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THE EFFECTS OF ISOLATION, ENCODING STRENGTH AND FEATURE DISTINCTIVENESS ON RECOGNITION AND CATEGORIZATION

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Abstract

Previous research has shown that in recognition tasks, a distinctive feature can increase hit rates and decrease false alarm rates associated with an isolated item in a similarity space. However, this is inconsistent with the prediction of the global activation models, such as the Generalized Context Model. Since it is generally assumed that recognition and categorization operate under the same similarity-based generalization mechanism, a distinctive feature should also affect categorization judgments in a similar manner. However, the effects of feature distinctiveness on categorization has yet to be explored. For this reason, the present paper investigates the effects of feature distinctiveness on recognition and categorization, alongside with the effects of isolation and encoding strength. The results of the experiment suggest that the feature-based distinctiveness effect arises in categorization tasks in a way that is consistent with the mirror effect in recognition tasks. These findings bolster the line of literature that categorization and recognition operate under the same generalization mechanism.

THE EFFECTS OF ISOLATION, ENCODING STRENGTH AND FEATURE DISTINCTIVENESS ON RECOGNITION AND CATEGORIZATION

by

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Introduction

Categorization is a fundamental cognitive process of arranging objects into categories. It enables us to pick up an accidental apple from a bowl of oranges, tell whether your friend's car is a sedan or an SUV, and know the animal that you are petting is a dog, not a cat. In everyday life, we learn category labels of objects and use them to sort new objects into categories.

One of the leading models explaining categorization, as well as other cognitive processes (namely, identification and recognition), is the Generalized Context Model (GCM; Nosofsky, 1986, 1988, 1991). The main idea of the GCM is that identification, categorization, and perceptual old-new recognition judgments can be predicted by the match between a probe item[1] and memory traces in memory – in other words, exemplars (also see Anderson, 1973). In this paper, I primarily investigate whether the GCM can account for categorization judgments in the presence of distinctive features. While prior research has shown the limitations of the GCM in the context of perceptual old-new recognition (Busey & Tunnicliff, 1999; Nosofsky & Zaki, 2003; Zaki & Nosofsky, 2001), the effects of distinctive features on categorization has yet to be explored.

Memory and generalization are two fundamental properties of memory decisions such as categorization and recognition. Firstly, memory decisions require previously acquired information, which is generally referred to as *memory*. We know that the friendly tail-wagging animal is called a dog because we acquired information from past experience and stored it in memory. Secondly, we generalize our responses to stimuli based on the acquired memory. This

[1] An item that is to be identified, categorized or recognized.

process is called *generalization* – generating the same memory decision to similar but different stimuli.

Generalization plays a crucial role in memory decisions, especially for categorization. For example, if it were not for generalization, we would only be able to assign a category label to previously learned objects[2]. This is due to the fact that no two objects in this world are exactly the same. For instance, no apples look exactly the same. No dogs look the same even if they are the same breed. We would not even be able to understand alphabets written in different fonts unless we learn them individually (see Figure 1). Furthermore, generalization also provides a reliable account for memory errors in identification and perceptual old-new recognition.

Figure 1*. The Alphabet A in different fonts.* Generalization enables us to understand alphabets written in different fonts.

Generalization occurs based on similarities between objects. The more similar the objects are, the more likely they will lead to the same memory decisions. One of the theories of similarity that influenced many cognitive models is the metric-scaling approach (e.g., Shepard, 1958, 1987). In the metric-scaling approach, similarity is represented as a metric distance between two items. In this framework, a psychological similarity space is constructed geometrically such that each continuous dimension represents a feature of an object. Each object is allocated a point in the similarity space based on its dimensional feature values so that the distance between two points represents the dissimilarity between two objects.

The GCM is one of the cognitive models that adopts the metric-scaling approach. Specifically, in the GCM, each exemplar is represented as a point and scattered across the psychological similarity space based on its metric dimensional values. When a probe is

[2] Identification; Further information on identification will be discussed later in the introduction.

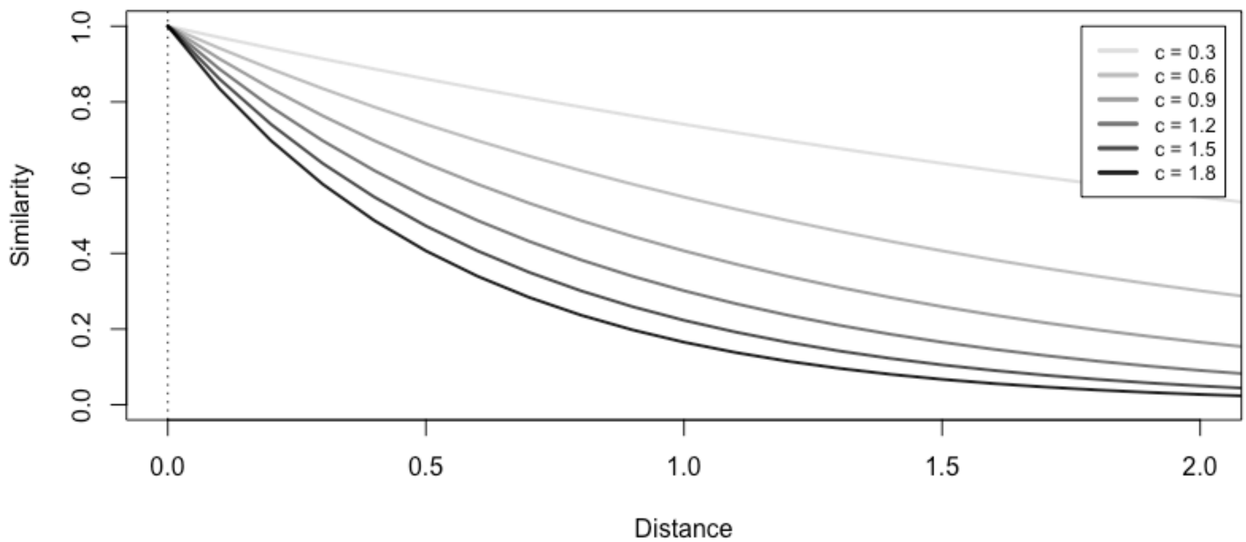

Figure 2. *Demonstration of the sensitivity parameter c.*

presented, the activation level of each exemplar is determined by the exemplar's similarity to the probe. The similarity is a decreasing function of metric distance and can be formulated as follows:

$$d_{ij} = \sum_{k=1}^{N} w_k \left| x_{ik} - x_{jk} \right| \quad (0 < w_k < 1, \sum w_k = 1) \tag{1a}$$

$$\eta_{ij} = e^{-cd_{ij}} \tag{1b}$$

where d_{ij} denotes the geometric distance between probe i and exemplar j, η_{ij} denotes the similarity between them, w_k denotes the attention weight on the k_{th} dimension, x denotes the dimensional value, and c is a specificity parameter. Note that it is assumed η_{ij} and η_{ji} are identical (symmetry axiom; see Tversky, 1977 for criticism) and η_{ii} has the maximum similarity value based on the metric-scaling approach of similarity. In other words, the similarity of, say, A to B and the similarity of B to A are the same (see Pothos et al., 2013 for examples) and matching an item with itself always generates maximum similarity (which is 1 in the GCM because e^0=1). The sensitivity parameter c can be considered as a generalization parameter in the sense that it distorts the contour map of the similarity space (Figure 2). Since the difference in similarity between two items becomes greater as the parameter value increases, the distinction between the items becomes clearer. Thus, a greater *c* parameter value will produce less overall generalization.

Identification is a process of finding the best-matching label that is unique to a probe. The difference between an identification judgment and a categorization judgment is that each item in identification tasks has its own label whereas items in categorization tasks share labels. For example, let us imagine several dogs in a park. Categorization is to know that they are dogs (shared label); identification is to notice that one of the dogs is your friend's dog, Max (individual label). The GCM assumes that the same underlying process of exemplar-based generalization operates in both identification and categorization paradigms (Nosofsky, 1986). According to the GCM, the identification judgment probability that stimulus i leads to response j is given by

$$P(R_J|S_i) = \frac{b_j \eta_{ij}}{\sum_{k=1}^{n} b_k \eta_{ik}} \tag{2}$$

where b parameters denote response biases that sum to 1. Similarly, categorization judgment can be formulated as

$$P(R_A|S_i) = \frac{\sum_{a \in A} M_a \eta_{ia}}{\sum_{a \in A} M_a \eta_{ia} + \sum_{b \in B} M_b \eta_{ib}} \tag{3}$$

where a denotes an exemplar in category A, b denotes an exemplar in category B, M denotes the memory strength of an item, and $P(R_A|S_i)$ denotes the probability of deciding whether stimuli i belongs to category A. Equation 3 can be further simplified as follows:

$$P(R_A|S_i) = \frac{Summed\ similarity\ of\ the\ probe\ i\ to\ cat.A}{Summed\ similarity\ of\ the\ probe\ i\ to\ cat.A\ +\ Summed\ similarity\ of\ the\ probe\ i\ to\ cat.B} \quad (4)$$

From the simplified equation above, it can be presumed that the more an item is similar to exemplars in category A, the more likely it will be classified as category A.

Besides identification and categorization, the GCM also predicts recognition judgments based on the metric-scaling similarity approach (Nosofsky, 1988, 1991). Unlike identification and categorization, the recognition model of the GCM does not require access to the activation of individual exemplars. Instead, overall activation of the exemplars caused by a probe, namely "familiarity," is used to model recognition judgments. The familiarity in the GCM is given by

$$F_i = \sum M_j\, \eta_{ij} \quad (5)$$

where *i* denotes the probe item, *j* denotes an index to the each of the exemplars in memory, and M_j denotes memory strength of each exemplar. The probability of the item *i* being recognized as being old is given by

$$P(Old|S_i) = \frac{F_i}{F_i + k} \quad (6)$$

where *k* denotes a response-criterion parameter (Clark, 1988; Estes, 1994; Nosofsky, 1992). Equation 6 implies that higher familiarity will make the probe more likely to be recognized as being old. To facilitate the understanding on this prediction, Equation 6 can be transformed into

$$P(Old|S_i) = \frac{F_i}{F_i + k} = \frac{F_i + k - k}{F_i + k} = 1 - \frac{k}{F_i + k}. \quad (7)$$

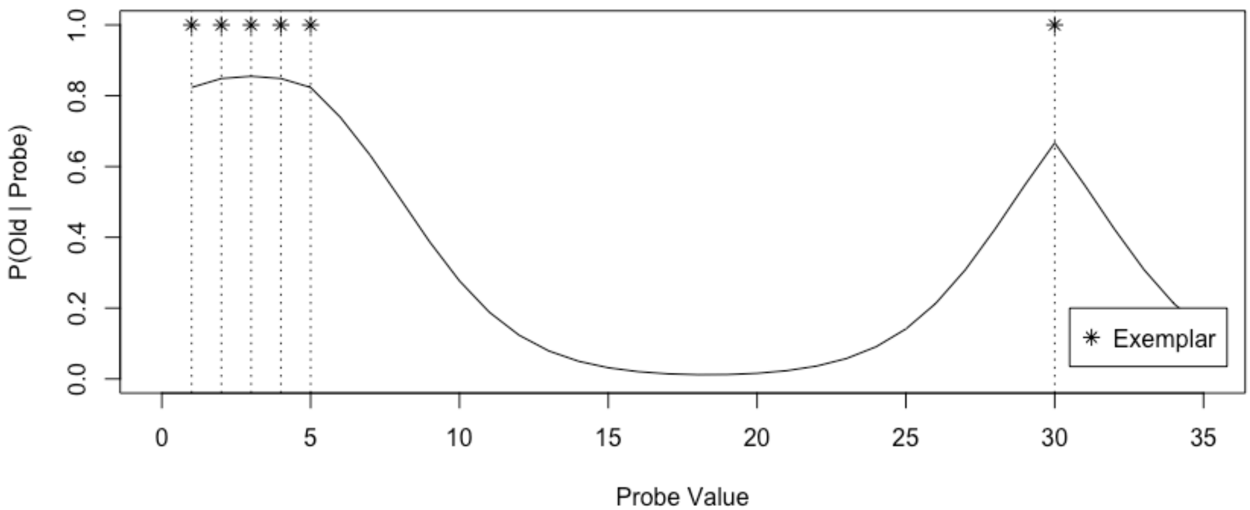

Figure 3. *Recognition probabilities for typical and isolated items. (k=0.5, c=0.5, M_i=1)*

As familiarity (F_i) increases, the denominator $F_i + k$ increases as well, which results in increasing the probability that the stimuli i would be recognized as old. That is, the greater the summed similarity of a probe to the exemplars in memory, the more likely the probe will be recognized as being old. Therefore, an item that is highly dissimilar to other items is less likely to be recognized as old. Figure 3 illustrates the recognition probability predictions for one dimensional stimuli when the exemplars consist of five similar items on the left (typical items) and one highly dissimilar item (isolated item) on the right side of the figure. Figure 3 suggests that a probe that is similar to the typical items are more likely to be recognized as old than a probe that is similar to the isolated item. Thus, both hit rates and false alarm rates that are associated with typical items should be higher than those that are associated with an isolated item.

Although an isolated item should less likely be recognized as being old compared to a typical item, sometimes the opposite is the case under certain circumstances – especially when the isolated item becomes "stronger" than all the typical items combined.[3] Although different models have different accounts for the nature of a stronger item, there is a lot of experimental

[3] Note that a stronger item in this study is operationalized as an item that has a higher hit rate.

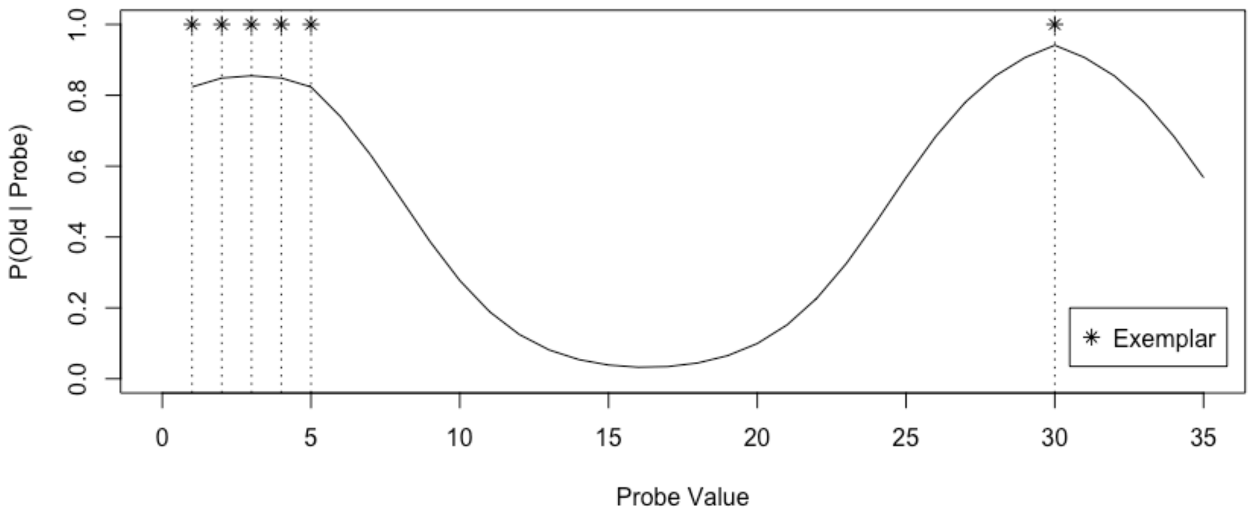

Figure 4. *Recognition probabilities for an isolated item with stronger memory (k=0.5, c=0.5, M_i=1, M_{30}=8)*

evidence that memory of an item is strengthened via extra study time or repeated presentation (see Murnane & Shiffrin, 1991b; Ratcliff et al., 1990). Mathematically, increasing memory strength for an exemplar in the GCM is equivalent to adding more copies of the exemplar to the memory because:

$$F_i = \sum M_j \eta_{ij} = \eta_{i1} + \eta_{i2} + \eta_{i3} + \eta_{i4} + \eta_{i5} + 8 \times \boldsymbol{\eta_{i30}}$$
$$= \eta_{i1} + \eta_{i2} + \eta_{i3} + \eta_{i4} + \eta_{i5} + \boldsymbol{\eta_{i30}} + \boldsymbol{\eta_{i30}} + \boldsymbol{\eta_{i30}} + \boldsymbol{\eta_{i30}} + \boldsymbol{\eta_{i30}} + \boldsymbol{\eta_{i30}} + \boldsymbol{\eta_{i30}} + \boldsymbol{\eta_{i30}} \quad (8)$$

when the memory strength of the isolated item is strengthened by, say, 8 times. Hence, the isolated item is no longer isolated because the number of isolated items in memory exceeds the number of typical items (∵ 8 > 5). As illustrated in Figure 4, the GCM predicts that a probe that is similar to the isolated item with greater memory strength is more likely to be recognized as old than is a probe that is similar to typical items. This finding is consistent with the predictions of other models of recognition such as the Search of Associative Memory model (SAM; Gillund & Shiffrin, 1984; Raaijmakers & Shiffrin, 1981) in the sense that repetitions of an item are accumulated together into a single stronger memory trace (Ratcliff et al., 1990; Murnane & Shiffrin, 1991b).

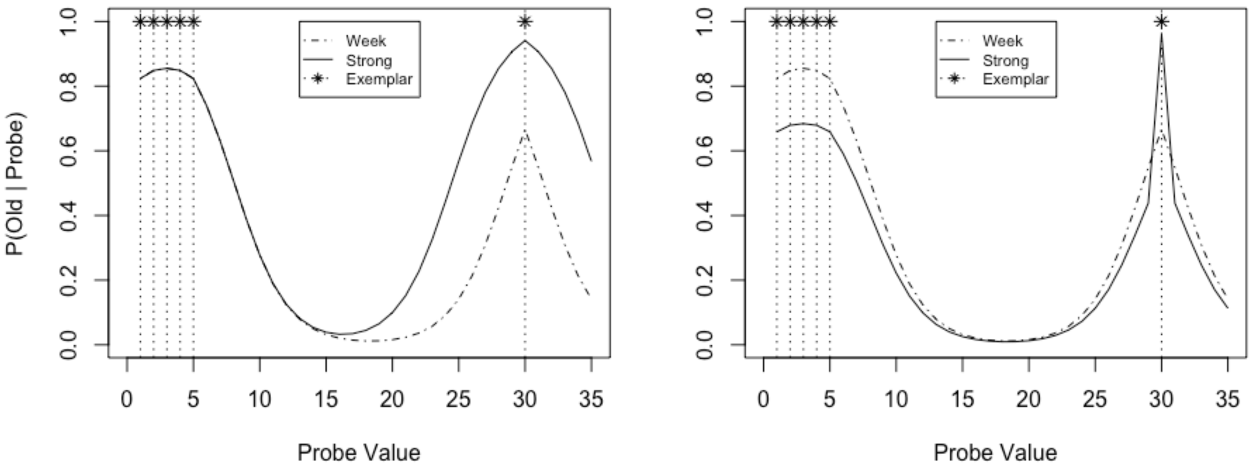

Figure 5. *Two conflicting effects of a stronger item in memory*

In brief, according to the GCM, hit rates and false alarm rates that are associated with an isolated item should be lower than those of typical items unless the isolated item is strengthened to overpower the summed similarity of the typical items (the left panel of Figure 5). However, it has been empirically shown that sometimes an isolated item can elicit higher hit rates and lower false alarm rates than those of typical items (the right panel of Figure 5), especially in face recognition experiments (Bartlett, Hurry, & Thorley, 1984; Busey & Tunnicliff, 1999; Light, Kayra-Stuart, & Hollander, 1979; Valentine and Ferrara, 1991; Vokey & Read, 1992). According to Busey and Tunnicliff (1999), a face that is isolated in the similarity space elicited higher hit rates and lower false rates than that of typical faces. This result poses a fundamental challenge to global activation models such as the GCM because an isolated item should not have a higher hit rate than that of typical items when there is little reason to believe the item is strengthened. Furthermore, even if the item was strengthened, global activation models have no built-in mechanisms to account for the opposite trend of hit rates and false alarm rates, which is sometimes referred to as *the mirror effect*.

Busey and Tunnicliff (1999) suggested that it might be a distinctive facial feature (such as facial hair) that caused the mirror effect in face recognition experiments. In concordance with their presumption, Nosofsky and Zaki (2003) found that an isolated item itself could not elicit the mirror effect in recognition tasks unless it had a distinctive feature in it. This result suggests that distinctive features, such as beards and mustaches, not only make an item isolated in a similarity space, but also make the item more recognizable. They proposed a modified version of the GCM to account for the advantage of feature distinctiveness by incorporating a feature-contrast mechanism (Tversky, 1977). The details of the model are reserved for the discussion section.

Since the same underlying mechanisms of generalization operate for recognition and categorization judgments in the GCM, a distinctive feature may also affect categorization judgments in a similar fashion. However, the effects of feature distinctiveness on categorization has not been extensively studied. For this reason, the primary goal of this paper is to simultaneously investigate the effects of distinctive features on recognition and categorization. Specifically, this study strengthens the isolated item by either increasing the encoding strength of the item or by increasing feature distinctiveness by adding a distinctive feature to the item. It was hypothesized that when strengthened by greater encoding strength, an isolated item should not give rise to the distinctiveness effect in both the recognition and categorization tasks such that the GCM should successfully predict the results. On the other hand, the distinctiveness effect should arise for both memory judgments when an isolated item is strengthened by adding a distinctive feature, and the GCM will fail to predict the result. Note that in this paper the *distinctiveness effect* incorporates the mirror effect and is defined as a phenomenon in which a stronger memory elicits weaker generalization than it is supposed to.

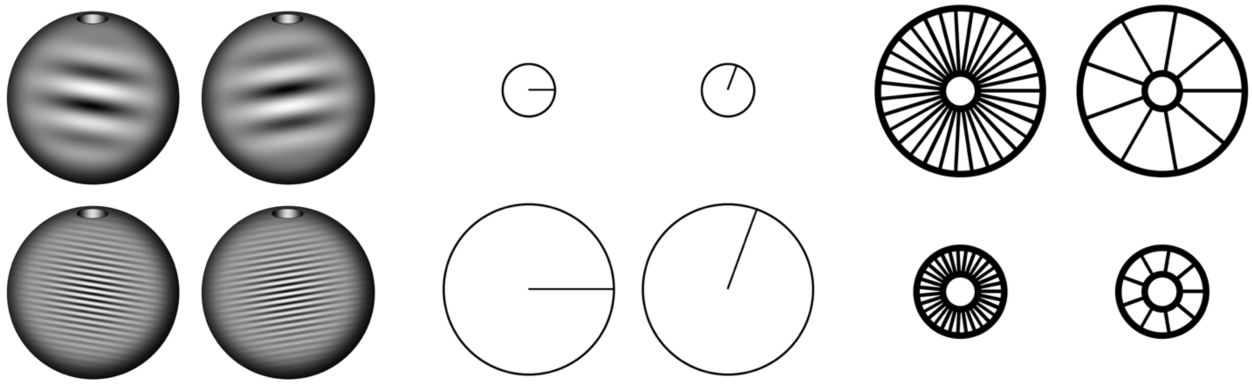

Figure 6*. Illustration of the four stimuli from each stimulus set that represent the four corners of the similarity space.*

Method

The experiment in the present research is a within-subjects design with three conditions: the *isolation*, *repetition* and *feature* conditions. The names of the conditions indicate how the isolated study item is manipulated in the experiment. The *isolation condition* serves a role as the control condition in which an item is simply isolated in the similarity space without strengthening. The isolated item in this condition should elicit lower hit rates and false alarm rates than that of typical items. Also, the probability of the item being categorized into its category should be lower than that of the typical items. In the *repetition condition*, an isolated item is presented repeatedly (5 times) to increase the encoding strength of the item. If the number of repetition is equal to or greater than the number of typical items, hit rates and false alarm rates that are associated with the repeated item should exceed those of the typical items. The categorization performance should be enhanced for the repeated item and more generalization should occur towards the nearby items. The *feature condition* has the same structure as the isolation condition, but an isolated item in the feature condition is presented with a distinctive

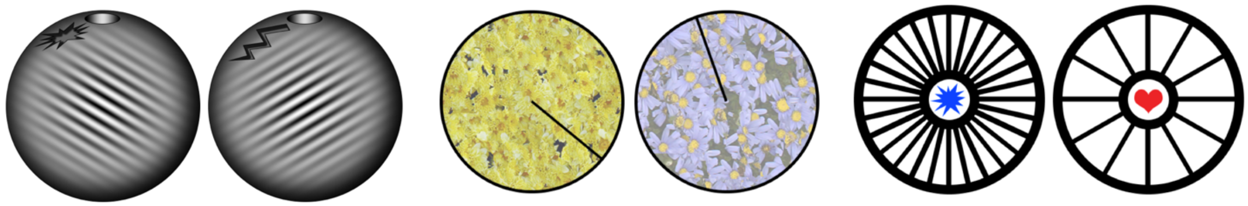

Figure 7. *Illustration of the stimuli with a distinctive feature on them.*

feature superimposed on them. It is predicted that the distinctive feature will result in the feature-based mirror effect in this condition. While the categorization probability should be enhanced for the featured item, drastic reduction in generalization around the item is expected to be observed.

Subjects

All 300 participants in this study were recruited from Syracuse University via SONA systems. They received partial course credit toward an introductory psychology course. The consent form along with demographic information (age and gender) were filled out electronically. The subjects completed all three conditions in a random order.

Stimuli

Three types of stimuli were randomly assigned to one of the three conditions without replacement. The types of stimuli used in the experiment are a) *Gabor patch beads*, b) *Shepard circles*, and c) *Wagon wheels* (see Figure 6). All the stimulus sets have two continuous dimensions and each of the dimensions is represented by a vector of 23 evenly spaced values. The total number of the stimuli in each stimulus set is therefore 529 (= 23^2). Each of the stimulus sets has two distinctive features that were randomly assigned to the categories within the stimulus set (see Figure 7).

The stimuli were generated in advance of the experiment and individually saved as 400 pixels by 400 pixels image files. The monitors that were used to display the stimuli were 23.6-inch monitors with 1920 x 1080 resolution (model: ASUS VS247-H-P). The actual size of the stimuli on the monitors varied from 65mm to 109mm in diameter depending on the types and dimensional values of the stimuli.

Design

In all conditions, a two-dimensional similarity space is divided diagonally into two regions and category labels A and B are randomly assigned to the regions. The reason that a diagonal line is used to divide the space is because if a horizontal or vertical line divided the space, only one stimulus dimension would be responsible for categorization. Each of the categories is once again divided into two regions, *dense* and *sparse*. Figure 8 illustrates the structure of the similarity space and the locations of the items. From each category, five study items are drawn from a dense region whereas only one study item is drawn from a sparse region. The test items included four new items from each region and all of the study items. In addition to the items in dense and sparse regions, there are two more types of items in the similarity space. *Intermediate* items lie between a dense and a spare region within a category, whereas *border* items lie between a dense and a sparse region of different categories. Since border items are placed on the category border, they are not assigned a category label. The overall structure of the experiment is summarized in Table 1.

Table 1. *The number of items by region and type.*

<table>
<tr><th>Region</th><th>Item Type</th><th>Category A</th><th>Category B</th></tr>
<tr><td rowspan="2">Dense region</td><td>Old</td><td>5</td><td>5</td></tr>
<tr><td>New</td><td>4</td><td>4</td></tr>
<tr><td rowspan="2">Sparse region</td><td>Old</td><td>1*</td><td>1*</td></tr>
<tr><td>New</td><td>4</td><td>4</td></tr>
<tr><td>Intermediate</td><td>New</td><td>2</td><td>2</td></tr>
<tr><td>Border</td><td>New</td><td colspan="2">4</td></tr>
</table>

Note: The old items in the sparse region are repeated 5 times in the repetition condition such that there are the same number of items from the dense and sparse regions. In the feature condition, these items are presented with distinctive feature superimposed on them. Two types of distinctive features are randomly assigned to the categories.

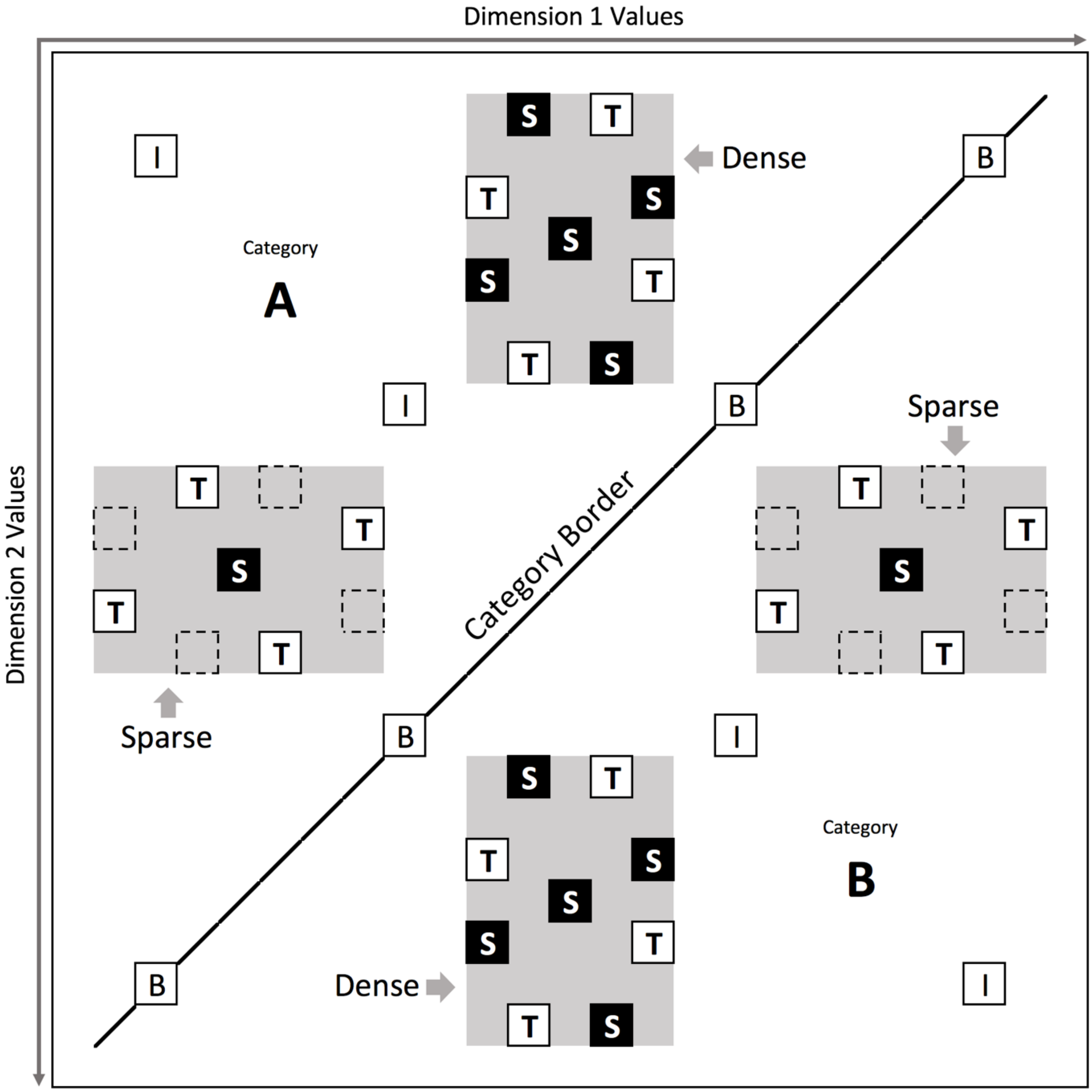

__Figure 8.__ The structure of the similarity space. The black boxes represent study items and the white boxes represent test items. All the study items are presented at tests. The boxes with a dotted outline are not presented in the study and test phase. S: study items; T: test items; I: intermediate items; B: border items.

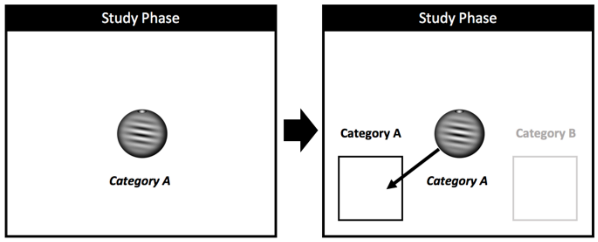

Figure 9a. *Illustration of the study phase*

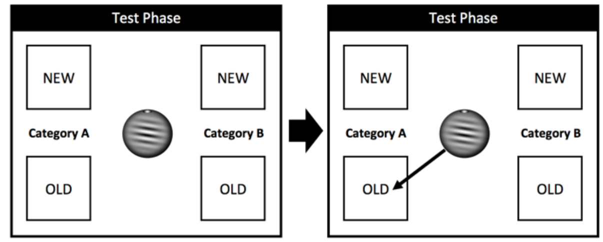

Figure 9b. *Illustration of the test phase*

Procedure

In the study phase, participants were asked to memorize 12 study items and their categories. The study items were randomly presented in the center of the screen with their category labels simultaneously presented below them. Each stimulus and its label remained on the computer screen for 5 seconds until two category slots appeared next to it. (See Figure 9a). Participants were asked to drag the stimulus to the correct category slot to move on to the next stimulus. The incorrect category slot was grayed out and inactivated to prevent confusion. The trials were separated by a one-second pause, during which the screen remained blank.

In the test phase, participants were asked to make recognition and categorization judgments on 12 studied items and 24 unstudied items (see Table 1). The recognition and category judgments were made simultaneously by dragging the probe item to one of the four slots located at the corners of the screen, as illustrated in Figure 9b.

Results

Statistical Analysis

Bayesian hierarchical modeling, specifically a method that was suggested by Kruschke (2013), was used to compare response probabilities between groups. Using this method, the model estimates three parameters through Bayesian inference: the mean, standard deviation, and

Table 2. *Mean recognition probability by region and condition*

Region	Item Type	Isolation	Repetition	Feature
Dense region	Old	0.68	0.67	0.70
	New	0.68	0.66	0.71
Sparse region	Old	0.61	0.76	0.88
	New	0.50	0.65	0.44
Intermediate	New	0.49	0.54	0.46
Border	New	0.48	0.49	0.43

Note: When calculating the recognition mean probabilities, the category information was removed since there was no category level difference observed in the data.

normality of the data. This method is the Bayesian equivalent of a paired sample t-test in the sense that it provides a way to test a null hypothesis concerning pairwise comparisons between two groups. In the current application, the null hypothesis is that the mean difference between the two groups is zero. Since Kruschke's model yields a distribution of each of the parameters, not a single value, it is practical to have a small range of parameter values that are considered to be equivalent to the null value. This small range of parameter values is called the *region of practical equivalence* (ROPE). The range of the ROPE can vary depending on the purpose of the application. In the current study, the ROPE is set to 5% (-0.025, 0.025). The null is accepted if 95% high density interval (HDI) of a parameter distribution lies within the ROPE. If 95% HDI and the ROPE do not overlap, the null is rejected. In all other cases, the null cannot be accepted or rejected, meaning the dataset does not provide sufficient proof to make a decision.

Recognition. The mean recognition probabilities (Table 2) by region and condition were calculated to get an overview of the recognition data. The general pattern of the recognition data in Table 2 shows that the hit rates and false alarm rates in dense regions are very similar to one

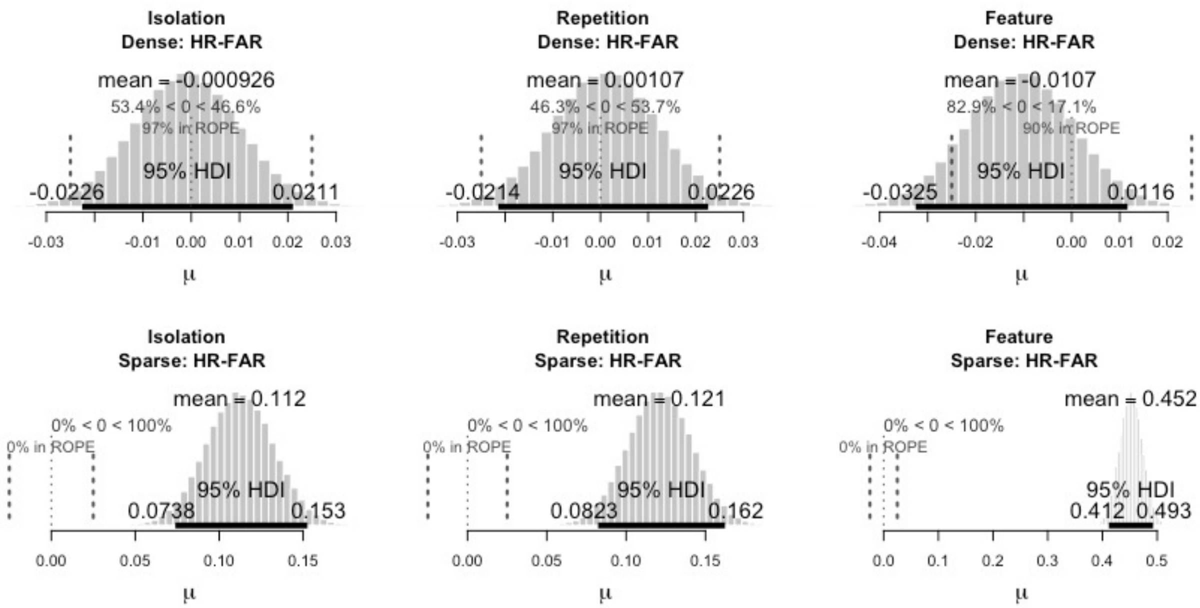

Figure 10. *Difference between hit rates and false alarm rate within region*

another while there are noticeable differences between them in sparse regions. Indeed, analyses reveal that none of the differences between the hit rates and false alarm rates within the dense regions are credible, in all conditions (Figure 10, upper panel). These results suggest that there are relatively small generalization gradients around the typical items in all three conditions regardless of the experimental manipulation. On the other hand, there are credible differences observed between the hit rates and false alarms within the sparse regions in all three conditions (Figure 10, lower panel). While the estimated mean differences in the isolation condition and the repetition condition are very similar in value (0.112 and 0.121 respectively), the mean difference in the feature condition is greater than the other two conditions (0.452). This may be indicative of the feature-based mirror effect occurring in the feature condition, which is absent in the repetition condition.

To confirm the existence of the mirror effect in the feature condition, all of the following four criteria should be met: a) in feature condition, the hit rate for the sparse region should be

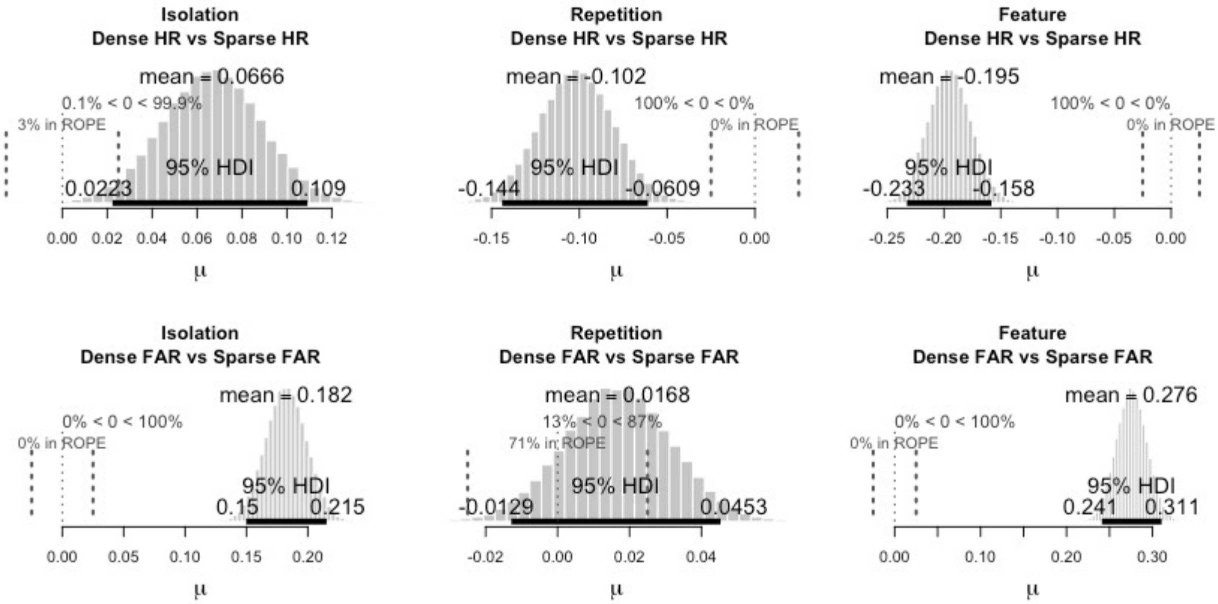

Figure 11*. Difference in HRs and FARs between dense region and sparse region by condition*

higher than that for the dense region; b) the false alarm rate for the sparse region in feature condition should be lower than that in the isolation condition; c) the hit rate for the sparse region in feature condition should be higher than that in the isolation condition; and d) the false alarm rate for the sparse region in feature should be lower than that of the isolation condition. Firstly, hit rates and false alarm rates were compared between regions within each condition. As reported in Figure 11, the hit rate for the sparse region is credibly higher than that of the dense region in both the repetition and feature condition. On the other hand, the repetition and feature conditions show opposite trends in the case of false alarm rates. While the false alarm rate for the sparse region is credibly greater than the dense region in the feature condition, the difference between false alarm rates in the repetition condition is small (0.0168) and undetermined. Secondly, the isolation condition was compared to the repetition and feature conditions for between-condition comparisons. As Figure 12 suggests, there were no credible differences between dense regions across conditions, whereas all of the sparse region comparisons show credible differences.

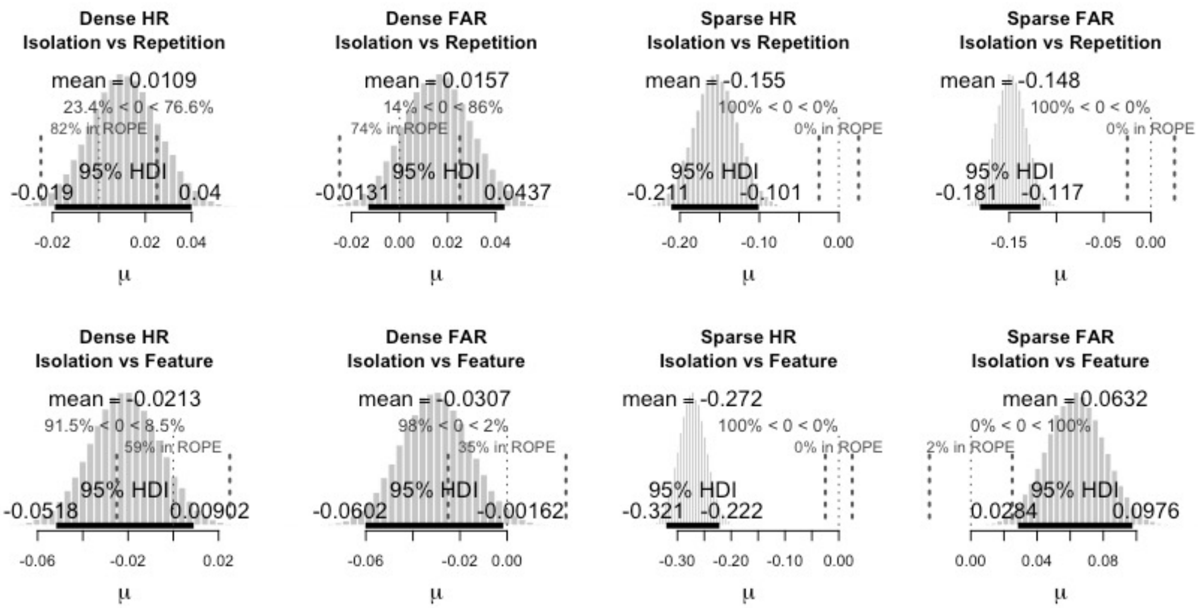

Figure 12. *Difference in HRs and FARs between conditions by regions*

Specifically, the hit rates for sparse regions in both the repetition and feature conditions are higher than that of the isolated condition; on the contrary, the false alarm rates for the sparse regions increase in the repetition condition, but decrease in the feature condition.

In brief, the results suggest that the mirror effect is observed in the feature condition. Although both repetition and an addition of a distinctive feature make an item stronger in terms of hit rates, it turns out only a featured item can elicit the mirror effect. That is to say, the repeated and featured items prompt opposite trends in the case of false alarm rates, as predicted by the hypothesis. In the repetition condition, the false alarm rates for the sparse region is higher than that of the isolation condition. As a result, the difference in false alarm rates between the sparse region and dense region becomes smaller in the repetition condition. In contrast, in the feature condition, the false alarm rate for sparse region is credibly lower than that of the dense region. Furthermore, it is also credibly lower than the false alarm rate for the sparse region in the isolation condition.

__Table 3__. Within-category mean categorization probabilities of $P(R_A|S_A)$ and $P(R_B|S_B)$.

Region	Item Type	Isolation	Repetition	Feature
Dense Region	Old	0.81	0.70	0.78
	New	0.81	0.71	0.79
Intermediate	New	0.77	0.76	0.75
Sparse Region	New	0.54	0.72	0.56
	Old	0.57	0.69	0.86

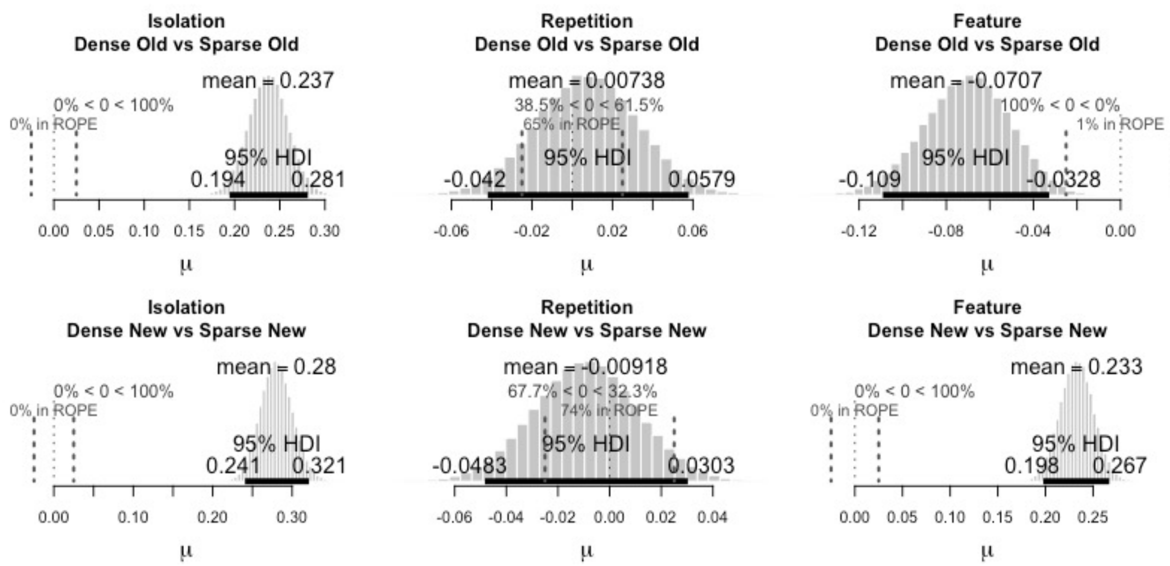

__Figure 13__. Difference in categorization probabilities between dense region and sparse region.

Categorization. The mean categorization probabilities by region and condition are reported in Table 3 to provide an overview of the categorization data. Firstly, the mean difference between dense and sparse region is estimated by item type and condition. As reported in Figure 13, in the isolation condition, the categorization probabilities for the dense region credibly exceed those for the sparse region for both old and new items. However, in the repetition condition, the difference between the dense and sparse region is no longer credible. In

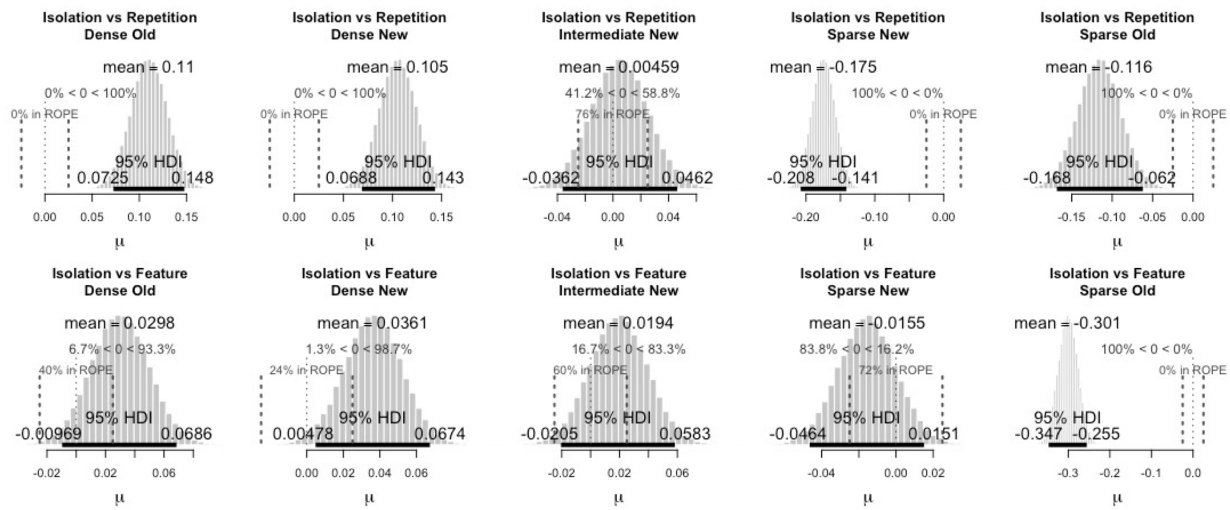

Figure 14. *Categorization probabilities comparison between conditions.*

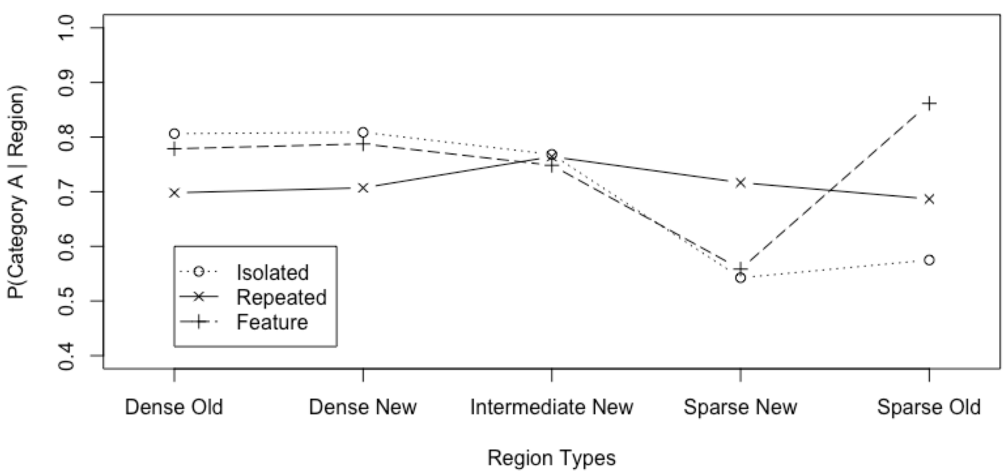

Figure 15*. Within-category mean categorizatino probabilities*

the feature condition, the featured item elicits a credibly greater categorization probability than the dense old items, whereas the dense new items have a higher categorization probability than the sparse new items.

For between-condition comparisons, all of the item types in the isolation condition are compared to those in repetition and feature conditions. The analyses reveal that the categorization probabilities for the dense region in the repetition condition are credibly lower than the isolation condition, while the probabilities for the sparse region are credibly higher

(Figure 14, upper panel). In contrast, the feature condition has a very similar pattern to the isolation condition except for the sparse old item, namely, the featured item (Figure 14, lower panel). In the comparison between the isolation and feature conditions, only the featured item shows credibly higher probabilities than the isolation condition. As illustrated in Figure 15, the overall pattern of the data suggests that the isolation condition and feature condition have very similar probabilities for all types of items except the sparse old items. The featured item has a probability of 0.86, which is much greater than that for the dense region.

Theoretical Analysis

The main focus of the theoretical analysis is to test if the GCM can account for the results of the three experimental conditions. The GCM should be able to provide a good account for the repetition condition as well as the isolation condition if the memory strength of the repeated item is allowed to vary. On the contrary, the GCM should fail to provide a good account for the feature condition, because merely increasing the memory strength of the featured item will not result in selective performance enhancement for the featured item.

The GCM was separately fit to recognition and categorization data because estimated shared parameter values (specificity and memory strength) from the two tasks may not be directly comparable. The reason is that the version of the GCM used in this study captures the determinacy of responses by adjusting other parameters. For example, if participants have a tendency to make category judgments more determinately than the categorization probabilities predict, the GCM will capture this tendency by increasing the specificity parameter. Later versions of the GCM incorporate the response scaling parameter, *gamma,* to capture this tendency. The gamma parameter scales the response probabilities by raising each of the summed similarities to the power gamma. This way, the model can provide an account for determinacy of the responses without impacting other parameters.

The response data were organized into 12 subgroups by region, recognition, and category label (see Figure 16). Note that the border items are labeled after the category label of the closest dense region for the ease of analyses. The parameters that minimize the log-likelihood discrepancy (G^2) between the aggregated data in each subgroup and corresponding GCM prediction were identified. The specificity parameter (c) and dimensional attention parameter (w) were constrained to be equal in all three conditions since there is no reason for these parameters to vary across conditions. Note, however, that the parameters *c and w* were separately estimated for recognition and categorization. While the old/new bias parameter for recognition (k) was freely estimated, the category label bias parameter for categorization (b) was fixed at 0.5. This is because the category labels were randomized for each participant to minimize category bias; however, randomization should not affect the old/new bias. The memory strengths for the manipulated items (repeated and featured items) were estimated separately across conditions to test if the changes in response probabilities caused by the manipulations can be explained by merely varying memory strength for the items. The memory strength for the isolated item in the isolation condition was set to 1 as all the other non-manipulated items since no items were strengthened during the study phase.

As illustrated in top and middle panels of Figure 16, the GCM provides good accounts for the isolation and repetition conditions in both recognition ($c=0.3941$, $w=0.4900$, $k=1.2583$, $m_{iso}=1$, $m_{rep}= 3.1726$, $m_{feat}=1.4899$) and categorization ($c=0.2106$, $w=0.4900$, $m_{iso}=1$, $m_{rep}=4.8517$, $m_{feat}=1.4321$). However, as hypothesized, the GCM cannot successfully fit either the recognition or categorization data for the feature condition. Specifically, the model fails to

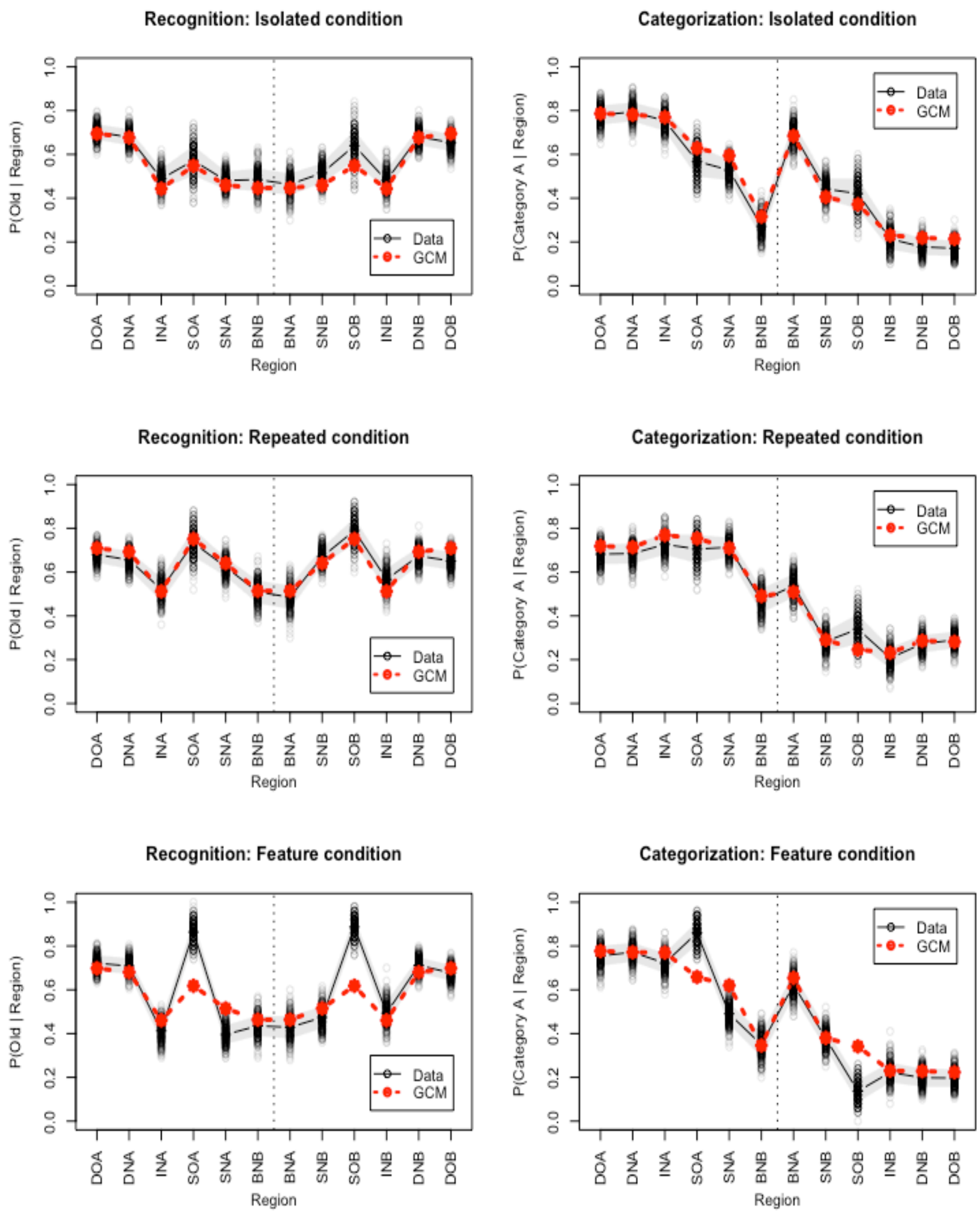

Figure 16. *The GCM fit to recognition and categorization data.*

Note: The labels on the *x* axis are named after the following rule:
Region (***D***ense, ***S***parse, ***I***ntermediate, ***B***order) / Old or New (***O***ld, ***N***ew) / Category (***A***, ***B***)

predict the enhanced recognition and categorization probabilities for the featured item. That is, merely increasing the memory strength of the featured item is not enough to account for the distinctiveness effect emerging in the feature condition. Theoretically, if the memory strengths of the items near the featured item were to decrease, the GCM should be able to provide a good prediction for the feature condition. However, in the current paradigm, there is little reason to believe the featured item would harm the memory strengths of other items. In conclusion, the GCM was able to provide a good account for the enhaced response probabities caused by increased encoding strength, while it fails to predict the selectively enhanced response probabilities caused by feature distinctiveness.

Discussion

According to the global activation models such as the GCM, typical items are more likely to be recognized as old than an isolated item. However, under certain circumstances, it is more likely for an isolated item to be recognized than typical items. For example, when the memory strength of an isolated item is strengthened (e.g. via repetition) its recognition probability can exceed that of typical items. In this case, the false alarm rates that are associated with the isolated item should also increase as the hit rate increases, in theory. That is, an isolated item that has been strengthened should elicit stronger generalization towards nearby items such that the item in question induces the same response for a wider range of items. Although much experimental evidence supports this prediction, some studies have shown that a higher hit rate can be accompanied by a lower false alarm rate for an isolated item.

Nosofsky and Zaki (2003) addressed this issue of the mirror effect in the context of the feature distinctiveness. They found that an isolated item itself cannot give a rise to the mirror effect unless it has a distinctive feature. The present study could successfully reproduce these findings. Firstly, as the GCM predicts, the items in the dense region have higher hit rates and false alarm rates than those of the items in the sparse region. Secondly, the differences between the two regions are no longer credible in the repetition condition, which is also consistent with the prediction of the GCM. Lastly, in the feature condition, the hit rates and false alarm rates in the sparse region are credibly higher and lower, respectively, than those of the dense region.

Given that recognition and categorization judgments are based on the same generalization mechanism in the GCM framework, a distinctive feature should also affect categorization judgments in a similar manner. As the nature of the mirror effect can be characterized by the discrimination between similar items,[4] the present study expected that a distinctive feature would have a much higher categorization probability than that of a nearby transfer item. Indeed, the results of the experiment suggest that the distinctiveness effect arises only in the feature condition. That is, the GCM provides a good account for the isolation and repetition conditions. However, in the feature condition, the difference between the categorization probabilities for the study item (0.86) and transfer items (0.56) is much greater than those in the isolation and repetition conditions. As reported in the model fitting results (Figure 16, bottom right panel), the GCM fails to provide a good account for the big difference between categorization probabilities for the items in the sparse region of the feature condition.

Conceivably, the most direct way to produce the distinctiveness effect is to boost the summed similarity of the target items and reduce the summed similarity of the foil (transfer) items. However, it is not possible to increase the self-matching similarity of a target item because the self-matching similarity is always the maximum value in the metric-scaling approach. This suggests that it requires more than metric similarity to achieve a higher hit rate for the target

[4] Note that discrimination is an antonym of generalization.

item. The only variable that can serve a role as "the similarity booster" in the frame of the traditional GCM is memory strength (see Equation 5). This is because memory strength and metric similarity are multiplicative in the familiarity function. If memory strength for each of the study items varied, the higher hit rate for the featured item could be explained by the featured exemplar with greater memory strength. Likewise, the lower false alarm rates could be explained by the reduction in summed similarity caused by smaller memory strength.

It may be possible for a feature to increase the encoding strength of a featured item. However, there is little reason to believe a featured item could weaken the encoding strength of items that are similar to the featured item during the study phase. For this reason, Nosofsky and Zaki (2003) suggested a hybrid similarity account of the phenomenon, instead of the varying memory strength account. They incorporated the Feature-Contrast model (Tversky, 1977) in the GCM's similarity function. The hybrid-similarity function is given by

$$H_{ij} = C \times D \times \eta_{ij} \qquad (C > 1, 0 < D < 1) \tag{9}$$

where C denotes the boost in similarity provided by having a matching feature, D denotes the reduction in similarity caused by a mismatching feature, and η_{ij} denotes the metric similarity calculated from Equation 1. By breaking the self-similarity constraint, the hybrid model boosts the self-similarity of a featured item and decreases the similarity of the featured item to other items in memory.

To sum up, the hybrid-similarity GCM provides an account for the feature-based mirror effect in recognition tasks by incorporating similarity boost/reduction caused by a distinctive feature: increased recognition accuracy for an old featured item is due to the boost in self-matching similarity caused by a matching feature. The model also argues that the seemingly drastic decrease in generalization caused by a featured item is, in fact, due to the underestimated similarity between the featured item and nearby non-featured items. That is, the mirror effect is not an exception to the law of generalization. Since the results of the present study suggest that a distinctive feature affects categorization judgment in a way that is consistent with the mirror effect in recognition, the hybrid-similarity model should be able to account for the categorization data obtained from this experiment.

Future analyses should test the hybrid-similarity GCM model under the current experimental design to confirm its accountability for both recognition and categorization judgments. Previous research testing the hybrid-similarity GCM had some limitations such as stimulus regions that had its own similarity space and an arbitrarily small between-region similarity (0.01). The strength of the current experiment is that all the regions are constructed on the same similarity space, which makes the interaction between the items more complicated. It would be interesting to see if the hybrid-similarity GCM would be able to account for recognition and categorization in a more stringent setup.

Furthermore, the effects of foils with a distinctive feature on categorization should also be examined to test the model's accountability for categorization judgments. Prior research has been shown that when a feature is present on the foils around the featured item, the mirror effect disappears in recognition tasks (Nosofsky & Zaki, 2003). However, such effects of distinctive foils on categorization have not been rigorously examined. According to the hybrid-similarity GCM, the featured item should elicit greater generalization towards foils with a matching distinctive feature, eliminating the distinctiveness effect. If this is not the case, an alternative approach – other than the hybrid-similarity approach – might be needed in order to provide a unified account for the distinctiveness effect in both recognition and categorization.

References

Anderson, J. A. (1973). A theory for the recognition of items from short memorized lists. *Pscyhological Review, 80(6)*, 417-438.

Bartlett, J. C., Hurry, S., & Thorley, W. (1984). Typicality and familiarity of faces. *Memory & Cognition, 12,* 219-228.

Busey, T. A., & Tunnicliff, J. L. (1999). Accounts of blending, distinctiveness, and typicality in the false recognition of faces. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 25,* 1210-1235.

Cohen, H., & Lefebvre, C. (2005). *Handbook of categorization in cognitive science*. Amsterdam, Netherlands: Elsevier.

Criss, A. H. & Howard, M. (2015). Models of episodic memory. In J. Busemeyer, J. T. Townsend, Z. Wang, & A. Eidels (Eds.) *Oxford handbook of computational and mathematical psychology*. Cambridge, UK: Oxford University Press.

Denton, S. E., Kruschke, J. K., & Erickson, M. A. (2008). Rule-based extrapolation: A continuing challenge for exemplar models. *Psychonomic Bulletin &* Review, 15, 780-786.

Erickson, M. A., & Kruschke, J. K. (1998). Rules and exemplars in category learning. *Journal of Experimental Psychology:* General, 127, 107-140.

Estes, W. K. (1994). *Classification and cognition.* New York, NY: Oxford University Press.

Gillund, G., & Shiffrin, R M. (1984). A retrieval model for both recognition and recall. *Psychological Review,* 91, 1-65.

Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Review, 99,* 22-44.

Kruschke, J. K. & Erickson, M. A. (1994). Learning of rules that have high-frequency exceptions: New empirical data and a hybrid connectionist model. In A. Ram & K. Eiselt (Eds.) *Proceedings of the sixteenth annual conference of the cognitive science society* (pp.514-519). Hillsdale, NJ: Erlbaum.

Lee, K. J., Byatt, G., & Rhodes, G. (2000). Caricature effects, distinctiveness, and identification: Testing the face–space framework. *Psychological Science, 11,* 379-385.

Light, L. L, Kayra-Stuart, F., & Hollander, S. (1979). Recognition memory for typical and unusual faces. *Journal of Experimental Psychology: Human Learning and Memory, 5,* 212–228.

Lockhead, G. R. (1970). Identification and the form of multidimensional discrimination space. *Journal of Experimental Psychology, 85,* 1-10.

Murdock, B. B., Jr. (1982). A theory for the storage and retrieval of item and associative information. *Psychological Review, 89,* 609-626.

Murnane, K., & Shiffrin R. M. (1991). Word repetition in sentence recognition. *Memory & Cognition. 19 (2)*, 119-130.

Nosofsky, R. M. (1986). Attention, similarity, and the identification-categorization relationship. *Journal of Experimental Psychology: General, 115,* 39-57.

Nosofsky, R. M. (1988). Exemplar-based accounts of relations between classification, recognition, and typicality. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 14,* 700-708.

Nosofsky, R. M. (1991). Tests of an exemplar model for relating perceptual classification and recognition memory. *Journal of Experimental Psychology*: *Human Perception and Performance, 17,* 3-27.

Nosofsky, R. M. (1992). Exemplars, prototypes, and similarity rules. In A. F. Healy, & S. M. Kosslyn (Eds.), *From learning theory to connectionist theory* (pp. 149-167). Hillsdale, NJ: Erlbaum.

Nosofsky, R. M. (1992). Similarity scaling and cognitive process models. *Annual Review of Psychology, 43*, 25-53.

Nosofsky, R. M., & Palmeri, T. J. (1997). An exemplar-based random-walk model of speeded classification. *Psychological Review, 104,* 266-300.

Nosofsky R. M., & Palmeri T. J. (1998). A rule-plus-exception model for classifying objects in continuous-dimension spaces. *Psychonomic Bulletin and Review, 5*, 345-369.

Nosofsky, R. M., Palmeri T. J., & McKinley, S. C. (1994). Rule-plus-exception model of classification learning. *Psychological Review, 101*, 53-79.

Nosofsky, R. M., & Zaki, S. R. (2003). A hybrid-similarity exemplar model for predicting distinctiveness effects in perceptual old-new recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 29*, 1194-1209.

Palmeri T. J., & Nosofsky R. M. (1995) Recognition memory for exceptions to the category rule. *Journal of Experimental Psychology, 21*, 548-568.

Pothos, E. M., Busemeyer, J. R., & Trueblood, J. S. (2013) A quantum geometric model of similarity. *Psychological Review, 120 (3)*, 679-696

Raaijmakers, J. G. W., & Shiffrin, R. M. (1981). Search of associative memory. *Psychological Review, 88,* 93-134.

Ratcliff, R., & McKoon, G. (1989). Similarity information versus relational information:

Differences in the time course of retrieval. *Cognitive Psychology, 21,* 139-155.

Ratcliff, R., Clark, S., & Shiffrin, R. M. (1990). List-strength effect: 1. Data and discussion. *Journal of Experimental Psychology: Learning. Memory, & Cognition, 16*, 163-178.

Shepard, R. N. (1958) Stimulus and response generalization: Tests of a model relating generalization to distance in psychological space. *Journal of Experimental Psychology*, 55, 509-523.

Shepard, R. N. (1958). Stimulus and response generalization: Deduction of the generalization gradient from a trace model. *Psychological Review, 65*, 242-256.

Shepard, R. N. (1964). Attention and the metric structure of the stimulus space. *Journal of Mathematical Psychology, 1*, 54–87

Shepard, R. N. (1987). Toward a universal law of generalization for psychological science. *Science, 237,* 1317-1323.

Shepard, R. N., & Arabie, P. (1979). Additive clustering representations of similarities as combinations of discrete overlapping properties. *Psychological Review, 86,* 87-123.

Shepard, R. N., & Chang J. (1963). Stimulus generalization in the learning of classifications. *Journal of Experimental Psychology, 65*, 94-102.

Shepard, R. N., & Hovland C. I., & Jenkins H. M. (1961). Learning and memorization of classifications. *Psychological Monographs: General and Applied, 75*, 1-42.

Tversky, A. (1977). Features of Similarity. *Psychological Review, 84 (4)*, 327-352.

Valentine, T., & Ferrara, A. (1991). Typicality in categorization, recognition and identification: Evidence from face recognition. *British Journal of Psychology, 82,* 87-102.

Vokey, J. R., & Read, J. D. (1992). Familiarity, memorability, and the effect of typicality on the recognition of faces. *Memory & Cognition, 20,* 291–302.

Zaki, S. R., & Nosofsky, R. M. (2001) Exemplar accounts of blending and distinctiveness effects in perceptual old-new recognition. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 27,* 1022-1041.

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