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Attitude generalization: Similarity, valence, and extremity ☆

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Abstract

Attitude generalization was explored as a function of object similarity and attitude valence and extremity. Participants in a computer game formed attitudes toward positive and negative, mild or extreme stimuli. How well these attitudes generalized to similar, novel stimuli was then examined. Visual similarity to game targets affected categorization of novel stimuli, such that greater resemblance resulted in more similar classification. However, generalization varied by valence and extremity. Negative attitudes generalized more than positive attitudes, requiring less resemblance for a novel target to be classified as negative. This pattern was more obvious with extreme attitudes than mild attitudes. That is, extreme attitudes were more influential and given more weight than mild attitudes. Also, specific conditions were identified under which positive attitudes proved more influential than negative attitudes.

Keywords: Attitudes; Attitude generalization; Attitude extremity; Valence asymmetry; Categorization

Most people enjoy receiving chocolates. However, within any assortment of chocolates, there are inevitably some chocolates that are preferred over others. Determining which chocolates are the liked and disliked ones is not always an easy task. Many candy companies provide a pictorial guide displaying what the different chocolates should look like. However, quite often the chocolates in the box do not look exactly like their depiction, thus making resemblance a matter of degree. The question then is how does one approach this selection of treats? Does one just dive in and sample all of the sweets, taking the good with the bad? Or, is one more selective and careful to consume only the chocolates which they are reasonably sure they will like? The decision to try an individual chocolate will depend on how it is categorized. But, what factors determine whether a given chocolate is categorized as, for example, nougat or caramel filled?

The focus of this paper concerns some understudied factors that may affect the initial categorization of novel or ambiguous targets and thus attitude generalization. The categorization literature in cognitive psychology emphasizes similarity to a known entity as a primary factor in labeling targets (Medin & Schaffer, 1978; Nosofsky, 1986, 1988). It is generally held that individuals have stored exemplars of a group, and membership to that group depends on similarity to the exemplars. The greater the resemblance, the more likely the target is to be categorized as part of the group. Returning to our example, the physical resemblance of an unknown chocolate to the chocolate guide or to a previously devoured chocolate certainly will affect categorization of the new chocolate. But, is similarity the only factor that determines categorization? Are there other factors, independent of resemblance, that influence categorization?

Recently, Fazio, Eiser, and Shook (2004) examined attitude formation as a function of exploratory behavior and the experience of positive or negative outcomes upon

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approaching a novel object. After participants formed attitudes toward these objects, generalization of the attitudes to novel stimuli was explored. As with the categorization work, Fazio et al. (2004) found that similarity was very influential in labeling the novel stimuli as good or bad. The more the novel targets visually resembled the known targets, the more likely the novel targets were assumed to share the same valence as the known targets. Interestingly, the newly formed attitudes did not all generalize to the same extent. Instead there was a generalization asymmetry. Negative attitudes generalized to novel stimuli more strongly than positive attitudes. That is, less resemblance to a known negative was required for a novel object to be deemed negative. Based on these findings, similarity alone did not determine categorization. The valence of the preexisting attitudes was also influential, such that participants exhibited a negativity bias. In fact, Fazio et al. (2004) explain the generalization asymmetry as being due to negative information being weighted more heavily than positive (for discussion of such negativity biases and reviews of relevant literature, see Baumeister, Bratslavsky, Finkenauer, & Vohs, 2001; Cacioppo, Gardner, & Berntson, 1997; Rozin & Royzman, 2001).

For the chocolate example, the valence of attitudes toward caramel and nougat will also affect categorization of the new chocolate. If the new chocolate looks similar to both the nougat and caramel filled chocolate pictures but one of the fillings is disliked, then the new chocolate is more likely to be assumed to be the disliked chocolate and avoided. But, is it always the case that we are not willing to sample something new or ambiguous if there is a chance that it might be negative? Are there not circumstances under which the positive attitude might outweigh the negative and enhance willingness to sample? For example, if one does not care for nougat but loves caramel, one might sample the chocolate, hoping to find a caramel. As nougat is only mildly disliked, the negative consequences of miscatergorization are not devastating and, hence, may be viewed as acceptable. Thus, under conditions of a much more extreme positive attitude competing with a mild negative attitude, one might be more likely to categorize a novel target as positive rather than negative, contrary to the overall finding observed by Fazio et al. (2004). In the opposite situation of an extreme negative compared to a mild positive, one would imagine that the negative attitude would be even more influential, as we know negative attitudes are given more weight than positive attitudes when extremity is equivalent. So, if one highly dislikes nougat or is allergic to it, sampling the chocolate in the hope that it is a caramel would not be worth the risk.

The present experiment was aimed at exploring these possibilities regarding the differential weighting of resemblance to a known negative versus a known positive. The experiment examined the generalization asymmetry across a broader range of attitude values than had been previously pursued. The purpose was to determine whether extremity, in addition to visual similarity and mere valence, affects generalization. We predicted that extreme attitudes would more strongly influence generalization, and, given the previously observed valence asymmetry, that extreme negative attitudes would be especially influential. Moreover, we expected to illuminate particular combinations of extremity and valence under which negative attitudes are *not* more influential than positive attitudes and potentially even less influential. More specifically, the experiment tests the hypothesis that resemblance to a positive can outweigh resemblance to a negative, contrary to the earlier findings, when the features competing for attention involve extreme positivity and mild negativity.

To test this reasoning, the BeanFest paradigm developed by Fazio et al. (2004) was utilized with a slight modification that permitted examination of the impact of a fuller range of attitudes—extremely negative, mildly negative, mildly positive, and extremely positive—on generalization. BeanFest is a computer game in which the participant's goal is to accumulate points by making judicious decisions about which specific beans to accept (approach) and which beans to reject (avoid). Each bean has a positive or negative value. Accepting a positive bean increases the participant's point value, whereas accepting a negative bean produces a decrease. If the bean is rejected, the participant's point value is unaffected. However, in such cases, the value of the bean is not learned. At any given time, the participant's cumulative point value ranges from 0 to 100.

The beans differ by shape and number of speckles. They can be viewed as forming a 10×10 matrix in which the x-dimension represents the shape of the bean, ranging from circular to oval to oblong, and the y-dimension represents the number of speckles, ranging from one to ten (see Fig. 1a). Within the matrix, six regions of beans (36 beans total) were selected for presentation during the game phase. These regions were selected very carefully, so that there was no linear relationship between the shape or number of speckles and the valence of the bean. Consequently, participants must associate each bean with the outcome that specific bean produces in order to increase their own point value. After completing the game phase, participants engaged in a test phase in which each bean from the matrix was presented and participants indicated whether it was a "good" or "bad" bean.

The test phase provides the primary measure of learning (attitude development) and attitude generalization. From participants' responses to the 36 game beans, it can be determined whether the beans were correctly learned as good or bad. Attitude generalization can be determined from participants' responses to the 64 novel beans. Similarity to the game beans was indexed by calculating the Euclidean distance in the 10×10 matrix from the novel bean to the nearest positive and nearest negative bean. Thus, novel beans could be classified as either more similar to positive or negative.

The extremity manipulation was implemented by varying the absolute value of the bean regions. In previous a

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
X1	2	2	2			-10	-10	-10		
X2	2	2			-10	-10	-10			
X3						-10				
X4									10	
X5		-10						10	10	10
X6	-10	-10	-10						10	10
X7	-10	-10								
X8					10					
X9				10	10	10			-2	-2
X10			10	10	10			-2	-2	-2

b

	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9	Y10
X1	10	10	10			-2	-2	-2		
X2	10	10			-2	-2	-2			
X3						-2				
X4									10	
X5		-10						10	10	10
X6	-10	-10	-10						10	10
X7	-10	-10								
X8					2					
X9				2	2	2			-10	-10
X10			2	2	2			-10	-10	-10

Fig. 1. (a) Bean matrix. X = shape, from circular (1) to oval to oblong (10); Y = number of speckles, from 1 to 10. (b) Bean matrix with extremity counterbalanced.

experiments, beans had a value of either positive or negative ten. In the present experiment, beans had either an extreme value (positive or negative ten) or a mild value (positive or negative two). These values provide an opportunity to examine how a much fuller range of attitudes—extremely negative, mildly negative, mildly positive, and extremely positive—interact with visual similarity to determine categorization.

Method

Participants

One hundred sixty-four Ohio State University students enrolled in introductory psychology courses (117 females and 47 males) participated in this experiment for research credit. At most, four participants were present for each session. Data from four participants were excluded from the analyses for either technical reasons, such as computer malfunctions, or the participant clearly not being engaged in the task.

Design

The design of the study involved two between-subjects variables: matrix and framing. Four matrices were created by counterbalancing the valence and extremity of the regions. In generating the bean matrices, the extremity manipulation needed to be carefully implemented to keep the game from becoming dependent on the applicability of a simple linear rule for determining bean value (e.g., the more speckles, the better). Also, we wanted to ensure that enough novel beans were located between mild and extreme regions in the matrices, so we could determine how the combination of valence and extremity affected generalization. As such, of all the possible matrix arrangements, we chose the two that minimized the correlation between shape or speckles and point value, while providing a reasonable number of the desired novel beans. Within each matrix, there was one region of +2 beans, one region of −2 beans, two regions of +10 beans, and two regions of −10 beans. The two mild regions were those at opposite corners of the matrix, as in Figs. 1a and b. The third and fourth matrices were created by reversing the valence of the beans shown in Figs. 1a and b.[1]

The BeanFest game needs to be framed in a way to provide participants with a goal. In past research, this has been accomplished by framing the game in either gains or losses (Kahneman & Tversky, 1988). Although this manipulation has not been found to affect attitude learning or generalization, it does provide a convenient, counterbalanced means of presenting the game. In the gain version, participants started with zero points and tried to increase points to reach 100 and win the game. Participants in the loss version started with 100 points and tried to avoid losing points and reaching zero, which represented losing the game.

Procedure

When participants arrived at the lab, they were seated in individual cubicles and provided written instructions for BeanFest. The experimenter read the instructions aloud, while the participants read along. At the beginning of BeanFest, participants underwent a practice block of six trials. One bean from each of the six regions of the matrix was presented. Participants were asked to accept each practice bean, in order to familiarize themselves with the feedback and point displays and begin to associate a few specific beans with their point values.

[1] We chose to use matrices that contained four extreme regions and two mild regions, arranged as in the figures, for a number of reasons. First, our interest focused on the weighting of resemblance to extreme positives versus mild negatives and vice versa. That dictated both the value of four of the regions and their arrangement in such a way as to permit the identification of novel beans over which positive and negative regions of the required extremity were, in effect, competing. With the remaining two regions, we wished to create competition involving positive and negative beans of equal extremity. Having these cases involve values of +10/−10, instead of +2/−2, allowed for exact replication of the earlier research. Moreover, the more extreme values resulted in matrices for which simple linear rules were less effective. That is, matrices designed with four extreme regions and two mild regions yielded smaller correlations between shape or speckles and bean value than did matrices with two extreme and four mild regions.

When finished with the practice phase, participants started the actual game phase, which consisted of three blocks of 36 trials. The 36 trials involved the beans within the selected regions of the matrix. Each bean was presented once in each block; thus, all 36 beans were seen three times. Trials were randomly ordered except for the first 12 trials of the first block, which involved the presentation of two beans from each of the six regions in a fixed order. These 12 trials were fixed to avoid an unlucky string of negative beans and early losses in the game.

During a trial, participants were presented with a bean in the upper portion of the monitor. They had to indicate whether they wanted to accept or reject the bean. Participants responded by pressing either the "yes" or the "no" button on their response boxes.

After responding to each bean, the lower portion of the monitor adjusted according to the participant's decision. All of the information about the participant's point value was located in the lower right corner of the monitor. The point value was represented both numerically and graphically as a bar ranging from 0 to 100. These fluctuated in response to the participant's decision to accept a bean as a function of the bean's value. In the lower left corner of the monitor, participants were presented with information about their response and the bean's value. The participant's response appeared as either "yes" or "no." The bean's value appeared below the response, but only if the participant chose to approach the bean.

Participants in the gains framing condition started the game with zero points and wanted to increase their points. Reaching 100 represented winning the game. Participants in the loss framing condition started with 100 points and wanted to avoid losing points. Reaching zero represented losing the game. If participants won or lost, the game restarted. Participants would restart at 0 or 100, respectively. The game restarted as many times as the participants won or lost. With any restarted games, the beans retained their original values. Thus, participants did not have to relearn the beans if they played multiple games.

When all participants were finished playing BeanFest, the experimenter distributed the test phase instructions. During this phase, participants were randomly presented with all 100 beans from the matrix in two blocks of 50 trials. Participants were asked to indicate whether they believed the bean to be "good" or "bad." If the participants believed that the bean would increase points during the game, they were to respond "good" on the response box. If the bean was believed to decrease points, participants were to respond "bad." During this phase, there was no point meter or feedback about the bean. Participants had ten seconds to view and respond to each bean. Upon completion of the test phase, they were debriefed and excused.

Results

Given that the extremity manipulation had not been implemented in previous research (Fazio et al., 2004), we considered it important to first examine whether the manipulation altered learning and to establish that the learning asymmetry observed in the earlier work could be replicated. Then, the generalization asymmetry was examined. Gender, instruction framing, and matrix counterbalancing produced no theoretically relevant effects. Thus, all results are collapsed across these variables.

Learning

Unlike previous experiments, all of the analyses were conducted with the bean as the unit of analysis instead of the participant.[2] The generalization analyses that were to be pursued required focus on each novel bean and its similarity to the neighboring beans in the matrix. Hence, for each bean from each matrix we computed scores across participants. To examine learning of the beans presented during the game, the proportion who correctly labeled a given bean as "good" or "bad" during the test phase was considered. A 2 (valence) × 2 (extremity) ANOVA revealed a valence main effect, $F(1, 284) = 80.50$, $p < .001$. Negatively valenced beans were correctly labeled ($M = .68$) more often than positively valenced beans ($M = .55$), just as in previous research. There was also an extremity main effect, $F(1, 284) = 68.31$, $p < .001$. Extremely valued beans were correctly labeled ($M = .68$) more than mildly valued beans ($M = .55$). These main effects were qualified by a valence × extremity interaction, $F(1, 284) = 8.99$, $p < .01$. As shown in Fig. 2, the valence asymmetry was more pronounced for the mild beans, $t(94) = 6.70$, $p < .001$, than for the extreme, $t(190) = 5.45$, $p < .001$.

Generalization

Generalization ratio scores

To examine attitude generalization, participants were presented with the 64 matrix beans that had not been presented during the game. Their categorizations of the novel beans as "good" or "bad" were scored as +1 and −1, respectively. However, these raw responses do not necessarily reflect generalization per se because such scoring does not take learning of the neighboring regions into account. If participants did not learn a given region well, then it would not be surprising that the value did not generalize to the proximal novel beans. To control for the learned value of the neighboring regions, generalization was indexed via the same equation used by Fazio et al. (2004).

$$\text{Generalization ratio} = .5 - [(p - r)/(p - n)]$$

For each condition, the average response to each game region and each novel bean was calculated. In the equation, p represents the mean response to the closest positive region; n represents the mean response to the closest negative

[2] The analyses of learning produced the same patterns of statistical significance when the unit of analysis was the participant.

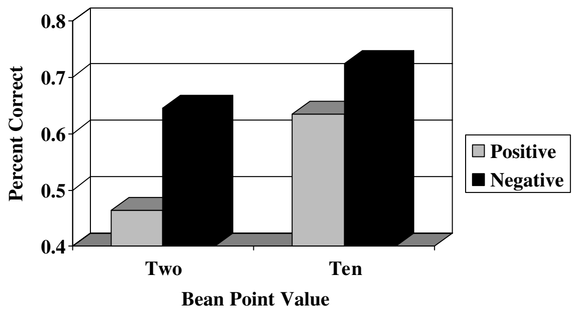

Fig. 2. Mean proportion of correct responses to game beans as a function of valence and extremity.

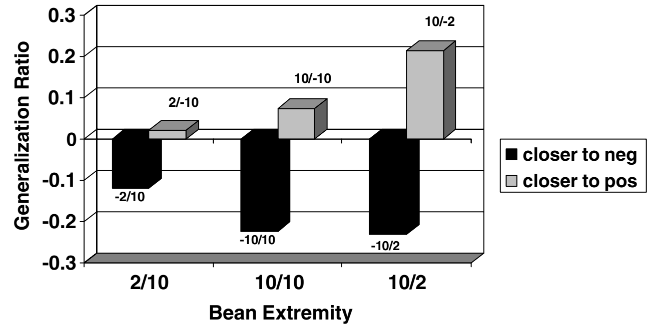

Fig. 3. Mean generalization ratio scores to novel beans as a function of similarity and extremity.

region; and r represents the mean response to the novel bean. The ratio term indexes the location of r within the range of p to n. The ratio was subtracted from .5 to ease interpretation. The variable then ranges from .5 to $-.5$ with positive numbers representing generalization to the positive region and negative numbers representing generalization to the negative region. Zero represents a lack of generalization to one region over the other; in other words, the novel bean has an average valence midway between the mean values of the nearest positive and the nearest negative region.

A 2 (similarity) $\times$ 3 (extremity) ANOVA was conducted on these generalization ratio scores. Similarity refers to whether the novel bean was more similar (or closer) to a positive or negative region and was determined by calculating the Euclidian distance between the novel bean and the closest game regions. These distances served as the basis for classifying novel beans as either closer to negative or closer to positive.[3] Extremity refers to the absolute value of the closest positive and closest negative regions to each novel bean. There are three combinations of regions between which each novel bean can be located (2/10, 10/2, 10/10) with the first number representing the closer of the two regions. Thus, together similarity and extremity provide the necessary information regarding the two closest game regions (+2/−10, −2/+10, −10/+10, +10/−10, −10/+2, +10/−2).

There was a similarity main effect, $F(1, 290) = 45.23$, $p < .001$. Novel beans that were closer to negative regions were assumed to be negative, $M = -.21$, and novel beans that were closer to positive regions were assumed to be positive, $M = .11$. The similarity main effect was qualified by a similarity $\times$ extremity interaction, $F(2, 290) = 3.89$, $p < .05$ (see Fig. 3). Understanding the nature of the interaction is most easily accomplished by considering the effect of proximity to a positive versus a negative region within each level of the extremity factor. For the novel beans that were located between two extreme regions (10/10), the results replicate Fazio et al.'s (2004) generalization findings. Novel beans located closer to a negative region were assumed to be negative, $M = -.23$, $t(73) = 6.74$, $p < .001$ (as compared to zero), and novel beans located closer to a positive region were assumed to be positive, $M = .07$, $t(73) = 1.72$, $p < .10$. However, the overall average ($M = -.08$) was significantly more negative than zero, $t(147) = 2.54$, $p < .05$, indicating that generalization of the negative attitudes was more substantial than generalization of the positive attitudes. Thus, the usual generalization asymmetry was present.

For novel beans that were more similar to a mild bean than an extreme bean (2/10), generalization as a function of similarity was greatly diminished. In fact, the responses to the novel beans closer to a mild positive region ($M = .02$) did not differ significantly from those closer to a mild negative region ($M = -.12$), $t(62) = 1.27$, $p = .21$. The latter beans (−2/+10) were only marginally likely to be categorized as negative, $M = -.12$, $t(31) = 1.64$, $p = .11$, and less so than had been observed in the earlier noted case of −10/+10 beans, $M = -.23$, $t(104) = 1.85$, $p < .07$. The former beans, those closer to a mild positive region, evidenced no indication of attitude generalization, $M = .02$, $t < 1$. Even though these beans more closely resembled a positive region, the beans were not more likely to be classified as positive than negative. In sum, this particular combination of greater proximity to a mild region than to a competing extreme region produced minimal generalization as a function of similarity.

For novel beans that were more similar to an extreme region than a mild region (10/2), there was yet another pattern of generalization. The novel beans closer to a negative extreme region (−10/+2) were classified negatively, $M = -.23$, $t(41) = 4.22$, $p < .001$, and to a similar extent

[3] Given the need to identify beans as more proximal to one region than another, the generalization analyses omitted the few equidistant beans ($n = 12$). The analyses were also restricted to beans that represented multiple levels of the extremity variable. That is, only beans located between a mild and extreme region in one pair of matrices and between two extreme regions in the other pair of matrices were included. For example, bean X1 by Y5 was always located between a mild and extreme region on all four matrices. Whereas, bean X3 by Y2 was located between two extreme regions on two matrices and a mild and extreme region on the other two matrices. Only beans of this latter sort provided a clean comparison of the effects of the extremity variation, unconfounded by the visual characteristics of specific beans. This criterion led to the omission of 15 additional beans. Thus, analyses of generalization were based on aggregated responses to each of 37 beans within each of the four matrix by two framing conditions, resulting in 296 observations.

as the novel beans located between two extreme regions (−10/+10), $t < 1$. The novel beans located closer to a positive extreme region (+10/−2) also exhibited significant generalization of the positive attitudes, $M = .21$, which not only differed significantly from zero, $t(41) = 4.09$, $p < .001$, but also was significantly more positive than the mean value of .07 that had been observed in the earlier noted case of +10/−10 beans, $t(114) = 2.05$, $p < .05$. Not only does this finding support the hypothesis that was advanced earlier, but it also represents the first instance in which substantial generalization of positive attitudes has been found. Thus, for this category of novel beans—those more similar to an extreme region than a mild region—generalization as a function of similarity was extensive and there was *no* generalization asymmetry.

Regression approach

In the interest of obtaining converging evidence for our central proposition that generalization is a function of more than sheer similarity, we pursued yet another approach to the data—one based solely on the observed responses to each bean and without reference to the extremity or valence of the game beans. For each novel bean, we noted the average response to its nearest neighboring region, as well as the average response to the second nearest, or competing, region and the Euclidean distance that separated the novel bean from this competitor.[4] These three variables, and their associated interaction terms, were entered in a hierarchical regression analysis predicting the average response to each novel bean. The main effects of both the nearest region and competing region were significant. However, the regression coefficient for the nearest region ($b = .74$), $t(292) = 11.22$, $p < .001$, was twice as large as that for the competing region ($b = .37$), $t(292) = 5.38$, $p < .001$. Thus, a strong similarity effect emerged; novel beans were more likely to be classified in accord with the beans that they most closely resembled. Also indicative of the influence of visual resemblance was a marginally significant interaction between the value of the nearest region and the distance of the competing region, $t(289) = 1.73$, $p < .09$. The weight assigned to the nearest variable increased as the distance from the competing region increased. Thus, the less similar the competitor, the greater the influence of the nearest region.

Most relevant to the hypothesis, however, was the significant interaction between the response to the nearest region and the response to the competing region, $t(289) = 2.08$, $p < .04$. Although the response to novel beans was generally related to the response to the nearest region, this relation was attenuated as the competing region was itself more negative in value (see Fig. 4). Thus, sheer similarity carried less weight as the competing region grew more negative.

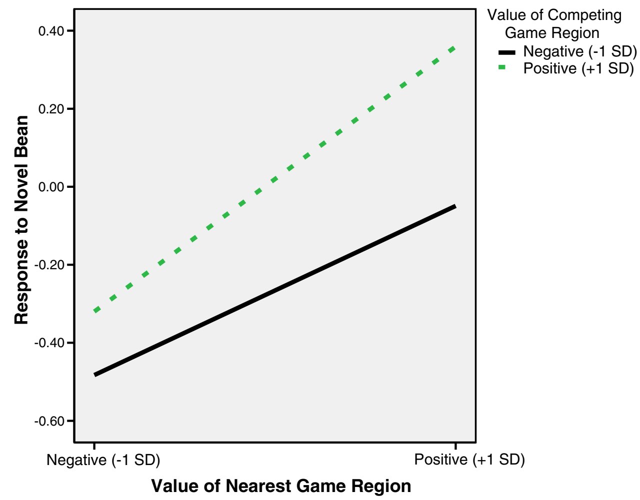

Fig. 4. Mean raw categorization of novel beans as a function of the value of the nearest region at values one standard deviation above and below the mean of the competing region.

Discussion

Although the beans in the present experiment included both mild and extreme values, the learning asymmetry observed in past research was replicated; negative beans were learned better than positive. However, this asymmetry was even stronger for beans with mild point values than extreme—an enhancement that is likely due to the influence of the regions proximal to the mild beans and the greater influence of extreme versus mild beans. The two regions that neighbored the mild positive region were both extremely negative; thus, beans with mild positive values were likely to be wrongly assumed to be negative. Hence, they were less likely to be sampled and their actual positivity revealed. In contrast, the mildly negative beans were neighbored by extremely positive beans and may have been wrongly assumed to be positive, which would encourage approach behavior and lead to discovery of the beans' negativity. Thus, these findings provide further corroboration for the fundamental asymmetry between approach and avoidance behavior that was highlighted by the original BeanFest research (Fazio et al., 2004). One learns only through approach. False presumptions that an object is positive are self-correcting because they encourage approach, but false beliefs that an object is negative are less likely to be disconfirmed because they encourage avoidance.

Attitude generalization was affected by similarity. Novel beans that more closely resembled particular game beans were generally assumed to have the same valence as the game beans. However, generalization of the positive versus negative and mild versus extreme attitudes was not of the same magnitude. When pitted against a competing region of extreme and opposite valence, mild attitudes did not generalize, even when the novel beans more closely resem-

[4] We did not consider the Euclidean distance from the nearest region because this distance assumed a value of 1 in 92% of the cases. In contrast, distance from the competing region was more variable, with only 24% of the cases assuming the minimum value of 2.

bled the mild. And, when the mild attitudes were associated with the more distant, competing region, they exerted little influence. In that case, generalization was substantially determined by resemblance to the more proximal, extreme region. When the two nearest neighboring regions were equivalent in extremity, generalization as a function of similarity was observed. However, a generalization asymmetry in favor of negative beans was evident.

These findings clearly indicate that attitude generalization is more complex than the sheer similarity of the novel object to the known entity. The valence and extremity of the attitude matter. Extremity had a substantial effect; resemblance to a mild bean mattered less than resemblance to an extreme bean. Moreover, more distant competing regions (ones that shared less resemblance to the novel bean than did the more proximal regions) were more influential, the more negative they were. Their negativity attenuated the extent to which the more similar objects dictated evaluative inferences about the novel objects.

Interestingly, however, the present research uncovered situations in which the generalization asymmetry was eliminated. When novel beans were located between a mild and extreme region, but closer to the mild region, no generalization asymmetry was found. Indeed, little or no generalization was observed as a function of similarity to a mild region. When the novel bean was closer to the extreme region, the generalization asymmetry also was eliminated. However, this was not due to a lack of generalization of the attitudes. Instead, the positive and negative extreme attitudes generalized to the same extent. The negative extreme attitudes generalized as they would if located between two extreme regions. The positive extreme attitudes, though, generalized to a greater extent than evidenced when novel beans were located between two extreme beans. In this case, the negative mild region did not exert a significant amount of countervailing influence to reduce the generalization of the extreme positive region. This constitutes further evidence that the mild regions were less influential in categorizing the novel beans. This also indicates, as predicted, that there are conditions under which resemblance to a known positive will prove more influential, and outweigh the influence of resemblance to a known negative on categorization of a novel object.

Based on these findings, in the beginning chocolate dilemma, categorization of the candy would depend not only on how similar it looked to the pictorial guide but also the extremity of any positive or negative attitudes held toward nougat and caramel. If either were viewed extremely negatively, the unknown chocolate bearing some resemblance to both possibilities would most likely be categorized negatively and avoided. However, if one was extremely liked while the other was only mildly disliked, the chocolate would most likely be categorized as the liked candy and sampled. Thus, categorization and the resulting behavior are not simply a function of similarity. The weighting of resemblance to a known positive versus a known negative and the extremity of the preexisting attitudes jointly affect attitude generalization, which ultimately determines whether a novel target is approached or avoided.

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