A potential reset mechanism for the modulation of decision processes under uncertainty

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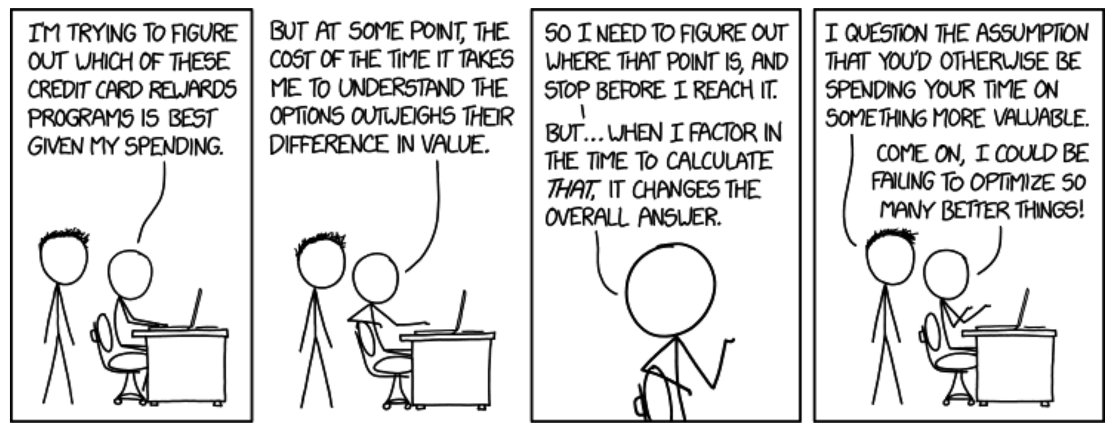
Introduction

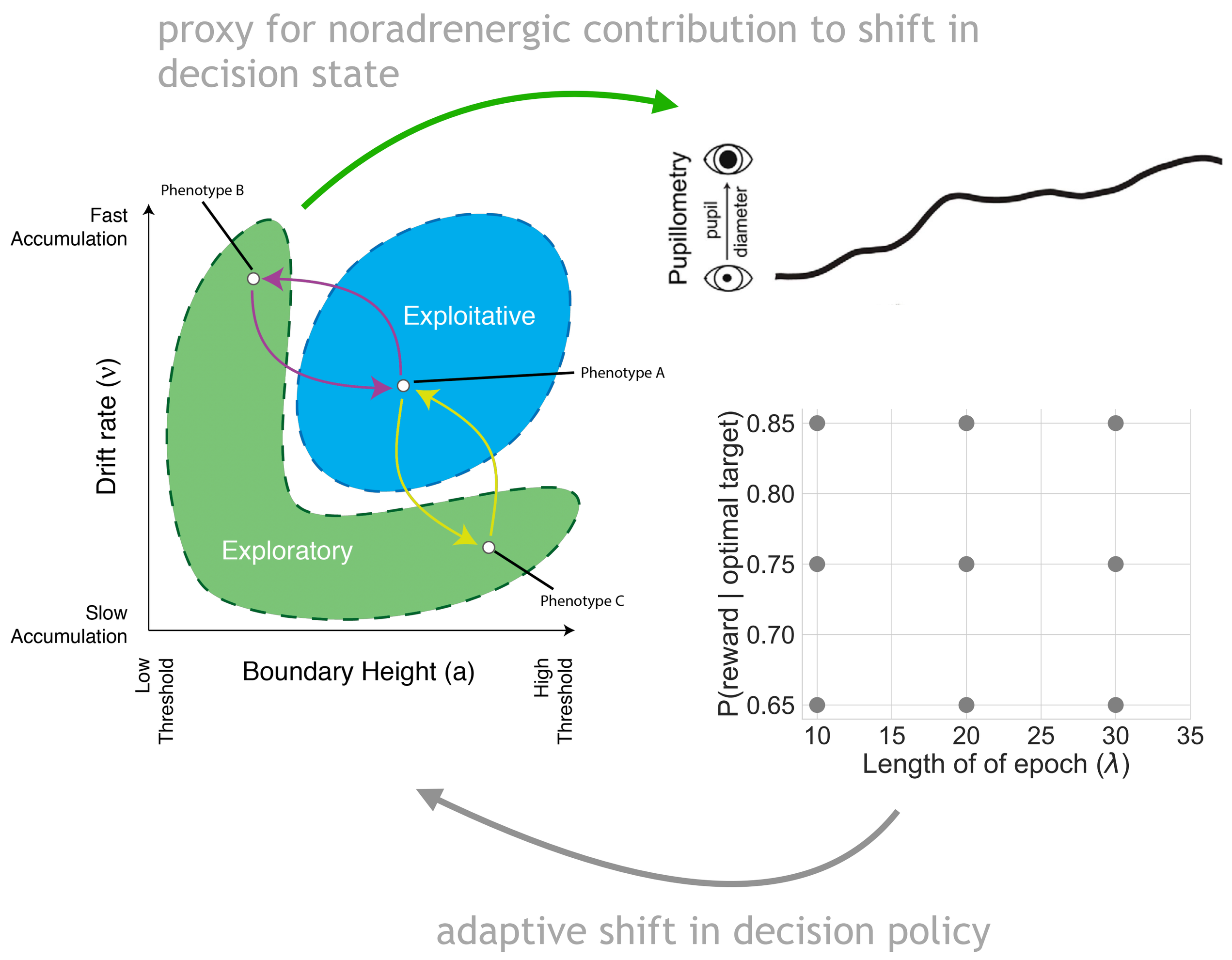
How do we make good decisions under multiple forms of uncertainty?

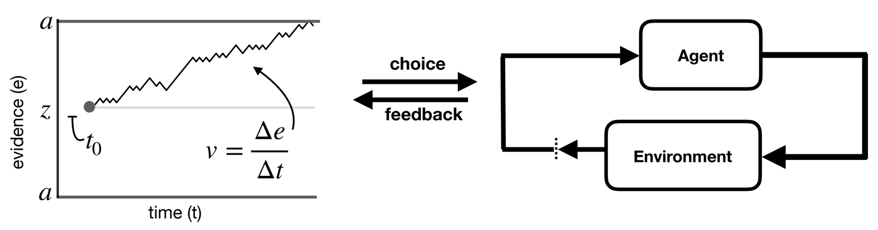
conflict: *a state of uncertainty in the relative estimate of action-value*

volatility: *sudden shifts in action-value associations over time*



Hypotheses





- The amount of evidence needed to make a decision decreases with environmental instability while the rate of evidence accumulation increases with belief in optimal choice value (Bond, Dunovan, & Verstynen, 2018)
- Hypothesized replication using a more expansive manipulation of belief and change point probability
- A phasic increase in noradrenaline will mediate the relationship between environmental instability and the amount of information needed to make a decision, facilitating the exploration process in response to change point detection.

Relative action-value

$$B_{t+1,c} = B_{t,c} + \alpha_t \delta_t$$
$$B_{t+1,u} = B_{t,u}(1-\Omega_t) + \Omega_t E(r)$$
$$E(r) = \frac{\bar{r}_{t_0} + \bar{r}_{t_1}}{2}$$
$$B_{\Delta_{t+1}} = B_{t,1} - B_{t,0}$$

Action-value updates

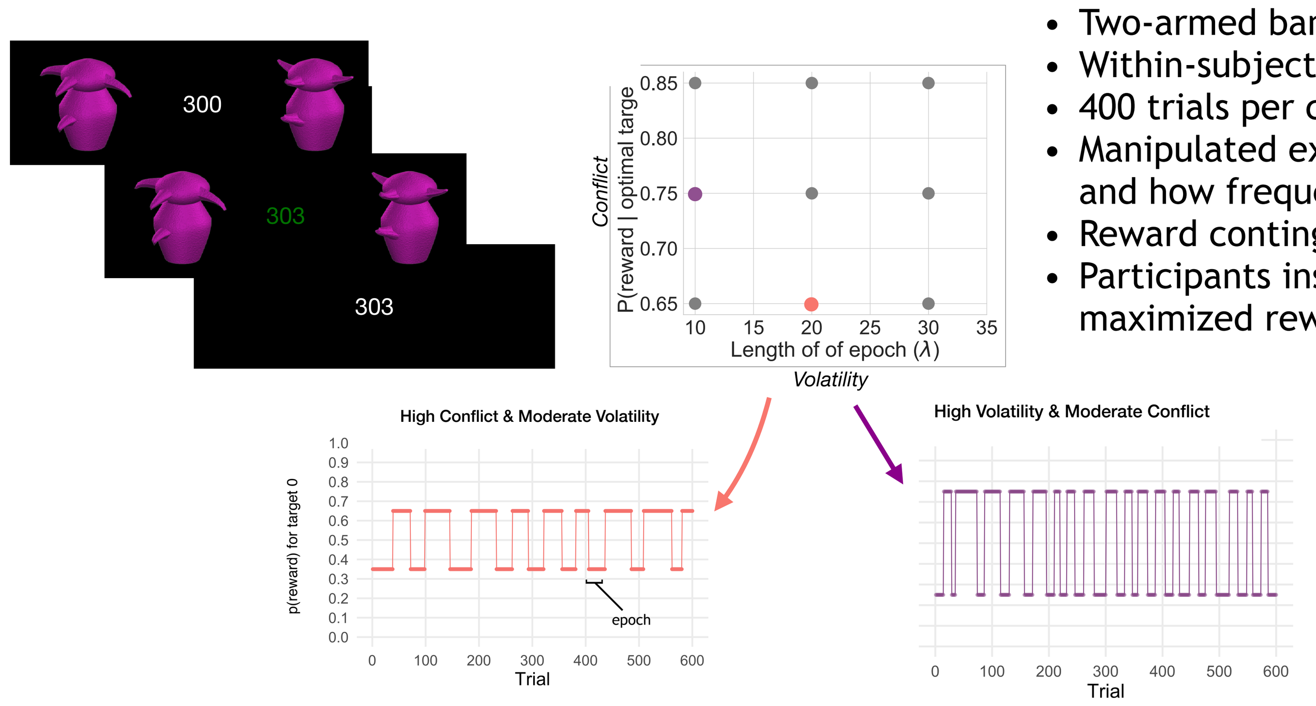
$$\Omega_t = \frac{U(r_{\Delta_t})H}{U(r_{\Delta_t})H + N(r_{\Delta_t}|B_{\Delta_t}, \sigma_t^2)(1-H)}$$
$$RU_t = \frac{\Omega_t\sigma_n^2 + (1-\Omega_t)(1-\phi_t)\sigma_n^2 + \Omega_t(1-\Omega_t)(\delta_t\phi_t)^2}{\Omega_t\sigma_n^2 + (1-\Omega_t)(1-\phi_t)\sigma_n^2 + \Omega_t(1-\Omega_t)(\delta_t\phi_t)^2 + \sigma_n^2}$$
$$\phi_{t+1} = 1 - RU$$

Update rules

$$\alpha_t = \Omega_t + (1-\Omega)(1-\phi_t)$$
$$\delta_t = r_t - B_{t,c} \qquad a_{t+1} = \hat{\beta}_a \cdot \Omega_t + a_0$$
$$\sigma_t^2 = \sigma_n^2 + \frac{(1-\phi_t)\sigma_n^2}{\phi_t} \qquad v_{t+1} = \hat{\beta}_v \cdot B_{\Delta_t} + v_t$$

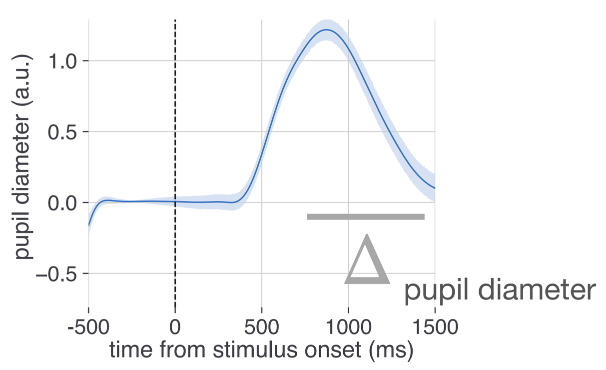
Methods

Task



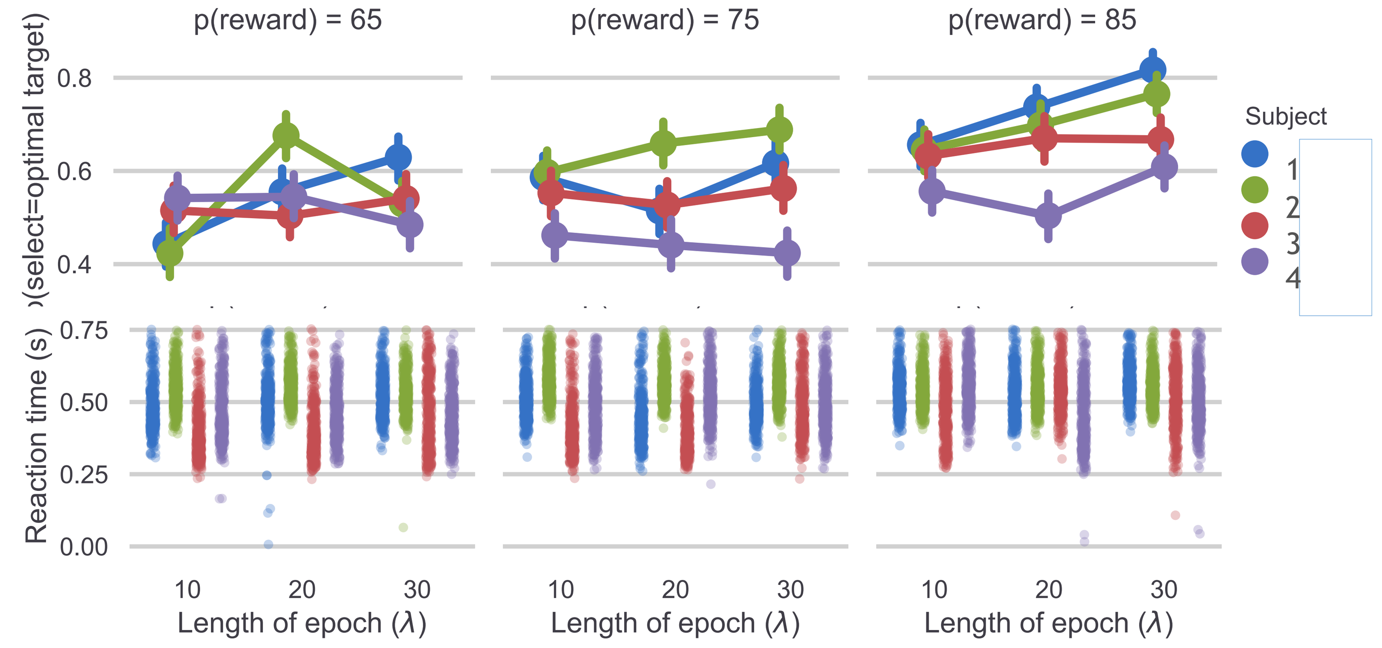
- Two-armed bandit task with constrained reaction time (.1 - .7 s)
- Within-subjects, replication-based design (N = 4)
- 400 trials per condition, 3600 trials per subject
- Manipulated expected value of rewards for each target (conflict) and how frequently the most rewarding target changed (volatility)
- Reward contingencies changed across epochs
- Participants instructed to select the sex identity of the greeble that maximized reward

Pupillometry



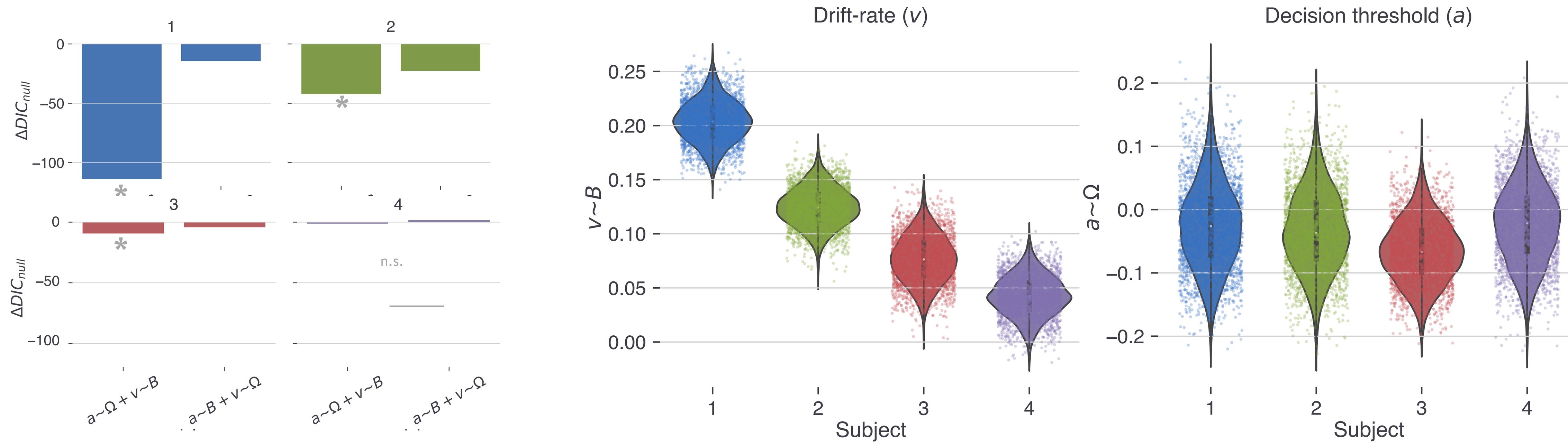
- Pupillometry data were sampled at 1 kHz
- Isoluminant conditions in a booth that minimized fluctuations in ambient light sources

Behavior



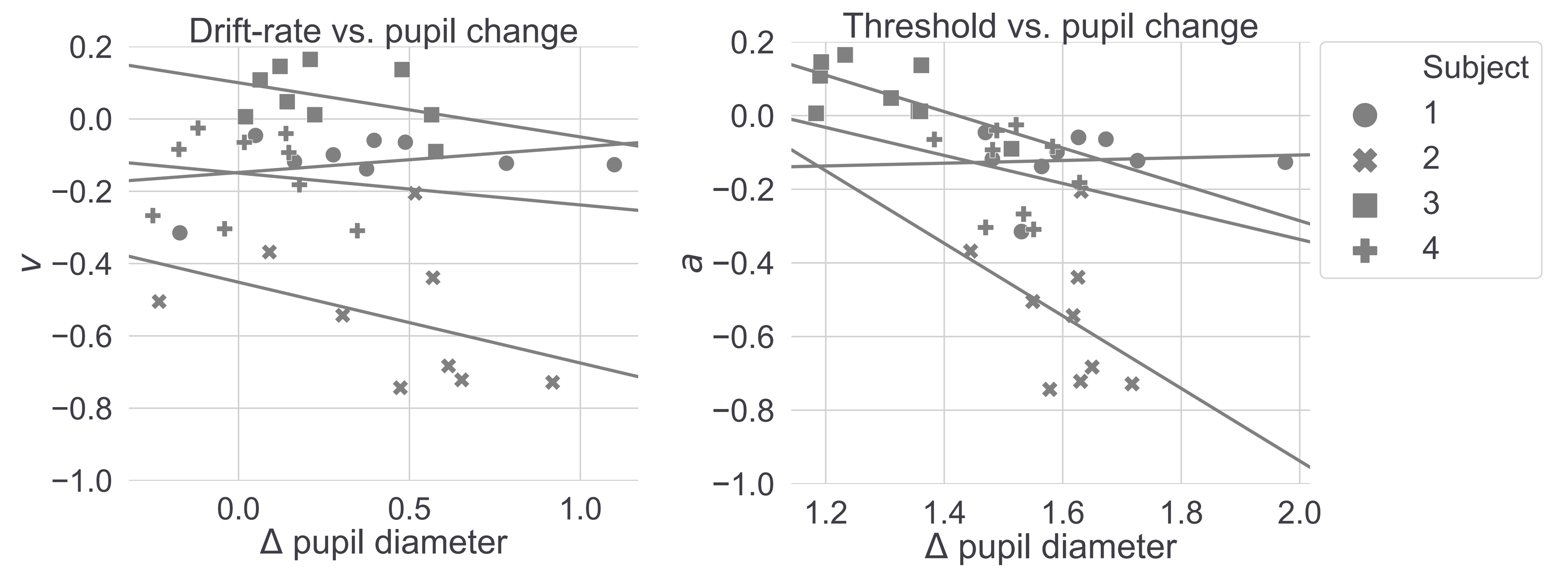
- As change point probability (CPP) increased, accuracy decreased ($p<0.01$ in 3/4 replicates, $\beta=-0.55\pm0.24$)
- Accuracy increased with belief in optimal target value ($p<0.03$, $\beta=0.15\pm0.1$)
- RTs decreased as CPP increased ($p<0.03$ in 3/4 replicates, $\beta=-0.02\pm0.01$)
- The belief in the value of the optimal target minimally impacted RTs ($\beta=0.00\pm0$ in 4/4 subjects)

Decision parameters



- Drift-rate increased with the belief in the value of the optimal target (observed $p(\beta_v<0) < .01$ in all cases; mean $p(\beta_v<0) = 0\pm0$)
- Change point probability weakly decreased the decision threshold (mean observed $p(\beta_a>0) = 0.27\pm0.11$)

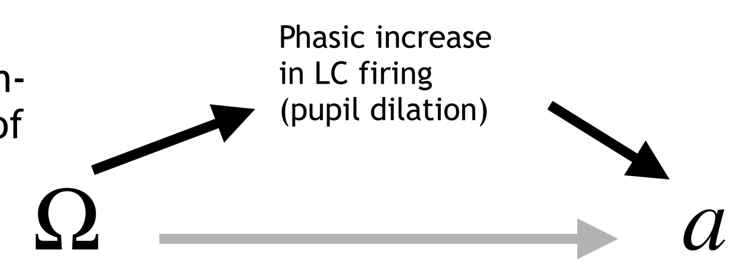
Preliminary pupillometry analysis



Preliminary analysis shows a decrease in threshold and drift-rate as the amplitude of the phasic pupillary response increases (3/4 replicates).

Conclusions and Future Directions

- Belief in the value difference between options had the greatest influence on decision processes, impacting drift-rate, while estimates of environmental change had a weak but detectable influence on the decision threshold.
- Taken together, these findings validate our previous model of adaptive decision-making showing how separate environmental signals impact different aspects of the decision algorithm. These previous findings were supported using:
  - new data
  - a more expansive sampling of the conflict and volatility space
  - a task with different superficial features
- Future work will test how phasic LC firing mediates the relationship between environmental instability and the amount of information needed to make a decision.



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