

Structure Mapping and the Predication of Novel Higher-Order Relations

Leonidas A. A. Doumas (adoumas@psych.ucla.edu)

John E. Hummel (jhummel@psych.ucla.edu)

Department of Psychology, University of California, Los Angeles
405 Hilgard Ave.
Los Angeles, CA 90095-1563

Abstract

Relations play a central role in human perception and cognition, but little is known about how relational concepts are acquired and predicated. For example, how do we come to understand that physical force is a higher-order multiplicative relation between mass and acceleration? We report an experiment demonstrating that structure mapping (a.k.a., analogical mapping) plays a key role in the predication of novel higher-order relations. This finding suggests that structure mapping—i.e., the appreciation of analogies—may play a pivotal role in the acquisition and predication of novel relational concepts.

Relational Reasoning

The processing of relations plays a central role in human perception and thought. It permits us to perceive and understand the spatial relations among an object's parts (Hummel, 2000; Hummel & Biederman, 1992; Hummel & Stankewicz, 1996), comprehend arrangements of objects in scenes (see Green & Hummel, 2004, for a review), and comprehend abstract analogies between otherwise very different situations or systems of knowledge (e.g., between the structure of the solar system and the structure of the atom; Gentner, 1983; Gick & Holyoak, 1980, 1983; Holyoak & Thagard, 1995). The power of relational thinking resides in its ability to generate inferences and generalizations that are constrained by the *roles* that elements play, rather than strictly the properties of the elements themselves: The sun is similar to the nucleus of an atom, not because of its literal features, but because of their shared relations to planets and electrons, respectively.

Experience can cause profound changes in the way we process relations. The difference between an expert chess player and a novice, for example, lies in the ability to quickly perceive and reason about the meaningful relations among the pieces on the board (and relations among those relations). Relational learning is central to both the most abstract and uniquely human cognitive abilities (including mathematical and scientific reasoning), and the most "everyday" reasoning using analogies, schemas and rules (Gentner, 1983; Holland, et al., 1986; Hummel & Holyoak, 1997, 2003).

In order to reason explicitly about a relation it is necessary to *predicate* that relation, that is, to represent it as an explicit predicate that takes arguments. Consider an example. In a match-to-sample task, an animal is shown a sample stimulus (e.g., a red square), and two alternatives,

one that matches the sample (another red square) and one that does not (e.g., a green square). The animal's task is to indicate which alternative matches the sample. Many animals, including honeybees (Giurfa et al., 2001), can learn to perform this task with simple stimuli such as colors and shapes (see Holyoak & Thagard, 1995, Thompson & Oden, 2000). The computational requirements for performing this task include the ability to explicitly represent values of the relevant feature dimension (e.g., "red" for the dimension "color"), and the ability to remember the value of that dimension in the sample for the purposes of choosing the correct alternative. Despite initial appearances, the task does *not* require the animal to explicitly appreciate that the correct choice item is in any way the "same" as the sample. For example, if color is the relevant dimension, then after the presentation of a red sample, the animal need only maintain a representation of "red" until the choice items appear. The animal need never reflect explicitly on the fact that the sample and the correct choice are the same color (Thompson & Oden, 2000).

However, the task can be generalized to require an explicit appreciation of "sameness." Consider a *relational* match-to-sample task, in which the sample depicts two triangles, alternative A depicts of circle and a diamond, and alternative B depicts two squares. Choosing B as the correct match to the sample requires the reasoner to represent B and the sample in terms of their shared relation (i.e., *same-shape* (x, y)). College students find this comparison trivial, yet only humans and symbol-trained chimpanzees are known to be able to perform this task reliably (Thompson & Oden, 2000). (Fagot, Wasserman & Young, 2001, claim to show relational matching to sample in the baboon, *Papio papio*. However, their data—in particular, the baboons' failure to learn the task when the sample and choice options each contained only two objects—are more consistent with the baboons' responding to stimulus entropy as a holistic perceptual feature, akin to color, rather than *same* as an explicit relation; Hummel & Holyoak, 2003.)

The assumption that people represent the relation *same-shape* in the same way for the squares as for the triangles provides an intuitive account of our ability to perform the relational match to sample, but it begs the question of *why* we see the relation "same shape" in the squares, whereas most other animals only see squares. What are the mental operations that allow us to discover and predicate *same-shape* as an explicit relation that retains its properties over

the sameness of squares to squares and the sameness of triangles to triangles?

The question of how we discover and predicate new relations is central to cognitive science because the kinds of problems a person (or cognitive model) can solve, and the characteristics of its solutions, depend critically on the relations the person (or model) does and does not represent explicitly. Models of human perception and cognition that represent relations explicitly (i.e., as predicates that take arguments) can solve problems far beyond the scope of models that do not represent relations explicitly (e.g., traditional connectionist models, which represent all concepts as simple lists of features; for reviews see Dumas & Hummel, in press; Hummel & Holyoak, 1997, 2003; Marcus, 1998). But to date, all the models that do represent relations are simply given, by the modeler, a vocabulary of relational concepts with which to reason (examples include ACT-R [Anderson & Lebiere, 1998], LISA [Hummel & Holyoak, 1997, 2003], SME [Falenhainer, Forbus & Gentner, 1989] and, SOAR [Rosenbloom, Newell, & Laird, 1991], among many others). The question of where these concepts come from, and the related question of how we know which relations to predicate in which contexts, is rarely if ever addressed, and the answer to this question is far from well understood. Understanding how the mind comes to represent relations as explicit predicates would contribute substantially to our understanding of the origins of human perception and thinking, and to the development of symbolic thought (Smith, 1989).

Relational Predication

The question of relational predication subsumes at least two related questions: First, how do we recognize and predicate familiar relations for use in novel situations? It is one thing to understand abstract relational notions such as *same-as*, *threatens* or *covaries-with*; it is another to recognize that a relation applies in a given situation and to explicitly predicate it in the service of understanding that situation. Second, how do we discover new relations? For example, what happens in the mind of a child between the time when she does not understand the relation *same-shape* (x, y), and the time when she does? Inasmuch as new relations are learned as combinations of familiar relations, or as familiar relations applied to novel dimensions, the question of relational discovery is clearly related to the question of predication: Especially for adults, discovering new relations may often be a process of discovering which familiar relations apply in a novel situation, and discovering how they are linked together by higher-order relations. Consider, for example, the physics student who is first learning to reason about force as a relation between mass, a basic property of an object, and acceleration, itself a relation between velocity and time. It is this version of the relation discovery question—how do we discover novel higher-order relations among familiar relations—that is the focus of the present paper.

Our ability to appreciate that the relation between the squares in the relational match to sample task is the same as the relation between the triangles—and to choose a pair of squares over a circle and a diamond as the correct match to a pair of triangles on the basis of that relation—illustrates that relations are *invariant* with their arguments (Hummel & Holyoak, 2003): *same-shape* (x, y) is the same relation, regardless of the particular shapes that happen to be bound to x and y at the time. It is precisely this invariance that allows us to appreciate what *same-shape* (triangle1, triangle2) has in common with *same-shape* (square1, square2). As a result of this invariance, *same-shape* ranges over *all possible* shapes, so it is not learnable in terms of the perceptual features of any particular pair of shapes (see Kellman, Burke, & Hummel, 1999). The ability to perform tasks based on such relations—and to discover and predicate them—is therefore fundamentally beyond the reach of any learning algorithm based strictly on the statistical regularities among the elements of the stimuli in its training set—i.e., the vast majority of all theories of learning (see Hummel & Holyoak, 2003).

The problem of relational learning and predication is further complicated by the sheer number of potentially relevant relations present in any given situation. The number of first-order relations among n items increases minimally with $(n^2 - n)/2$ (and this assuming that all relations are commutative, which is not the case for most relations). Worse yet, the number of higher-order relations over these first-order relations is literally unbounded. Any task (e.g., category learning, problem solving, etc.) that calls for the discovery of new higher-order relations is therefore functionally impossible without additional constraints on the selection of which relations to predicate.

Given this, how do people discover and predicate new relations? An important theme that has emerged in the literature on relational reasoning is that *structure mapping* (a.k.a. *analogical mapping*)—the process of finding relational correspondences between the elements of two systems—plays a central role in all forms of relational reasoning (see Hofstadter, 2001; Holyoak & Thagard, 1995). A primary hypothesis motivating the present research is that structure mapping may also play a central role in discovery and predication of new relations. The reason is that structure mapping is driven more by the relational roles that objects play than by the features of the objects themselves. By revealing relational similarities between otherwise different-seeming systems, structure-mapping may bootstrap the discovery of any higher-order relations the two systems have in common. Consistent with this hypothesis, several previous studies have demonstrated that structure mapping bootstraps the induction of abstract relational schemas (e.g., Gick & Holyoak, 1983; Ratterman & Gentner, 1998; Sandhofer & Smith, 2001; Yamauchi & Markman, 2000), and that comparison helps people appreciate what lower-order relations might be relevant to a specific task (Gentner & Namy, 1999; Namy & Gentner, 2002; Yamauchi & Markman, 1998).

The current experiment was designed to investigate whether analogical mapping may also help people to discover the higher-order relations that analogous systems have in common—that is, whether analogical mapping may bootstrap the discovery of novel higher-order relations. If it does, then analogical mapping may not only be a process that depends on the relations we can predicate, but may also be a process that aids us in the predication of new relations.

Experiment

The experiment used a category-learning paradigm to measure relational predication. Categories were defined by an unfamiliar higher-order relation between the elements of exemplars. Each exemplar consisted of drawings of three simple “cells” inside a circular frame (see Figure 1). Within an exemplar, the cells varied in their location in the frame, their shape, the thickness of their membrane, the roundness of their nucleus, and the number of organelles. Categories were defined by a higher-order relation between the cells’ membrane thickness and the roundness of their nuclei: In Category A, the thicker a cell’s membrane, the rounder its nucleus; in Category B, the thicker the membrane the more elliptical its nucleus. The cells’ locations in the frame, shape, and number of organelles varied randomly and were uncorrelated with category membership.

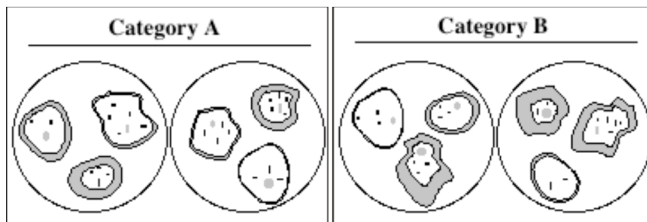


Figure 1. Two stimuli from Category A and two from Category B.

The exemplars were designed to make category learning impossible without discovering the higher-order relation between relative membrane thickness and nucleus roundness. Absolute thickness and roundness were non-predictive of category membership because the thinnest membrane (or least round nucleus) in one exemplar of a category was potentially the thickest (or roundest) in another exemplar of the same category. For the same reason, conjunctions of specific roundnesses and thicknesses were also non-predictive. Every exemplar, regardless of category, had three cells, one of which had a thickest membrane and another of which had a thinnest (with the third in between), so the categories were not learnable in terms of relative (or absolute) membrane thickness. Likewise, every exemplar, regardless of category, had one cell with a more round nucleus than the others and one with a more elliptical nucleus (with the third in between). In other words, the categories were not definable, or learnable, in terms of any basic features or even first-order relations.

For this reason the category structure is unlearnable by any model that codes exemplars in terms of their features (e.g., location, color, width, orientation, etc.) or conjunctions of their features, but cannot explicitly represent relations among those features and relations among relations. Such models constitute the vast majority of mathematical and computational models of category learning (e.g., Krushke, 1992, 2001; Nosofski, 1988; Nosofski & Palmeri 1998), including all connectionist models (see Doumas & Hummel, in press; Hummel & Holyoak, 2003; Marcus, 1998).

By contrast, the categories are learnable in the space of *conjunctions* of *relative* membrane thickness and *relative* nucleus roundness—that is, in terms of a higher-order relation between the first-order relations of relative thickness and relative roundness (which is simply a restatement of the category-defining higher-order relation).

Two groups of subjects were trained to categorize exemplars into the two categories. One group (the *Map* group) performed a mapping task halfway through the category-learning task; the other group (the *No Map* group) did not. Subjects in the *No Map* condition simply studied a pair of exemplars from the same category (either A or B, counterbalanced); subjects in the *Map* condition viewed a pair of exemplars from the same category and were asked to indicate which cell in one exemplar corresponded to which in the other and why.

Our predictions were as follows: (1) To the extent that the category-relevant higher-order relation between cells’ relative membrane thickness and relative nucleus roundness is unfamiliar to our subjects, categorization performance on the pre-mapping trials ought to be near chance. (2) To the extent that mapping helps subjects to predicate this relation, post-mapping categorization performance of subjects who map correctly in the *Map* condition should jump abruptly to ceiling (as a result of predicating the category-defining relation), but performance in the *No Map* condition, and the performance of those who map incorrectly in the *Map* condition, should remain near chance.

Methods

Participants: 20 UCLA undergraduates participated for course credit.

Materials: Each exemplar consisted of three drawings of simple cells in a circular frame. The cells differed in their shapes, location, membrane thickness, nucleus roundness, and number of organelles (see Figure 1).

Seven membrane thicknesses and seven nucleus roundnesses were used to construct the stimuli, making it possible for the thickest membrane (or roundest nucleus) in one exemplar of a category to be the thinnest (or most elliptical) in another exemplar of the same category, thus making it impossible for subjects to categorize correctly based on absolute thickness or roundness (i.e., it is necessary to respond on the basis of *relative* thickness and roundness between cells in an exemplar).

The locations, shapes, and number of organelles of the cells in an exemplar varied randomly, subject to the constraint that no cells ever overlapped in the frame. Each cell was one of 6 different shapes and contained between 1 and 6 organelles.

We created exemplars used in the pre-mapping, post-mapping, and mapping phase of the experiment (described more fully below) withholding membrane thicknesses 3 and 7 (the thickest), and nucleus roundnesses 1 (least round) and 5 for construction of transfer exemplars. The exemplars used in the transfer phase were created under the constraints described above, with the additional constraints that at least one novel thicknesses and one novel roundness appeared in each exemplar, and each novel thickness and roundness appear in at least three of the six transfer exemplars (see below). The withheld thicknesses and roundnesses consisted of values both within the bounds of the values seen by subjects during the training and test phases of the experiment and values outside those bounds. Thus, transfer trials required subjects to both interpolate and extrapolate learning to new values.

The exemplars used during the mapping phase consisted of two exemplars from the same category placed side by side.

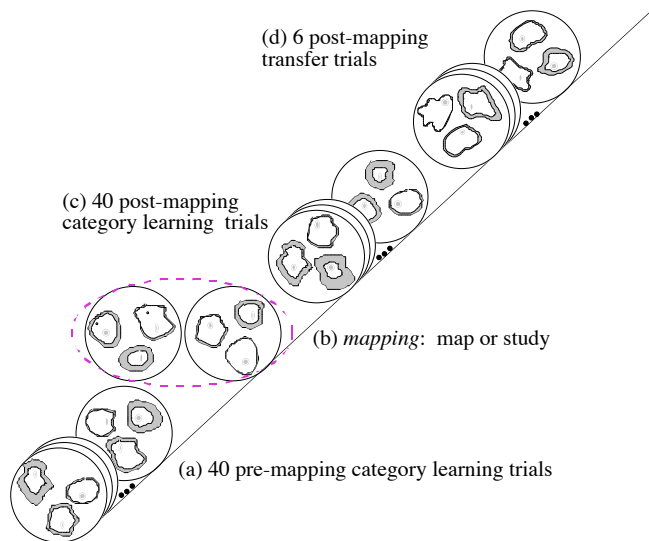


Figure 2. Structure of the experimental procedure. (a) Training phase, 40 trials; (b) mapping phase; (c) test phase, 40 trials; (d) transfer phase, 6 trials.

Procedure: Ten subjects were randomly assigned to each experimental condition. All stimuli were presented on a computer screen. All subjects received 40 pre-mapping training exemplars (20 A's and 20 B's) in a random order (Figure 2a). Their task was to indicate (with a key press) whether each exemplar belonged to Category A or B. Each response was followed by accuracy feedback. Following the initial training phase, subjects were presented with one

of the two mapping sets (either two As or two Bs; Figure 2b). Subjects were informed that both exemplars belonged to the same category but they were not told which category they belonged to. Subjects in the No Map condition were instructed to study the mapping set for one minute. Subjects in the Map condition were asked to indicate which cell in the exemplar on the left corresponded to each cell in the exemplar on the right, and to state the reason or reasons for each correspondence. Conditions and mapping sets were fully counter-balanced. All subjects then received 40 post-mapping training trials (20 A's and 20 B's) in a random order (Figure 2c). Responses were followed by accuracy feedback as before. In the final transfer stage of the experiment subjects were presented with the six transfer exemplars (3 A's and 3 B's) in random order and their task was to categorize each (Figure 2d). They received no accuracy feedback during this part of the experiment.

Scoring: All participants were scored for number of correct responses in the pre- and post-mapping trials (maximum 40 correct for each) and the transfer trials (maximum 6 correct). We also recorded the mappings made by participants in the Map condition. At the end of the experiment all subjects were also asked to state the rule(s) they had used to categorize the exemplars.

Results

The results of the experiment were exactly as predicted. An independent-samples t-test showed no main effects for mapping, $t(18) = 1.13$, $p > .25$, on the pre-mapping training trials (mean-proportion-correct_{MAP} = .52, mean-proportion-correct_{NO-MAP} = .47), which is expected, as the groups received exactly the same treatment prior to mapping. Performance in neither group differed significantly from chance (50% correct).

A second independent-samples t-test was run for performance on the post-mapping trials (Figure 3a). Post-mapping, categorization performance in the Map condition was significantly more accurate (mean-proportion-correct_{MAP} = .77) than in No Map (mean-proportion-correct_{NO-MAP} = .48), $t(18) = 3.84$, $p < .01$. Accuracy in the No Map group did not differ from chance.

A similar pattern of results obtained on the transfer trials (Figure 3b). Subjects in the map condition performed significantly more accurately (mean-proportion-correct_{MAP} = .83) than those in the no map condition (mean-proportion-correct_{NO-MAP} = .42), $t(18) = 4.16$, $p < .01$. Performance of the No Map group on the transfer trials did not differ from chance.

The participants' reports of their mappings and rule use also revealed interesting patterns. First, none of the 10 subjects in the No Map group, and 7 of the 10 subjects in the Map group correctly stated the rule defining category membership at the end of the experiment. Second, there was a perfect 1:1 correspondence between subjects who correctly mapped the cells during the mapping phase and those who correctly stated the rule: All and only those subjects who identified the correct mappings were able to

state the category-defining rule at the end of the experiment. All other subjects either missed the relevant dimensions completely or mapped based on absolute membrane width and absolute nucleus roundness, which, as stated previously, were not sufficient for correct categorization.

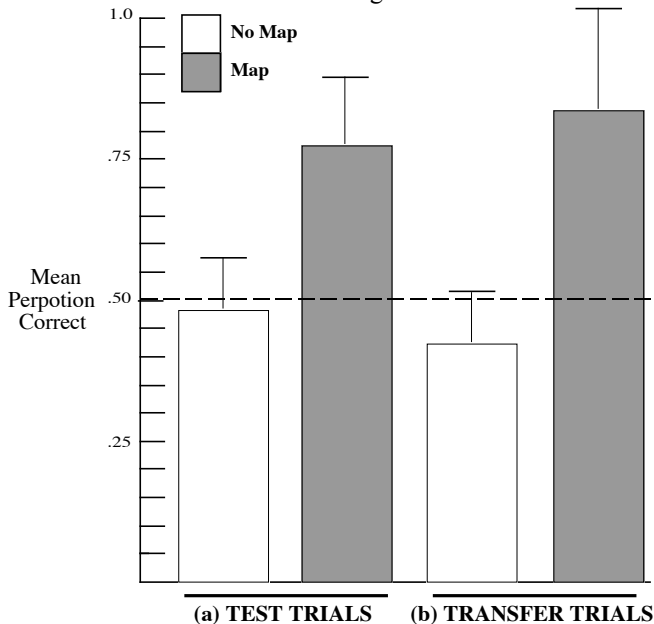


Figure 3. (a) Mean number of correct responses on post-mapping trials as a function of condition. (b) Mean number of correct responses on transfer trials as a function of condition. The dashed line indicates chance.

Discussion

Relations play a central role in human perception and thinking, yet little is known about how relational concepts are acquired and predicated. The problem of relational predication is especially difficult because it is underconstrained. We hypothesized that structure mapping might aid in the discovery and predication of novel higher-order relations.

The results of a category learning experiment support this hypothesis. Subjects who mapped exemplars from the same category onto one another were much better able to learn the novel, category-defining higher-order relation than subjects who did not map. Indeed, performance of the latter group never got above chance.

Additionally, subjects who mapped were able to both interpolate and extrapolate learning to new exemplars with novel stimulus values (i.e., novel membrane thicknesses and nucleus roundnesses) and to verbally state the relational rule that defined category membership. Subjects who did not map were unable to either transfer to new stimuli or to state the category-defining rule. These findings suggest that mapping aids in the predication of novel relations, and that the resulting relations are explicit, in the sense of being available to bind to novel inputs (recall the transfer trials; also, see Hummel & Holyoak, 1997, 2003).

More broadly, the findings reported here suggest that the same cognitive mechanisms that underlie our ability to make analogies—namely, those underlying structure mapping—may also underlie our ability to discover and predicate new relational concepts. If this suggestion is correct, then the evolution of the capacity for generalized structure mapping may well be the “great leap forward” (Newell, 1990) that ultimately gave rise to our capacity for generalized symbolic thought.

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References

- Anderson, J. R. & Lebiere, C. (1998). *The atomic components of thought*. Mahwah, NJ: LEA.
- Beiderman, I. (1987). Recognition by components: A theory of human image understanding. *Psychological Review*, 94, 115-147.
- Doumas, L. A. A., & Hummel, J. E. (in press). Approaches to modeling human mental representations: What works, what doesn't, and why. In K. J. Holyoak & R. Morrison (Eds.), *The Cambridge Handbook of Thinking and Reasoning*. Cambridge: Cambridge University Press.
- Fagot, J., Wasserman, E. A., Young, M. E. (2001). Discriminating the relation between relations: The role of entropy in abstract conceptualization by baboons (*Papio papio*) and humans (*Homo sapiens*). *Journal of Experimental Psychology: Animal Behavior Processes*, 27(4), 316-328.
- Falkenhainer, B., Forbus, K. D., & Gentner, D. (1989). The structure-mapping engine: Algorithm and examples. *Artificial Intelligence*, 41, 1-63.
- Gentner, D. (1983). Structure-mapping: A theoretical framework for analogy. *Cognitive Science*, 7, 155-170.
- Gentner, D., & Namy, L. L. (1999). Comparison in the development of categories. *Cognitive Development*, 14, 487-513.
- Gick, M. L., & Holyoak, K. J. (1980). Analogical problem solving. *Cognitive Psychology*, 12, 306-355.
- Gick, M. L., & Holyoak, K. J. (1983). Schema induction and analogical transfer. *Cognitive Psychology*, 15, 1-38.
- Giurfa, M., Zhang, S., Jennett, A., Menzel, R., & Srinivasan, M. V. (2001). The concepts of 'sameness' and 'difference' in an insect. *Nature*, 410, 930-933.
- Green, C., & Hummel, J. E. (2004). Relational perception and cognition: Implications for cognitive architecture and the perceptual-cognitive interface. In B. H. Ross (Ed.) *The psychology of learning and motivation*. Vol 44. (pp. 201-223). San Diego: Academic Press.
- Hofstadter, D. R. (2001). Epilogue: Analogy as the core of cognition. In D. Gentner, K.J. Holyoak, & B.N. Kokinov

- (Eds.), *The analogical mind: Perspectives from cognitive science*. Cambridge, MA: MIT Press.
- Holland, J. H., Holyoak, K. J., Nisbett, R. E., & Thagard, P. (1986). *Induction: Processes of inference, learning, and discovery*. Cambridge, MA: MIT Press.
- Holyoak, K. J., & Hummel, J. E. (2001). Toward an understanding of analogy within a biological symbol system. In D. Gentner, K. J. Holyoak, & B. N. Kokinov (Eds.), *The analogical mind: Perspectives from cognitive science*. Cambridge, MA: MIT Press.
- Holyoak, K. J., & Thagard, P. (1995). *Mental Leaps: Analogy in Creative Thought*. Cambridge, MA: MIT Press.
- Hummel, J. E. (2000). Where view-based theories break down: The role of structure in shape perception and object recognition. In E. Dietrich and A. Markman (Eds.), *Cognitive Dynamics: Conceptual Change in Humans and Machines*. Hillsdale, NJ: Erlbaum.
- Hummel, J. E., & Biederman, I. (1992). Dynamic binding in a neural network for shape recognition. *Psychological Review*, 99, 480-517.
- Hummel, J. E., & Holyoak, K. J. (1997). Distributed representations of structure: A theory of analogical access and mapping. *Psychological Review*, 104, 427-466.
- Hummel, J. E., & Holyoak, K. J. (2003). A symbolic-connectionist theory of relational inference and generalization. *Psychological Review*.
- Hummel, J. E., & Stankiewicz, B. J. (1996). Categorical relations in shape perception. *Spatial Vision*, 10, 201-236.
- Kellman, P. J., Burke, T. & Hummel, J. E. (1999). Modeling perceptual learning of abstract invariants. *Proceedings of the Twenty First Annual Conference of the Cognitive Science Society* (pp. 264-269). Mahwah, NJ: Erlbaum.
- Kotovsky, L., & Gentner, D. (1996). Comparison and categorization in the development of relational similarity. *Child Development*, 67, 2797-2822.
- Kruschke, J. K. (1992). ALCOVE: An exemplar-based connectionist model of category learning. *Psychological Review*, 99, 22-44.
- Kruschke, J. K. (2001). Toward a unified model of attention in associative learning. *Journal of Mathematical Psychology*, 45, 812-863.
- Marcus, G. F. (1998). Rethinking eliminative connectionism. *Cognitive Psychology*, 37, 243-282.
- Namy, L. L., & Gentner, D. (2002). Making a silk purse out of two sow's ears: Children's use of comparison in category learning. *Journal of Experimental Psychology: General*, 131, 5-15.
- Nosofsky, R. M. (1988). Exemplar-based accounts of relations between classification, recognition and typicality. *Journal of Experimental Psychology: Learning, Memory & Cognition*, 14, 700-708.
- Nosofsky, R. M., & Palmeri, T. J. (1998). An exemplar-based random walk model of speeded classification. *Psychological Review*, 104, 266-300.
- Ratterman, M. J., & Gentner, D. (1998). More evidence for a relational shift in the development of analogy: Children's performance on a causal-mapping task. *Cognitive Development*, 13, 453-478.
- Rosenbloom, P. S., Newell, A., & Laird, J. E. (1991). Toward the knowledge level in Soar: The role of the architecture in the use of knowledge. In K. VanLehn (Ed.), *Architectures for intelligence: The Twenty-second Carnegie Mellon Symposium on Cognition*. Hillsdale, NJ: LEA.
- Ross, B. H., Perkins, S. J., & Tenpenny, P. L. (1990). Reminding-based category learning. *Cognitive Psychology*, 22, 260-492.
- Sandhofer, C. M., & Smith, L. B. (2001). Why children learn color and size words so differently: Evidence from adult's learning of artificial terms. *Journal of Experimental Psychology: General*, 130, 600-617.
- Smith, L. B. (1989). From global similarity to kinds of similarity: The construction of dimensions in development. In S. Vosniadou and A. Ortony (Eds.), *Similarity and analogical reasoning*, 146-178, Cambridge: Cambridge University Press.
- Spalding, T. L., & Ross, B. H. (1994). Comparison-based learning: Effects of comparing instances during category learning. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 20, 1251-1263.
- Thompson, R. K. R. & Oden, D. L. (2000). Categorical perception and conceptual judgments by nonhuman primates: The paleological monkey and the analogical ape. *Cognitive Science. Special Issue: Primate cognition*, 24(3), 363-396.
- Yamauchi, T. & Markman, A. B. (1998). Category learning by inference and classification. *Journal of Memory and Language*, 39, 124-148.
- Yamauchi, T., & Markman, A. B. (2000). Learning categories composed of varying instances: The effect of classification, inference and structural alignment. *Memory & Cognition*, 28, 64-78.