

On a given trial, if the evidence in frame f is e_f and the (correct) categorical identity of the stimulus is a binary variable $C \in \{-1, +1\}$, then evidence in favor of $C = +1$ after F independent frames is:

$$p(C = +1|e_1, \dots, e_F) \propto p(C = +1) \prod_{f=1}^F p(e_f|C = +1).$$

In the case of the brain, a decision-making area computing a belief about the correct choice only has access to a sensory representation of the stimulus, x , not to the outside stimulus e directly: $\underbrace{\log \frac{p_f(C = +1)}{p_f(C = -1)}}_{\text{LPO}_f} \equiv \underbrace{\log \frac{p_{f-1}(C = +1)}{p_{f-1}(C = -1)}}_{\text{LPO}_{f-1}} + \underbrace{\log \frac{\int_x p(e_f|x)p(x|C = +1)dx}{\int_x p(e_f|x)p(x|C = -1)dx}}_{\text{LLO}_f}.$

In Lange et al. (2018) we showed that computing this expression on the basis of an approximate representation of the posterior belief in the sensory area entails a bias in favor of early evidence frames over late ones (Fig. 1a-c). Our model predicts that the strength of the bias depends both on the brain's assumption about how temporally correlated the sensory evidence is (Fig. 1g) and how strong the top-down feedback to sensory areas are (Fig. 1h). In **Experiment 1** we vary the temporal correlations in the visual input by varying the frame length from 42ms to 166ms and show that the bias is invariant in 'frame-time', not physical time (Fig. 2abde). This implies that the subject's have adapted their computations to the frame duration, and provides evidence that the cause for the bias is computational, not biophysical in terms of neural adaption or similar. In **Experiment 2** we vary the size of the stimulus to test a recently proposed hypothesis (Zhaoping et al 2017 and 2018) that top-down feedback are stronger for cortical neurons with receptive fields in the fovea compared to those with receptive fields in the periphery. Data from 7 naive subjects across the two conditions show no significant difference between the slopes of the weighting profiles for the two types of stimuli that were matched in all other relevant aspects for the model (Fig 2c+f). This suggests that the strength of the feedback signals in the periphery is similar to that near the fovea over the range of eccentricities tested in our experiment (2deg to 9deg visual angle).

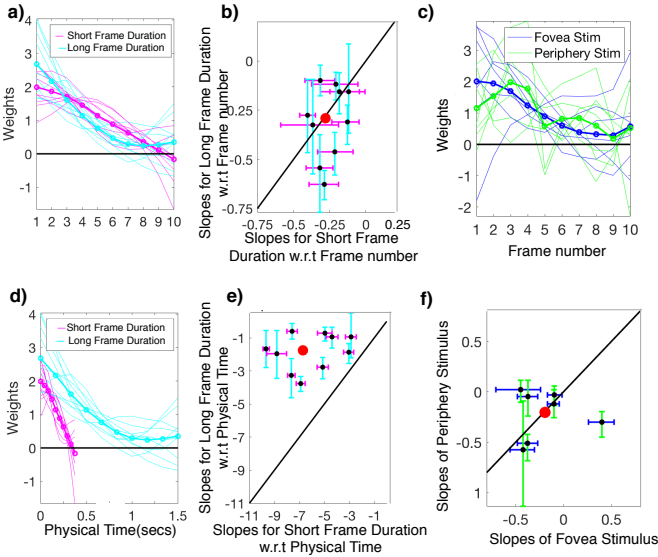


Figure 2: Empirical Data for Experiments a) Primacy in weighting across frame number for 10 subjects in Experiment 1. b) No significant difference in slope of the weighting profiles when averaged across all subjects (red dot), for the two conditions in Experiment1. c) Primacy in weighting across frame number for 7 subjects in Experiment 2. d) Steeper weighting profile in trials with short stimulus frame duration when plotted w.r.t physical time. f) No significant difference in slope of the weighting profiles when averaged across all subjects (red dot), for the two conditions in Experiment2.

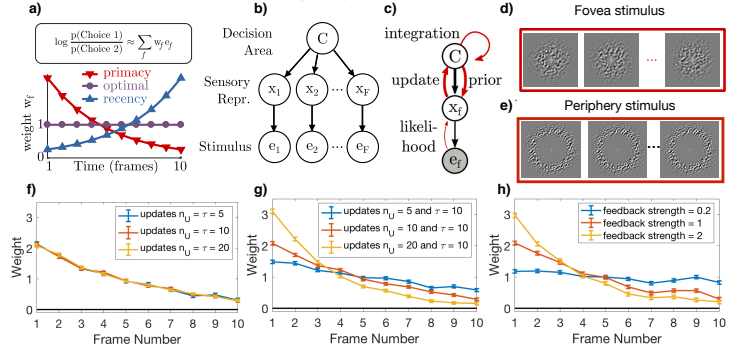


Figure 1: Predictions from Sampling-based Inference Model for Visual Discrimination Task

a) Possible temporal weight profiles for evidence integration tasks. b) The generative model of time-changing external evidence, e_f . The category is denoted by C and the sensory representation in the brain is x_f . c) Approximate inference model: Red lines show information flow with our assumption that a posterior over x_f is represented and evidence integration happens in a decision area representing C . Strong feedback from C to x gives primacy weighting. d-e) Example band-passed grating stimulus in fovea and periphery f-g) Model Simulations: When the $\tau = n_U$ then there is no change in slope of weights (strength of primacy) with change in n_U . If $\tau \neq n_U$, then primacy strengthens with increase in number of belief updates n_U . h) Stronger top-down feedback from C to x gives stronger primacy weighting.