The cognitive categorization of objects which SHEPARD describes and addresses is quite sophisticated. (See the third paragraph of sect. 1.10.) It involves precise categorizing of objects according to, as he says, basic kinds. A dog, but not a statute of a dog, is recognized as a dog. (This is my example.) Such precise categorization is beyond the reach of perceptual capacities. Stimulus similarity of objects from disparate basic kinds causes faulty recognition because perceptual systems are tied to stimulus configurations. The evolutionary success of mimicry and other deceptions is ample testimony to the intrinsic limitations of perception to pick out basic kinds accurately.

SHEPARD may hold that the cognitive resources of an individual involved in the type of categorization which he has in mind are not restricted to perceptual resources. At least he seems to be going in this direction. (See the first paragraph of the section.) Involvement of a broad range of cognitive resources increases the likelihood of precise recognition according to basic kinds. We have become better at differentiating the real from the fake. Collection of evidence and logic have aided us along this path. (For example, I can accurately infer that I am looking at a statue of a dog, not a real dog, from the fact that the thing has not moved a hair's breadth in five minutes.) However, many cognitive capacities which are involved in object recognition do not derive from internalization of universal regularities. Belief systems, for example, are enormously plastic. At one time, many people believed they saw Zeus when they looked at a cloud containing the shape of a bearded head. That belief does not occur very much anymore. Fluidity of beliefs seems to be a prerequisite for steady progress toward precise identification (even regarding basic kinds). In contrast, perceptual mechanisms, which are more likely to involve evolutionary internalization of universal regularities, are unreliable.

Another concern arising from SHEPARD's proposal is this: not all of those things which Shepard calls "basic kinds" are universal. Animal species arise, decline, and disappear, others arise, and so on. Therefore, the cognitive mechanisms which induce recognition of a specific animal (e.g., a lion) have not in general become tuned to universal regularities, but to contingent regularities. This consideration, it would seem, blocks application of Shepard's theory to representation of basic kinds. I have touched on one way only in which contingency blocks Shepard's attempt to theoretically capture representation of basic kinds. In order to recognize objects in this world adequately, the tie of cognitive systems to universal regularities must be strictly limited. This applies to perceptual mechanisms as well, insofar as they induce object recognition, because, generally speaking, the objects at issue are not universal.

In making his case, SHEPARD talks in terms of connected regions in representational space which correspond to basic kinds. (See second paragraph of the section.) These regions are constructed by an individual's judgement of similarity of consequences. This way of describing things does not seem to diminish my criticisms. Many types of consequences in ordinary environments are just as contingent and fluid as many basic kinds, requiring that the mechanisms which underlie judgements of similarity of consequences must be substantially cut loose from universal regularities. As an example of the contingency of consequences, consider the contrast between the consequence of encountering a live rattlesnake and that of encountering a dead one. In order to differentiate between these two consequences, cognition cannot be completely tied even to semi-permanent regularity, such as the size and colouration of the rattle snake.

If my criticism holds, SHEPARD's mathematical project (described in his conclusion) is in jeopardy with respect to representations of kinds of objects. Because these representations in the main are not tied to universal regularities, mathematical models which link these representations to universal regularities are bound, in general, to have only limited scope. Of course, sophisticated mathematics can be, and is, fruitfully used to model representations of basic kinds, but not in general to tie these representations to universal regularities; instead mathematics can be, and is, often used to model representations which are tied to contingent, even radically contingent, regularities.

Three deadly sins of category learning modelers

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Abstract: Tenenbaum and Griffiths's article continues three disturbing trends that typify category learning modeling: (1) modelers tend to focus on a single induction task; (2) the drive to create models that are formally elegant has resulted in a gross simplification of the phenomena of interest; (3) related research is generally ignored when doing so is expedient. [TENENBAUM & GRIFFITHS]

Overview. TENENBAUM & GRIFFITHS's (henceforth T&G) article continues three disturbing trends that typify category learning modeling: (1) modelers tend to focus on a single induction task, which drastically limits the scope of their findings; (2) the drive to create models that are formally elegant has resulted in a gross simplification of the phenomena of interest and has impeded progress in understanding how information is represented and processed during learning; (3) related research on the role of theories, prior knowledge, comparison, analogy, similarity, neurospychology, and cognitive neuroscience is generally ignored when doing so is expedient. These three shortcomings are all interrelated and mutually reinforcing.

Induction tasks: The unwarranted assumption of universality. T&G exclusively focus on how subjects generalize from positive examples of a single target concept. This learning mode can be characterized as unsupervised learning under intentional conditions because subjects are aware that they are in a learning task and all of the training examples are from the same target concept (i.e., discriminative feedback or supervision is not provided). T&G ignore other learning modes such as classification learning, inference-based learning, and unsupervised learning under incidental conditions. This oversight is important because the ease of acquiring target concepts differs greatly depending on which of these learning modes is engaged. For example, inference-based learning is more efficient than classification learning when the task is to acquire two contrasting categories that are linearly separable (i.e., there is a linear decision boundary in representational space that separates examples of categories "A" and "B"), but is less efficient than classification learning for nonlinear category structures (Love et al. 2000; Yamauchi & Markman 1998). Recent work in my lab (in preparation) demonstrates strong interactions among all four of the learning modes mentioned above.

Given these interactions between learning problems and learning modes, focusing exclusively on a single learning mode is problematic to any theory that intends to explain category learning and generalization in any comprehensive sense. Currently, the category learning literature focuses on classification learning, which limits the field's ability to construct general theories of category learning. This narrow focus also raises concerns of ecological validity because, as Yamauchi and Markman (1998) have demonstrated, classification learning does not support inference (i.e., predicting an unknown property of an object from a known category). Ostensibly, inference is a major use of categories. The current fascination with classification learning can be traced back to Shepard et al.'s (1961) seminal studies which, oddly enough, are not considered by T&G.

It doesn't have to be pretty to be beautiful. T&G invoke evolutionary arguments, but higher-level cognition is probably best regarded as a "hack" involving multiple learning, memory, and control systems – many of which were probably co-opted or developed rather recently in our evolutionary history. The growing consensus in the memory literature is that memory is not unitary, but instead involves multiple systems (e.g., semantic, episodic, declarative, etc.) that operate in concert (Cohen & Eichenbaum 1993; Squire 1992). Some category learning researchers have recently embraced this idea with multiple system learning models (Ashby et al. 1998; Erickson & Kruschke 1998). Even work that argues against the multiple systems approach (e.g., Jacoby 1983; Roediger et al. 1989) emphasizes the importance of how a stimulus is processed at encoding. In light of these results, the search for a universal (monolithic) theory of learning seems at best misguided.

In general, the field has been attracted to models that are rather abstract and that can be construed as optimal in some sense (e.g., Ashby & Maddox 1992; Nosofsky 1986). Unfortunately, it seems unlikely that an ideal observer model (of the type commonly deployed in psychophysics research) can be applied to understanding human category learning in any but the most trivial sense (e.g., to understanding Boolean concept acquisition via classification learning as in Feldman 2000). Clearly, theories cannot be formulated at an abstract informational level because learning modes that are informationally equivalent (e.g., inference-based vs. classification learning; intentional vs. incidental unsupervised learning) lead to different patterns of acquisition.

What is needed are models that account for the basic information processing steps that occur when a stimulus is encountered. Current category learning models err on the side of the abstract (neglecting processing) and do not make allowances for basic processing constraints (e.g., working memory limitations). Accounting for basic processing mechanisms will lead to insights into the nature of category learning. For example, SUSTAIN's (SUSTAIN is a clustering model of category learning; see http://love.psy. utexas.edu/ for papers) successes are largely attributable to its characterization of how and when people combine information about stimuli.

T&G move even farther away from issues of processing and representation. Contrary to appearance, their framework lacks explanatory power. In their model, many layers of representation and processing (e.g., constructing hypothesis, resolving conflicting hypotheses, updating model memory) are collapsed into a hand-coded hypothesis space. This framework makes it impossible to address important issues like whether people are interpolating among exemplars, storing abstractions, applying rules, constructing causal explanatory mechanisms, and so forth, because all possibilities are present and lumped together. Additionally, there is little psychological evidence that humans perform Bayesian inference. Instead, humans tend to focus on the most likely alternative, as opposed to performing a weighted (by probability) summation over all alternatives and the corresponding values (Murphy & Ross 1994).

Let's learn from others. Category learning modelers show an alarming disregard for research in related literatures. I will leave it to the other commentators to castigate T&G for dismissing the last twenty years of research in analogy and similarity based on what amounts to a thought experiment. It suffices to say that relations are not features and that features and relations are psychologically distinct (Gentner 1983; Goldstone et al. 1991).

While many other category learning modelers are guilty of not making contact with related work (e.g., the role of prior knowledge in learning), T&G actually fail to make contact with other models of category learning by example. T&G dismiss other models of category learning in their "Alternative approaches" section 3.3, without addressing any of the data supporting these "alternative" models.

Tribute to an ideal exemplar of scientist and person

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Abstract: Roger Shepard's creativity and scientific contributions have left an indelible mark on Psychology and Cognitive Science. In this tribute, I acknowledge and show how his approach to universal laws helped Oden and me shape and develop our universal law of pattern recognition, as formulated in the Fuzzy Logical Model of Perception (FLMP).
[SHEPARD; TENENBAUM & GRIFFITHS]

It is fitting that *BBS* should sponsor a forum on Roger SHEPARD's seminal contributions to the understanding of mind and behavior. His work has always been earmarked by creativity, innovation, and relevance. All of this by a most unassuming person. I shared a plane ride with him after he had just been awarded the Presidential Medal of Science at the Whitehouse. He was as interested, curious, and supportive as always, without exposing any hint of the great honor he had just received.

Laws are lofty targets out of reach by most of us. SHEPARD created a law imposing order on one of the oldest problems in experimental psychology. How do we account for behavioral responses to stimuli that are similar but not identical to a stimulus that has been previously shown to be informative? Generalization was not simply a matter of failure of discrimination (Guttman & Kalish 1956); and what function could possibly describe the myriad conglomerate of findings across organisms, stimuli, tasks, and so on? SHEPARD's solution was to enforce a distinction between the physically measured differences between stimuli and the psychological differences between those same stimuli. In many respects, this move was simply an instantiation of his general dissatisfaction with the prevalent behaviorism of the era. SHEPARD imposed order on unorderly data by making this distinction. His analysis of a broad range of data across different domains produces a highly consistent and universal function that describes generalization. When generalization between stimuli is predicted from distances between points in a psychological space, the resulting generalization function is exponential.

We have proposed the fuzzy logical model of perception (FLMP; Oden & Massaro 1978) as a universal law of pattern recognition (Massaro 1996; 1998). The assumptions central to the model are: (1) persons are influenced by multiple sources of top-down and bottom-up information; (2) each source of information is evaluated to determine the degree to which that source specifies various alternatives; (3) the sources of information are evaluated independently of one another; (4) the sources are integrated to provide an overall degree of support for each alternative; and (5) perceptual identification and interpretation follows the relative degree of support among the alternatives. In a two-alternative task with /ba/ and /da/ alternatives, for example, the degree of auditory support for /da/ can be represented by a_i, and the support for /ba/ by $(1-a_i)$. Similarly, the degree of visual support for /da/ can be represented by v_j, and the support for /ba/ by $(1-v_j)$. The probability of a response to the unimodal stimulus is simply equal to the feature value. For bimodal trials, the predicted probability of a response, P(/da/) is equal to:

$$P(/da/) = \frac{a_i v_j}{a_i v_j + (1-a_i)(1-v_j)} \tag{1}$$

In the course of our research, we have found that the FLMP accurately describes human pattern recognition. We have learned that people use many sources of information in perceiving and understanding speech, emotion, and other aspects of the environment. The experimental paradigm that we have developed also al-