Research Statement

How does the brain adapt to an ever-changing environment? How does it strike a balance between continuity and change? What neural mechanisms underlie this fundamental cognitive ability? These challenging research questions require converging evidence from multiple methodologies and disciplines. The billions of neurons in the brain interact in complex ways to produce behavior, which is itself complex and varied. To make progress in the study of learning, a researcher must master a range of domains and techniques and engage in highly collaborative research with experts in various fields. These are important characteristics of my research.

My specific contribution to the study of learning consists of two interrelated strands. First, behavioral experiments reveal the dynamics of learning in non-stationary environments as a function of context, task difficulty, feedback, and other factors. I use state-of-the art psychophysical methods to track improvements in performance on time scales from seconds to days. This quantitative probing of behavior integrates seamlessly with the second strand of my research program—the development and testing of various learning models. Such models are indispensable conceptual tools for bridging the gap between brain and behavior. Therefore, in addition to experimental psychology and neuroscience, I have to be proficient in computer simulation and mathematical analysis of complex systems. I develop decentralized and interactive models—connectionist, symbolic, or mathematical—that incorporate biologically plausible learning mechanisms and are informed by an integrated cognitive architecture. My expertise in both neural networks and symbolic cognitive architectures makes me particularly qualified for this kind of work.

My present research focuses on the mechanisms of perceptual learning. A recent *Psychological Review* article (Petrov, Dosher, & Lu, 2005) exemplifies the benefits of combining quantitative experimentation and formal modeling. An experiment revealed perceptual learning effects that were partially specific to the context surrounding the target stimuli: Switch costs (interference) occurred whenever the context changed. A multi-channel selective reweighting model provides an existence proof that an incremental Hebbian mechanism can account naturally and quantitatively not only for this novel result, but for the well-documented stimulus and task specificity of perceptual learning, as well as for its detailed dynamics in non-stationary environments. The model has a fully functional perceptual subsystem that works on the images themselves and is consistent with the physiology of the primary visual cortex. Mathematical analyses and computer simulations show that the recurring switch cost pattern arises from the differential predictive value of certain context-dependent stimulus features. This conceptual understanding allowed us to make novel predictions about the role of feedback in perceptual learning, which were confirmed in a follow-up experiment (Petrov, Dosher, & Lu, resubmitted, *Vision Research*). More experiments are currently under way.

The work in perceptual learning complements my research on category rating and absolute identification. The combination of quantitative experimentation and formal modeling proved fruitful in this domain as well. A second *Psychological Review* article (Petrov & Anderson, 2005) consolidated the scattered literature on direct psychophysical scaling and exposed the intimate relationship between direct scaling and associative memory. A series of studies revealed that human response distributions are markedly non-stationary and non-uniform even when the stimulus distributions are stationary and uniform. Moreover, skewed stimulus distributions induce context effects in opposite directions depending on the presence or absence of feedback. A memory-based model called ANCHOR accounts for these and many other dynamic effects.

In the near future, I plan to build upon and extend the research programs established by the two *Review* articles mentioned above. In collaboration with Randall O'Reilly, I am currently modeling the retinal specificity of perceptual learning as a function of task difficulty and feedback. This project leverages the successes of the learning model of Petrov, Dosher, and Lu (2005) and the model of position-invariant object recognition of O'Reilly and Munakata (2000). Experiments are under way to constrain the model and test its predictions. In particular, feedback manipulations allow us to evaluate whether the neural plasticity mechanism is predominantly Hebbian or error-correcting.

The ANCHOR project has a lot of potential too. The model can be extended to do magnitude estimation in addition to category rating and identification. It also motivates interesting empirical work bearing on the long-standing controversy between prototype and instance-based categorization. The key idea is to exploit that, unlike the concept learning task used in most categorization studies, category rating does not require external feedback. Without feedback, prototype-based learning and instance-based learning follow different dynamics under non-uniform stimulus distributions. Based on some encouraging pilot data, I am writing a grant proposal along these lines.

All these examples illustrate how the study of learning can advance our understanding of cognition in general, and how the synergy of experimentation and modeling can achieve results that neither method can achieve alone. Reprints, data sets, and additional examples of my research are available on-line at http://www.socsci.uci.edu/~apetrov/

Alexander Petrov   Boulder, CO, Oct 10, 2005