Precision-weighted evidence integration predicts time-varying influence of memory on perceptual decisions

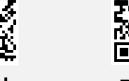




Ari Khoudary, Megan A. K. Peters*, Aaron M. Bornstein*

Department of Cognitive Sciences, University of California, Irvine





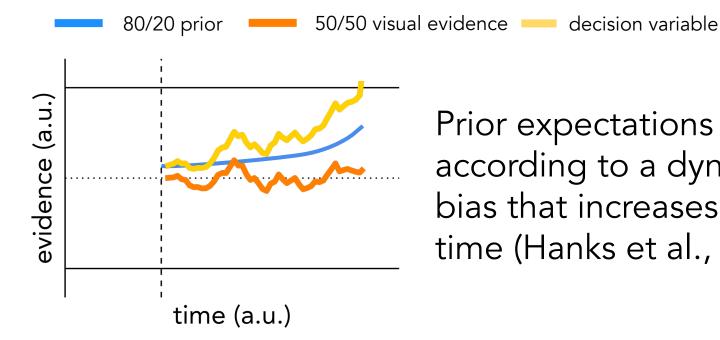
Poster

Motivation

How are expectations integrated with sensory evidence during decision making under uncertainty?

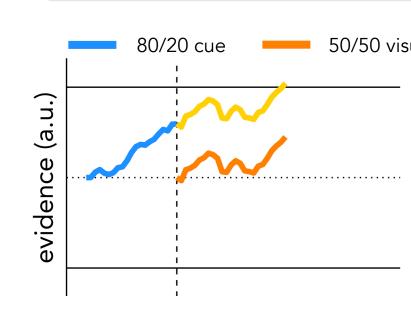
Two different studies found time-varying effects of expectations (the *prior*) on perceptual evidence accumulation:

Late effect: slow mixing of prior over time

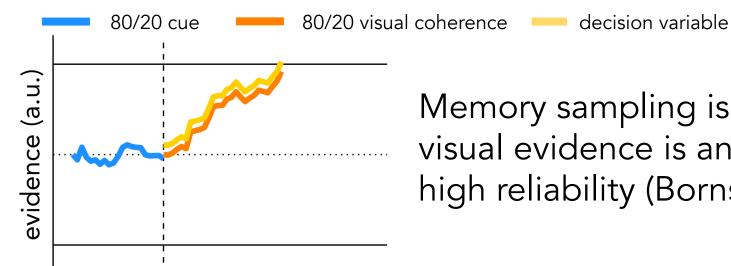


Prior expectations are incorporated according to a dynamic additive bias that increases with decision time (Hanks et al., 2011)

Early effects: adaptive memory sampling



Memory evidence is sampled more strongly during pre-stimulus period when upcoming visual evidence is anticipated to have low reliability (Bornstein et al., 2018)



Memory sampling is attenuated when visual evidence is anticipated to have high reliability (Bornstein et al., 2018)

We propose dynamic, relative reliability-weighted integration as a unifying explanation.

Precision-weighted multi-source sequential sampling model

The simulated agents treat each evidence source s as reflecting an independent probability of observing target X:

$$p(x_s) \sim Beta(\alpha_s, \beta_s)$$

where $s = \{memory, vision\}$

At each timepoint t, evidence samples o are drawn from a Bernoulli distribution with reliability θ and additive Gaussian

$$o_{S_t} \sim Bernoulli(\theta) + Normal(0, 1)$$

Memory samples are drawn at ¼ the rate of visual samples to approximate the ratio of theta oscillations (~8Hz) to visual sample presentation rate (30Hz).

Each sample updates the probability of observing target X:

$$p(x_s)_t \sim \begin{cases} Beta(\alpha_{s_{t-1}} + 1, \beta_{s_{t-1}}) & if o_{s_t} > 0 \\ Beta(\alpha_{s_{t-1}}, \beta_{s_{t-1}} + 1) & if o_{s_t} < 0 \end{cases}$$

The precision of each evidence stream is computed as the inverse variance of the updated Beta distribution:

$$precision_{s_t} = \frac{\alpha_{s_t} \beta_{s_t}}{\left(\alpha_{s_t} + \beta_{s_t}\right)^2 (\alpha_{s_t} + \beta_{s_t} + 1)}^{-1}$$

The weight placed on each sample at each timepoint is computed as the *relative* precision of each stream at that

$$v_{mem_t} = \frac{precision_{mem_t}}{precision_{mem_t} + precision_{viz_t}}$$

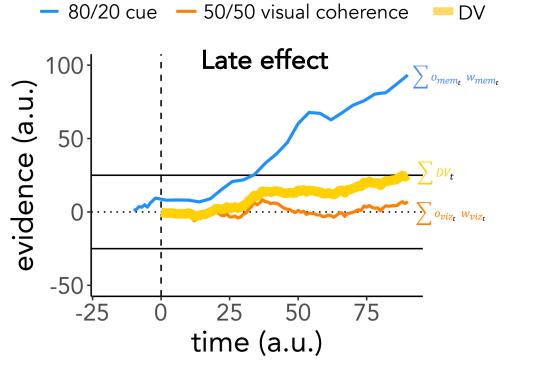
$$w_{viz_t} = \frac{precision_{viz_t}}{precision_{mem_t} + precision_{viz_t}}$$

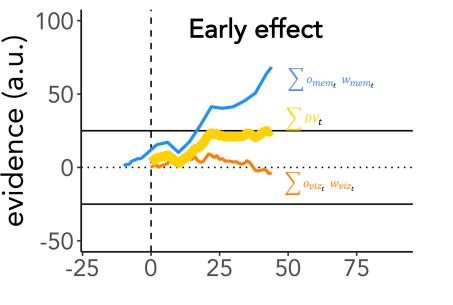
The decision variable is a weighted sum of samples from each evidence stream:

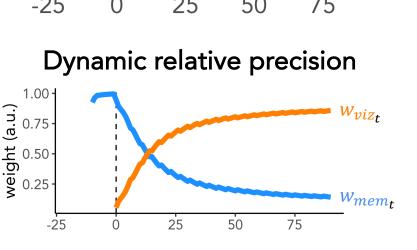
$$DV_t = DV_{t-1} + o_{mem_t} w_{mem_t} + o_{viz_t} w_{viz_t}$$

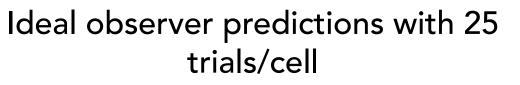
Simulation results and predictions

Dynamic precision weighting captures late and early effects of prior on DV

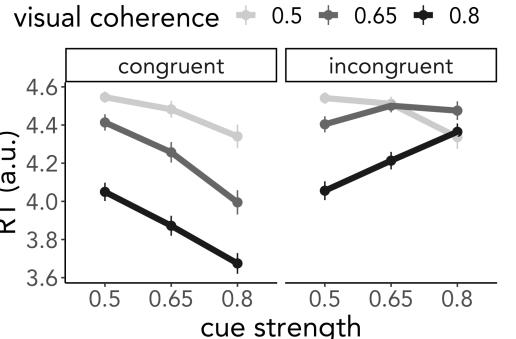


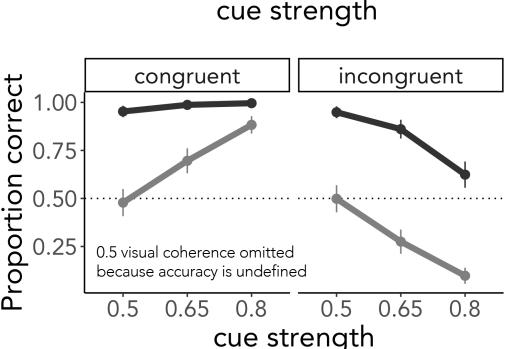






n=50, error bars = \pm 1 SEM

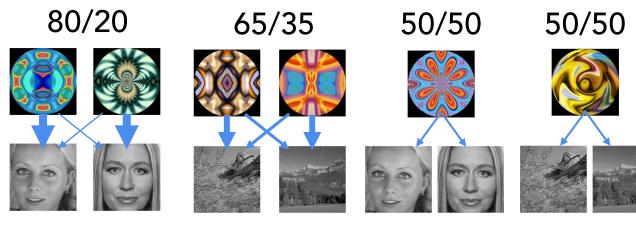




Stronger memory associations result in faster and more accurate decisions for congruent visual evidence, while slowing responses and impairing accuracy for incongruent visual evidence (all $\beta > 0.04$, all p < .001).

Task design

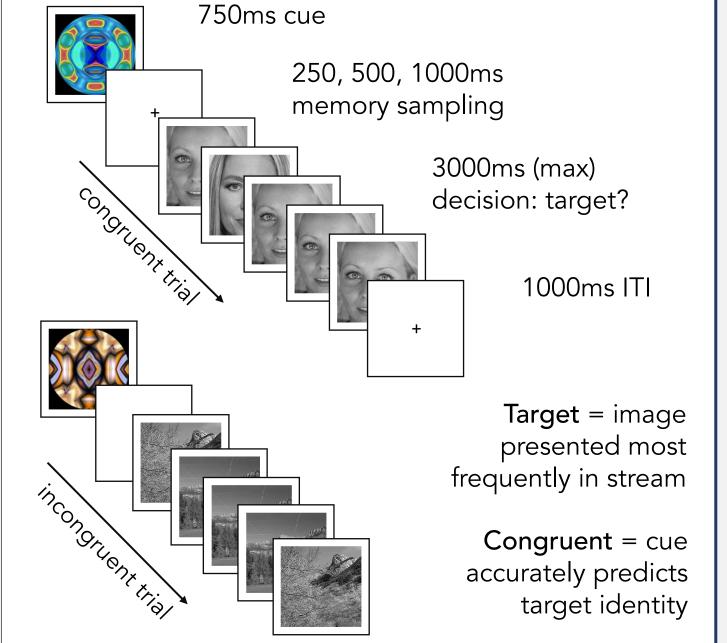
Learned prior target probabilities



Visual coherence: proportion of frames containing target image



Cued perceptual inference



Future directions

- Collect behavioral and EEG data to test model predictions.
- Investigate how *subjective* confidence in each evidence stream modulates their integration.

email: ari.khoudary@uci.edu • twitter: @ari khoudary

Hanks, T. D., Mazurek, M. E., Kiani, R., Hopp, E., & Shadlen, M. N. (2011). Elapsed decision time affects the weighting of prior probability in a perceptual decision task. The Journal of Neuroscience: The Official Journal of the Society for Neuroscience, 31(17), 6339–6352. Bornstein, A. M., Aly, M., Feng, S. F., Turk-Browne, N. B., Norman, K. A., & Cohen, J. D. (2018). Perceptual decisions result from the continuous accumulation of memory and sensory evidence. In bioRxiv. bioRxiv. https://doi.org/10.1101/186817