Bayesian Inference With Stochastic Synapses: A Neural Model of Probabilistic Decision Making

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Recently, there have been growing behavioral evidence that the brain encodes sensory information in terms of conditional probabilities and uses this information to make decisions [1]. An open question is how the required computations are instantiated by neurons in a biophysically plausible way. To elucidate neural mechanisms underlying combination of evidence from different cues, neurophysiologists have trained monkeys to perform a task similar to the weather prediction task [2]. In this task a monkey chooses between two targets, based on evidence about possible reward by observing 4 shapes which appeared on a screen sequentially. These shapes were selected randomly from a set of 10 distinguishable shapes, each of which were allocated a unique weight of evidence (WOE) about possible reward, defined by the log likelihood ratio. It was found that the monkey is able to learn the evidence associated with each shape and its choice behavior is influenced by the sum of evidence from four presented shapes in each trial. Moreover, neurons in the posterior parietal cortex area LIP exhibit activities correlated with accumulated WOE.

Here we show that a biophysically-based model of decision-making, endowed with reward-dependent Hebbian synaptic plasticity [3], can reproduce salient experimental observations in this probabilistic categorization task. In our model, each shape stimulus activates two sets of modifiable synapses, one onto each of two competing neural pools (selective for the two targets) of a decision network. We show that, in a task in which only one shape is presented in each trial, the strength of synapses onto a decision neural pool dynamically changes to estimate the posterior probability that this alternative is the correct response. Since choice probability in our model is a sigmoid function of the difference in synaptic strengths, the model instantiates a probabilistic version of Bayesian decision rule. When the model simulates the weather prediction task in which four shapes are presented in each trial, the log of choice probability is found to be the sum of evidence from all presented shapes, as observed in the monkey experiment. This is because, in our model, the log of choice probability ratio for a given pattern (i.e. combination of four shapes) is a linear function of the sum of the difference in synaptic strengths for all shapes presented in that pattern. Moreover, the firing rate of model neurons in two target-selective pools varies with the strength of inputs through plastic synapses, thereby reflects the summated WOE as observed in LIP neurons. These results show that our neural circuit model naturally implements Bayesian inference for two alternative choice task. Testable predictions will be discussed. This work was supported by NIH grant MH073246.

References

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