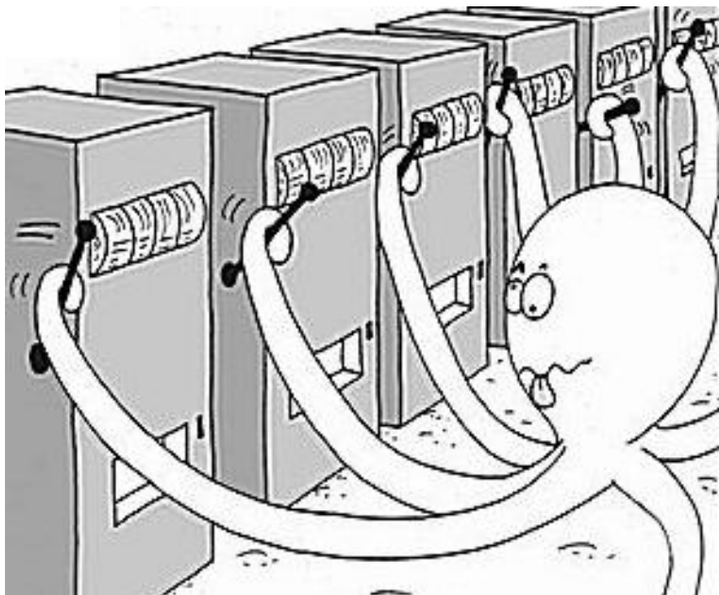
Learning and Decision Making under Uncertainty: From Basic Science to Psychiatry and Back Again

Angela Yu

Cognitive Science &
Halıcıoğlu Data Science Institute
UC San Diego



Learning & Decision-Making under Uncertainty

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Repeated Decisions ⇒ Stochastic Outcomes

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Restaurants, research projects, dating

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Repeated Decisions ⇒ Stochastic Outcomes

Restaurants, research projects, dating

Each choice ⇒ immediate return + information gain

Outline

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- **Computational modeling**

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Conceptual Framework

Learning
(Information Processing)

- inferring state of the world
- predicting outcomes
  (short-term & long-term)
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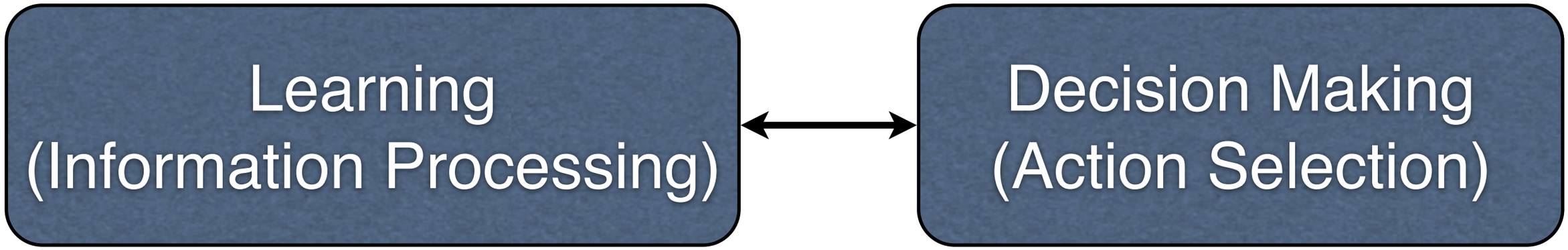

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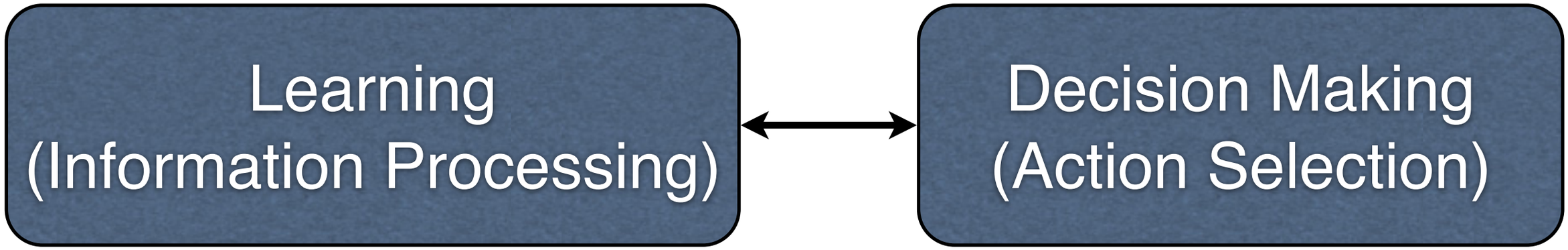

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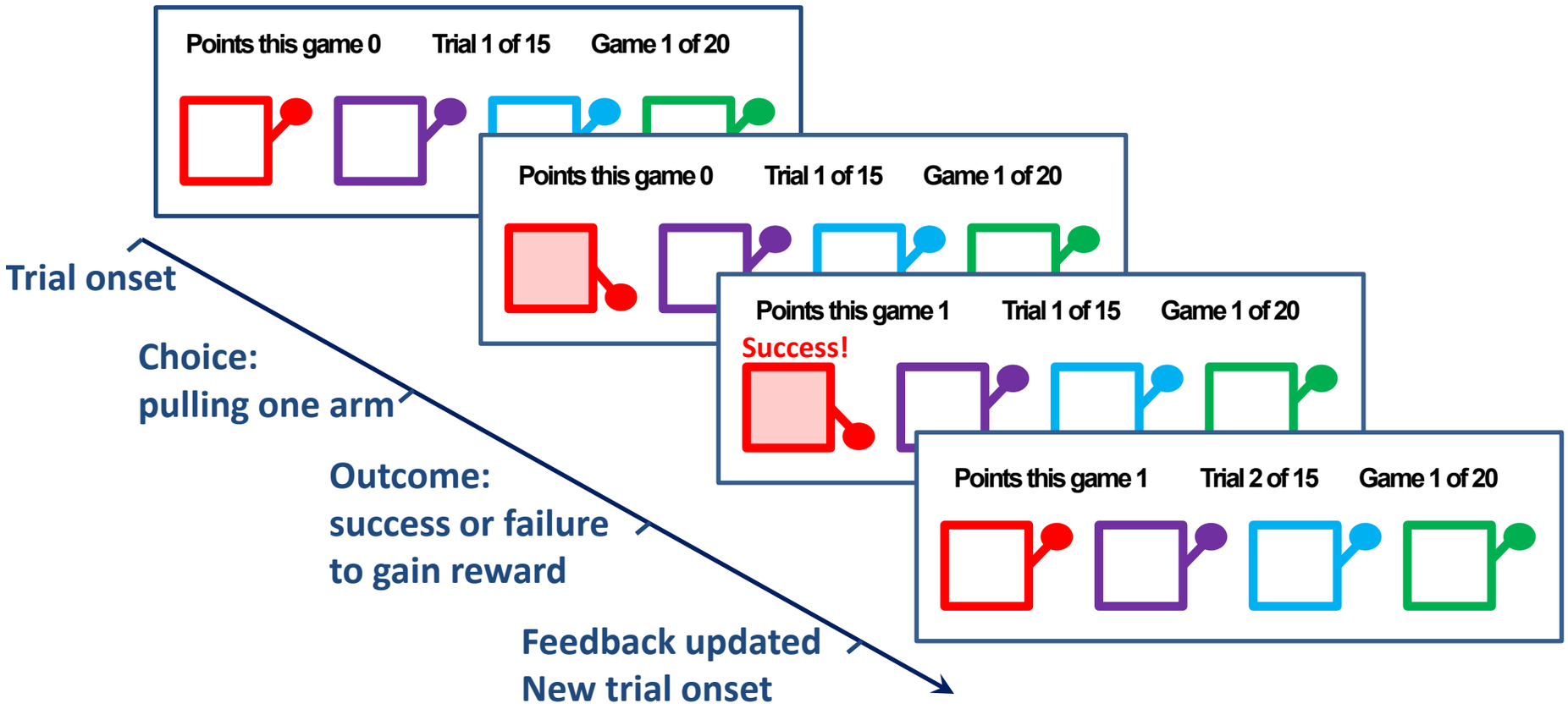
Canonical experimental paradigm: multi-armed bandit task

Multi-Arm Bandit Task



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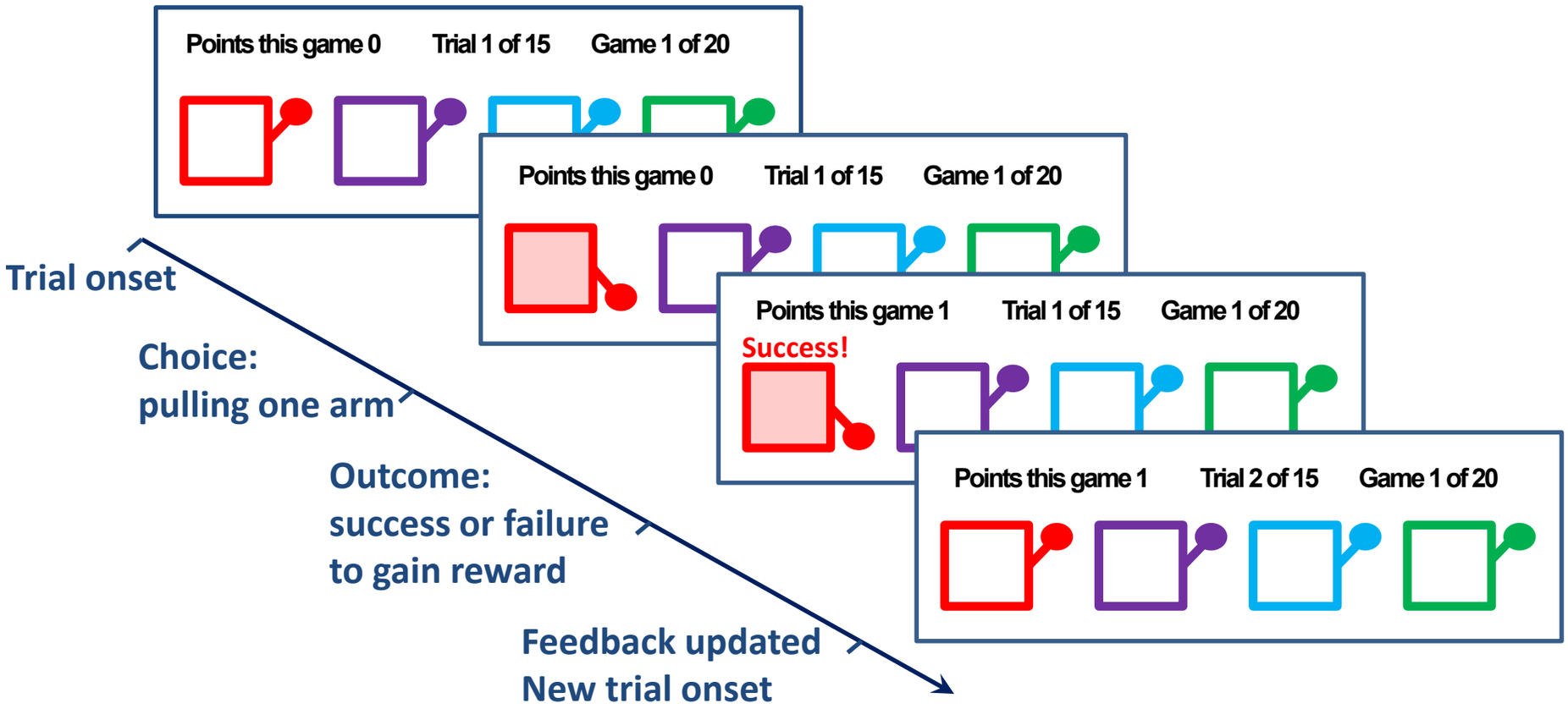

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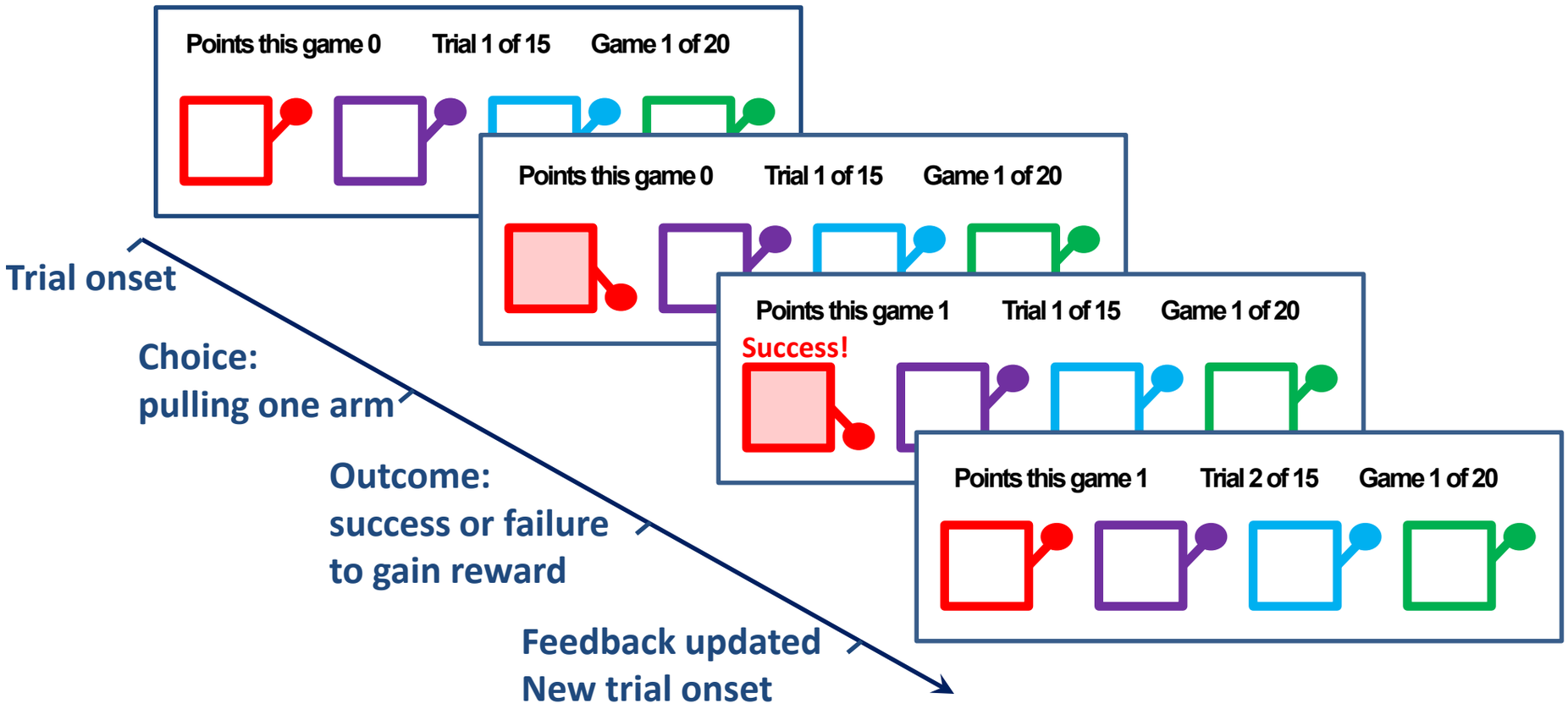

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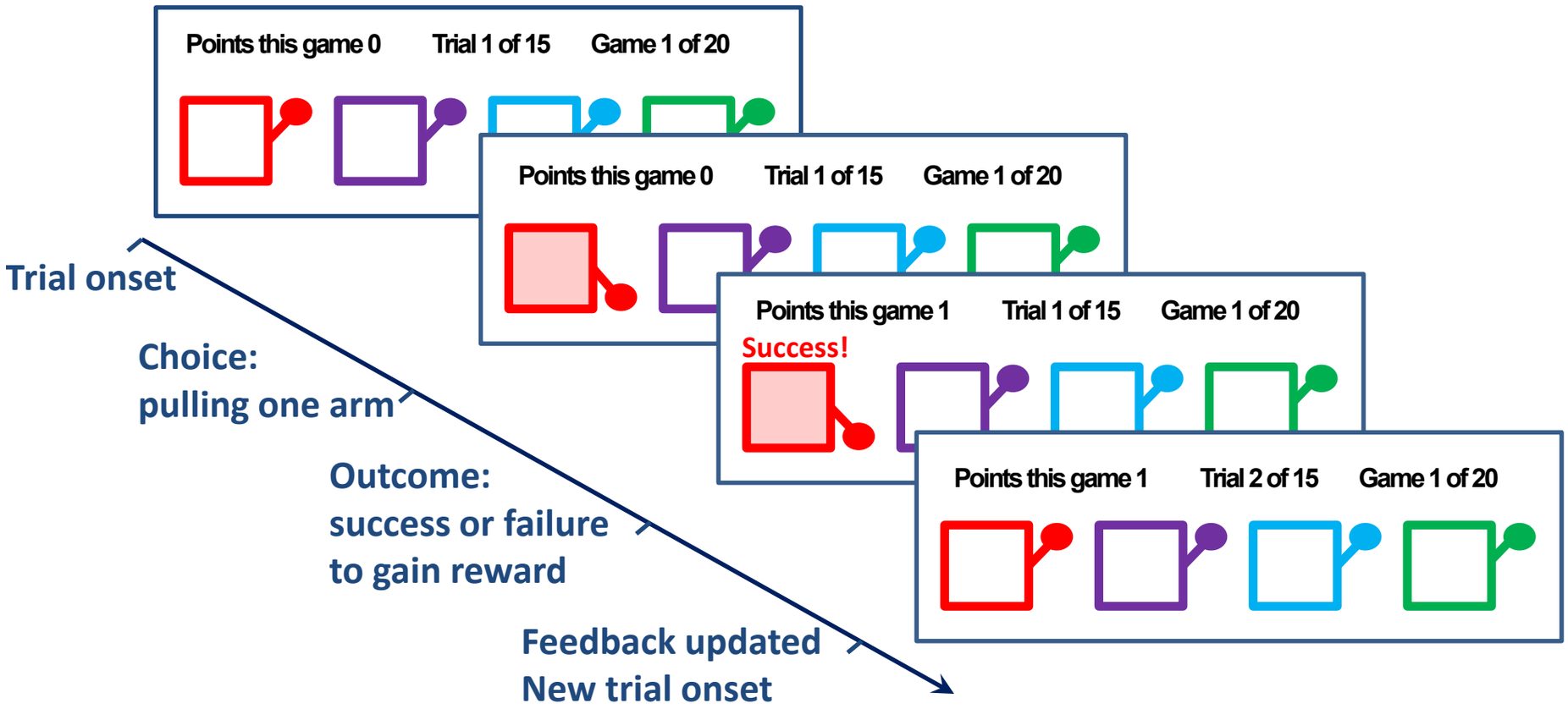

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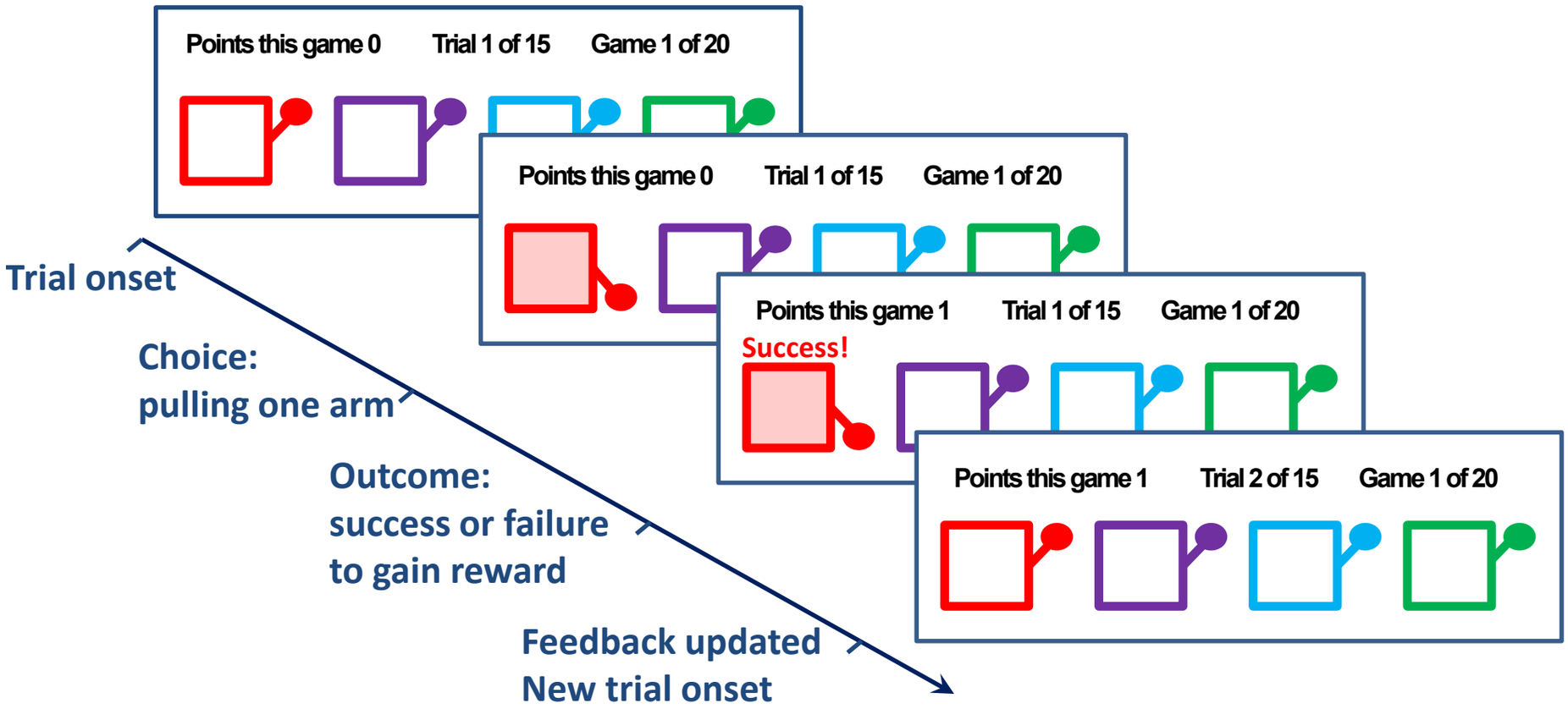

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- need to balance between exploitation and exploration

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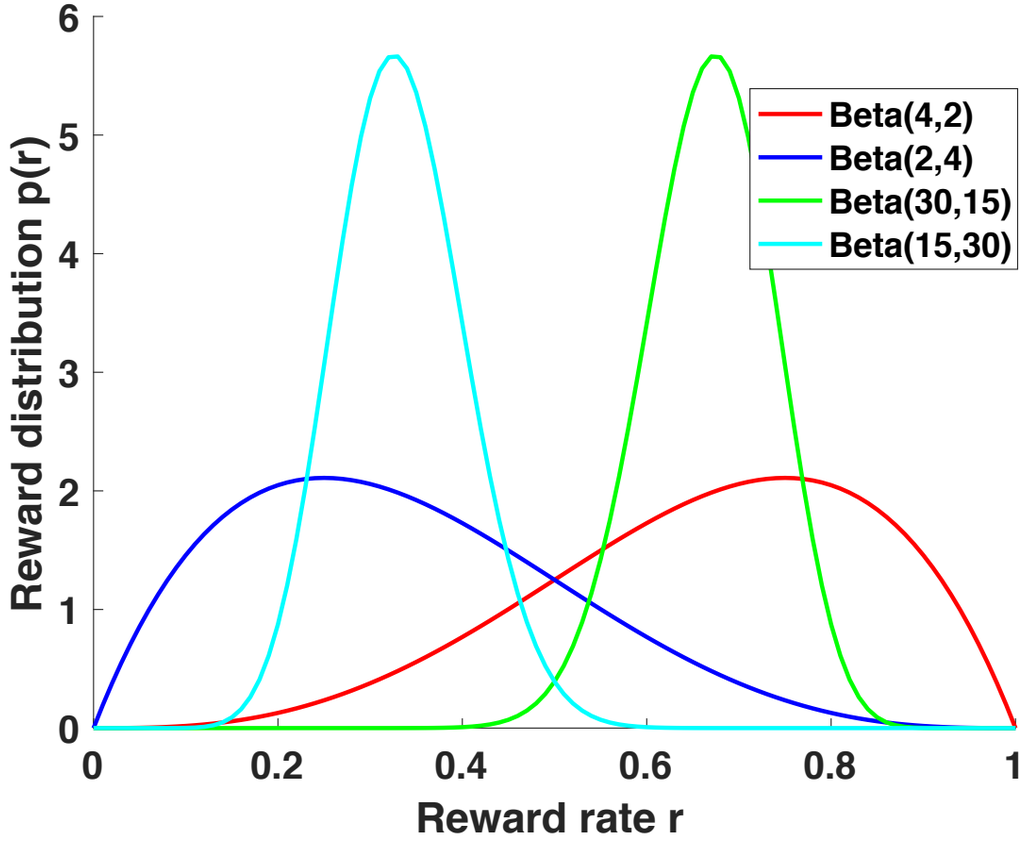

Accurate Representation of Prior?

Subjects report E[reward] for unseen arms

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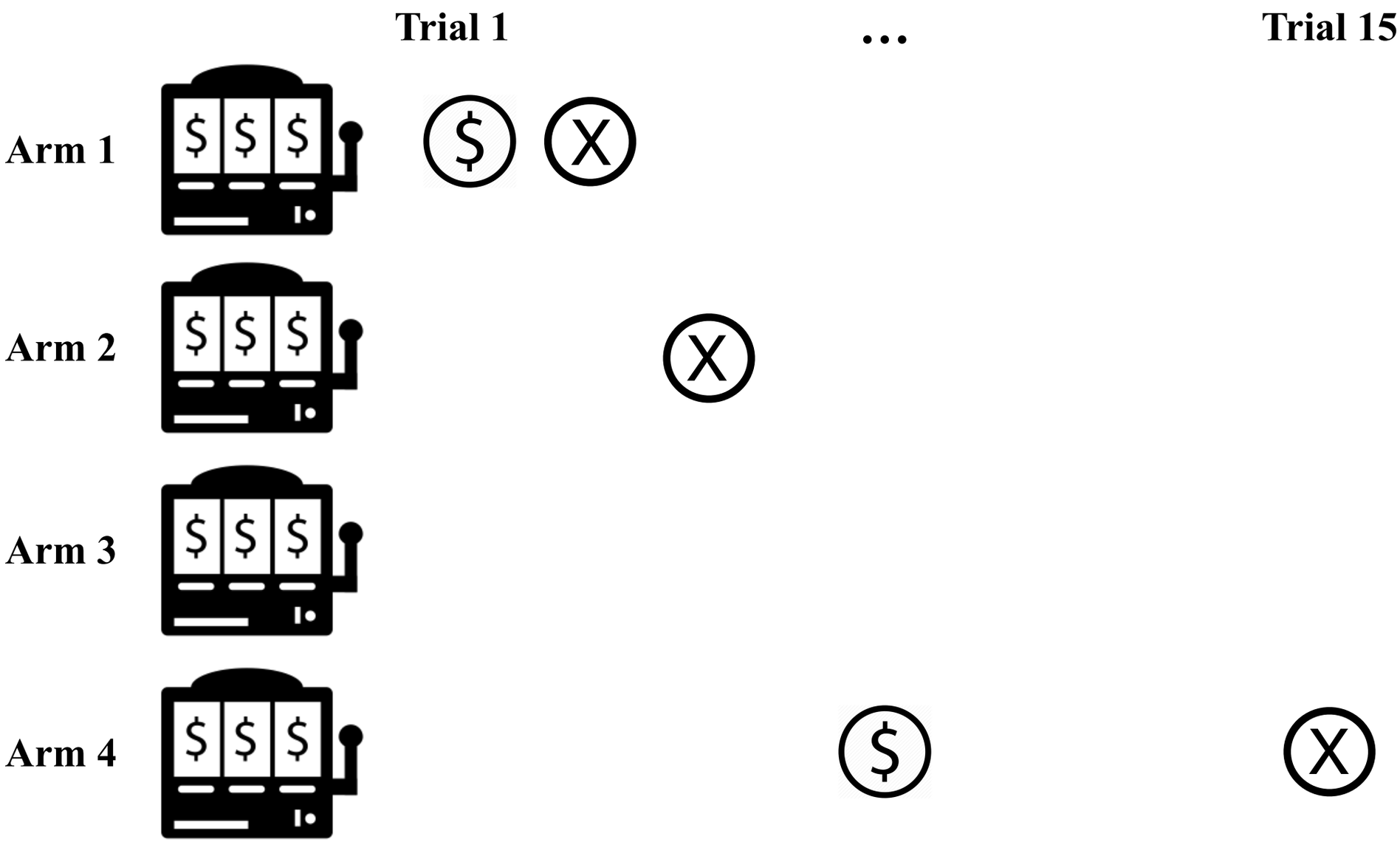

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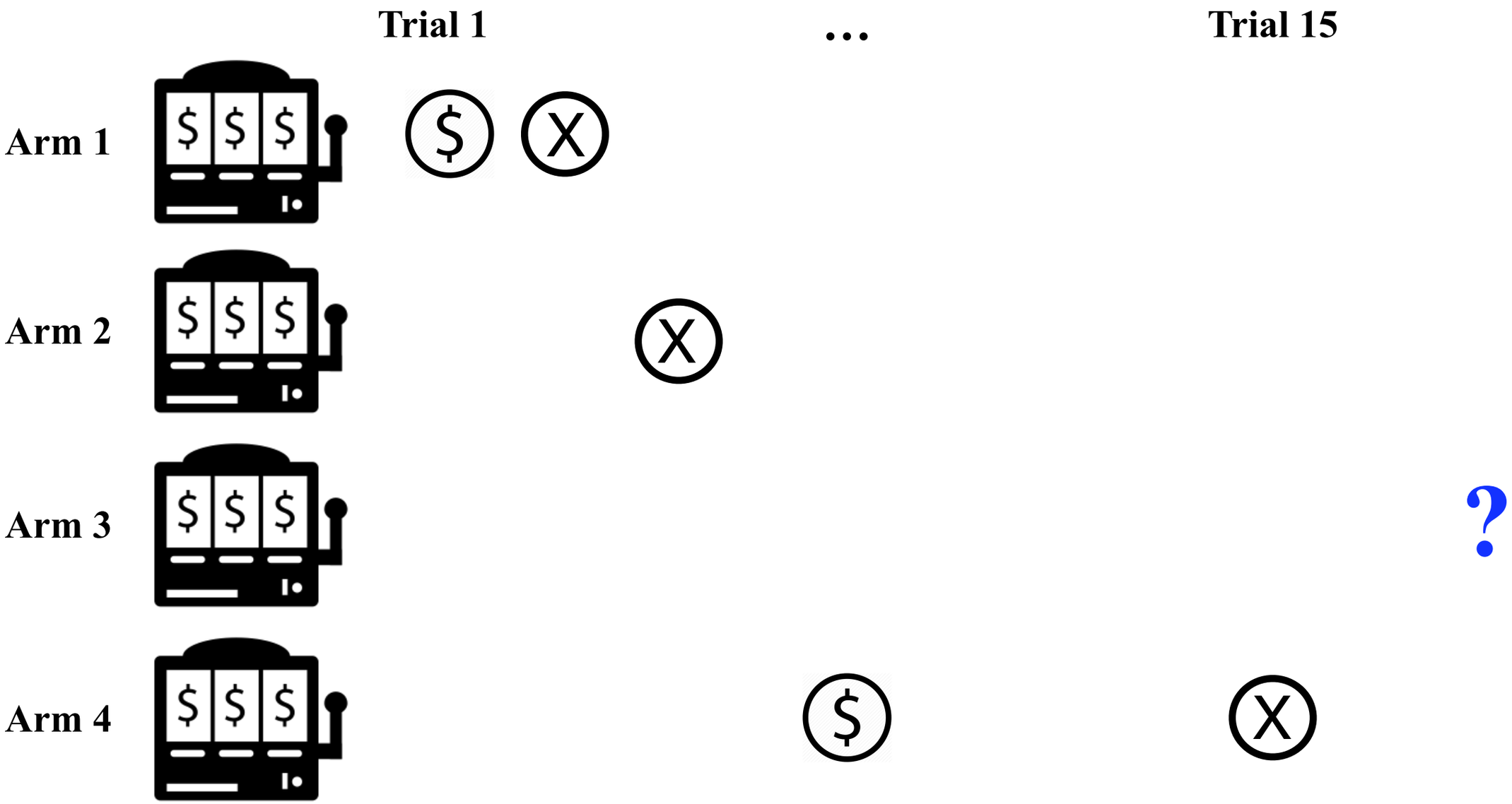

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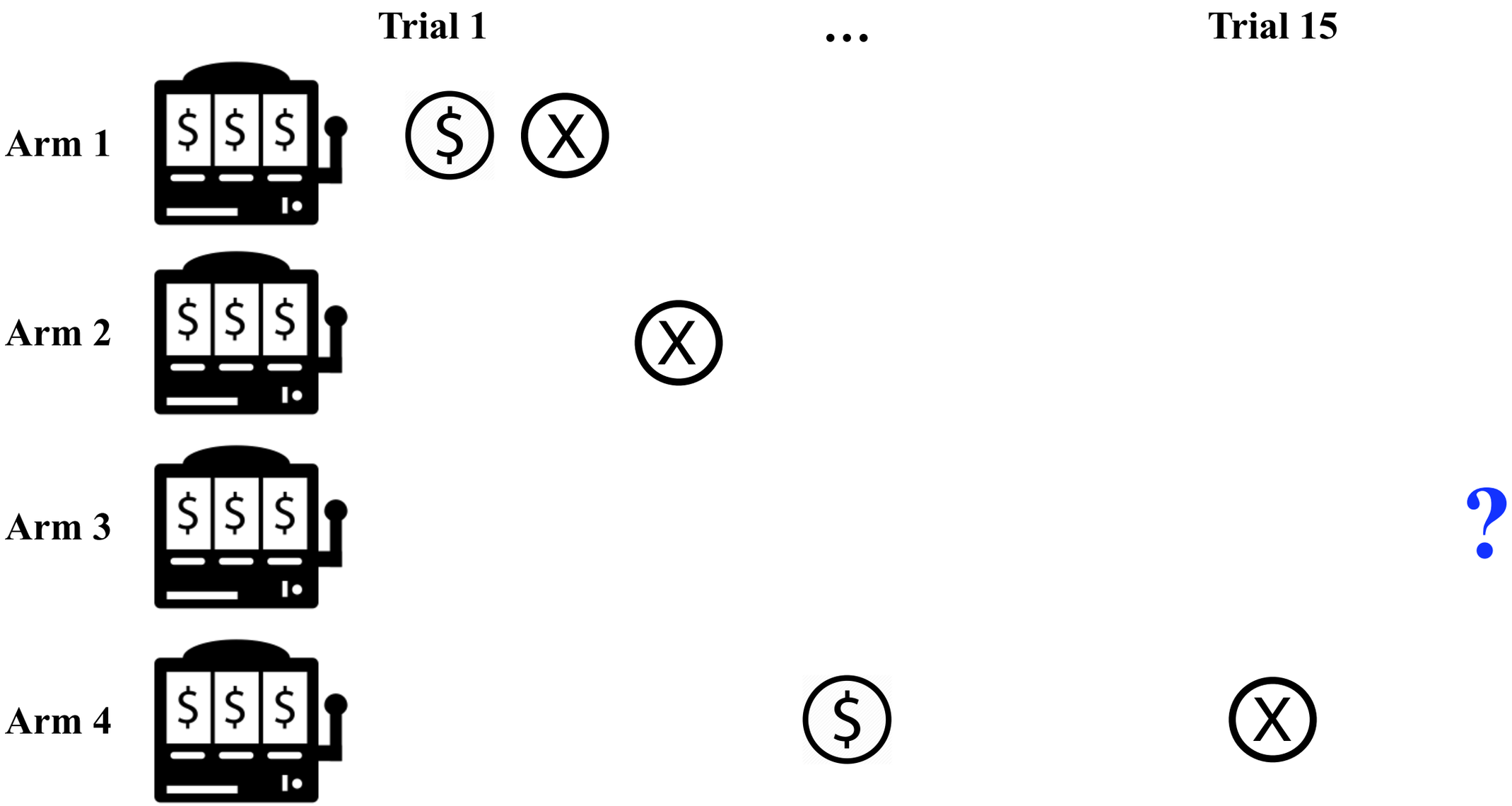
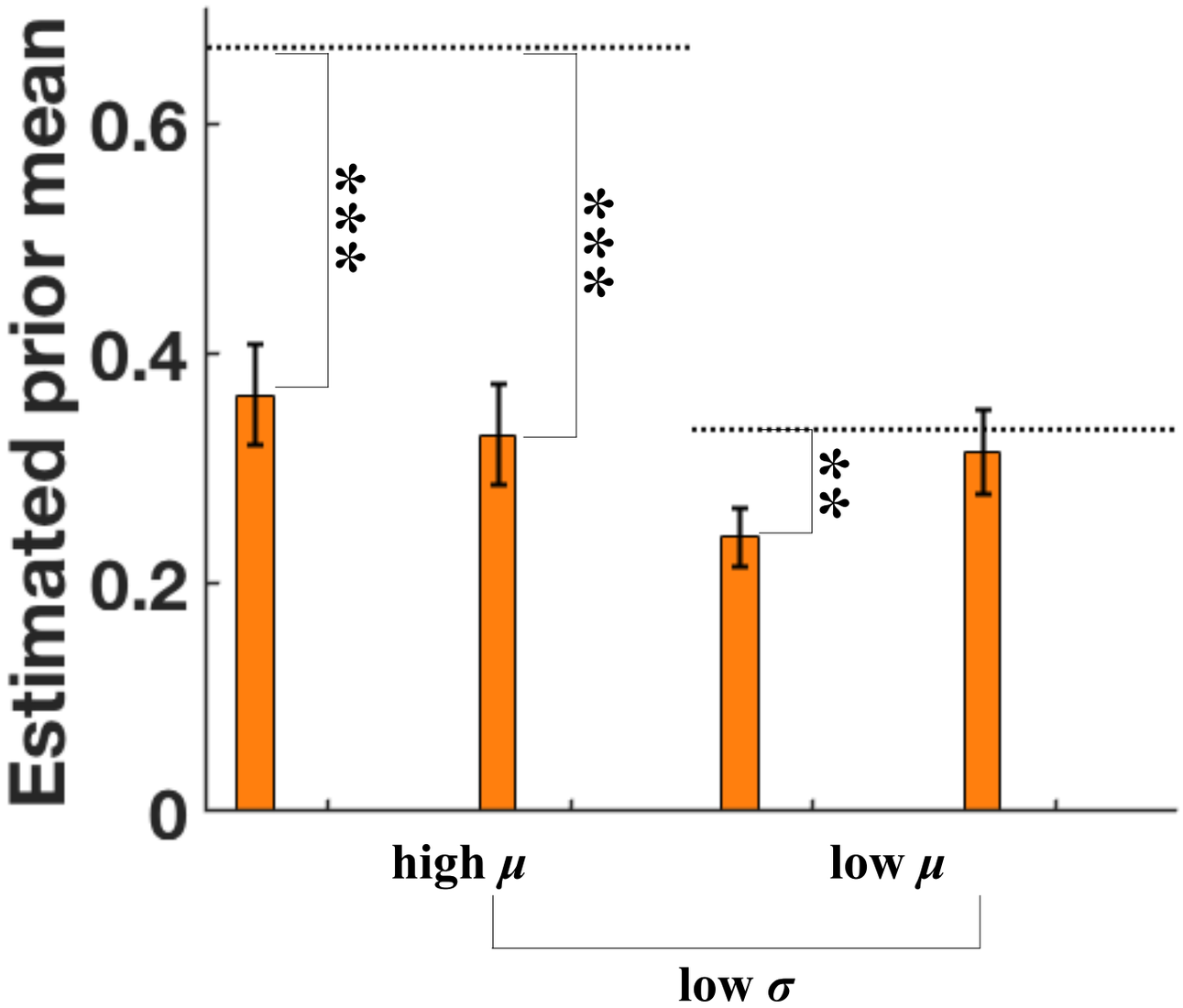


*"You did not choose arm **3** in this game. If you were to choose it 10 times, how many fish would you expect to catch?"*

Self-Report: Reward Underestimation



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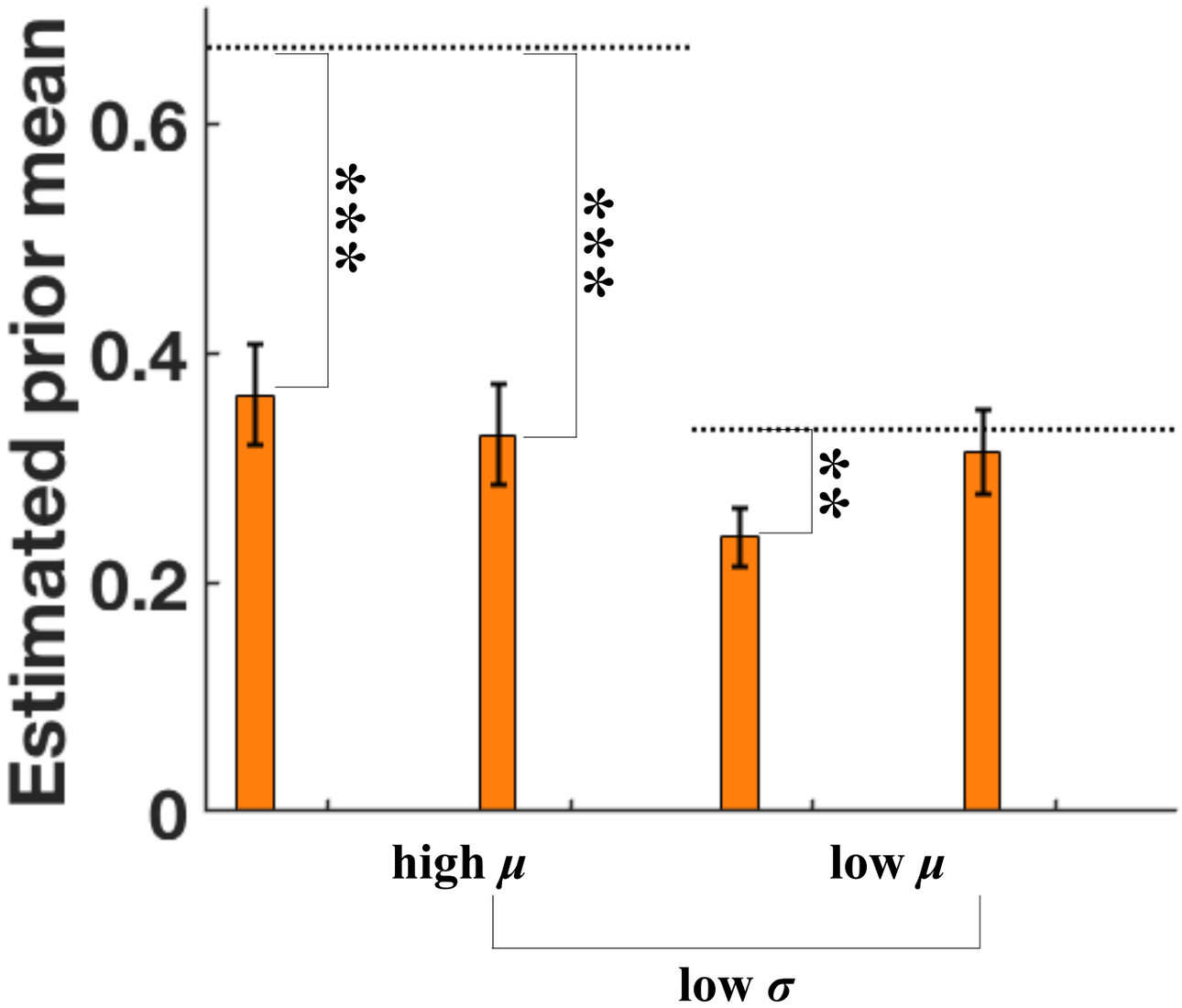

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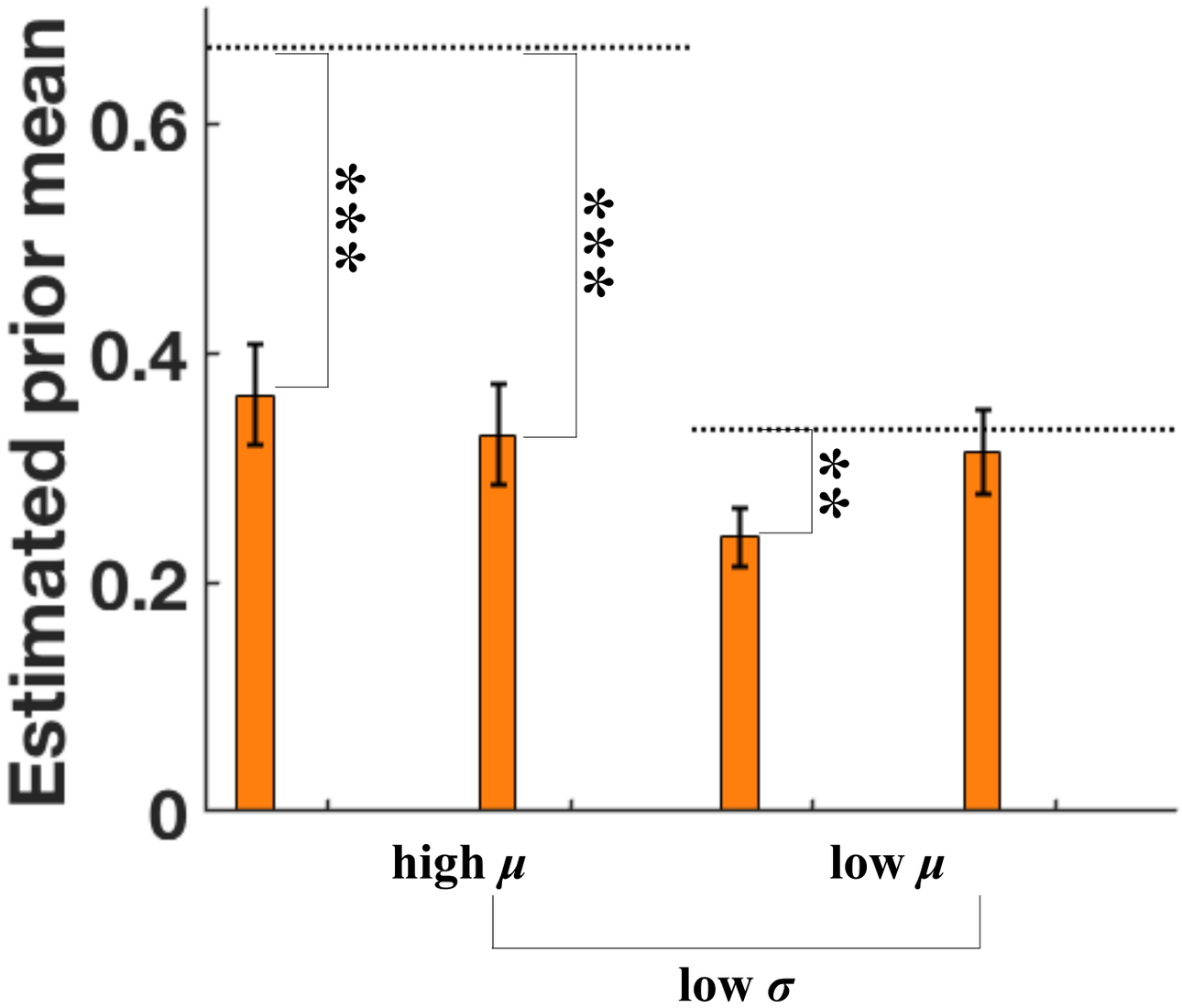

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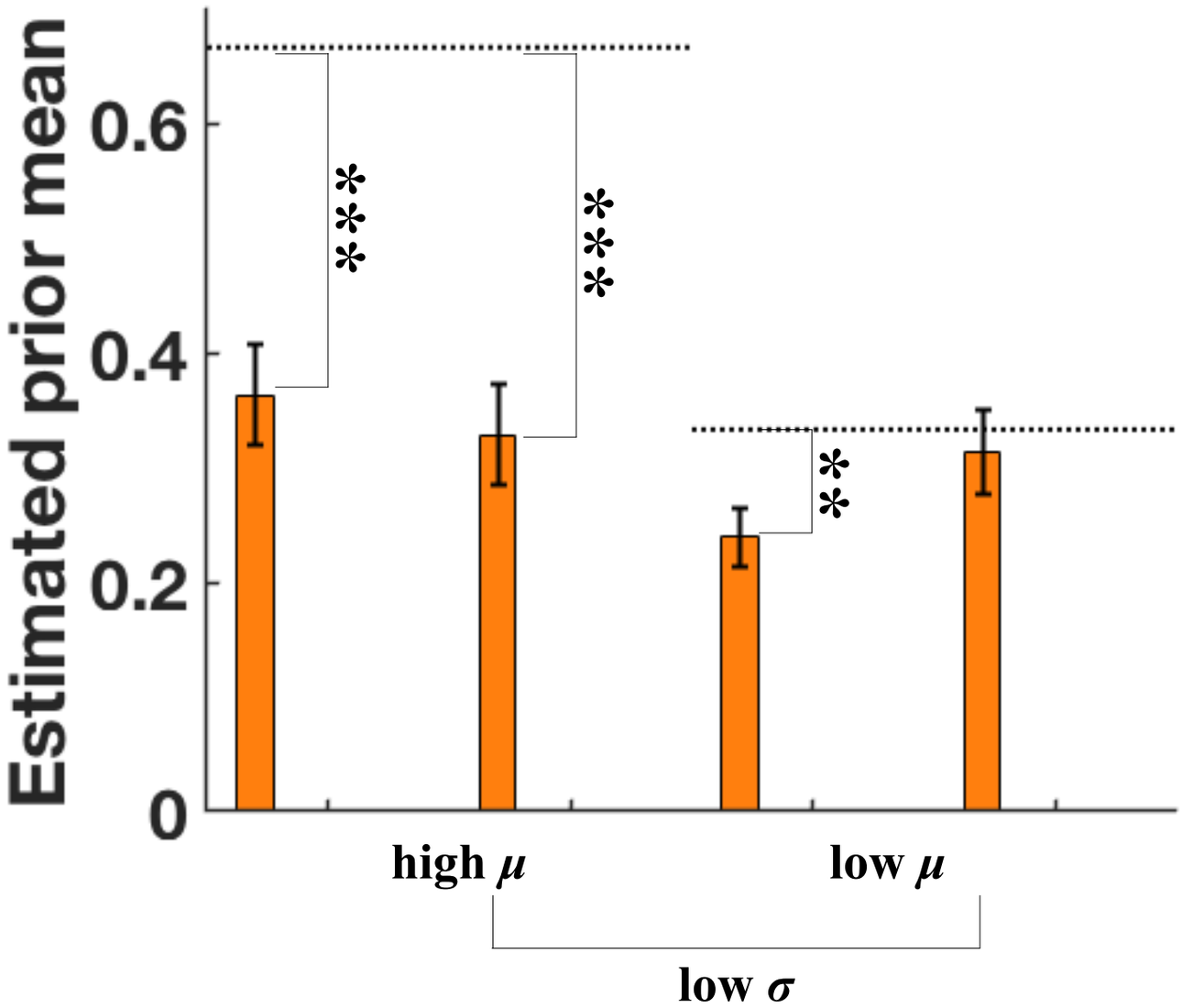

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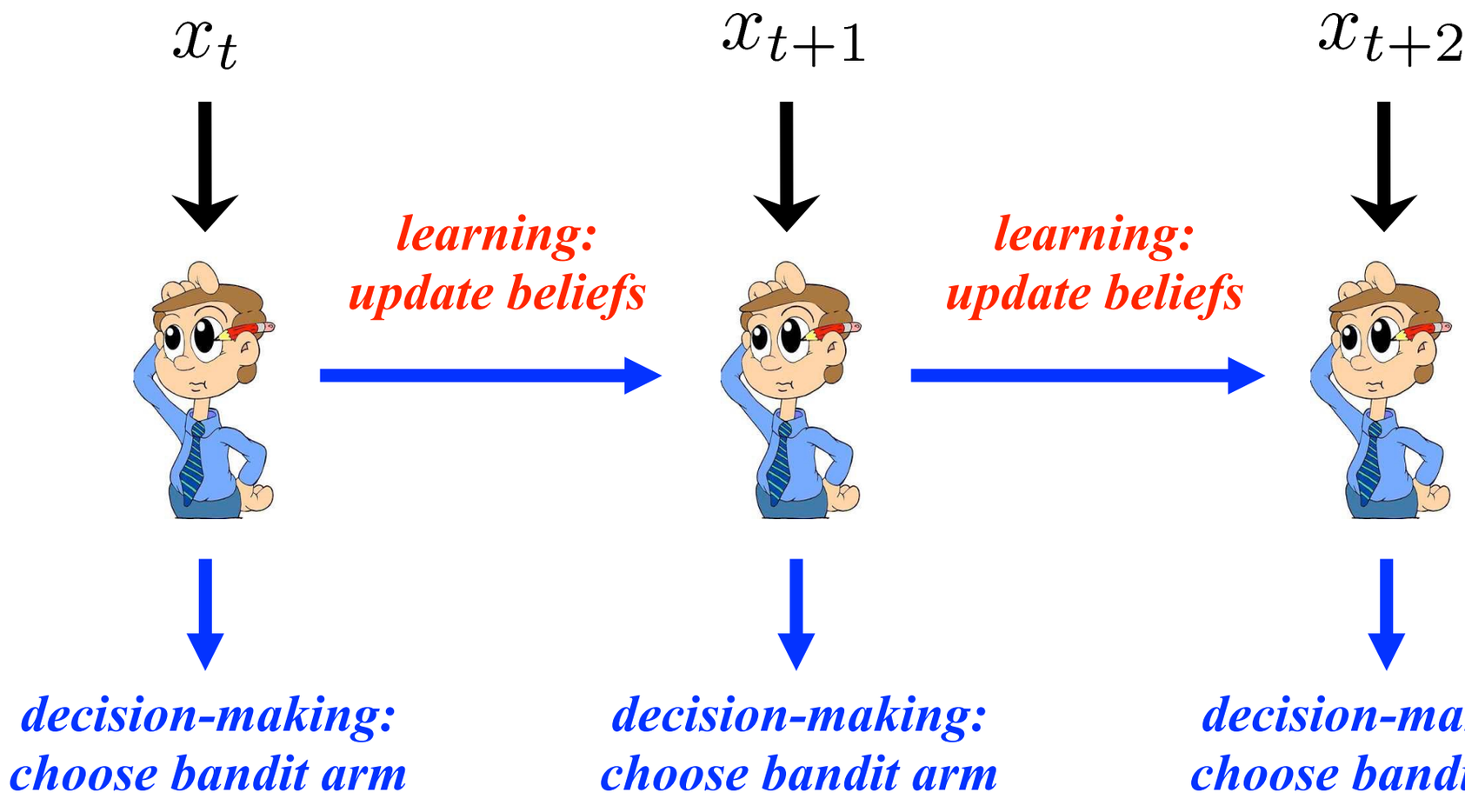
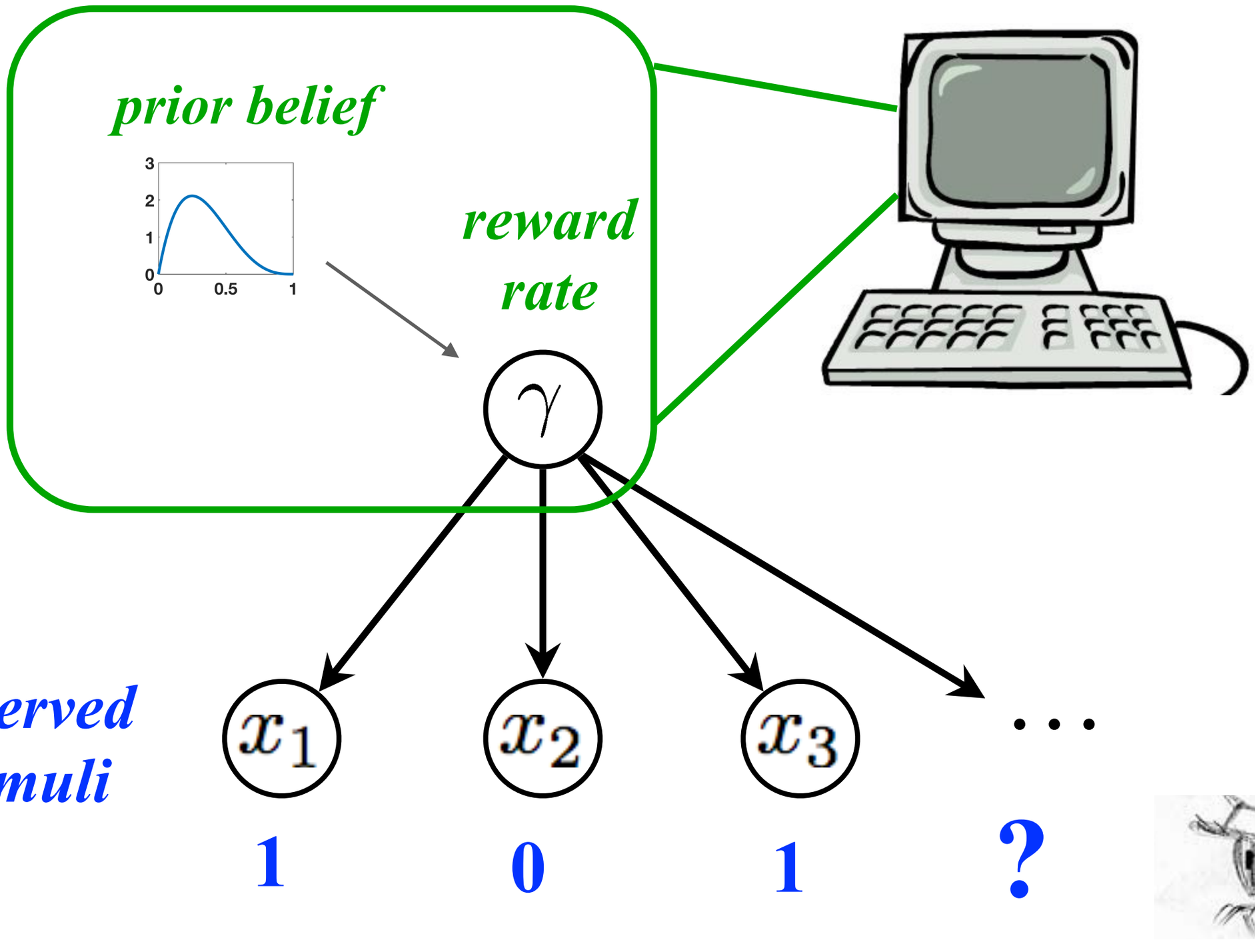
- Is this real? Or *selection bias? Confirmation bias?*
- Alternative approach: model behavior ⇒ still under-estimation?

Sequential Learning & Decision-Making

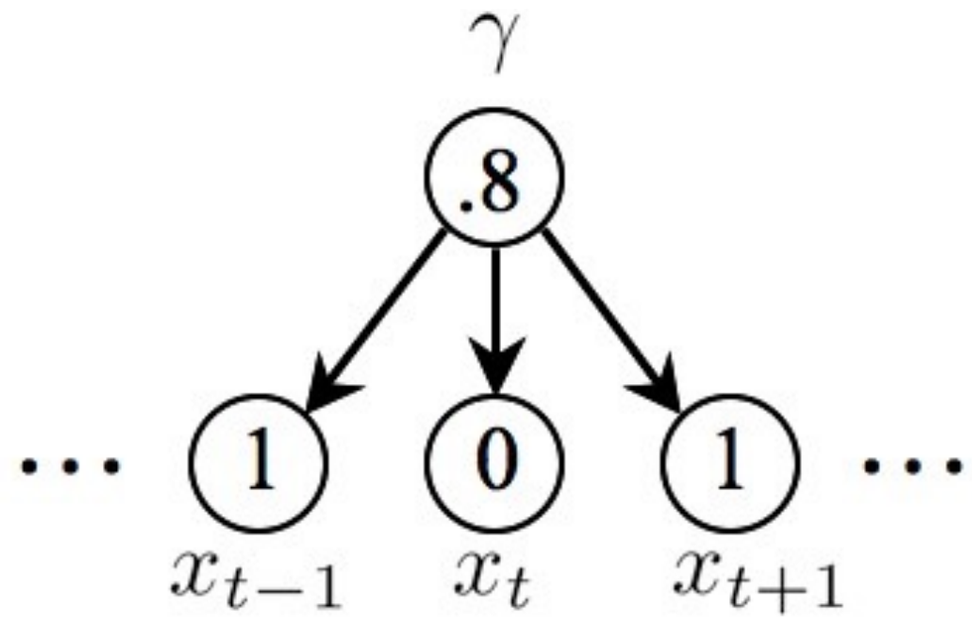


Learning Model I: Fixed Belief Model (FBM)

(Yu & Cohen, *NIPS*, 2009; Zhang & Yu, *NIPS,* 2013)



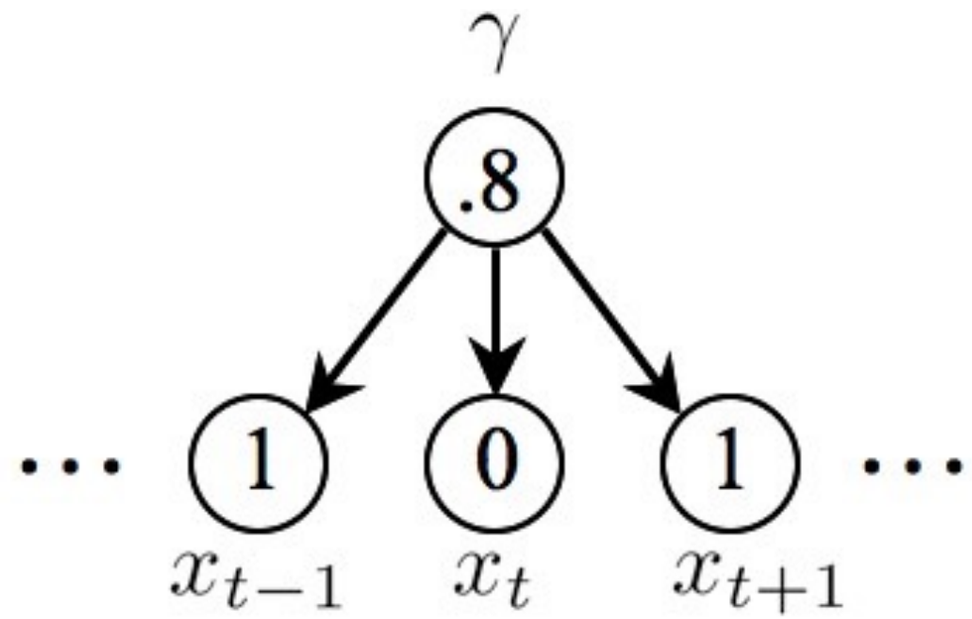
Bayesian Inference



Generative Model
(what subject "knows")

$$P(x_t|\gamma) = Bernoulli(x_t;\gamma)$$

Bayesian Inference



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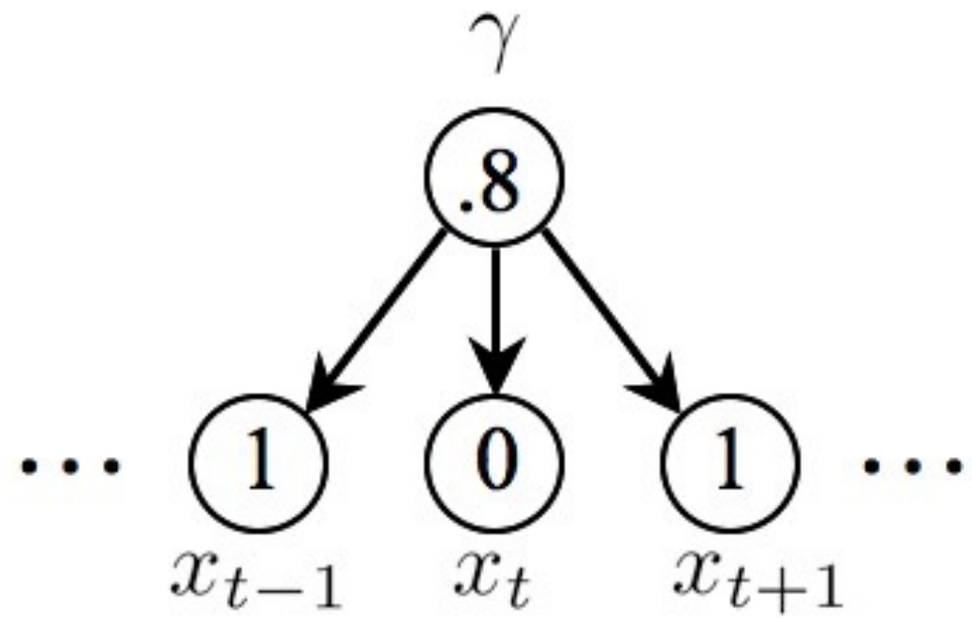

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Belief Updating
(Bayes' Rule)

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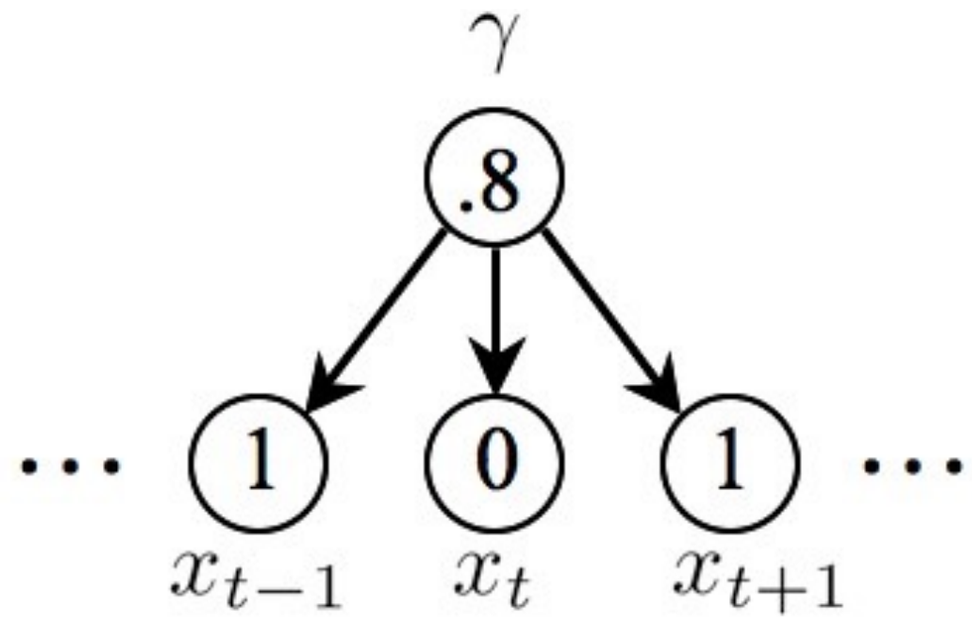

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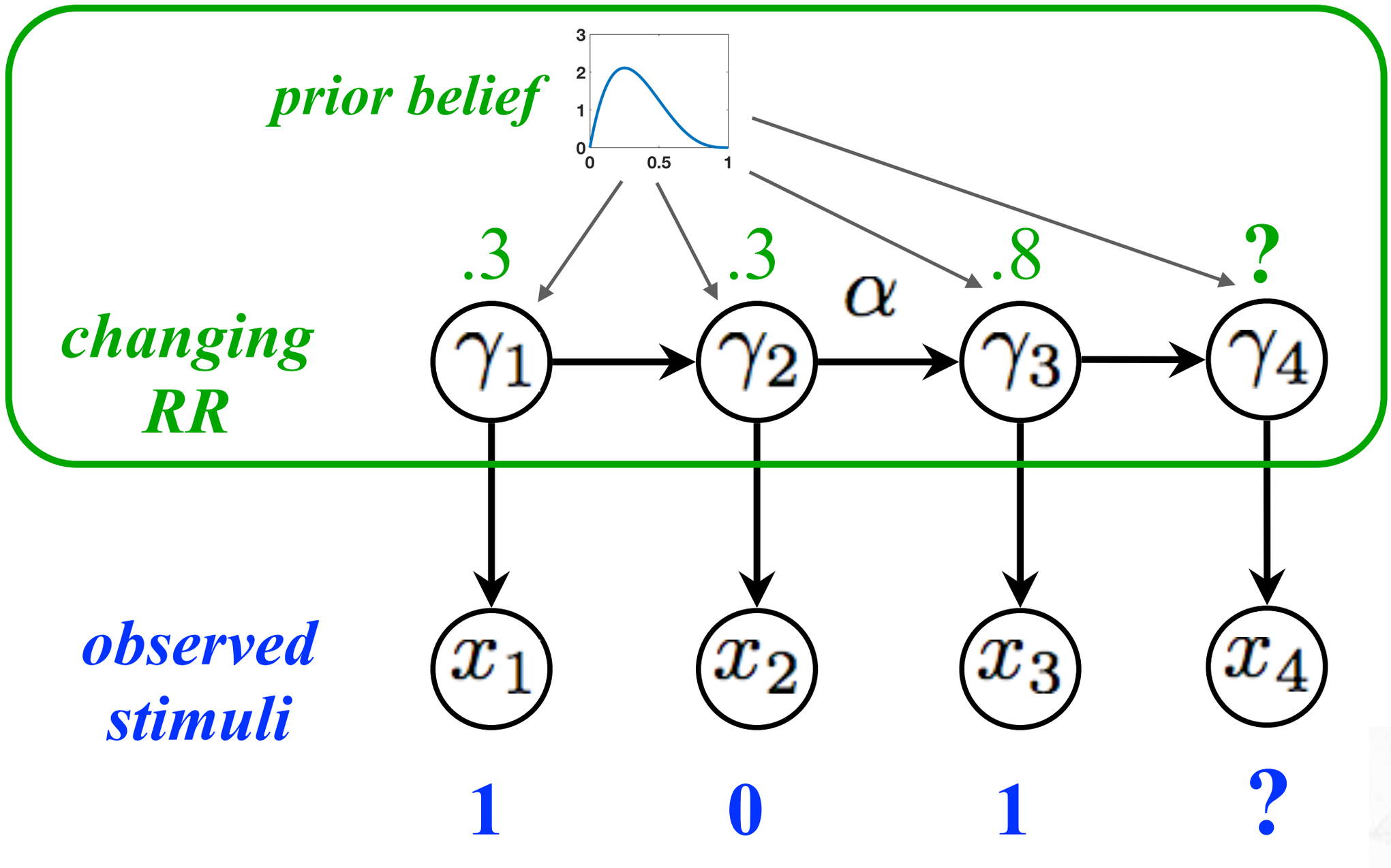
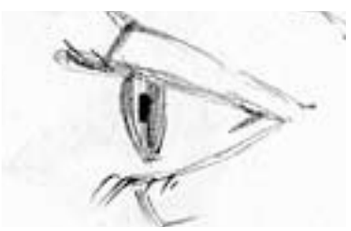
Learning Model II: Dynamic Belief Model (DBM)





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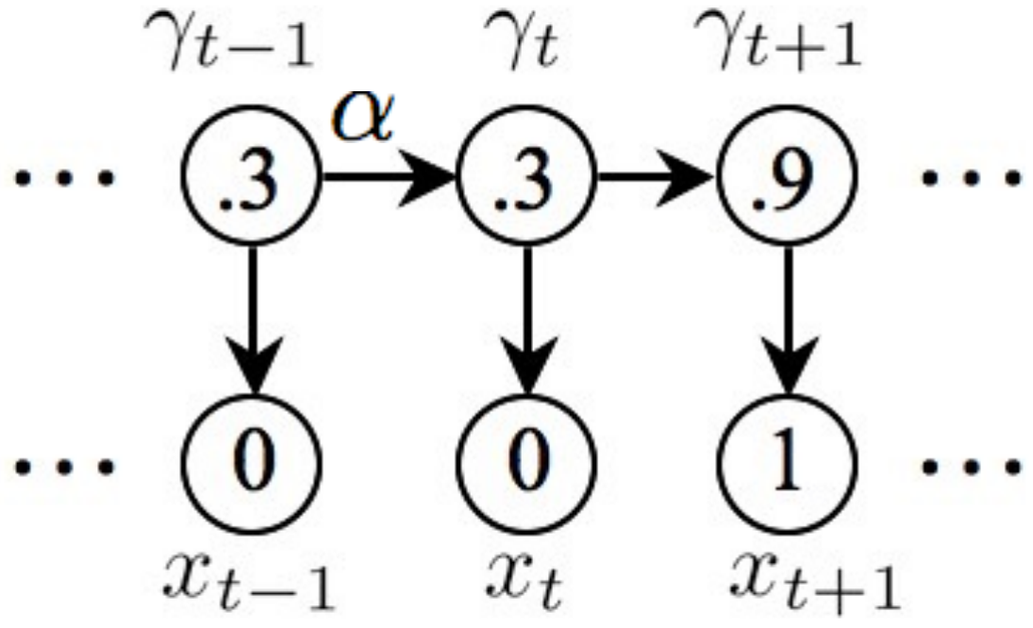

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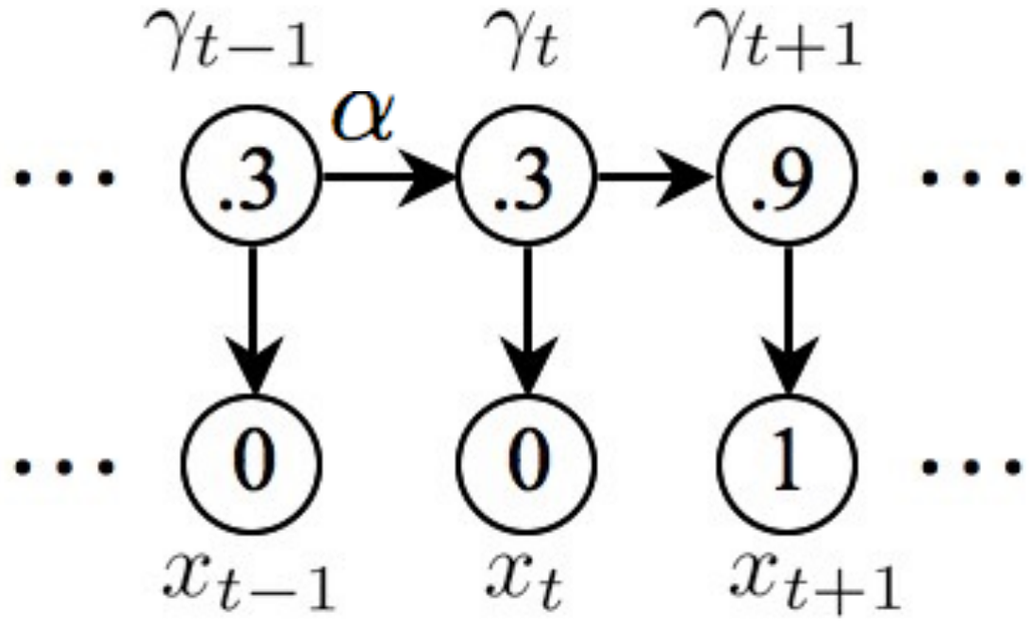

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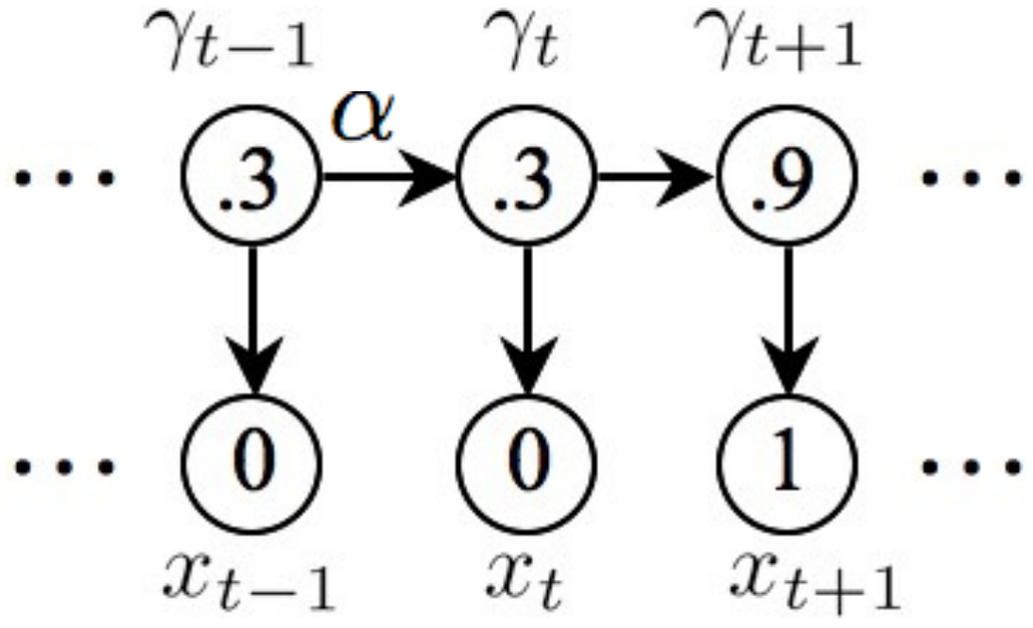

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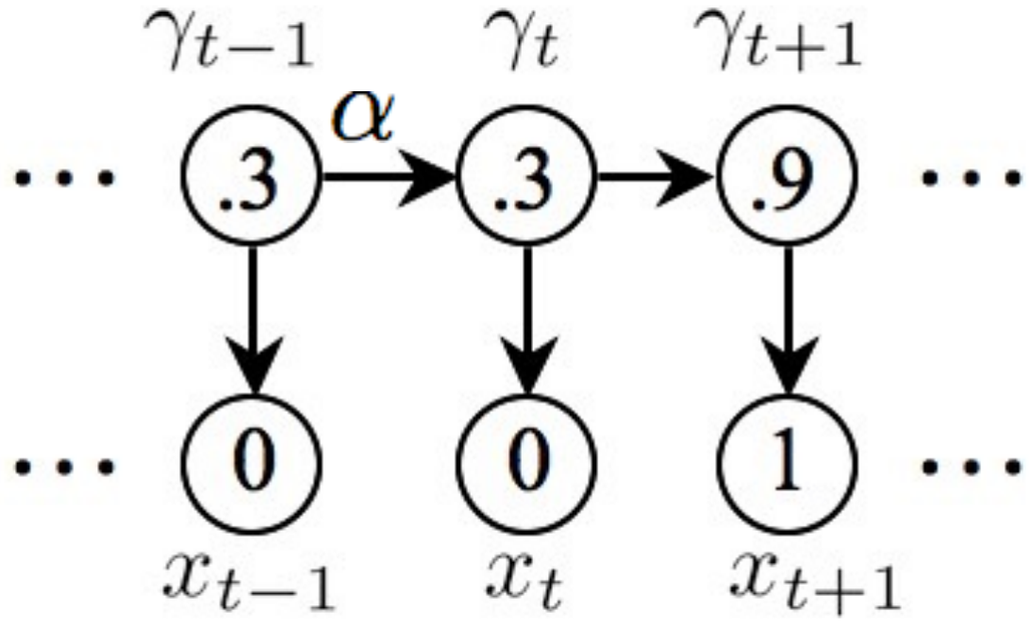

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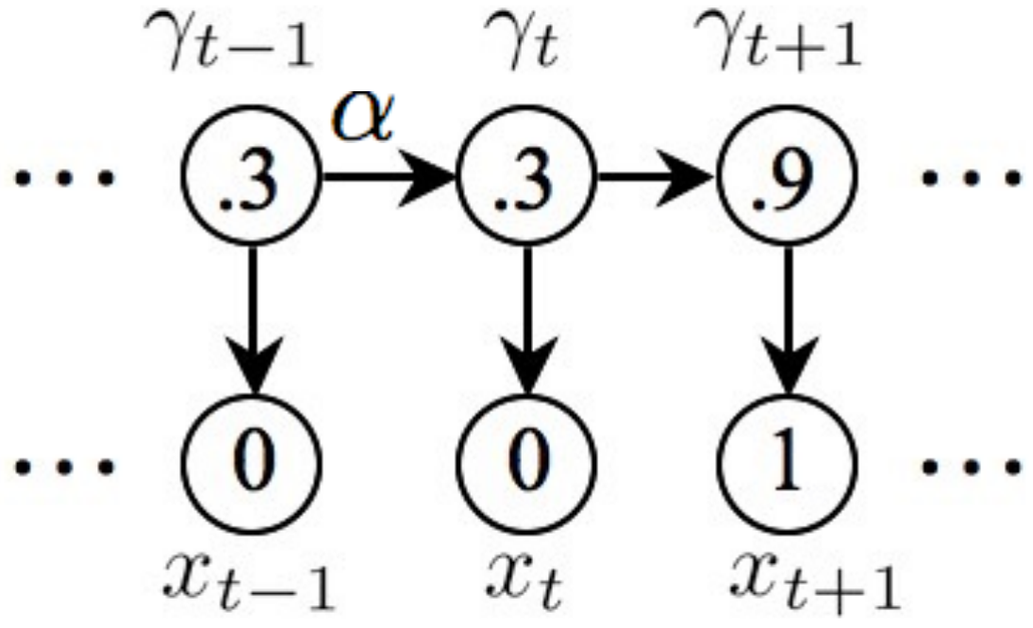

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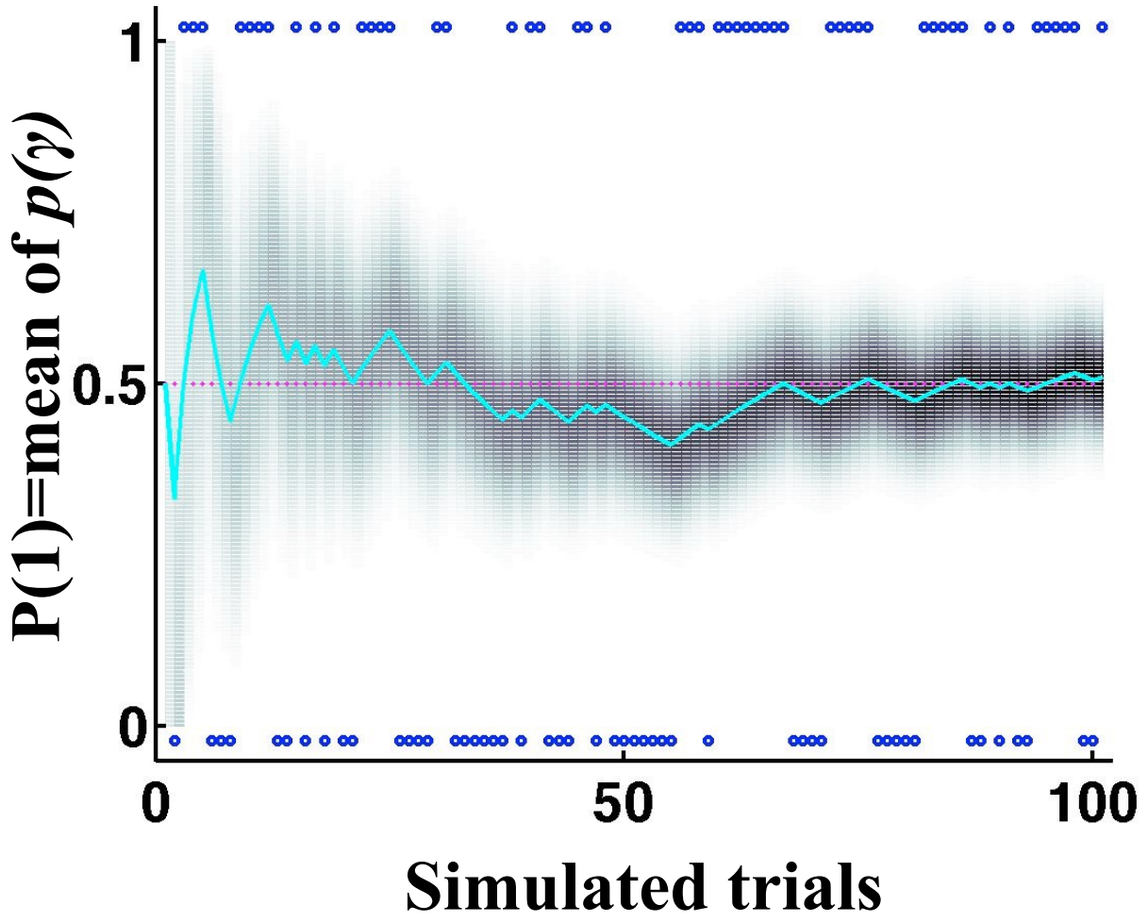
Sequential Learning: FBM vs. DBM

Given a sequence of Bernoulli data from *fixed* reward rate (γ = .5) …

FBM: posterior *p*(γ)



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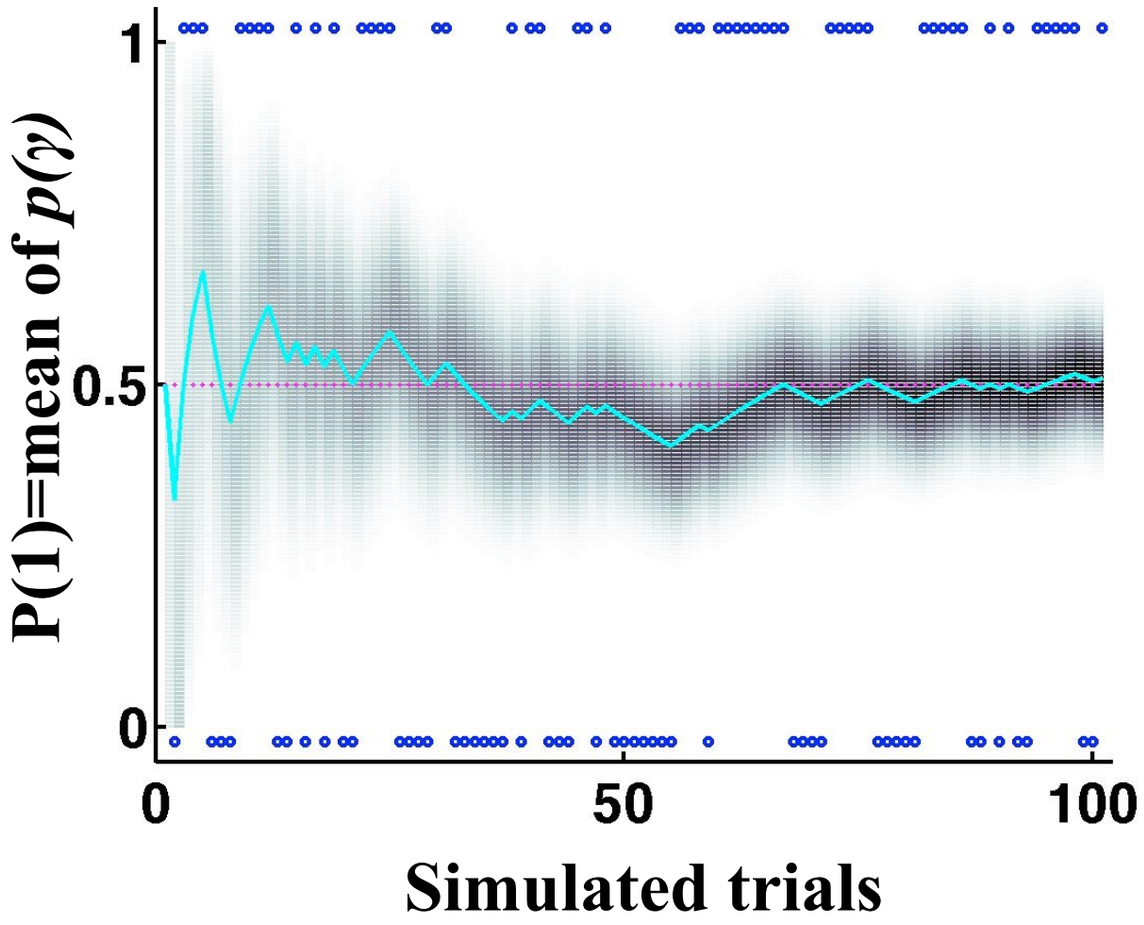

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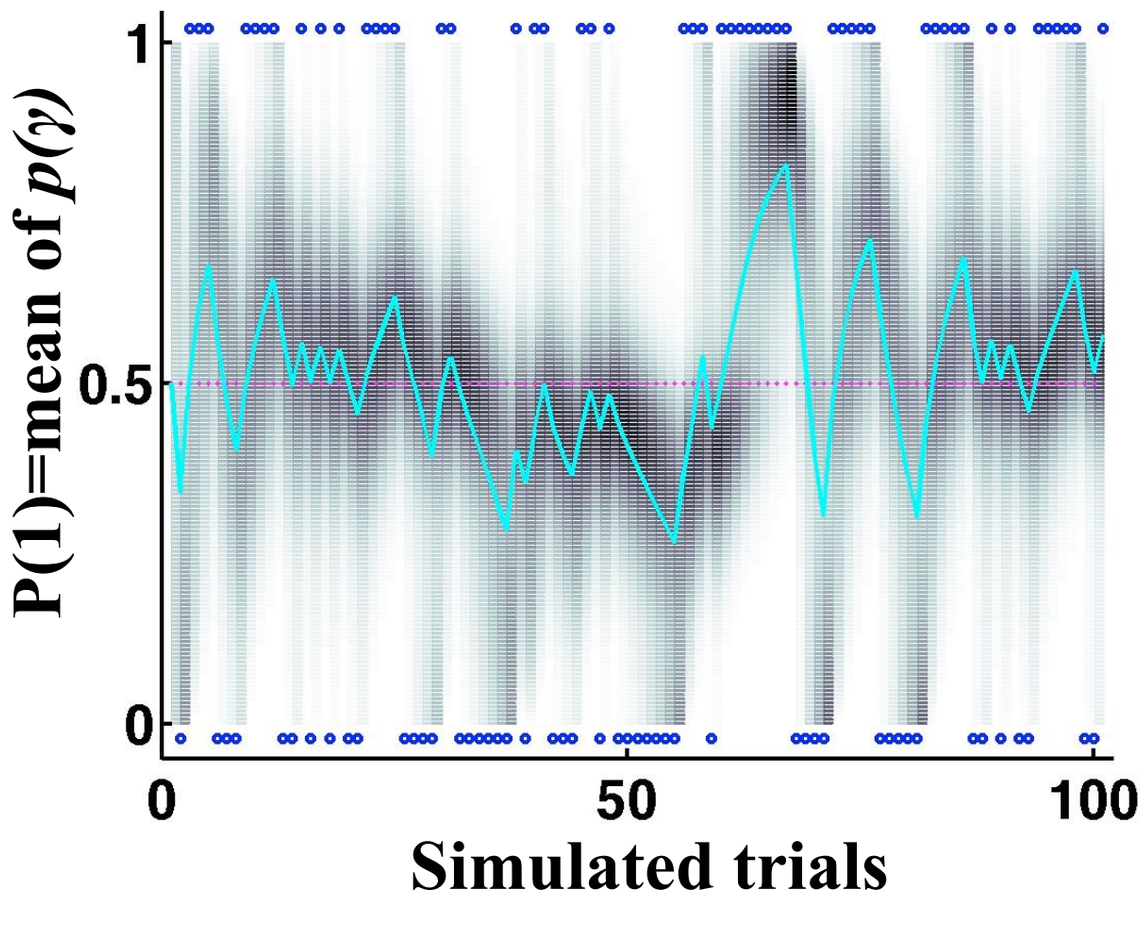

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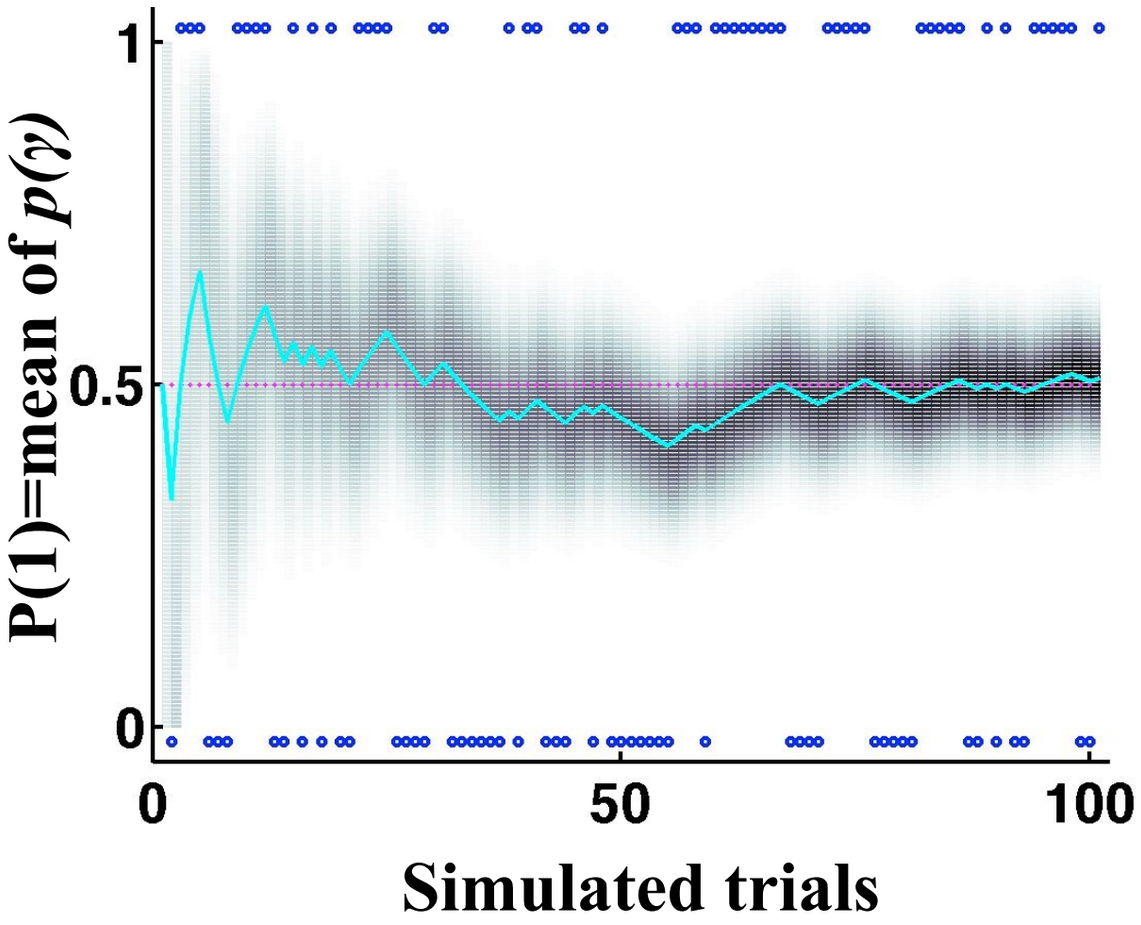

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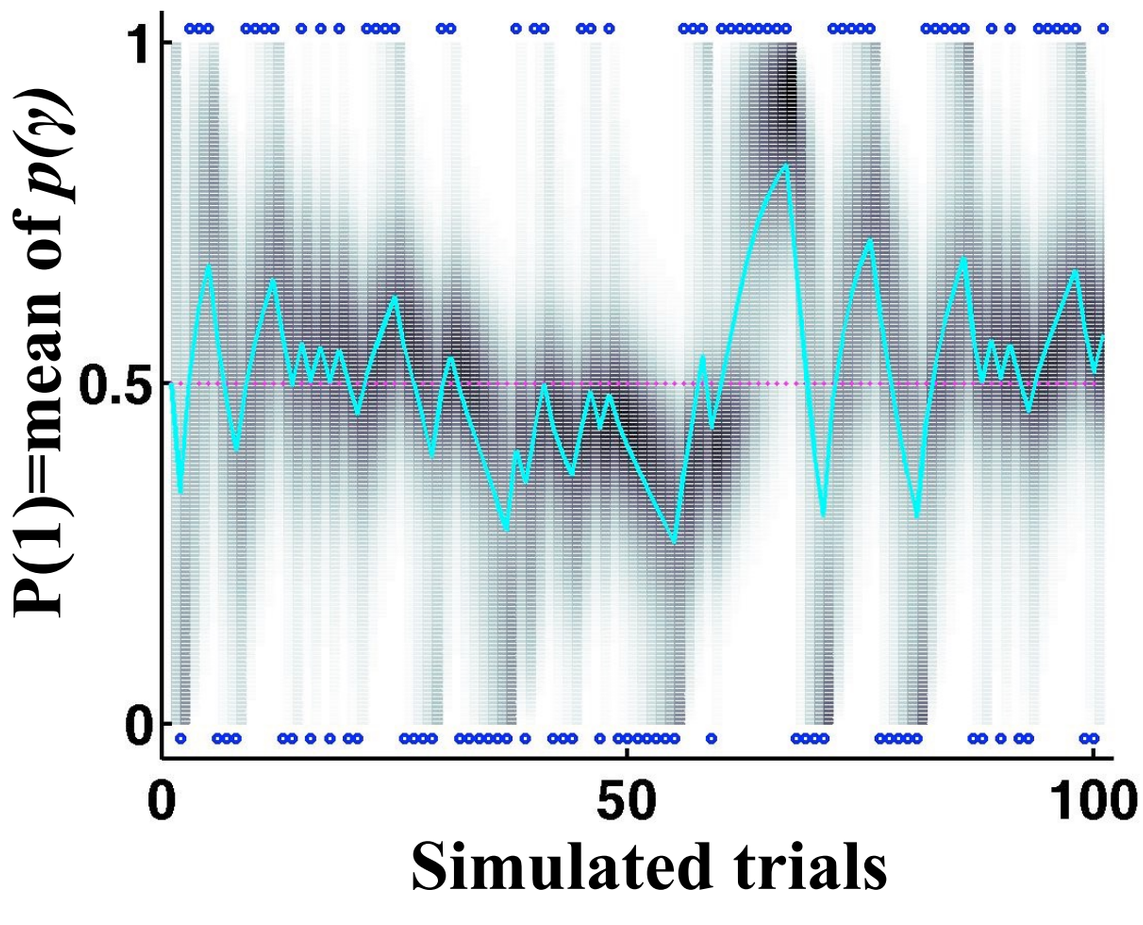

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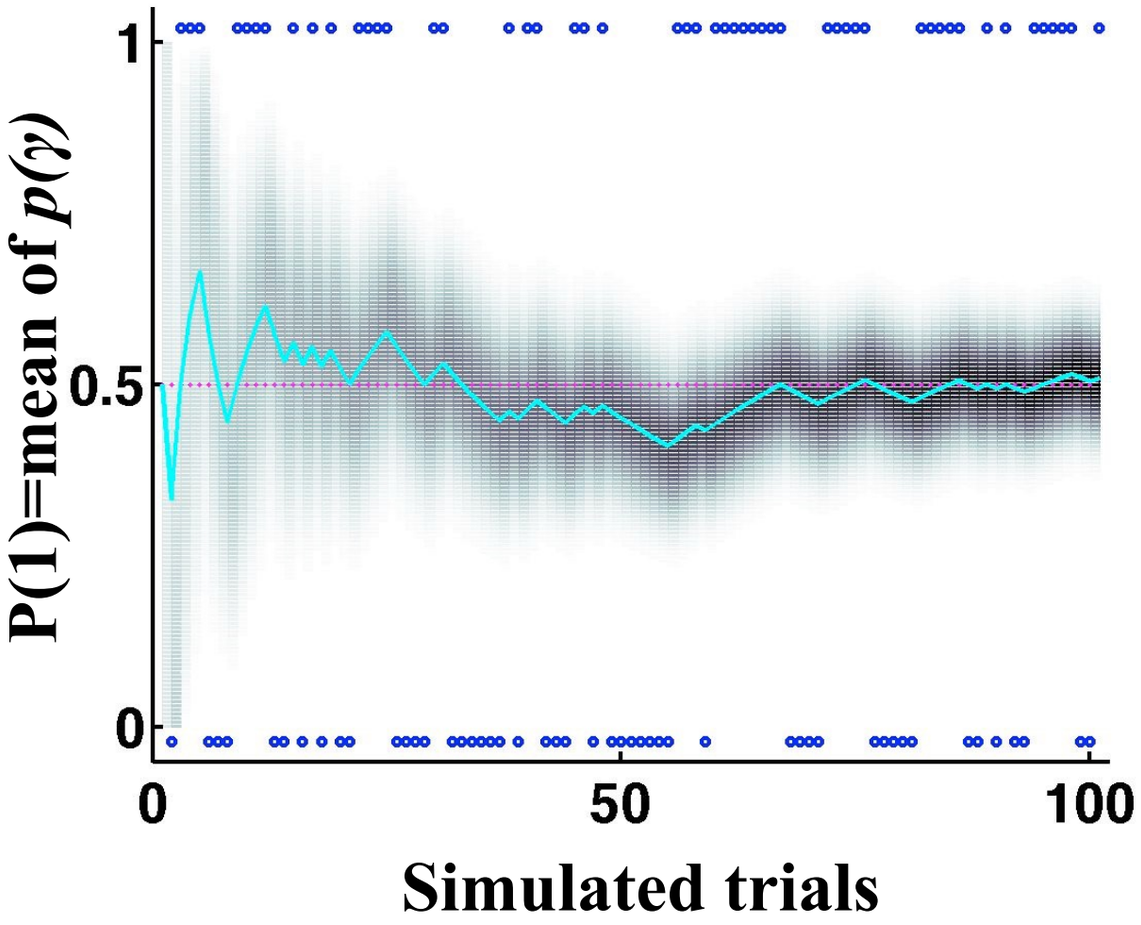

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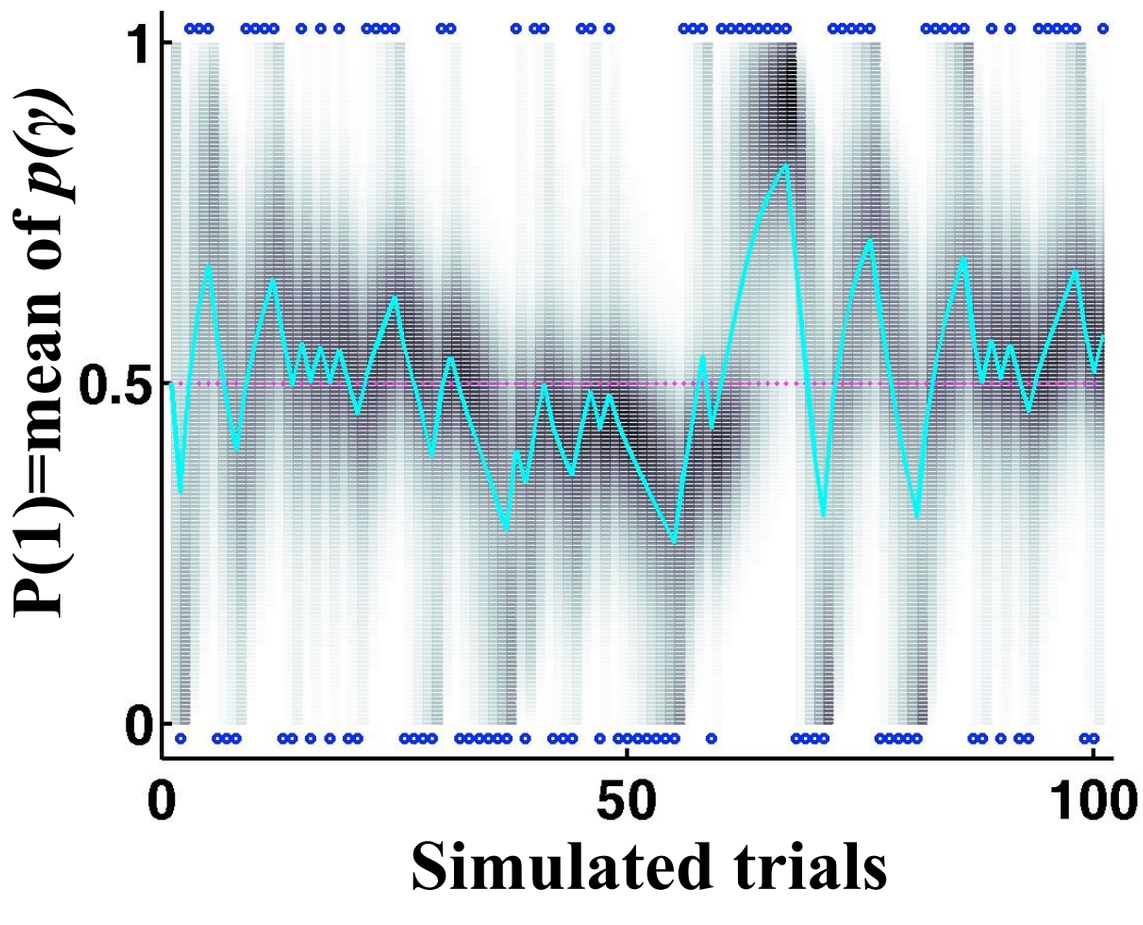

Driven by *local* patterns

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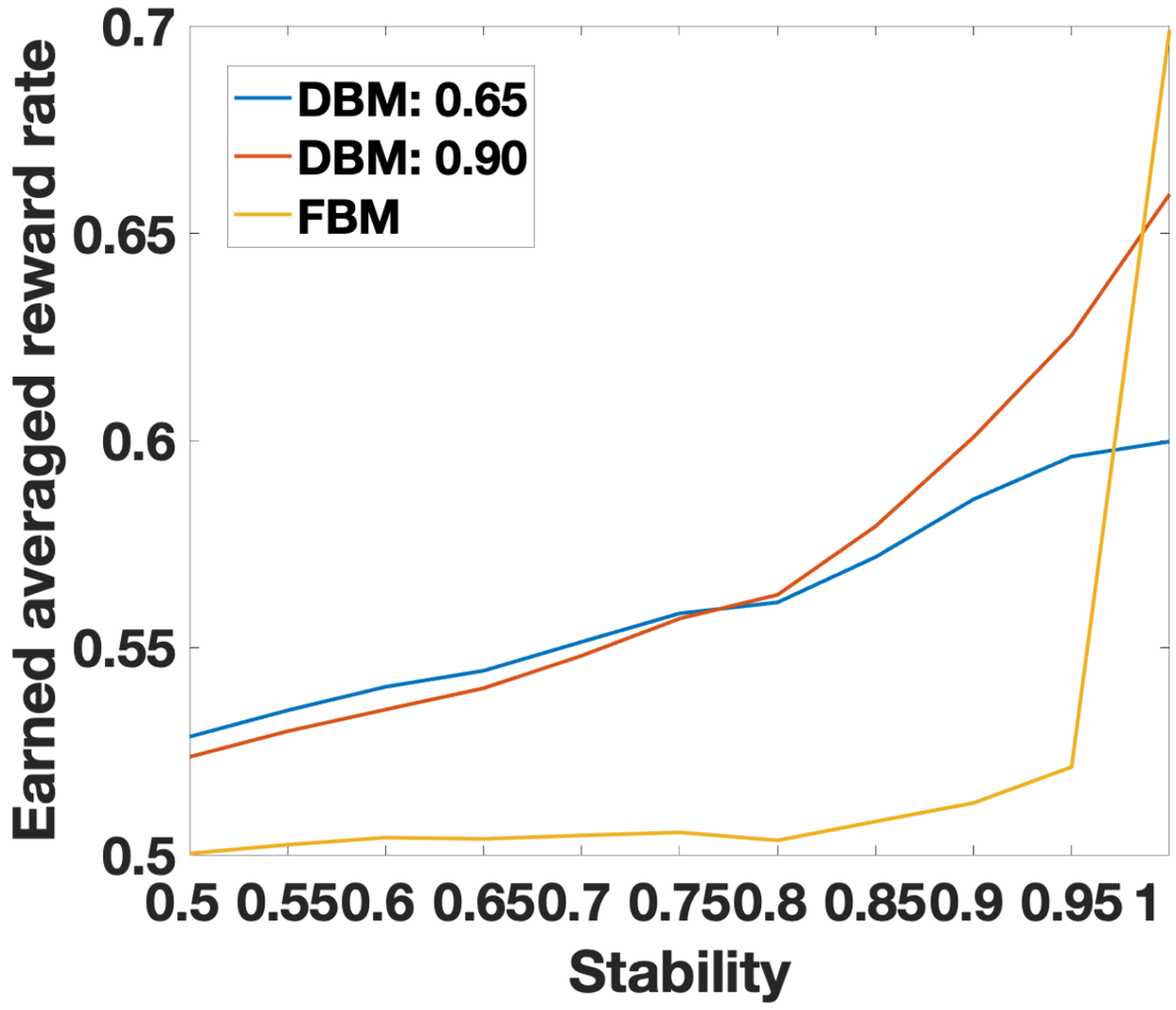

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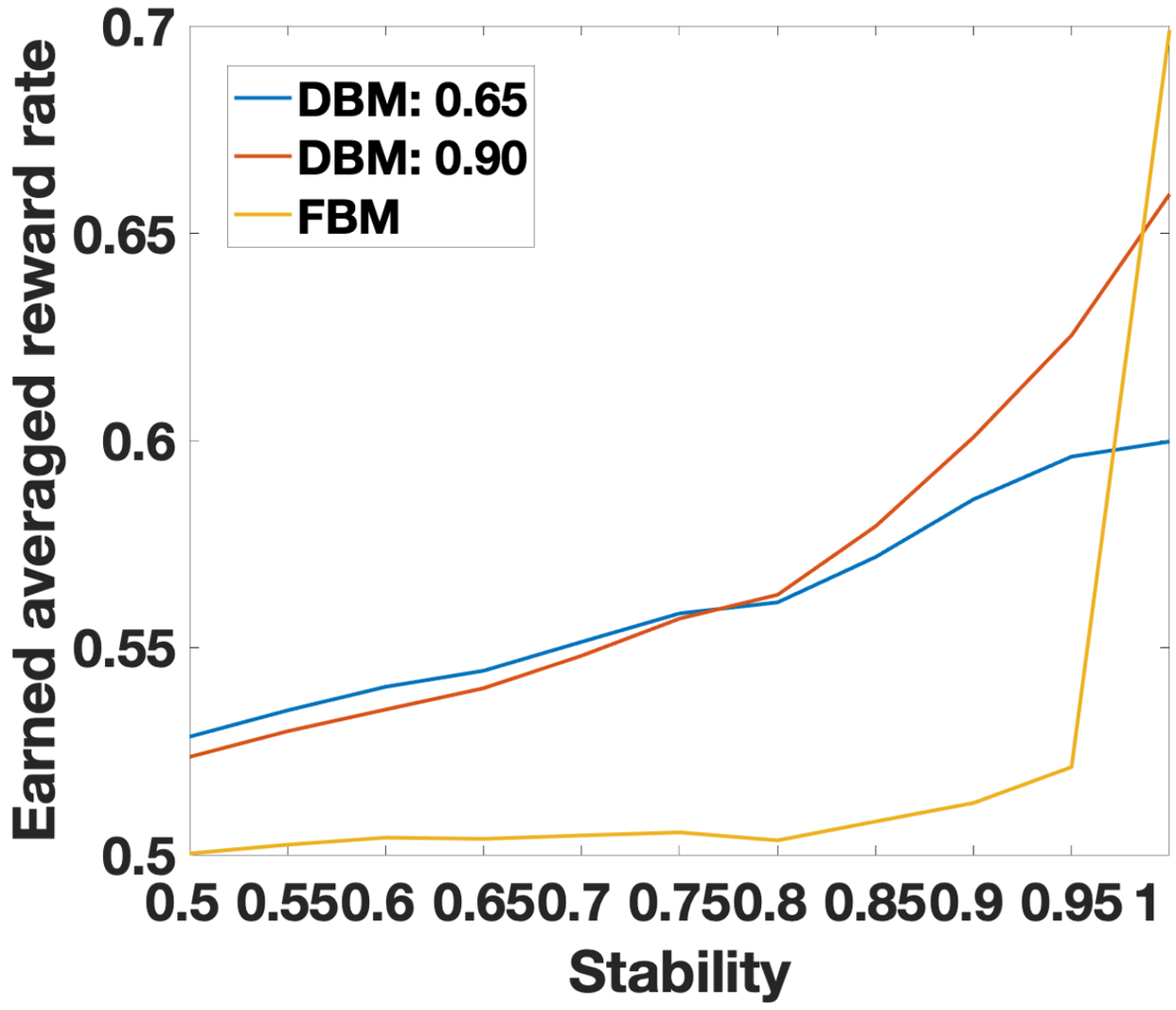

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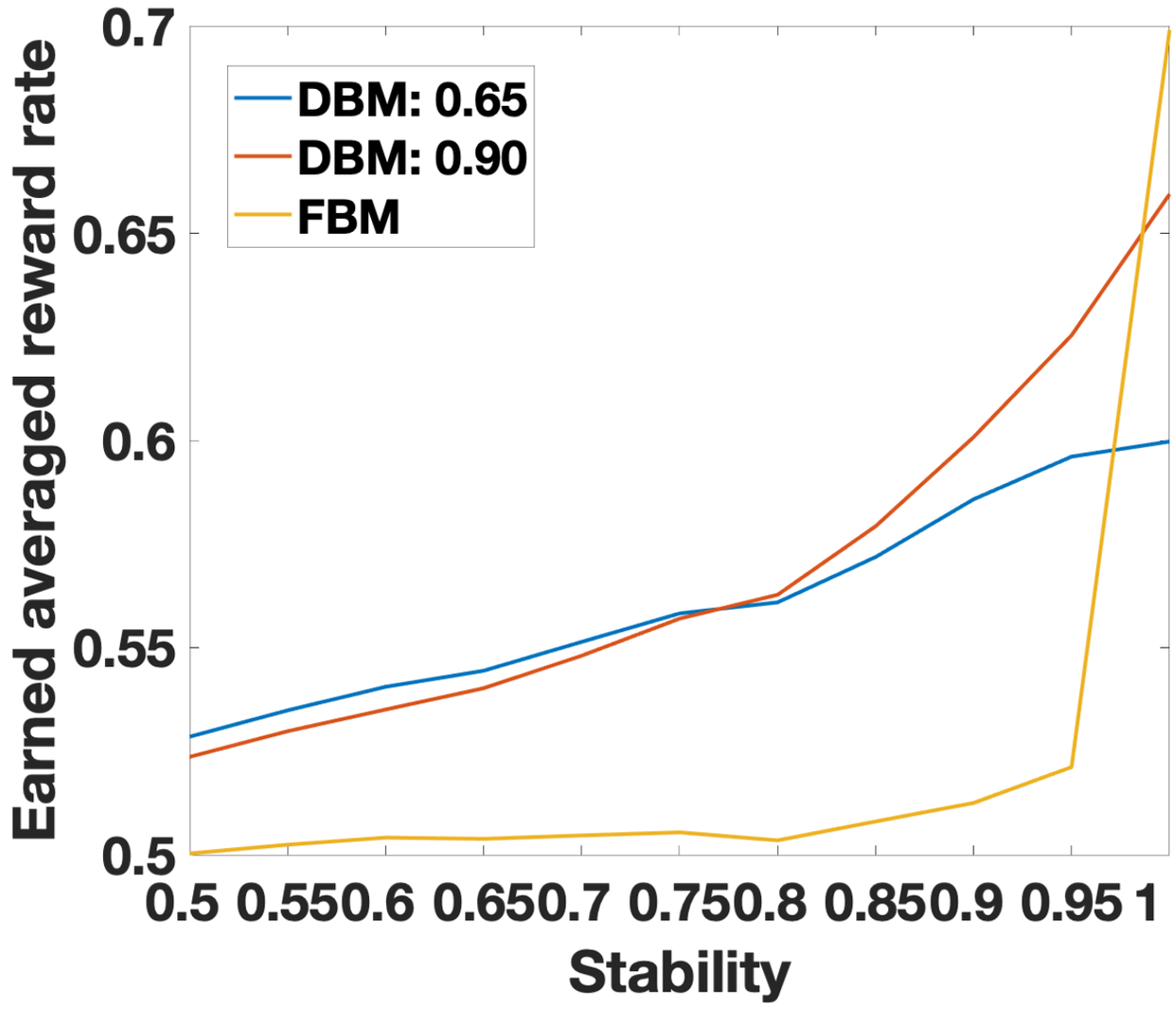

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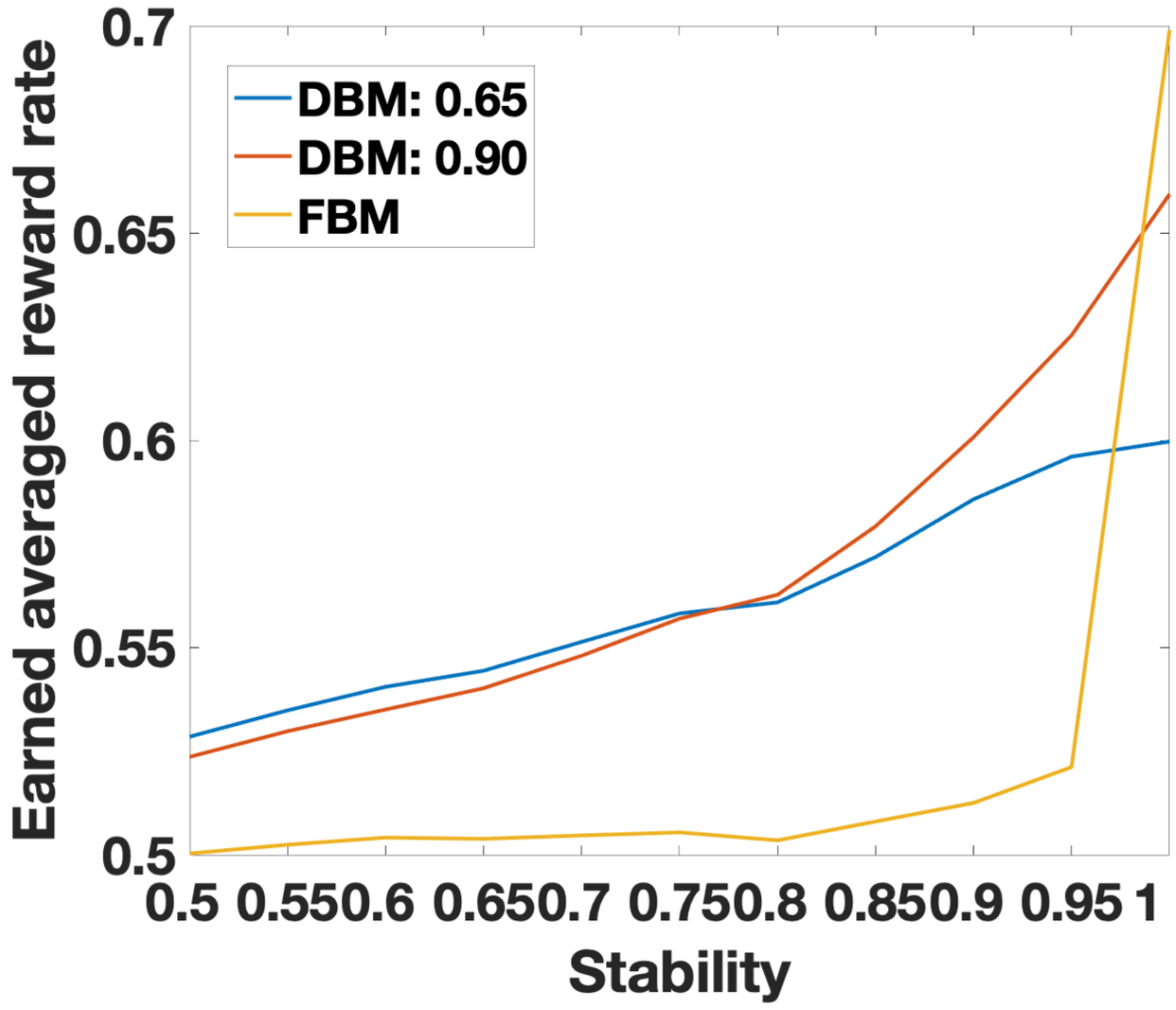

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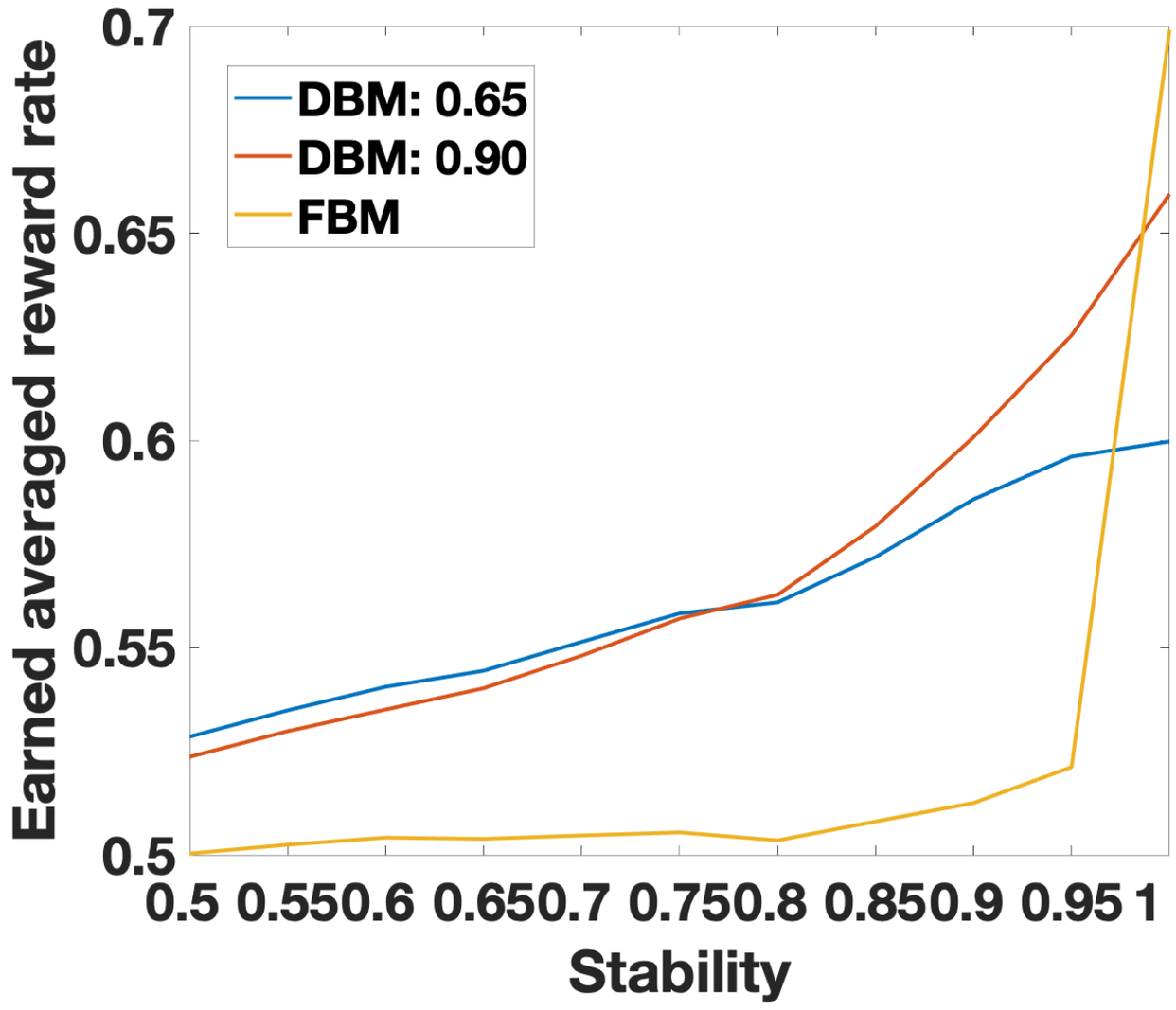

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- ⇒ "Sweet spot" for stability (indeed we always find estimated human stability parameter to be around 0.75-0.90)

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- Unchosen arm (related to "forgetting" Q-learning):

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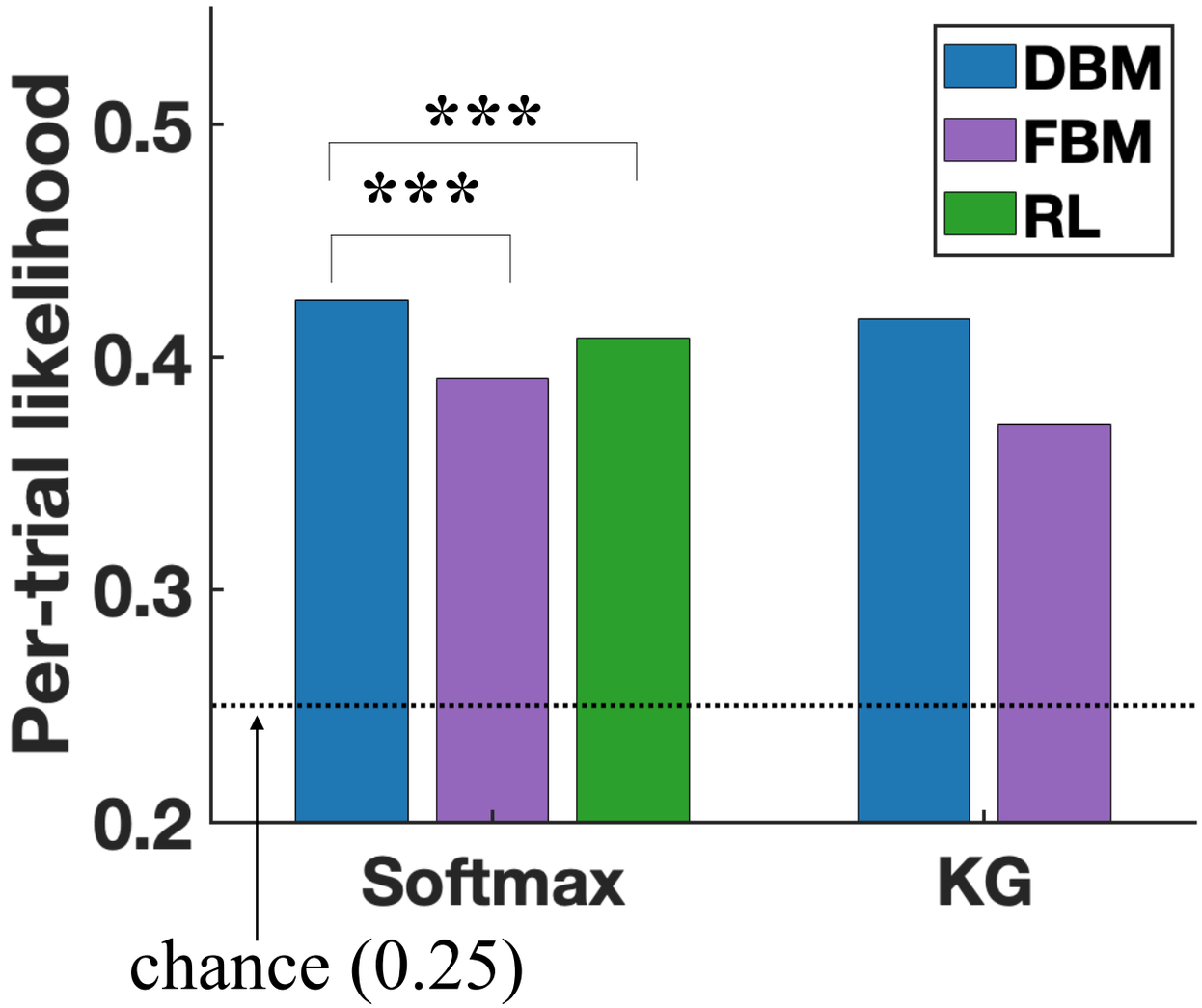
Model Comparison



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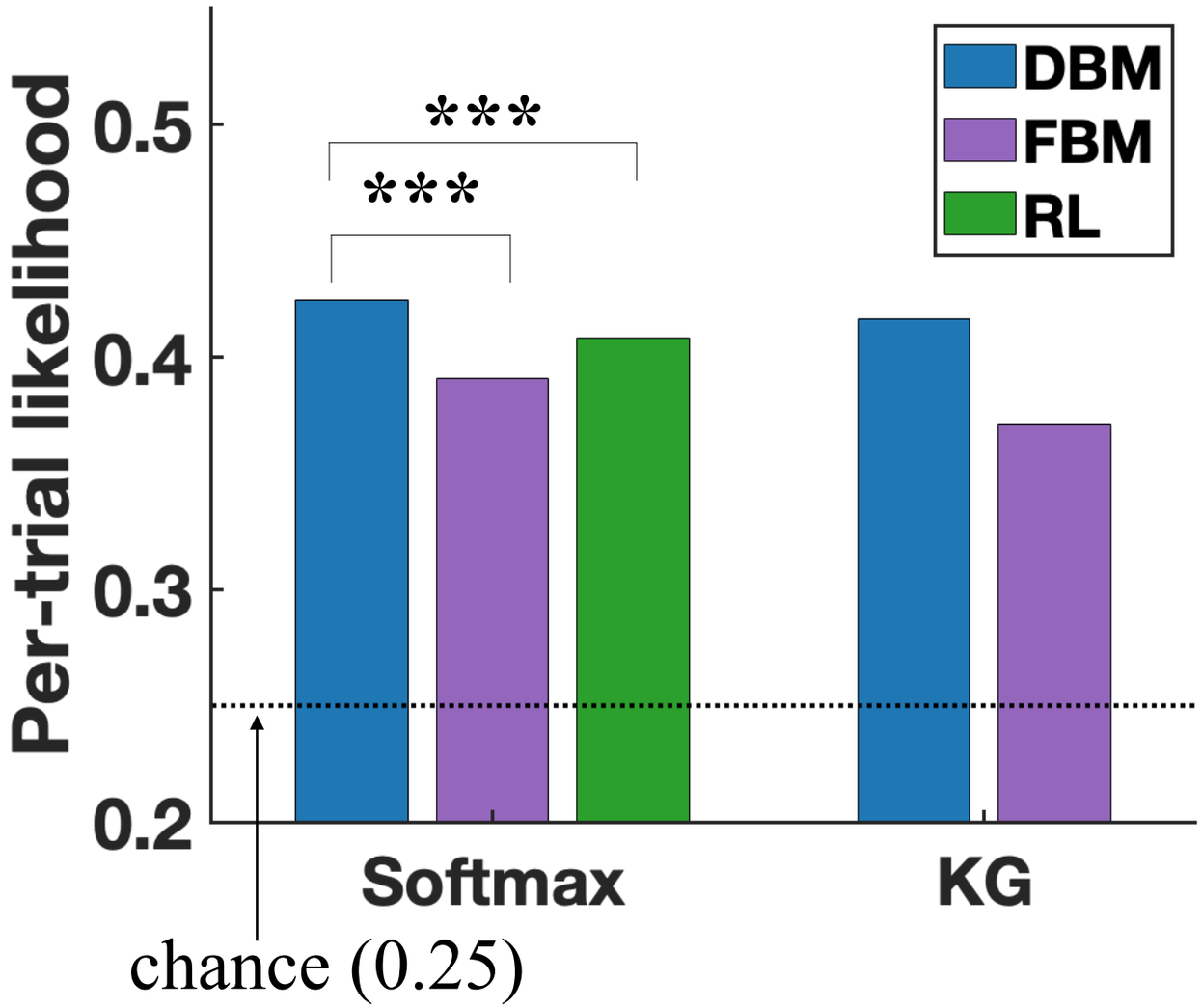

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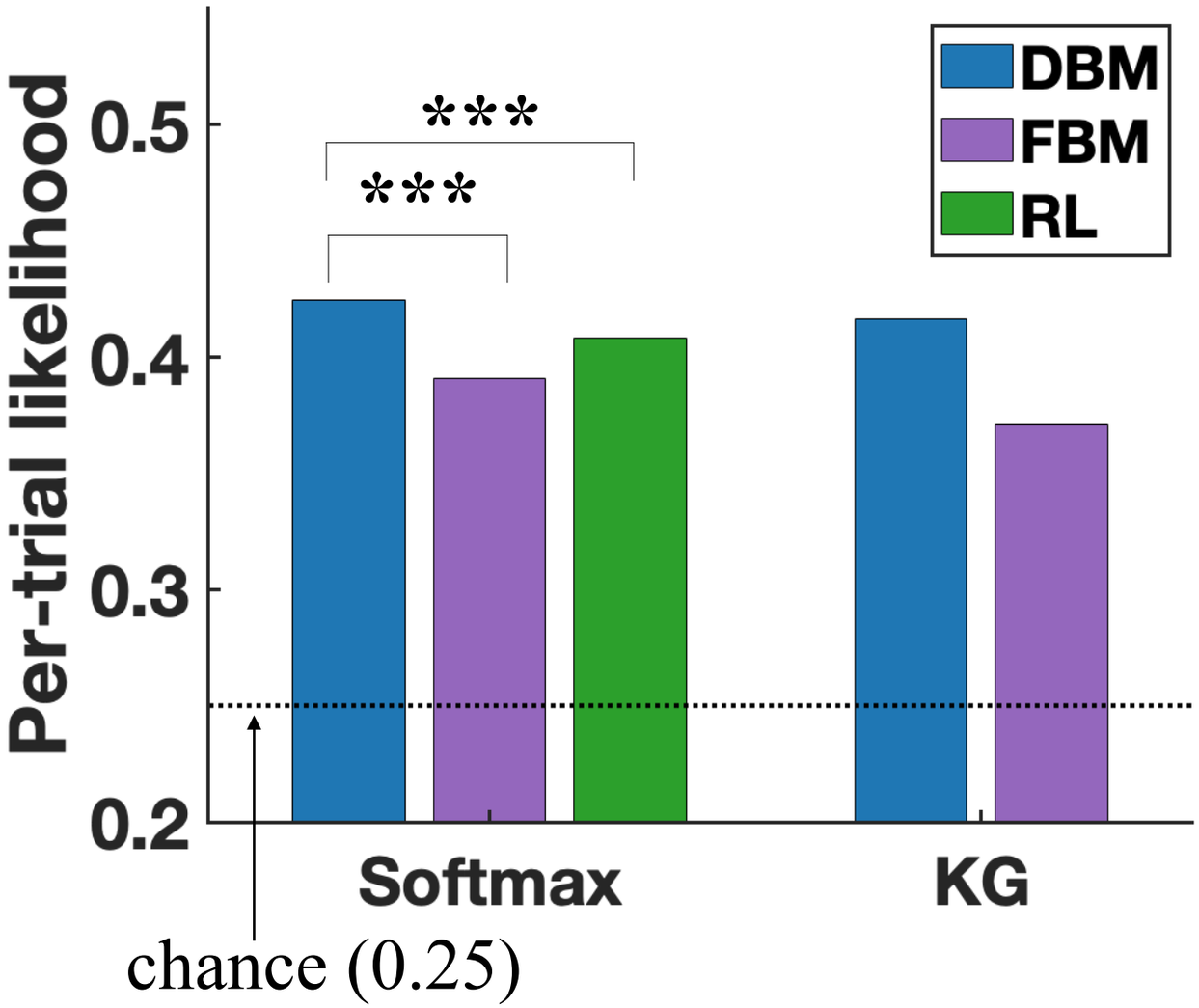

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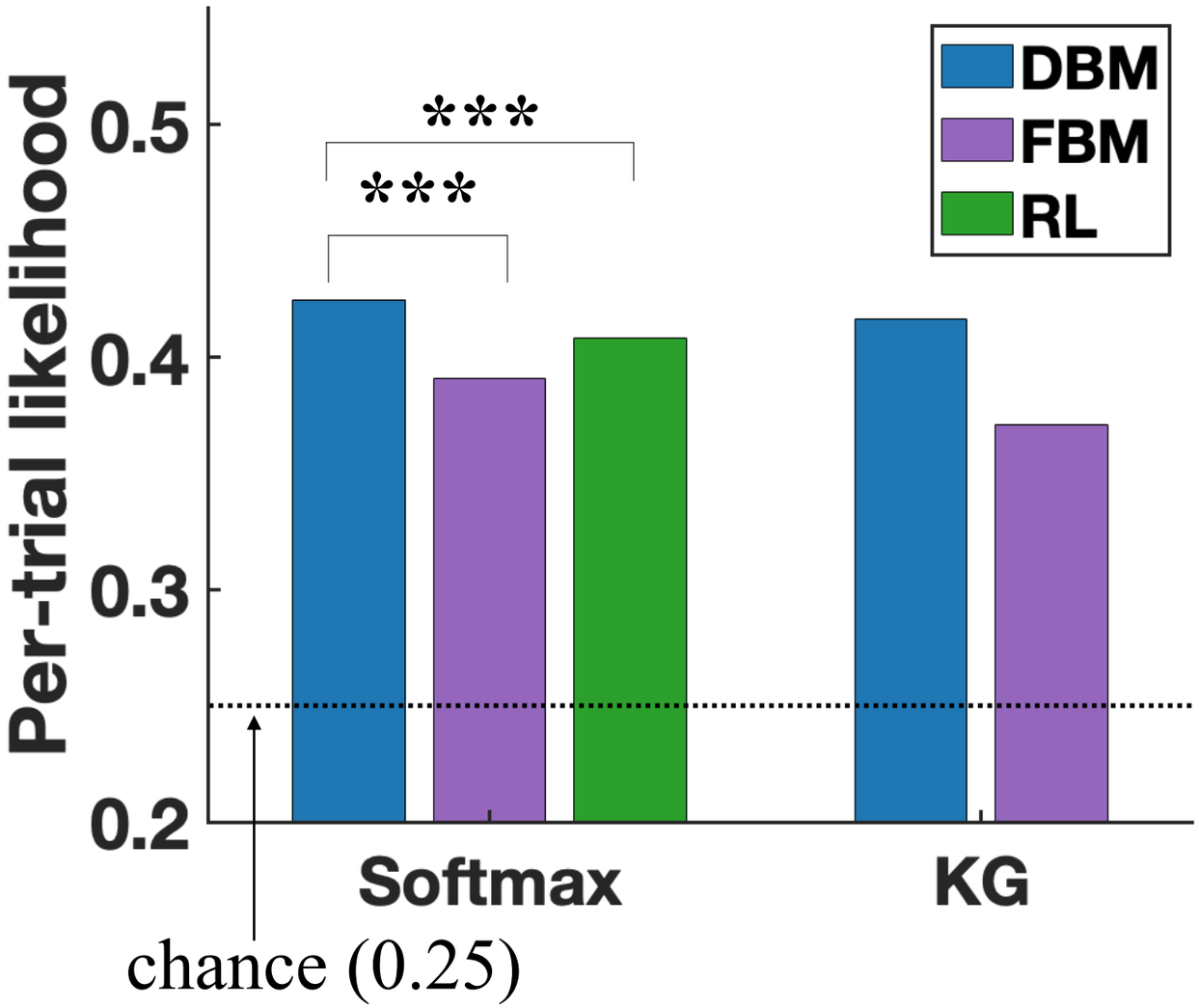

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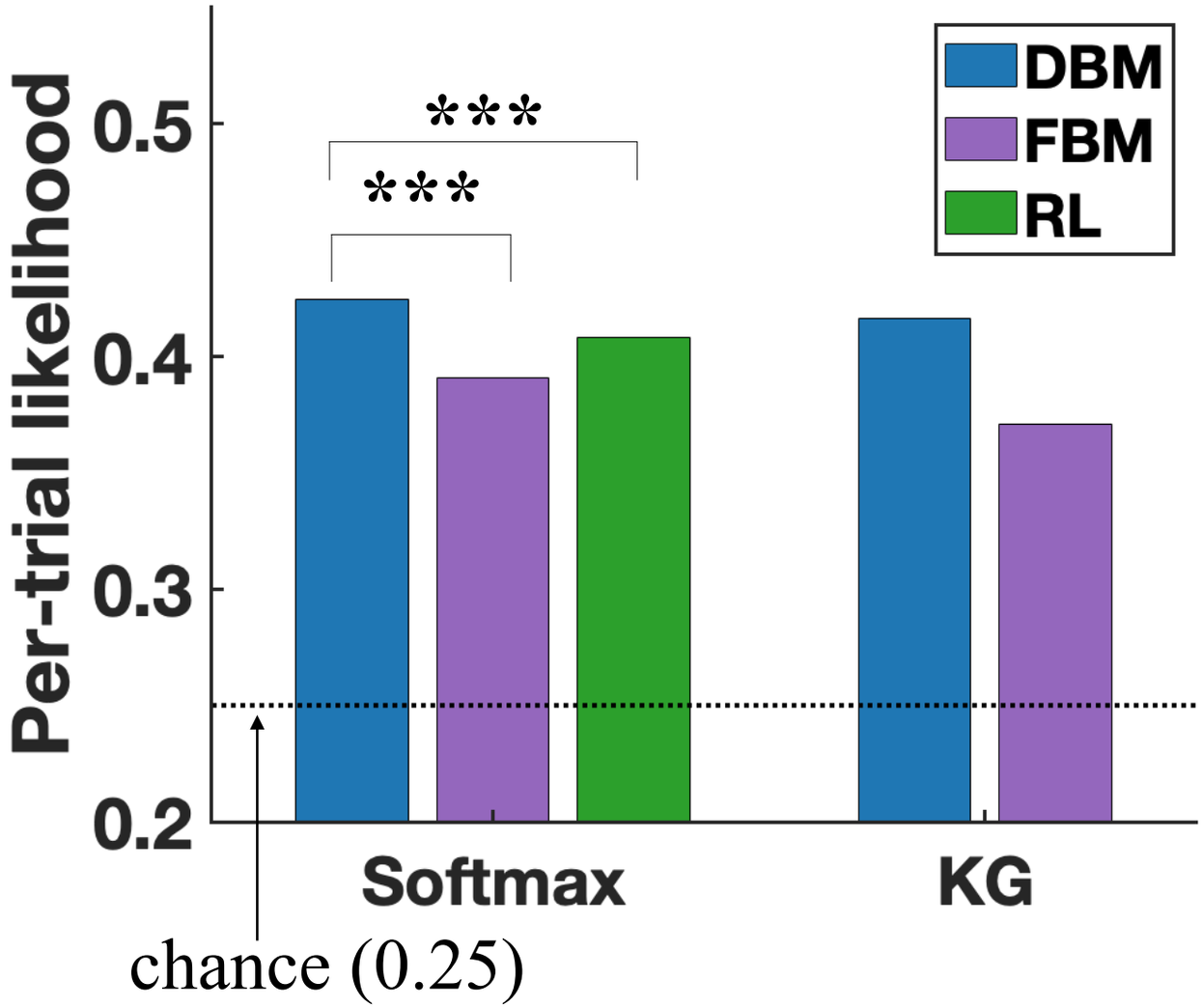

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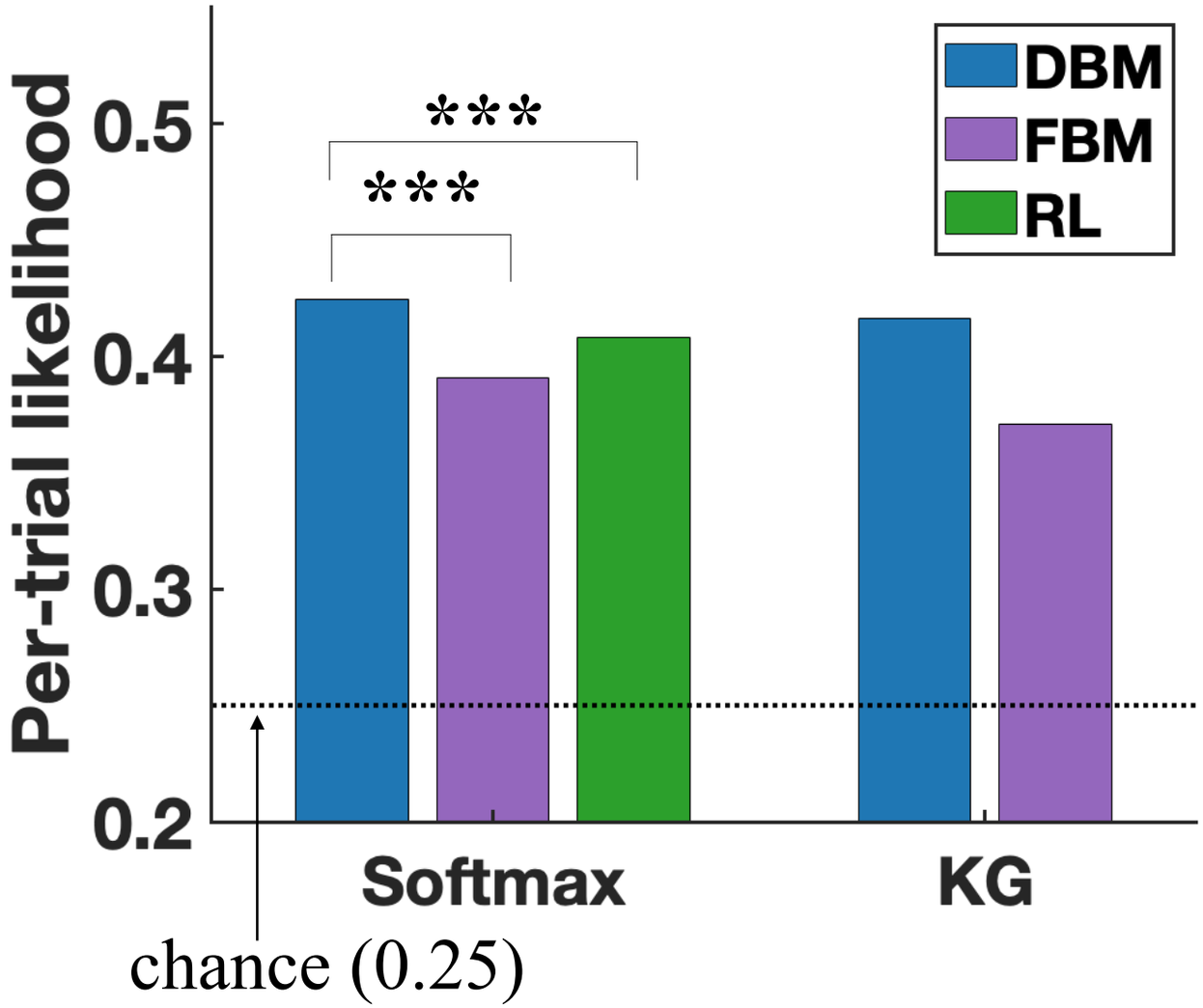

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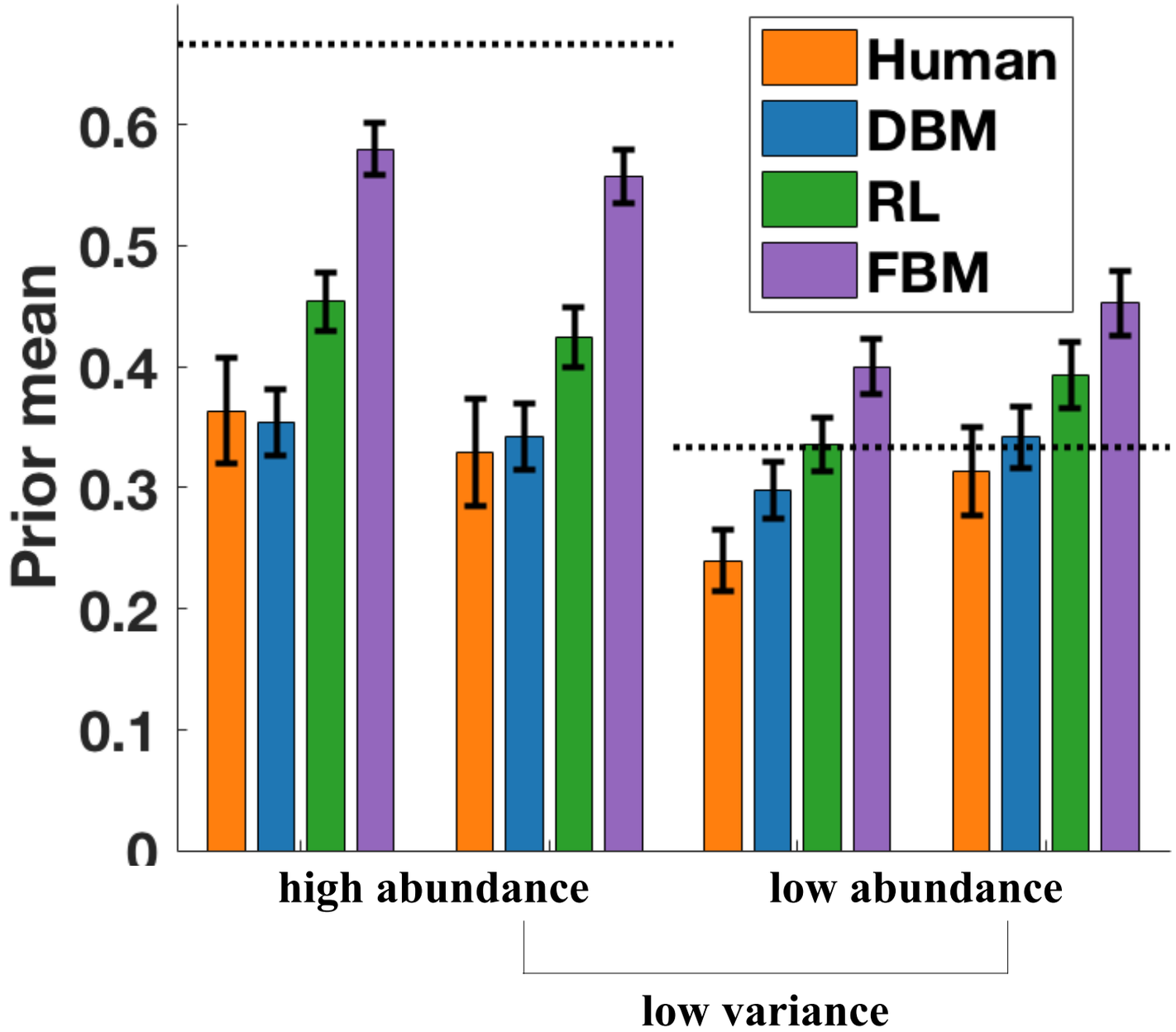
- Softmax > knowledge gradient: KG explicitly computes value of exploration vs. exploitation (Zhang & Yu, 2013), but humans behave more like simpler softmax

Estimated Prior Mean of Reward



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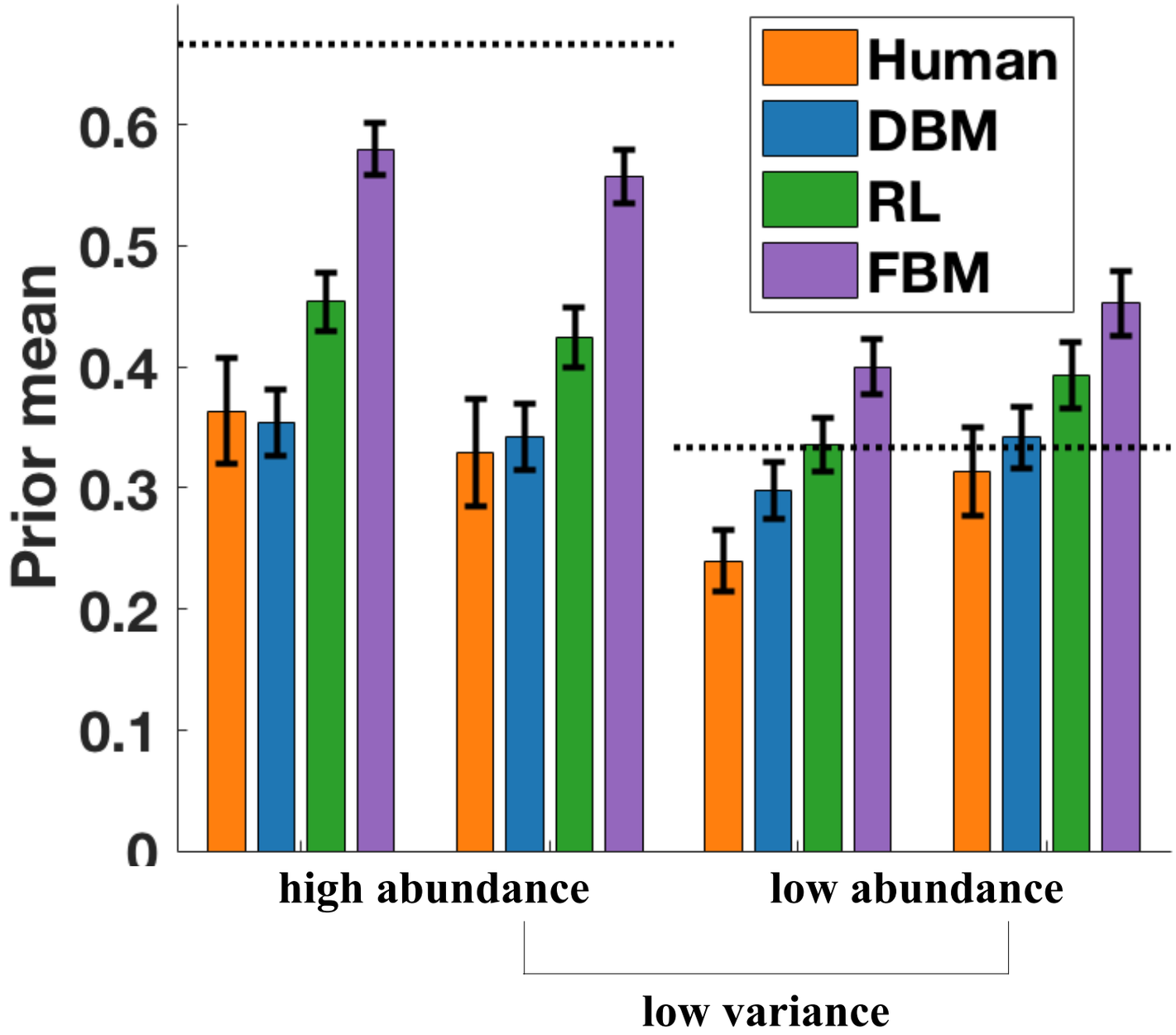

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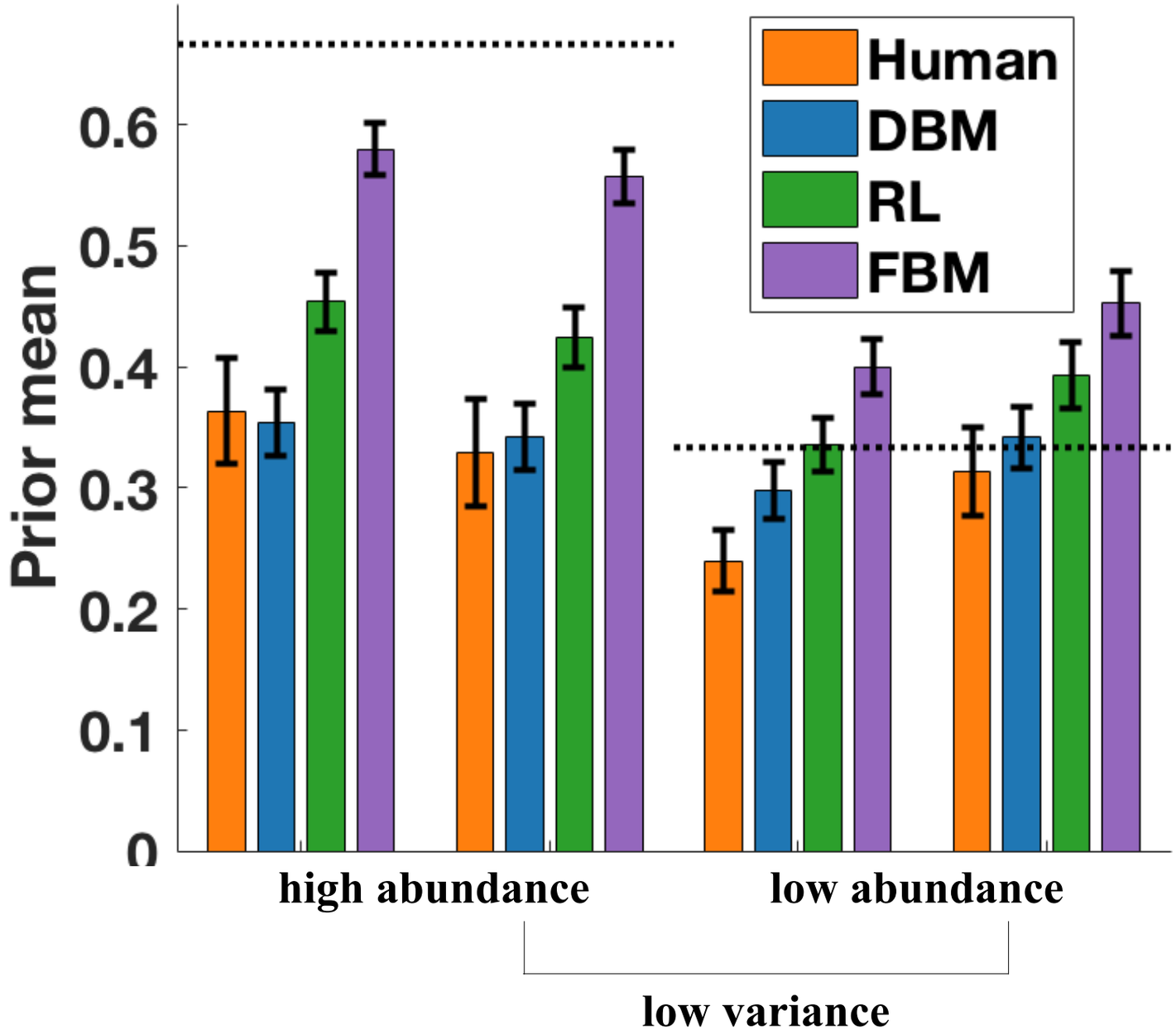

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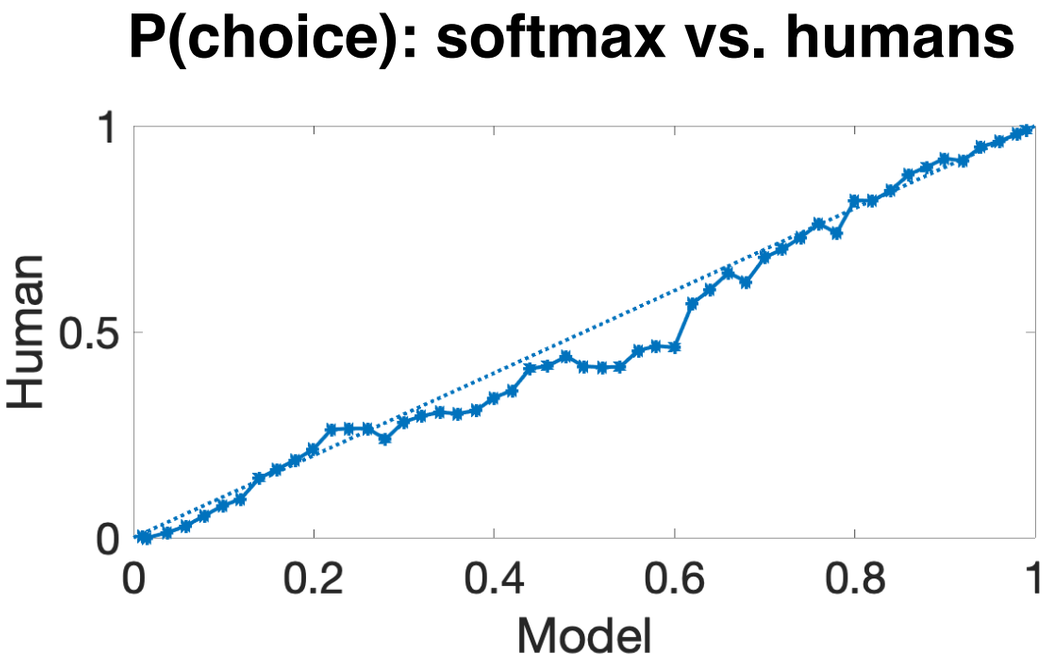
- FBM & RL under-estimate magnitude of under-estimation

Choice of Decision Model



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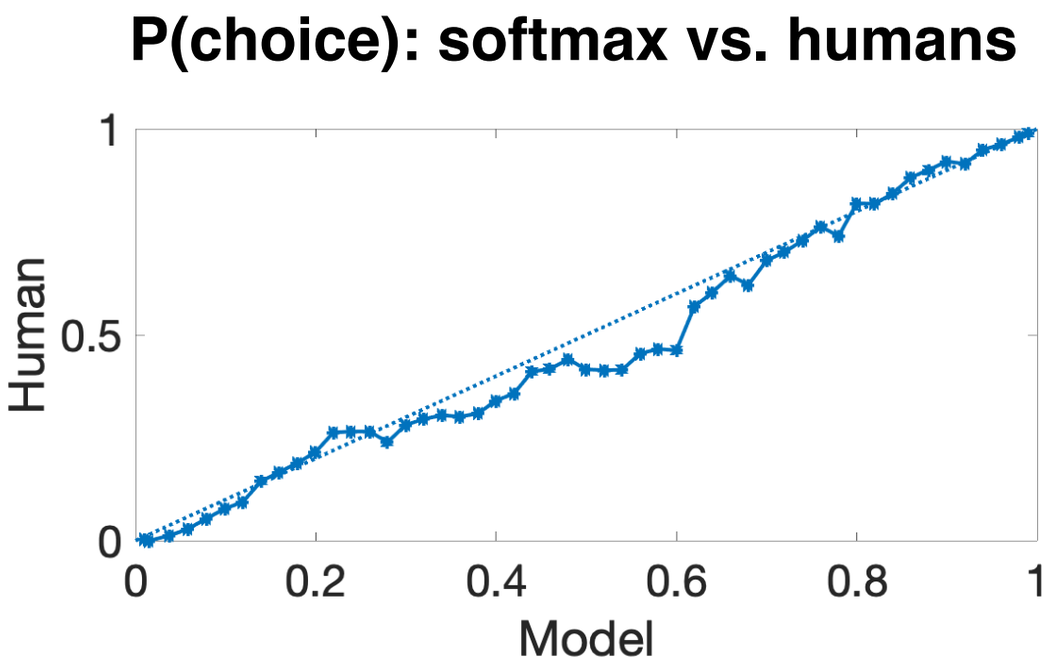

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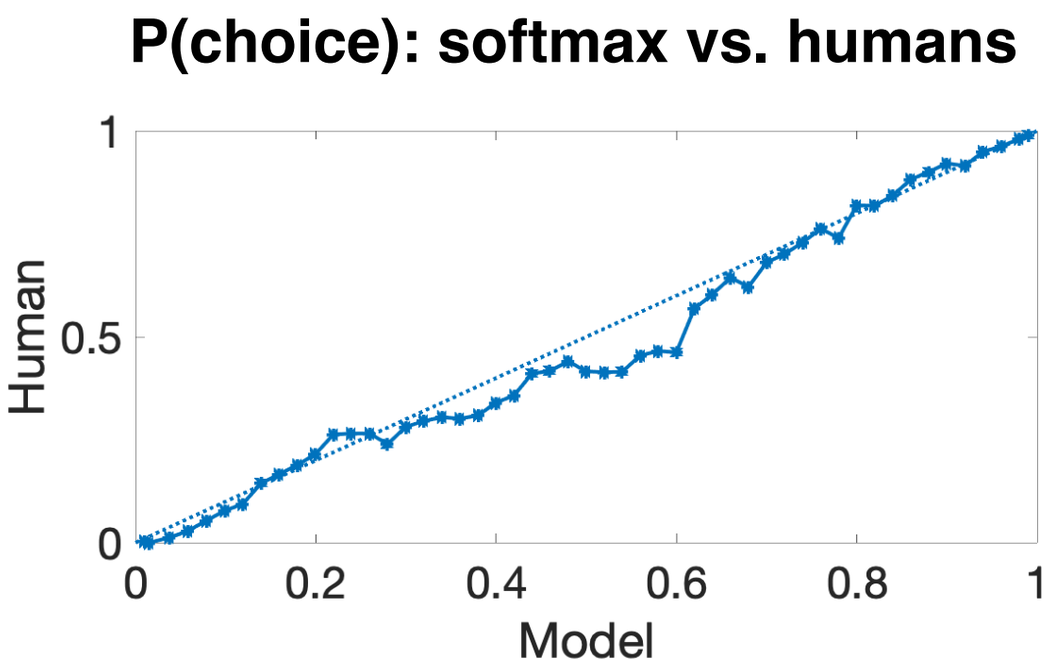

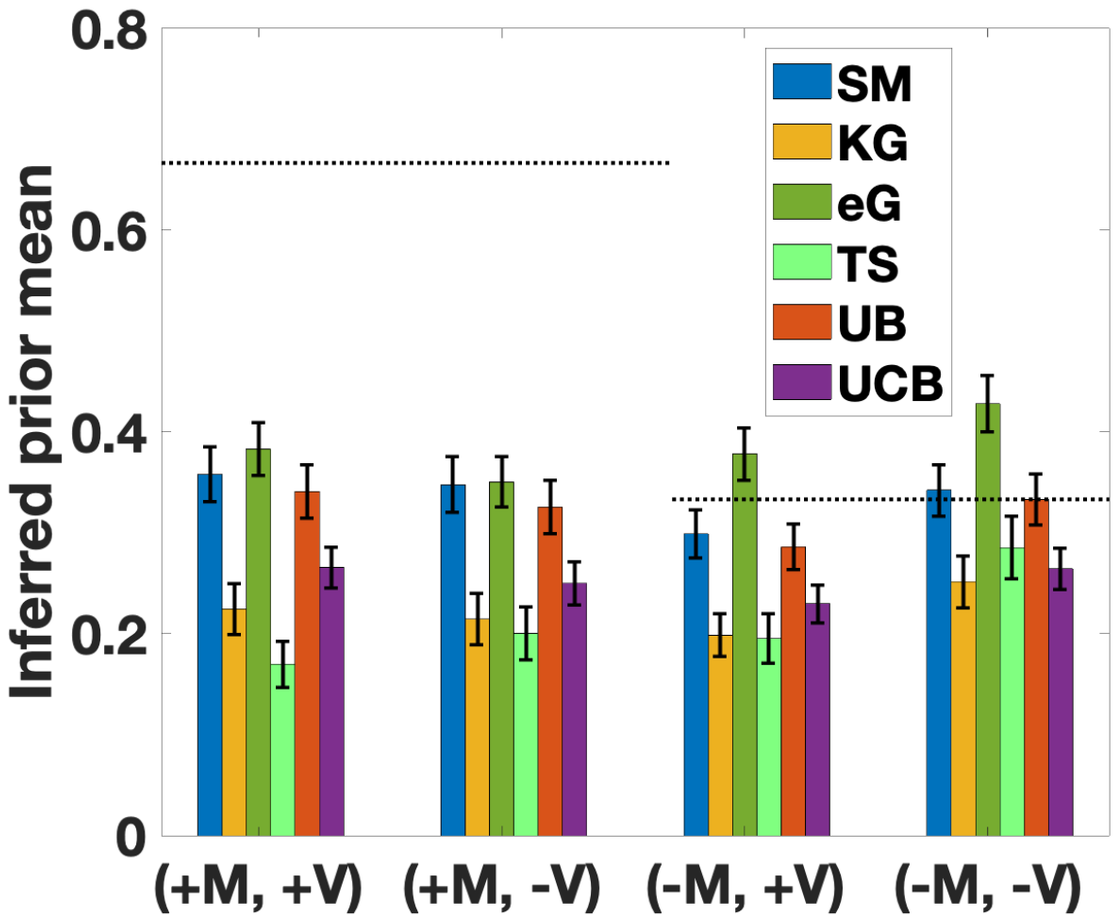

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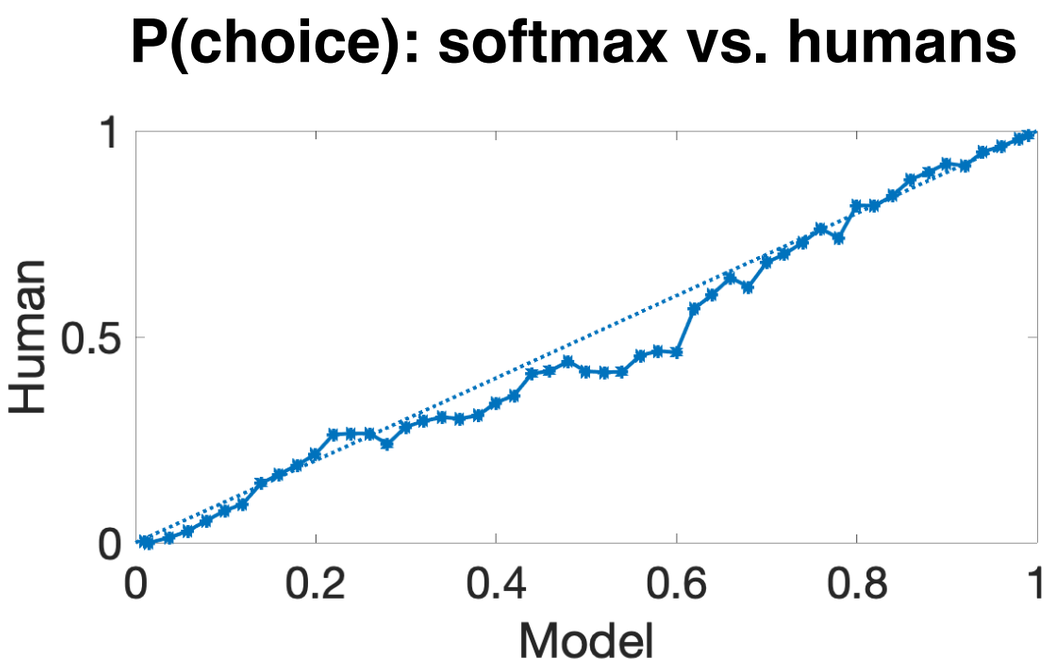

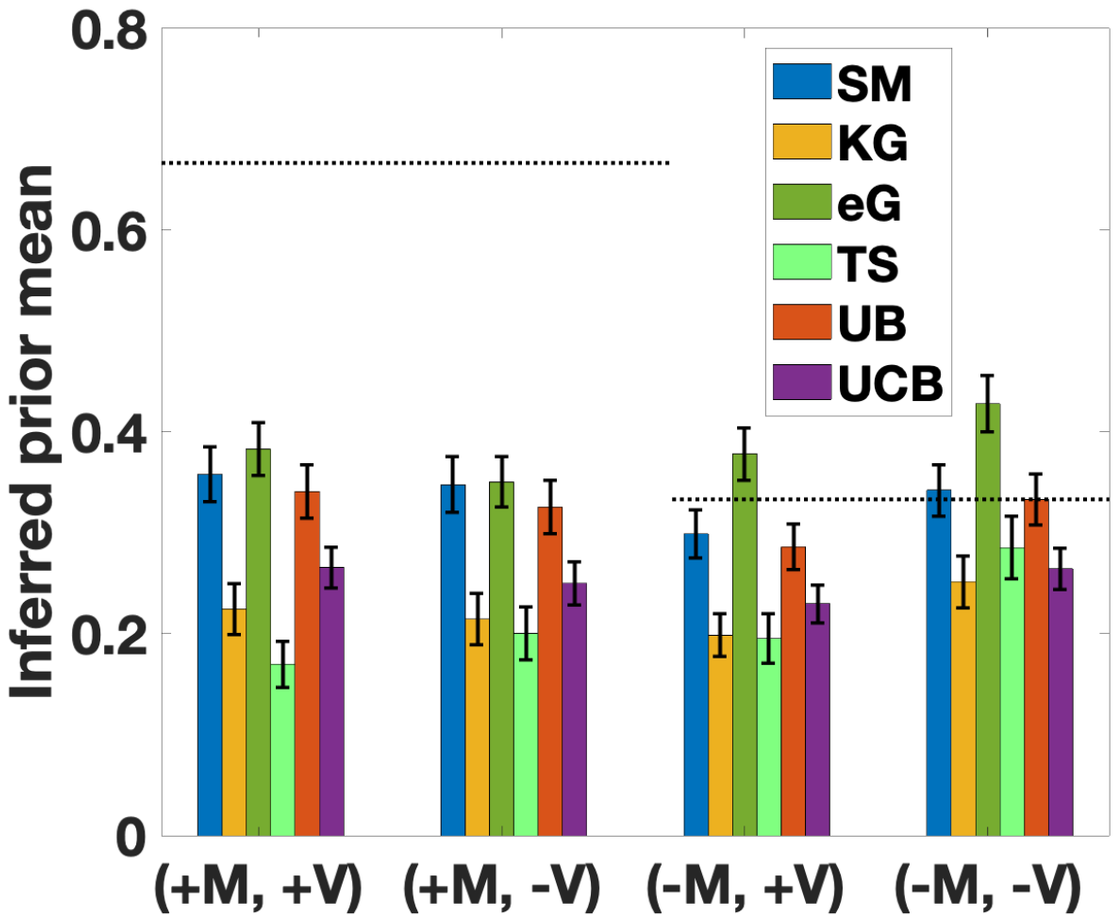

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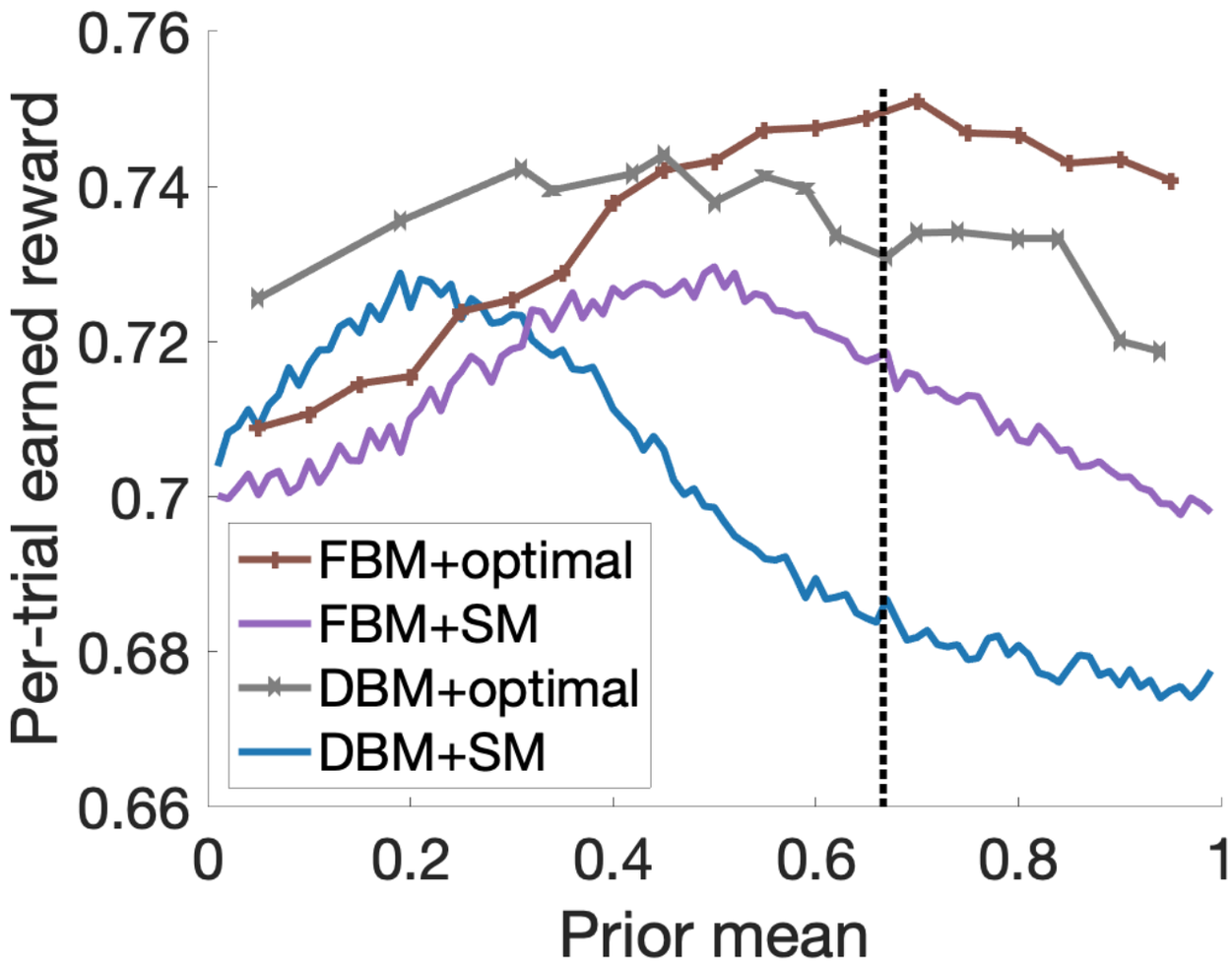

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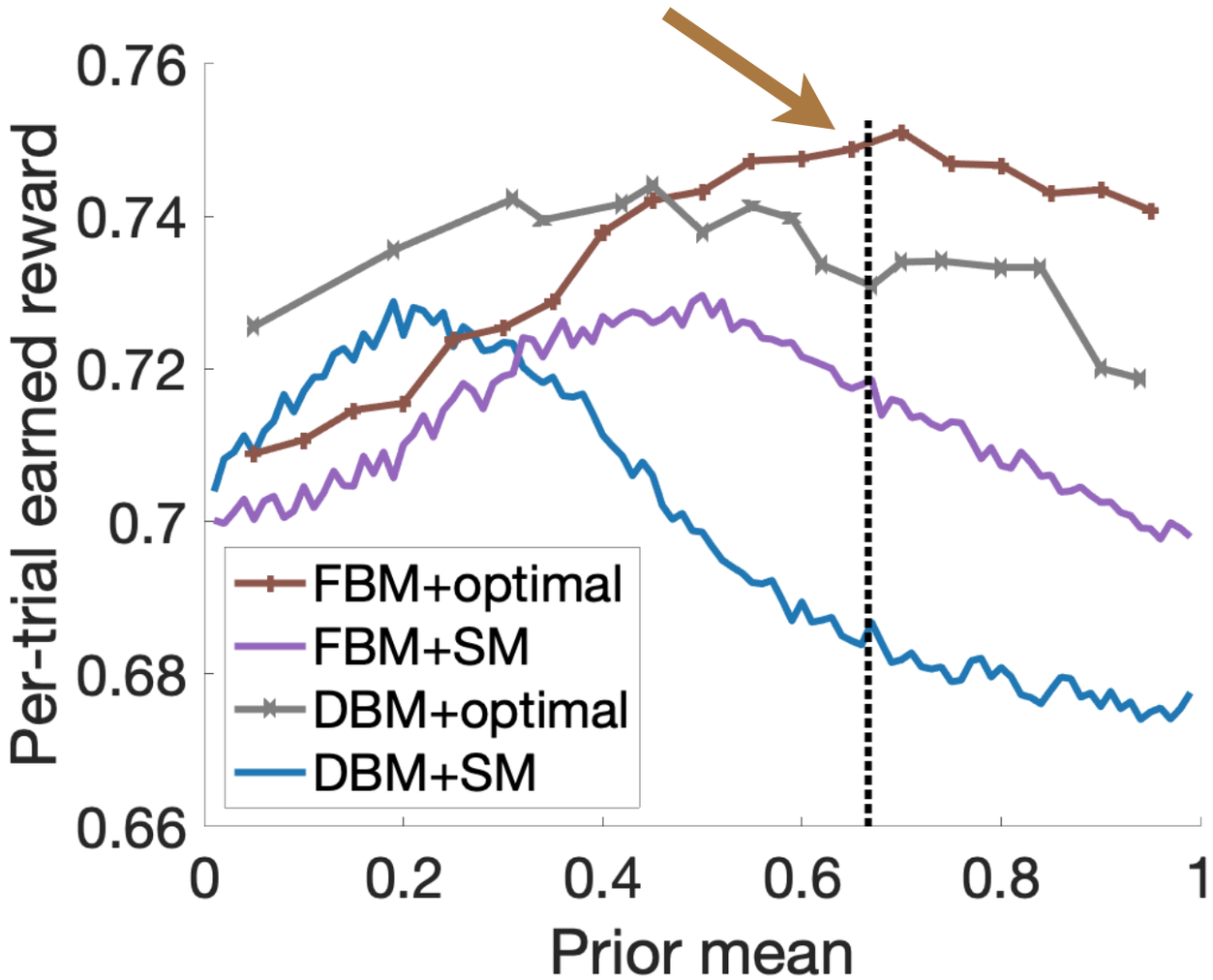

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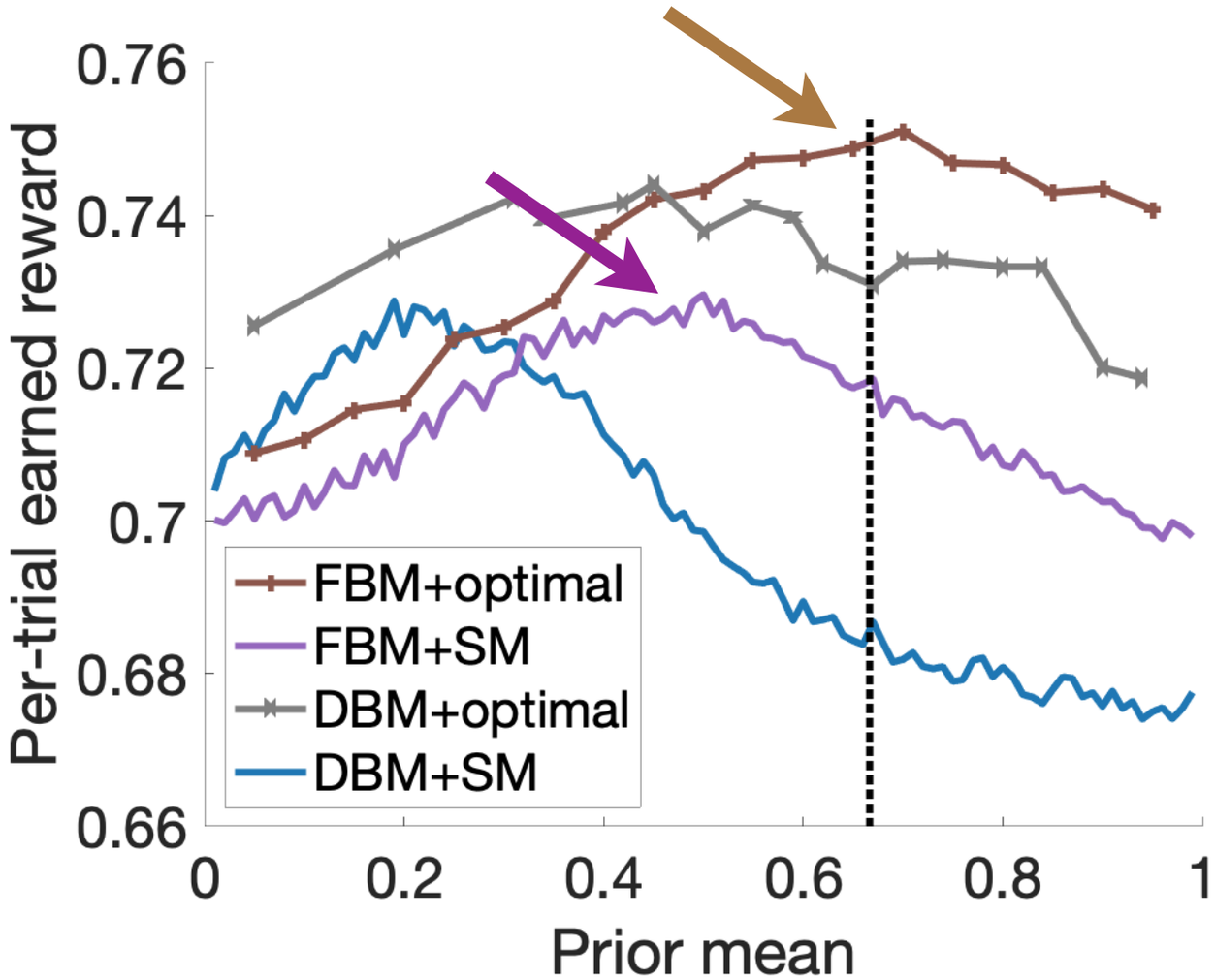

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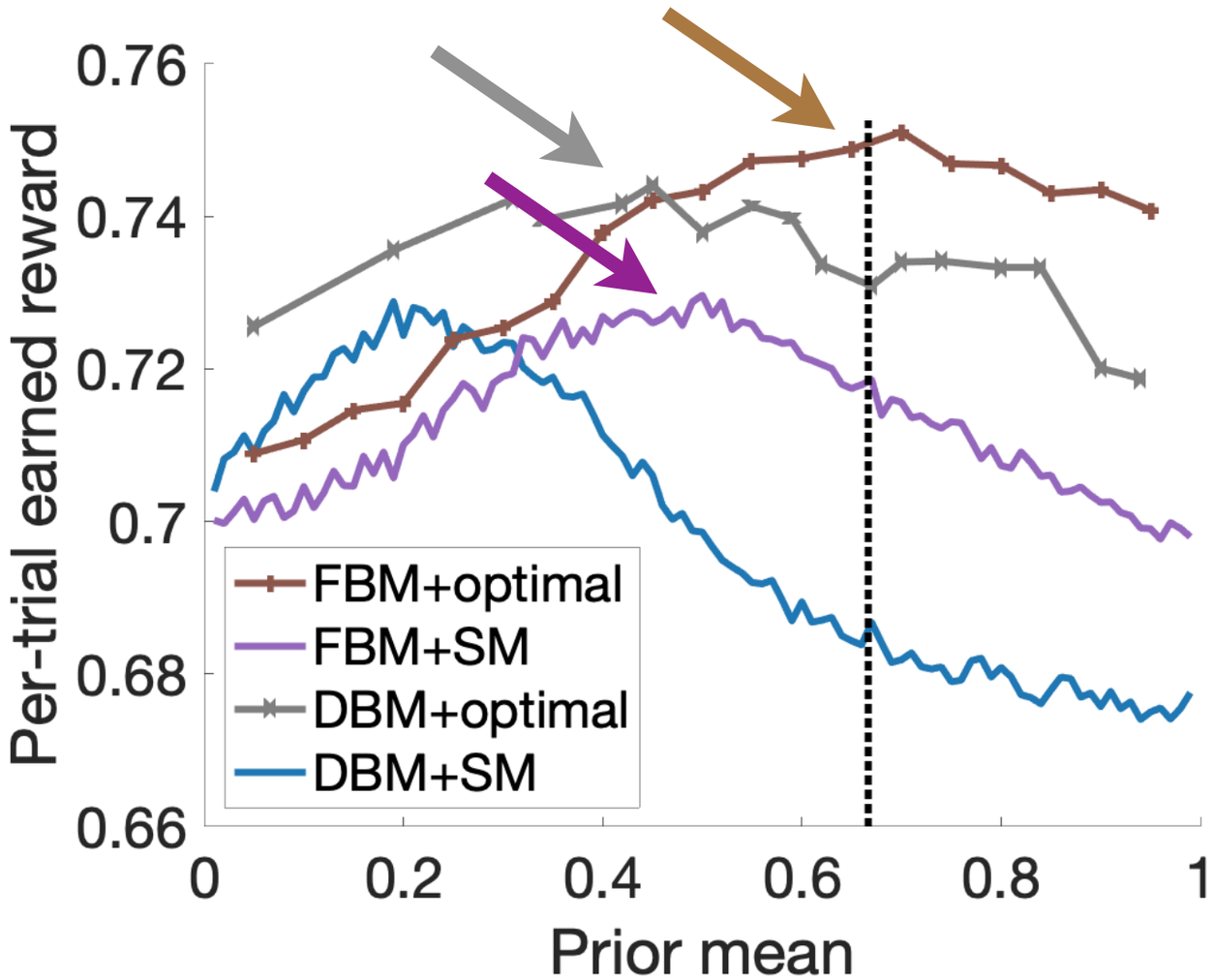

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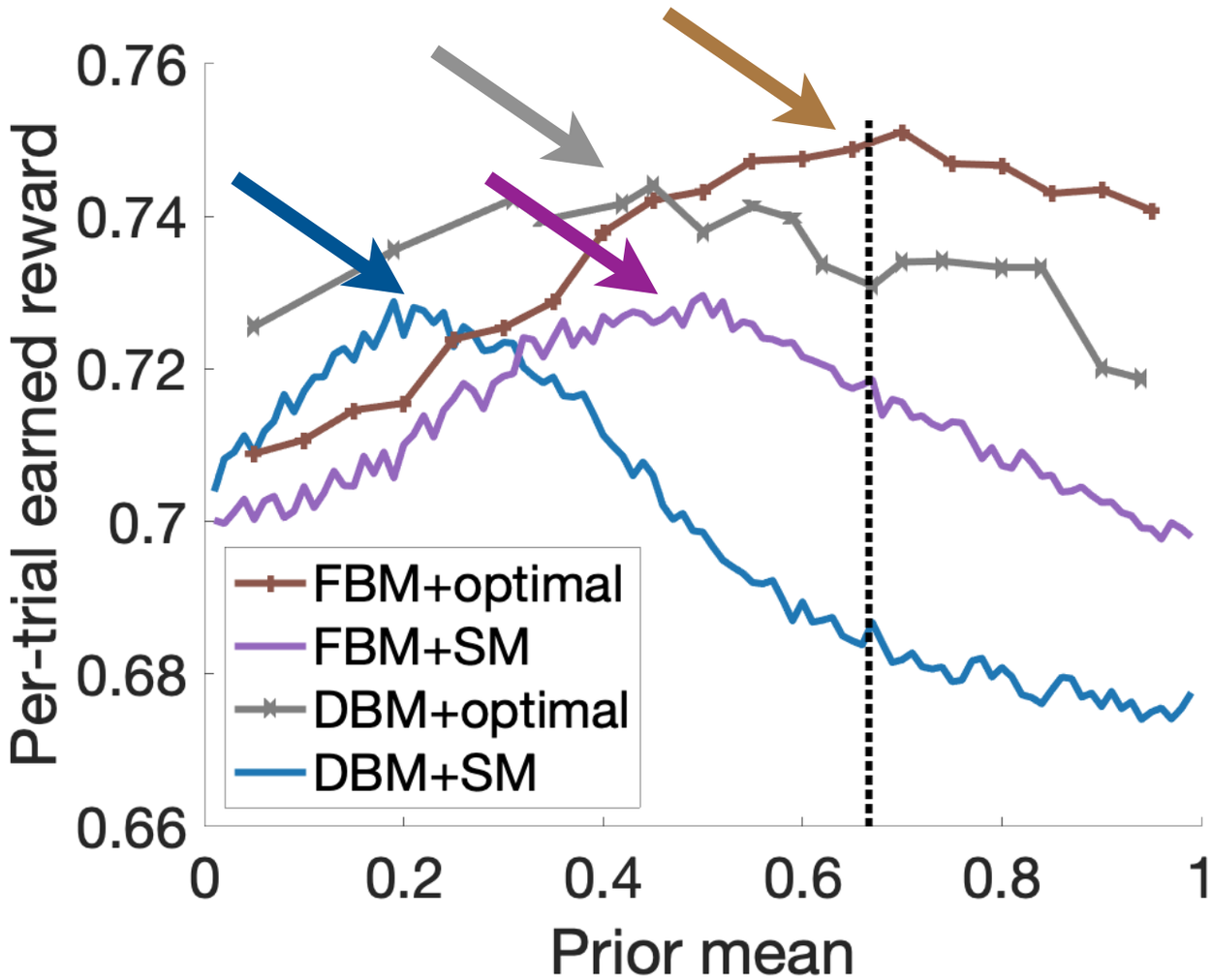

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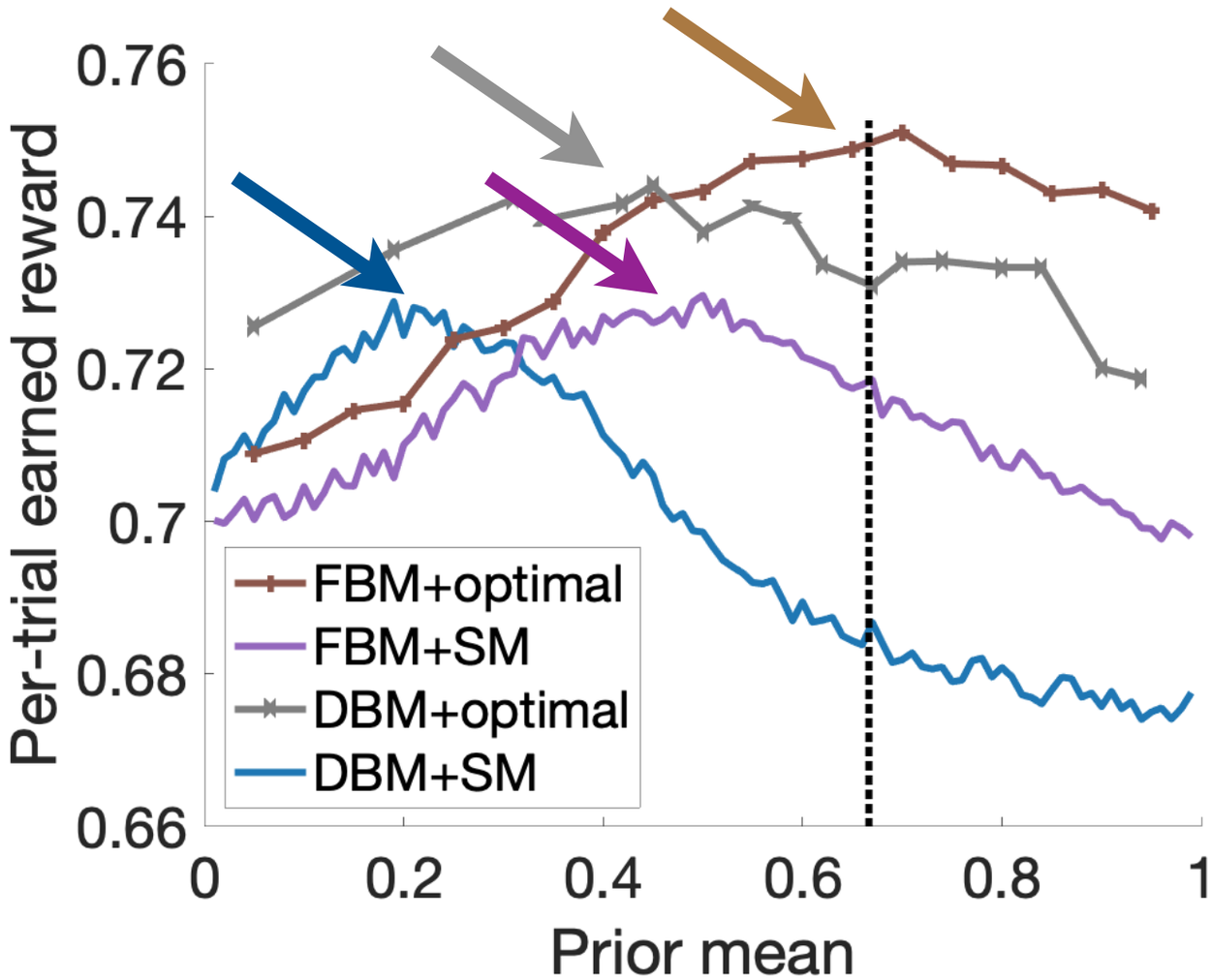

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- FBM vs. DBM: lower prior for DBM almost entirely compensates for false volatility assumption

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- Lower prior for **unchosen** arms: discourages shifting!

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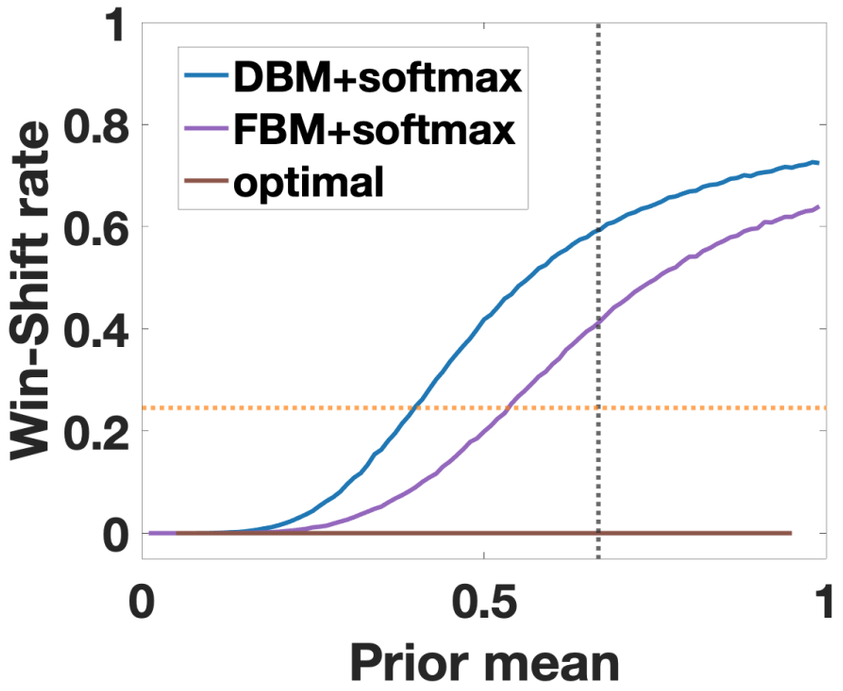
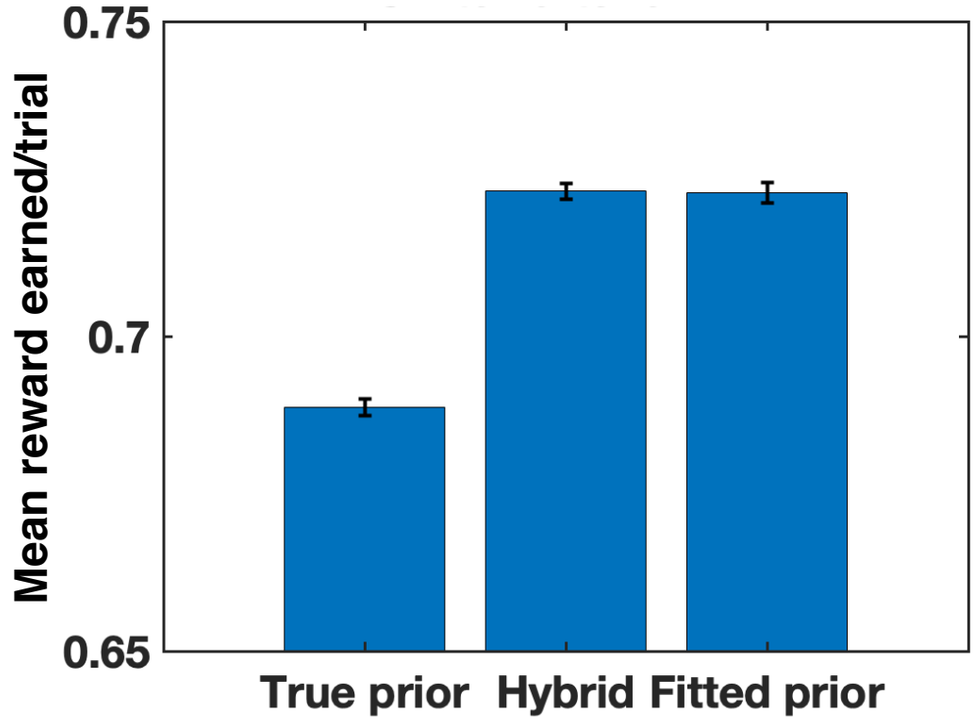
Lower prior mean ⇒ ↓ P(win-shift)



Lower prior mean ⇒ ↑ performance



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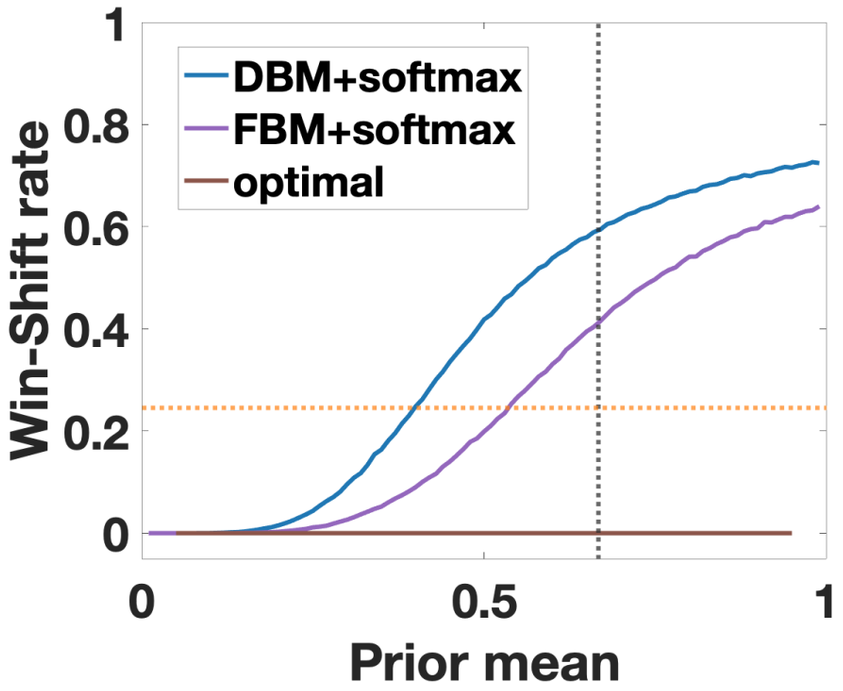

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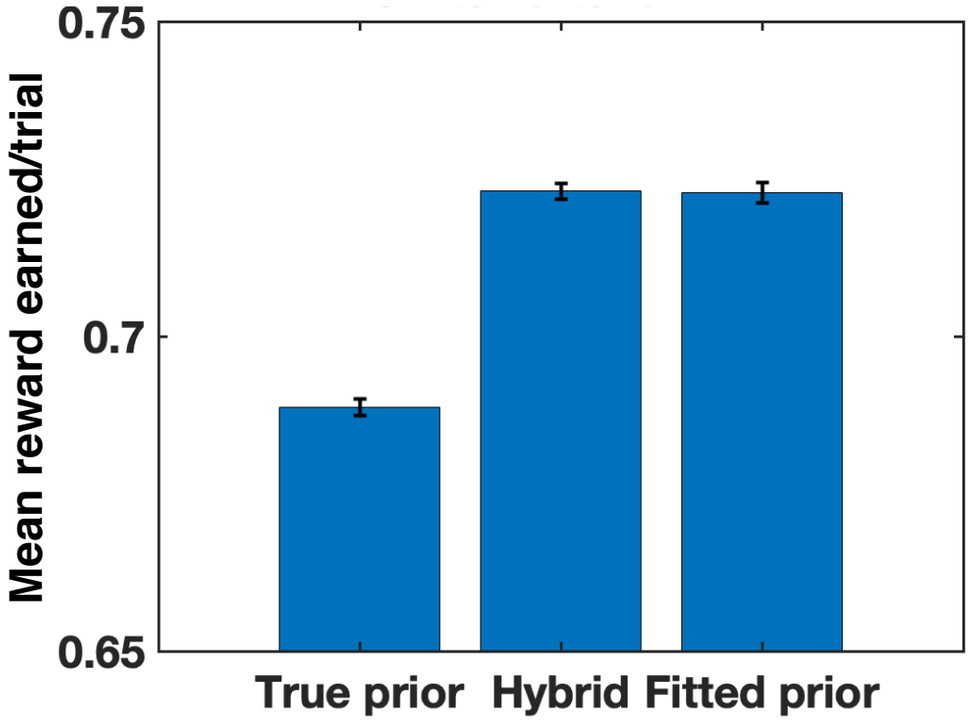

Simulation results

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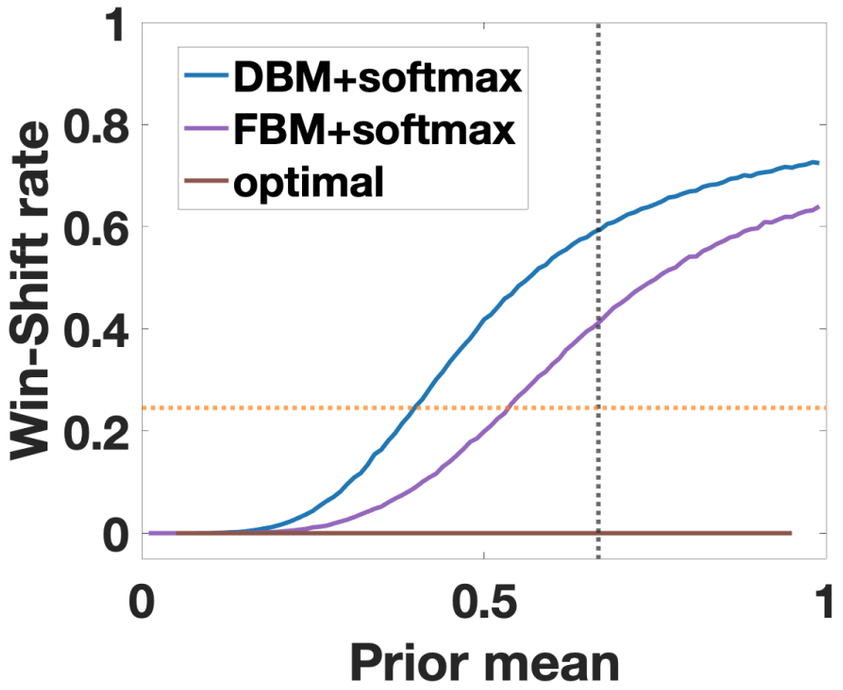

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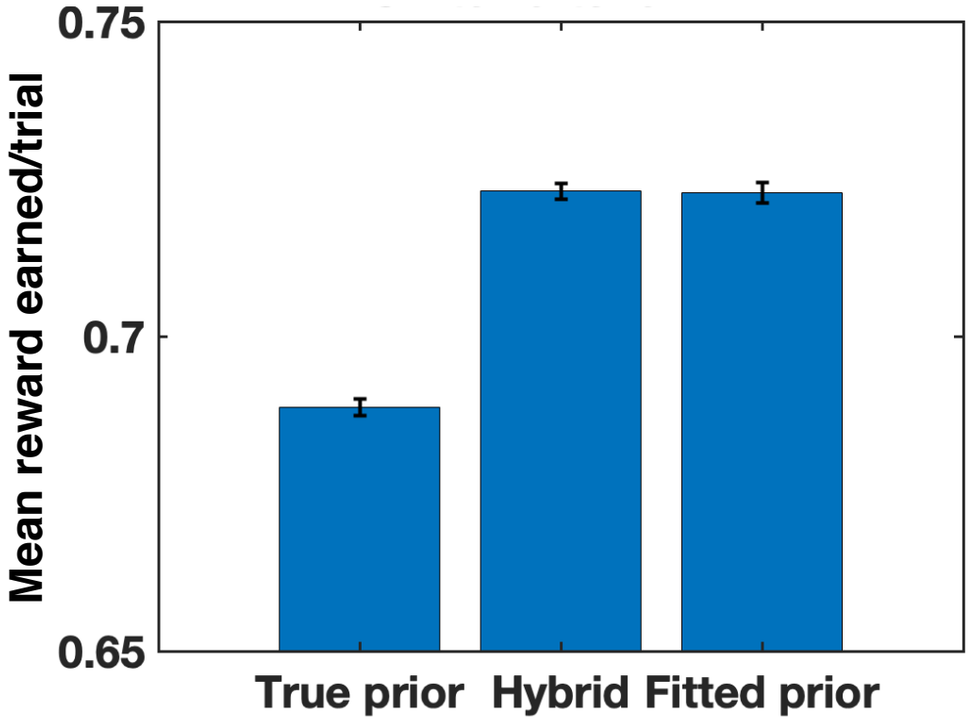

Simulation results

- Lower prior mean decreases P(win-shift); optimal policy has P(win-shift)=0

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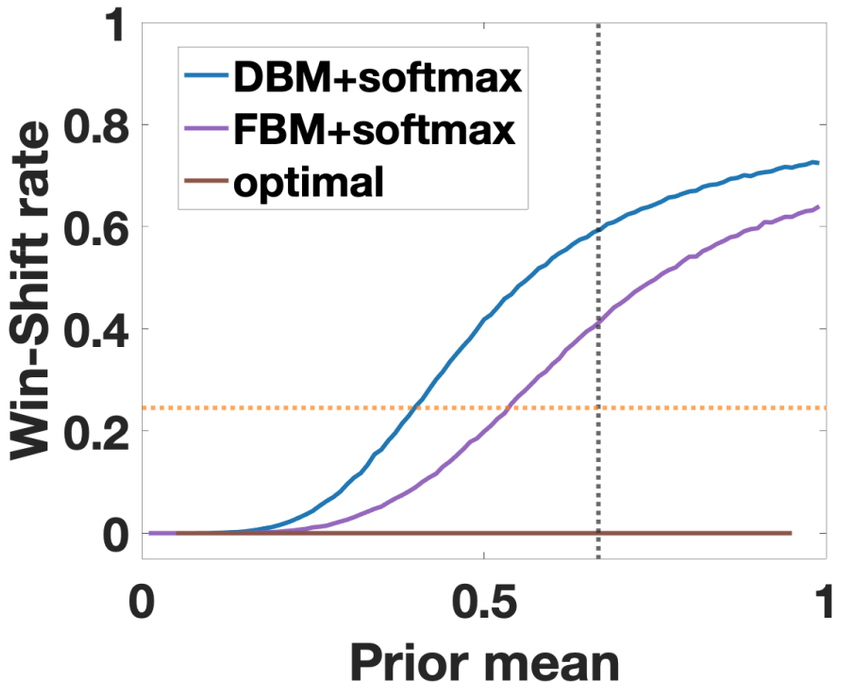

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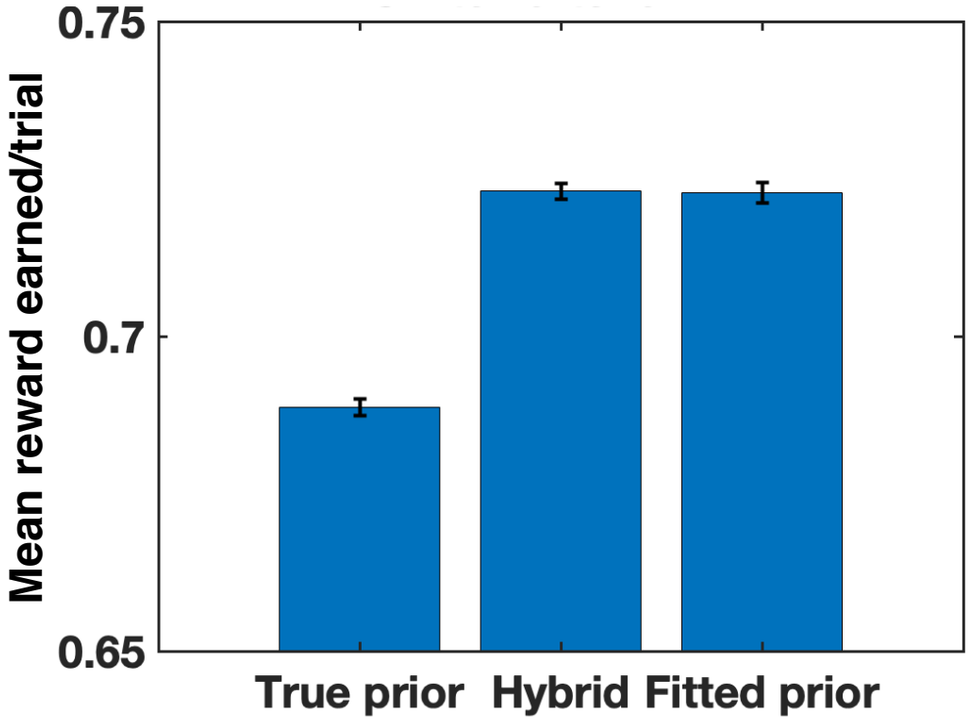
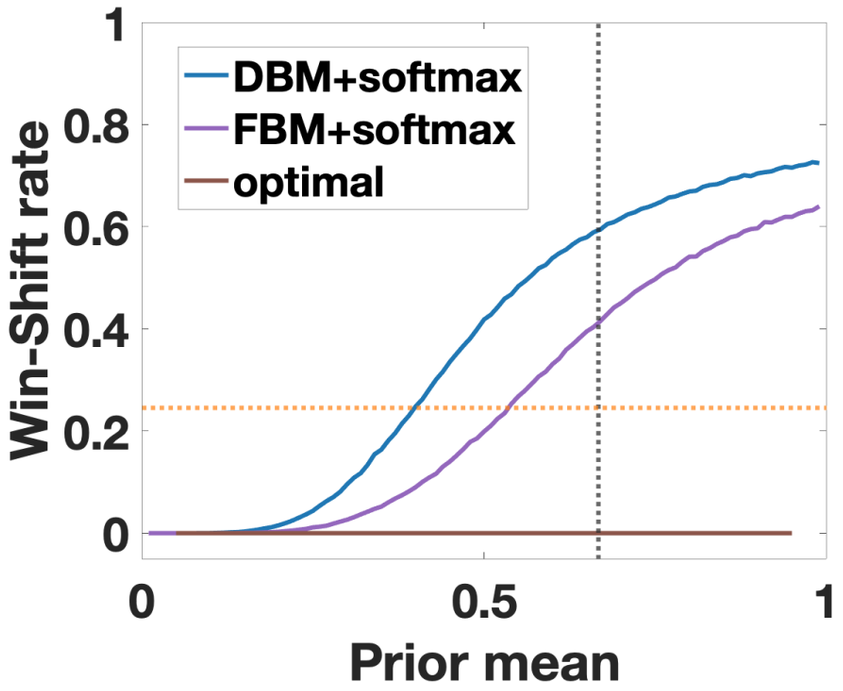


Simulation results

- Lower prior mean decreases P(win-shift); optimal policy has P(win-shift)=0
- Replacing true prior with fitted prior after each **win**: entirely captures benefit of lower prior

Why does lower prior mean help?

Lower prior mean ⇒ ↓ P(win-shift)



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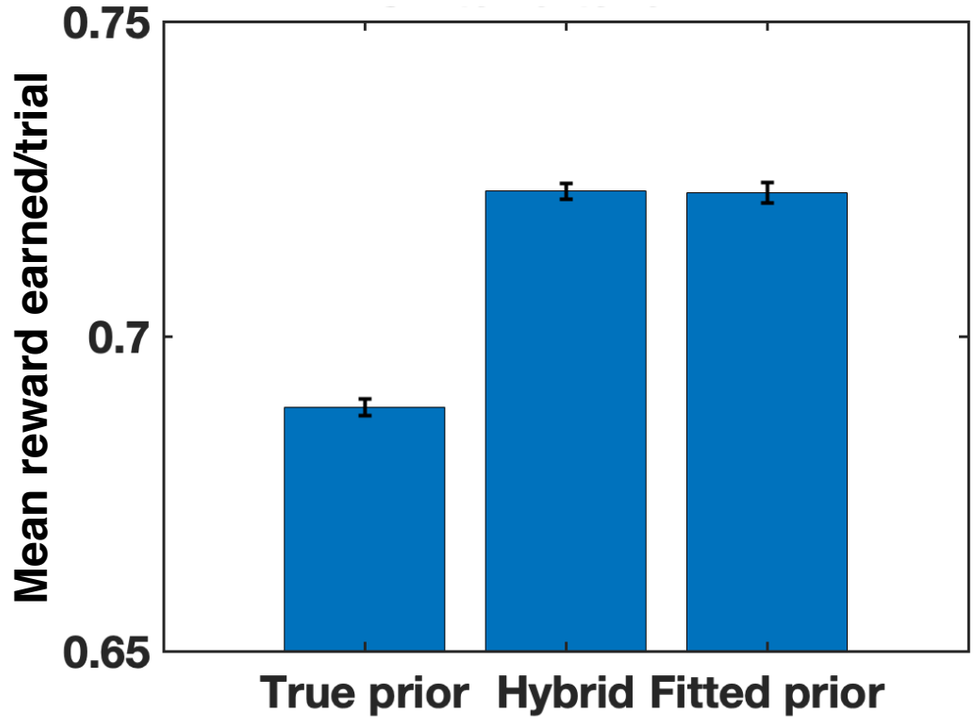

Simulation results

- Lower prior mean decreases P(win-shift); optimal policy has P(win-shift)=0
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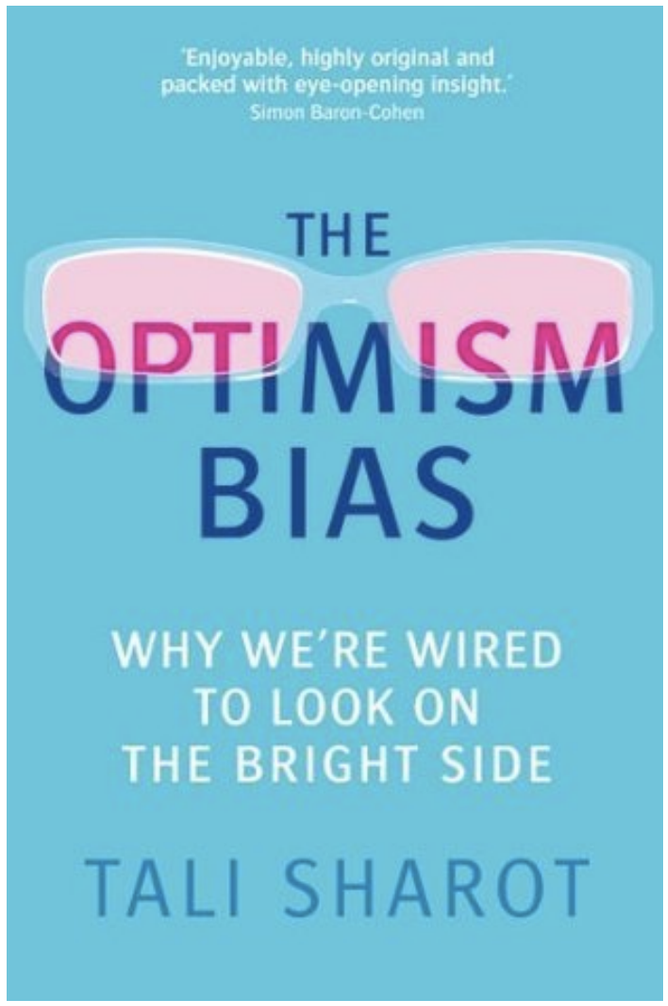
- Lower prior mean affects **unchosen** arm more than **chosen** arm
  ⇒ **relative optimism** about chosen arm

And What of Optimism Bias?



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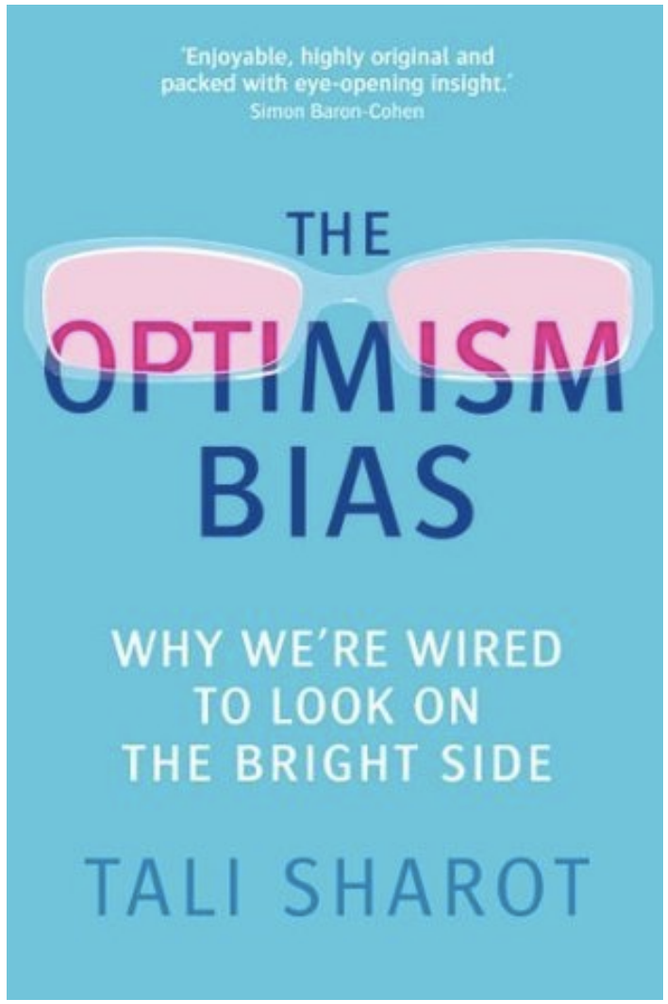

nature neuroscience

How unrealistic optimism is maintained in the face of reality

Tali Sharot[1,4], Christoph W Korn[2–4] & Raymond J Dolan[1]

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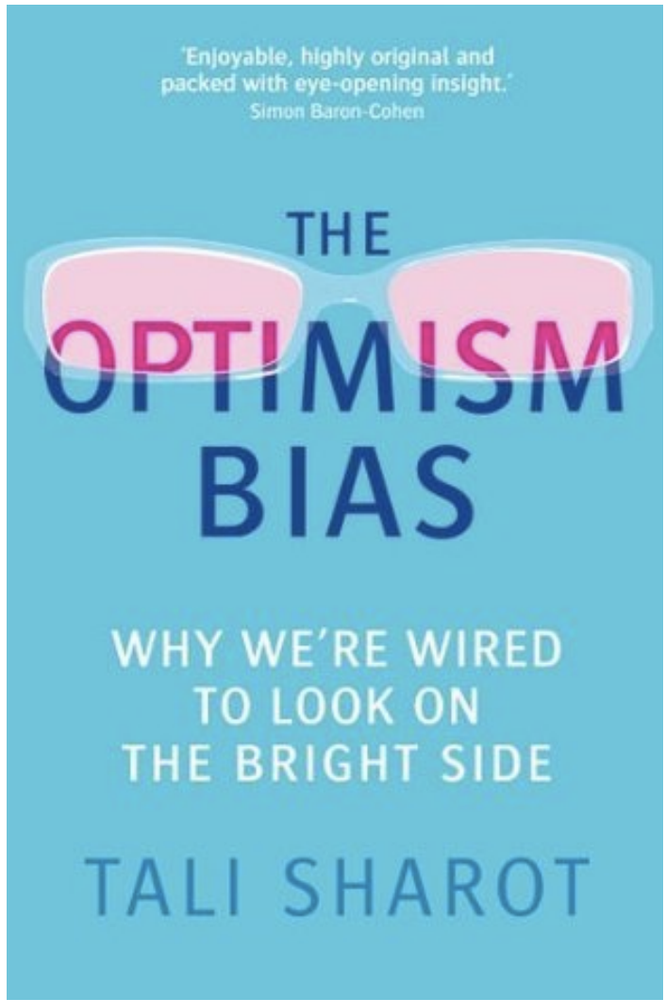

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nature human behaviour

ARTICLES

PUBLISHED: 20 MARCH 2017 | VOLUME: 1 | ARTICLE NUMBER: 0067

Behavioural and neural characterization of optimistic reinforcement learning

Germain Lefebvre[1,2], Maël Lebreton[3,4], Florent Meyniel[5], Sacha Bourgeois-Gironde[2,6] and Stefano Palminteri[1,7]*

When forming and updating beliefs about future life outcomes, people tend to consider good news and to disregard bad news. This tendency is assumed to support the optimism bias. Whether this learning bias is specific to 'high-level' abstract belief update or a particular expression of a more general 'low-level' reinforcement learning process is unknown. Here we report evidence in favour of the second hypothesis. In a simple instrumental learning task, participants incorporated better-than-expected outcomes at a higher rate than worse-than-expected ones. In addition, functional imaging indicated that inter-individual difference in the expression of optimistic update corresponds to enhanced prediction error signalling in the reward circuitry. Our results constitute a step towards the understanding of the genesis of optimism bias at the neurocomputational level.

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(Zhou, Guo, Yu, *Cogsci*, 2020)

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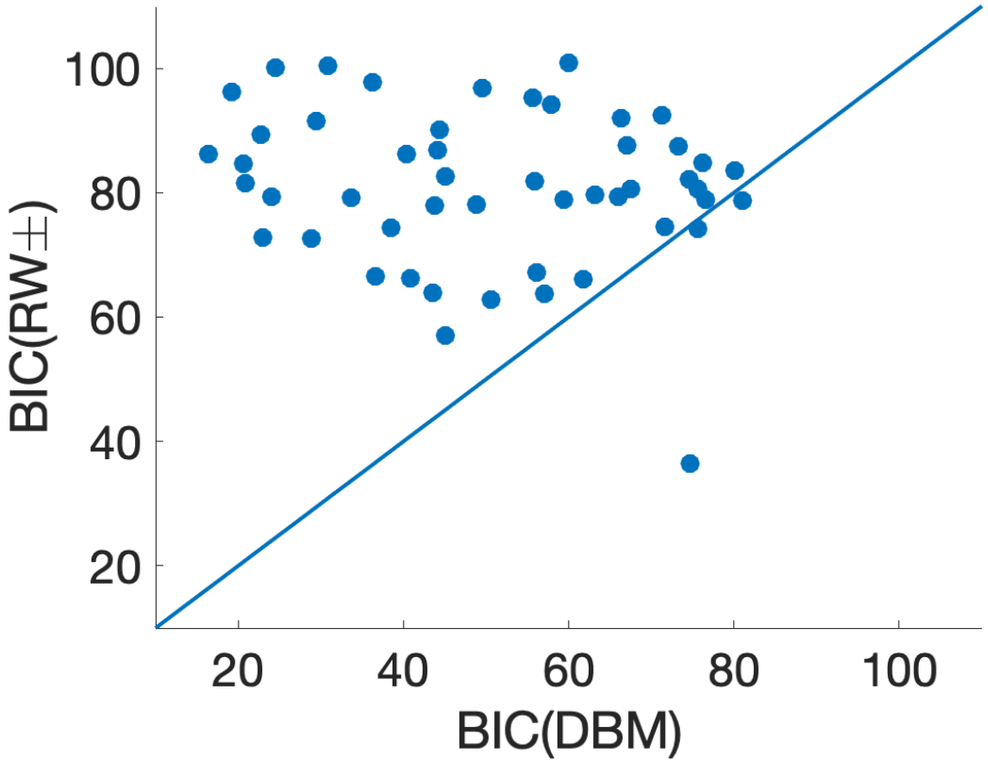

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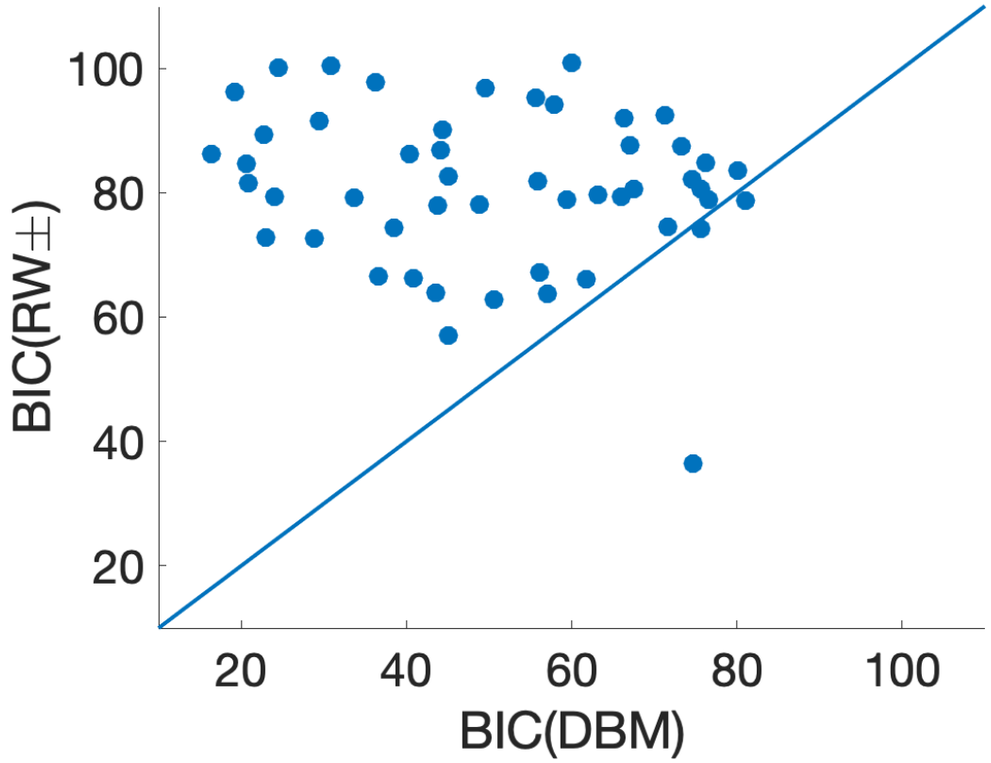

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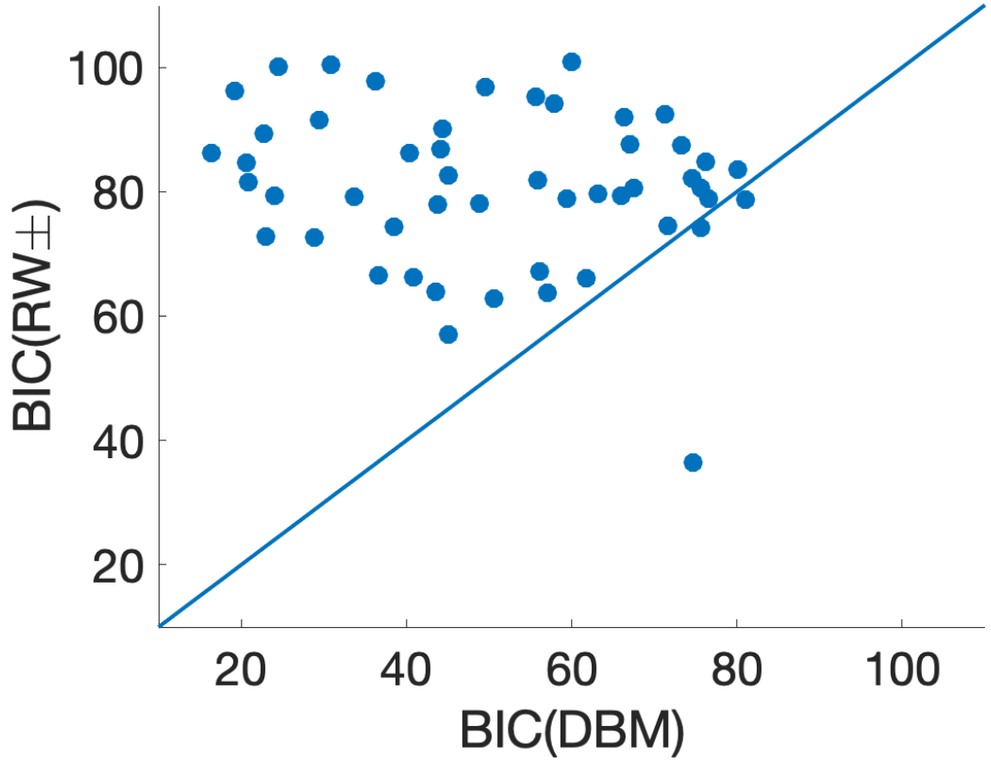

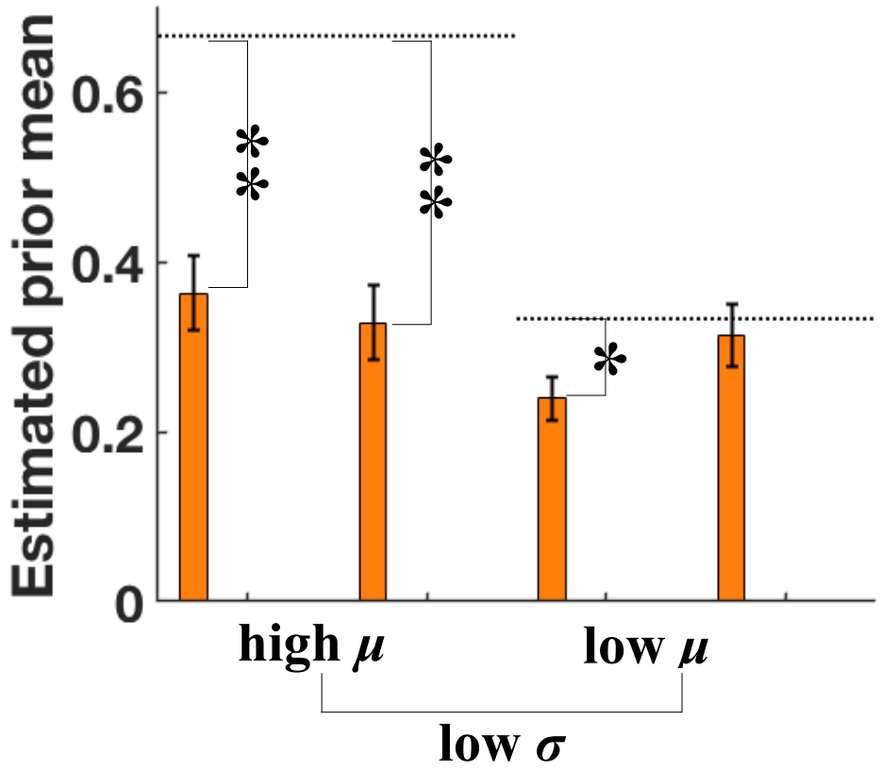

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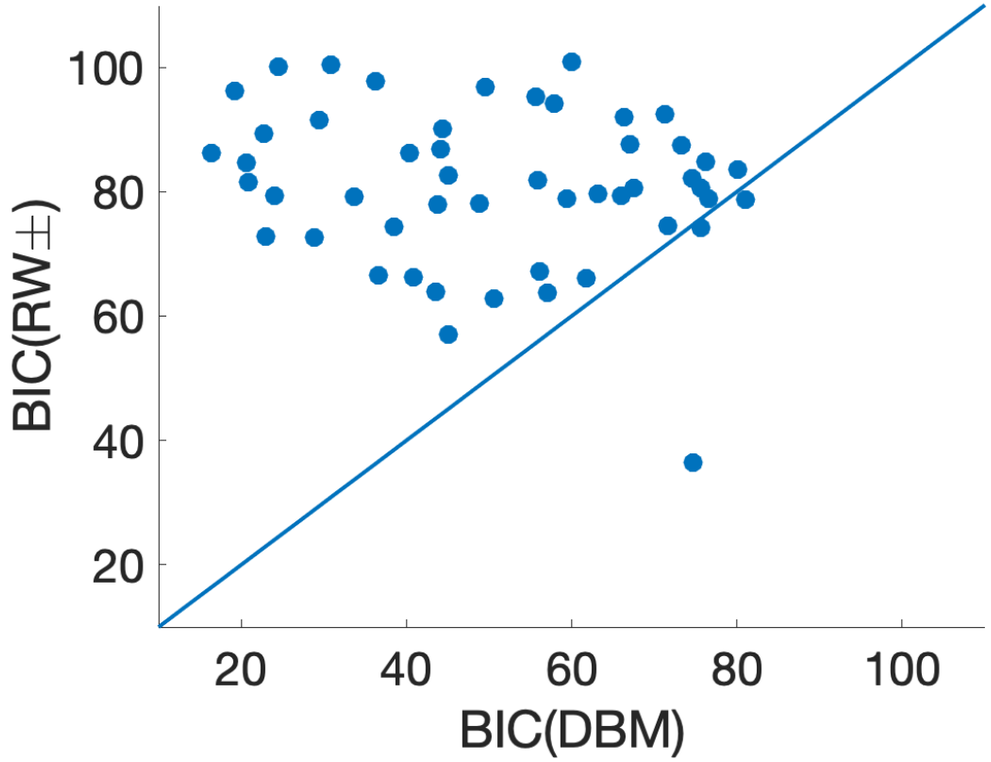

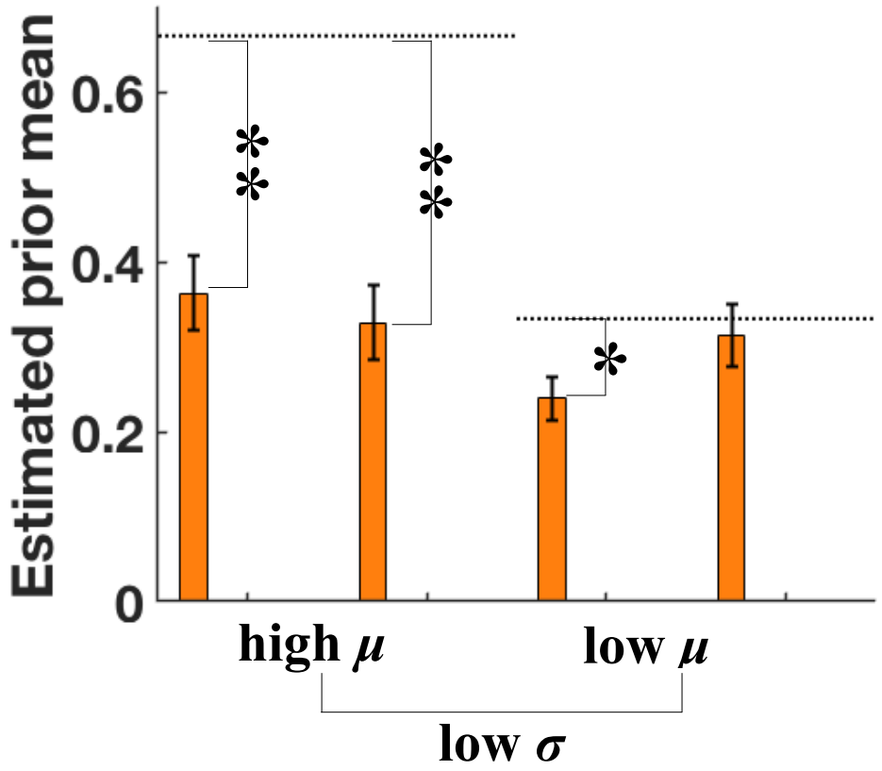

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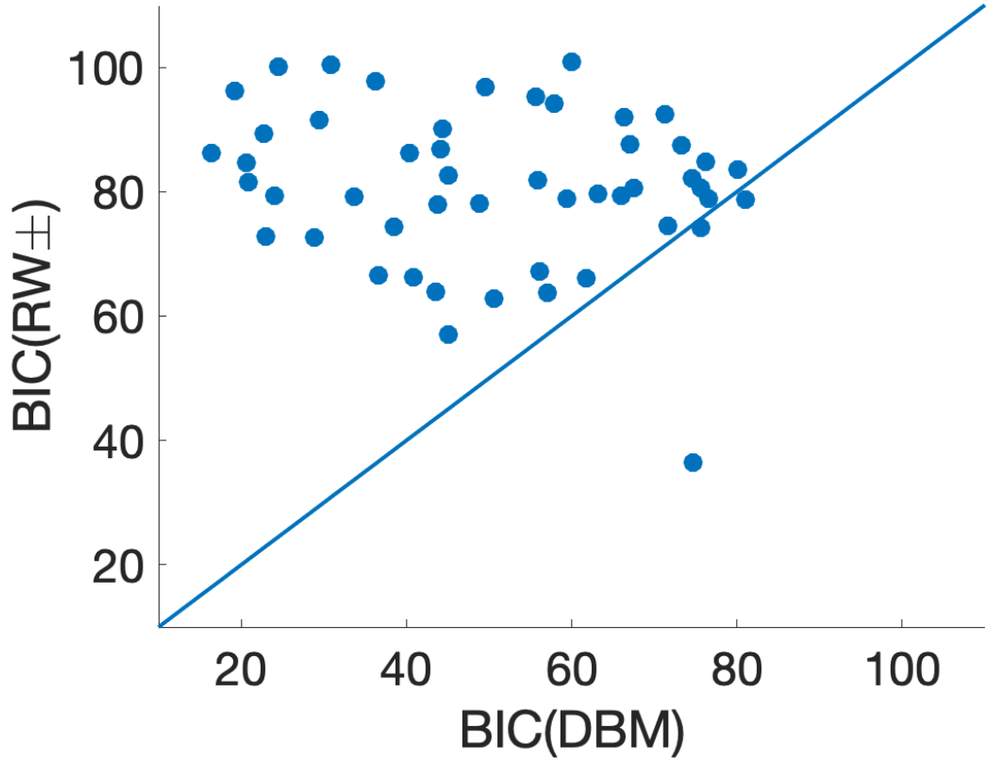

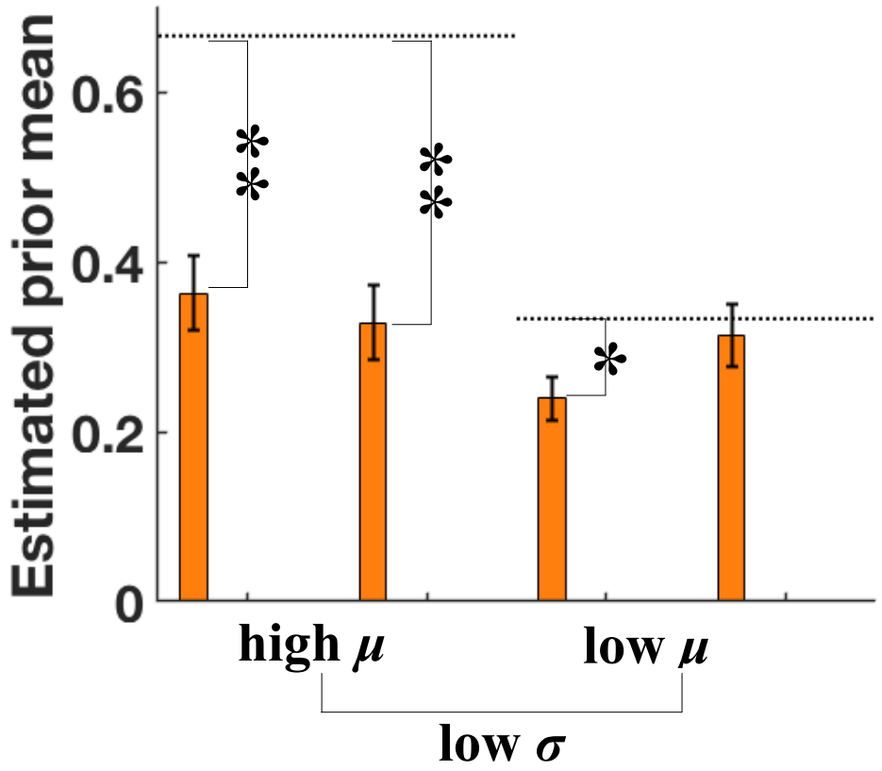

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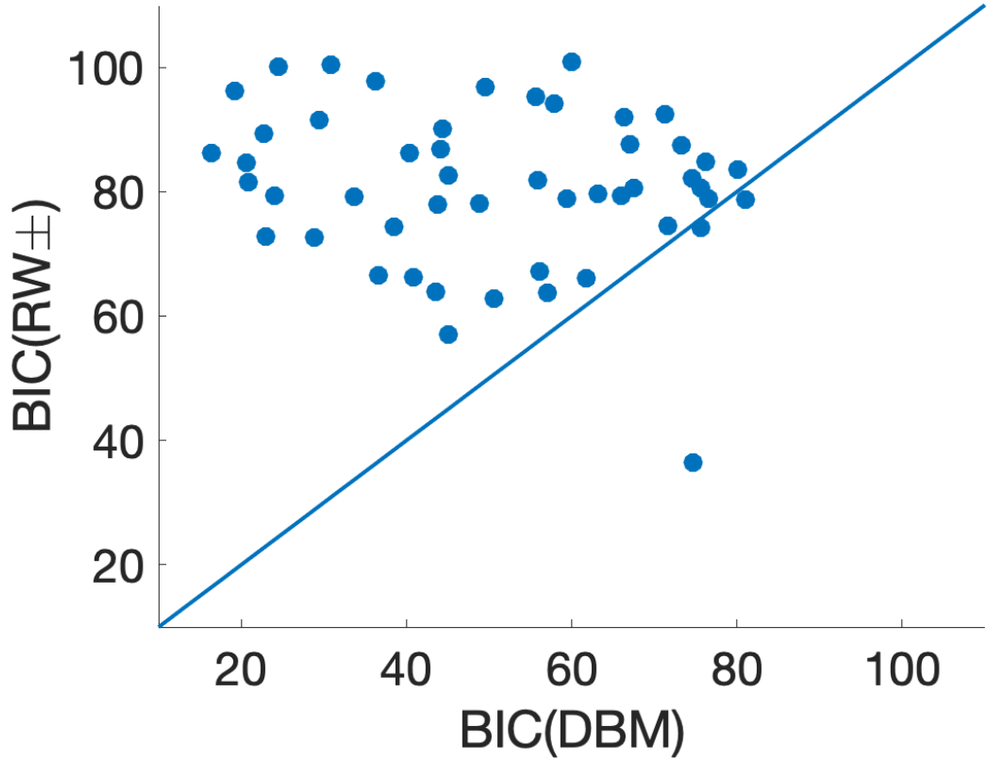

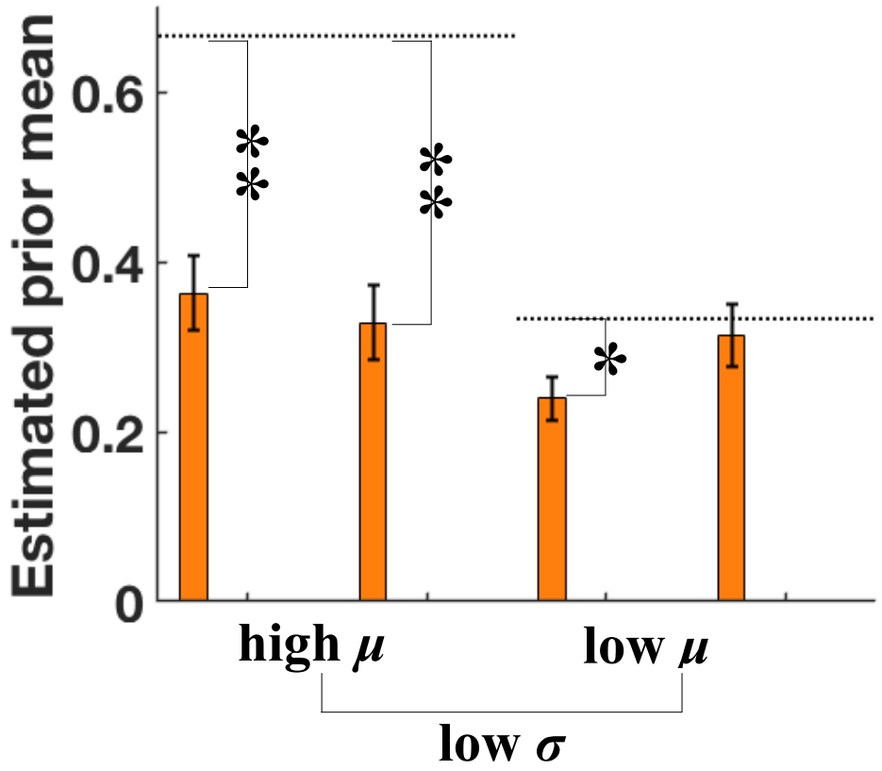

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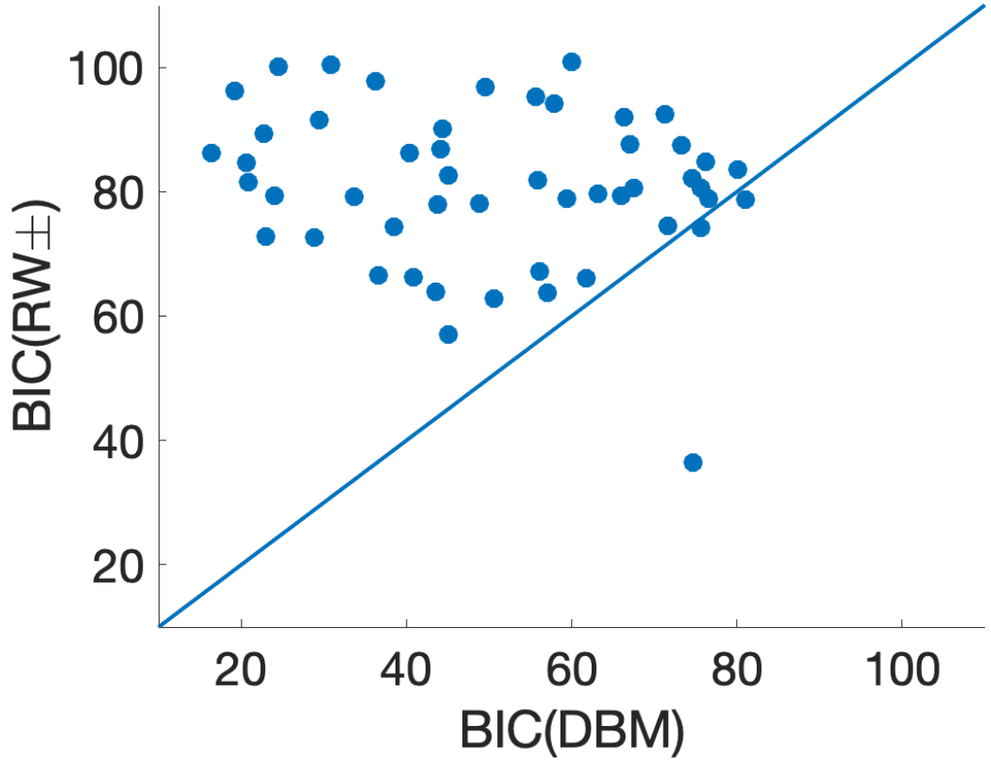

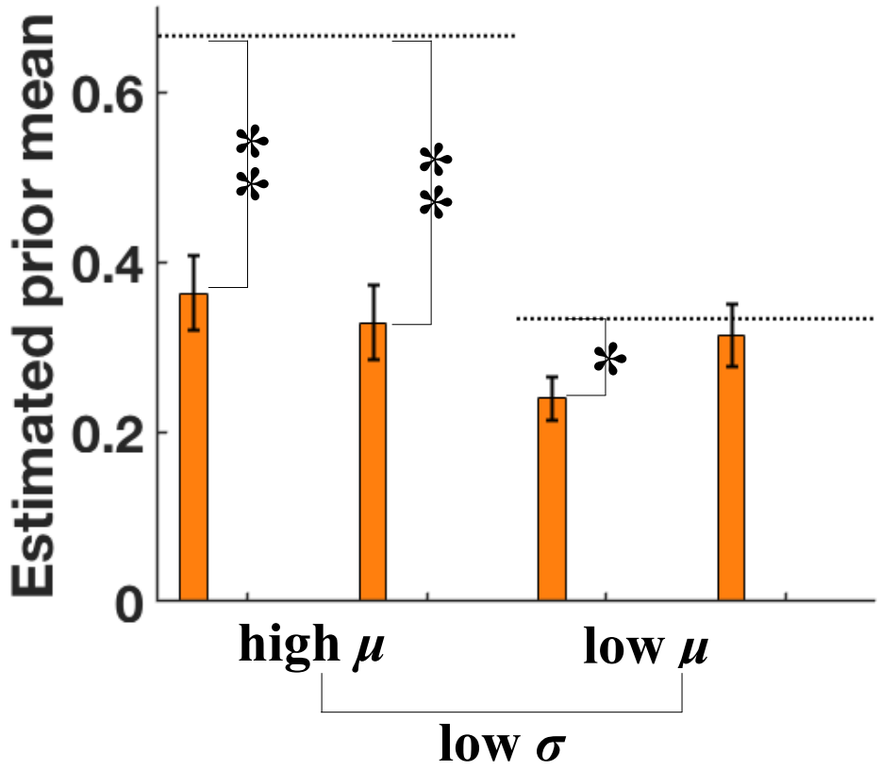

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  - Increasing devaluation of unchosen arm: choice history (not only reward history) matters
  - Leveraging the property: high choice frequency correlated with high reward rate in individuals who can "find" the good options (bad news for individuals who are stuck in bad choice patterns, e.g. addiction)

Outline

- Computational modeling
- **Applications to psychiatry**
  - ✳ **Addiction**
  - ✳ Depression/anxiety
- Discussion

Gambling Addiction

(Dezza, Noel, Cleeremans, Yu, *Translational Psychiatry*, 2021)

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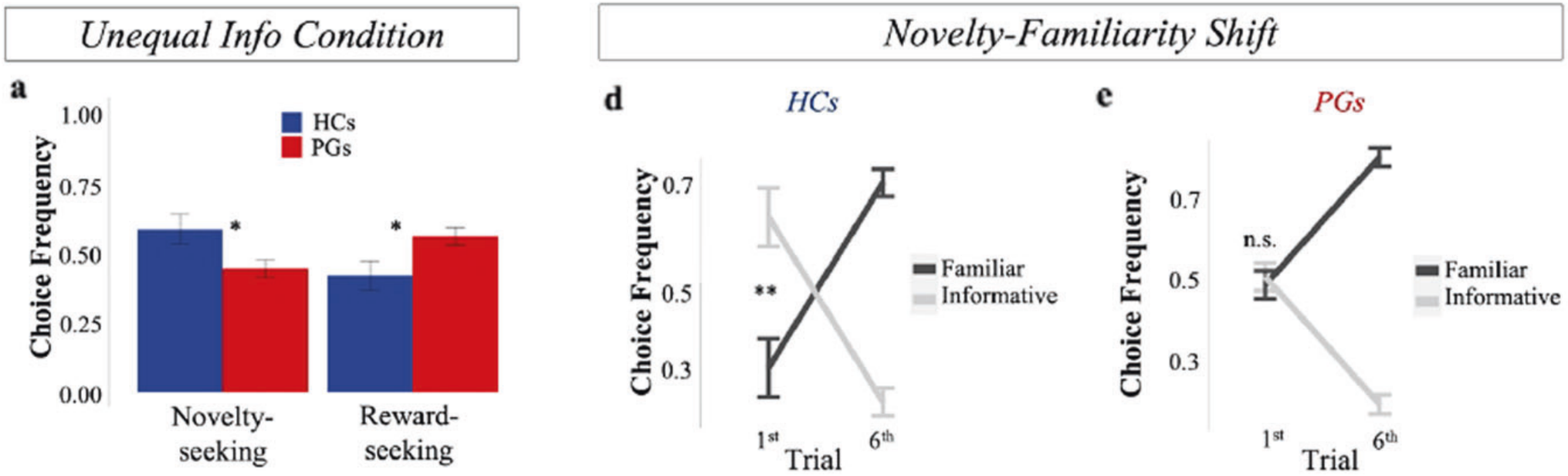

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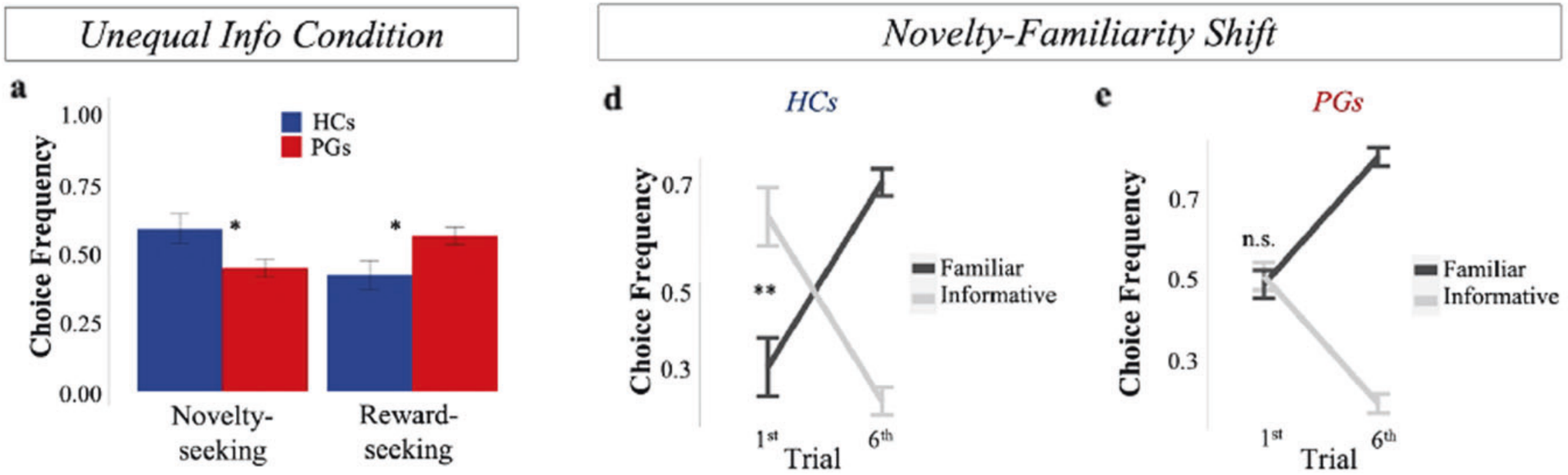

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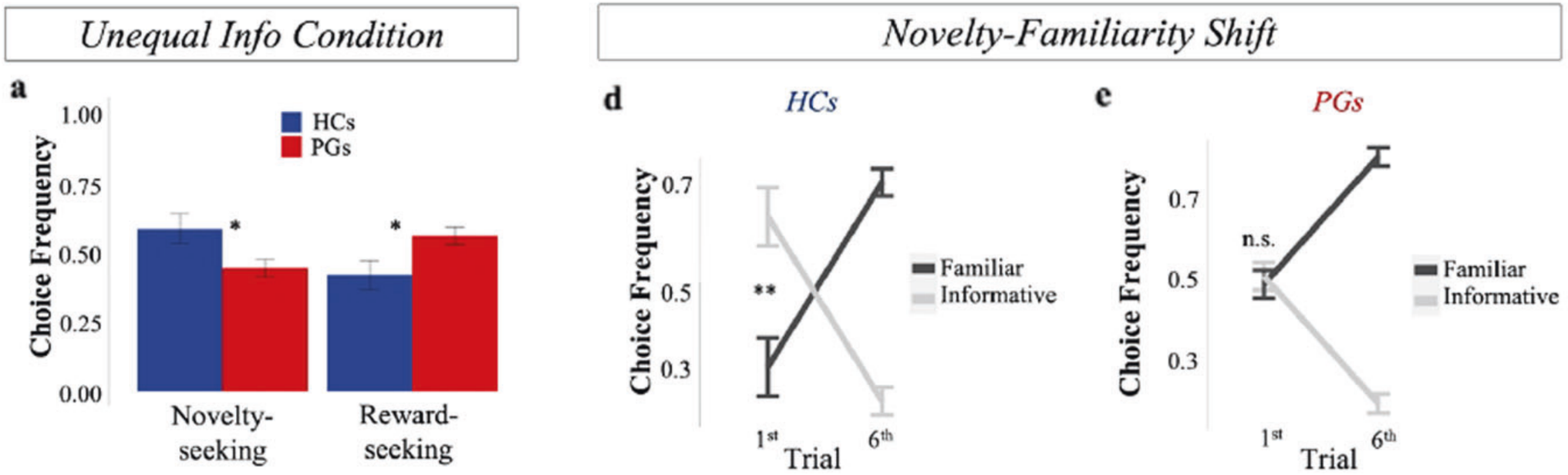

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- From 1st to 6th forced trial, HC show a significant novelty-familiarity shift, PG show no preference for novelty at the start but do show preference for more familiar options later on

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$$V_{t,j}(c) = Q_{t+1,j}(c) + \sum_{1}^{t} i_{t,j}(c) * k + 1_{\text{novel}} * \nu$$

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- PG show smaller novelty bonus, but also an uncertainty penalty/familiarity bonus!

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$$V_{t,j}(c) = Q_{t+1,j}(c) + \sum_{1}^{t} i_{t,j}(c) * k + 1_{\text{novel}} * \nu$$

- Decision policy
  - Q-value (E[reward$_{t+1}$|data$_t$]): computed via RW, DBM
  - $k < 0$ (uncertainty bonus; Wilson et al 2014, Dezza et al 2017)
  - $v > 0$ (novelty bonus; Gottlieb et al, 2013)
- HC: large $v > 0$, $k \approx 0$, PG: smaller $v > 0$, larger $k > 0$
- HC do not exhibit a general uncertainty bonus, only novelty bonus!
- PG show smaller novelty bonus, but also an uncertainty penalty/familiarity bonus!
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- No group differences in overall performance; simulations: both modes of behavior "optimal"
- But! Reward rates fixed in current design. In non-stationary environment, the PG pattern can be trapped into suboptimal patterns of behavior (addiction ⇒ worse Wisconsin Card Sorting Task, Hosak et al; 2012)

Methamphetamine Addiction

(Harlé, Zhang, Schiff, Mackey, Paulus, Yu, *Frontiers in Psychology*, 2015)

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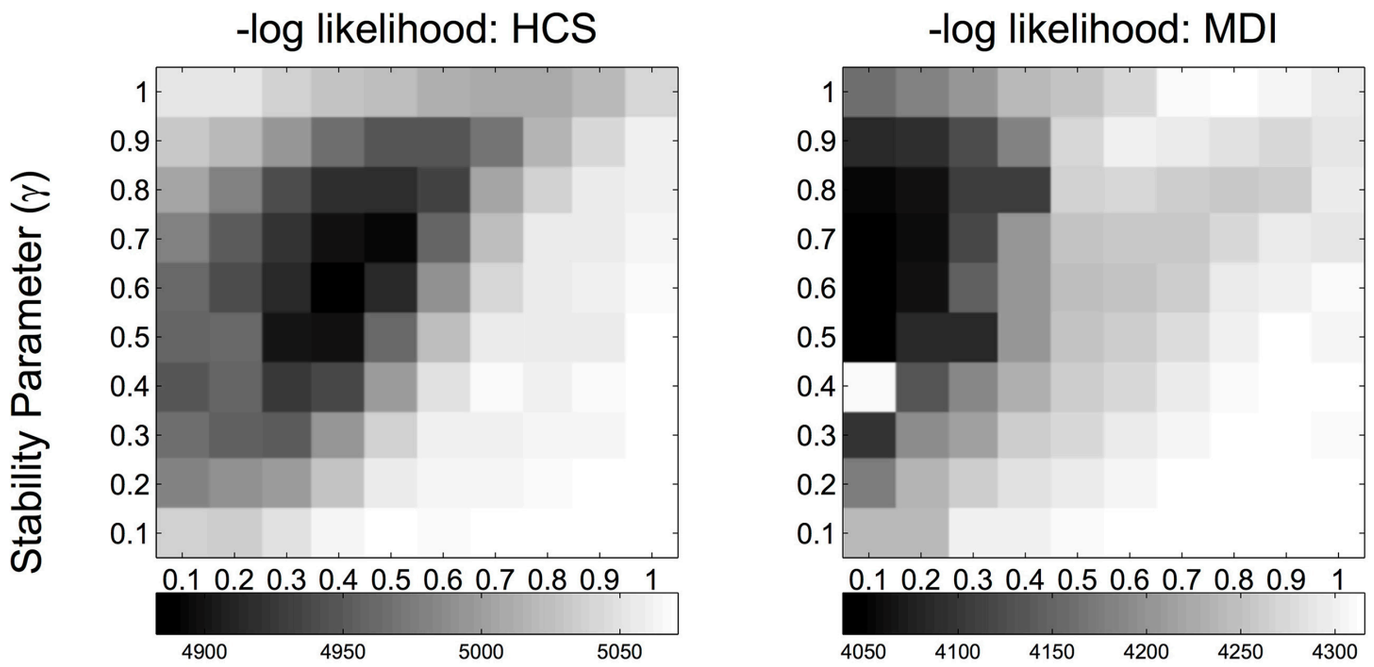

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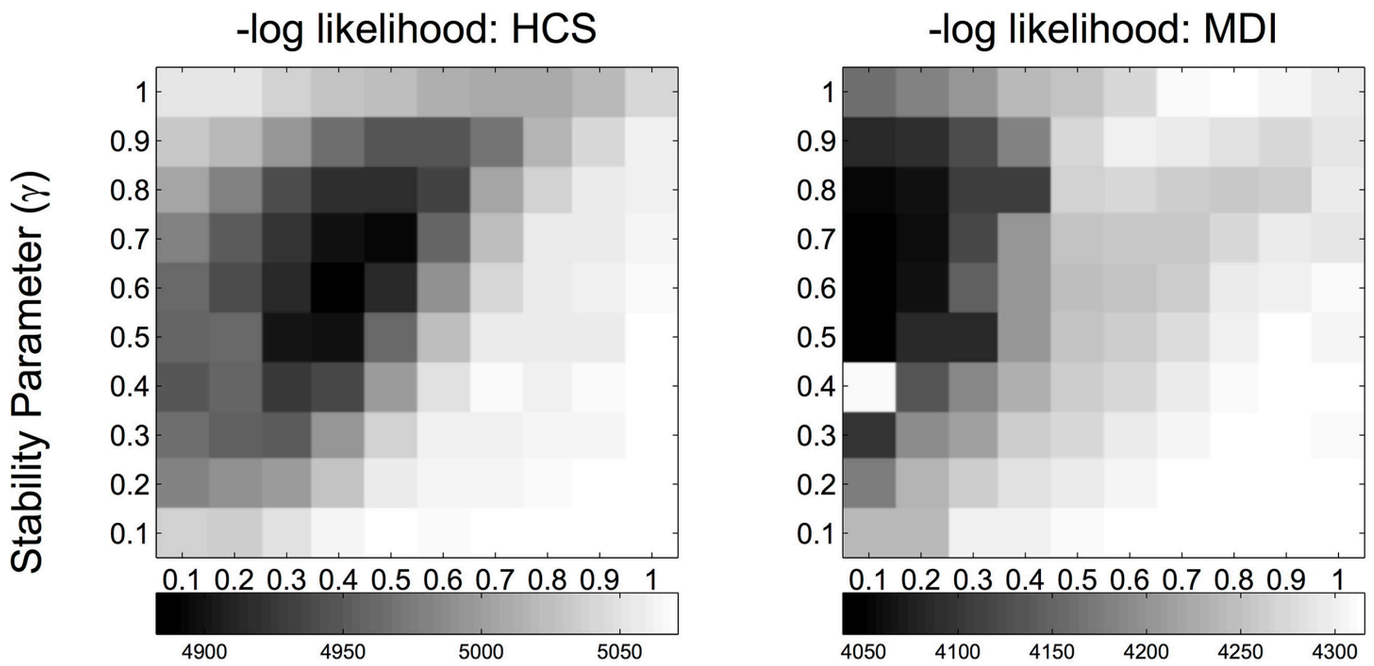

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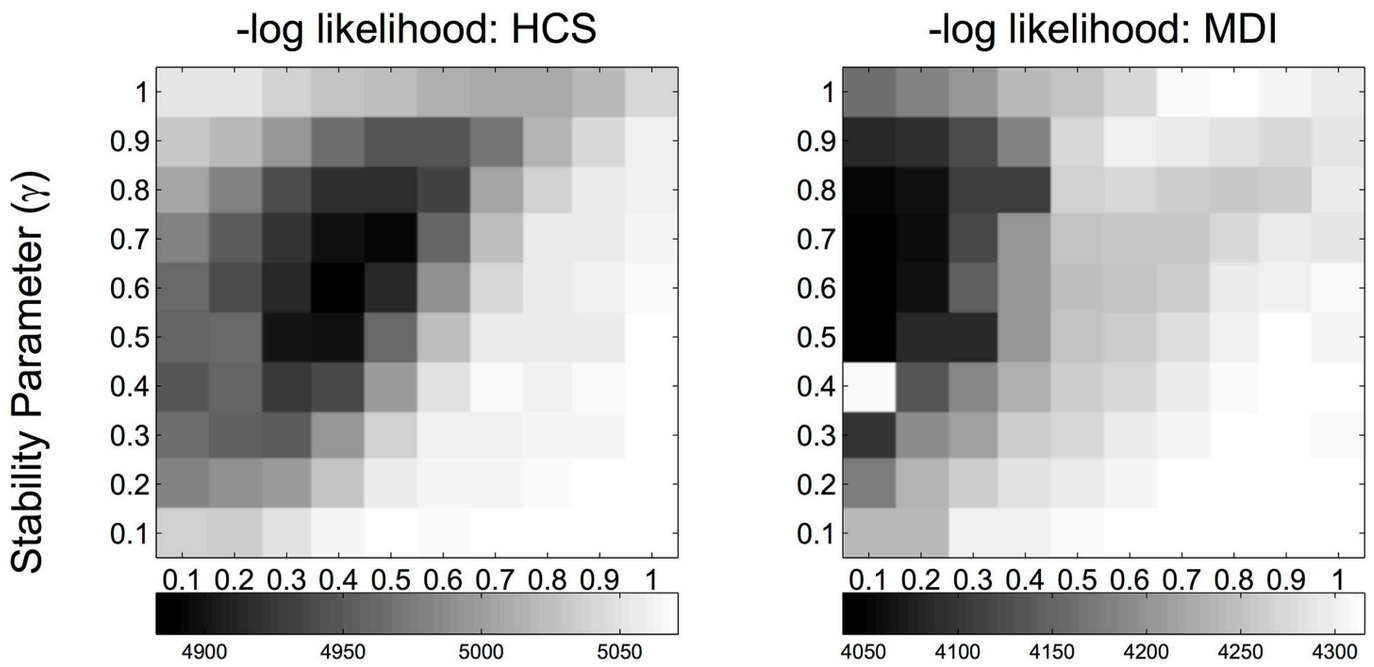

- MDI expected much lower reward rate in the environment than HCS (similar stability assumptions)
- ⇒ excessive tendency to stick with familiar option (devaluing of unchosen option, not due to assumptions about greater stability)

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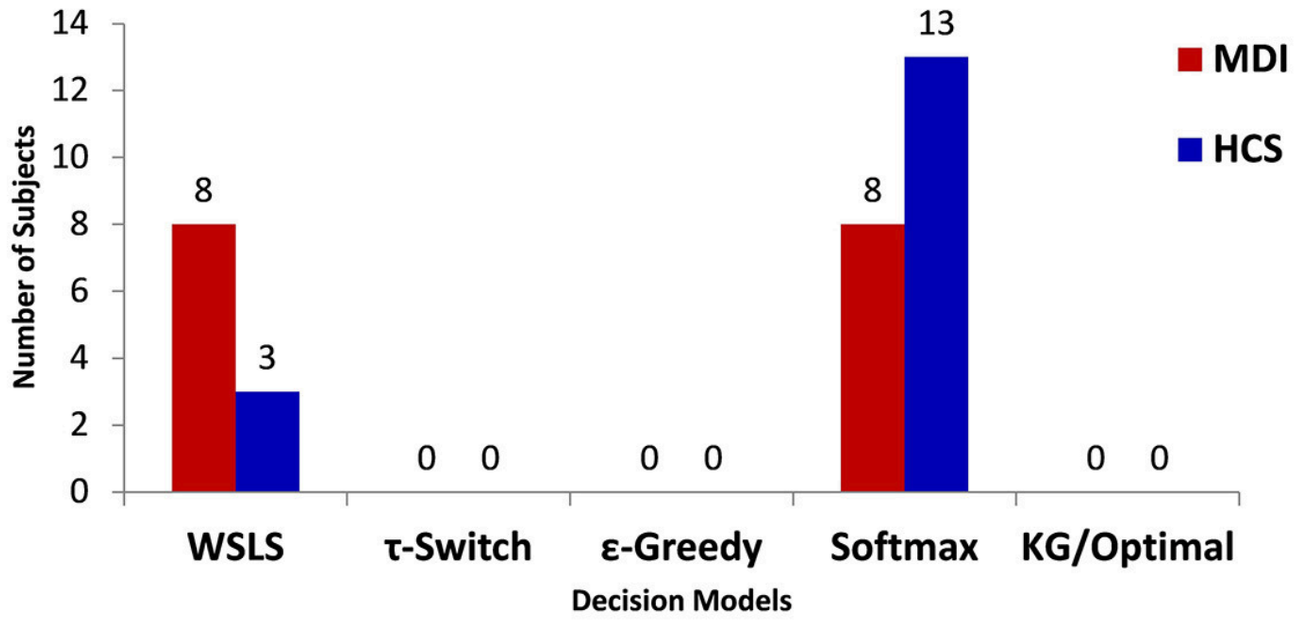

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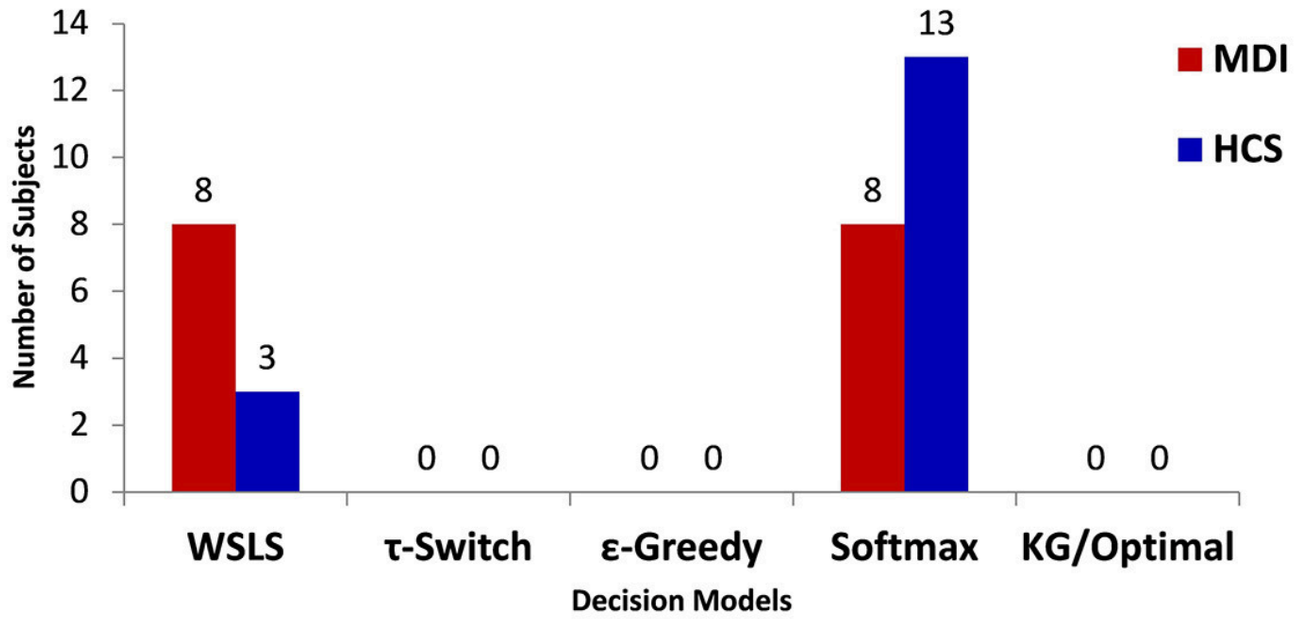

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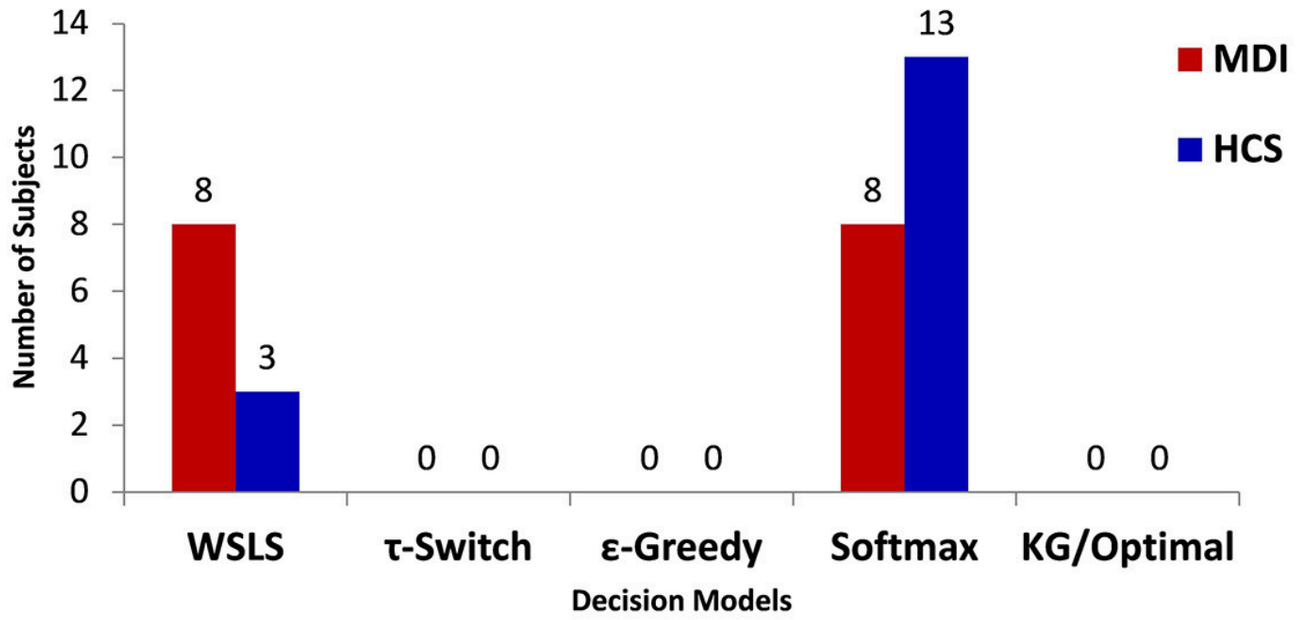

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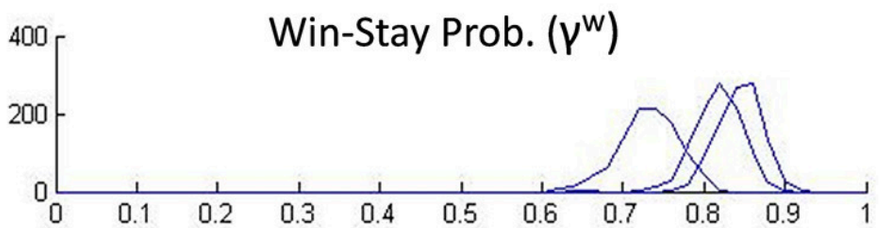

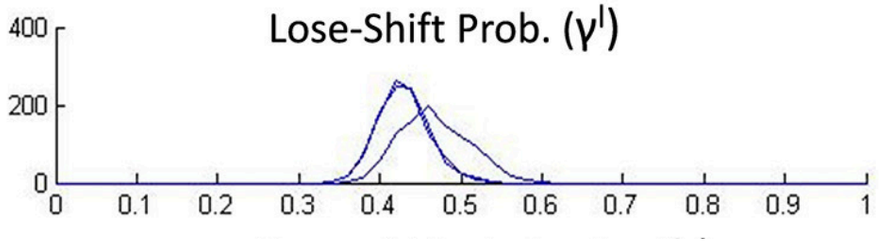

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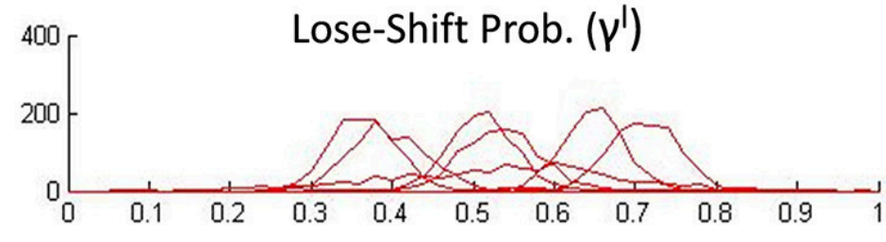

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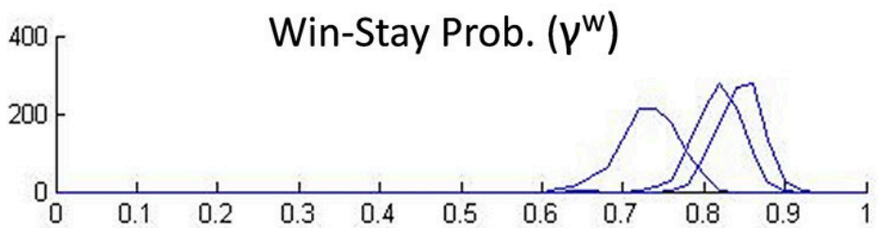

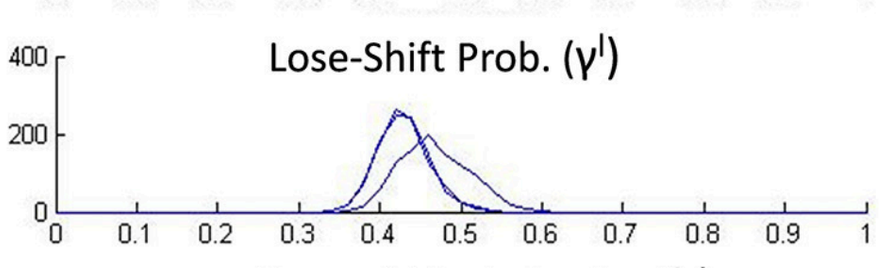

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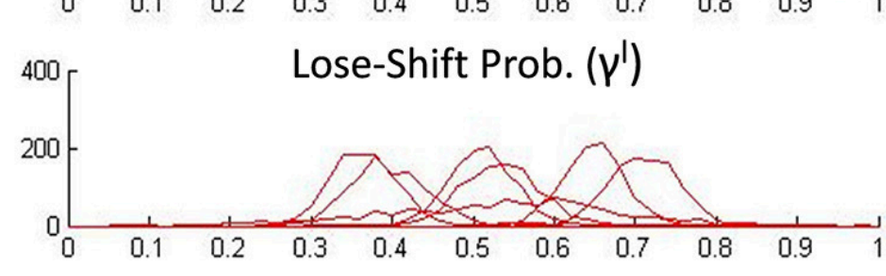

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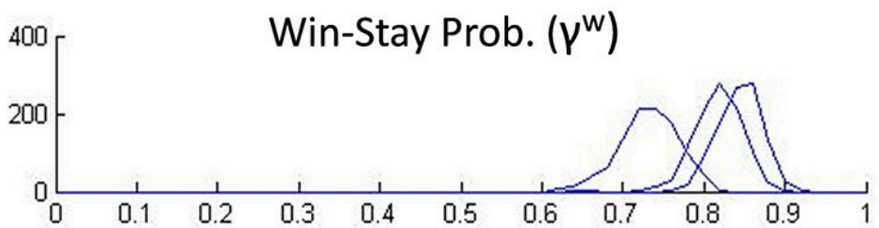

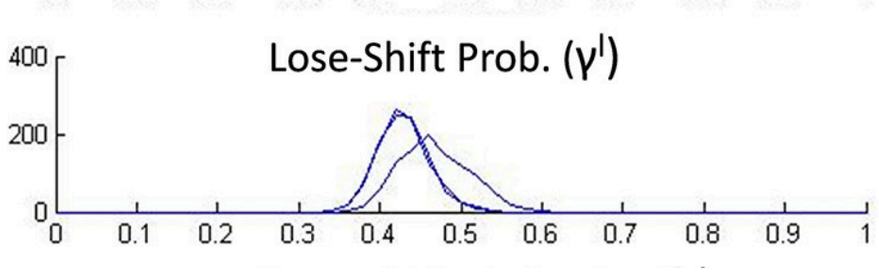

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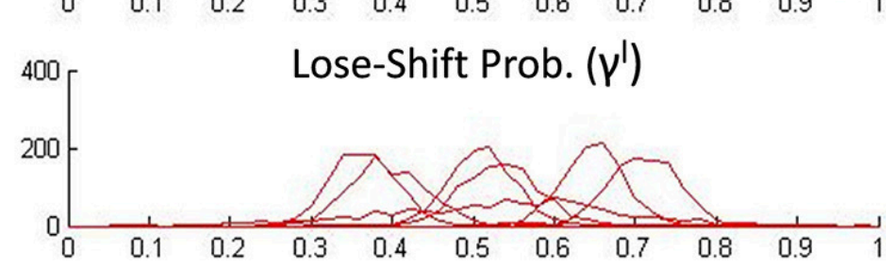

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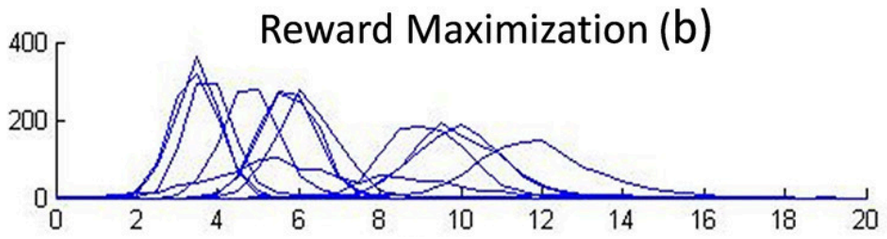

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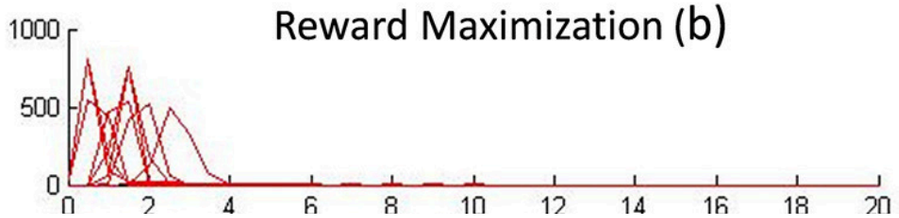

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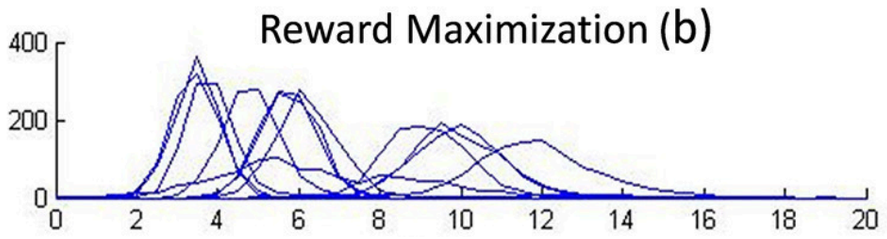

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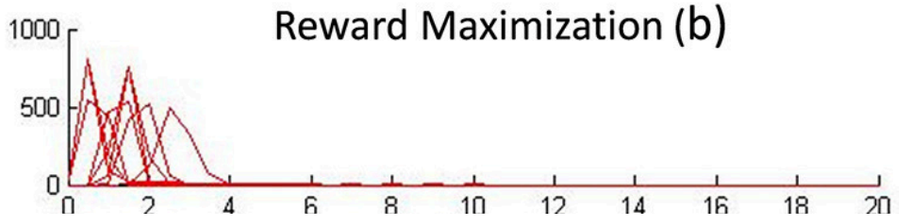

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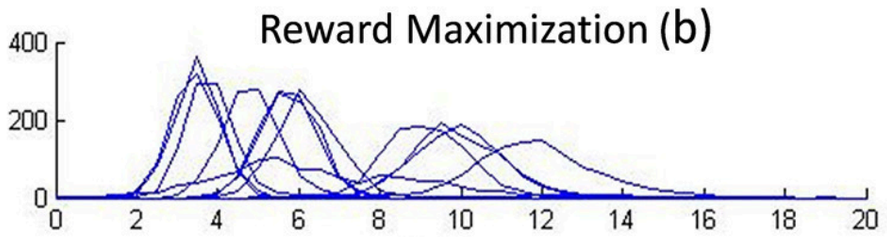

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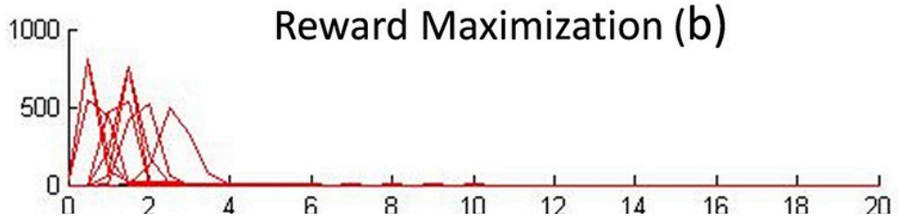

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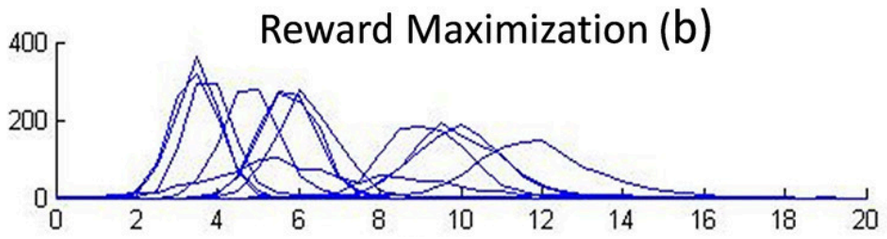

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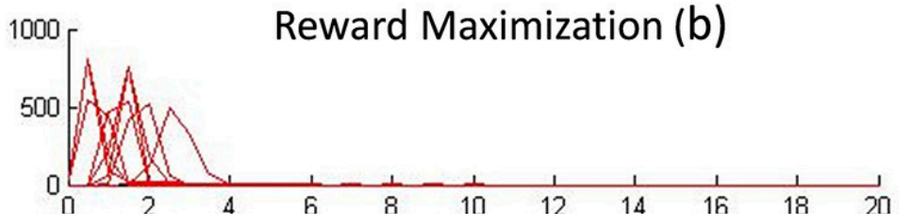

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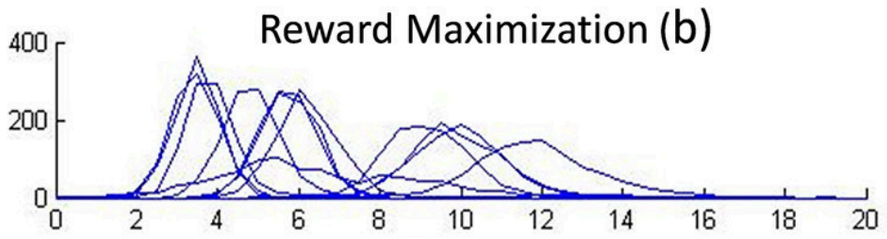

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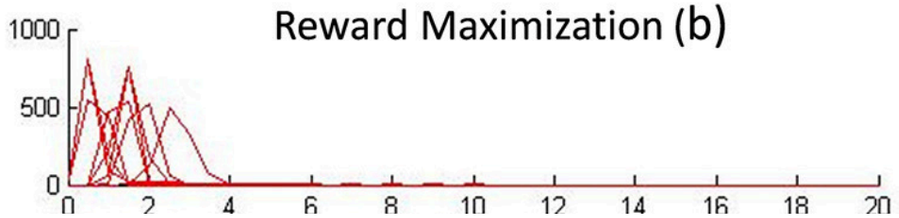

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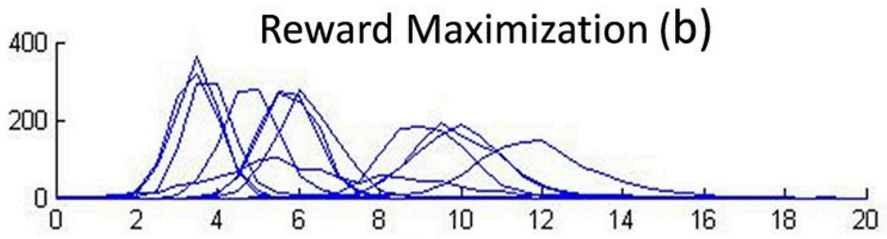

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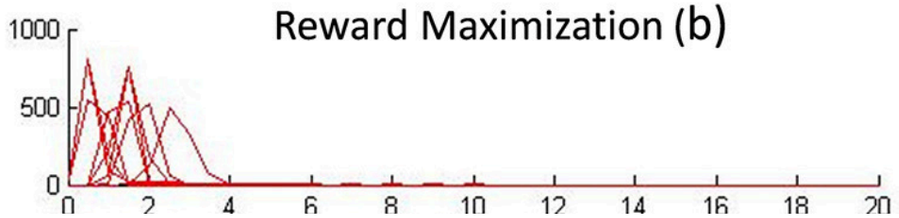

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- DL nucleus reciprocally connected to ACC (expectancy violation & change detection, Ide et al, 2013)

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- Future direction: non-stationary task environments, e.g. change points

Outline

- Computational modeling
- **Applications to psychiatry**
  - Addiction
  - **Depression/anxiety**
- Discussion

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(Harlé, Guo, Zhang, Paulus, Yu, *PLOS One*, 2017)

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  - Among “softmax subjects", higher anhedonia ⇒ less likely to choose more rewarding option; but since only 2 options, unclear if it is more random stochasticity or some other motivational factor like novelty or uncertainty

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- May serve as a better model for identifying neural correlates and understanding the computational roles played by different brain areas

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Basic Science ⇒ Psychiatry

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- Cognitive representations and internal states, e.g. prior beliefs, uncertainty, novelty
- Better integration of results/insights from different tasks
- Better latent variables for identifying brain correlates, and thus possible targets of future clinical interventions
- Better differentiation of different psychiatric populations

Psychiatry ⇒ Basic Science

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- Internal "knobs" that can be tuned too far one way or the other, e.g. prior belief about unchosen options
- New brain areas that deserve a closer look, e.g. what does the thalamic LD nucleus do?!

Acknowledgment

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- **Yu Lab**
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  - Modeling/data analysis: Dalin Guo, Shunan Zhang, Chaitanya Ryali, Corey Zhou, Zoe He

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- **Funding**
  - CRCNS (NSF BCS, NIH NIDA), ARL, MURI, UCSD

Openings: Postdoc, PhD

AJYU@UCSD.EDU

Questions?

Learning & DM under Uncertainty

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- Exact reward distribution of options unknown, but can learn from experience, and may have general info about "environment"

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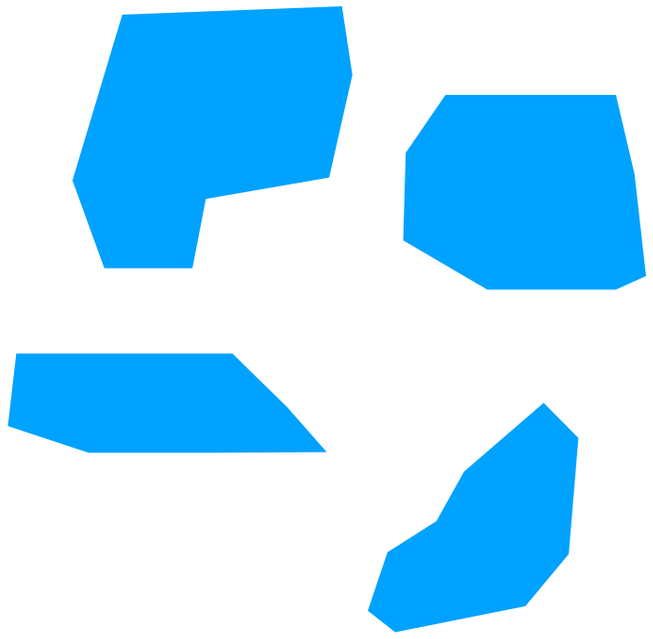
  - characterize human learning & decision processes
  - understand provenance & consequence of these processes

Cover Story: Ice fishing Game



4 environments

(4 lakes)

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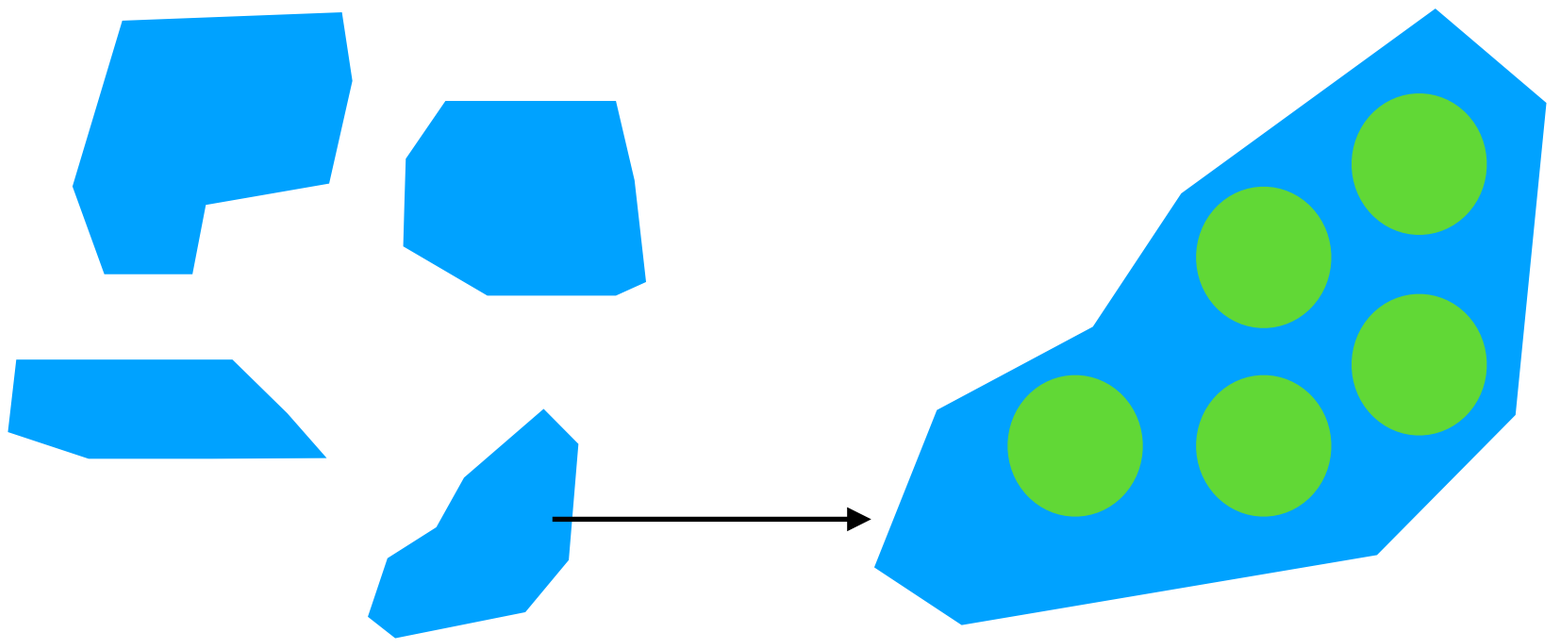

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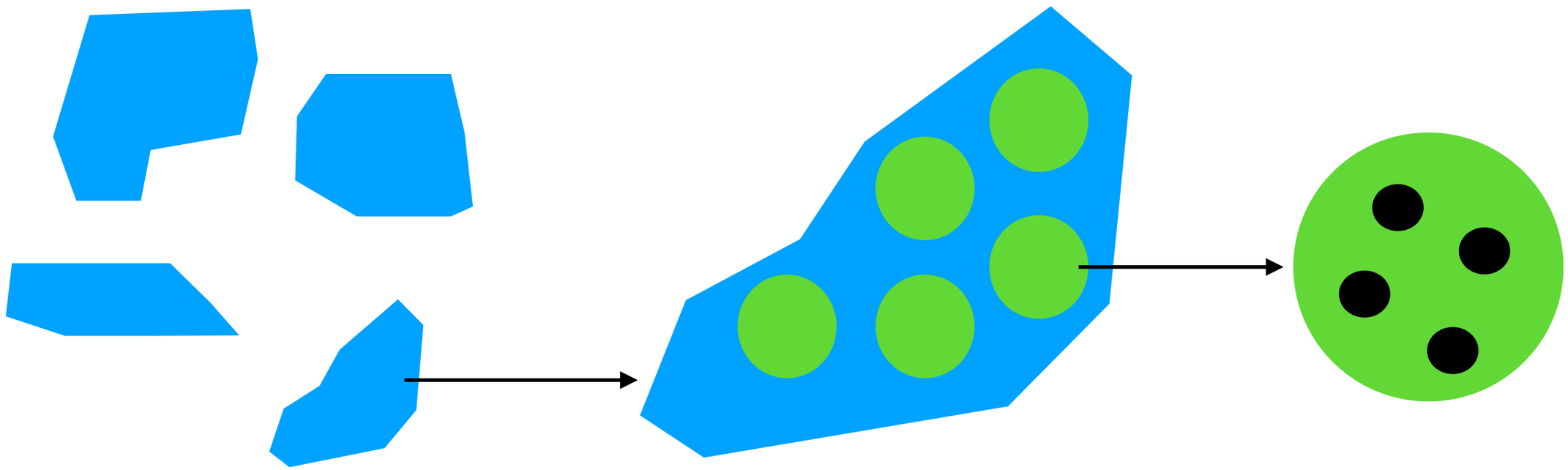

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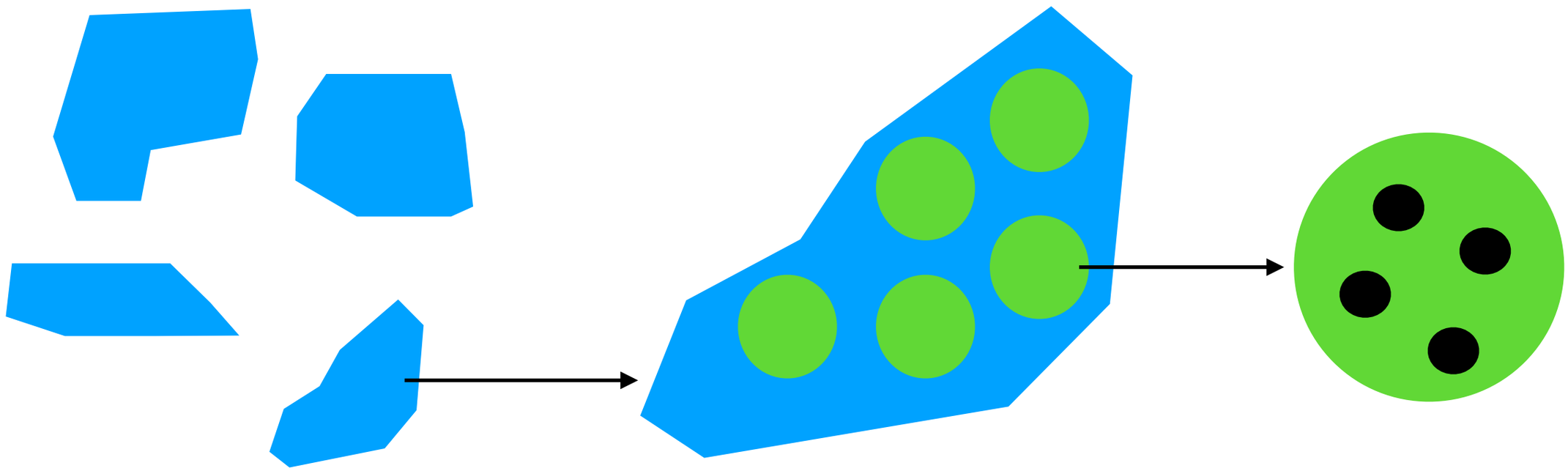

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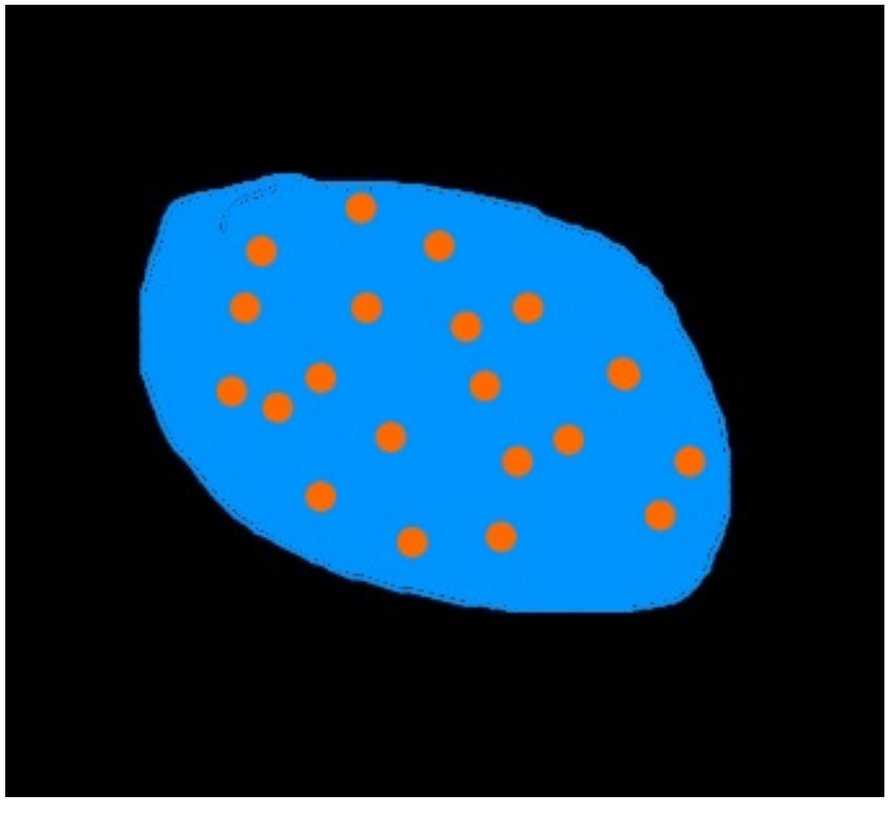
The 4 lakes differ in

- Overall abundance of fish
- Variability of abundance across holes within each lake

Prior Info: Fishing Report



Exploratory fishing report of 20 exploratory holes				
5	7	5	7	7
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High abundance, low variance

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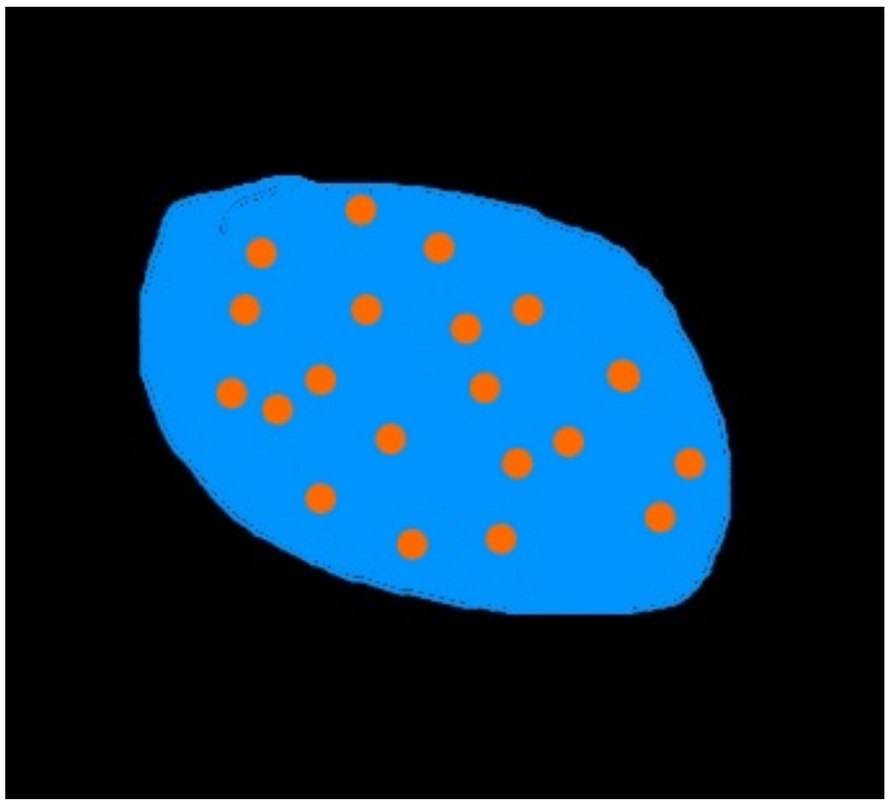

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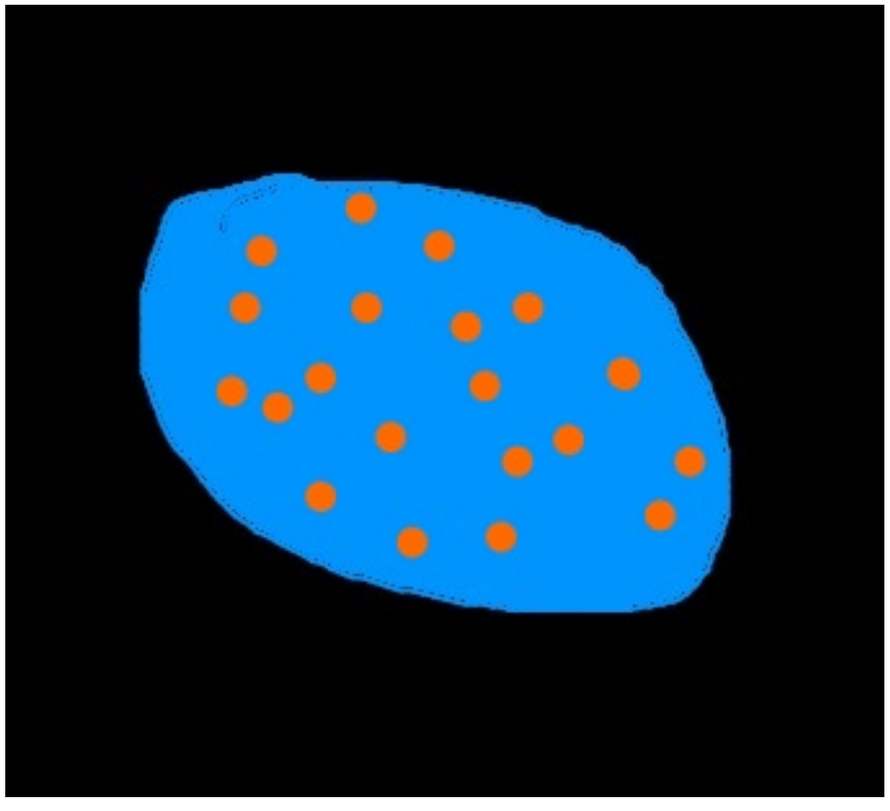

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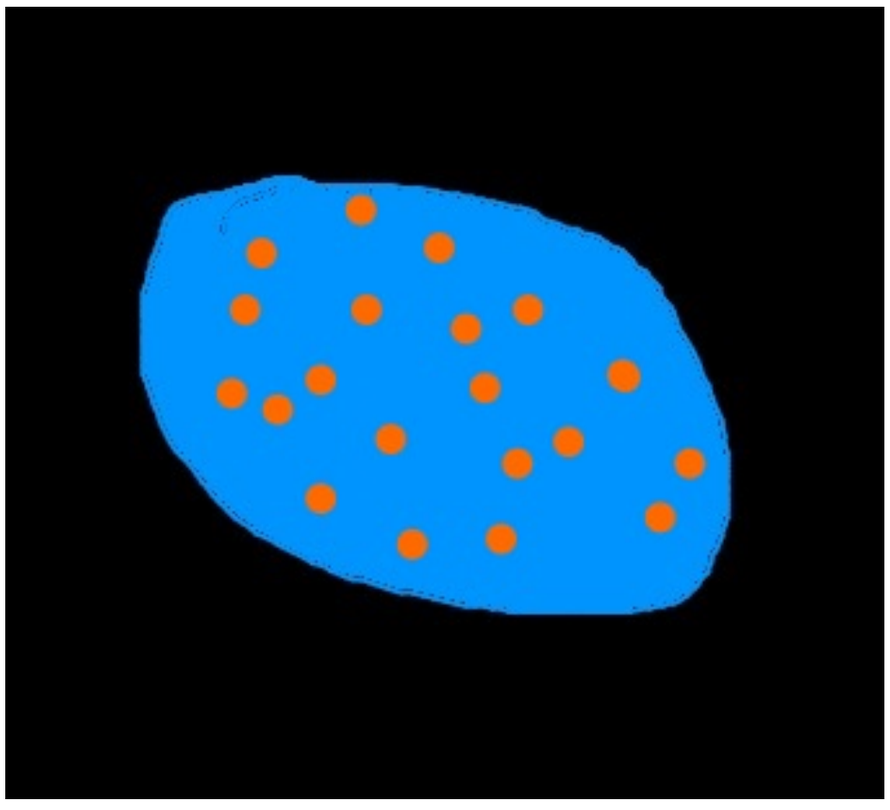
- Number: **# fish caught out of 10 attempts**



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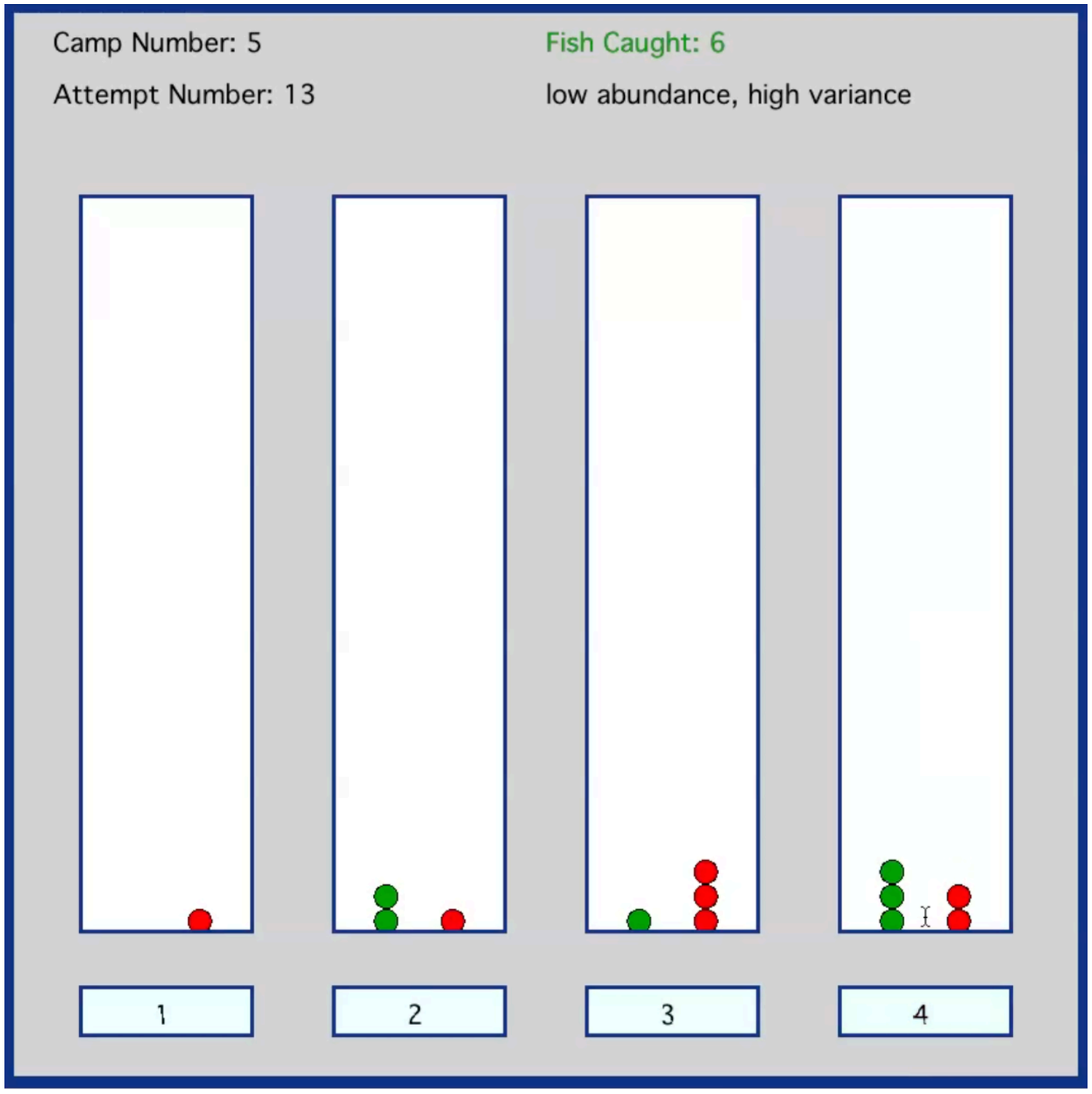

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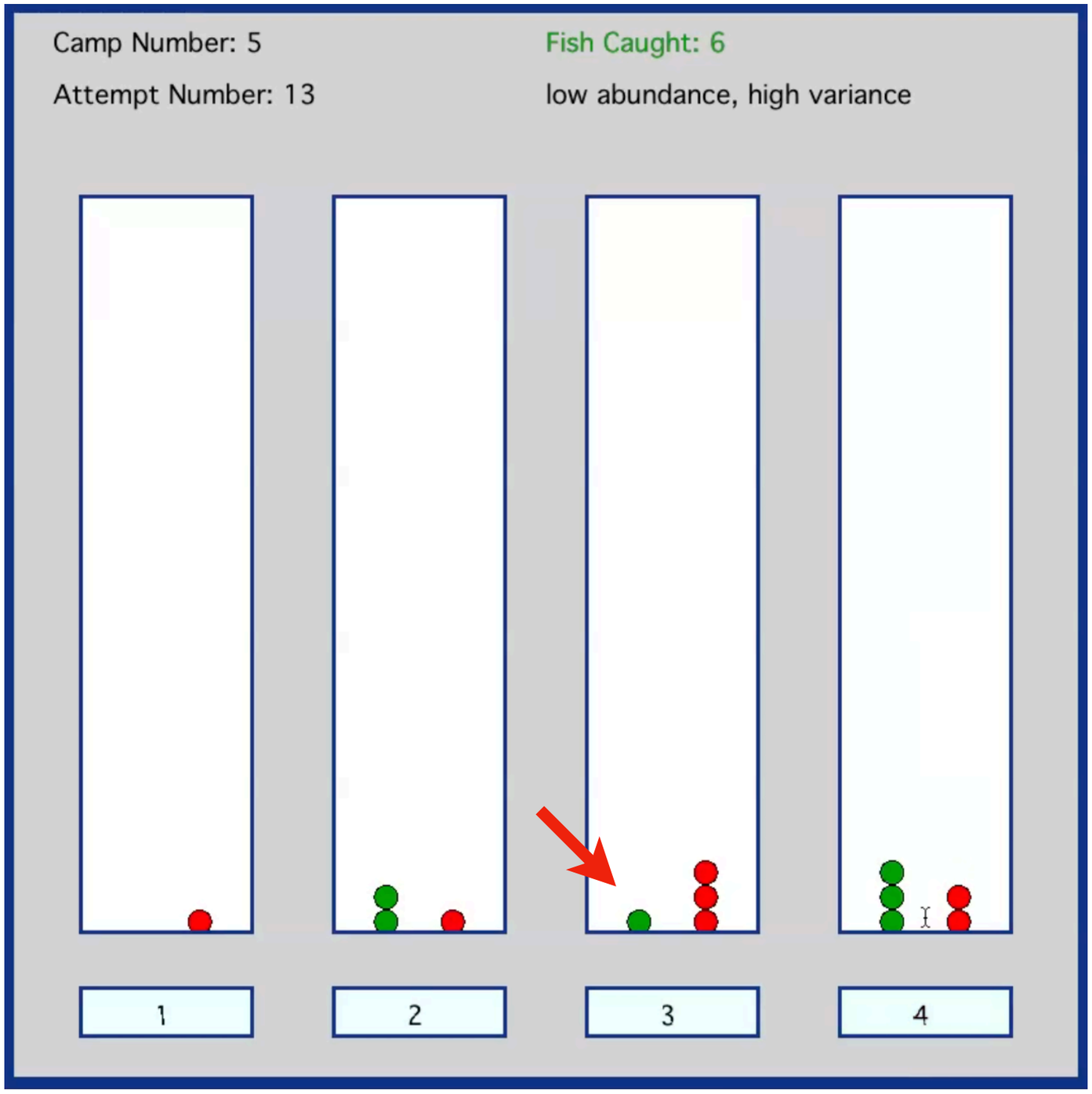

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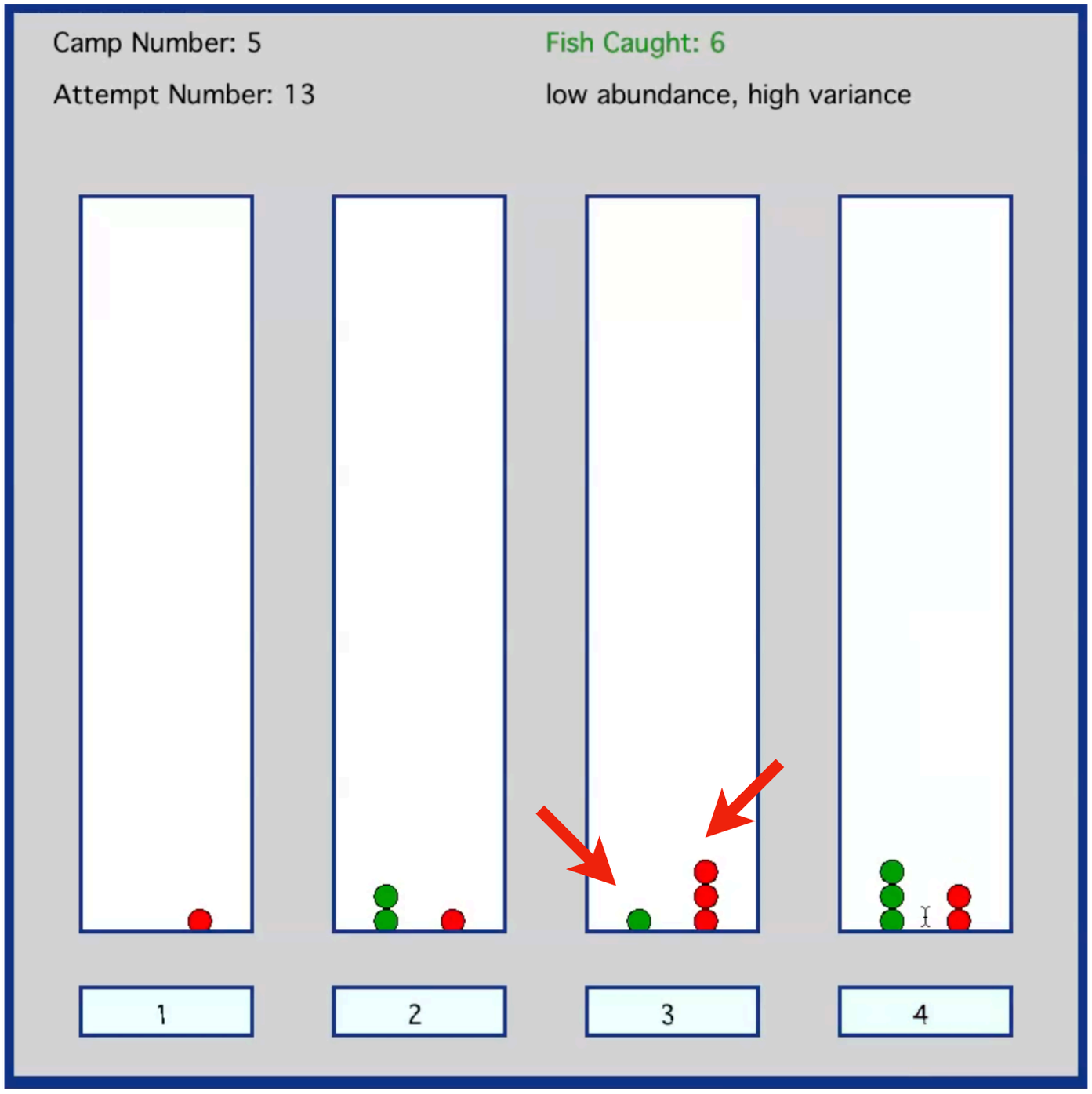

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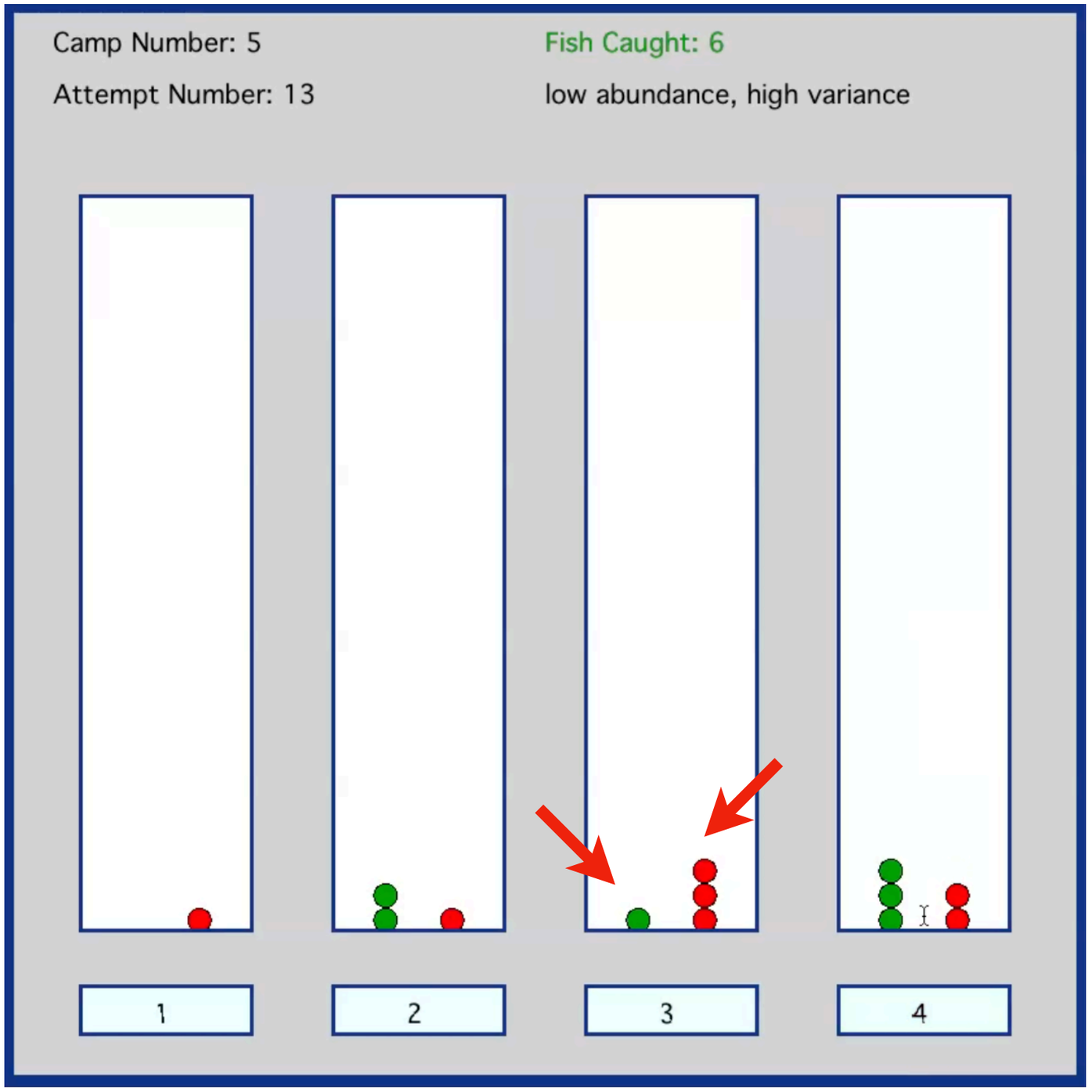

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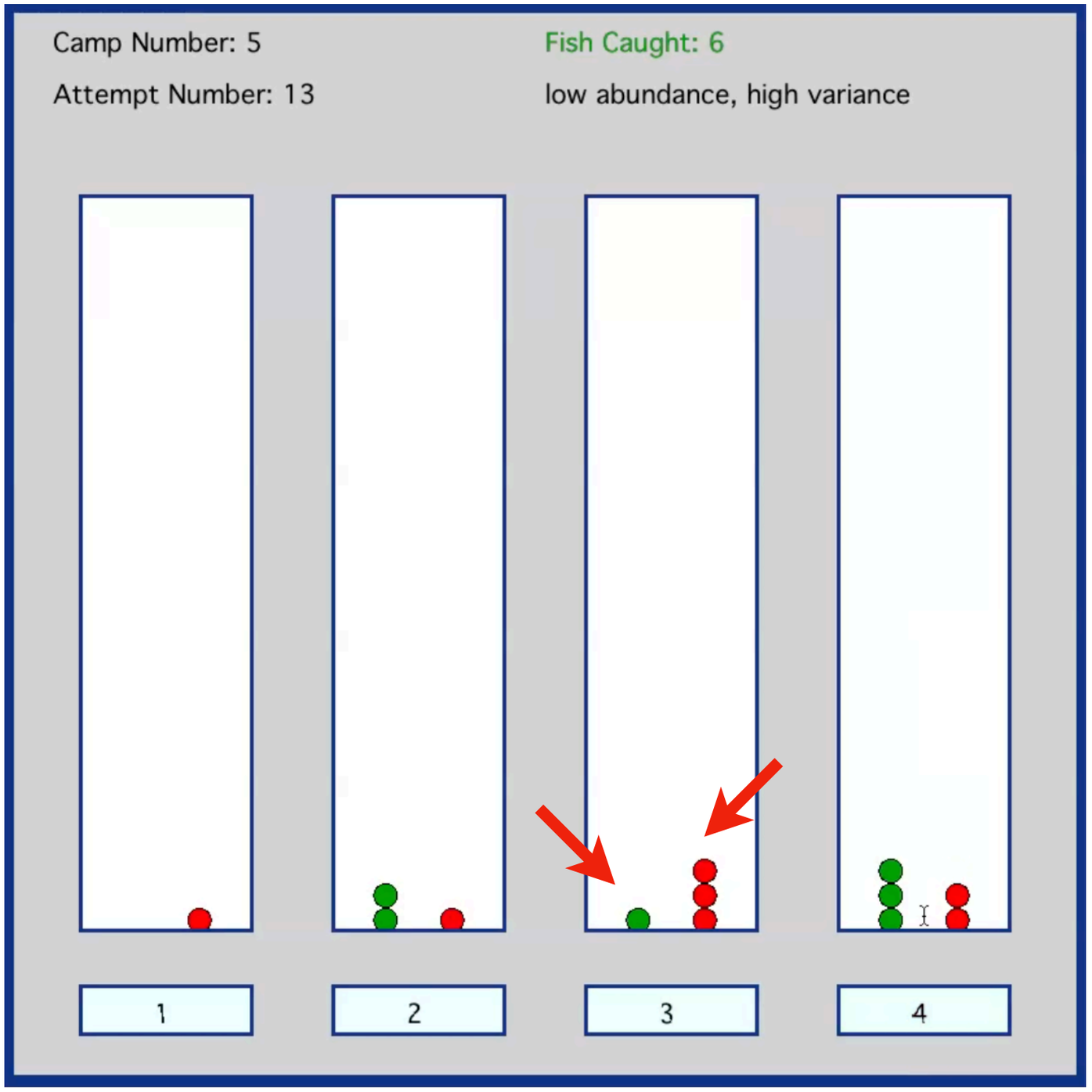

- green: reward
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- also info about environment & attempt #
- visual display minimizes working memory demands/variability

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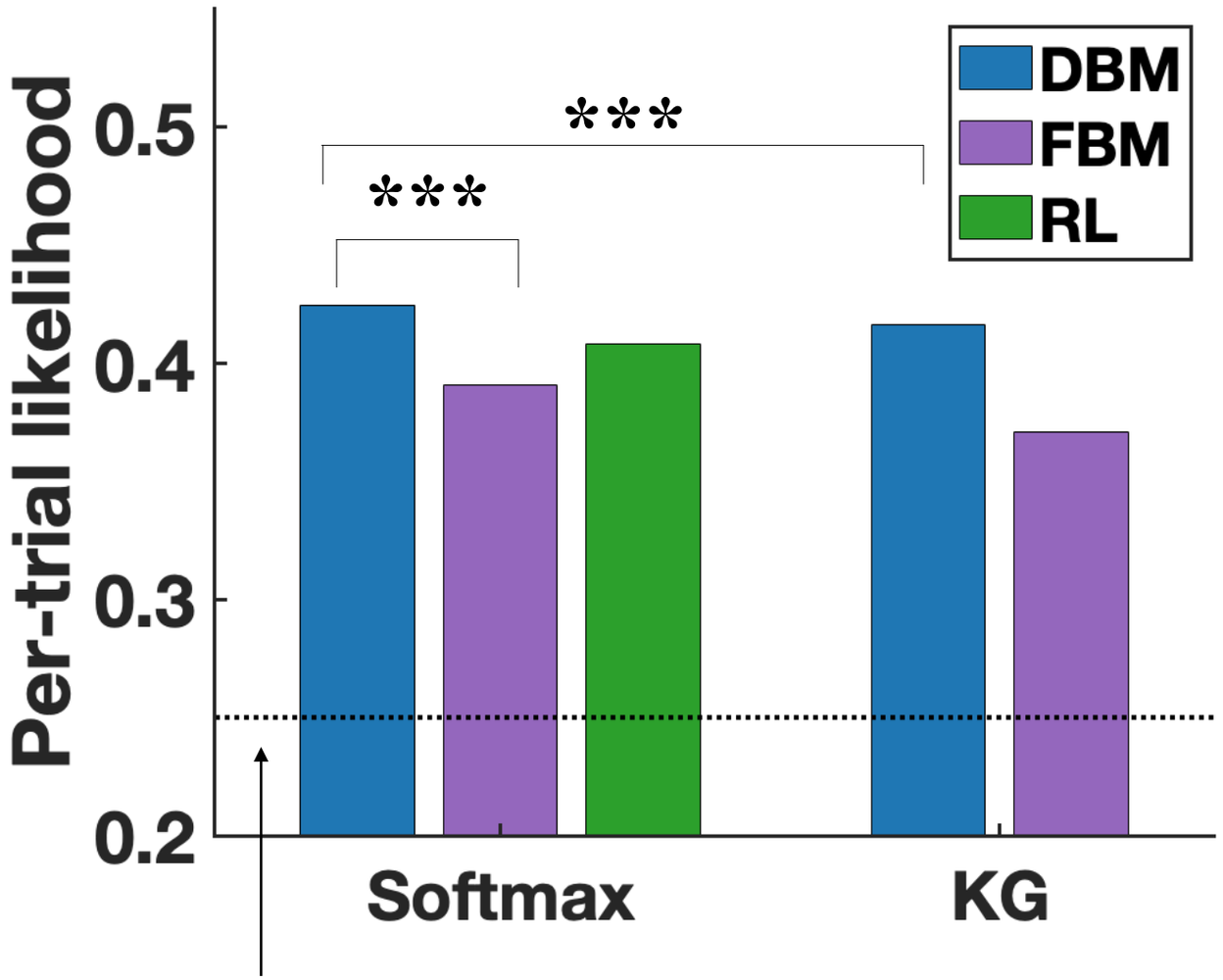
- expected reward = prior mean, e.g. 2/3, 1/3

Decision Model: Knowledge Gradient (KG)

- An **approximation** to the optimal policy *(Ryzhov et al., 2012)*
- Computationally cheaper than the optimal policy
- **Myopic**: when computing the knowledge gain, it commits to one more exploratory decision, and assumes to exploit in all remaining trials
- Decision rule: **current estimated reward rate** + **knowledge gain * horizon** (how many trials left)

Model Comparison



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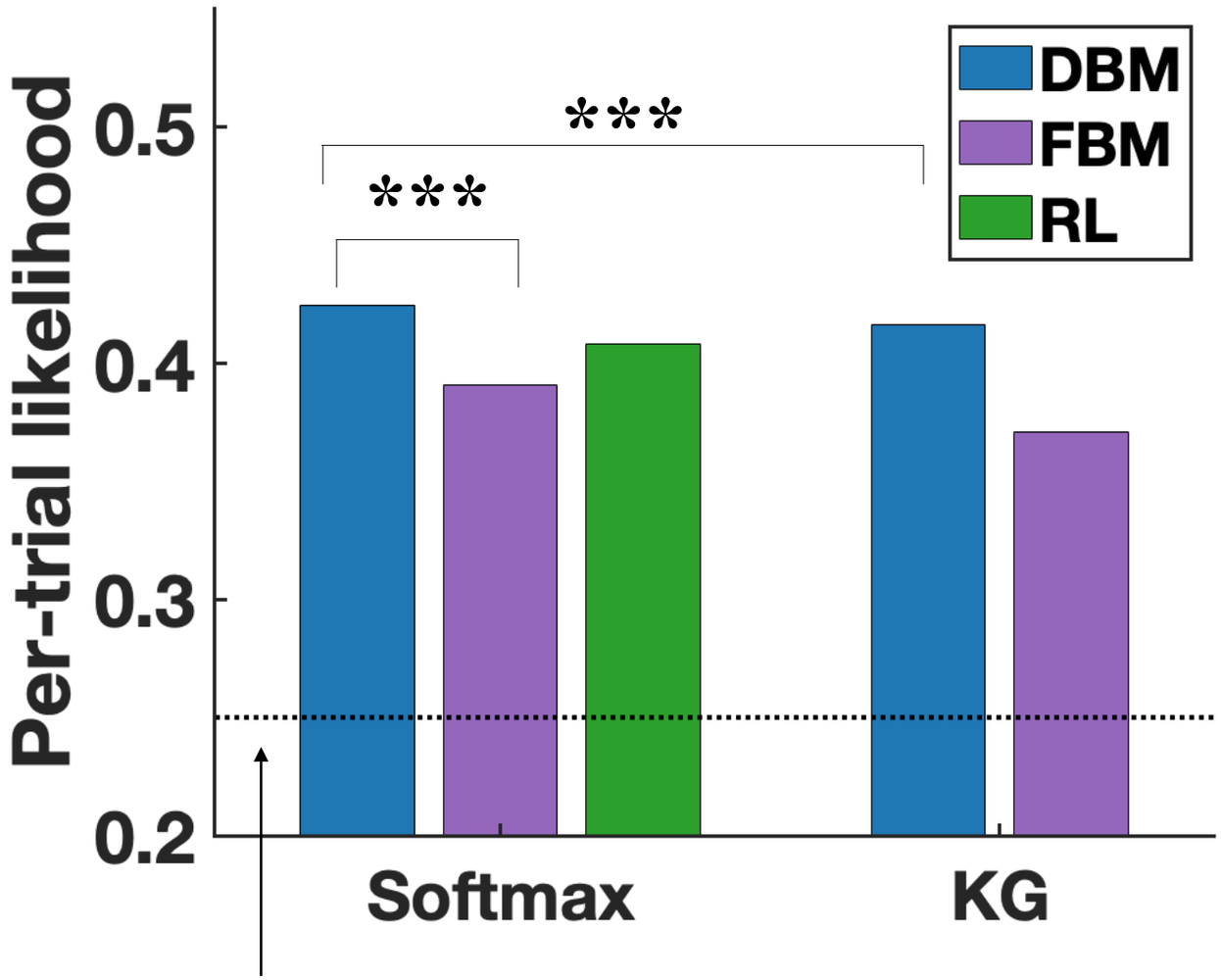

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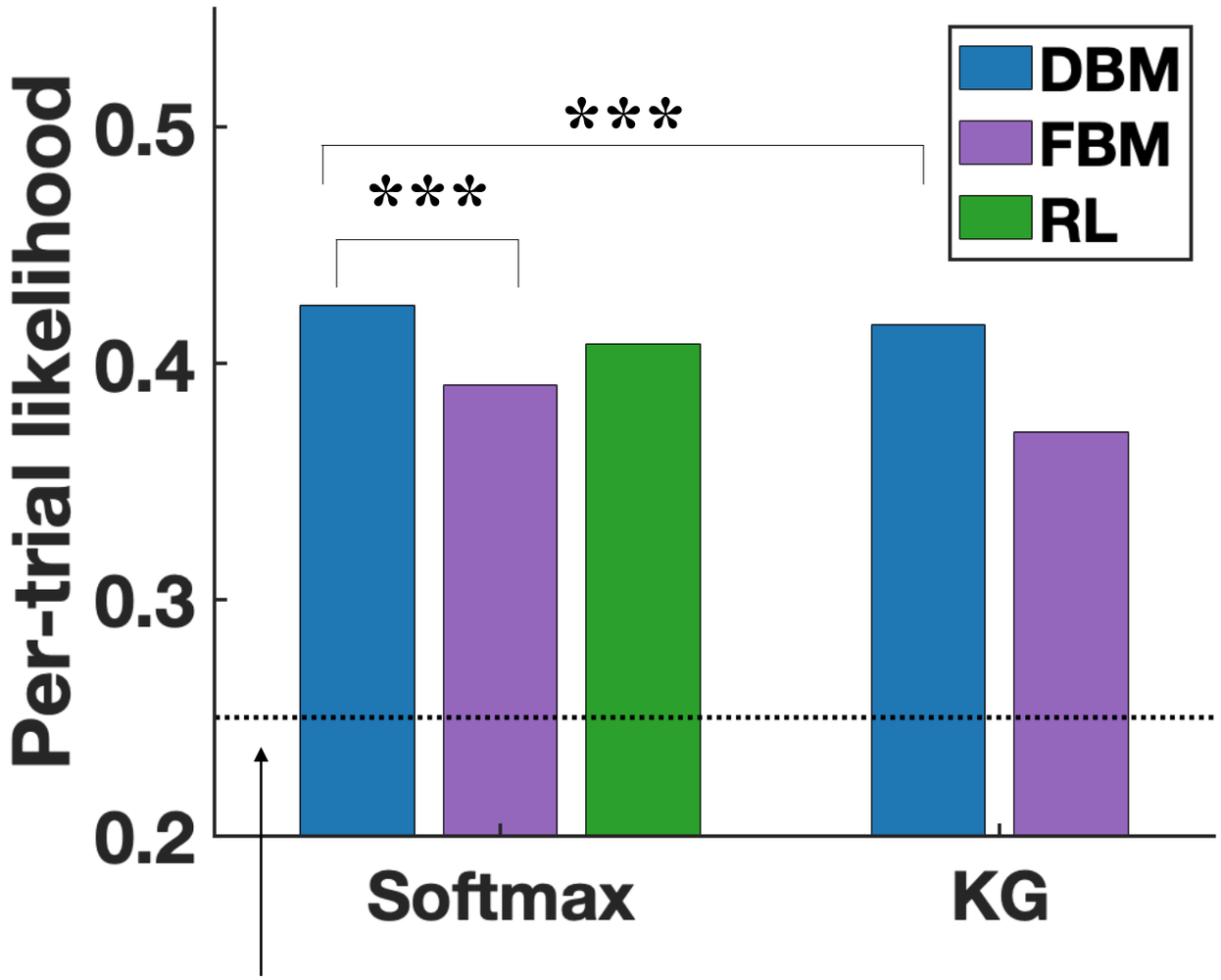

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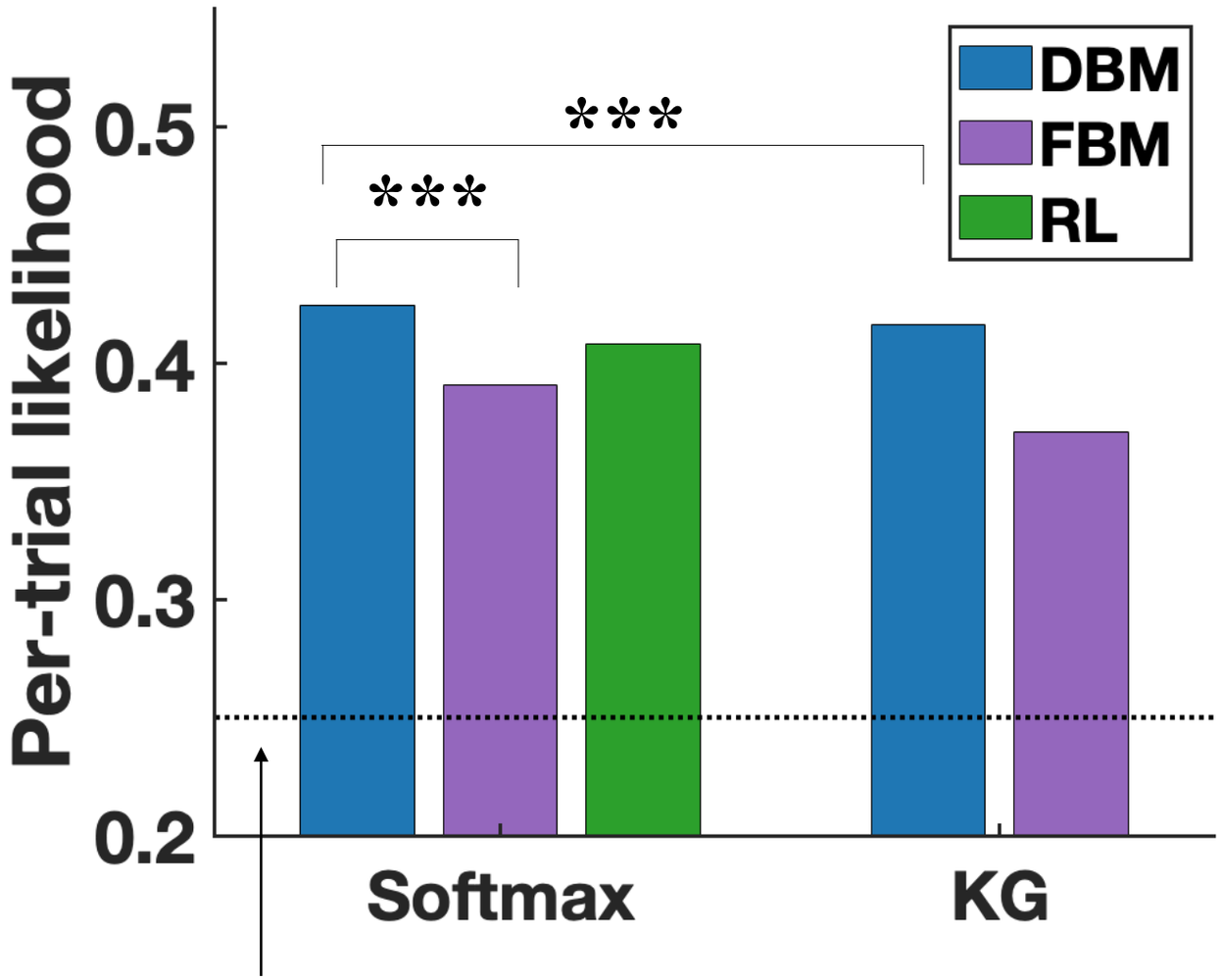

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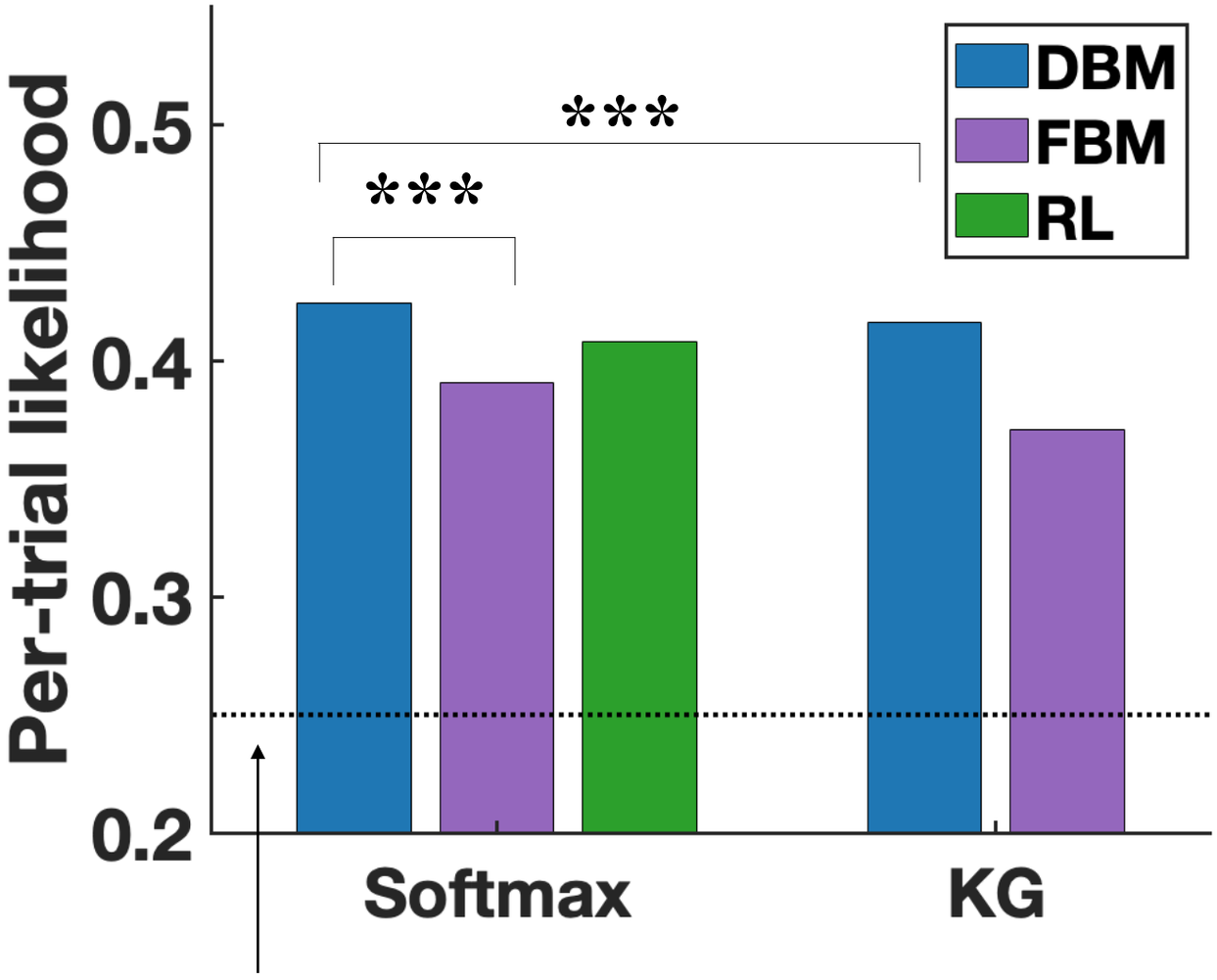

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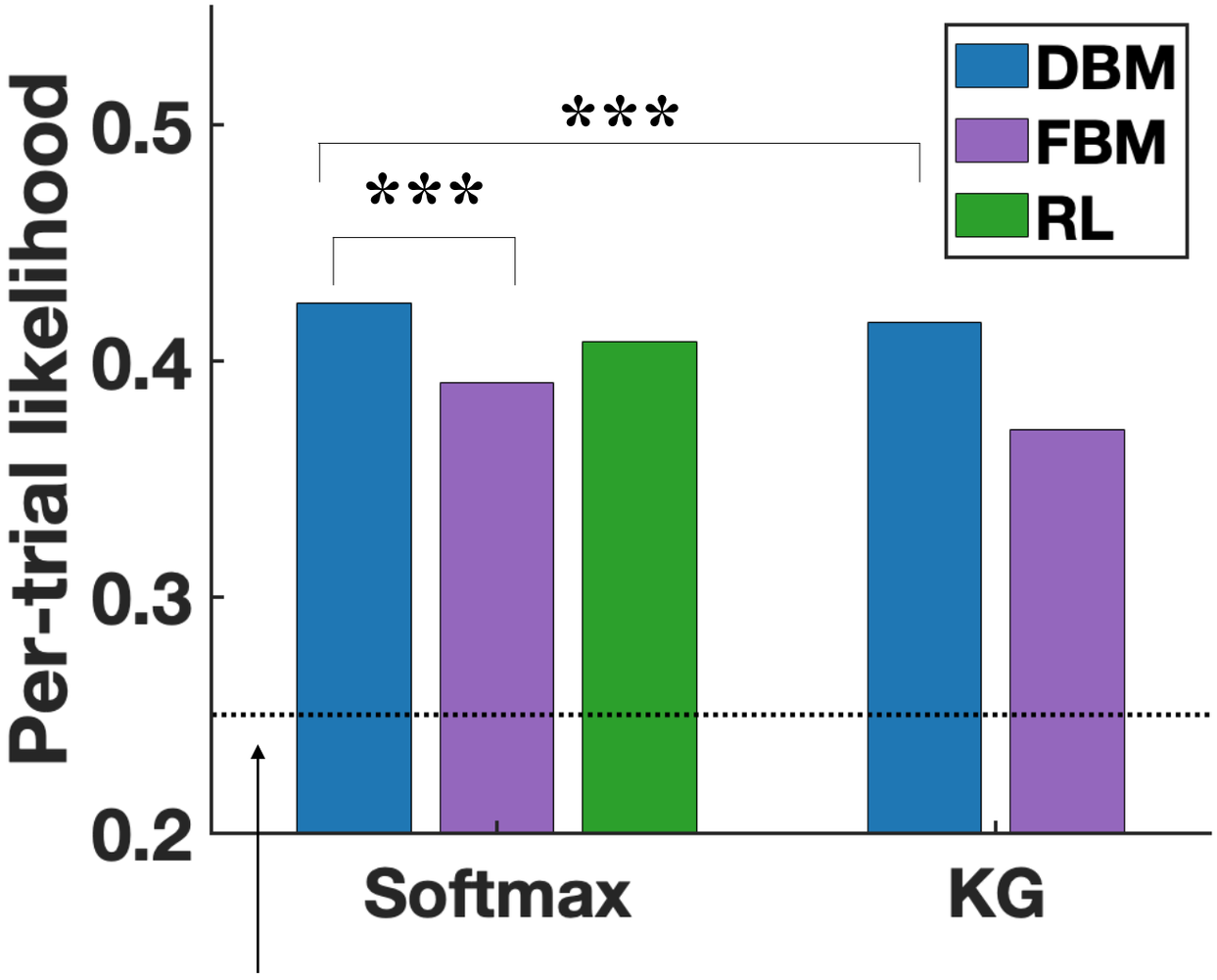

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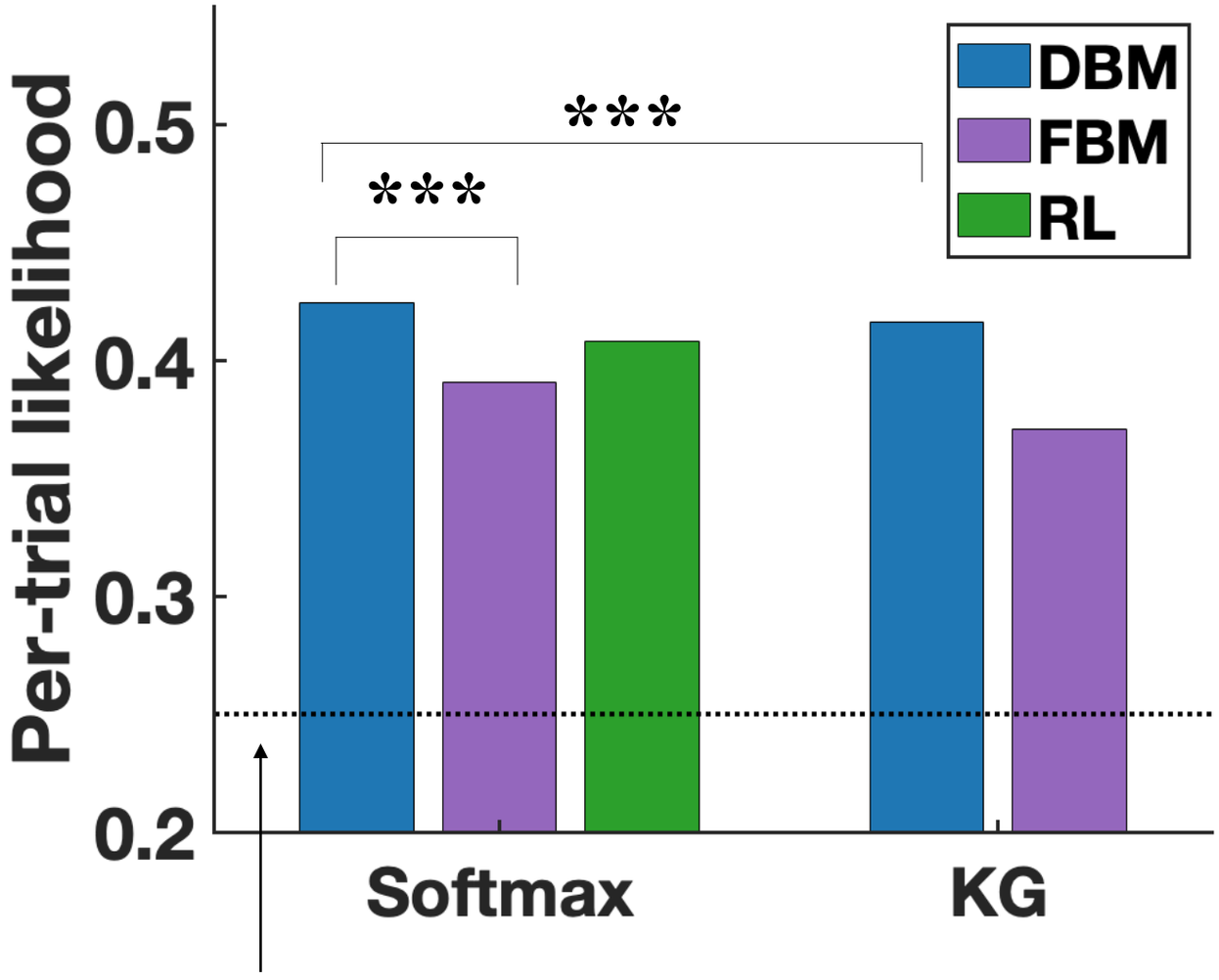

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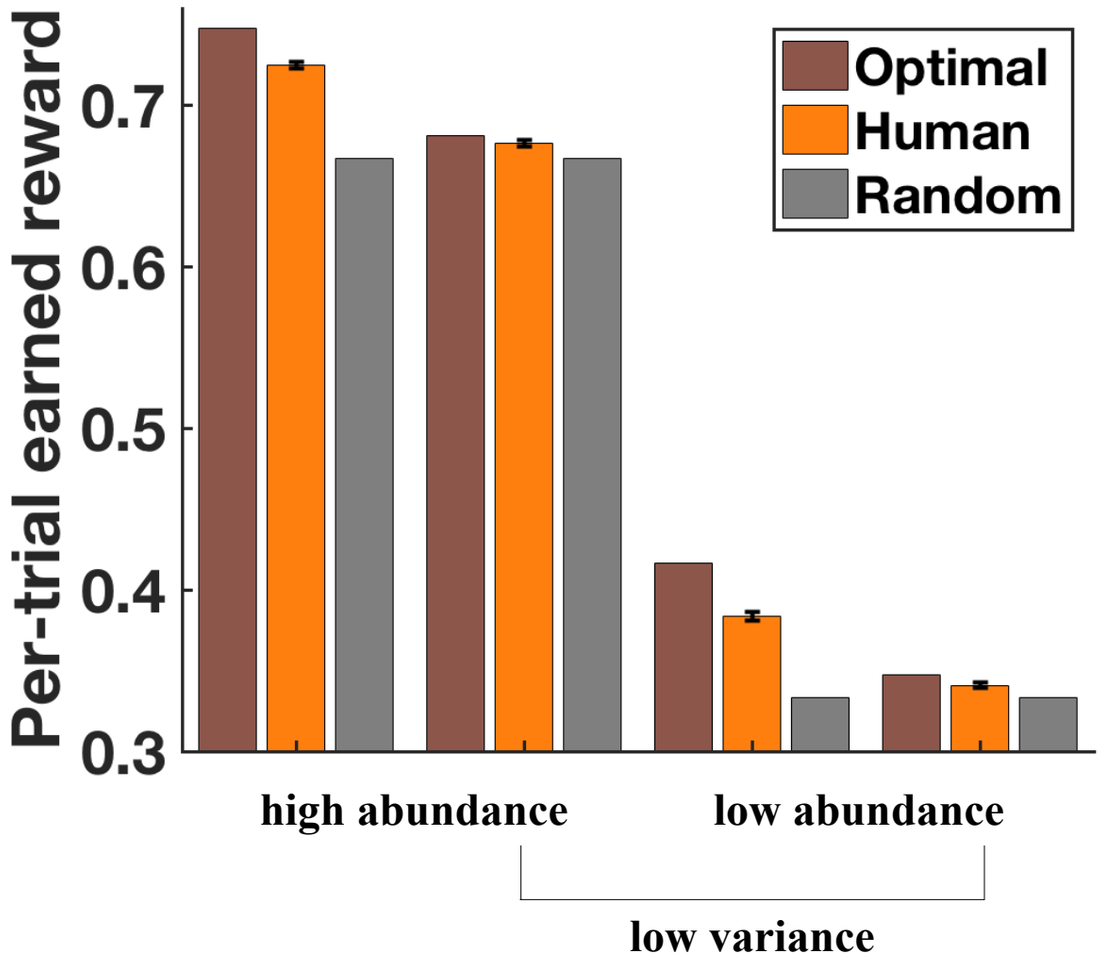
Human Comparison to Baselines

Performance: average reward per trial



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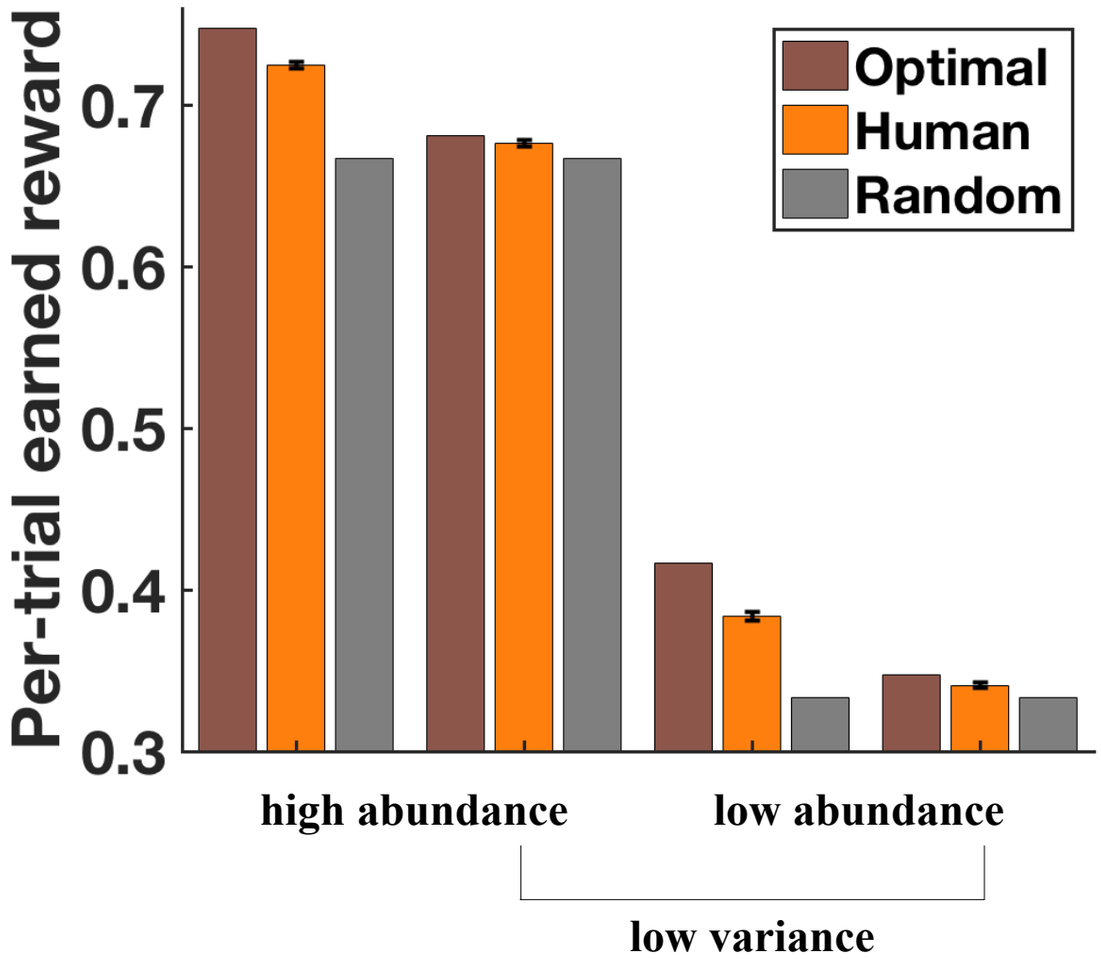

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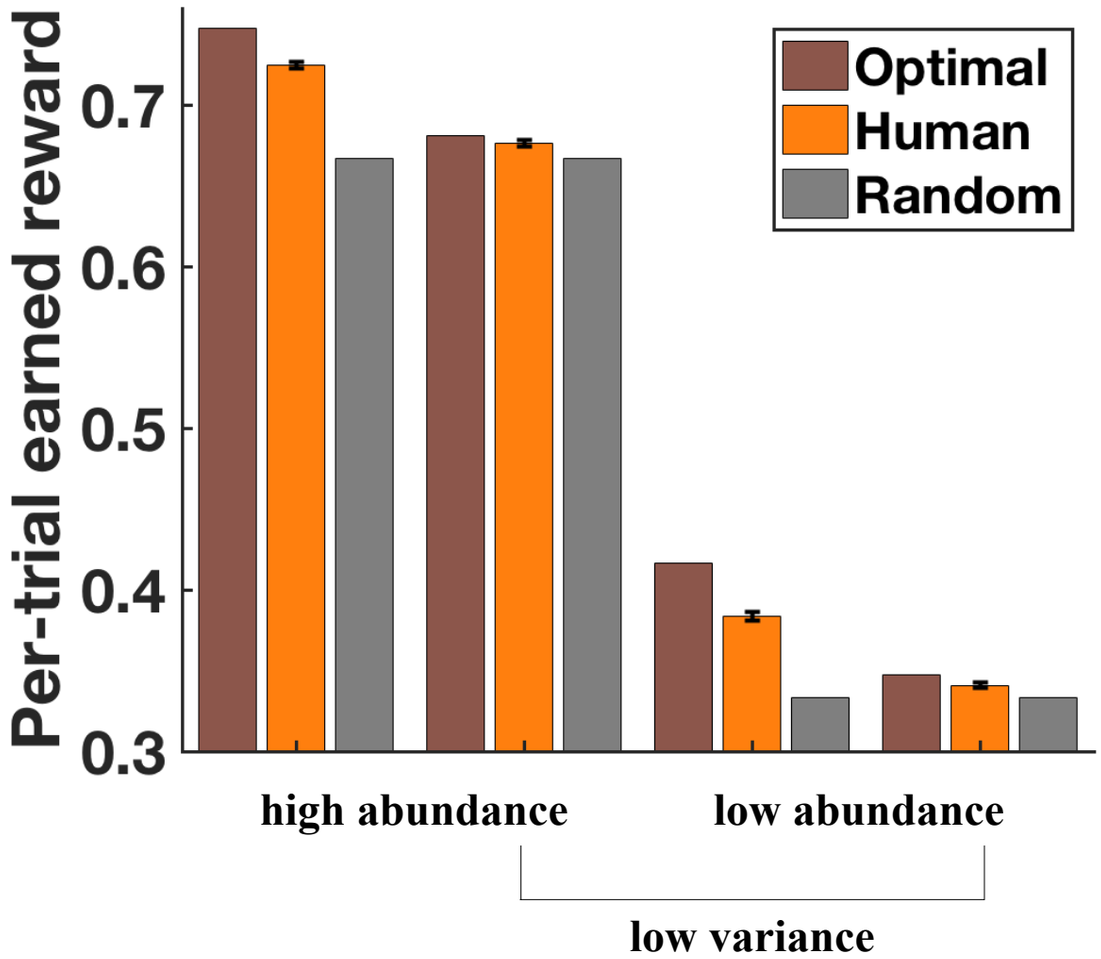

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- Biased E[reward] even more mysterious: experienced average reward > true prior mean

Nearly Optimal: Knowledge Gradient (KG)

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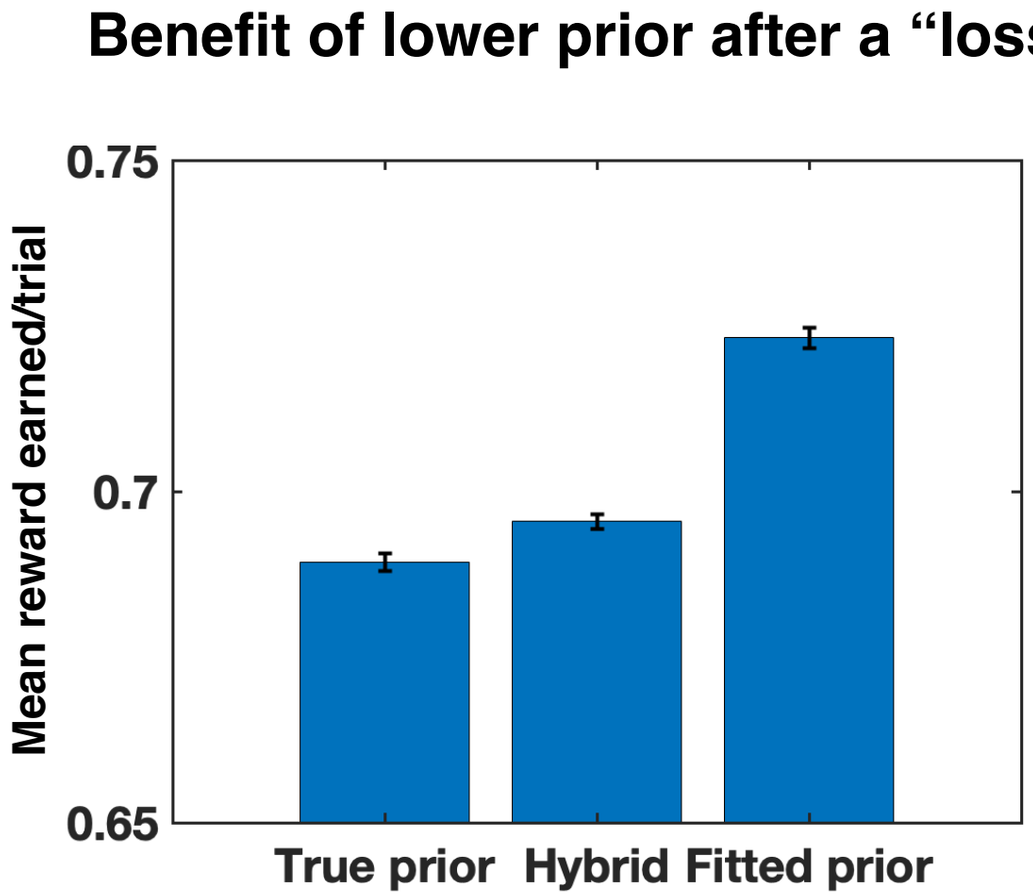
- Captures different aspects of human behavior than softmax

Simulation: Lower Prior Post-Loss Helps a Bit



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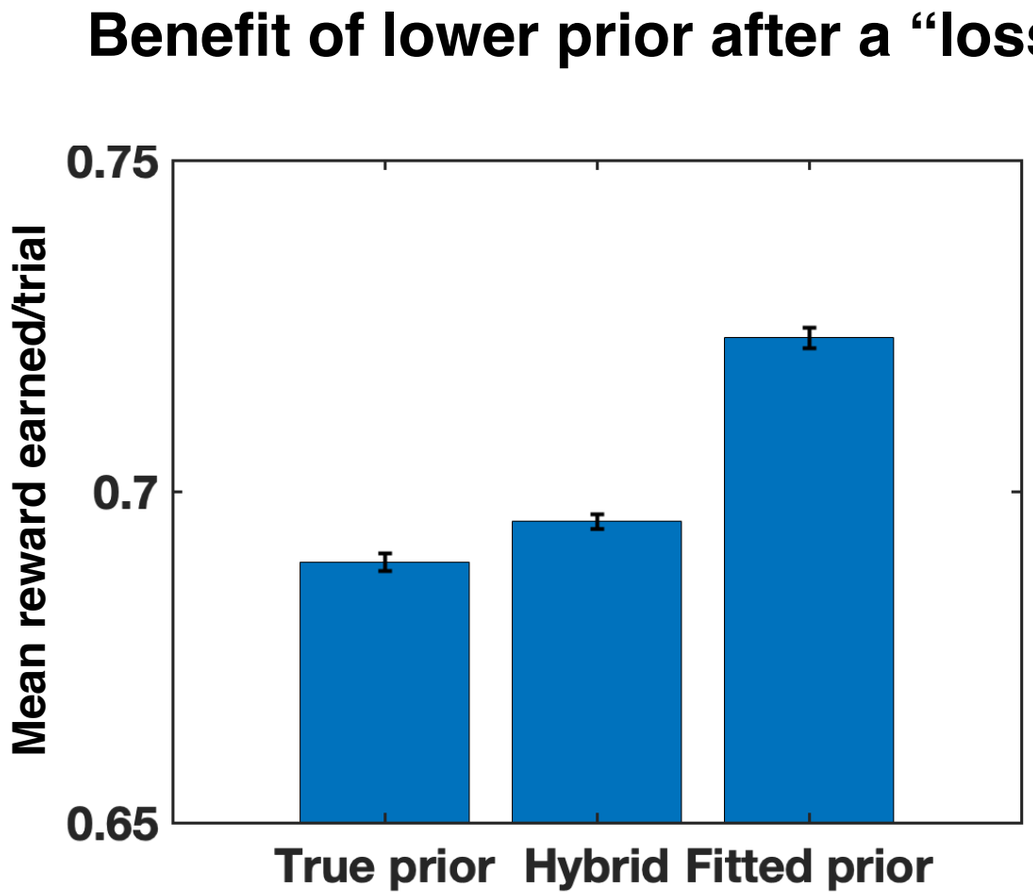

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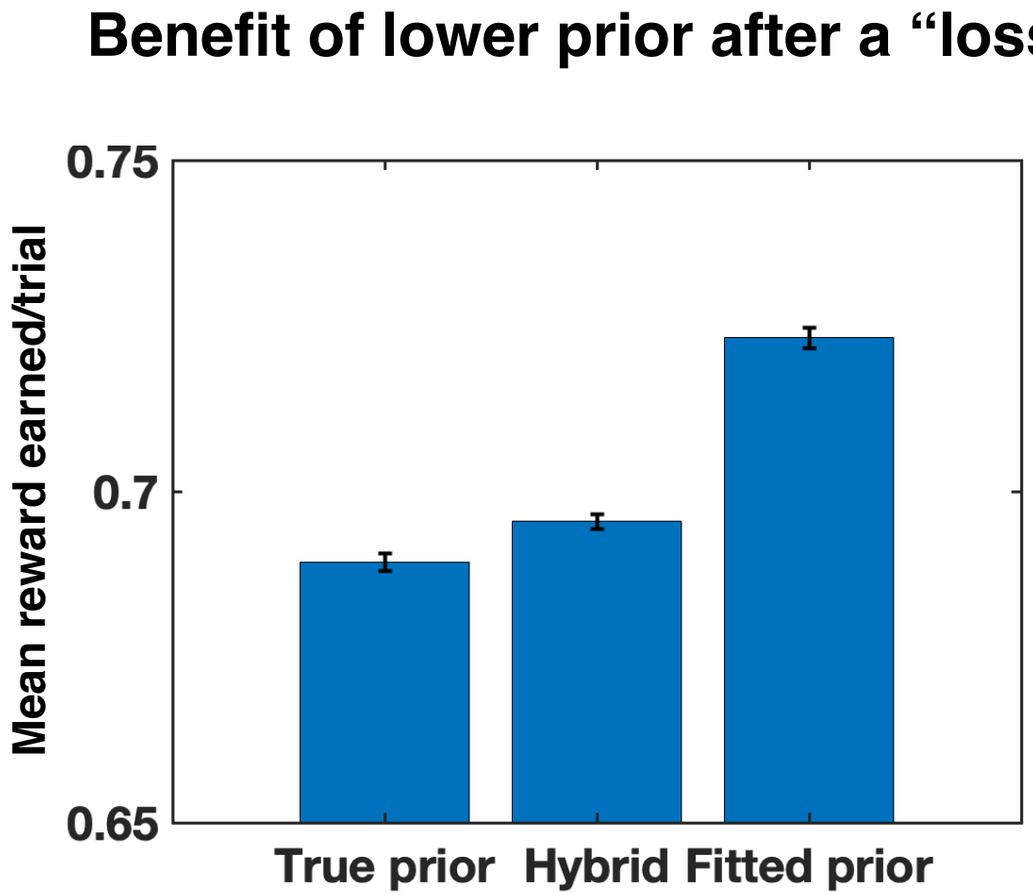

- Fitted prior (θ_0= .35) earns more reward than true prior (θ_0=.67)
- Hybrid model (replacing true prior with fitted prior after each **loss**) captures **some** of the benefit

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- pbRL has simply leaky integrating dynamics (neurally plausible)

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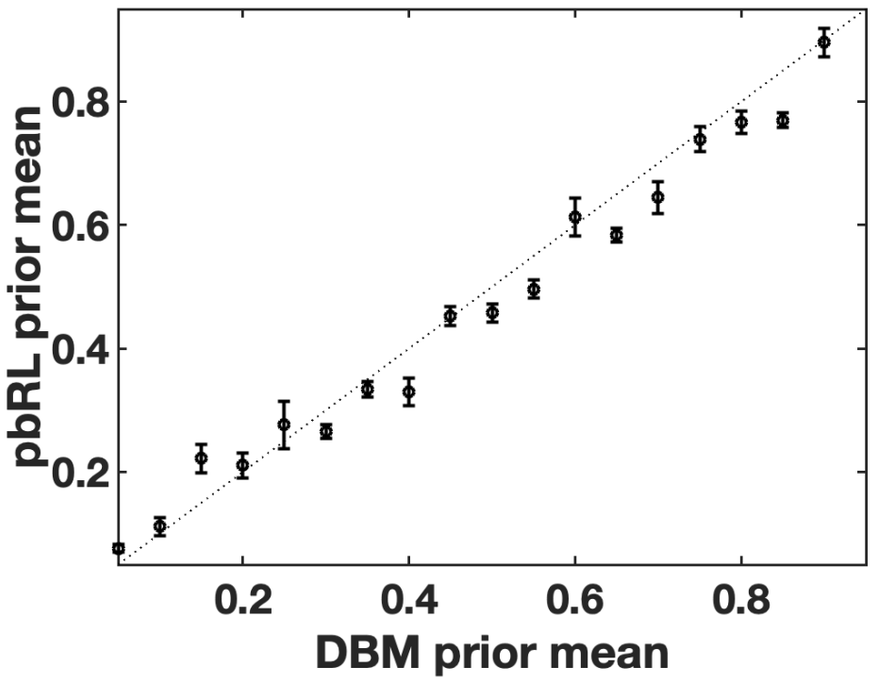
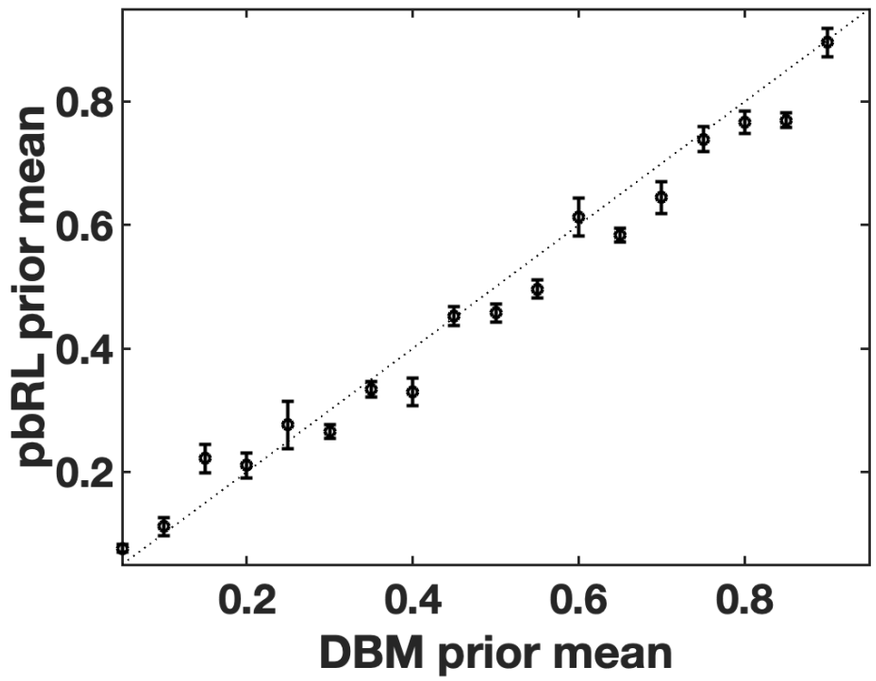
Estimation of *α*



Estimation of prior mean



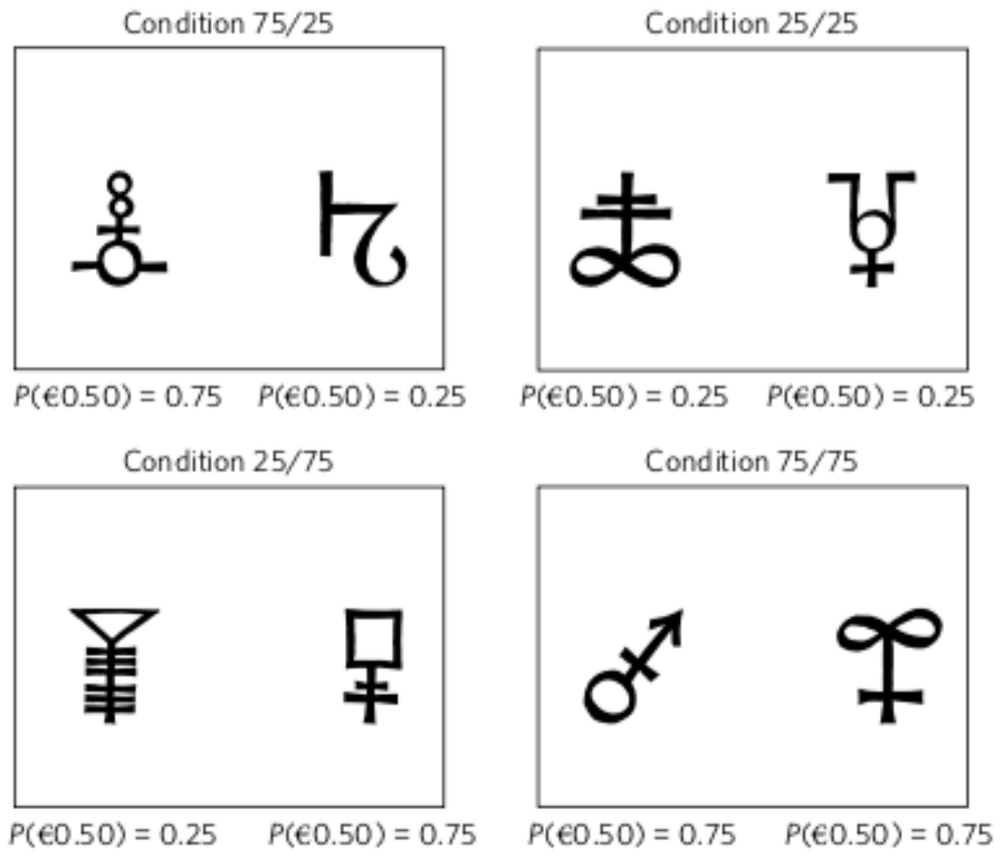
$$\hat{\theta}_k^t = a + b\hat{\theta}_k^{t-1} + cR_t$$

- pbRL has simply leaky integrating dynamics (neurally plausible)
- Proven equivalence between DBM and pbRL makes it possible to fit pbRL directly and statistically interpret parameters
- Validated on our dataset ⇒ normative (statistical) grounding of RL

And What of Optimism Bias?

(Lefebvre et al, 2017)

Experimental Design



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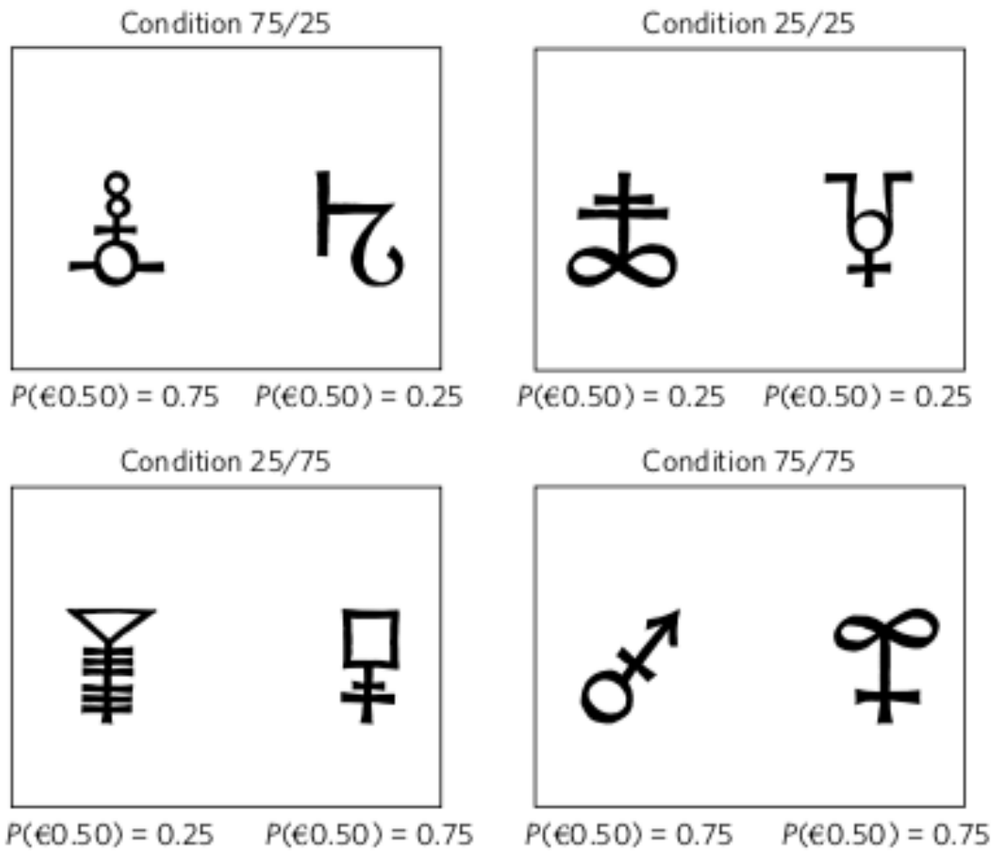

- 2-armed bandit task

And What of Optimism Bias?

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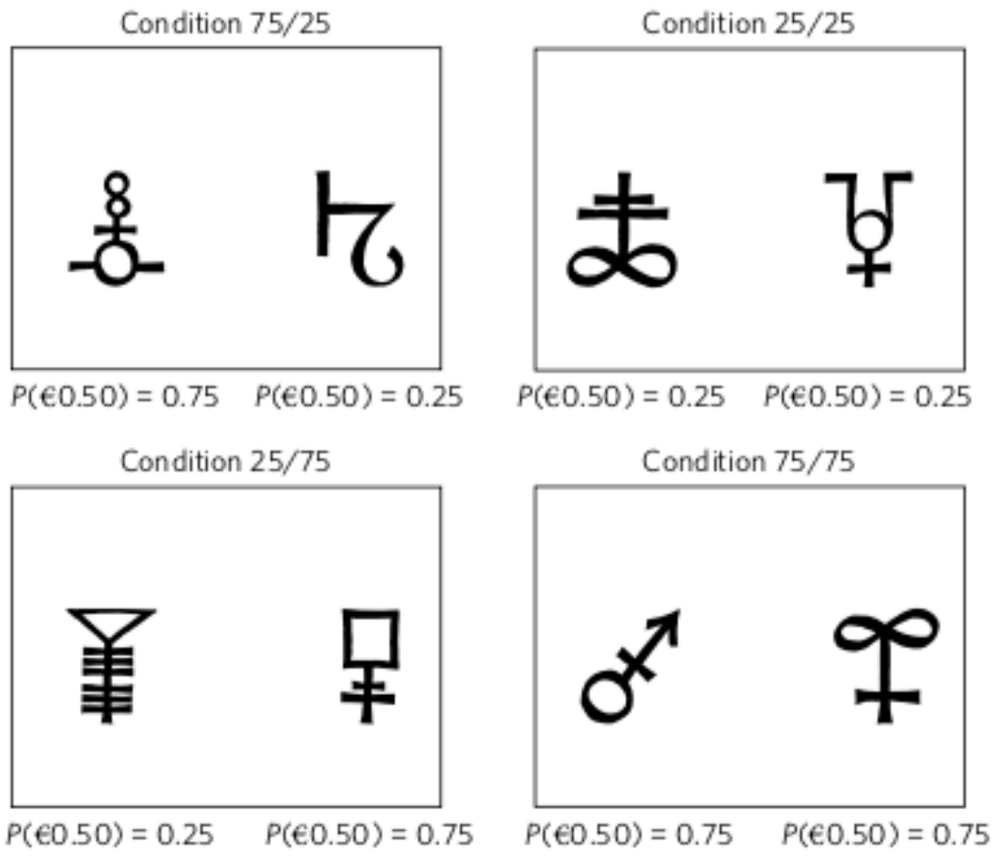
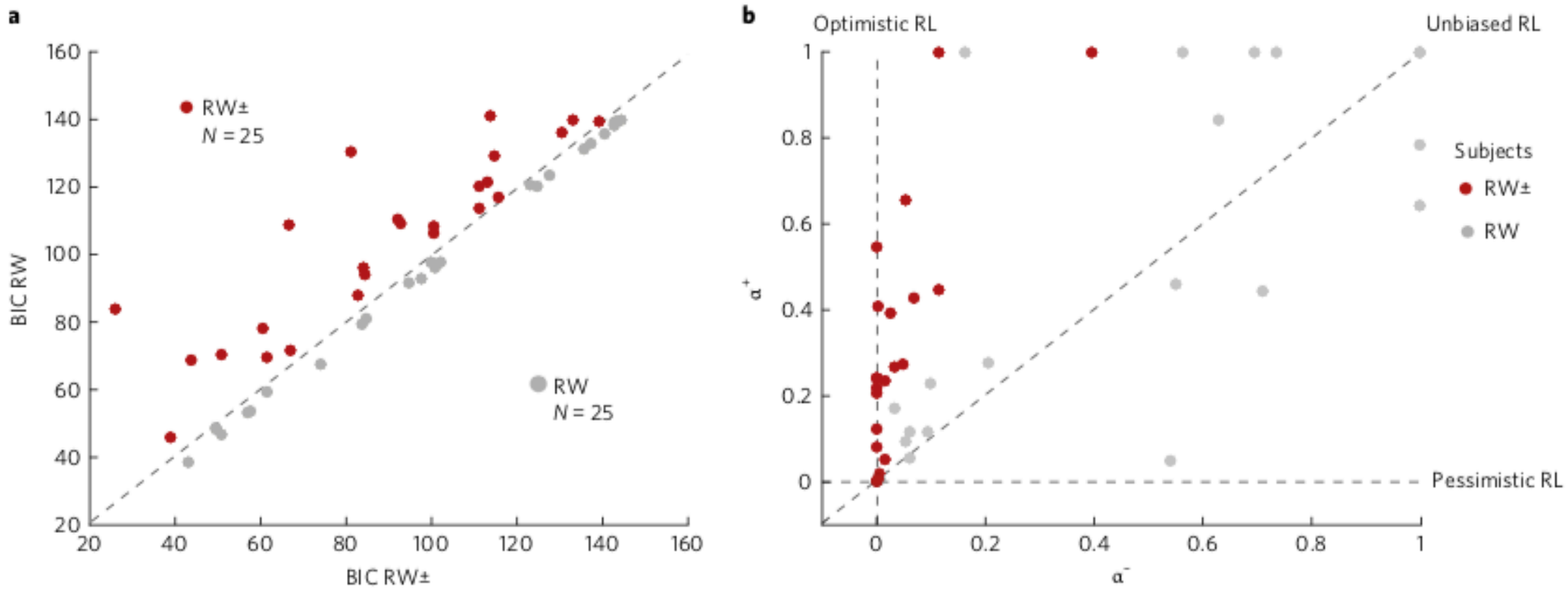
Experimental Design



- 2-armed bandit task
- 2 x 2 design: mean x variance

And What of Optimism Bias?



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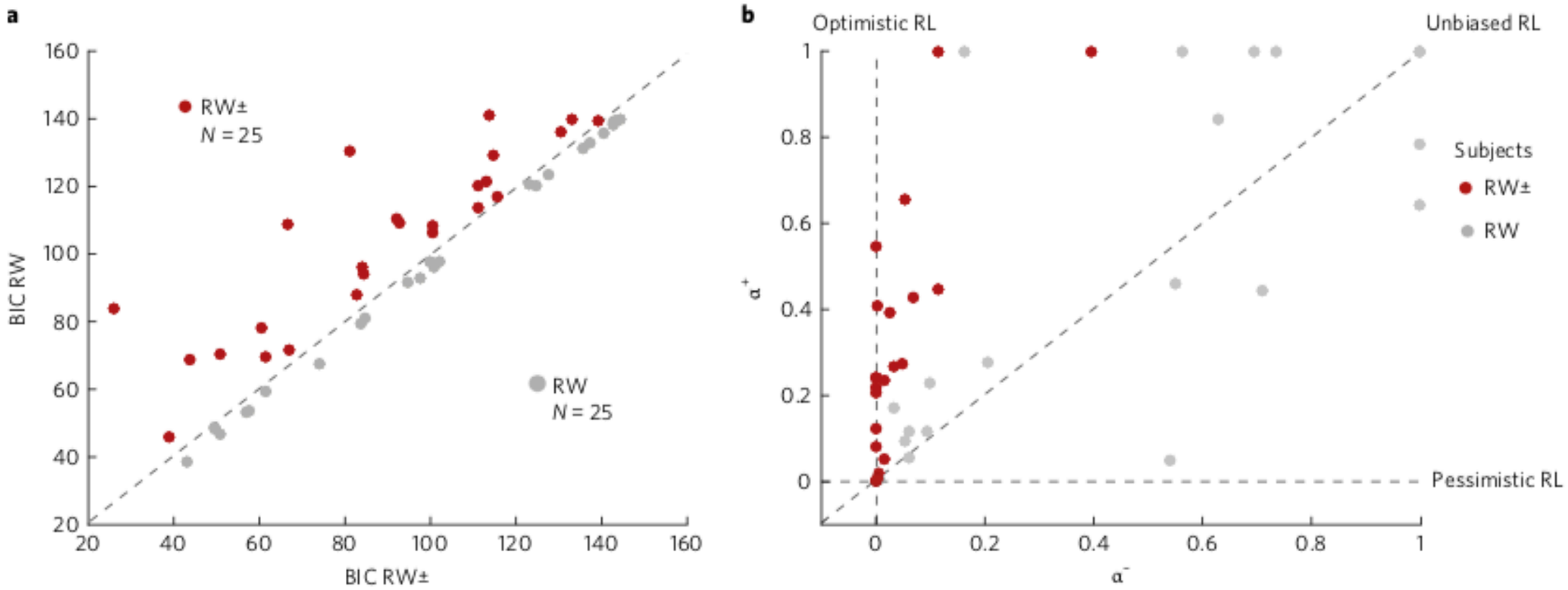

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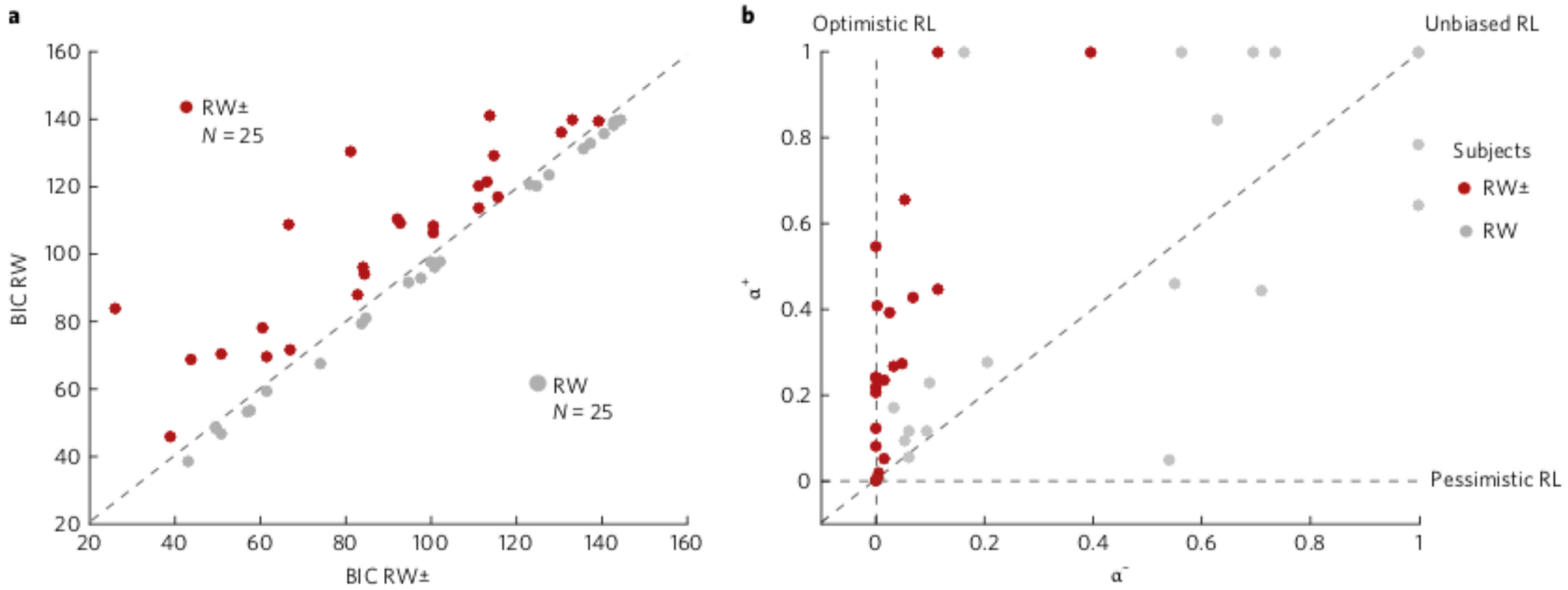

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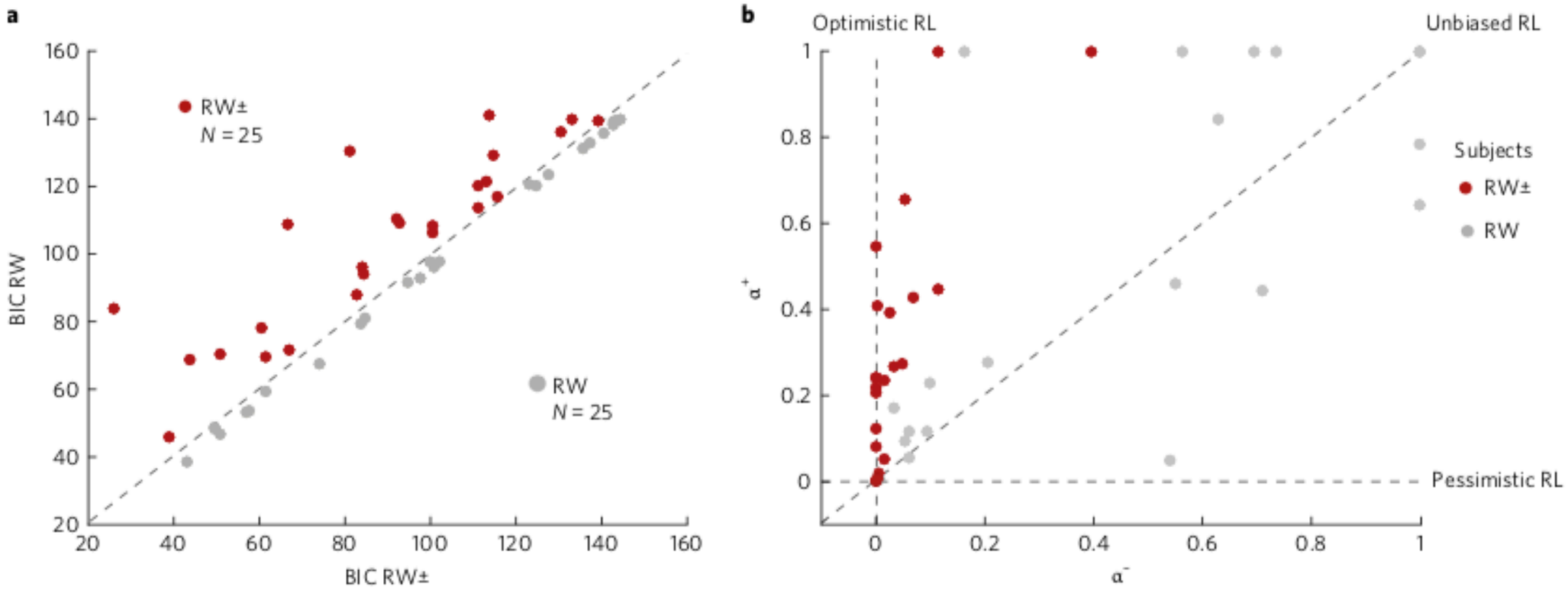

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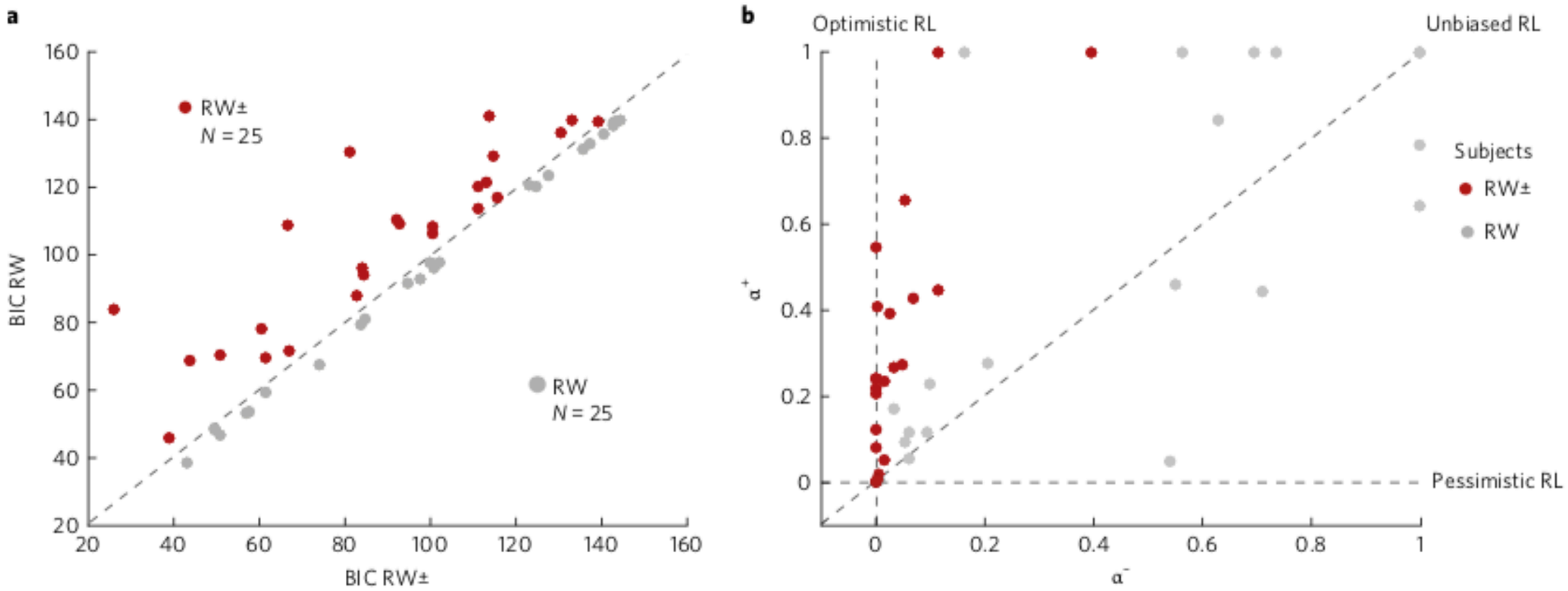

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- Could this actually be explained by reward rate under-estimation?
  - apparent contradiction: devaluation of chosen arm = pessimism
  - however: devaluation of unchosen arm = optimism