A Distributed Push-Pull Brain Network Governs Human Irrationality During Gambling

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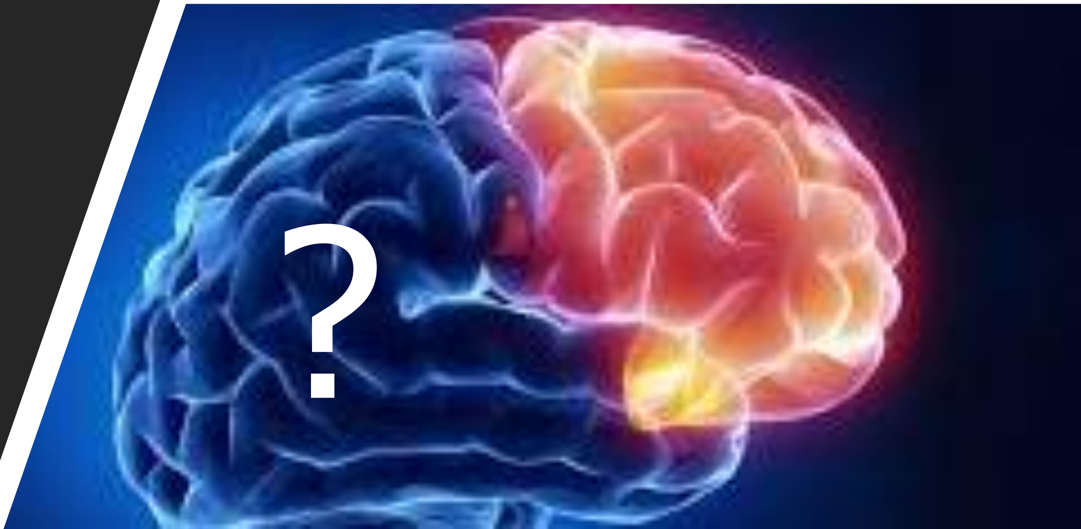
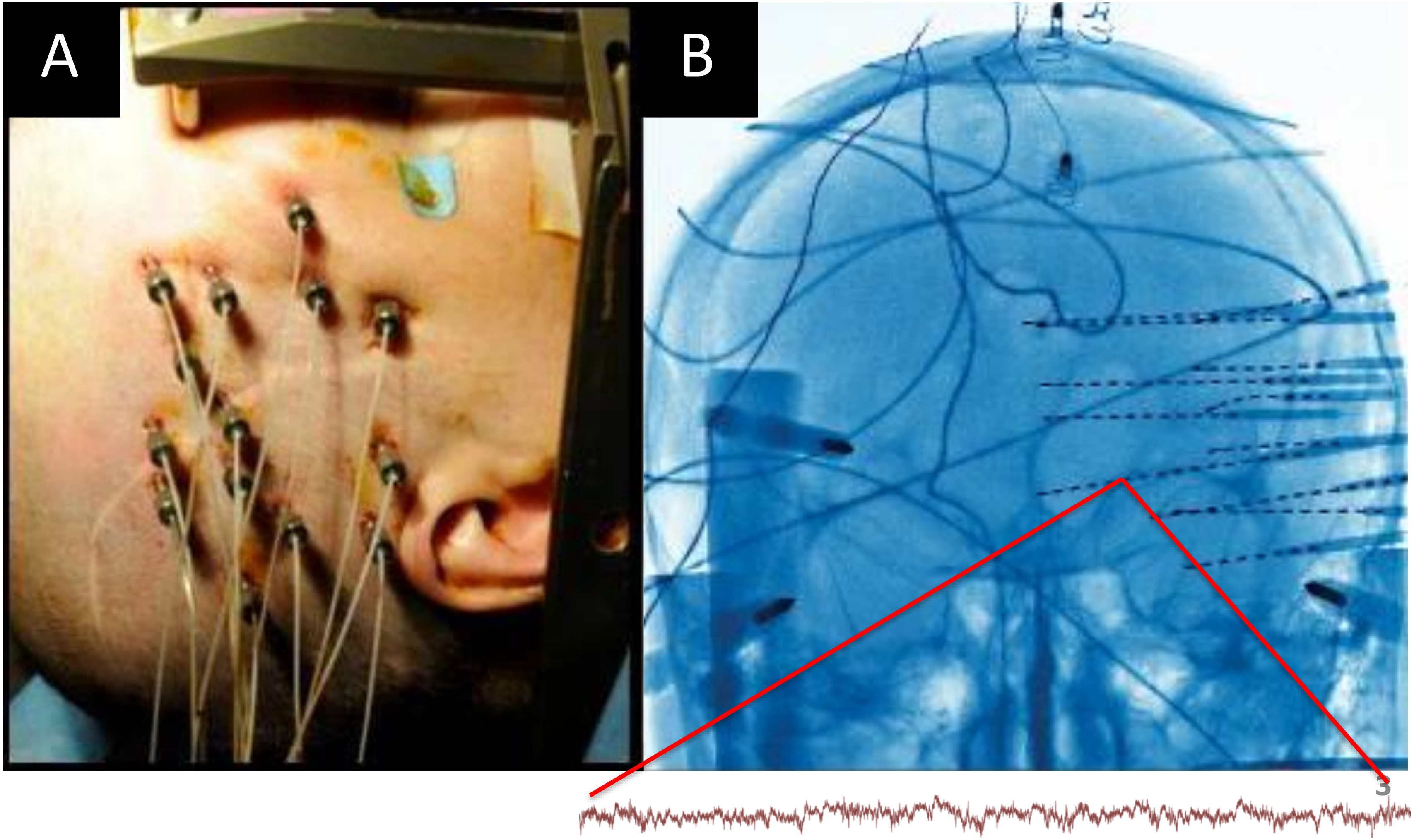
Human decisions vary even when options stay the same

- **Internal bias** (emotions, confidence, motivation) plays a non-trivial role in DM
- Internal bias is **dynamic**
- Neurobiology of internal bias less understood
- Internal bias must go beyond frontal brain regions
- Internal bias is hard to measure

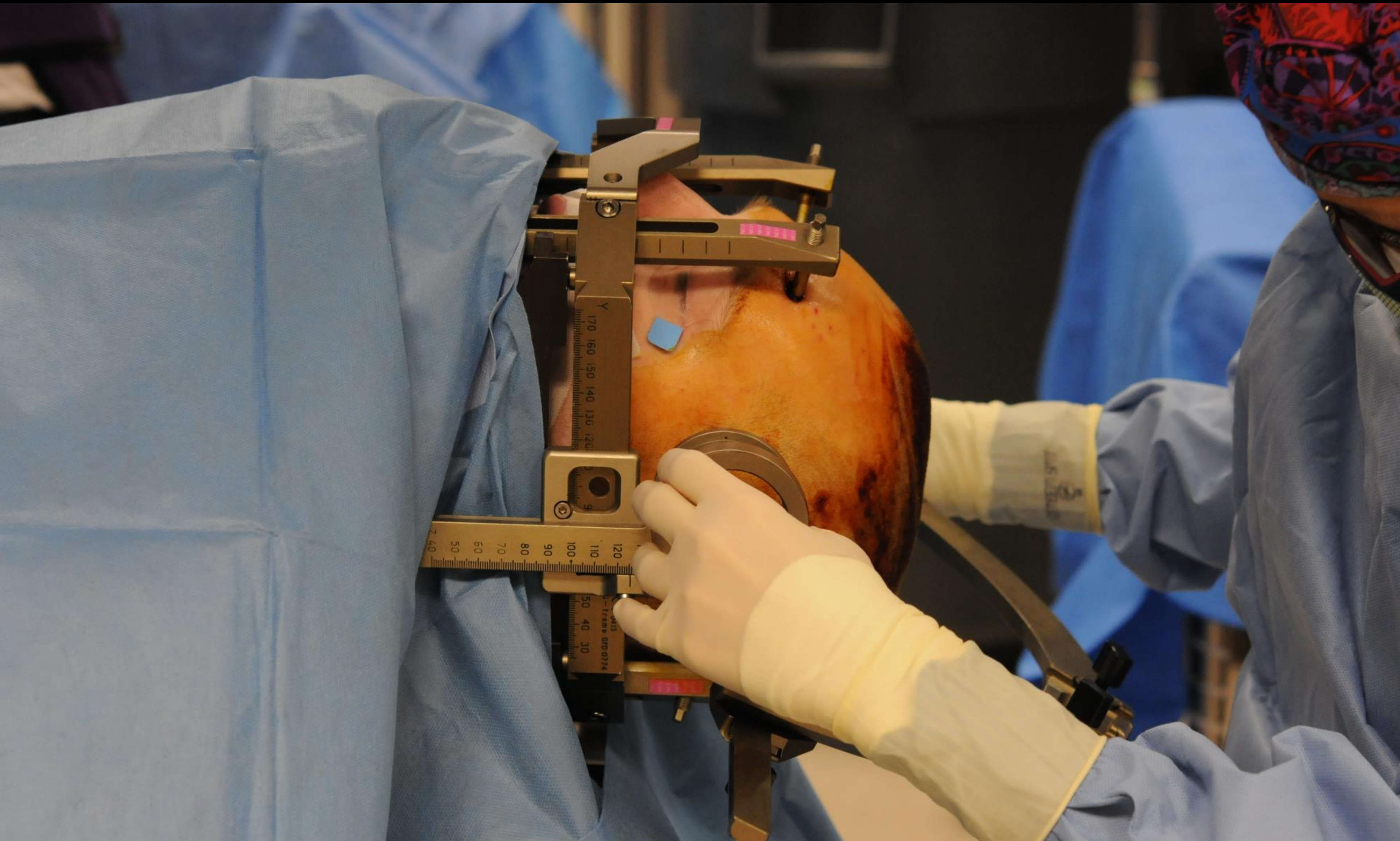


Mapping internal bias with stereoEEG

10 subjects with SEEG implantation (10-12 depth electrodes) participated



Neuromedical
Control
Systems
Lab



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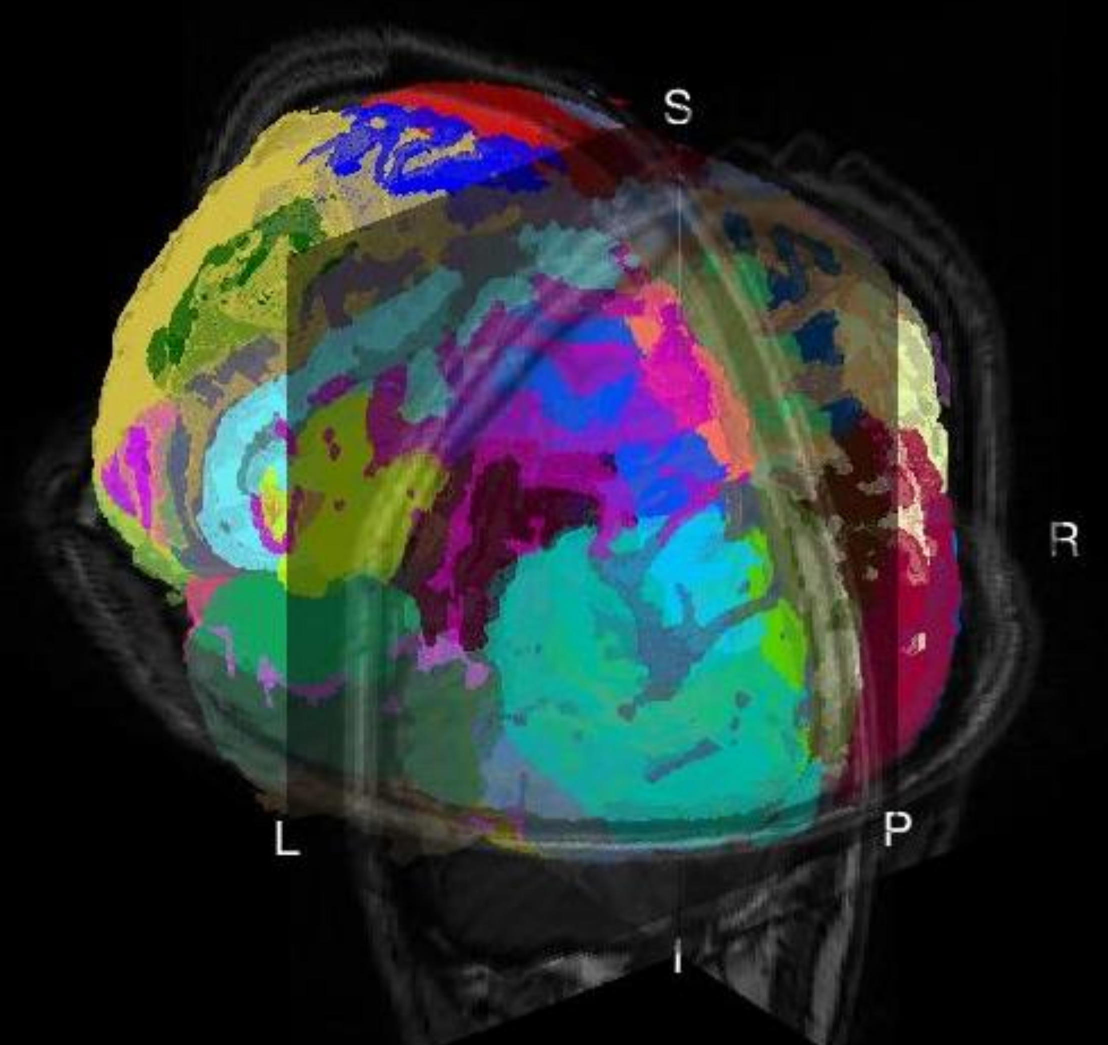
Brain coverage with stereoEEG



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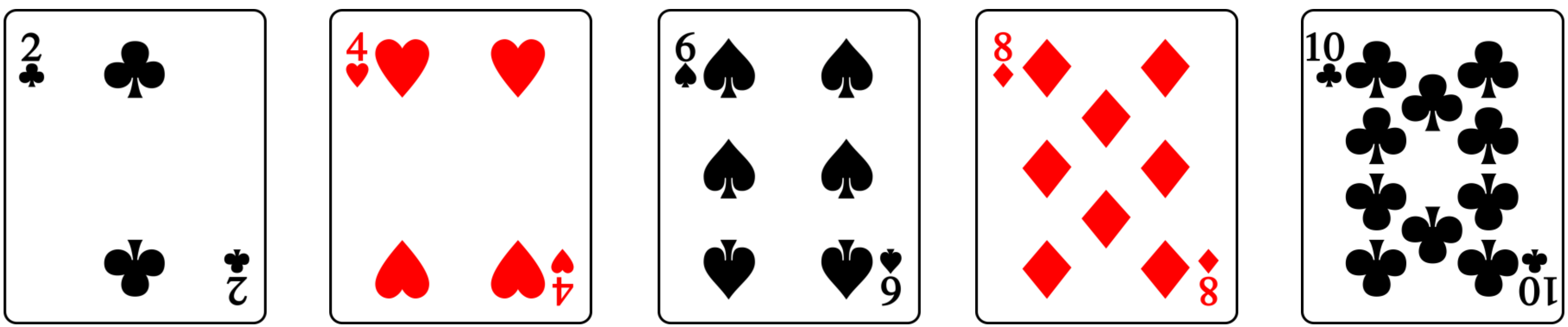
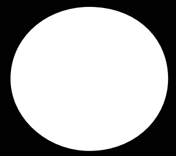
Our gambling task elicits internal bias

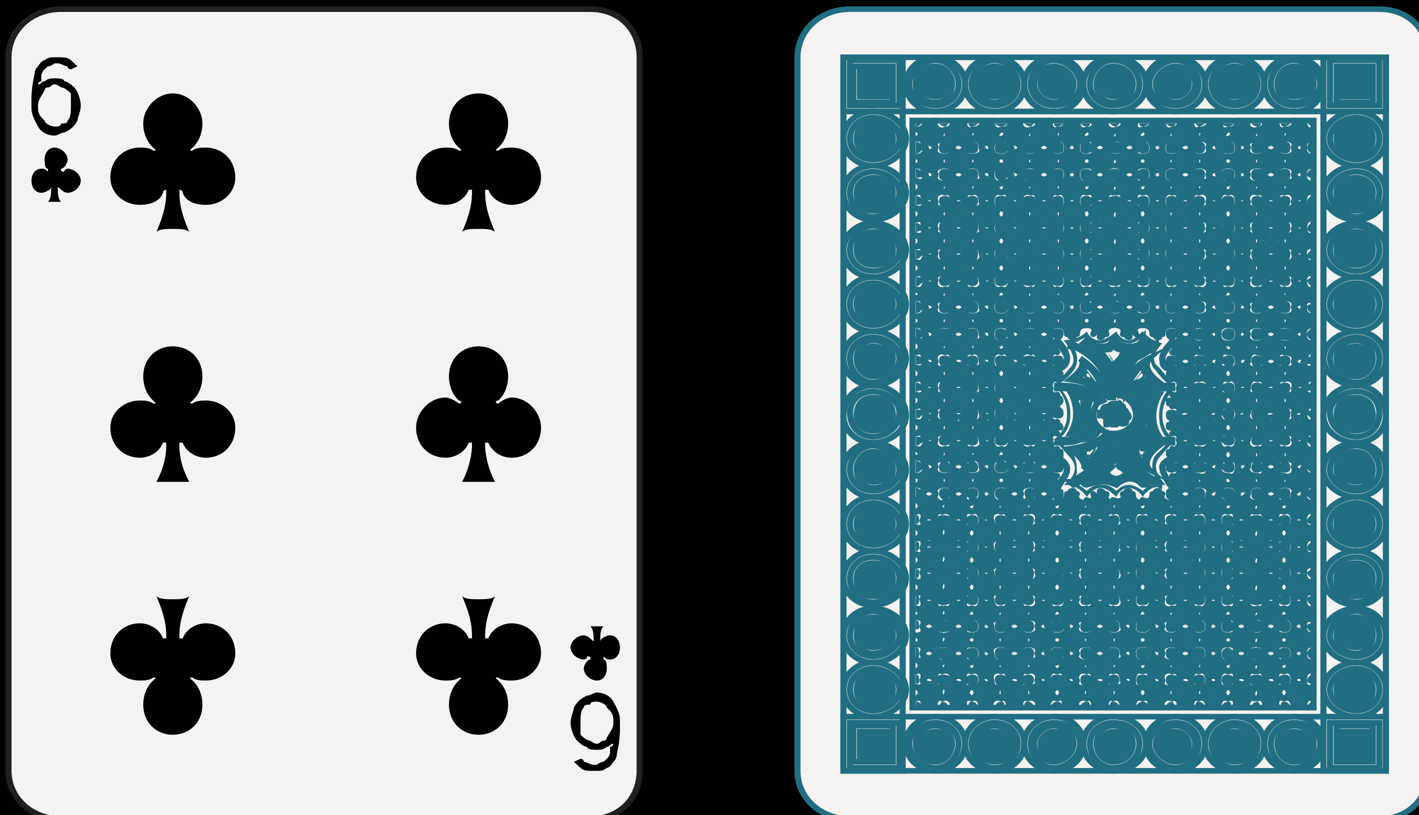
infinite deck

5 possible cards



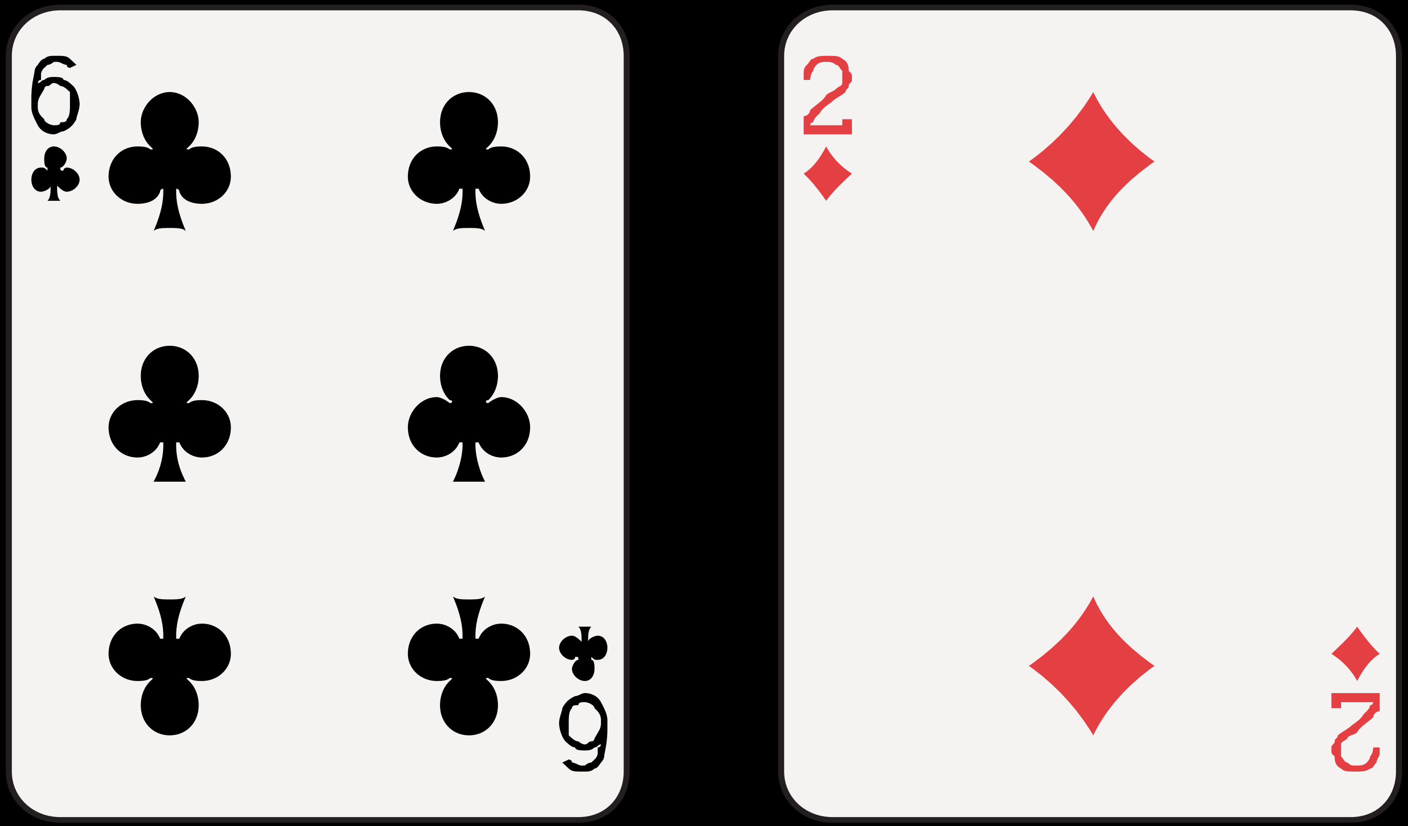
all cards equally likely




6

$5

$20


6
2

Win $5!

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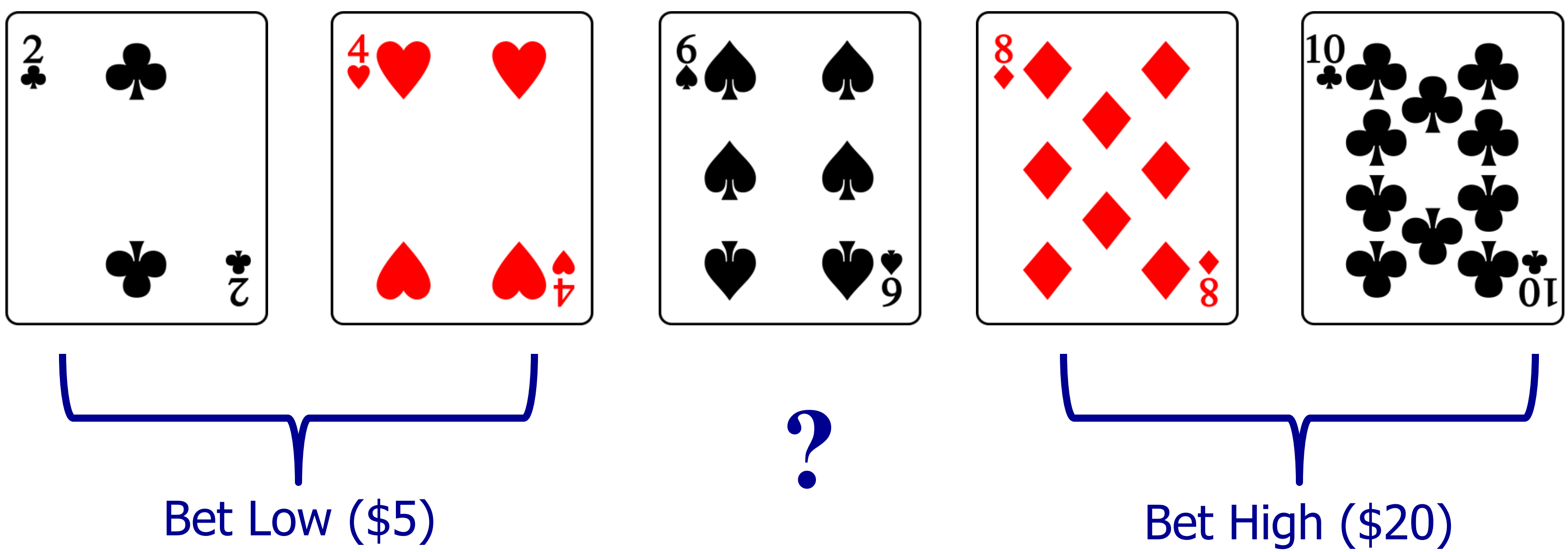
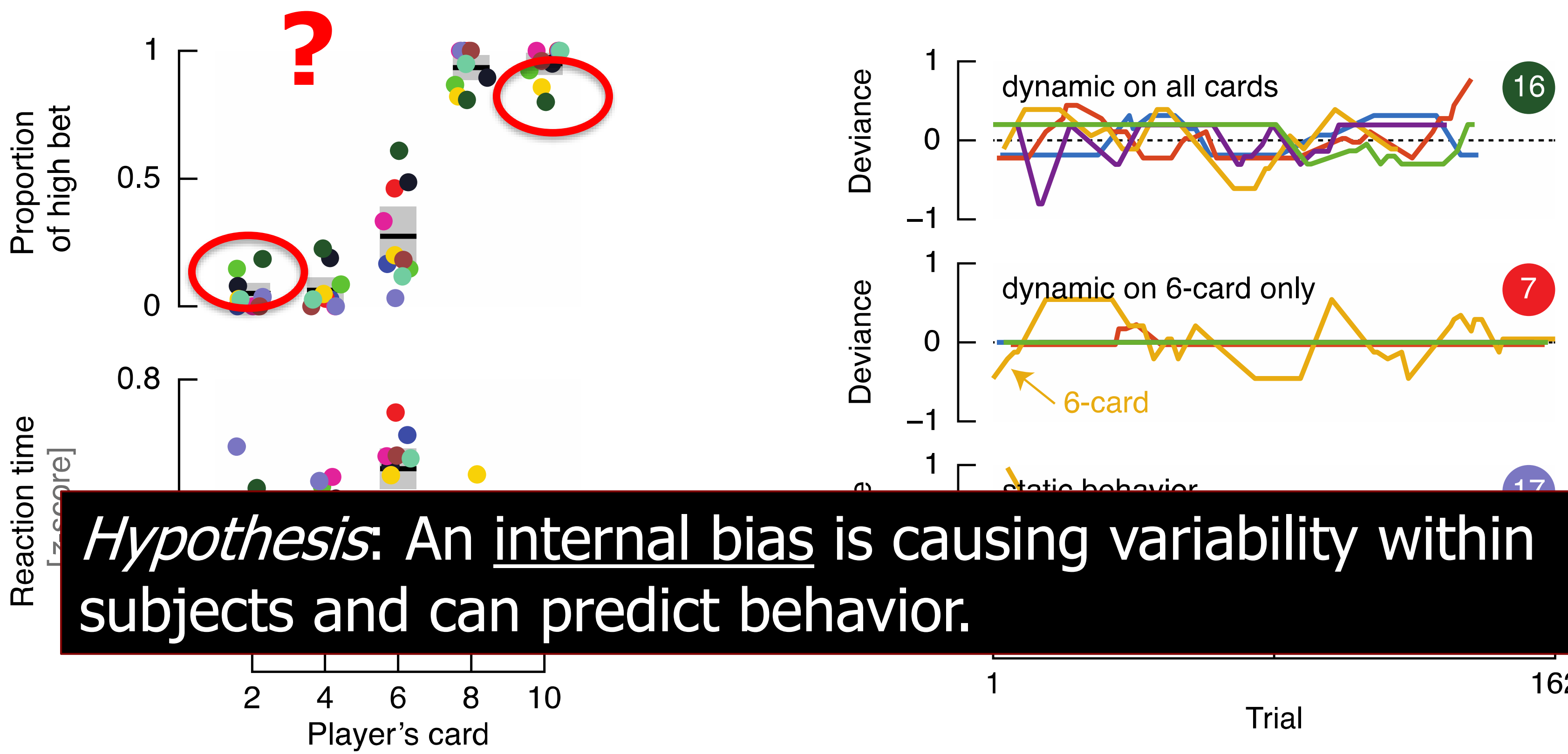
Our gambling task elicits internal bias



Decision strategies vary across subjects and trials

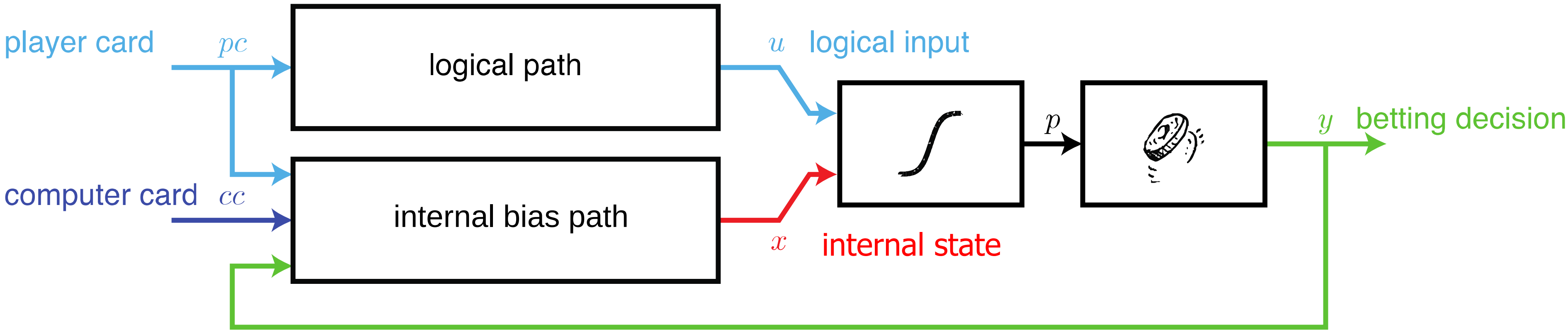


Hypothesis: An <u>internal bias</u> is causing variability within subjects and can predict behavior.

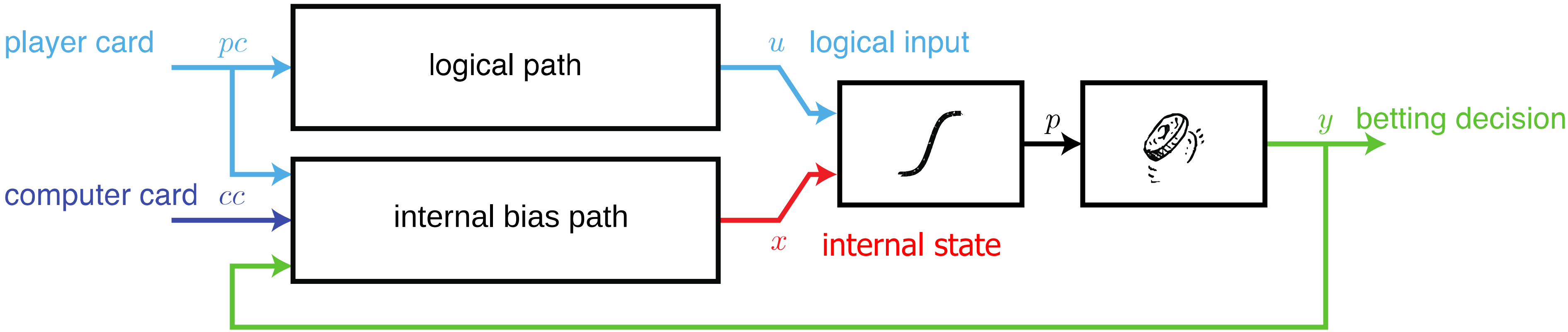
Test: estimate internal bias with <u>state-space model.</u>

Closed-loop decision making system

Closed-loop decision making system



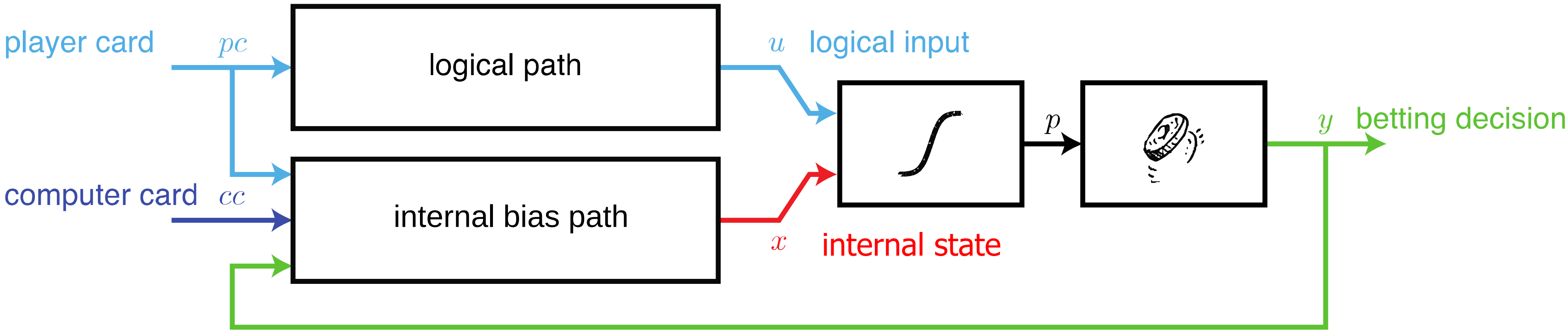
Closed-loop decision making system



$$\mathbf{prob}(y_t = 1) = p_t$$

$$log\left(\frac{p_t}{1-p_t}\right) = cx_t + d_0 + d_1 u_t$$

Closed-loop decision making system



$$\mathbf{prob}(y_t = 1) = p_t$$

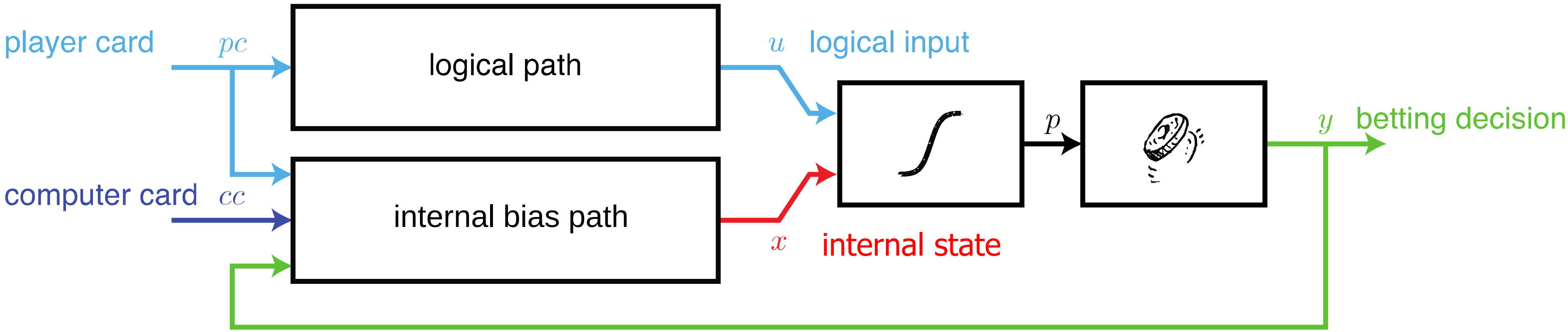
$$log(\frac{p_t}{1-p_t}) = cx_t + d_0 + d_1 E_{q|pc_t}$$

internal bias

baseline (risk averseness)

logic

Closed-loop decision making system



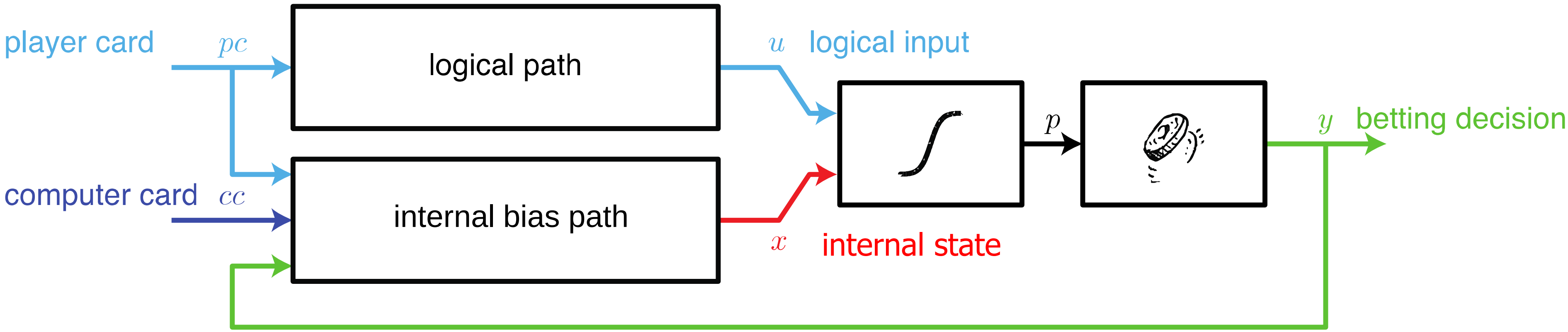
memory drift

card value

risk * prediction error

$$x_{t+1} = a x_t + b_1 E_{q|pc_t} + b_2 \sigma_{r|pc_t, y_t} \left[r_t - E_{r|pc_t, y_t} \right] + w_t$$

State-space model of system



$$x_{t+1} = a x_t + b_1 E_{q|pc_t} + b_2 \sigma_{r|pc_t, y_t} [r_t - E_{r|pc_t, y_t}] + w_t$$

$$log\left(\frac{p_t}{1-p_t}\right) = c x_t + d_0 + d_1 E_{q|pc_t}$$

$$\Theta = \{a, b_1, b_2, c, d_0, d_1, \Sigma_w\}$$

Model parameter estimation

observed output

unobserved state

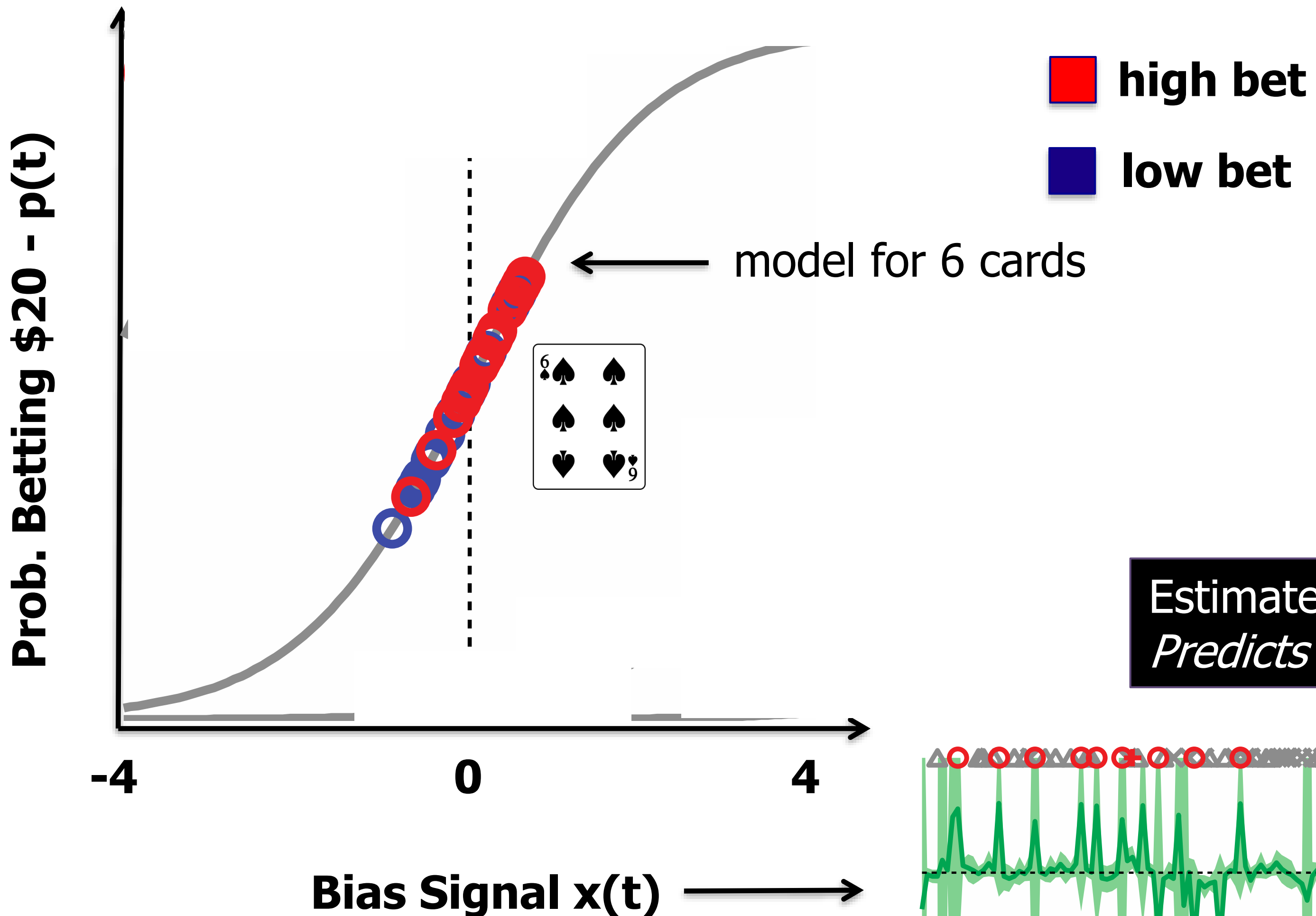
$$\text{maximize} \quad \ell(\theta) = \log \mathcal{L}(\theta) = \log p_\theta(y) = \log \int_{\mathcal{X}} p_\theta(y, x)\, dx$$

$$\hat{\theta}_{\mathrm{ml}} = \operatorname{argmax}_\theta\, p_\theta(y)$$

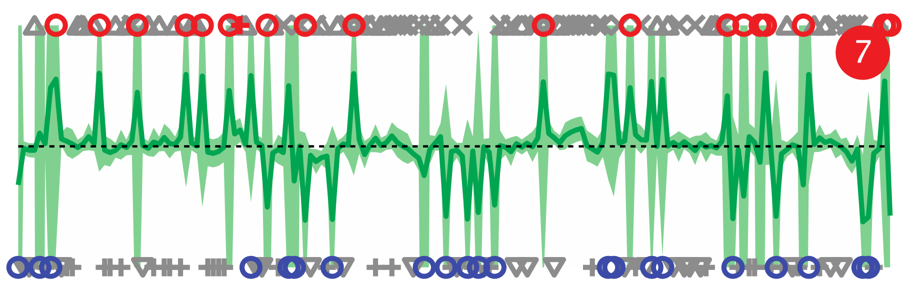
E-Step: $Q(\theta \mid \theta^{(i)}) = \mathbf{E}_{X \mid Y, \theta^{(i)}} \log p_\theta(y, x)$

M-Step: $\theta^{(i+1)} = \operatorname{argmax}_\theta\, Q(\theta \mid \theta^{(i)})$

Model results (subject 7)



Estimated "Bias"
Predicts 6 Card Bets!



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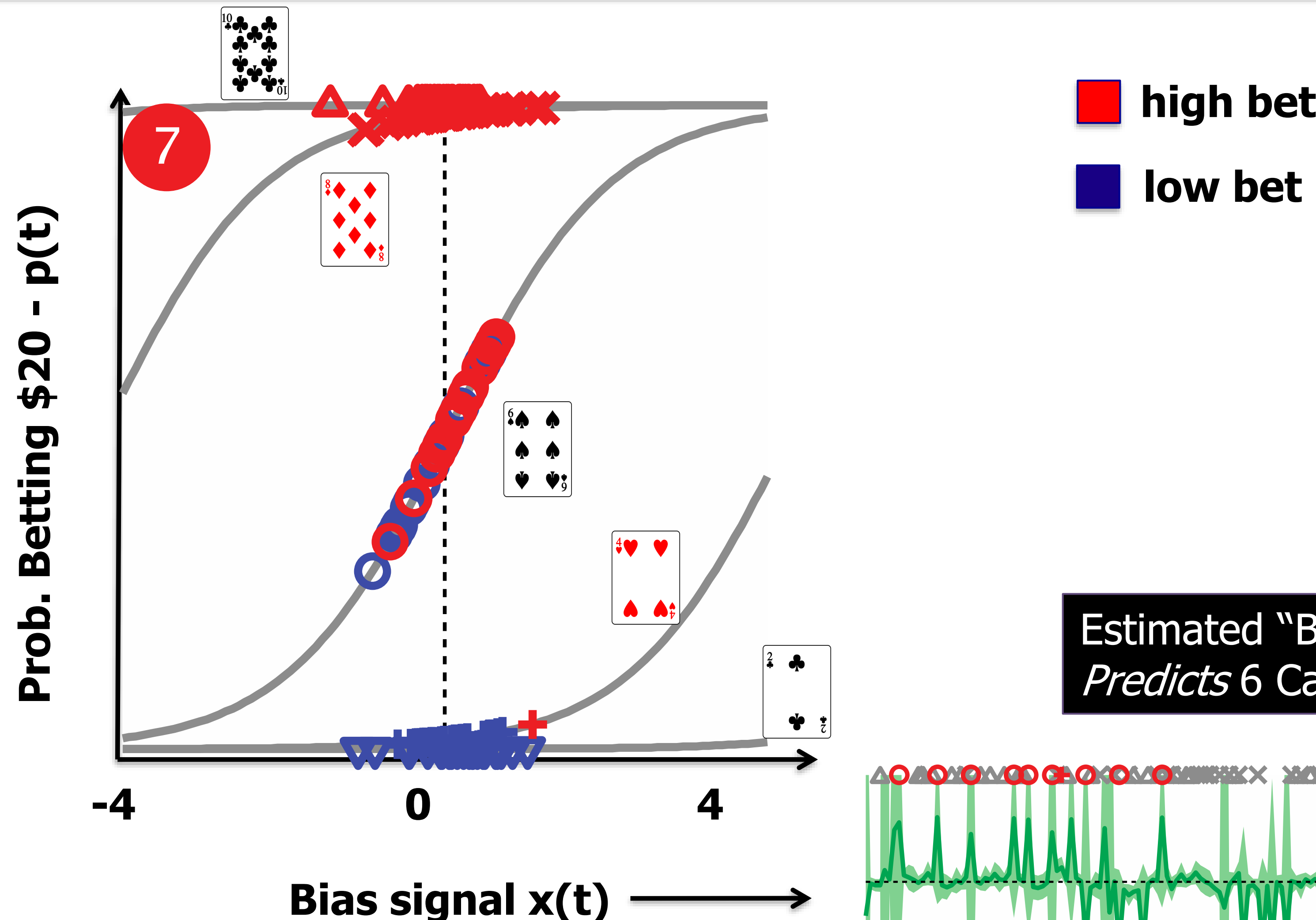

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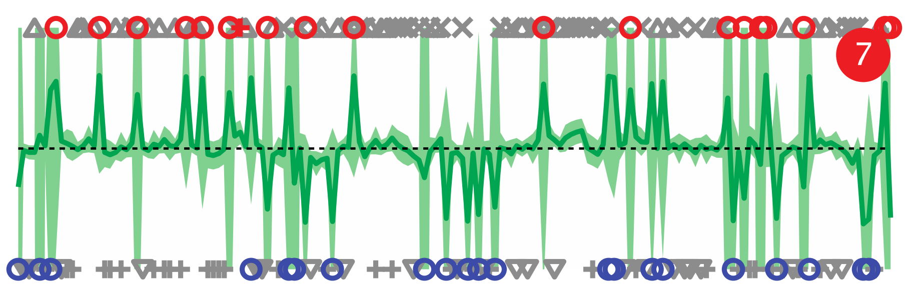
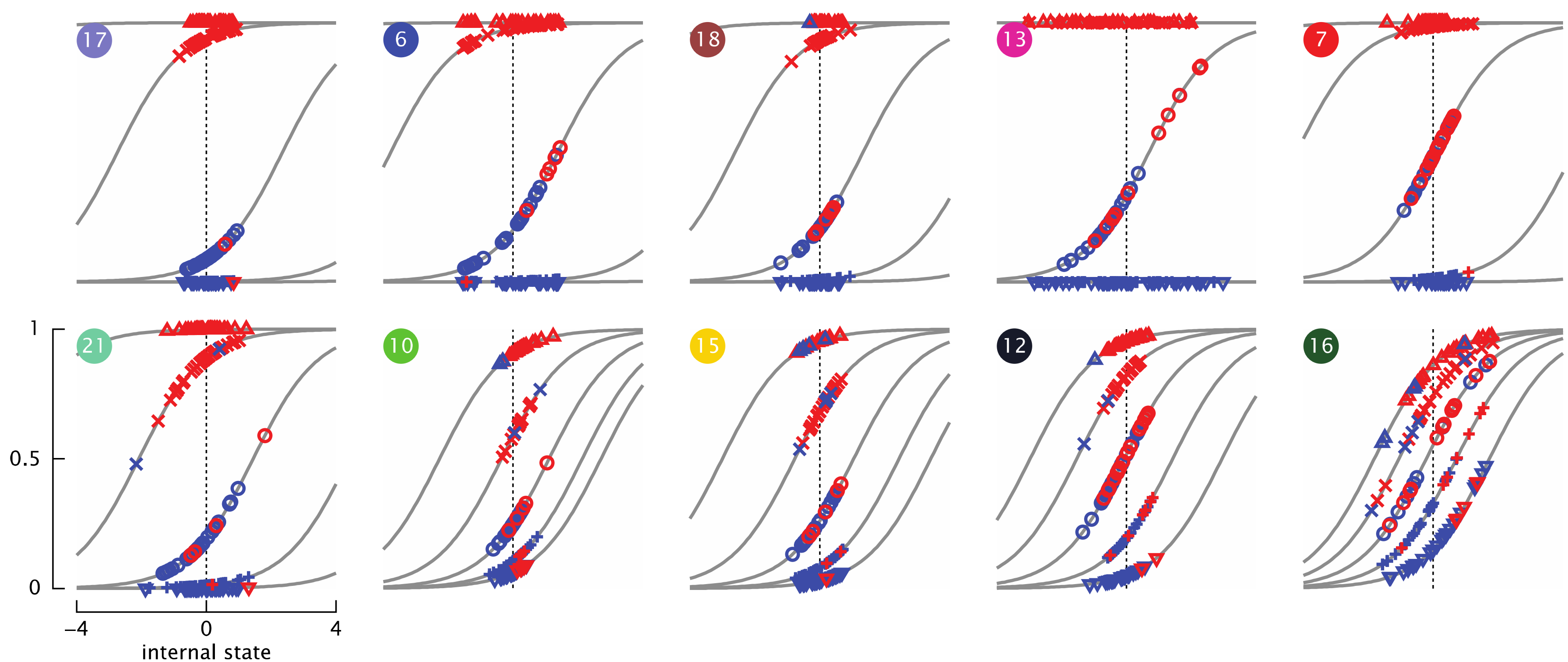


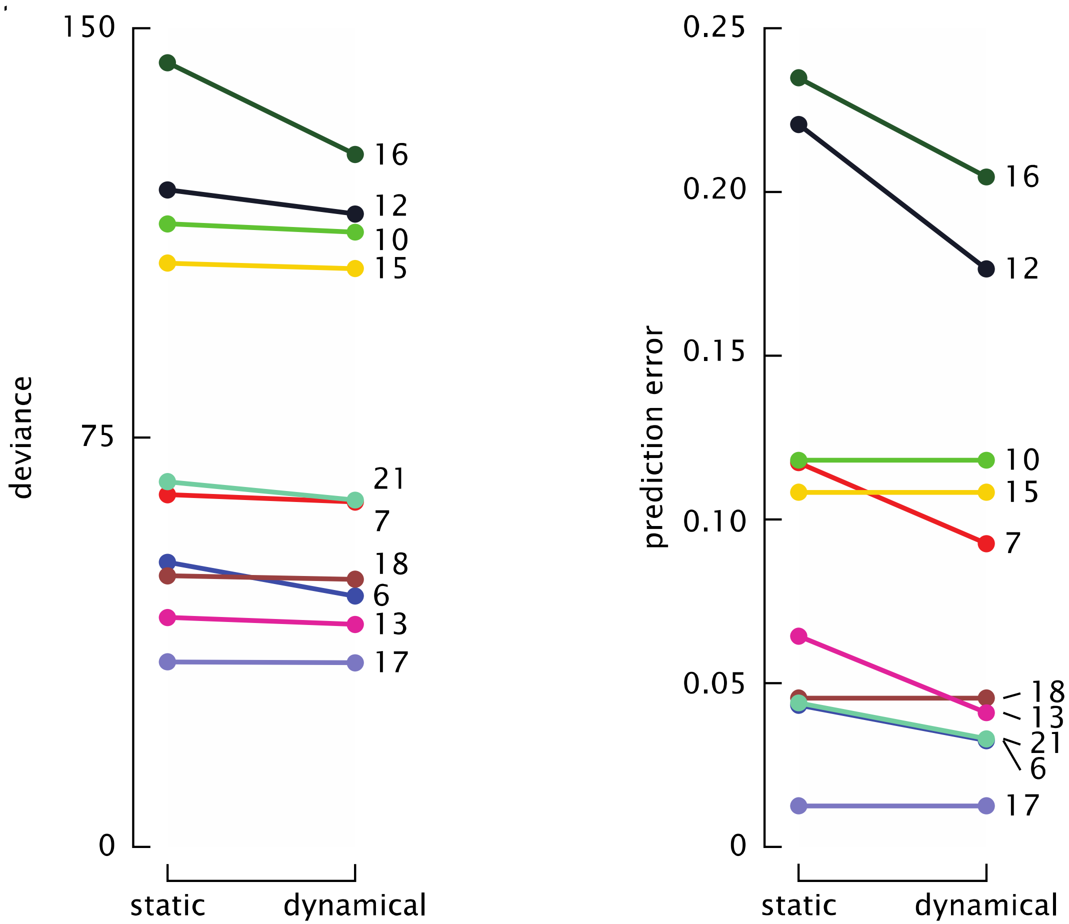
Model results (all)

"Logical"



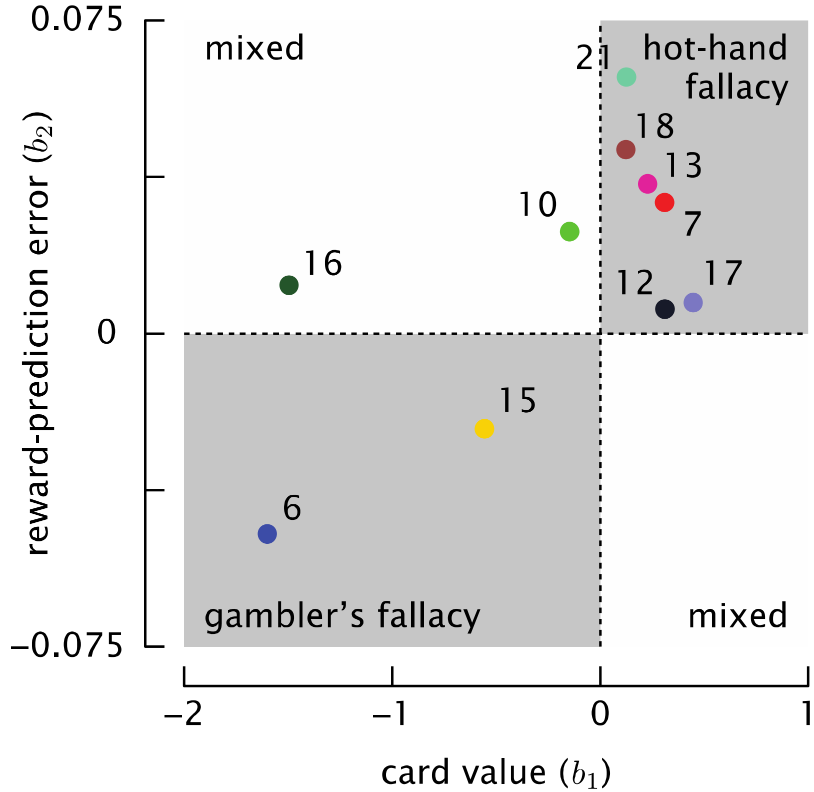
"Biased"

Model evaluation



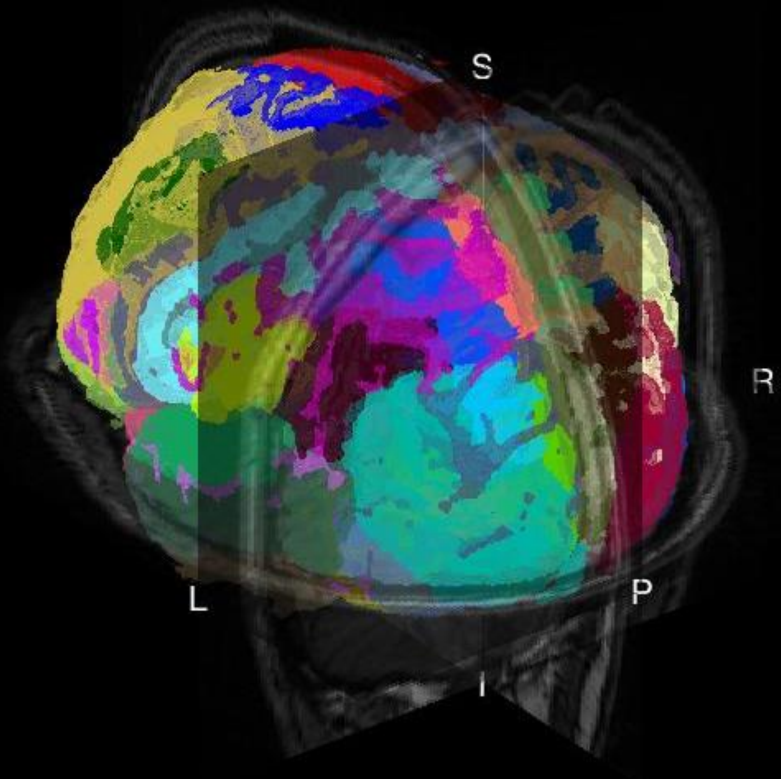
models with state perform better...

Model parameters reveal different types of gamblers



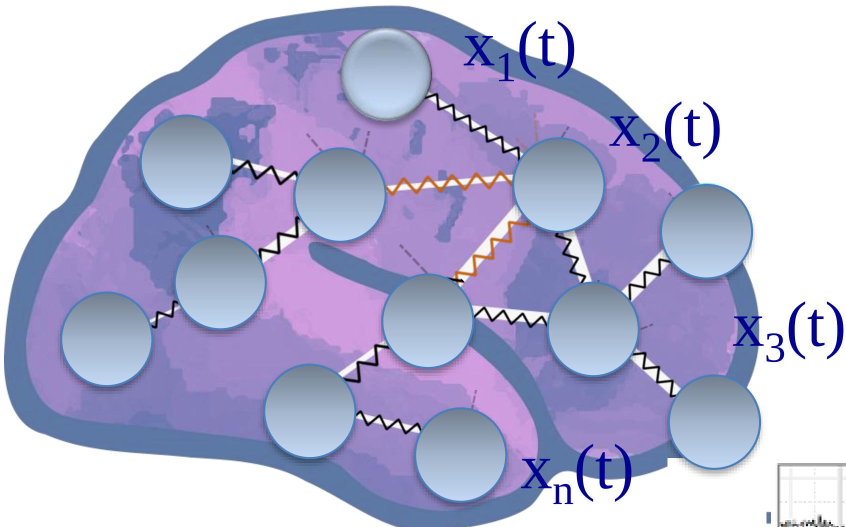
$$log(\frac{p_t}{1-p_t}) = cx_t + d_0 + d_1 E_{q|pc_t}$$

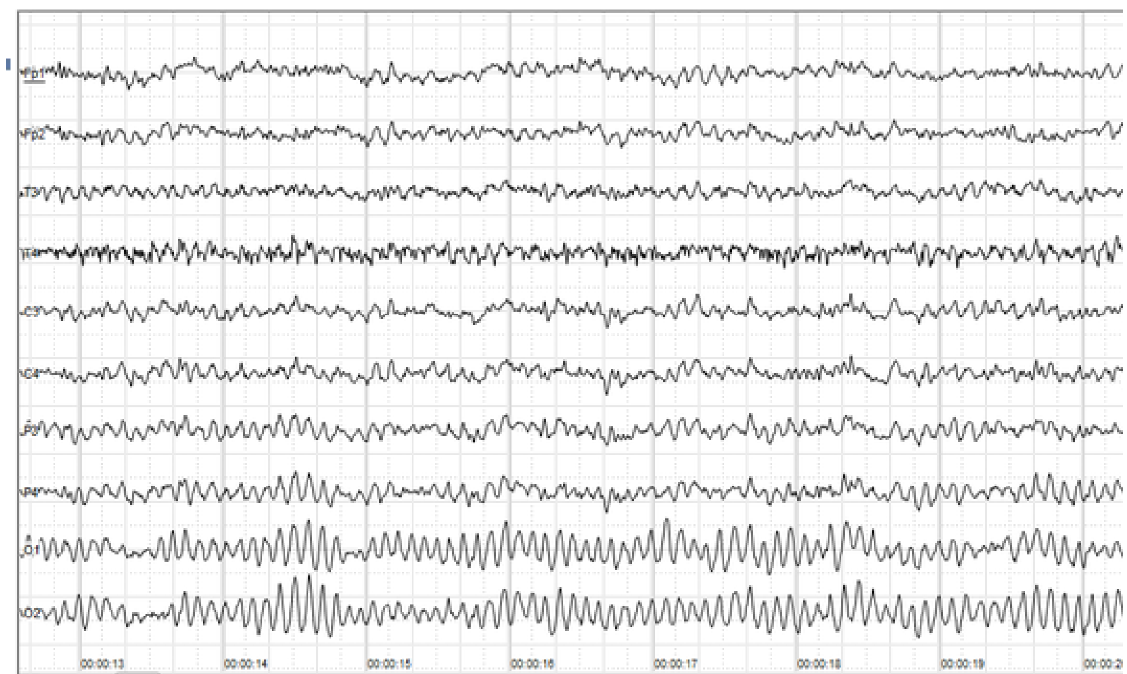
$$x_{t+1} = ax_t + b_1 E_{q|pc_t} + b_2 \sigma_{r|pc_t,y_t}[r_t - E_{r|pc_t,y_t}] + w_t$$



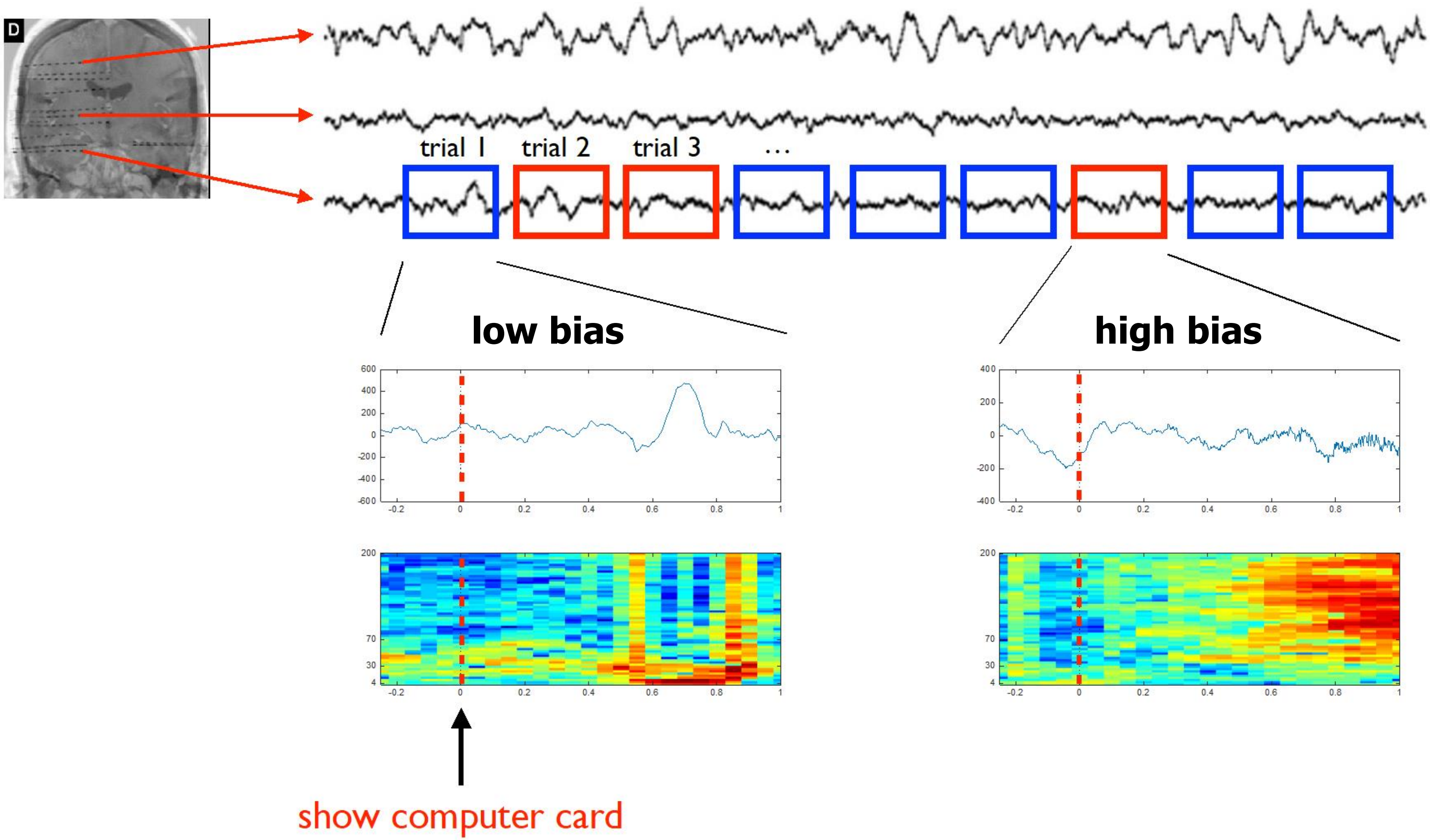
Where is Bias in the Brain?

Brain is viewed as distributed network of oscillators

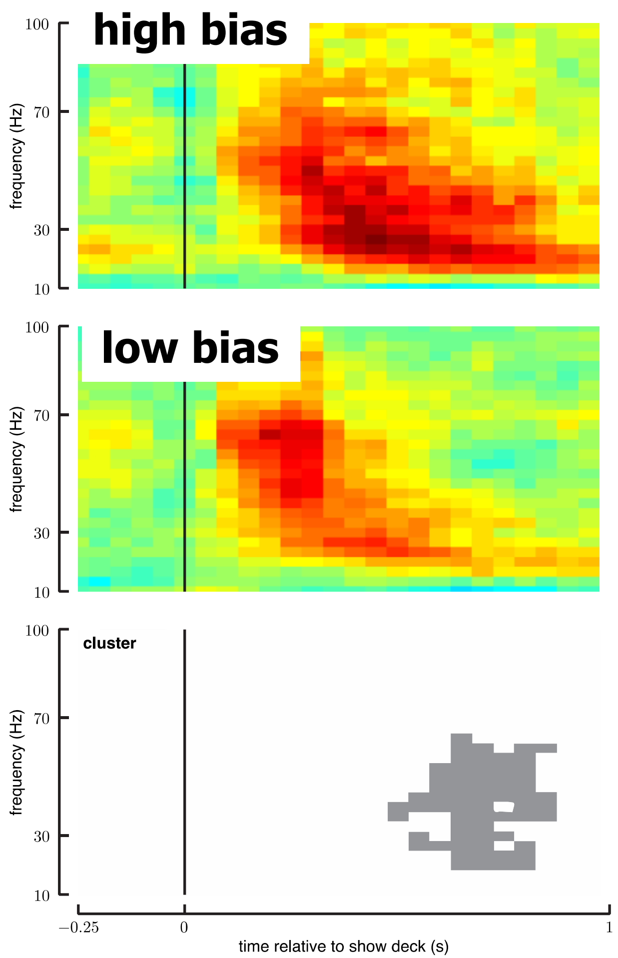




Estimate power spectral density for each snapshot in each trial



Use a nonparametric statistical test with clusters

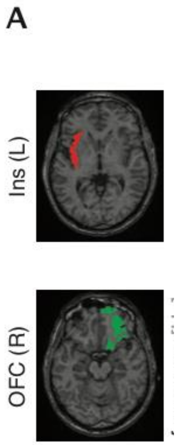


Avoid multi comparison problem
as the level of dependence between
time-frequency windows is unknown
making a Bonferroni correction unsuitable

Avoid a priori assumption
on the distribution across trials
that may be non-Gaussian

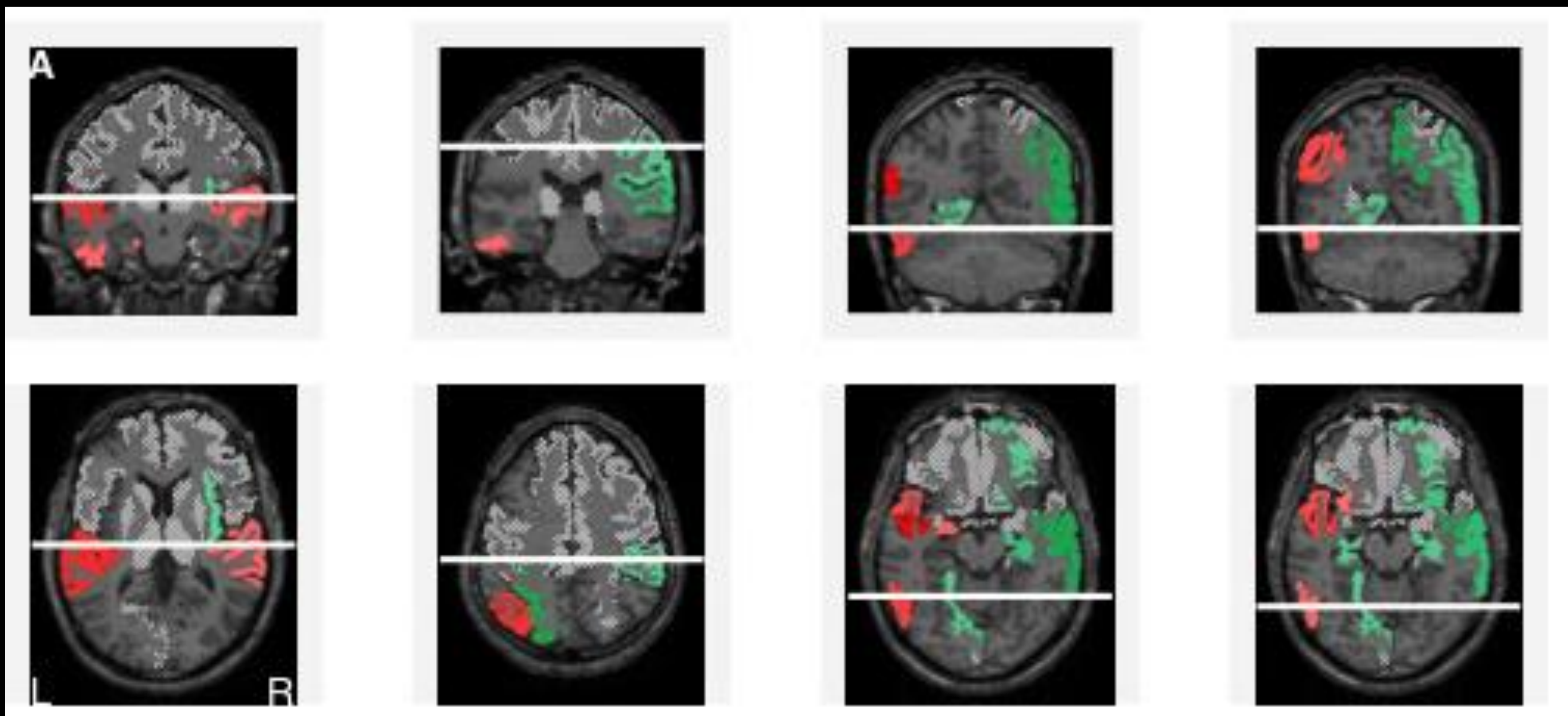
(Maris and Oostenveld 2007)

Examples of regions encoding bias

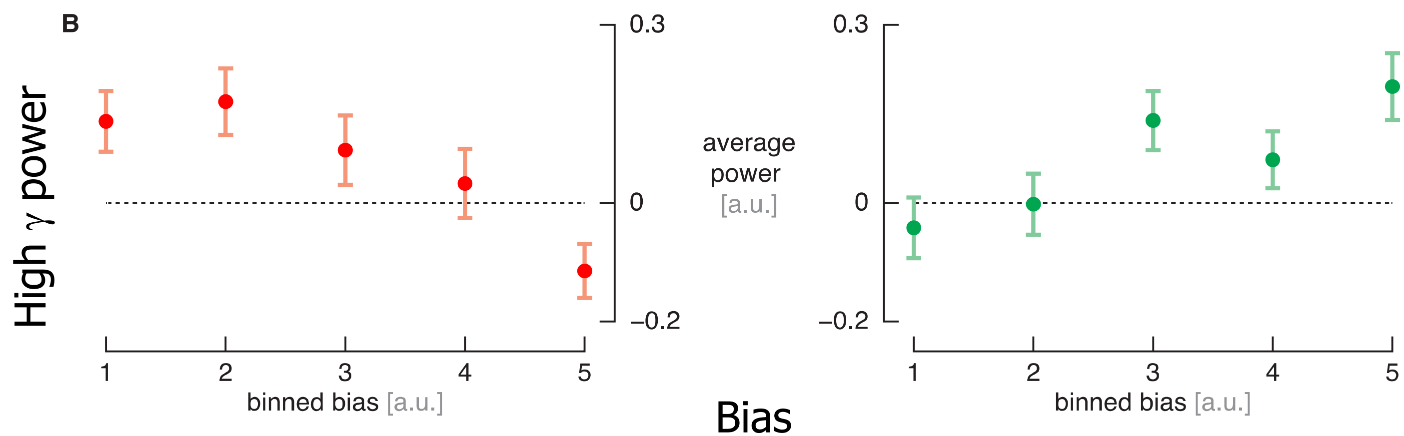


Global view of bias encoding

Show Card **Show Bet** **Computer Card** **Show Reward**



Bias is a right-left push-pull system



Conclusions and next steps…

- Why high gamma? Related to neuronal firing?
- Why push-pull? Pervasive?
  - Motor control: go-no go
  - Vision: on-off receptive fields
- Why lateralized? Evolutionary involved with enhancement of cognition?
  - approach–avoidance motivation and positive–negative emotions (valence hypothesis) seems to have an evolutionary benefit, where minimizing competition between two conflicting behaviors enhances processing efficiency
  - Lateralization has been observed before in PFC and amygdala
- Alter behavior with “rigged” deck or electrical stimulation…

Decision Making in Social Networks

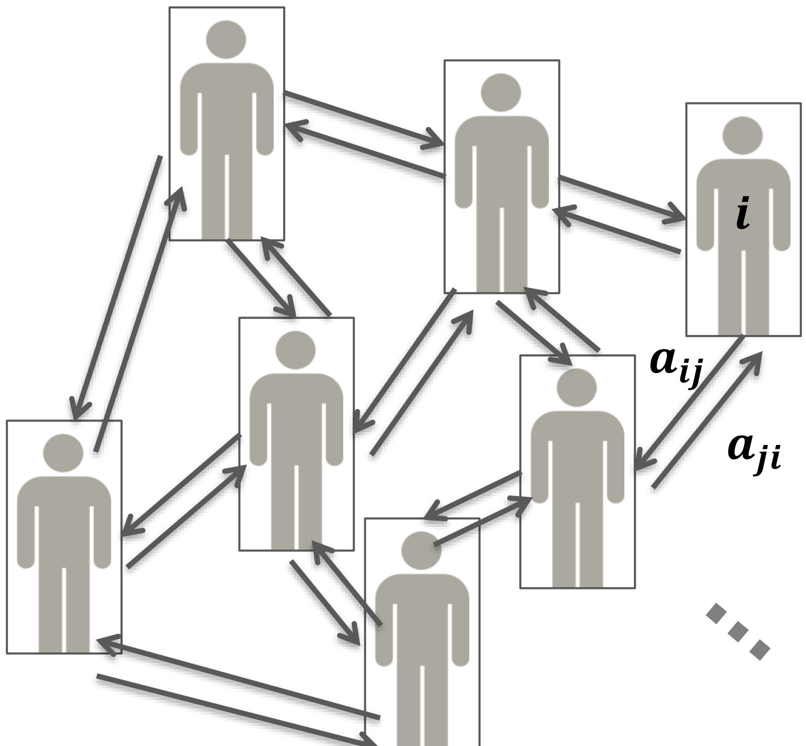
$$\log\left(\frac{p_t^i}{1-p_t^i}\right) = c_1 x_t + c_2 \sum_{j=1}^{N_i} a_{ji}(x_t^j + p_t^j) \; + d_2^i u_t + d_2^i$$

self internal bias

neighbor's internal biases and decisions

logic

baseline (risk averseness)



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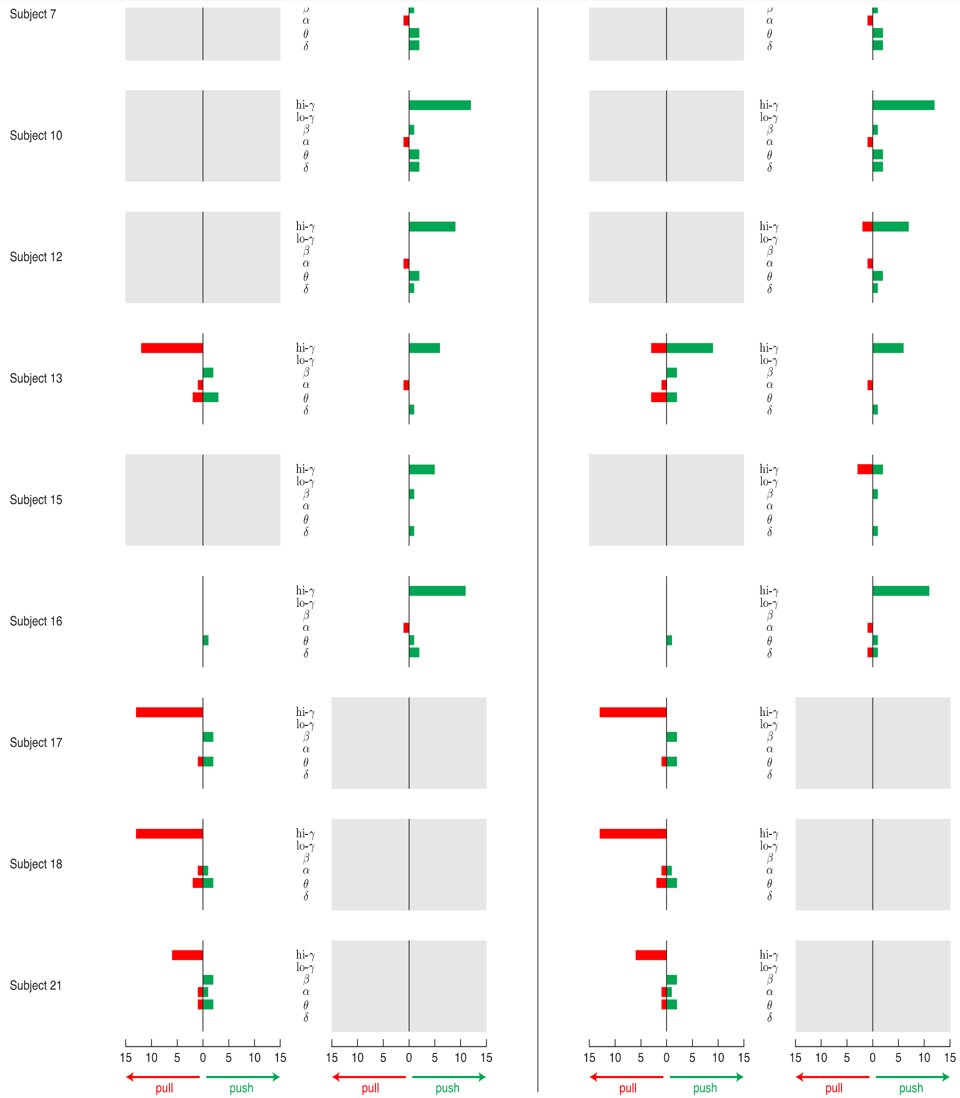
NSF

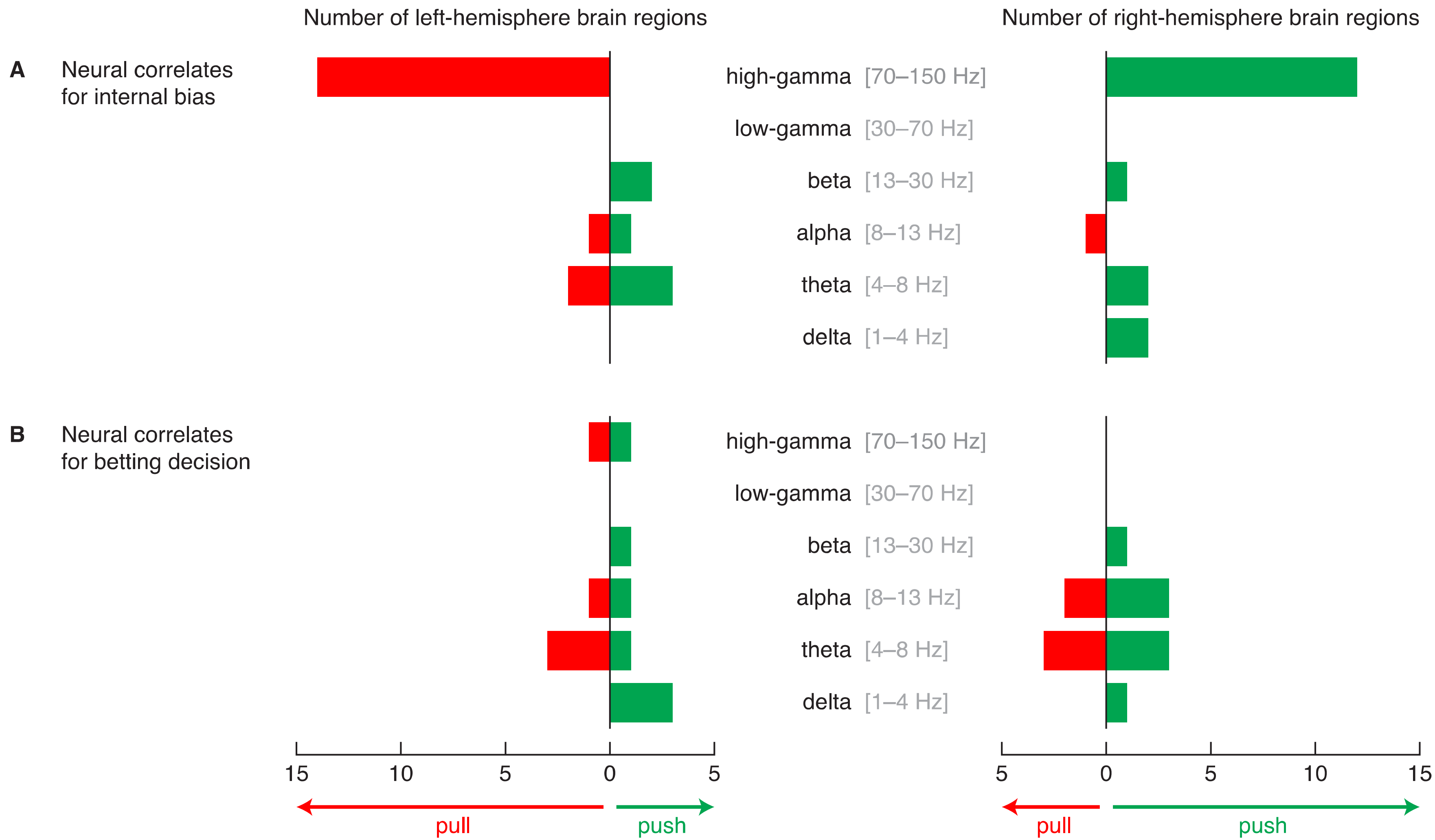
Kavli NEUROSCIENCE DISCOVERY INSTITUTE

Bridging Biology, Engineering and Data Science.

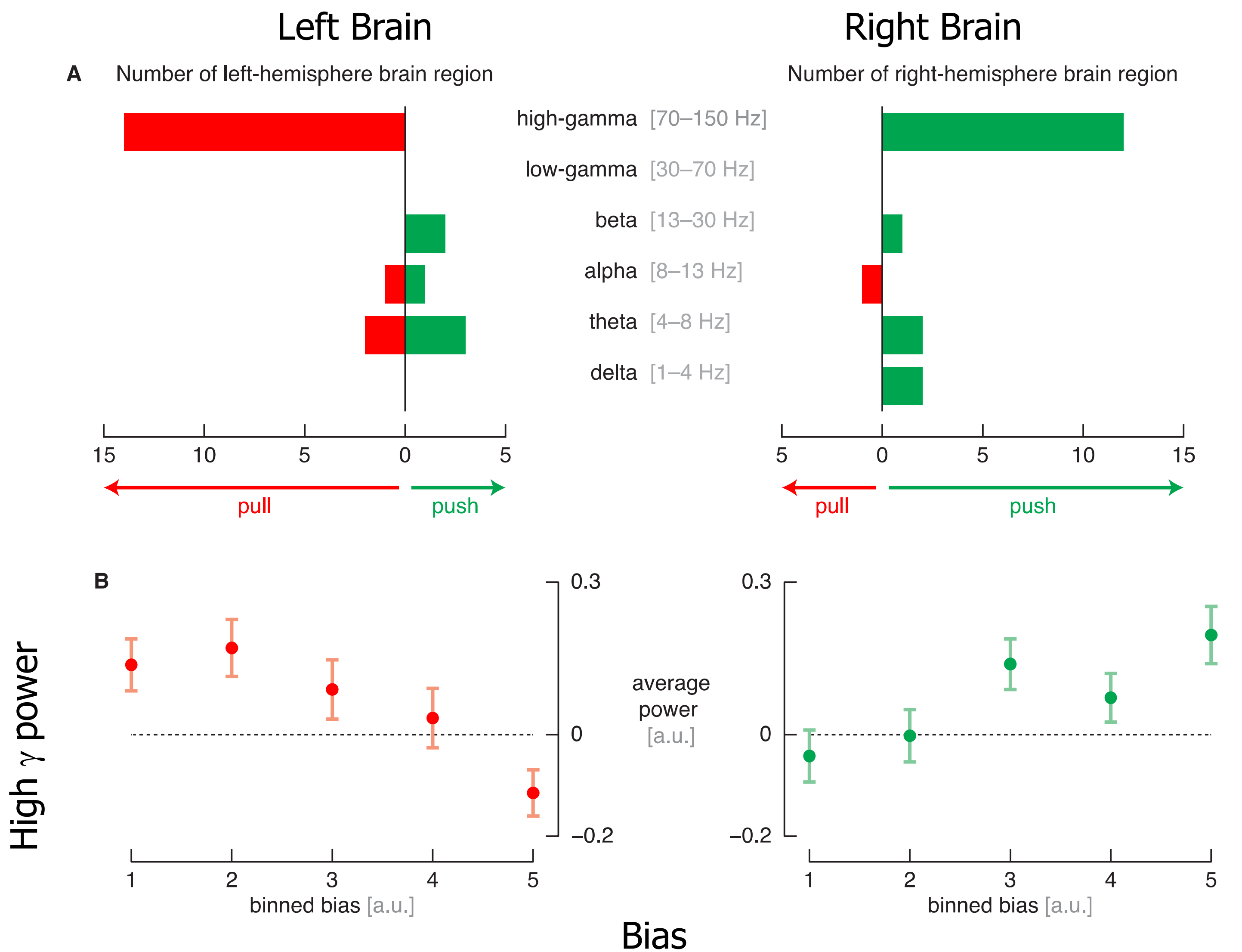
Results not driven by single subject



Bias is not attention



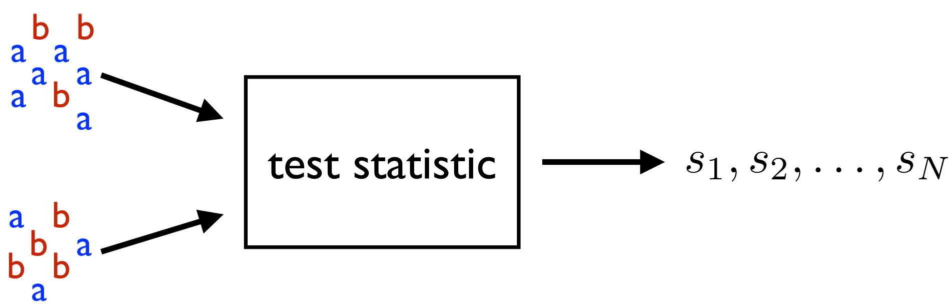
High gamma shows push-pull encoding

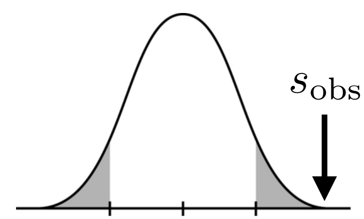


Infer significant differences in neural response between low and high bias conditions

1. Compute a test statistic that captures the difference between the observed conditions

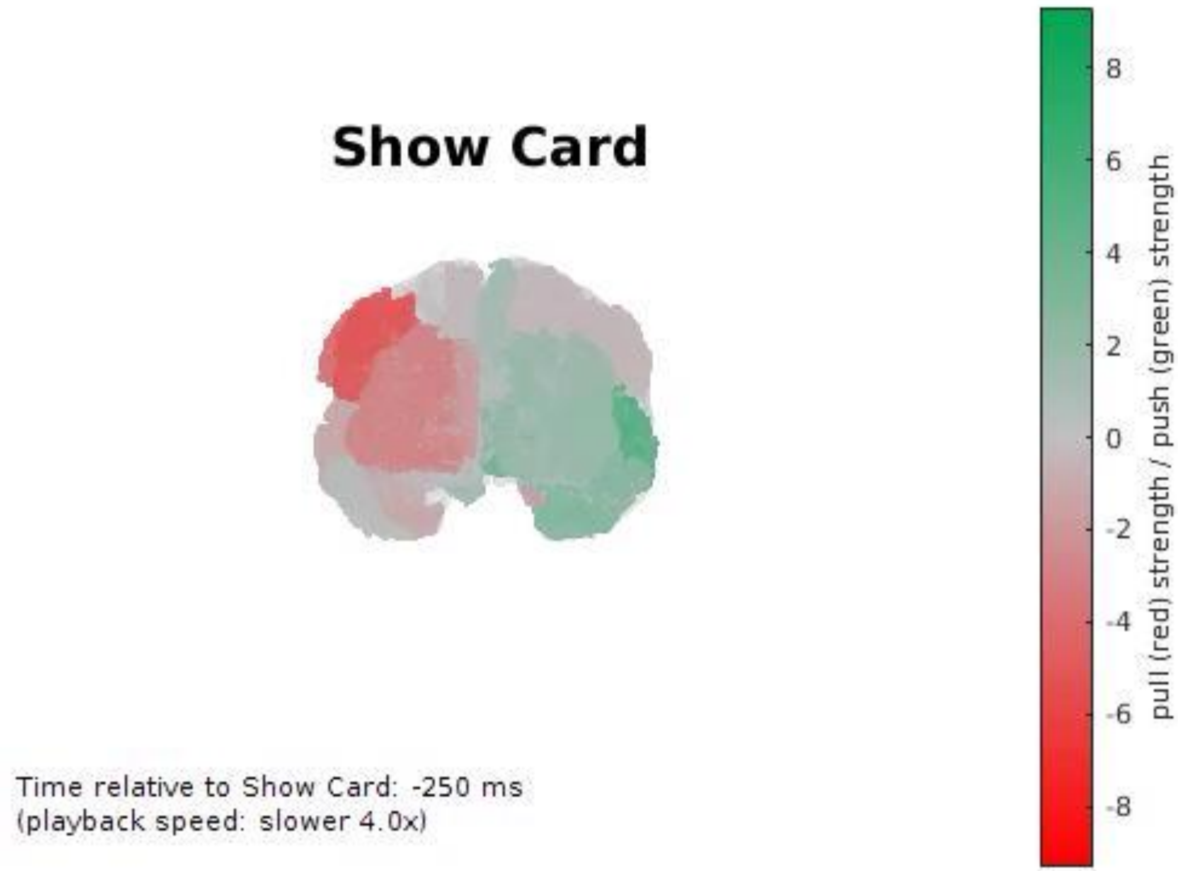
2. Estimate the null distribution of the test statistics for permuted condition labels (N times)



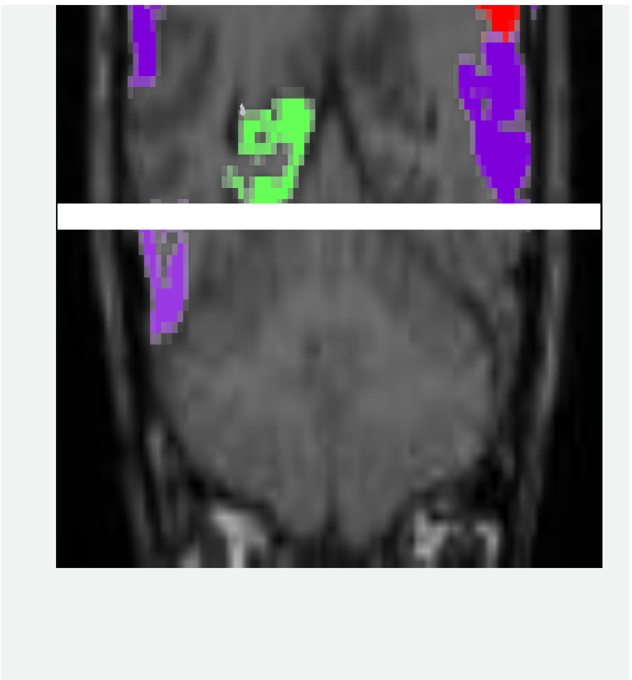


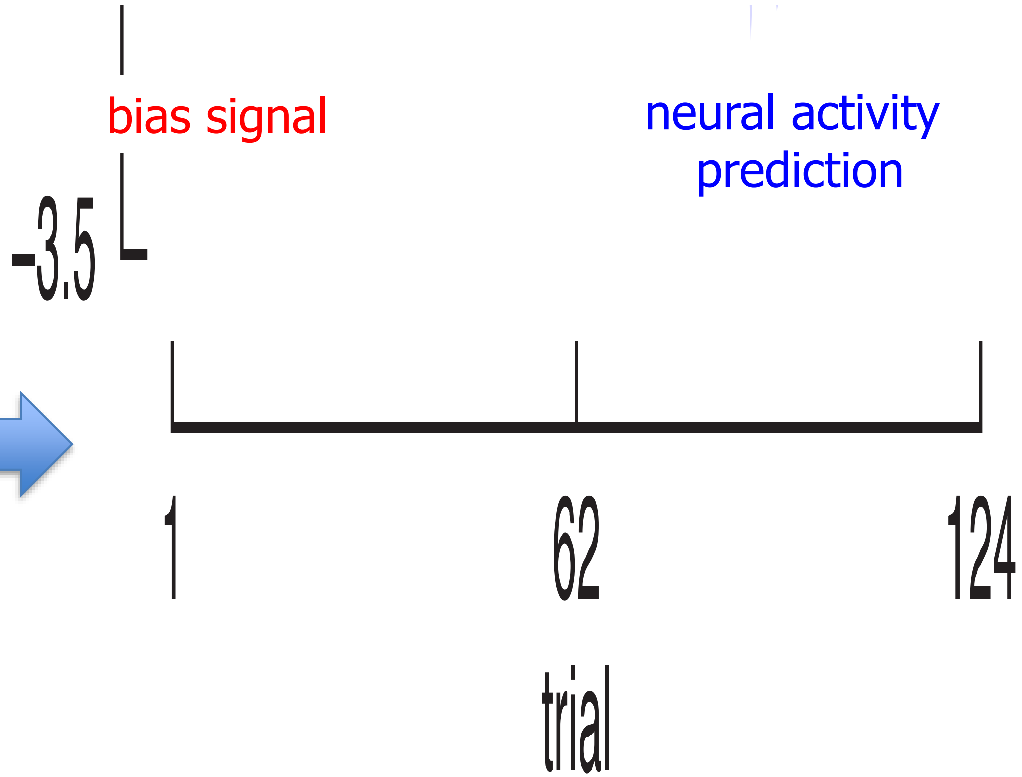
3. Compare the observed statistic to the null distribution

Push-Pull in Action



Decoding bias from the brain





Sacré et al. (2018) Risk-taking bias in human decision-making is encoded via a right–left brain push–pull system. *Proc Natl Acad Sci* U S A.