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The effects of dual verbal and visual tasks on featural vs. relational category learning

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Abstract

Many studies have examined the distinction between feature- and relation-based categories (Gentner, 2005; Genter & Kurtz, 2005; Jung & Hummel, 2009; Tomlinson & Love, 2011). Those findings suggest that featural and relationl categories have fundamentally different learning algorithms, where relational categories rely on explicit representations and thus require working memory and attention, as opposed to featural categories which may be learned more implicitly. In this study, we investigated further the distinction between feature-and relation-based category learning using a dual task methodology. Our results revealed an interaction: featural category learning was more impaired by a visuospatial dual task than by a verbal dual task, whereas relational category learning was more impaired by the verbal dual task. Our results suggest that in contrast to featural category learning, which may involve mainly non-verbal mechanisms, relational category learning appears to place greater demands on more explicit and attention-demanding verbal or verbally-related learning mechanisms.

Key words: featural category learning; relational category learning; dual task; verbal dual task; visuospatial dual task; category learning algorithms

The ability to categorize plays a central role in human mental life. We use categories to makes sense of the world. They allow us to generalize knowledge form one situation to another, to decide which objects in the world are fundamentally the same, and to infer the unseen properties of novel category members. Research on categorization has mainly focused on *feature-based* categories—that is, categories defined by their exemplars' features, as when "bugs" in one category tend to have a particular kind of head, body and tail and "bugs" in the opposite category tend to have a different kind of head, body and tail (e.g., Taylor and Ross, 2009)—and comparatively little on *relation-based* categories—i.e., categories by the relations between exemplars' parts, or by relations between category exemplars and other objects in the world (for reviews, see Gentner, 2005; Goldwater, Markman, & Stilwell, 2011; Jung & Hummel, 2009; Kittur, Hummel & Holyoak, 2004).

The distinction between featural and relational categories matters because features and relations are *very* different things—so different that we can have little or no confidence that anything learned about category learning using feature-based categories will generalize at all to the case of relational categories. For example, the kinds of learning algorithms that work well with feature-based categories (i.e., various kinds of statistical learning) are completely incapable of learning relational categories (Doumas, Hummel & Sandhofer, 2008; Hummel & Holyoak, 2003; Jung & Hummel, 2009; Kittur et al., 2004, 2006).

One of the clearest examples of this difference comes in the form of peoples' ability to learn *probabilistic* (aka *family resemblance*) category structures. It has been known since the 1970s that people have no difficulty learning categories with probabilistic structures, in which any given feature is likely to belong to a given category (e.g., "bugs" in category A are likely to have one kind of head whereas "bugs" in category B are likely to have another), but no feature is deterministically associated with any given category (e.g., sometimes, bugs from category B will have heads typical of bugs from category A and vice-versa; see Murphy, 2002, for a review). However, as noted by Kittur et al. (2004), such *prototype* effects have always been observed with feature-based categories. With categories defined by the relations between their exemplars' features, such prototype effects have proven difficult or impossible to observe (Jung & Hummel, 2009, 2011; Kittur et al., 2004, 2006).

These differences between peoples' ability to learn featural and relational categories are consistent with the claim that fundamentally different learning algorithms may be at work in the two cases. For example, whereas associative learning may work in the case of featural categories, relational category learning may require a more sophisticated algorithm based, for example, on structured intersection discovery, in which learners compare examples to one another, retaining what the examples have in common and discarding or discounting the details on which they differ (Gick & Holyoak, 1983; Hummel & Holyoak, 2003; Jung & Hummel, 2009, 2011; Kittur et al, 2004, 2006).

A fundamental assumption underlying this *intersection discovery* hypothesis is that people's mental representations of relational categories are explicitly relational (see Hummel & Holyoak, 2003; Jung & Hummel, 2009, 2011). That is, we assume that people notice and explicitly represent the relations between objects (and object parts) and use these relations as the basis for making their categorization responses. This assumption also leads to another critical contrast with feature-based approaches to mental representation and categorization. In contrast to feature-based representations, which come to us effortlessly, relational representations require attention and working memory (see, e.g., Hummel & Holyoak, 1997, 2003; Logan, 1994; Maybery et al., 1986).

In this study, we examined what kinds of working memory might be involved in feature- or relation-based category learning. In particular, our interest was in how featural and relational category learning tasks respond to verbal and visuospatial dual tasks. If featural and relational category learning are based on different learning algorithms, then they might be differentially sensitive to different kinds of dual tasks.

Other researchers have also argued for multiple systems of category learning (Ashby et al., 1998). Miles and Minda (2011) showed that verbal dual tasks, which impose an executive functioning load, impaired rule-defined category learning, whereas a visual dual task impaired non-rule-defined learning regardless of executive functioning demand. Their findings provided evidence that verbal working memory and executive functioning are engaged in the rule-defined system, and visual processing is more engaged in the non-rule-defined system.

Our experiment will test the prediction that relational category learning will be more subject to *verbal dual-task interference* than feature-based category learning. By contrast, feature-based learning will be more subject to *visuospatial dual-task interference* than relational learning.

We used deterministic category structures; i.e., there was always one relation or feature that was deterministically predictive of category membership. The reason for using deterministic categories is that the categories must be learnable, even in the relational case, so that we can observe the effects of our manipulation on trials to criterion (i.e., how long it takes subjects to learn the categories).

We orthogonally crossed relational vs. feature-based categories with verbal dual task vs. visual dual task vs. no dual task. In the verbal dual task conditions, subjects had to perform a task known to interfere with relational processing (memorizing digits) while they simultaneously performed the category learning task. In the visual dual task condition, subjects had to memorize the locations of filled squares in 3 X 3 grids while simultaneously learning the categorization. In the no dual task condition, subjects simply performed the category learning task by itself.

Method

Participants. A total of 75 subjects participated in the study for course credit. Each participant was randomly assigned to one of the six conditions.

Materials. Each exemplar consisted of a grey ellipse and a grey rectangle. Each exemplar had both relational properties (e.g., ellipse bigger than rectangle) and featural properties (e.g., ellipse of size 4). Each subject was tasked with deciding whether the objects they saw belonged to one of two featural or one of two relational categories.

Each exemplar was defined by three category-relevant properties: size (absolute in the featural condition or relative in the relational condition), darkness (absolute or relative) and orientation (absolute or relative). In the featural condition, the orientation of the ellipse was deterministically associated with category membership (i.e., horizontal orientation for category A, vertical for category L), whereas in the relational category condition, the relative orientation of the ellipse and rectangle (i.e., either *same* or *different*) was deterministically associated with category membership (with *same* for category A and *different* for category L). The other properties were probabilistically associated with category membership.

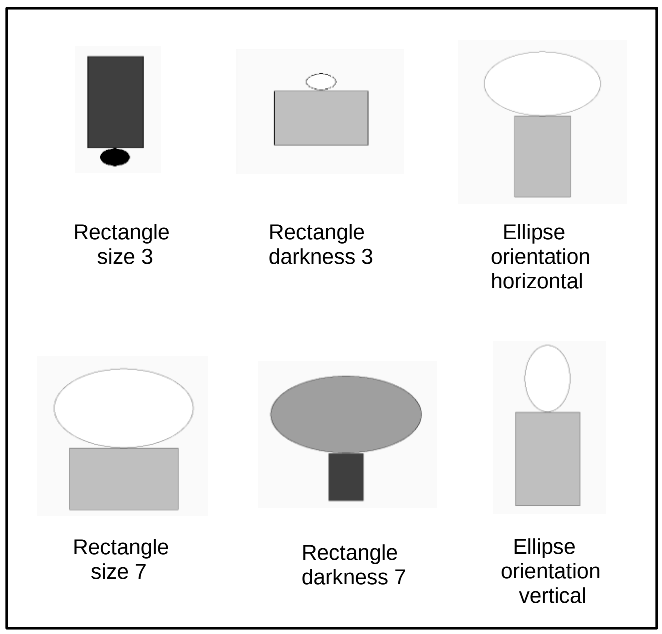

Figure 1. Three relevant properties in the featural condition: category A (above) and L (below)

For the featural category condition, the prototypes of the categories were defined as [1,1,1] for category A and [0,0,0] for L, where [1,1,1] represents an rectangle size 3 [out of 9] for category A, 7 for category L, the color 3 [out of 9] for category A, 7 for category L, and horizontal orientation for category A, vertical for category L (Figure 1). Similarly, for the relational category condition, the prototypes were defined as [1,1,1] for category A and

[0,0,0] for L, where [1,1,1] represents an ellipse *larger*, *darker*, and *same orientation* and [0,0,0] represents a rectangle *larger*, *darker*, and *different orientation* (Figure 2). Exemplars of each category were made by switching the value of one dimension in the prototype (e.g., relational category A exemplar [1,0,1] would have the ellipse *larger*, *lighter*, and *same* orientation as the rectangle). Four copies of each exemplar type were presented on each block, two paired with a "Yes" responses on the dual task and two with a "No" responses, resulting in 32 trials per category per block.

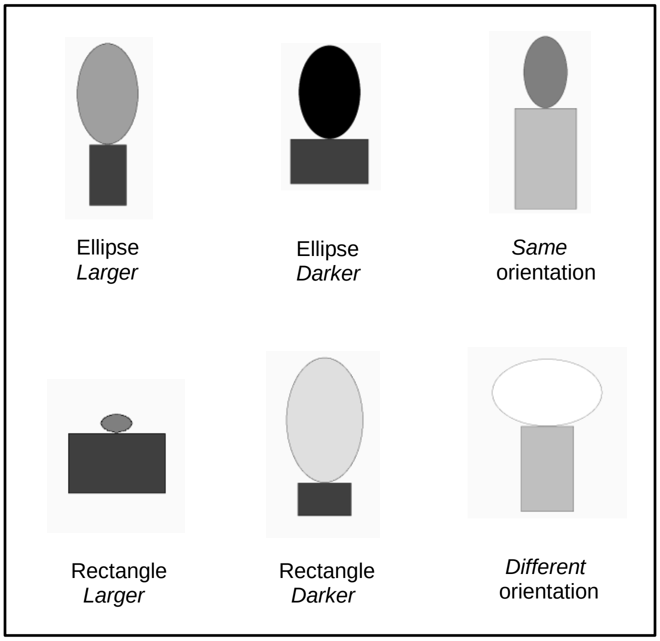

Figure 2. Three relevant properties in the relational condition: category A (above) and L (below)

Design. The experiment used a 3 (dual task: *none* vs. *verbal* vs. *visuospatial*) X 2 (relevant property: *features* vs. *relations*) between-subjects design.

Procedure. Participants were assigned randomly to one of the six groups. For the dual task conditions, on each trial, a memory task was provided first and followed by a categorization task and by a recall task. For the control conditions, only the categorization task was provided (Figure 3). Both categorization and dual task responses were followed by accuracy feedback.

Participants in the verbal dual-task condition were first given a verbal working memory task, in which 5 random digits were displayed for two seconds with spaces between them (so that they appeared to be individual numbers rather than digits of a single number). Participants were asked to memorize the digits while they performed the categorization task. In the categorization task, an exemplar consisting of a rectangle and an ellipse was shown. Participants were instructed to press the A key if the stimulus belonged to category A and the L key if it belonged to L. Each exemplar remained on the screen until the participant responded. Responses were followed by accuracy feedback. Participants then saw one random digit and were asked to decide whether it was in the set they saw previously.

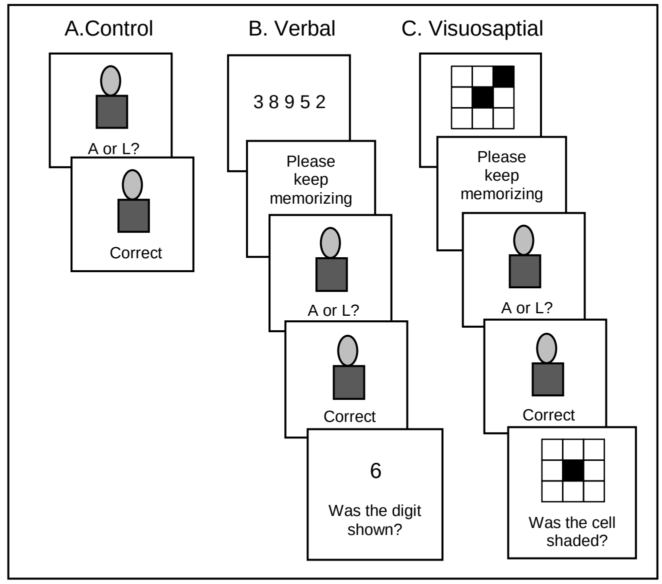

Figure 3. Experimental design by each condition

In the visuospatial dual-task condition, a 3 by 3 grid was displayed in the middle of a screen for two seconds with two randomly-chosen cells filled. Participants were asked to memorize the locations of the filled cells until they completed the categorization task. In the recall task, one filled cell was displayed in the grid and participants were asked whether the cell had been filled in the original display. The experiment consisted of 30 blocks (960 trials) and continued until the participant responded correctly on at least twenty nine of thirty two trials (90.6% correct) for two consecutive blocks or until all 30 blocks had transpired, whichever came first.

Results

Dual task accuracy. We discarded the data from participants whose accuracy was below 70% correct on the dual task (2 subjects in the verbal/featural condition). Mean accuracy on the verbal dual task was M = .94 (SD = .03) for the featural category learning condition, and M = 0.91 (SD = 0.06) for the relational learning condition. Mean accuracy on the visual dual task was M = 0.91 (SD = 0.06) for the featural condition, and M = 0.89 (SD = 0.04) for the relational condition. There was no reliable difference between the verbal and visuospatial tasks [$t(51) = 1.61$, $p = .114$], suggesting that these tasks occupied cognitive resources to roughly the same extent.

Category learning task accuracy: trials to criterion. Since our primary interest is the rate at which participants learn the categories as a function of the dual tasks, we report our data first in terms of trials to criterion. These analyses are conservative in the sense that participants who never learned to criterion were treated as though they reached criterion on the last block. Figure 4 shows the mean trials to criterion by condition. A 3 (dual task) × 2 (category learning task) between-subjects ANOVA revealed a main effect of dual task [$F(2, 69) = 5.058$, $MSE = 579014.858$, $p < 0.01$]. Since our main interest is in how different dual tasks affect the different kinds of category learning, one-way ANOVAs were conducted for the featural and relational learning conditions. The results revealed reliable differences between dual tasks in the featural category learning condition [$F(2,35) = 4.981$, $MSE = 617725.846$, $p < 0.05$]. Planned comparisons in the featural category learning showed that there was a reliable difference between the verbal ($M = 386$, $SD = 387$) and visuospatial dual task ($M = 697$, $SD = 411$) [$t(35) = -2.288$, $p < 0.05$]. There was also a reliable difference between the visuospatial and the control condition ($M = 262$, $SD = 191$) [$t(35) = 3.014$, $p < 0.01$]. The difference between the verbal and the control condition was not reliable [$t(35) = 0.877$, $p < 0.386$]. The ANOVA results from the relational condition revealed reliable differences between the dual tasks [$F(2,34) = 7.641$, $MSE = 799483.887$, $p < 0.01$]. Planned comparisons revealed that there was a reliable difference between the verbal ($M = 739$, $SD = 352$) and visuospatial dual task ($M = 330$, $SD = 362$) [$t(34) = 3.221$, $p < 0.01$]. There was also a reliable difference between the verbal and control conditions ($M = 276$, $SD = 222$) [$t(34) = 3.014$, $p < 0.01$]. The difference between the visuospatial and control conditions was not reliable [$t(34) = 0.404$, $p < 0.689$]. No other main effects were statistically reliable. Most interestingly, there was a reliable interaction between dual task and category learning, indicating that relational category learning was disrupted more by the verbal dual task, whereas featural category learning was disrupted more by the visuospatial dual task [$F(2,69) = 2.475$, $MSE = 855659.946$, $p < 0.01$].

Response times. Since the category learning accuracy results yielded a reliable interaction between the dual and category learning tasks, we also analyzed these tasks in terms of participants' mean response times on individual trials in order to gain insight about the strategies participants in each condition may have adopted. A 3 (dual task) × 2 (category learning task) between-subjects ANOVA revealed a main effect of dual task [$F(2, 69) = 3.202$, $MSE = 0.961$, $p< 0.05$]. One-way ANOVAs were also conducted in each category learning condition. The main effect of dual task was not reliable [$F(2, 35) = 2.137$, $MSE = 0.612$, $p = 0.133$] in the featual learning condition. But since the accuracy data showed that participants in visuospatial feature-learning required many more trials than to reach to the criterion than participants in verbal featural learning, we expected a reliable difference between two conditions in a planned comparison analysis. Our prediction was confirmed. There was a reliable difference between the verbal ($M = 0.99$, $SD = 0.31$) and visuospatial dual task ($M = 1.41$, $SD = 0.78$) [$t(35) = -2.037$, $p < 0.05$], indicating that response times in visuospatial feature-learning condition were longer than those in verbal feature-learning. No other differences were statistically reliable. There were no reliable differences in the relational learning condition. Also, ANOVA showed a reliable main effect of category learning [$F(1, 69) = 3.883$, $MSE = 1.166$, $p = 0.053$], indicating that feature learning ($M = 1.17$, $SD = 0.55$) was marginally faster than relational learning ($M = 1.42$, $SD = 0.56$) (Figure 5).

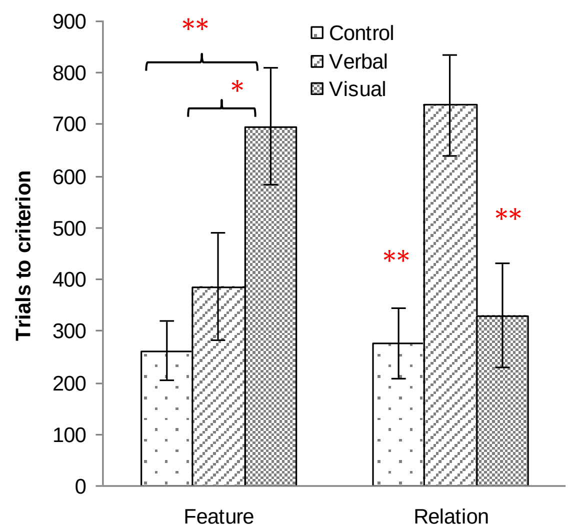

Figure 4. Accuracy by category learning condition

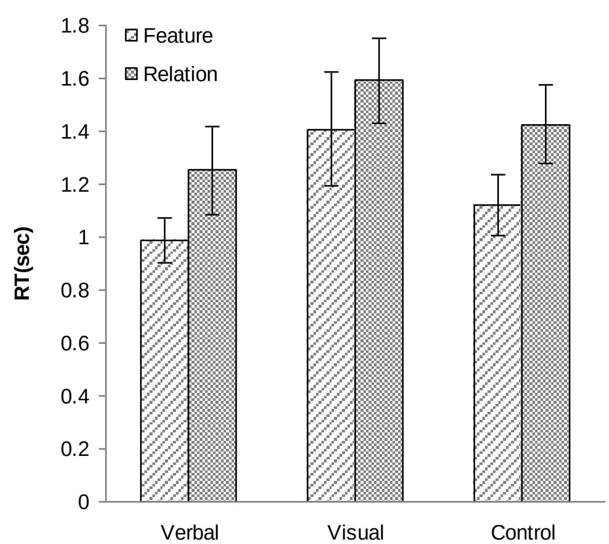

Figure 5. Response times by dual condition

Discussion

To the extent that relational concepts are qualitatively similar to feature-based concepts, our understanding of concepts can be expected to generalize from the (extensively investigated) case of feature-based categories to the (largely neglected) case of relational categories. However, there is reason to believe they are not, casting doubt on our ability to generalize our conclusions from studies using feature-based categories to the case of relational concepts.

Most notably, people have no difficulty learning feature-based categories in which no single feature remains invariant across all members of a category (see Murphy, 2002). By contrast, Kittur and colleagues showed that relational categories are extremely difficult to learn when there is no such relational invariant (i.e., property that holds over all members of a category; Kittur et al., 2004, 2006). Jung and Hummel (2009, 2011) provided additional evidence that relational learning requires some kind of invariant in order to succeed. These findings suggest that featural and relational learning rely not only on qualitatively different forms of mental representation (namely, features vs. relations; see, e.g., Hummel, 2010; Hummel & Holyoak, 1997, for a discussion of the difference) but also that they rely on qualitatively different kinds of learning algorithms (e.g., associative learning in the featural case and something more akin to structured intersection discovery in the relational case; Jung & Hummel, 2009, 2011).

The current experiment provides additional evidence for this sharp distinction between featural and relational category learning. In the current experiment, featural learning was impeded by a visual dual task (i.e., one that might be expected to interfere with visual feature processing as required for featural learning) but not by a verbal dual task. Relational category learning, in sharp contrast, was interfered with by a verbal dual task (which has been shown to interfere with relational processing; Waltz et al., 2000), but not by a visual dual task. This double dissociation between visual vs. verbal dual task interference on the one hand and featural vs. relational category learning on the other adds to the growing evidence that these two kinds of category learning rely on qualitatively different and dissociable learning systems.

Acknowledgements

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