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Response-Time Approach to Contrasting Models of Perceptual Classification

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14. ABSTRACT The long-term objective of this work is the development of general computational models of human perceptual classification and memory. An important goal is to develop and test models that explain the time course of classification and recognition decision making. The first specific goal involved the extension of Nosofsky and Palmeri's (1997) exemplar-based random-walk (EBRW) model of classification response times (RTs) to the domain of memory search. Several empirical studies demonstrated successful applications of the new theory in this domain. The second goal involved the development and testing of a new set of logical-rule models of classification RTs. Various cognitive architectures may underlie the application of logical rules in classification, including serial-, parallel-, and coactive-processing architectures. A highly diagnostic paradigm was developed that yielded sharply contrasting predictions from these alternatives. Several sets of experiments provided support for the logical-rules framework and allowed one to identify which processing architectures were used under alternative experimental conditions.					
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Introduction

Among the most fundamental cognitive processes are classification and recognition. In classification, people group distinct objects into categories. In recognition, people make judgments about whether objects are old or new. A wide variety of formal models have been proposed to capture the cognitive processes that underlie categorization and recognition decision making. The central theme of the present work was to use varieties of response-time data to develop stronger tests and contrasts among these competing classes of formal models.

In the domain of categorization, a key preliminary issue concerns that nature of the classification task that needs to be performed. In many cases involving natural categories found in the real world, it appears that no simple rules and definitions exist for deciding category membership. Instead, categories appear to be held together by a similarity-based family-resemblance structure. One of the major psychological models of human classification performance in these domains is Nosofsky's (1986) generalized context model (GCM), which posits that people represent categories by storing individual exemplars of the categories in memory, and classify objects according to their similarity to these stored exemplars. The GCM has also been extended to account for classification response-time (RT) data in the form of Nosofsky and Palmeri's (1997) exemplar-based random walk (EBRW) model. In the EBRW model, retrieved exemplars drive a random-walk evidence-accumulation process that leads to classification decisions. Numerous tests of the EBRW model have been reported in the classification literature.

A key theme of this exemplar-based modeling is that there may be close relations between the fundamental processes of classification and old-new recognition. In the present project, this theme was pursued by developing an extended version of the EBRW model that is applicable to predicting old-new recognition RTs and by providing extensive tests of this new model in a variety of memory-search paradigms.

The second major theme of research was to examine classification performance in domains in which categories *are* well described in terms of simple logical rules. A natural idea is that people may use such rules as a basis of classification in such domains. Remarkably, however, few attempts have been made in the past literature to develop rigorous predictions of what RT data should look like if these logical-rules are being used. The goal of the present research project was to fill that gap, develop a formal set of logical-rule models of classification RTs, and provide extensive empirical tests of this new set of models.

Scientific Objectives of Research

One of the classic ideas in cognitive psychology and cognitive science is that people develop and use logical rules as a basis for classifying objects into logically-defined categories. However, a variety of very general alternative models of human classification performance have been developed, including exemplar models and connectionist models, which can also account for classification performance in domains involving rule-based categories. In general, it has been difficult to distinguish among the formal predictions of such models based on analysis of choice-probability and accuracy data alone.

Remarkably, there have been few attempts to develop rigorous predictions of what *response-time* (RT) data should look like if people are using logical rules as a basis for classification. Because RT data often open windows into cognitive processing that would not be evident based on analysis of choice-probability data alone, pursuing such an avenue could yield great insights into the nature of people's category representations and processing strategies in cases involving rule-described categories. Thus, a major objective of this research was to develop and formalize a set of logical-rule models of classification, provides tests of such models in a variety of empirical domains, and develop contrasts between these models and alternative models of human classification performance.

A key issue in pursuing this objective, however, is that a wide variety of processing strategies might underlie the use and application of logical rules. For example, in cases in which rules are defined along multiple dimensions, the observer needs to make decisions about a test stimulus's value along each of those dimensions, and then needs to combine those separate decisions to determine if the overall classification rule has been satisfied. As detailed in the technical-approach section, to formulate the logical-rule models, one therefore needs to specify both the time course of processing along each of the individual dimensions, as well as specify the process by which those separate decisions are combined. Furthermore, designs are needed that allow one to distinguish between the predictions of rule models with these differing processing architectures, as well as to distinguish the class of rule models from important competing models.

As noted in the introduction section, many categories in the natural world do not appear to be organized in terms of simple logical rules, and much different classification strategies may be adopted in those situations. One of the most well known formal models of human classification in such domains is Nosofsky's (1986) exemplar-based GCM, which Nosofsky and Palmeri (1997) extended to account for classification RTs by developing their exemplar-based random-walk (EBRW) model. A long-standing theme of exemplar-based modeling of classification is that there may be close relations between the processes of classification and old-new recognition, because both may be based on evaluating the similarity of test objects to old exemplars stored in memory. However, there have been few attempts to extend and apply the EBRW model in the domain of

recognition RTs, and those initial tests were very limited. A major objective of the present work was to develop a more fully specified and rigorous version of the EBRW model and to apply it in a variety of domains involving memory search and recognition RT data. A further objective was to obtain rigorous tests of the EBRW-recognition model, using both classic data sets and new empirical tests, and thereby further the goal of developing a unified theoretical account of the processes of categorization and recognition.

Technical Approach

The formalization of the logical rule-based models of classification RT involved an integration of decision-bound models of classification; random-walk evidence-accumulation models of decision making; and alternative architectures of information-processing for combining decisions across multiple dimensions. Furthermore, an experimental paradigm was developed that allowed one to develop strong qualitative contrasts among different members of the class of logical rule-based models at the level of mean RTs and through examination of detailed RT-distribution data.

An illustration of the main experimental paradigm and a sketch of part of the complete theory is illustrated in Figures 1 and 2 below.

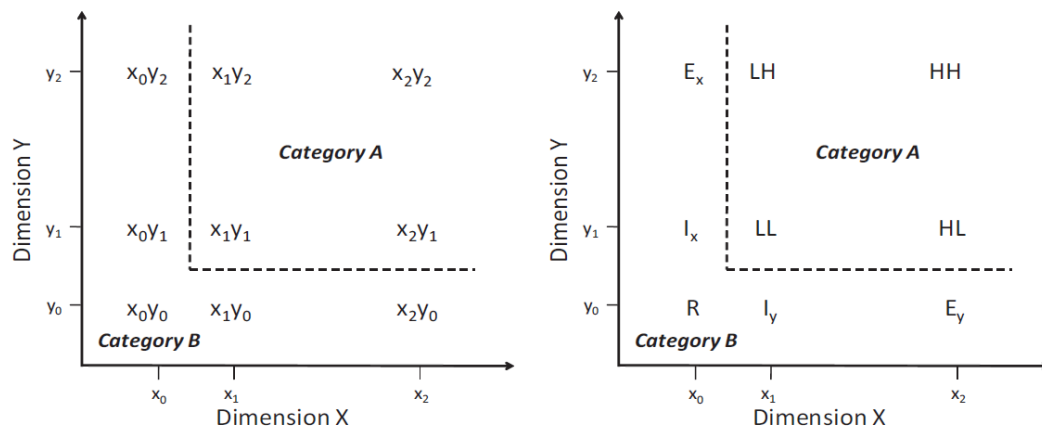


Figure 1. Left panel: Schematic illustration of the category structure used for testing the logical-rule models. The stimuli are composed of two dimensions, x and y , with three values per dimension, combined orthogonally to produce the nine members of the stimulus set. The stimuli in the upper-right quadrant of the space are the members of the “target” category (A), whereas the remaining stimuli are the members of the “contrast” category (B). Right panel: Shorthand nomenclature for identifying the main stimulus types in the category structure. H and L refer to the high- and low-salience dimension values, respectively; R = redundant stimulus; I = interior stimulus; E = exterior stimulus.

As shown in Figure 1, the stimuli varied along two continuous dimensions with three values per dimension, combined orthogonally. Membership in the “target” category (A) is defined by a conjunctive rule: A stimulus is a member of Cat. A if it has value greater than or equal to x_1 on Dimension X and has value greater than or equal to y_1 on Dimension Y. Membership in the “contrast” category (B) is defined by a complementary disjunctive rule: A stimulus is a member of Cat. B if it has value less than x_1 on Dimension X or less than y_1 on Dimension Y. Decision making on each dimension was presumed to be governed by a perceptual sampling process that drove a random walk. For example, as illustrated in Figure 2, each value on Dimension X was assumed to give rise to a perceptual distribution, and the observer was presumed to divide the perceptual space into response regions (A vs. B) by setting a criterion (decision bound) on that dimension. This component of the modeling leads to the well known finding that

stimulus values farther from the decision bound (e.g., x_2 in Figure 2) would lead to faster and more accurate decisions along that dimension.

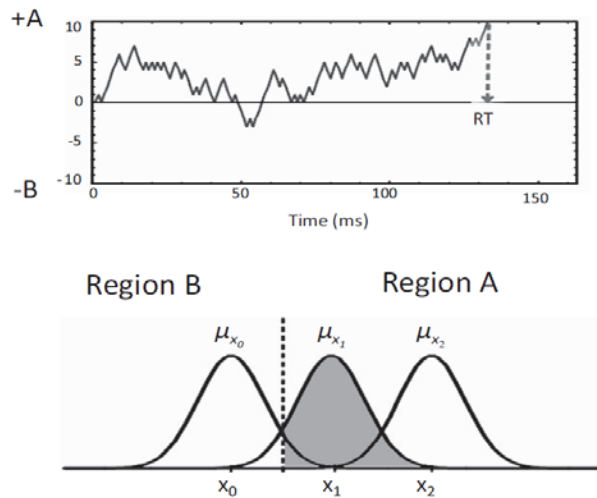


Figure 2. Schematic illustration of the random-walk process that governs decision making on each individual dimension. In the illustration, x_1 is the presented stimulus value. Percepts sampled from distribution x_1 that fall to the right side of the decision boundary lead the random walk on Dimension x to take steps toward Criterion $+A$. RT = response time.

To make a categorization response, the decisions along each individual dimension need to be combined to determine which logical rule is satisfied. For example, an object is judged to be a member of the target category only if both the X and Y random walks lead to Region-A decisions. The general theory made allowance for the possibility that the dimensions were processed in either serial, parallel, or coactive fashion; and that either a self-terminating or exhaustive stopping rule was used. As explained in the Progress and Results section, the paradigm yields sharply contrasting predictions of patterns of classification RTs depending on which information-processing architecture underlies the rule-based classification decisions.

Part 2: Space limitations allow me to provide only a sketch of the extensions of the EBRW model to the domain of old-new recognition RTs. As in the standard model, items from a study list are presumed to be stored as individual exemplars in memory. The exemplars are represented as points in a multidimensional similarity space. Based on factors such as recency of presentation, the exemplars reside in memory with differing strengths. In the extended recognition model, we imagine that “background” or “criterion” elements also exist in memory, with strengths that are, at least in part, under the control of the observer. When a test item is presented, it causes the stored exemplars to be activated. The activation is determined jointly by the memory strength of the exemplar and its similarity to the test item. The exemplars and criterion elements race to be retrieved with rates proportional to their activations. If an old exemplar is retrieved, a random walk process steps toward an “old” response threshold; whereas if a criterion element is retrieved, the random walk steps toward a “new” response threshold. The retrieval process continues until one of the response thresholds is reached. The RT is determined by the time that it takes the random walk to reach one of the thresholds.

Progress Made and Results Obtained

Logical-Rule Model Project. As noted in the Technical Approach section, the Figure-1 paradigm used for testing the logical-rule models allowed one to derive sharply contrasting qualitative predictions of performance from the different candidate architectures, as well as to contrast the predictions of the rule models from major alternatives. The predictions at the level of mean RTs are shown schematically in Figure 3 (next page). The crucial point is that, combined across the target and contrast categories, each individual logical-rule model of classification RT yields its own unique signature of performance, so the paradigm is highly diagnostic. In addition, through use of detailed RT-distribution data and analyses, one can even discriminate between the predictions of the rule models and extremely general single-channel models of RT data that do not include concepts of serial or parallel processing. (It should be noted that the qualitative tests derived for the models extended significantly an earlier diagnostic battery that had been developed by Townsend and his colleagues.)

The general theory was tested in a wide variety of experiments. In the initial presentation of the general theory, Fific, Little and Nosofsky (2010) conducted validation tests in which subjects were given explicit instructions to use a particular serial self-terminating logical-rule strategy in which the dimensions were to be processed in a fixed order. In order to facilitate the use of this strategy, the experiment involved use of highly separable-dimension stimuli in which the relevant parts of the stimuli were presented in non-overlapping spatial locations. The resulting patterns of mean RTs and detailed fits of the models to the individual-subject RT-distribution data provided strong support for the fixed-order serial self-terminating rule model. In more interesting empirical tests, Little, Nosofsky, and Denton (2011) had subjects engage in free-strategy classification. In one experiment, they used the same non-overlapping separate-parts stimuli as did Fific et al. (2011). In a second experiment, they tested stimuli composed of separable dimensions that were presented in overlapping spatial locations of the display. In the separate-locations design, the results again pointed decidedly to a serial self-terminating logical-rule strategy, with some subjects processing the dimensions in a fixed order across trials, and other subjects processing in a mixed order. The individual-subject mean RTs from that experiment are displayed in Figure 4. Comparing to Figure 3 (see next pages), it can be seen that the results point decidedly toward the serial self-terminating models. By contrast, in the experiment involving separable dimensions that occupied overlapping spatial locations, strong support was still obtained for the logical rule models, but now with the processing architecture involving a mix of serial and parallel self-terminating processing. Finally, in a third major set of studies, Little, Nosofsky, Donkin and Denton (in press) tested the paradigm using highly integral-dimension stimuli. In accord with their predictions, the pattern of mean RTs as well as the detailed fits to the RT-distribution data now pointed decidedly toward a *coactive* processing architecture, in which information from the individual dimensions was pooled into a common processing channel.

(Progress Section is continued following Figures 3 and 4.)

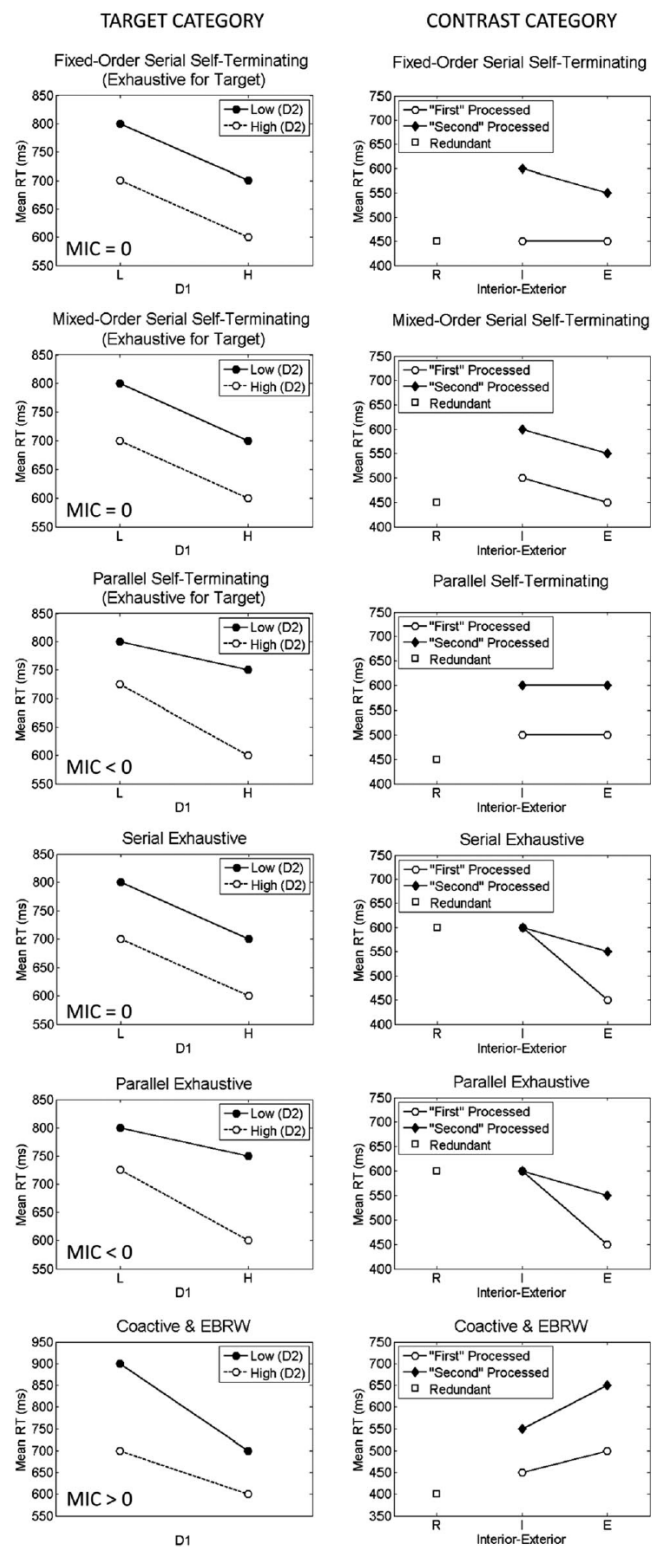
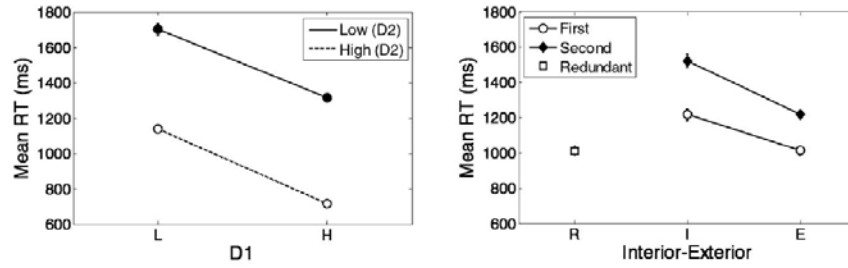
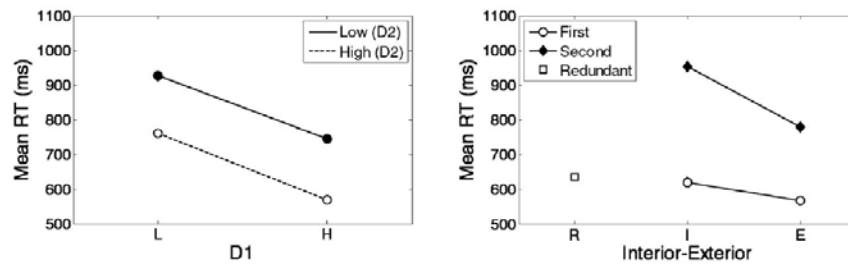


Figure 3

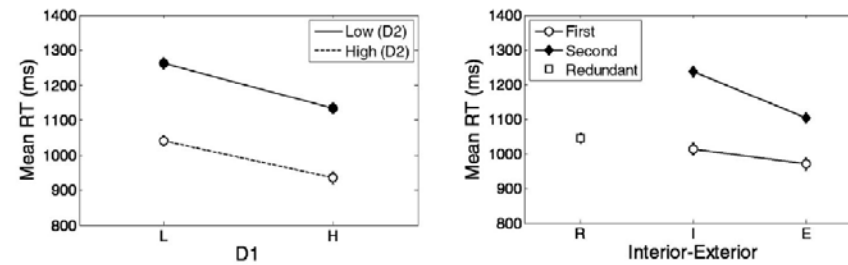
Participant L1



Participant L2



Participant L3



Participant L4

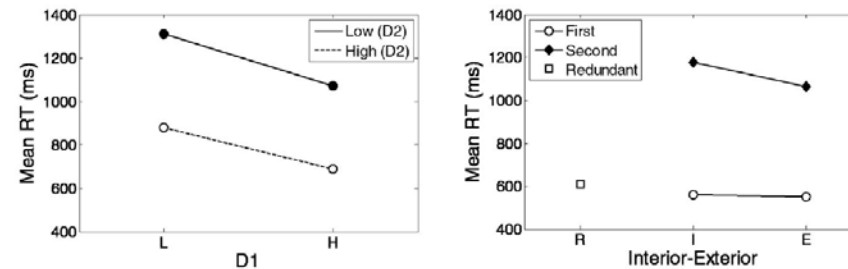


Figure 5. Experiment 1: Observed mean response times (RTs) for the individual participants and stimuli. The left panels show the results for the target-category stimuli, and the right panels show the results for the contrast-category stimuli. Participants are referred to as L1–L4, in which the L designates the lamp-stimuli experiment. Left panels: L = low-discriminability dimension value; H = high-discriminability dimension value; D1 = Dimension 1; D2 = Dimension 2. Right panels: R = redundant stimulus; I = interior stimulus; E = exterior stimulus. For ease in making comparisons with the prediction graphs in Figure 3, the contrast-category stimuli are labeled with respect to whether they are on the “first-processed” or “second-processed” dimension, as defined in the text.

Figure 4

Recognition Response Times Project.

The EBRW model of categorization RTs was extended to account for varieties of recognition-based and categorization-based memory search. The nature of the extensions was outlined in the Technical Approach section. The extended theory was tested in several new studies.

In the major paper (Nosofsky, Little, Donkin, & Fific, 2011; see also Donkin & Nosofsky, 2012a), we showed that the EBRW accounted in natural fashion for wide varieties of phenomena from classic short-term memory scanning studies. Furthermore, we illustrated that the model also accounted in natural fashion for performance in extended versions of memory-scanning paradigms that involved memorized stimuli embedded in continuous-dimension similarity spaces. For example, in Experiment 1 of Nosofsky et al. (2011), the stimuli were a set of 27 Munsell colors varying along dimensions of hue, saturation, and brightness. Similarity-scaling studies were used to derive a multidimensional scaling (MDS) solution for the colors to precisely measure their similarities. In an independent memory-scanning experiment, 300 different memory/test lists were constructed. The lists varied in memory set size (1-4 items); whether the test probe was old or new; and, if old, the lag with which the test probe was presented on the study list. Colors were randomly sampled from the stimulus space to construct the lists, thereby providing an extremely comprehensive test of the model. Three observers engaged in the memory-scanning experiment for 20 sessions, with each of the individual memory/test lists presented once per session. The model yielded very similar results for the three subjects, so the main analyses considered performance averaged across the subjects. The summary results from the experiment are displayed in Figure 5. The top panels plot observed performance, whereas the bottom panels show predictions from the model. It can be seen that the model captures in extremely accurate fashion how mean RTs and error rates vary as a function of the variables of memory set size, old/new status of the test probe, and lag. Moreover, as shown by Nosofsky et al. (2011), the model also captured reasonably well the mean RTs and error rates associated with each of the individual 300 lists. These data varied considerably across different tokens of the individual lists, because of their hugely varying similarity structures. Thus, the ability of the EBRW model to capture performance at this individual-list level is an extremely important achievement.

In another study, Donkin and Nosofsky (2012b) showed that the exemplar-based evidence-accumulation model accounted extremely accurately for detailed RT-distribution data associated with hits, misses, false alarms and correct rejections in a memory-scanning experiment involving longer lists. Furthermore, an interesting discovery was that the model provided a parsimonious account of the complete set of data by assuming that memory strength of the stored exemplars was a power function of their lag of presentation. A goal of future research is to ascertain the detailed psychological mechanisms that may give rise to this discovered power law of memory strength.

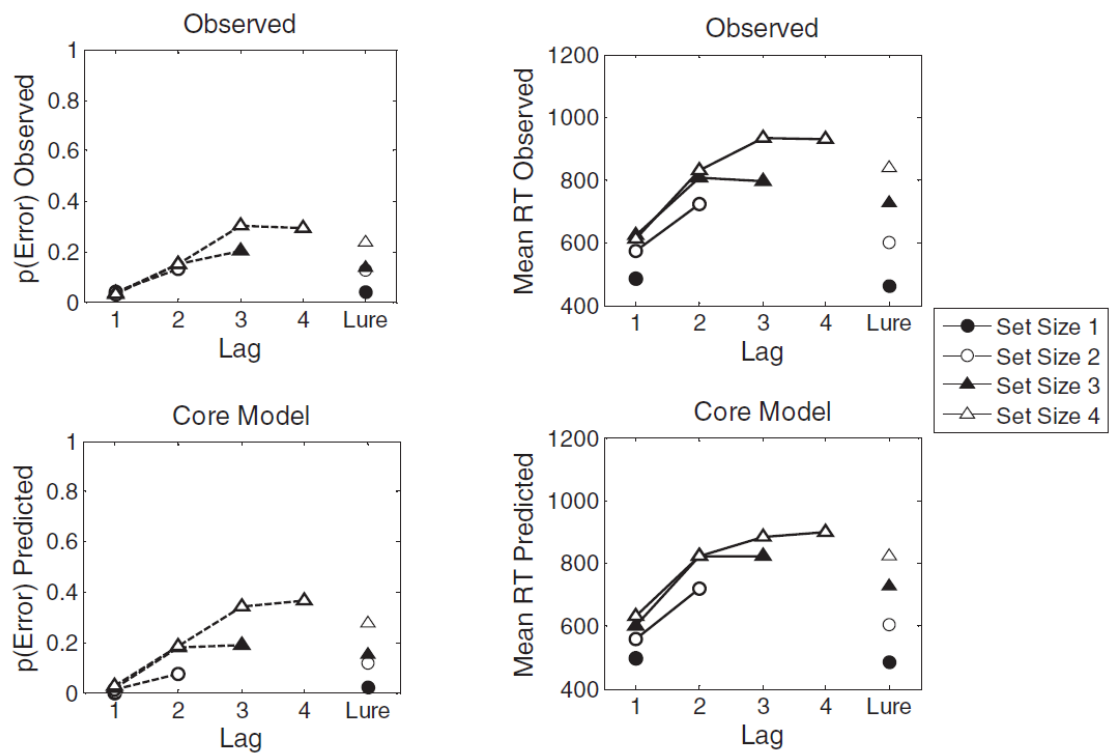


Figure 5

4. Significance of Results and Impact on Science

Part 1: Logical Rule Models of Classification Response Times

One of the classic ideas in cognitive psychology and cognitive science is that people may formulate and evaluate logical rules as a basis for classifying objects into rule-defined categories. Despite the idea's long history, researchers have not developed theories that would allow them to predict what classification RTs should look like if people are indeed using these rule-based strategies. Because it is often extremely difficult to distinguish between alternative models based on examination of choice-probability data alone, the use of RT data can open new windows into the decision-making mechanisms that underlie categorization behavior. This research was the first to formulate rigorously-defined models of logical-rule-based classification RTs. An important aspect of the formalization involved the idea that a variety of information-processing mechanisms may underlie the application of the logical rules. A paradigm was developed that allowed one to test the rule models against major alternatives, and that allowed one to diagnose the particular information-processing architecture that may have mediated the rule-based decisions. The experiments provided strong support for the general logical-rules framework, and yielded a highly interpretable pattern of results for how information-processing architectures varied across conditions. The theory and methods now provide extremely valuable tools for better understanding the nature of the representations and psychological processes that underlie rule-based categorization decision making.

Part 2: Memory Scanning Viewed as Exemplar-Based Categorization

Whereas the emphasis in the Part-1 studies was on rule-based forms of categorization, in the Part-2 project the emphasis was on exemplar-based forms of categorization and how these might be related to basic memory processes. The exemplar-based random-walk model, which has been applied successfully to varieties of categorization RT data in past work, was extended to the domain of short-term memory scanning. Remarkably, the model provided natural accounts of wide varieties of results involving the time course of memory-based decision making. The work suggests the intriguing possibility that the cognitive processes that are involved in forming categories and in probing memory may be very closely related.

5. Publications Resulting From the Research

Research funded solely from the AFOSR grant:

- Fific, M., Little, D.R., & Nosofsky, R.M. (2010). Logical-rule models of classification response times: A synthesis of mental-architecture, random-walk, and decision-bound approaches. Psychological Review, 117, 309-348.
- Nosofsky, R.M., & Little, D.R. (2010). Classification response times in probabilistic rule-based category structures: Contrasting exemplar-retrieval and decision-bound models. Memory & Cognition, 38, 916-927.
- Nosofsky, R.M. (2011). The generalized context model: An exemplar model of classification. In E. Pothos and A. Wills (Eds.), Formal approaches in categorization. Cambridge University Press.
- Little, D.R., Nosofsky, R.M., & Denton, S.E. (2011). Response -time tests of logical-rule models of categorization. Journal of Experimental Psychology: Learning, Memory, and Cognition, 37, 1-27.
- Nosofsky, R.M., Little, D.R., Donkin, C., & Fific, M. (2011). Short-term memory scanning viewed as exemplar-based categorization. Psychological Review, 118, 280-315.
- Donkin, C., & Nosofsky, R.M. (2012a). A power-law model of psychological memory strength in short-term and long-term recognition. Psychological Science, 23, 625-634.
- Donkin, C., & Nosofsky, R.M. (2012b). The structure of short-term memory scanning: An investigation using response-time distribution models. Psychonomic Bulletin & Review, 19, 363-394. {Note: awarded “best article” in Psychonomic Bulletin & Review, 2012}
- Little, D.R., Nosofsky, R.M., Donkin, C., & Denton, S.E. (in press). Logical rules and the classification of integral-dimension stimuli. Journal of Experimental Psychology: Learning, Memory, and Cognition,

(Continued)

Research that was partially funded by the AFOSR grant:

Gureckis, T.M., James, T.W., & Nosofsky, R.M. (2011). Re-evaluating dissociations between implicit and explicit category learning: An event-related fMRI study. Journal of Cognitive Neuroscience, 23, 1697-1709.

Nosofsky, R.M., Little, D.R., & James, T.W. (2012). Activation in the neural network responsible for categorization and recognition reflects parameter changes. Proceedings of the National Academy of Sciences, 109, 333-338.

Nosofsky, R.M., Denton, S.E., Murphy-Knudsen, A.F., & Unverzagt, F.W. (2012). Studies of implicit prototype extraction in patients with mild cognitive impairment and early Alzheimer's disease. Journal of Experimental Psychology: Learning, Memory, and Cognition, 38, 860-880.

Stanton, R.D., & Nosofsky, R.M. (in press). Category number impacts rule-based and information-integration category learning: A reassessment of evidence for dissociable category-learning systems. Journal of Experimental Psychology: Learning, Memory, and Cognition,