Uncertainty in stimulus dynamics drives asymmetries in evidence integration | Tahra Eissa

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The timescale at which an environment changes is critical to informing our beliefs about the environment and its task-relevant statistics. In working memory, learning fairly stable features of the environment based on past experience supports more efficient coding schemes for maintaining estimates of current observations. In contrast, past experiences should be discounted in highly dynamic environments, since they will be irrelevant to the current estimate. Here, we derive a dynamical model which infers the optimal evidence discounting rate in a delayed estimation task. The true stimulus value (e.g., color) on each trial evolves according to a random walk with independently sampled Gaussian steps, assuming the variance is known by the observer. Then, breaking optimality, we determine how over/underestimations of the step variance contribute to working memory error. We find an asymmetry whereby assuming the walk variance evolves faster than it truly does generates far smaller response errors than assuming the walk evolves more slowly. Thus, an impoverished view of the world that discounts relevant past information is more beneficial than incorporating past irrelevant information. We then extend this model using Bayesian sequential analysis whereby the observer can learn the step variance parameter from observations. The inferential model can be approximately implemented in a neural field model which produces bump attractors (whose peak represents the stimulus value estimate) and whose connectivity evolves according to plasticity with a tunable timescale. We propose a metaplasticity mechanism that recursively tunes the timescale to implement hierarchical inference of the random walk variance based on mismatches between neural activity and synaptic potentiation profiles. These models provide a testbed for understanding how the brain can accomplish adaptive, multi-timescale inference using a combination of neural activity dynamics and metaplasticity.