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Interdisciplinary Collaborative Consortium on the Cognitive Neuroscience of Category Learning

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1. Objectives & Significance

The study of category learning has been a central paradigm within cognitive psychology for over twenty-five years. For a number of reasons, cognitive neuroscientists have recently been drawn to this paradigm. First, there is a large body of pre-existing empirical and theoretical analyses of category learning. Neuropsychological studies of brain-damaged populations and neuroimaging of healthy subjects have provided preliminary insights into the cognitive neuroscience of category learning. Second, category learning has aspects of both elementary associative learning as well as higher order cognition. On one hand, category learning can be viewed as a “cognitive skill” that shares many behavioral properties, and possibly some neural substrates, with motor-skill learning, and conditioning. On the other hand, categorization underlies many higher order cognitive abilities. When a connoisseur distinguishes a cabernet from a merlot, when a doctor recognizes that a patient’s symptoms are due to a particular disease, or when a weather forecaster uses today’s barometric pressure to predict tomorrow’s weather, they are all doing complex categorization. It is this dual nature—part elementary skill, part higher cognition—which makes category learning a valuable paradigm for studying fundamental and important aspects of human learning, at both the behavioral and neural levels of analysis.

In a typical category learning experiment, subjects are presented with stimuli that vary along several different dimensions. For example, the stimuli might be geometric figures of different size, shape, and color, such as large black squares and small white triangles. Other experiments have used random dot patterns, stimuli that vary along continuous stimuli (e.g., length or angle), or those which consist of the presence or absence of various features (e.g., patient symptoms in a medical diagnosis task). Subjects are typically required to classify each item into one of a number of contrasting categories. For example, based on a list of symptoms (features) a subject may be asked to make a disease diagnosis (categorization). Although subjects may initially have to guess, they can eventually learn which features and patterns are more likely to fall into one category versus another based on trial-by-trial feedback.

Like the stimuli, the structure of the categories can vary in a number of ways, including how different features are associated with each category, whether or not the rules for category assignment are probabilistic or deterministic, and the nature of the feature-feature correlations. Some category learning experiments focus on how well, and how quickly, subjects can learn a single categorization, while others studies focus more on transfer generalization: how training on a previous set of stimulus exemplars transfer to novel stimuli. Building on an extensive base of empirical data from psychological studies of category learning over the last thirty years, mathematical modelers have developed rigorous quantitative models of category learning that account for a wide range of behavioral phenomena and predict novel psychological phenomena. Building on these behavioral models, cognitive neuroscientists have just begun to explore and exploit the richness of category learning.

Although still in its early stages, work on the cognitive neuroscience of category learning has, already yielded many informative results. For example, neuropsychology studies have shown that many forms of category learning are impaired in patients with damage to their basal ganglia from Parkinson’s disease or Huntington’s disease. In contrast, some category learning tasks appear to be relatively intact in amnesics with medial temporal lobe damage, at least early in training. This pattern of data, mimicking what is often found with motor skills, provides some support for viewing some category learning as a cognitive skill. Other recent and ongoing neuropsychological studies are examining how category learning is affected by schizophrenia, Alzheimer’s disease, Tourette’s, Obsessive Compulsive Disorder, and Attention Deficit Disorder . Parallel to these neuropsychological studies, human brain imaging studies of category learning have identified several key brain regions critical to category learning, including the medial temporal lobes, basal ganglia, and pre-frontal cortex.

Mathematical models provide a third line of research. Some researchers have used these models to analyze the nature of the underlying deficits in category learning in Parkinson's disease in order to develop detailed hypotheses about the functional role of the basal ganglia and medial temporal lobes. Other researchers have used neural network models of these brain structures to begin to understand their contribution to category learning.

But the field is not without controversy. While some researchers have claimed that data on category learning in amnesic and Parkinson's patients provides evidence for independently operating memory systems in the brain, others have argued that—while multiple memory systems may well exist—current neuropsychological studies of patient populations have yielded data that can just as easily, and more parsimoniously, be explained by parametric variations within single-system memory models. Thus, while the cognitive neuroscience of category learning is a new and exiting direction with the potential to meld theoretical and behavioral analyses from cognitive psychology with techniques from cognitive neuroscience, there remain numerous unanswered questions regarding the nature of the neural substrates of category learning, and how these two scientific traditions can be effectively integrated. We have yet to fully leverage the cumulative empirical and theoretical contributions from cognitive psychology to create new and meaningful mappings between brain and cognition.

By uniting members of three (mostly, but not entirely) separate communities of researchers in this area, our collaborative consortium hopes to make strides toward establishing these mappings. The first group are those who have already participated in interdisciplinary collaborative teams studying the cognitive neuroscience of category learning. This group contains several existing networks of researchers who combine two or more of the following approaches: neuropsychological studies of patients, relevant behavioral analyses of healthy subjects, functional brain imaging, and mathematical or computational modeling.

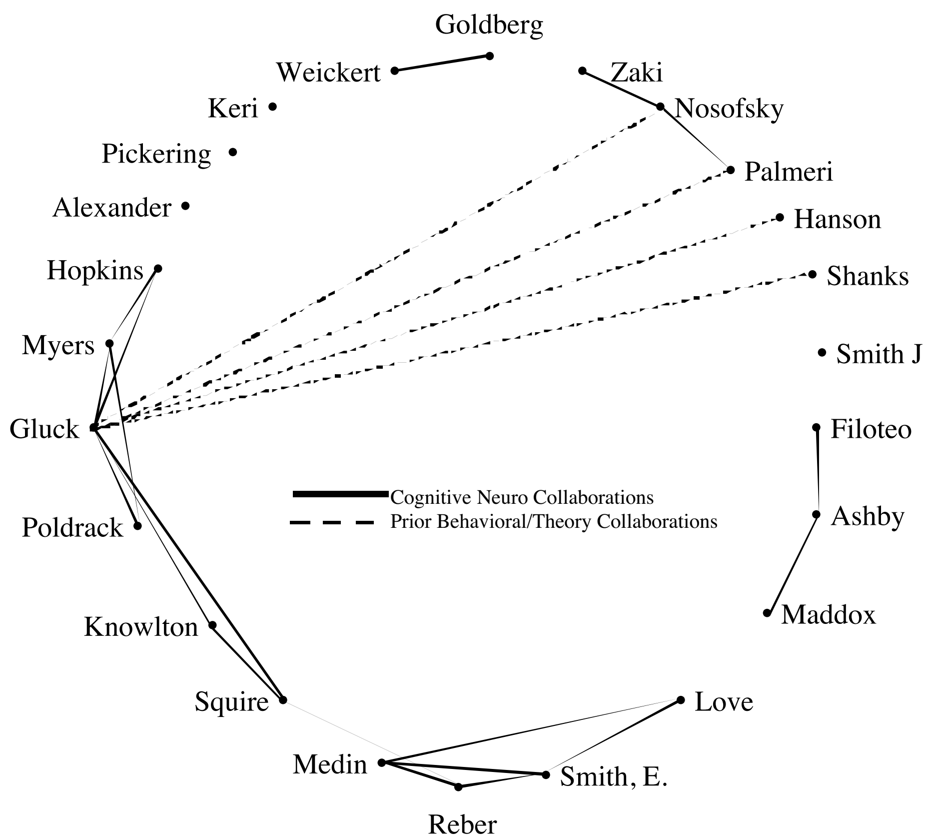

Figure 1. ***Collaborative relationships among participants. Solid lines are cognitive neuroscience collaborations; dashed lines are earlier theoretical or behavioral collaborations)***

As schematized in Figure 1, there are four (partially overlapping) sub-networks of collaborators in group 1: (1) **Gluck**, **Myers**, **Poldrack**, and **Hopkins** are using modeling, brain imaging, and clinical studies, (2) **Squire, Knowlton, Reber, and Gluck** have collaborated on clinical studies, (3) **Reber, Medin, Love,** and **Ed Smith are** using brain imaging and clinical studies, and (4) **Ashby, Maddox,** and **Filoteo** are integrating modeling and clinical studies.

A second community of contributors to this field are those whom we might classify as the "Critics and Theoreticians". Coming primarily from cognitive psychology, they include **Zaki**, **Palmeri**, **Shanks**, **Nosofsky**, and **J. Smith**, all of whom have provided theoretical analyses and commentary in the literature on this field, often engaging in spirited debates with some of the cognitive neuroscience researchers from the first group. Each of them has sought to bring rigorous behavioral and theoretical analyses from cognitive psychology to bear on the interpretation of neuropsychological studies of category learning in clinical populations. However, without access to patient populations themselves, they have not been able to directly test their theories or alternative interpretations of other people's neuropsychological data. Others, including **Hanson** and **Pickering,** have contributed neural-network models of category learning that offer constraints on the mechanisms and behaviors underlying category learning.

The final community in our consortium are clinically-oriented neuropsychologists who have been using category learning to study the learning impairments in various clinical populations, including those with schizophrenia and ADHD. These include **Keri**, **Alexander**, and **Weickert** & **Goldberg**. While these researchers have adopted some of the category learning paradigms from researchers in the first two communities, they have not been closely associated with others in the field, due to geographical constraints or the nature of their clinical orientation.

These three broad categories of participants are, at best, "fuzzy." In reality, many people's work crosses over from one type to another. For example, Palmeri has recently been involved with fMRI studies, and Keri has recently presented a computational modeling analyses of his prior data. By the end of the three-year grant we expect to see more of these cross-overs, further eroding the distinctions and divisions between different communities of researchers.

There has already been some interaction among some subsets of these research groups, including two prior symposia organized by the P.I. on the cognitive neuroscience of category learning, one at a Psychonomics Society Annual Meeting and the other at a Memory Disorders Society Annual Meeting. For the most part, however, these researchers have lacked a mechanism for ongoing substantive interaction and collaboration. This has held back progress in this area, because the work depends so critically on the effective melding of subtle behavioral analyses and theoretical models from cognitive psychology with the techniques and data from neuropsychology and neuroimaging. We believe that our understanding of the behavioral and brain bases of human learning will move forward faster and better if there is a framework for interaction, critique, education, and collaboration among the 24 researchers identified above. All bring specialized skills and training which can contribute and inform the research and thinking of others in the network. Together, this group offers the potential for a synergistic collective effort on convergent and interdisciplinary approaches to the following sixteen key issues in the cognitive neuroscience of category learning:

(1) How can behavioral analyses and mathematical theories from cognitive psychology inform neuroimaging and neuropsychological studies of category learning?
(2) Do functional imaging and neuropsychological studies provide converging views about category learning? What are the relative strengths or weaknesses of each as tools for understanding brain bases of category learning? How can these two methodologies work together to illuminate the brain bases of category learning?
(3) Could pharmacological approaches, in healthy or brain-damaged populations, be a valuable tool to consider?

(4) What kinds of neural-network models will facilitate our understanding of the brain-behavior relationships in category learning? What novel predictions can these make?
(5) How do the basal ganglia, medial temporal lobe, and pre-frontal cortex interact during category learning? What other brain regions are involved?
(6) What neurotransmitter systems might be implicated in category learning?
(7) How do task demands, stimulus design, surface features, and training methods in category learning experiments influence the brain regions involved?
(8) How does the underlying structure of the feature-feature and feature-category relationships affect how categories are learned and which brain regions are involved?
(9) How do probabilistic category structures influence category learning differently than deterministic or rule-based structures?
(10) Are there multiple strategies by which subjects can solve category learning tasks and, if so, do different strategies rely differentially on distinct brain regions? What factors promote the use of one strategy (and associated brain regions) versus others?
(11) How can animal research enhance our understanding of the cognitive neuroscience of category learning? In particular, do animal lesion studies provide converging insights for studies of neurologically impaired clinical human populations, and do animal electrophysiology studies provide converging insights into human brain imaging studies?
(12) How is learning from instances generalized to novel exemplars, and how is this affected by different brain regions?
(13) How does the higher-level structure of a knowledge domain affect the cognitive and neural processes involved in category learning?
(14) To what extent do categorization and recognition share common or distinct cognitive and brain mechanisms?
(15) How does awareness affect category learning?
(16) Can category learning tasks contribute to our understanding and treatment of neurological and psychiatric disorders?

Further background on the cognitive neuroscience of category learning, and details of the individual contributions of our 24 participants, is presented in the next section.

2. Scientific Background and Collaborative Participants

Our 24 collaborative participants represent most of the key people working in this area, although only subsets of them are currently collaborating or interacting with each other on a regular and substantive basis. As noted above, we have characterized the field as having three main sub-communities, including four distinguishable, but overlapping, interdisciplinary collaborative networks (see Figure 1). We review here in more detail the contributions and publications of each, identifying collaborative participants to this proposal in bold face type.

Behavioral studies of category learning have yielded several powerful formal mathematical models of human learning and memory. Early theories of category learning focused on simple rule-based categories (e.g., red»category A, blue»category B), the learning of which were well described by hypothesis-testing models. A subsequent development showed that a wide range of category learning and transfer generalization studies could be explained by the following claim: people store individual training exemplars, and then match new items to these stored exemplars using a non-linear similarity matching rule, in which each features influence on categorization was highly sensitive to the context (i.e., the other features) in which it occurred; developed by **Doug Medin** and colleagues in the early 1970s. This theory is known as the "exemplar trace" or "context" model and was initially used to evaluate correspondences between human and non-human primate studies of categorization (Medin & Schaeffer, 1978).

Rob Nosofsky generalized this model, relating it to a wide range of other phenomena in similarity and attention, and showed how it could be elaborated to incorporate selective attention. He thereby demonstrated a unified framework for both recognition and classification learning (Nosofsky, 1986; 1991). Another line of mathematical models of learning developed by Greg Ashby focused more on learning perceptual categories, drawing on the influential formalisms of signal detection theory from psychophysics (Ashby, 1992; Ashby & Townsend, 1986). In the mid 1980s, **Mark Gluck** developed a new line of category learning models that integrated formalisms of earlier animal conditioning theories with the new methods of connectionist, or neural-network, models (Gluck & Bower, 1988). This work showed that many properties of human associative learning and categorization could be understand as elaborations of similar principles seen in animal conditioning. A related line of studies by **David Shanks** showed that these animal-human correspondences are broad and encompass a wide range of contingency learning situations (Shanks, 1991).

Building on Gluck and Bower's earlier psychology experiments and models in the late 1980s, Gluck and **Catherine Myers** sought in the early 1990s to test if behavioral correspondences between animal and human learning might also point towards neurobiological correspondences between animal conditioning and human category learning. To explore this bridge, they drew on their cortico-hippocampal model of classical conditioning (Gluck & Myers, 1993). The animal model was based on studies of conditioning in animals with damage to the hippocampal region, corresponding roughly to the brain damage seen in people who suffer anterograde amnesia due to anoxia, herpes encephalitis, or other etiologies that result in relatively selective damage to the medial temporal lobes, including the hippocampus.

Gluck and colleagues at Rutgers developed several new category learning tasks based on variations of the Gluck and Bower (1988) experiments, including one known as the "weather prediction" task. This task uses four cards with geometric patterns as stimulus features. On each trial, the subject sees one or more of these cards and is asked to predict whether the next day's weather would be rain or sunshine. The actual weather category is determined by a probabilistic rule based on the cards: each card predicts rain or sunshine with a fixed probability. Thus, the circle card might be strongly predictive of rain while the triangle card might be strongly predictive of sunshine. The probabilistic relationships between cues and outcomes ensures that it was impossible for subjects to learn the categorization with complete certainty, although it was possible to achieve significant learning by inducing how diagnostic each card was for each category.

Larry Squire, **Barbara Knowlton** and Gluck used this task to study category learning in amnesic patients (Knowlton, Squire, & Gluck, 1994). Amnesic patients and control subjects were trained to classify stimulus patterns that varied on four dimensions into one of two categories. Initially, amnesic patients learned to associate stimulus cues with the appropriate outcomes at about the same rate as control subjects, improving from chance performance (50% correct) to approximately 65% correct over the first 50 trials. With extended training, however, control subjects outperformed amnesic patients. Thus, from a behavioral perspective, the effects of hippocampal-region damage in amnesics was apparent only late in training.

Gluck and Myers analyzed the Knowlton et al. (1994) category data using the Gluck and Myers (1993) model of conditioning, assuming that features are treated analogous to conditioned stimuli, and categories are treated analogous to unconditioned stimuli (Gluck, Oliver, & Myers, 1996). In this way, a conditioning model can be applied to category learning experiments. Within this model, a hippocampal-region network develops new stimulus representations; however, early in learning, before these new representations develop, the brain regions that support long-term memory (other than the hippocampal region) must rely on pre-existing stimulus representations. Later in training, as the hippocampal representations become available, these new representations are acquired by other brain regions; this enables further improvement in categorization performance. In contrast, only the pre-existing representations are ever available in the amnesic (hippocampal-region lesioned) model. Thus, early in training, categorization performance is expected by the model to be similar in the amnesic and intact conditions. However, as training progresses over later trials, the intact model outperforms the amnesic model because it can take advantage of the new stimulus representations developed earlier in training. This qualitative pattern mimics the data from Knowlton et al. (1994), as well as other late-training amnesic deficits found in Squire and Frambach's (1990) study of cognitive skill learning. A more recent study of amnesic patients learning the weather prediction task was reported by Gluck, Myers, and **Mona Hopkins** (Hopkins, et al. 2001).

In other studies, Barbara Knowlton, Larry Squire and colleagues found that patients with basal ganglia damage from Parkinson's disease were impaired on the weather prediction task and, thus, argued that probabilistic category learning necessitates the involvement of the basal ganglia (Knowlton et al, 1996a; 1996b). This study showed that patients with Parkinson's disease were slow to learn to predict the weather when compared to control subjects, especially early in training. However, after training, they had no trouble answering questions that tested for explicit memory of the training episode.

Recently Gluck, Myers, and colleagues have developed a series of strategy analyses for category learning tasks, and have shown that while healthy subjects start with a simple strategy and then shift to more complex strategies, Parkinson's patients stick with the simpler strategies throughout all three days of training on the weather prediction task (Shohamy et al., 2001a; 2001b). In a related line of computational modeling, they have demonstrated that this pattern of learning is consistent with a lower reinforcement rate in a computational model of cortico-basal-ganglia networks of this kind of learning (Kalanithi, Myers, Shohamy, & Gluck, 2002).

Paul J. Reber, who, like Knowlton, worked with Squire as a postdoctoral fellow, has been examining the neural correlates of a simple visual category learning task in which participants learn to identify members of a category of dot patterns without realizing they have learned a category. This type of learning has previously been shown to be intact in amnesic patients (Knowlton & Squire, 1993) and patients with Parkinson's disease (Reber & Squire, 1999) indicating that neither the medial temporal lobe nor the basal ganglia materially support this form of learning. A series of fMRI studies (Reber, Stark & Squire, 1998a,b; Reber, Wong & Buxton, submitted; Reber, Gitelman, Parrish & Mesulam, submitted) examining this task have found consistent changes in processing as a result of learning. They observed a Categorical Fluency Effect (CFE), in which categorical stimuli evoke less activity in posterior visual cortex than non-categorical stimuli. The CFE reflects a rapidly acquired change in visual processing that generalized to novel category members and may indicate the neural substrate of this form of nondeclarative memory. An ongoing study of theirs has found evidence that this type of learning is retinotopically specific: that is, when the study stimuli are presented to only one side of space (e.g., the right side), both successful categorical discrimination and the CFE only occur for test stimuli subsequently presented on the same side (Kim et al., 2002). This result provides further evidence that the CFE represents representational change that supports category knowledge. Reber and colleagues have developed a simple connectionist model that demonstrates how unsupervised learning can extract an underlying category from a set of examples (Reber, 2002). They intend to use this model to motivate further studies examining the underlying learning mechanisms of CFE.

In another line of research, Reber and Squire have examined the phenomenon of Artificial Grammar Learning in patients with Parkinson's (Reber & Squire, 1999) and using fMRI (Skosnik et al., 2001). This task involves learning of a category of stimuli that conform to an underlying rule structure. These investigators have recently been extending these studies to new categorization tasks in which they manipulate the complexity of the category in order to identify conditions in which nonconscious (nondeclarative) categorization succeeds and fails. More recently, Reber has joined with **Doug Medin** and **Edward Smith**, two seminal figures from the development of experimental and theoretical analyses of category learning in cognitive psychology. Along with **Bradley Love**, they are trying to bring more sophisticated categorization theory to studies of neuropsychology and neuroimaging.

Russ Poldrack was one of the first researchers to use functional neuroimaging to investigate the neural basis of category learning in healthy individuals. He initially used the weather prediction task in healthy adults with a blocked-design fMRI and found a widespread network of cortical and subcortical regions, including the caudate nucleus, was active for classification compared to a perceptual-motor baseline task (Poldrack, Prabakharan, Seger, & Gabrieli, 1999). More recently , Poldrack, Clark, Paré-Blagoev, Shohamy, Creso Moyano, Myers, & Gluck, (2001) used event-related fMRI to examine learning-related changes in brain activity during category learning. Parametric analyses of activation over time showed that the medial temporal lobes were active very early in training whereas the basal ganglia remained inactive. However, this activation pattern switched rapidly as learning proceeded. These results are in direct conflict with previous proposals which argued that although probabilistic category learning relies primarily on the basal ganglia, the medial temporal lobe becomes important later in training (i.e., when amnesics show the greatest deficit in performance). Instead, these imaging results suggest that the late-training impairment of amnesics on the weather-prediction task may arise from a lack of MTL activity early in training, which may be important for structuring task representations in order to allow optimal performance. In order to determine whether MTL and BG might be interacting during learning, Poldrack et al. (2001) performed a functional connectivity analysis to examine correlation between activity across brain regions. This analysis found that activity in the MTL was negatively correlated with activity in the BG across subjects; that is, increased activation of the BG was associated with greater deactivation in the MTL.

Thomas Palmeri, a former student of Nosofsky, and his colleagues have also used functional imaging to explore the neural bases of category learning. Flanery & Palmeri (2001) examined differential brain activation using fMRI in the a dot-pattern task (see Reber & Squire, 1999) and the probabilistic weather prediction task as a function of categorization experience. In Flanery et al. (2000), they examined brain activation using fMRI during explicit dot-pattern category learning tasks, manipulating category familiarity and degree of category membership. In earlier contributions, Palmeri and Flanery (1999, 2001) provided critiques of the methods typically used to demonstrate preserved category learning in amnesia.

Greg Ashby and **Todd Maddox** and **Vincent Filoteo** have worked over the years in an interdisciplinary collaboration that has shown how computational models of learning and signal detection can inform and guide neuropsychological studies of patients with basal ganglia damage. Ashby, Alfonso-Reese, Turken, and Waldron (1998) proposed a computational neuropsychological theory of category learning, called COVIS, that assumes separate explicit (rule-based) and implicit (procedural-learning) category learning systems that compete throughout training. Initially, the system weight favors the explicit system, but it is then adjusted up and down depending on the relative success of the two systems. In addition to accounting for category learning in healthy young adults, COVIS also accounts for available data from a variety of special neuropsychological populations (e.g., the elderly; patients suffering from Parkinson's disease, Huntington's disease, medial temporal lobe amnesia, or lesions of the prefrontal cortex). Many recent papers from Ashby's lab have tested and extended this theory (Ashby, Isen, & Turken, 1999;Ashby & Waldron, 1999; Ashby, Waldron, Lee, & Berkman, 2001; Waldron & Ashby, 2001).

In a related line of studies, Ashby's former student, Todd Maddox, has also been examining the neural substrates involved in categorization. In a recent study, Filoteo, Maddox, & Davis (2001a) trained amnesic patients on a non-verbal information-integration categorization rule across two sessions, and demonstrated that these amnesic patients showed normal learning during both sessions. A second study (Maddox & Filoteo, 2001) examined Parkinson's patients' ability to learn the same rule, as well as a second verbal rule-based categorization rule. Parkinson's patients showed deficits in information-integration rule learning, but normal learning of the verbal rule. A third study (Filoteo, Maddox & Davis, 2001b) examined Huntington's patients' ability to learn the same two categorization rules. These patients showed deficits for both rules. The authors argue that their results suggest an important role of the striatum in nonverbal information-integration categorization rule learning, but little or no role in verbal rule-based categorization rule learning.

Knowlton, Squire and others have drawn on neuropsychological results to support the claim that there are two independent memory systems: a declarative memory system based in the hippocampus and medial temporal lobes and a non-declarative system dependent on the basal ganglia and other brain regions. But this claim has yielded some heated dialogue in the literature and some criticism from cognitive psychologists. Nosofsky, working with **Safa Zaki,** proposed a single-system interpretation of the Knowlton and Squire (1993) dissociations between categorization and recognition (Nosofsky & Zaki, 1998). Healthy participants in their experiment were given the Knowlton and Squire (1993) recognition or categorization test either immediately after training or following a one-week delay. The results of the delayed group were similar to those exhibited by the Knowlton and Squire amnesic group in that there was a large decline in recognition performance but little decline in categorization performance. The authors argued that a formal exemplar model, which incorporated a difference in memory sensitivity across the two groups, provided an excellent quantitative fit to the recognition and categorization data. In a related paper, Zaki & Nosofsky (in press), addressed a single-system account of the dissociation observed by Reed, Squire, Patalano, Smith, and Jonides (1999) in which amnesic patients performed at near normal levels in a categorization task involving stimuli with discrete features, but showed impaired recall of the features. The results suggested that participants use only a few of the dimensions in the categorization task, whereas they must use many dimensions in the cued-recall task. The authors conclude that different memory demands across the two tasks may be responsible for the observed dissociation. Thus, these researchers have claimed that current neuropsychological studies of category learning do not necessarily provide support for independent memory systems in the brain.

David Shanks, in London, has studied the relationship between category learning and explicit/declarative memory. Like Nosofsky, he argues that there are simpler single-system interpretations of the neuropsychological data on category learning. Kinder & Shanks (2001) showed that data from a standard categorization task (artificial grammar learning) and a memory version of the same task (recognition) can be explained without the need for separate neural systems. The authors argue that a unitary neural network model can account for normal performance and for the selective impairment in memory (but not categorization) seen in amnesia, and thus they question the utility of the procedural/declarative distinction.

The work of Nosofsky and Shanks highlights one of the key problems in the field: there is an apparent lack of consensus between neuropsychologists and mathematical modelers from the cognitive psychology tradition. The former tend to emphasize the neural architecture of category learning and place great emphasis on dissociations whereas the latter generally seek to understand a broad range of phenomena on the basis of a simple set of computational principles. Reconciling these two approaches is a key challenge for the field, and for our interdisciplinary collaborative consortium.

Another participant to these debates has been **J. D. Smith**. Smith and Minda (2000) reconsidered the amnesic dissociation between categorization and recognition that Knowlton and Squire ascribed to prototypes in categorization but which Nosofsky and Zaki ascribed to less sensitive exemplar processes in categorization. Smith and Minda claim that exemplar-based approaches qualitatively fail to explain the amnesia data and argue in favor of the original interpretation of Knowlton and Squire. Given the focus in many of the recent analyses of amnesic performance on the earliest stages of learning, Smith's earlier behavioral work may also be relevant. Smith and Minda (1998) argued that there is an extended period early in category learning during which performance is explained well using prototype models and theory but poorly using exemplar models and theory. More recently, Smith, Minda, & Washburn (2001) have begun to explore correspondences between human and non-human primate category learning, using a classic task that was previously studied experimentally and theoretically by Gluck and Nosofsky, called the six Shepard-Hovland-Jenkins tasks.

Stephen Hanson, working with Gluck, has conducted additional neural-network analyses of these Shepard-Hovland-Jenkins tasks and shown how these learning patterns might emerge from more global or integral interaction of cues (cf. Gluck & Bower, 1988) within neural network algorithms (Hanson & Gluck, 1991). In other experimental and computational analyses of category learning, Hanson has developed interpretations of the nature of the representations that would be required to support the combination of stimulus features in an integral or seperable manner (Hanson & Burr, 1990).

Alan Pickering in England, has provided additional theoretical contributions through the use of pharmacologically-based computational models. Pickering and Gray (2001) applied a three-factor dopamine learning rule to a category learning task and argued that variations in reinforcement strength (i.e. varying the dopaminergic reinforcement signal) across different simulated subjects did not materially affect the rate of category learning. In other work (Salum, Roque da Silva, & Pickering, 1999), Pickering proposed an account of how such a dopaminergic learning rule might contribute to the Kamin blocking effect, a behavioral phenomenon which has been essential to the development of animal and human theories of contingency learning and categorization. In earlier work, Pickering (1997) presented a model-based account that suggested that the hippocampus might be involved in the construction of the exemplar representations that may underlie some forms of category learning.

Clinically, category learning has become an ever increasing and broadly used behavioral paradigm for the study of a wide range of neurological disorders. In Hungary, **Szabolcs Keri** has been conducting an extensive series of clinical studies on the phenomenology and mechanisms of perceptual category learning. Keri has collected evidence from patients with schizophrenia, Alzheimer's disease, Tourette syndrome, and basal ganglia lesions. Keri et al. (1998) studied schizophrenic patients who participated in a category learning task in which continuously interpolated exemplars consisting of two conjoining features (size and shape) were presented. The patients showed an impaired categorization performance when exemplars were serially shown in the learning phase. This impairment was still present after an extended training phase. In contrast, the patients performed similarly to the controls when they received the verbal description of categories. In a follow-up to that study, Keri et al. (1999a) trained schizophrenia patients on a category learning task in which exemplars consisting of two conjoining features were included. The patients showed an impaired categorization performance when exemplars were serially presented and when feedback corrections were provided. Keri et al. (1999b) tested a group of patients with Alzheimer's disease (AD) and age-matched healthy control subjects with dot pattern recognition and categorization tests (Knowlton & Squire, 1993). Consistently with the amnesic syndrome of AD, the patients showed an impaired recognition performance. In addition, they failed to categorize prototype dot patterns, whereas there was no significant within-group difference in the case of distorted category exemplars. In Keri et al. (2000) patients with schizophrenia were able to improve their performance in a probabilistic classification learning task, the weather prediction task (Knowlton, Squire & Gluck, 1994), whereas they exhibit significant difficulties when they are asked to use explicit knowledge about category cues. This pattern of performance closely resembles to that seen in amnesic patients with medio-temporal or diencephalic lesions. More recently Keri et al (2001) showed that schizophrenic patients successfully learn dot pattern categories, even when their Wisconsin Card Sorting Test performance is severely impaired. This, they argue, provides evidence that dot pattern category learning is not mediated by the prefrontal executive system. Beginning to integrate theoretical modeling into their work, Keri et al (Trends in Cognitive Sciences, in press) present a brief overview on dot pattern category learning and sensory neocortical functions in Alzheimer's disease. This paper also summarizes a new artificial neuronal network model of category learning in which they argue that the "lesioned" version of the model behaves similarly to Alzheimer's patients in the dot pattern category learning task. On another line of work, Keri and collaborators (Neuropsychologia, in press) have worked with children with Tourette's syndrome, and shown that these subjects exhibit a less efficient learning in the weather prediction task when compared with matched controls, while their explicit memory performance and executive/visuospatial functions are spared.

Due to the geographic isolation of this group in Eastern Europe, it is more difficult to keep a sufficient scientific interaction with other groups from the main stream of research in the United States and England. That should change with the proposed collaborative consortium.

At the NIMH intramural laboratories, **Thomas Weickert** and **Terry Goldberg**, working in the laboratory of Daniel Weinberger, have also been studying the weather prediction task in schizophrenic patients. Previous studies have suggested that probabilistic learning associated with the weather prediction task relies on normal striatal processing. In their current work, the weather prediction task was used given to 35 patients with schizophrenia and 35 healthy controls. Patients with schizophrenia displayed significant performance differences from controls; however, cognitive-skill learning in patients appeared equivalent to controls on the basis of learning rate. The authors argue that the performance in the weather prediction task by patients with schizophrenia is most consistent with normal striatal processing and abnormal loading of striatal systems via cortical circuitry. This work is not yet published.

At the Yale Child Study Center, **Gerianne Alexander** has been using similar paradigms to study Tourette's syndrome. Altered structural and functional properties of the basal ganglia are implicated in the pathophysiology of Tourette's Syndrome, suggesting abnormalities in the neuroanatomical basis of motor control. This explains, in part, the uncontrolled motor movements and vocalizations that characterize Tourette's. The basal ganglia appear to also subserve implicit learning, including the implicit learning of probabilistic categories (Knowlton, Squire, & Gluck, 1994). To investigate whether altered functional properties of the basal ganglia in Tourette's Syndrome include atypical cognitive function, Alexander and colleagues administered multiple measures of implicit learning, including the weather prediction task to 55 healthy control adults and children and 110 adults and children with a neurodevelopmental disorder of impulse control (i.e., Tourette Syndrome, Obsessive Compulsive Disorder, and Attention Deficit Disorder with Hyperactivity). Currently, they are assessing group differences by comparing the percentage of correct responses and cue utilization across trials. Participation in the proposed consortium will provide this clinically-oriented group with valuable new training that will permit an evaluation of learning strategies that may also differ between these patient groups.

3. Proposed Collaborative Consortium Programs

We propose to promote progress through five programs:

(1) An annual workshop for core participants. Here network members will present their ongoing work, critique and discuss each other's work, and participate in focused round-table discussions on the key questions listed in Section 1. In the first year, these will be supplemented by a series of educational and historical tutorials on the background, methods and models of category learning from cognitive psychology. In addition to the core network members, we will invite additional specialists to comment and critique the research presentations. These would include other researchers with expertise in category learning (e.g., W. K. Estes), medial temporal lobe function and amnesia (e.g., J. Gabrieli), basal ganglia function and learning (e.g., T. Robbins, A. Graybiel, M. Packard), cortical function and learning (e.g., E. Miller, R. Desimone, N. Logothetis) and functional brain imaging (e.g., A. Martin, L. Ungerleider, S. Petersen). The role of these specialists will be to ensure that the research on the cognitive neuroscience of category learning has a broader relevance to big-picture issues linking brain, behavior, and cognition.

(2) Summer support for cross-laboratory training of students and postdocs. Transfer of methods and expertise from one research group to another often depends on the physical transfer of a young researcher from one lab to another for a period of training. Priority will be given for cross-disciplinary summer rotations that will import a new skill or expertise from one lab to another. While some of these may result in just technical training, other rotations are expected to be the genesis of new interdisciplinary collaborations.

(3) Support for collaborative neuropsychological patient resources. Although theoreticians, modelers, and cognitive psychologists have recently begun analyzing neuropsychological and neuroimaging results in category learning, most of the "Critics and Theoreticians" identified in Section 2 do not have access to patient populations. Several of the modelers, especially those from the cognitive psychology tradition, have proposed specific tests of their models or their criticisms of current work which could be evaluated through new studies of Parkinson's and amnesic patients. Without direct access to patients, these theoretical contributions remain isolated from empirical validation (or rejection!) that would further inform progress in this field. We propose to expand both the number and accessibility of amnesic and Parkinson's recruited and tested through the Rutgers Memory Disorders Project (covering a geographical range that includes New Jersey, Pennsylvania, New York, and Connecticut). This will allow for new collaborative studies to be initiated, especially with the "Critics and Theoreticians" identified earlier. Current resources at Rutgers are insufficient to entertain such collaborations at present. Among the potential predictions we would be able to test with expanded facilities for collaborative neuropsychological testing would be:

- Nosofsky & Johansen (2000) argued that "a critical direction for future research is to design new experiments that will distinguish our exemplar-based accounts of the phenomena from the multiple-system accounts. For example, suppose that our parameter-difference explanation of Knowlton and Squire's (1993) categorization-recognition dissociation is correct. Then it ought to be possible to design new, more diagnostic categorization problems in which the lowered level of memory sensitivity of the amnesics will in fact lead to worse-than-normal performance. By contrast, if Knowlton and Squire's hypothesis of separate memory systems governing categorization and recognition is correct, then amnesics should perform as well as normals regardless of the difficulty of the categorization problem that is involved." (p. 396). Support for amnesic testing would allow these predictions to be empirically tested.
- Pickering (1997) predicted that amnesic patients should be unable to learn category learning tasks that required the use of exemplar representations during learning. This prediction has not been directly tested.
- Shanks' work suggests that it is important to study artificial grammar classification in which the complex grammars, such as biconditional grammars. Although normal performance has been observed in amnesia with the simple grammars used by Knowlton & Squire, Shanks expects more complex grammars to show different patterns of data. This would parallel related studies by Reber and colleagues.
- Palmeri and others have pointed out that an important unresolved question is why some category learning tasks, such as the weather prediction task, are impaired in Parkinson's patients, even though these same patients are normal on the dot pattern task as well as the grammar learning task. The weather prediction task differs from the dot pattern task and the grammar learning task on many dimensions: in addition to its probabilistic nature, it permits the formation of verbalizable rules, uses stimuli with discrete distinct features, and involves learning multiple category labels; the dot pattern and grammar learning tasks lack these features, as well as others. It seems fruitful to conduct a full parametric exploration of the parameters of category learning tasks that cause Parkinson's patients, amnesics, and others problems with this task.

Additional collaborative neuropsychological studies of amnesic and Parkinson's patients are expected to evolve over the tenure of the consortium. When possible and appropriate, we will also seek to encourage novel collaborations using other techniques such as fMRI and pharmacological interventions, but direct support for these studies will need to come from past and future research grants from other sources. However, as noted below, we will be able to seed the development of imaging and other collaborations.

(4) Interdisciplinary collaborative visits. To facilitate researchers starting new projects and developing new collaborations, travel and lodging support will be provided for participants to travel from their own laboratory to spend one or several days visiting in the laboratories of other participants. These visits may include talks, learning new skills, and meetings to plan possible new collaborations. These visits are expected to be of several types:

- Bridging methodological boundaries., These visits will bring different techniques (e.g., fMRI, neuropsychology, neuropharmacology, computational modeling together. For example, the availability of high resolution magnets is limited. Support from this program would allow researchers who do not have access to imaging facitilities to travel to sites that do have these facilities to develop new collaborative imaging studies.
- Bridging geographical boundaries. These visits will bring together researchers from Western and Eastern Europe with colleagues in the United States, who may not have had sufficient interaction in the past to appropriately inform each other's work. For example, the Hungarian group and the NIMH researchers having similar aims—measuring vulnerability and trait characteristics of neuropsychiatric disorder—and interactions between these two groups would seem natural.
- Collaborative planning for neuropsychological studies. Researchers will meet to devise tests for theoretical predictions of models, as noted in the several projects detailed above. These meetings would allow for the development and use of the collaborative neuropsychological resources at Rutgers.
- Grants planning. The collaborations and cooperation supported by this program is expected to form the basis for future interdisciplinary and multi-institution research proposals to NSF and NIH.

(5) **An edited volume at end of three years on "*Interdisciplinary Approaches to the Cognitive Neuroscience of Category Learning.*"** We propose this with some caution, recognizing that many edited books are often of poor quality, reviewing work that has been published elsewhere or containing studies that would likely not survive rigorous peer review. As such, we recognize that many edited books have minimal impact and modest readership. Nevertheless, we believe that a volume would contribute to the field if it is tightly edited, peer-reviewed (both by members of the collaborative network and outside reviewers) and successively refined through presentation and feedback at three annual meetings. In addition, we believe that the value of such a volume to the contributors and the readers will be enhanced if the authors (a) adopt a common format and organization to facilitate the book's coherence and (b) specifically relate their work to others in the volume. The P.I. edited a volume within these parameters several years ago on the topic "Computational Models of the Hippocampus and Learning" which appeared as a special issue of the journal Hippocampus, following two symposia organized by the P.I. on that topic. Publishing as a special issue of a respected journal (versus a stand-alone book) insures that contributors treat these as peer-reviewed articles and that the volume will be read, at least, by the journal's regular subscribers, as well as by those who may purchase the single issue alone. We would seek a similar arrangement and format with an appropriate journal for the proposed volume.

These five programs, supporting an interdisciplinary collaborative consortium of 24 researchers, focussing on sixteen key issues, working together for three years, will move the field of learning and memory forward, by ensuring that the work conducted manifests the best of all the contributing methodologies and disciplines.

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