Sequential Effects: Annoying Quirk or Adaptive Behavior?

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Just as visual illusions reveal the principles and mechanisms underlying natural visual processing, “statistical illusions” provide similar insight into statistical inference and learning in natural behavior. In a variety of behavioral tasks, subjects show a sequential effect: they respond faster and more accurately to a stimulus if it is consistent with the recent trend of stimuli, compared to when it violates the trend. This is true even if the experiment has a randomized design such that stimulus identity cannot be predicted from previous history. In this work, we use a normative Bayesian framework that examines the hypothesis that such quirky idiosyncrasies reflect adaptive mechanisms important for learning about changing statistics in the natural environment. We show that a prior belief in non-stationarity can induce an otherwise Bayes-optimal algorithm to exhibit a pattern of sequential effects similar to human behavior. The Bayesian algorithm is shown to be well approximated by linear-exponential filtering of past observations, something also observed in human and animal behavior in response to true changes in experimental contingencies – this serves as further evidence that randomized experimental design nevertheless taps into statistical learning mechanisms appropriate for non-stationary environments. We explicitly derive the approximately linear relationship between the assumed rate of change in the Bayesian generative model, and the time constant of exponential discounting in the linear-exponential filter. We show how neurons implementing standard leaky integration dynamics, with appropriate tuning, can easily implement these computations. We also show that near-optimal tuning of the leaky-integration process is possible, using stochastic gradient descent based only on the noisy binary inputs. This is a proof of concept that not only can neurons implement near-optimal prediction based on a history of noisy inputs using standard neuronal dynamics, but that they can also learn to tune the processing parameters without explicitly representing probabilities. We verify the validity of our model by comparing its predictions with human and animal behavior in both stationary and non-stationary task settings.

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