Abstract

Recent studies demonstrate that biases found in human behavior can be explained by rational agents that make incorrect generative-model assumptions. While predicting a sequence of uncorrelated events, humans are biased towards overestimating its serial correlation. We demonstrate how such biases may also be the consequence of considering noisy observations over limited timescales of previous observations. We use the Kalman filter (KF) to study the upper-bound on human prediction performance. We investigate how the brain could estimate the necessary parameters for the KF based on the only source of information available to it, previous observations. We develop a variant of the KF model (dual memory) that obtains estimates of the KF parameters and its state over limited timescales of previous observations. The dual memory model predicts that the serial correlation should be veridical in responses for observations that are correlated in time and should be overestimated for uncorrelated ones. Second, the extent of overestimated correlation in the responses should be robust to varying noise-levels. Third, the overestimated correlation should persist regardless of whether previous observations are shown or not, if the same world-model is used. To test these hypotheses we performed an experiment where human observers were asked to predict time series, each with varying autocorrelations and noise-levels. One group was provided brief feedback whereas another was provided the history of observations. We found that the behavior of the participants was consistent with all three predictions. Further, we found a strong agreement between predictions of the dual memory model and previous empirical reports of bias in human forecasts of time series. We conclude that a markovian state-
estimation model that would otherwise be optimal in predicting time series, displays the same biases in its predictions as humans do if it obtains parametric information over limited timescales of noisy observations.

Meeting abstract presented at VSS 2016

This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License.