Neural encoding of rapidly adapting risk preferences

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Introduction

Background

- Studies of economic decision making, often assume that people seek to maximize subjective value or "utility". Utility functions are often assumed to be idiosyncratic but stable over time.
- A recent theory based on ergodicity (Peters, 2019) proposes that people maximize the growth rate of their wealth. This predicts that utility functions should change as a function of the dynamics of the environment
- Specifically: additive dynamics predict linear utility, while multiplicative dynamics predict logarithmic utility.
- Recent evidence suggests that people quickly adapt their utility functions to the dynamics of the environment (Meder et al., 2021; Skjold et al., 2024).

Here we explore how this affects the neural encoding of value.

Task & Data

We here looked at the passive learning task from Meder et al. (2021). For each participant ($n = 16$ included), there is data from a session with an additive dynamic with a multiplicative dynamic (2 runs each).

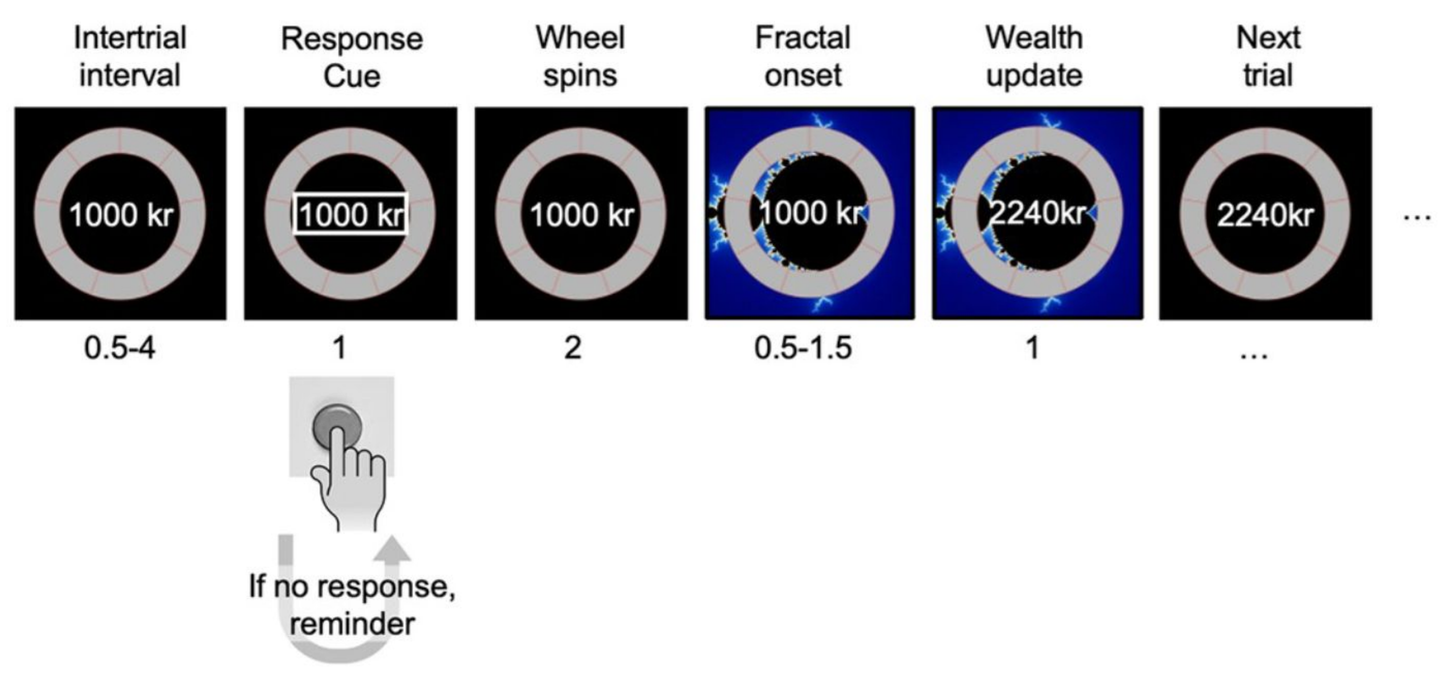

Fig. 1: Adapted from figure 1 of: Meder et al. (2021). Published under CC-BY-4.0 (https://creativecommons.org/licenses/by/4.0/). Participants trigger a spinning wheel indicating the random selection of the next image, after the image is displayed participants see its effect on their wealth. The nine images have stable, unique, growth-rates within a session.

Modeling Change in Utility

To study how subjective changes in wealth are encoded in the brain, we use an isoelastic utility function. This function contains linear ($\eta = 0$) and logarithmic utility ($\eta = 1$) as special cases:

$$\Delta u = u(x)_t - u(x)_{t-1}$$

$$u(x) = \begin{cases} \frac{x^{\eta-1}-1}{1-\eta}, & \text{if } \eta \geq 0, \eta \neq 1 \\ ln(x), & \text{if } \eta = 1 \end{cases}$$

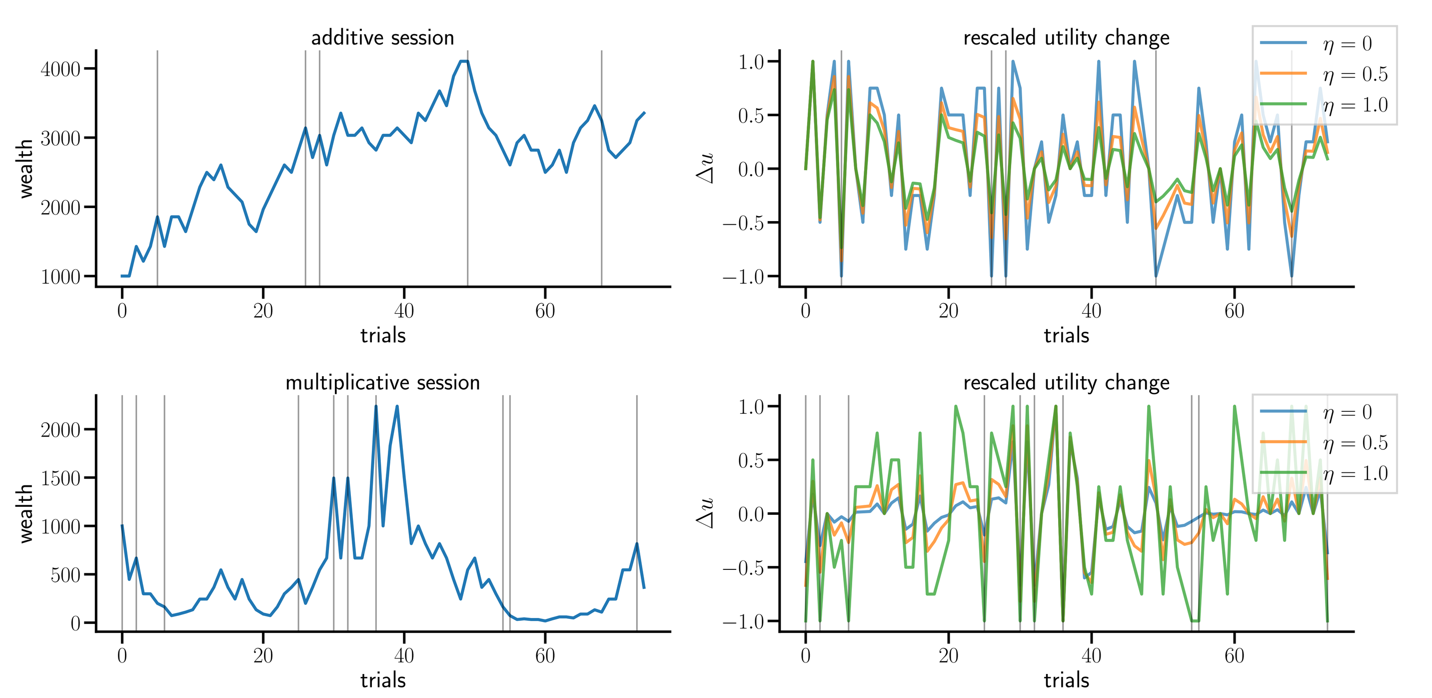

Fig. 2: The top left row is an example trajectory from the additive session, the bottom row from the multiplicative session for the first 75 trials. On the right, the changes in utility are plotted. To indicate that the stimuli have a stable growth rate only under the correct mapping, vertical lines indicate the occurrence of the stimulus with the most negative growth rate.

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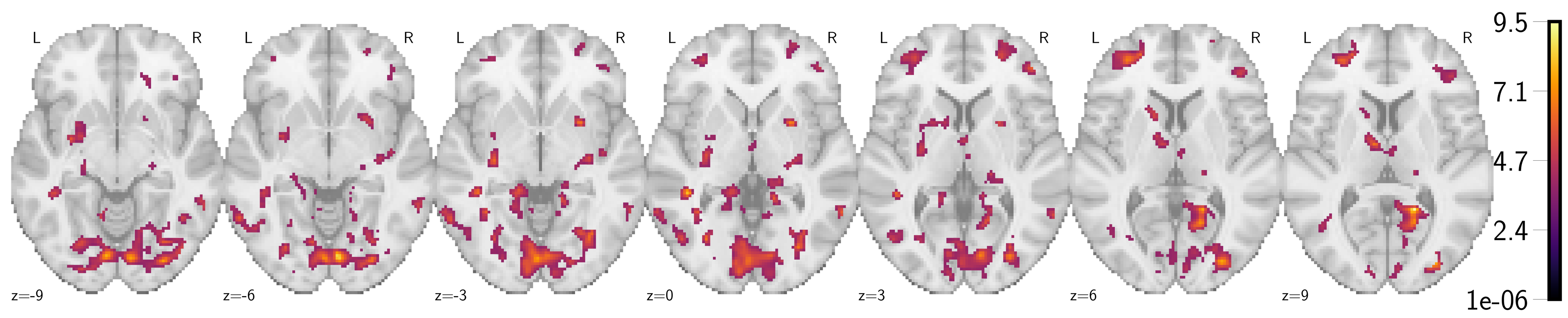
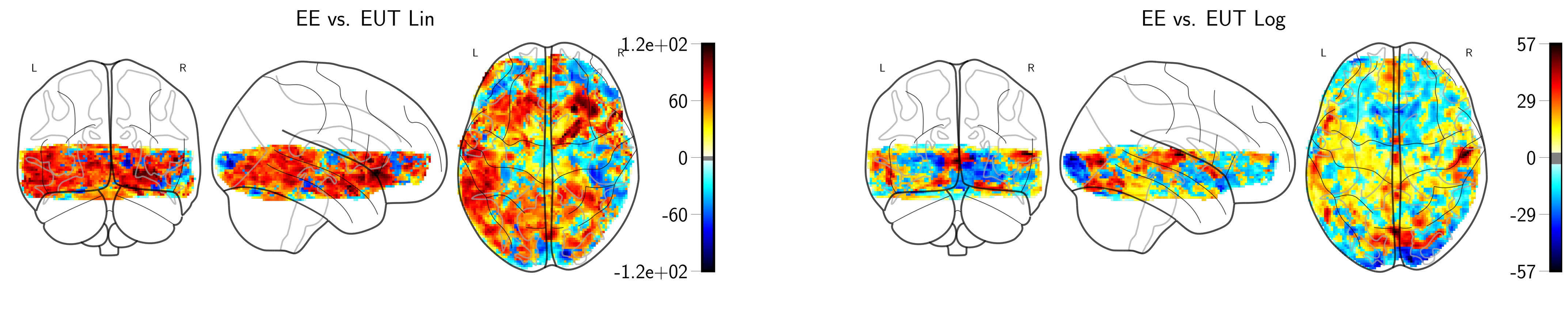
Classic Analyses: Δu



(a) Activation: Statistical map of a classic GLM analysis of the second level contrast of a parametric modulator with $\eta^+ = 0$ and $\eta^* = 1$ (t-test, threshold, $p < 0.001$, cluster threshold, $k_e = 109$)



(b) Model comparison: LogBF maps of the comparison of three GLMs differing only in their parametric modulators (EE: $\eta^+ = 0, \eta^* = 1$; EUT Lin: $\eta^+ = 0, \eta^* = 0$, EUT Log: $\eta^+ = 1, \eta^* = 1$) (Soch and Allefeld, 2018)

Fig. 3: The analyses presented here are in principle based on parametric modulators of an impulse response at the time of reward outcome. In the additive session Δu is defined by η^+ and in the multiplicative by η^*. All runs and sessions were concatenated.

Bayesian method: Computational Parametric Mapping

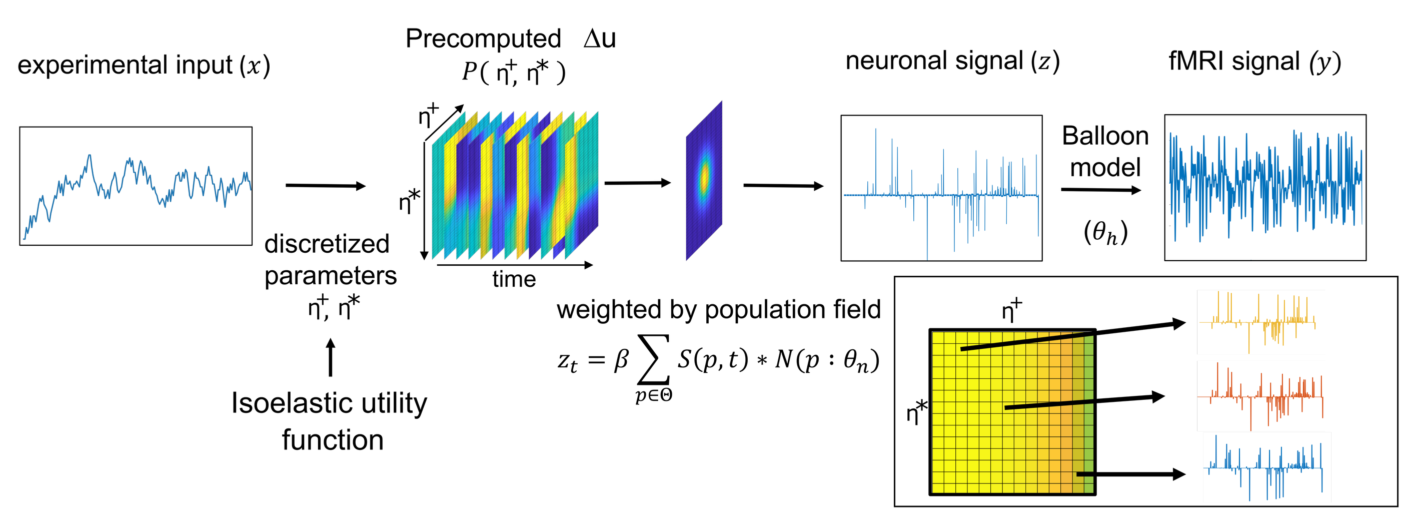
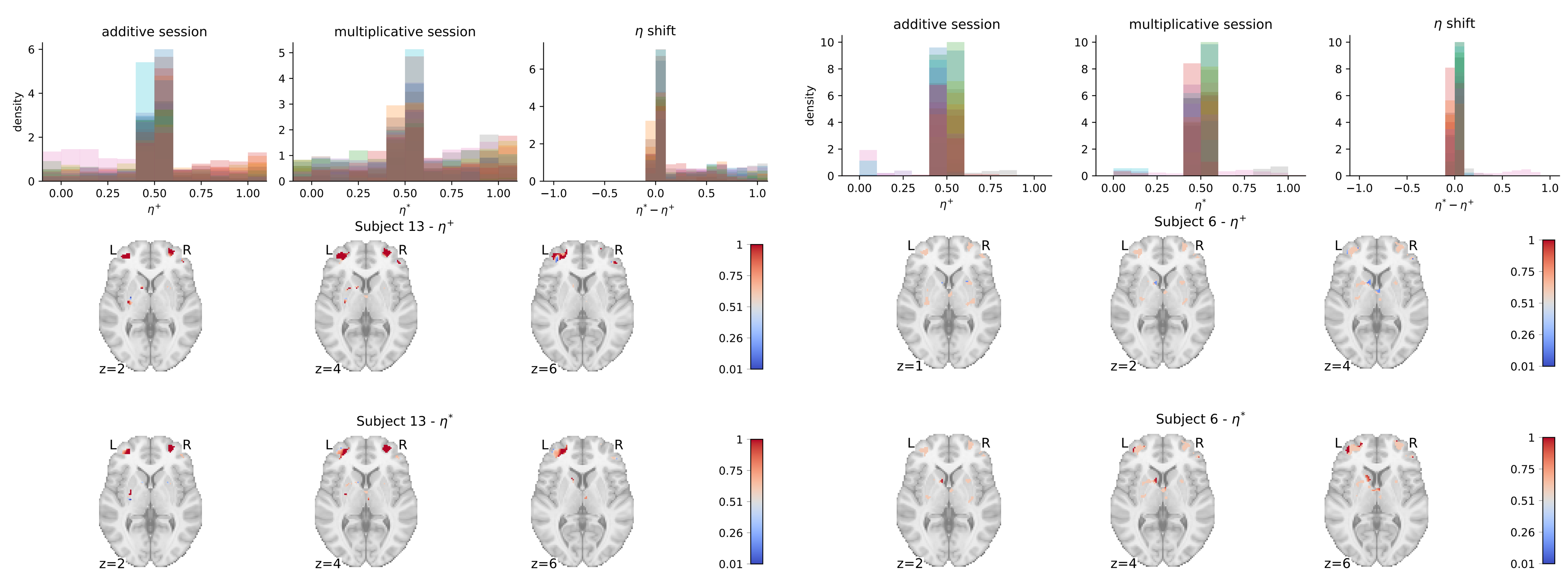


Fig. 4: Schema of the Bayesian method: We discretize the parameter space over η^+ and η^* and try to find the location, where the average "neural" signal after convolution with an HRF, has the best fit to the BOLD signal (Steinkamp et al., 2022).

Preliminary: η-estimation



(a) MLE approach: After model fitting, η^+ and η^* were extracted from voxels where the log-likelihood was greater than the log-likelihood of a null-model and where the signal scaling parameter was greater than 0. The upper row shows density histograms of parameter estimates of each participant for voxels, that survived the thresholding ($n = 168 - 730$). The lower plots show the masked data of the participant with the highest number of surviving voxels.

(b) Bayesian approach: After model fitting, the MAP estimates of η^+ and η^* were extracted from voxels where the posterior probability of the scaling parameter was > 0.75 and where the signal scaling parameter was greater than 0. The top row shows density histograms of parameter estimates of each participant for voxels, that survived the thresholding ($n = 64 - 1246$). The lower plots show the masked data of the participant with the highest number of surviving voxels.

Fig. 5: We aimed to quantify the voxel-wise η^+ and η^* across the two runs and sessions, for this analysis it was done in a partial mask derived from Fig. 3a. We used two approaches, maximum likelihood estimation (Fig. 5a) and a variational Bayes approach that is inspired by receptive field modeling (Fig. 5b, Fig.4).

Conclusion

Here we present a demonstration of mapping cognitive parameters onto the brain, including a novel Bayesian method. The results are too preliminary to draw conclusions about whether the neural data reflect behaviorally observed changes in risk preferences.

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