Optimal decision-making with probabilistic population codes
Ma WJ, Beck JM, Pouget A
Dept of Brain and Cognitive Science. Univ. of Rochester. Rochester, NY 14627

We are constantly faced with situations in which we have to decide which action to perform given unreliable sensory information. Most of these decisions involve continuous variables with non-stationary statistics, i.e., variables whose reliability changes over time. For instance, a tennis player must decide when and how to hit the ball based on its continuous motion. The motion of the ball must be obtained from its image whose quality varies over time: it is hard to see when it is on the other side of the court, but it becomes easier to discern as it moves closer to the player. None of the current neural models (diffusion to bound, point attractor networks) can deal with this general setting because they are designed for binary targets with stationary statistics.

We present the first neural model of decision-making that can perform the integration of the sensory evidence and the selection of motor response optimally for continuous and discrete variables with non-stationary statistics. As an example, we use a standard task in which subjects are asked to discriminate motion direction in a random-dot kinematogram in which a fraction of the dots move coherently in the same direction. Subjects respond with a saccadic eye movement in the perceived direction of the dots. This decision-making process consists of two stages: the accumulation of motion evidence and the selection of a saccade. The Bayes-optimal strategy in this case is to first compute the posterior distribution over saccades given all sensory evidence available since the start of the trial, and then collapse this distribution onto the maximum-a-posteriori (MAP) estimate.

We show that given the Poisson-like nature of response variability in the cortex, both integration and action selection can be implemented optimally in neural networks. For the integration, neurons (possibly in LIP) need to compute the temporal sum of the spikes generated in MT (assuming that MT provides the sensory evidence). This automatically generates a probabilistic population code representing the posterior distribution over saccade direction given all spikes from MT since the start of the trial. This neural integration remains optimal even when the coherence of the dots changes during the course of a single trial or across trials. For action selection, the MAP estimate can be recovered by a two-dimensional attractor network. In general, attractor networks cannot extract the MAP estimate from a probabilistic population code but for Poisson-like variability, optimality is guaranteed. This works for arbitrary correlations and arbitrary tuning curves.

We have implemented this model and found that it captures the speed accuracy trade-off that has been reported in humans and monkeys. It also accounts for the temporal evolution of neural activity in LIP and SC during decision-making. In addition, our framework predicts that LIP encodes a posterior distribution over motion direction at all times. We have tested this prediction on LIP data and found that it is indeed the case. This result is particularly surprising because, according to the diffusion to bound model of decision-making, LIP activity does not and cannot encode a posterior distribution. Yet, our analysis strongly suggest that it does, lending strong support to our approach. Finally, we predict the evolution of LIP activity for experiments involving 4 or more discrete targets, a continuous variable, or stimulus with non-stationary statistics.

Acknowledgments
This work was supported by ONR, NSF, NIDA and the James S. McDonnell Foundation.