Adaptive Precision Pooling of Model Neuron Activities
Predicts the Efficiency of Human Visual Learning

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This supplementary document contains material not contained in the CoSyne ’09 abstract. Much additional material can be found in Jacobs (2008; revised manuscript submitted to the Journal of Vision).

Visual Slant Discrimination Task: On each trial, a visual display depicted a planar surface defined by a “noisy” grid of horizontal and vertical lines. A surface was rotated in depth about its vertical axis. Based on this display, a human subject or a computational model judged whether a surface’s left-side or right-side was closer. Supervised feedback was provided on each trial. Subjects or models were trained for 14 blocks of 240 trials each.

Representational Front-End: The input to each computational model was the output of a fixed representational front-end. We used the same front-end (with the same parameter values) as Petrov, Dosher, and Lu (Psychological Review, 112, 715-743, 2005). The input to the front-end was a pixel-based representation of images from our psychophysical task. An image was filtered using a battery of spatially local, linear filters. The receptive fields of these filters resembled simple cell receptive fields of various spatial frequencies and orientations (e.g., Gabor filters). The filtered images were then rectified using the half-squaring operator. The resulting values formed a set of phase-sensitive maps (one for each orientation, frequency, and phase) which can be interpreted as activation patterns across a retinotopic population of simple cells in area V1. The retinotopic maps of phase-sensitive units were then combined into phase-invariant maps (analogous to complex cells) by pooling phase-sensitive units that form quadrature pairs. Each phase-invariant map was normalized by dividing it by a frequency-dependent normalization term, thereby producing a map whose total activation was approximately constant for above-threshold stimulus contrasts. Lastly, each phase-invariant map was pooled across space using a Gaussian weighting kernel. The final output of the representational front-end was the response values of 315 output units (9 spatial regions × 5 frequencies × 7 orientations). These output units are referred to as “model neurons”.

Ideal Observer: The ideal observer reported in this document, referred to as the Anisotropic Ideal Observer, was a Gaussian mixture model with two Gaussian distributions, one for images depicting left-closer surfaces (left-side of surface was closer to the observer) and the other for images depicting right-closer surfaces. The observer’s input was the output of the representational front-end. On each trial of the slant discrimination task, the observer used Bayes’ rule to decide whether an image depicted a left-closer or right-closer surface. The Gaussian distributions of the Anisotropic Ideal Observer shared a common covariance matrix and this matrix was restricted to be a diagonal matrix (the observer represented the variances of its inputs, but covariances among pairs of inputs were assumed to be zero). The observer updated its parameter values on every trial by setting these values to statistically optimal values (in a maximum a posteriori sense). Thus the ideal observer was also an ideal learner.

Selection of Simulation Results: A selection of the simulation results are reported here (many additional results can be found in Jacobs [2008; revised manuscript submitted to the Journal of Vision]).

- The Anisotropic Ideal Observer performed nearly perfectly starting from the first training block. Thus, its learning curves were relatively flat at about 100% correct.
- The performances of human subjects either improved gradually during the course of training or were characterized by sudden, abrupt improvements. At the end of training, subjects performed at a level of about 85% correct. Because the Anisotropic Ideal Observer performed nearly perfectly at the end of the first training block whereas human subjects performed at about 85% correct at the end of fourteen training blocks, we conclude that subjects did not learn as much on each trial as they theoretically could have. That is, human subjects were inefficient learners (based on the assumptions underlying the Anisotropic Ideal Observer).
- Although the Anisotropic Ideal Observer received the responses from all 315 model neurons, it made significant use of the responses of only about half the neurons when making decisions about the slants of depicted surfaces.
• We measured the performances of observers that received the responses of only a subset of the model neurons, where the subset was selected at random. A model that received the response of a single neuron selected at random performed poorly. However, a model that received the responses of sixteen neurons selected at random performed extremely well. Human subjects’ performances at the end of training were nearly equal to those of an observer that received the responses of eight neurons selected at random.

• We measured (in units of $d'$) the ability of each individual model neuron’s responses to distinguish images depicting left-closer versus right-closer surfaces. The distribution of $d'$ values is a heavy-tailed distribution. That is, there are a small number of neurons with large $d'$ values, and a large number of neurons with small or moderate $d'$ values.

• We rank ordered the model neurons according to their $d'$ values. We then measured the performances of observers that classified images based on the responses of a single model neuron. Observers based on neurons ranked 1, 5, 10, and 20 achieved performances of 99, 95, 87, and 80 percent correct at the end of training, respectively. Thus, to achieve approximately the same level of performance as the human subjects, an observer needed to use the $10^{th}$ most informative neuron (out of the population of 315 neurons).

Adaptive Precision Pooling Hypothesis: The fact that an ideal observer needed to use a model neuron in the top 3% of most informative neurons to match human performance suggests an explanation as to why human subjects in our experiment were sub-optimal learners. It may be that, during the course of training, subjects “searched” for the neurons in visual cortex which were most informative for the experimental task. When a subject found a neuron which was more informative than the neurons it had previously identified, the subject’s performance improved. Because highly informative neurons are rare, a subject’s performance was frequently imperfect.

To evaluate this explanation, we implemented an observer which is an adaptive decision maker consistent with this hypothesis. This observer used a competitive learning scheme to perform a greedy hillclimbing search for a good model neuron. At the start of a simulation, two model neurons were selected at random. One of these was randomly selected as the “winner”, whereas the other is referred to as the “competitor”. During a training block, the observer’s judgements were based on the winning neuron. However, judgements based on the competitor were also calculated. At the end of a training block, the neuron with the best performance was designated as the new winner. The other neuron was discarded, and a new model neuron was randomly sampled to serve as the competitor. This learning process continued for the duration of training.

In some simulations, performance improved gradually with training time. In other simulations, performance rose abruptly, sometimes to a near-optimal level. In still other simulations, performance improvements were small or non-existent. In terms of their shape and scale, the learning curves qualitatively resembled those of the human subjects. That is, the learning process studied here produces a range of learning performance dynamics that resembled the range of dynamics exhibited by human subjects. Indeed, simulations with several different types of computational models indicate that many models can show negatively accelerating learning curves (the rate at which performance improves decreases monotonically over time). However, the only neurally plausible way we have found to obtain learning curves that show abrupt improvements in performance in the middle of training is by limiting the pool of neurons contributing to decision making and by forcing neurons to compete for inclusion in this pool. Neural competition is thought to play a role in many forms of learning and development, and our simulations suggest that it may also play a role in the type of perceptual learning studied here.

Because the adaptive precision pooling model accounts for the variety of learning curves shown by human learners, but other models do not, the simulation results favor the adaptive precision pooling model as a good candidate model of human visual learning. We, therefore, tentatively conclude that human perceptual decision making involves pooling the responses of small subsets of visual neurons, and that human perceptual learning involves a search, possibly governed by competitive learning mechanisms, for more informative neurons.