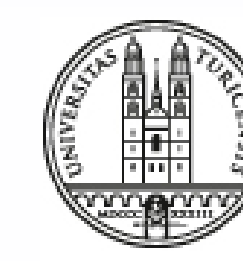


Controllability and resource-rational planning

Falk Lieder, Noah D. Goodman, Quentin JM Huys
contact: falk.lieder@gmail.com



University of
Zurich^{UZH}



ETH

Introduction

- Controllability bounds the differential utility of different actions
- Therefore, rational agents should invest less time into planning, the less control they have over their environment
- What is the optimal tradeoff between planning time and expected gain, and how does it depend on controllability?
- Can the optimal tradeoff explain aberrant planning and decision making?

Resource-Rational Planning

Sample-based planning:

Here we model how the brain solves large Markov decision problems (MDPs) as Monte-Carlo tree-search based on [1]:

$$\hat{Q}(s, a) = \frac{1}{k} \sum_{i=1}^k \left(r(s, a, s_i) + \hat{V}(s_i) \right), \quad s_i \sim P(S_{t+1} | s_t, a) \quad (1)$$

$$\hat{V}(s) = \max\{\hat{Q}(s, a_1), \dots, \hat{Q}(s, a_N)\} \quad (2)$$

1. $\hat{Q}(s, a)$: est. expected cumulative reward for action a in state s
2. $V(s)$: value of state s

Resource-Rationality:

The resource-rational [2] decision which actions to simulate and how often (**c**) maximizes the **value of computation** (VOC):

$$\mathbf{c} = \arg \max_{\mathbf{c} \in \mathcal{C}^n} \text{VOC}(\mathbf{c})$$

$$\text{VOC}(\mathbf{c}) = \mathbb{E}_{P(B|\mathbf{c})} \left[\max_a \mathbb{E}_{P(Q, S|\mathbf{c})} [Q(s, a)] - \text{cost}(\mathbf{c}) \right]$$

Uncertain MDP and prior knowledge about control

In general, the MDP is partially unknown. Planning under uncertainty about outcome probabilities θ was formalized as an augmented MDP:

$$M(\theta) = (\mathcal{S}' = \mathcal{S} \times \mathcal{B}, \mathcal{A}, P(S_{t+1} | S_t, a_t), P_\theta(R_t | S_t, a_t))$$

$$P_\theta(R_t | S_t, a_t) = \text{Multinomial}(\theta_{s,a})$$

$$P_t(\theta_{s,a}) = \text{Dirichlet}(B_t(s, a));$$

- B_t : belief about outcome probabilities
- \mathcal{S}' : combines world-state S_t with belief B_t
- $B_0(s, a) = \alpha \cdot \mathbf{1}$ is informed by abstract knowledge about control: high $\alpha \Rightarrow$ random outcome independent of $a \Rightarrow$ no control [3, 4]

Cognitive control as a meta-level MDP

VOC can be maximized by solving a simpler meta-level MDP [5]:

$$M^{\text{meta}} = (\mathcal{S}_Q, \mathcal{C}, P_S^{\text{meta}}, R^{\text{meta}}, s_0^{\text{meta}}) \quad (3)$$

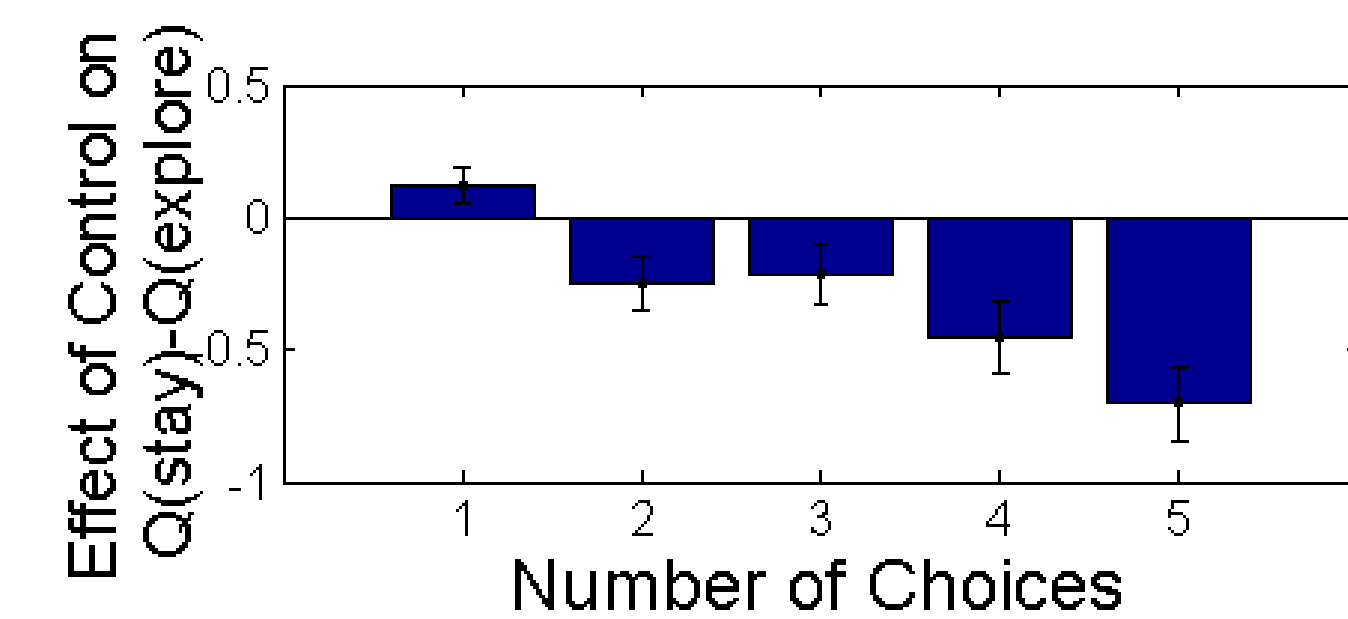
- meta-level states $S_Q^t = \{(\mu_i^t, \tau_i^t)\}$ are beliefs about Q-values: $P(Q(s, a_i)) = \mathcal{N}(\mu_i^t, \tau_i^t)$.
- comp. actions \mathcal{C} : \perp : stop planning, c_i : simulate action i
- P_S^{meta} : Bayesian learning from $q \sim \mathcal{N}(Q(s, a_i), \tau_i^{\text{sample}})$
- reward fct. R^{meta} : $-\text{cost}(c_i)$ for computations, cumulative reward expected under current meta-level belief for \perp .

Analytic results enable efficient approximate solutions [5, 6].

Resource-Rational Effects of Control

1. Effect on exploration vs. exploitation

Control determines the differential value of exploration vs. exploitation [3, 4]. Our model explains how controllability can be taken into account with a cognitively plausible amount of computation.



Estimated value of exploration in the 8-armed bandit task by [3] for high vs. low control based on 200 simulations with $k = 2$ samples per inner node.

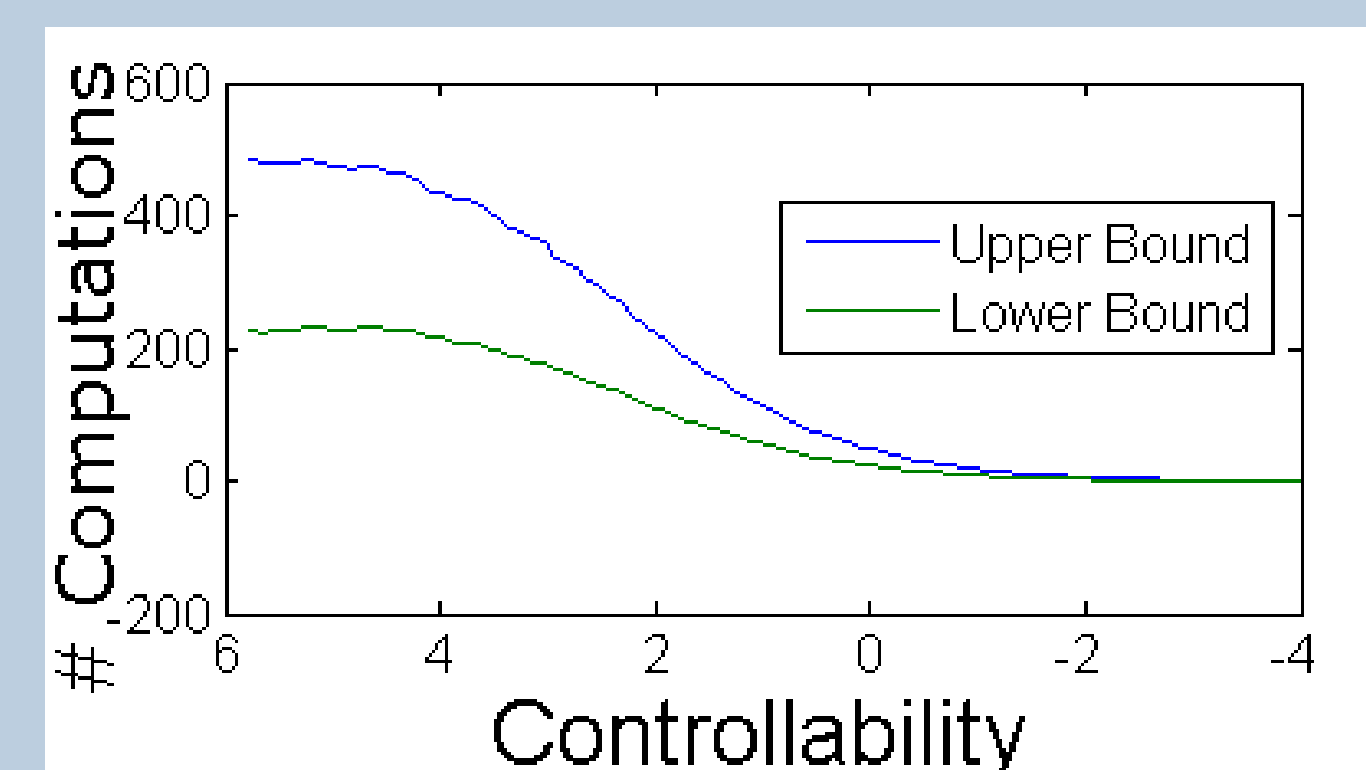
2. Effect on mental effort

We derived bounds on the number of simulations n chosen by the optimal meta-level policy

$$n \leq \frac{k}{\min_i \tau_i^{\text{sample}}} \cdot \left(\frac{1}{c \cdot \sqrt{2\pi}} - \min_i \{\tau_i^0 + \tau_i^{\text{sample}}\} \right)$$

$$n \geq \frac{1}{\max_i \tau_i^{\text{sample}}} \cdot \left(\frac{1}{c \cdot \sqrt{2\pi}} - \max_i \{\tau_i^0 + \tau_i^{\text{sample}}\} \right).$$

- high cost of computation $c \Rightarrow$ low bounds.
- low control ($-\log(\alpha)$) \Rightarrow high certainty τ_i^0 about $Q(s, a) \Rightarrow$ low n .



Perceived uncontrollability makes it irrational to plan ahead.

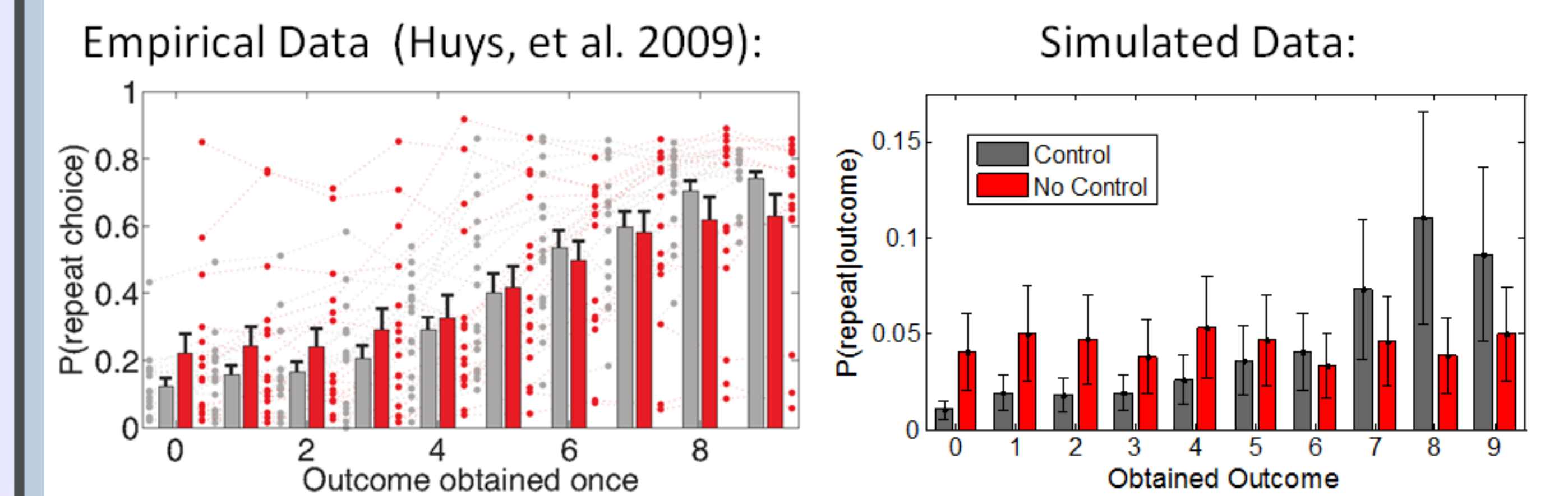
Major Depression (MDD) and Control

Lower repeat modulation in MDD [3]:

- 8-armed bandit task with 8 sequential choices
- independent, unknown reward distributions ($R \in \{0, \dots, 9\}$)
- MDD patients exerted less control: less likely to stick with good arms and move away from bad arms (repeat modulation).

Simulations:

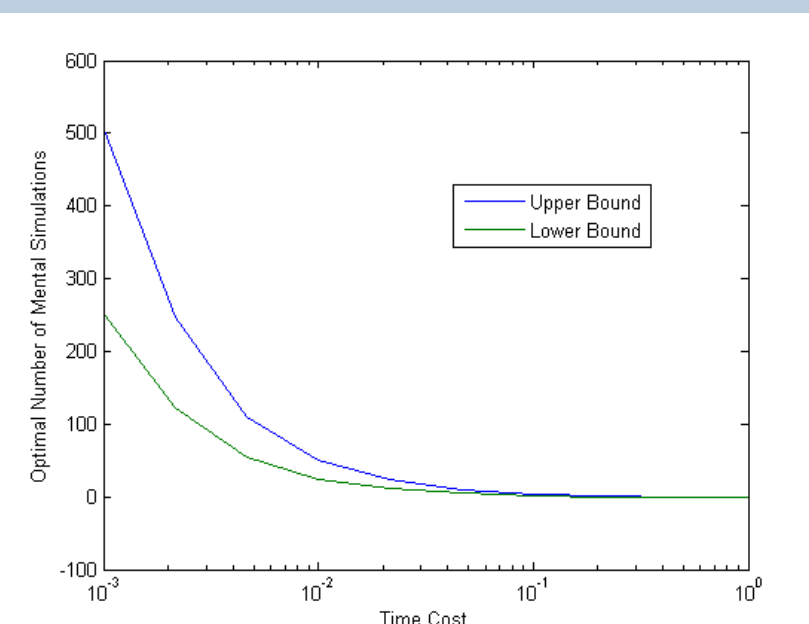
perceived lack of control (high α) \Rightarrow reduced repeat modulation



Discussion

Alternative Explanations:

1. reduced processing speed \rightarrow increased cost of comp. \rightarrow less planning (see \rightarrow)
2. perceived lack of control impairs learning (cf. [7])



Conclusions

1. Resource-rationality [2] explains *why* people track control and *how* it shapes learning and decision-making
2. Impaired decision-making and learning [7] in major depression may result from the perceived lack of control (helplessness)
3. Uncontrollability reduces the utility of goal-directed decision making. This may trigger a shift to habitual or Pavlovian choice.

References

- [1] Kearns, Mansour, and Ng. *Machine Learning*, 49(2), November 2002.
- [2] Lieder, Griffiths, and Goodman. *NIPS 2012*, 2013.
- [3] Huys, Vogelstein, and Dayan. *NIPS 2008*, 2009.
- [4] Huys and Dayan. *Cognition*, (3), December 2009.
- [5] Hay, Russell, Tolpin, and Shimony. *UAI*, August 2012.
- [6] Hay and Russell. Technical report, EECS, UC Berkeley, 2011.
- [7] Lieder, Goodman, and Huys. In *CogSci 2013*, submitted.