addition, the replacement model has the

same difficulties explaining the results of Experiments 2 and 3.

A promising approach to the problem of generalization is pro-

vided by a model that combines elemental and configural repre-

sentations and associations (Schmajuk, Lamoureux, & Holland,

1998). In this model, associations are formed both from elements

to outcomes and from configurations to outcomes, with both types

of associations competing for strength during learning. If the

configural path is characterized by narrow generalization, this

model can account for broad and narrow generalization. However,
to the extent that the model describes a single learning process, it

can still not explain the results in Experiment 2. Experiment 2

manipulated temporal orientation at test and showed different

levels of generalization after an identical learning phase. Unless

participants are assumed to independently and simultaneously

learn using two different systems, an identical learning phase

should not lead to radically different patterns of results depending

on what happens at test. In addition, the model does not predeter-

mine levels of stimulus generalization; they depend on randomly

determined initial values of element–configuration associations.

Dual process models. Recently, researchers have found evi-
dence that participants use abstract rules in nonlinear discrimina-

tion paradigms (e.g., Lachnit & Lober, 2001; Lachnit, Lober,

Reinhard, & Kinder, 2001; Shanks & Darby, 1998). Abstract rules,
as such as “single cues lead to the outcome but combined cues do

not” could be used when nonabstract, error-driven learning with

elemental representation fails, as is the case in a negative pattern-
ing task. However, note that the summation design used in our

studies does not seem to necessitate any abstract rules during

learning. In addition, it is difficult to see how an abstract rule, such

as single cues lead to the outcome but combined cues do not,

would be useful in our Experiment 3, because half the single cues

and half the combined cues led to one outcome and the other half

led to the opposite outcome. Finally, it is difficult to explain why

and how the use of abstract rules would differ between conditions

in our experiments.

Conclusion

In summary, we are confident that human associative learning

relies on two distinct processes, one with broad generalization and

characterized by cue interaction and one with narrow generaliza-
tion and configural representation that is less prone to cue inter-

action. We have good reasons to suspect, in addition, that the first
process represents information elementally and that the latter has a learning rule different from the delta rule. No matter how reasonable, of course, suspicions remain mere suspicions until they are put to the test.

References


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