Aging of the exploring mind: Older adults deviate more from optimality in complex environments

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Introduction

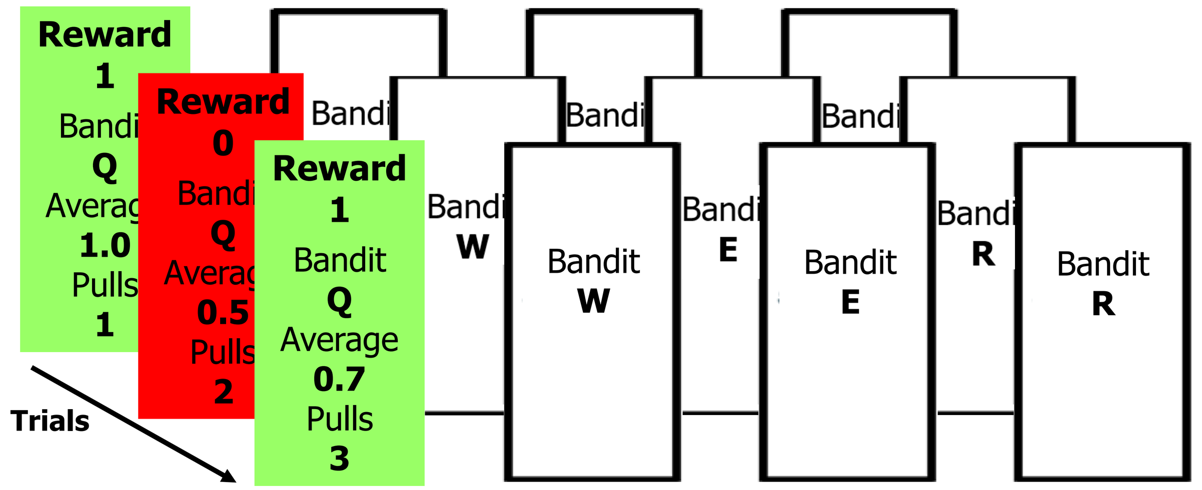
- Exploration-exploitation tradeoffs are ubiquitous in the daily environments of younger adults (YA) and older adults (OA)
  - There are often too many options available to explore exhaustively
  - E.g. managing work activities, health, finances, etc.
- Optimal models such as Thompson sampling achieve high performance by weighing observed rewards with the number of times that an option has been sampled (uncertainty)
- Past work shows how OA under-rely on uncertainty processing, goal-directed learning, and model-based strategies in related tasks (Eppinger, Walter, Heekeren, & Li, 2013; Nassar, Bruckner, Gold, Li, Heekeren, & Eppinger, 2016; Worthy, Cooper, Byrne, Gorlick, & Maddox)
- We study how these mechanisms depend on task complexity, using 4- and 8-armed bandit problems with observed rewards and number of pulls always displayed on the screen

Predictions

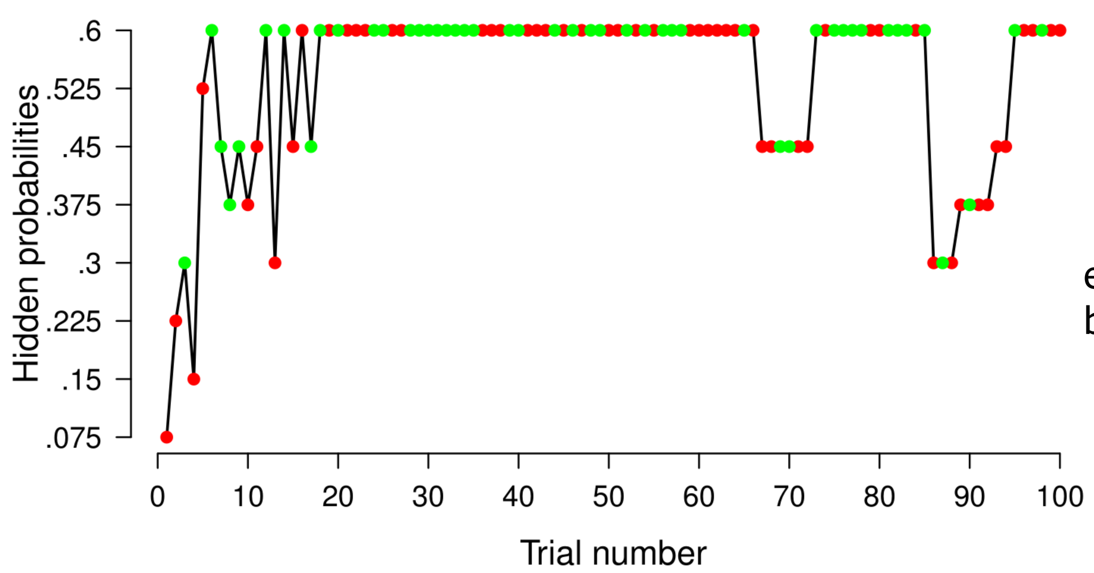
1. OA perform worse in more complex environments
2. OA sub-optimally process cognitively demanding information
3. OA rely more on simpler strategies

Design

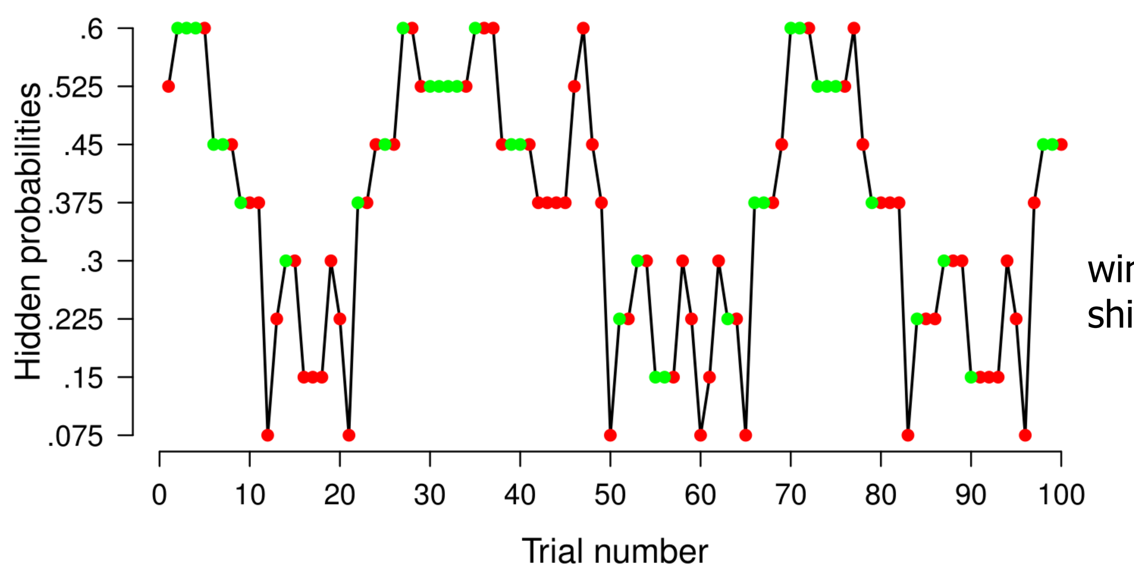
- 4 and 8-armed bandits, binary rewards
- 100 trials, 16 games, ~ 30 min
- Participants are informed that the best bandit has p = .6
- Number of pulls and running averages displayed on each bandit
- 32 YA and 29 OA



Example choice profiles

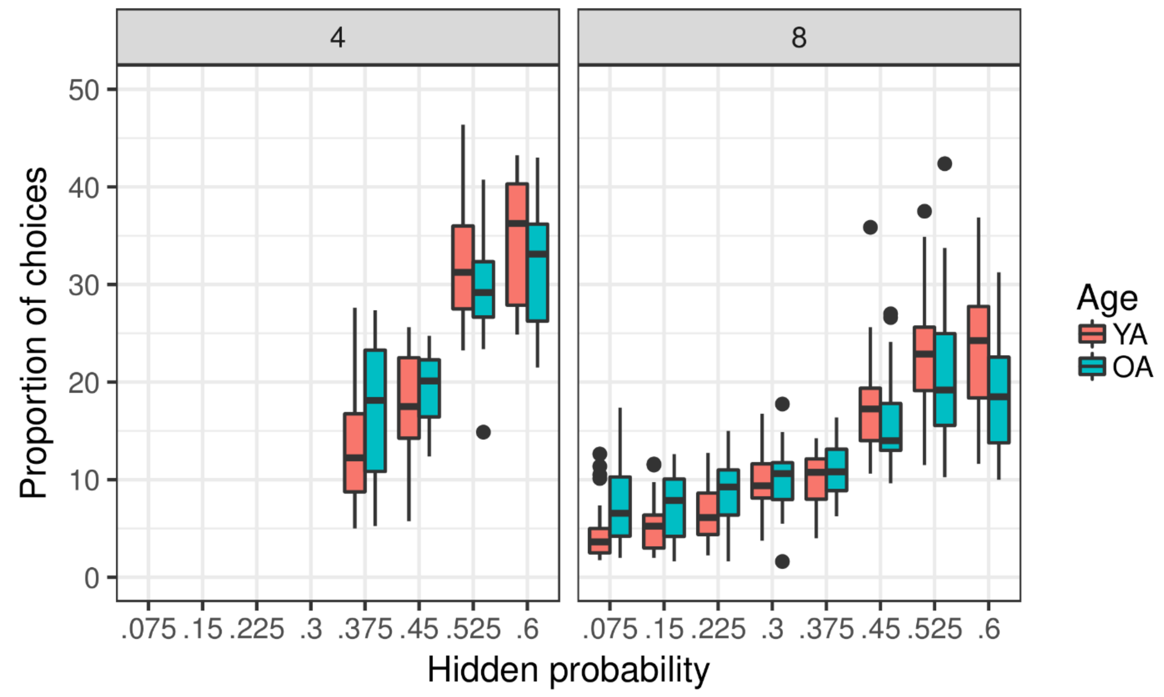


exploration in the beginning



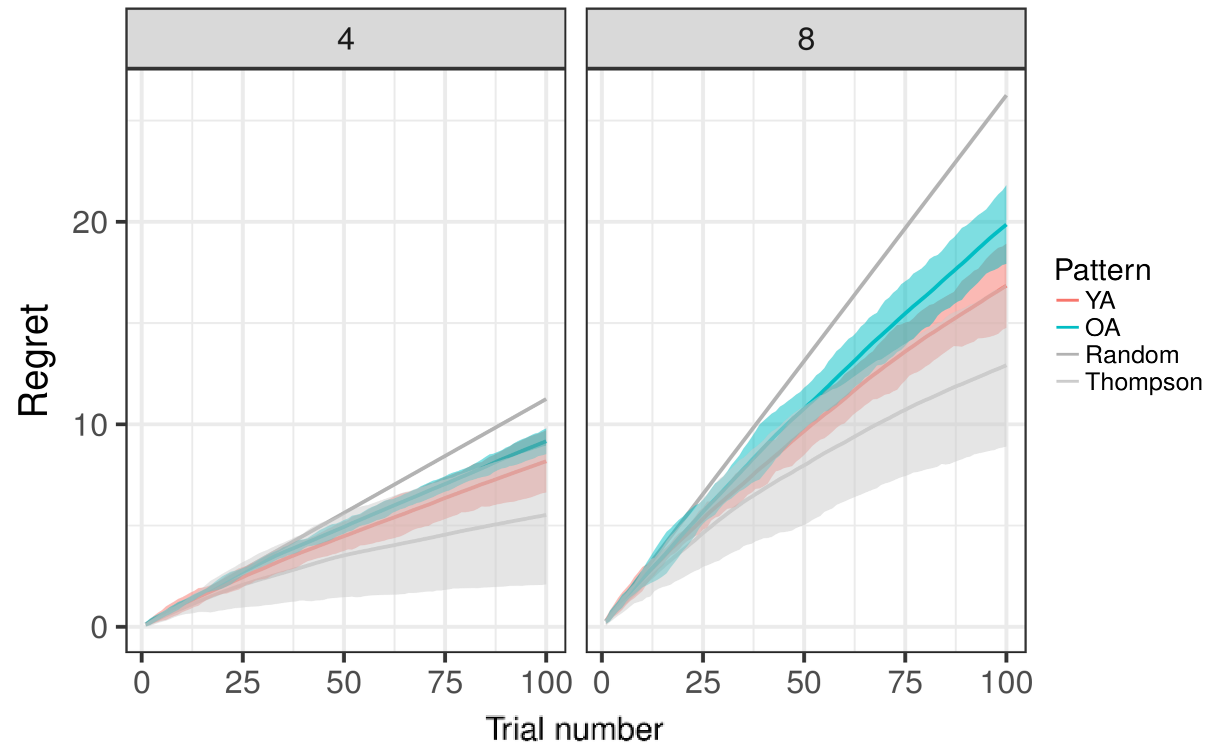
win-stay-lose-shift strategy

Choice proportions



↑OA choose less often from the better options

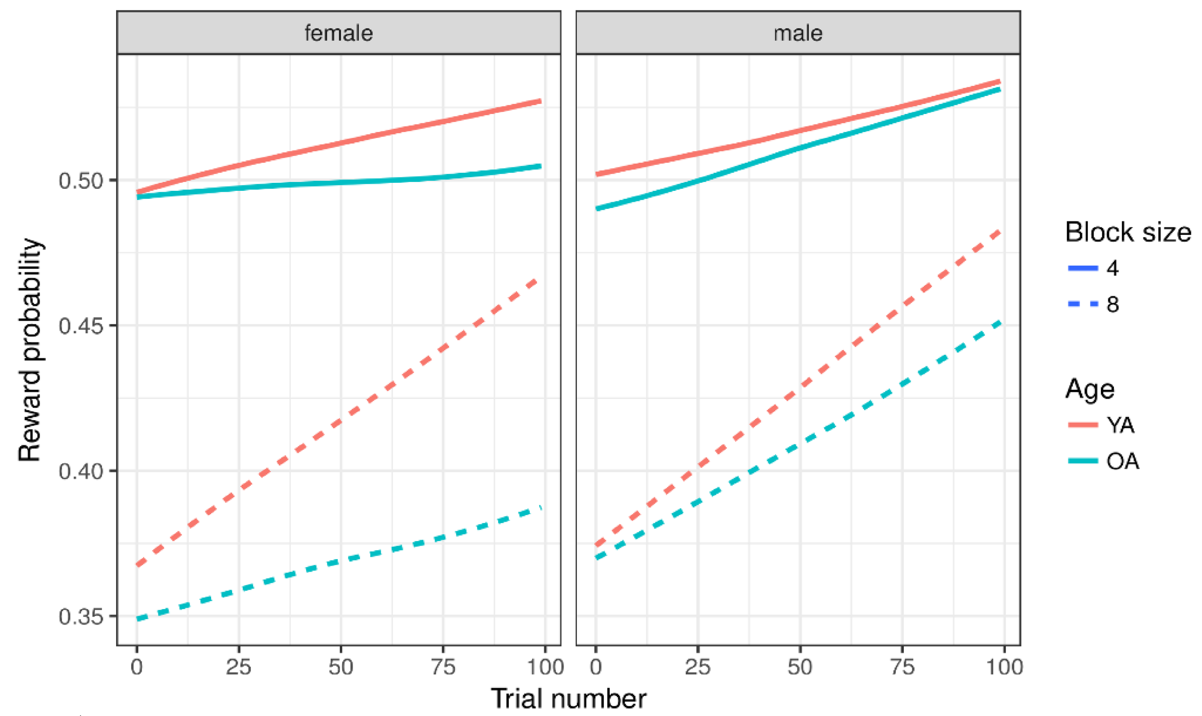
Regret patterns over trials



↑ $R_T = \sum_{i=1}^{100} \left(p_{opt} - p_{B(i)}\right)$, where p_{opt} = .6, and $p_{B(i)}$ is the hidden probability of a chosen bandit

- Random choice regret: 11.25 (4 options), 26.25 (8 options)
- Optimal choice regret: 6.5 (4 options), 11.0 (8 options)

Linear mixed effects regression model

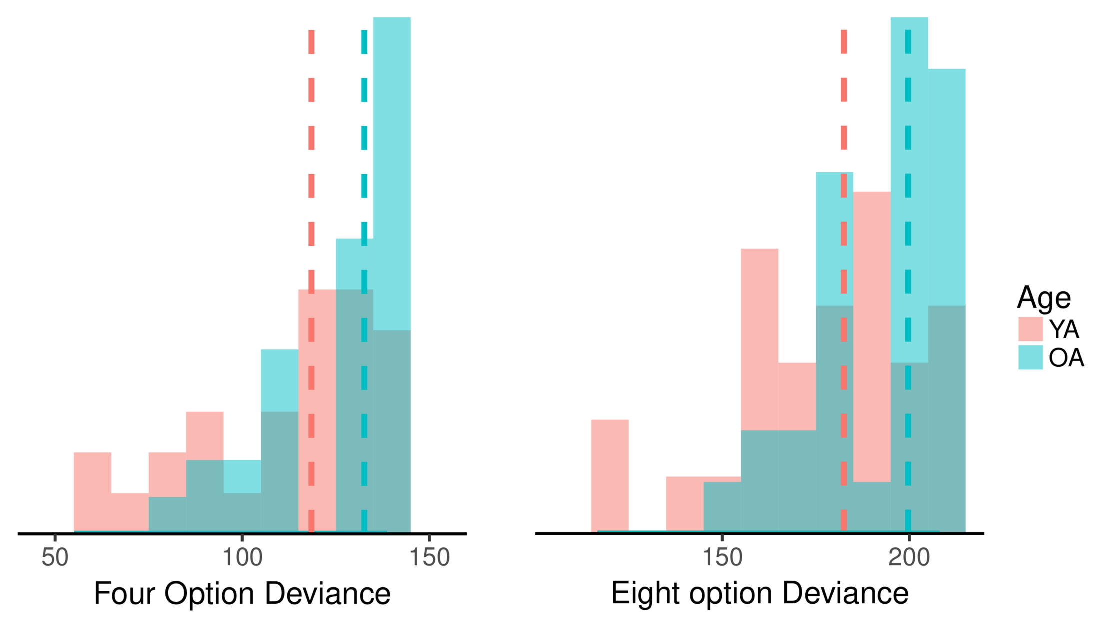


↑
```
hidden p of a chosen bandit ~ (#options + #trial + age)^3 + (1|participant ID) + (1|problem ID) + (1|bandit ID)
```

Three largest effects:

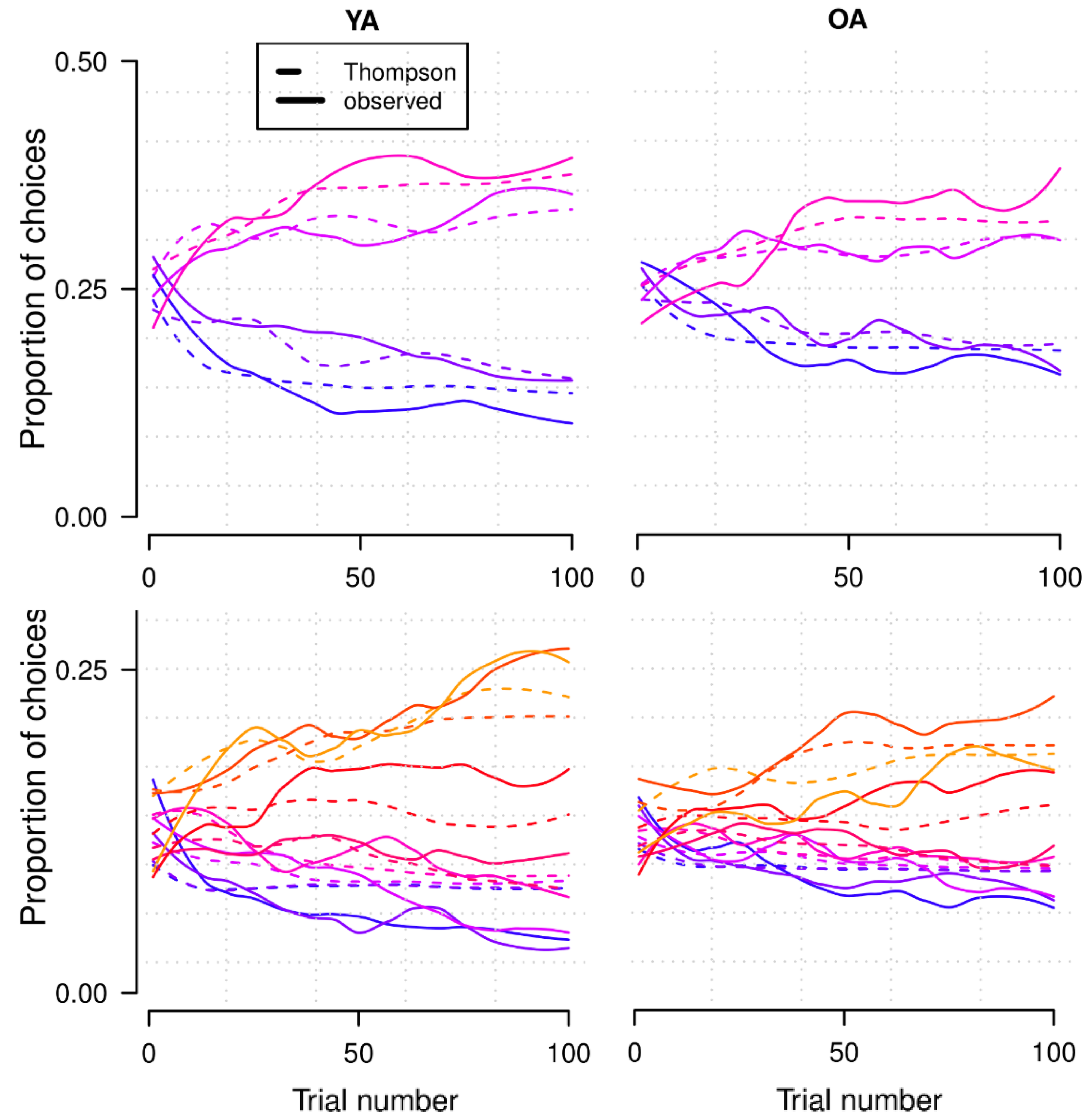
- OA perform worse in 8 options (p < .0001)
- Female OA perform worse in 8 options (p < .0001)
- Both YA and OA improve more in 8 options (p < .0001)

Deviance from fitted Thompson sampling



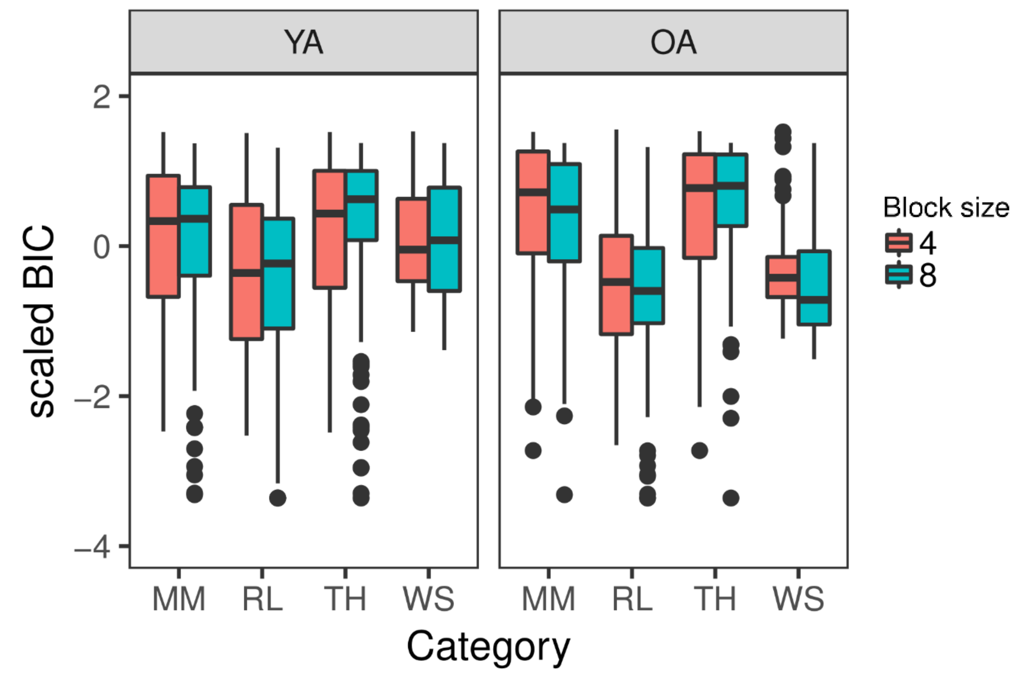
↑Deviance (minimized negative log likelihood) from Thompson sampling using softmax with inverse temperature θ [0.003 - 30].

Choice trajectories



↑Smoothed trajectories of choice proportions and one-step ahead predictions of fitted Thompson sampling. Blue colors represent lower probabilities.

Individual differences



↑BIC statistics for four models across single games, fitted with maximum likelihood and a softmax rule.

- **MM** – always follows the maximum mean
- **RL** – uses a delta rule to update action values
- **TH** – Thompson sampling
- **WS** – Win-stay-lose-shift

Summary

1. OA perform worse in more complex environments
   - OA perform worse in eight options over trials
   - OA explore longer
   - OA have faster increasing regret, leading to a large regret difference for 8 options and medium for 4 options
2. OA sub-optimally process cognitively demanding information
   - OA show larger regret difference to Thompson sampling
   - OA deviated more from fitted Thompson sampling
     - OA inverse temperature θ was also significantly higher
   - OA show less differentiation in one-step-ahead predications
3. OA rely more on simpler strategies
   - OA rely more on win-stay-lose-shift

Conclusions

- Age-differences in explore-exploit tradeoffs depend on task demands
- High performance requires processing of rewards and uncertainty (see e.g. Thompson sampling)
- Why do OA consider such important information less effectively than YA as the choice environment gets more complex?
  - Working memory should be minimal
  - General "slowing", gender effects, more cautious risk taking, etc.
  - Inadequate future reward representations specifically point to under-reliance on goal-directed learning

Acknowledgements

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References

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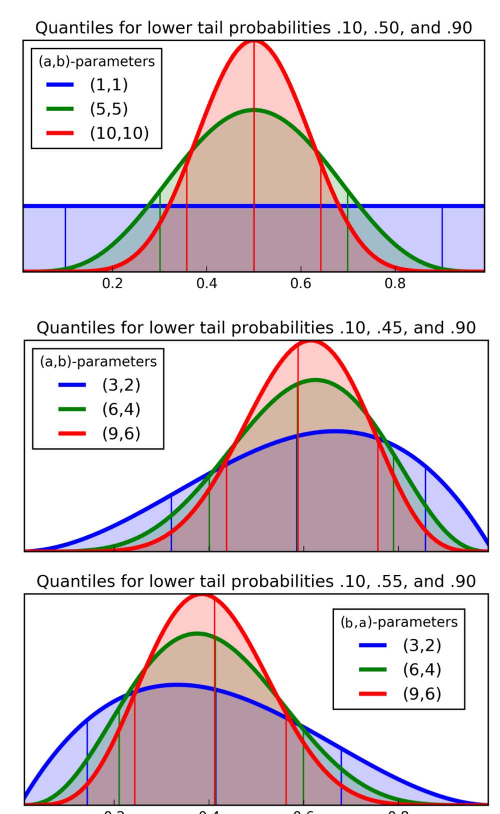
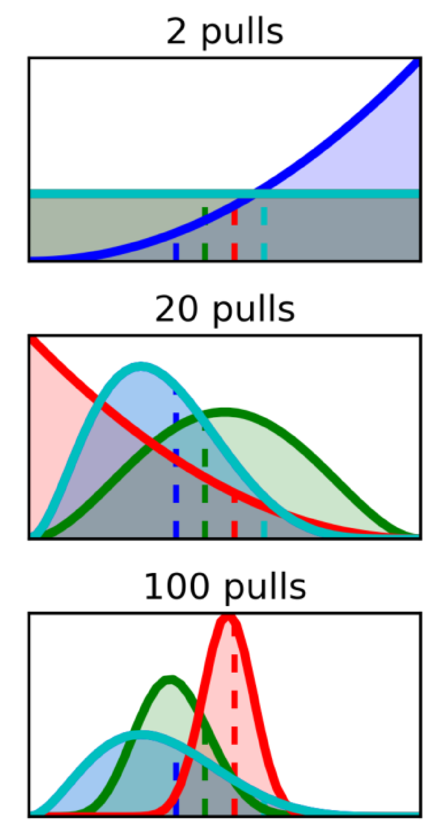
Box 1: Thompson sampling

Step	Computation
Init	$wins = rep(0, n)$
	$pulls = rep(0, n)$
Choose	$choice = max(qbeta(x, \alpha, \beta))$
Update	$wins = wins + reward$
	$pulls = pulls + choice$
	$\alpha = 1 + wins$
	$\beta = 1 + pulls - wins$

Pseudocode and examples of Thompson sampling, where `n` is the number of options, `x` is a randomly generated probability, and `qbeta` is a function for looking up quantiles from the Beta distribution.



↑How posteriors are updated over time



↑How quantiles compare for different parameter values