Computational Parametric Mapping: A Method For Mapping Cognitive Models Onto Neuroimaging Data

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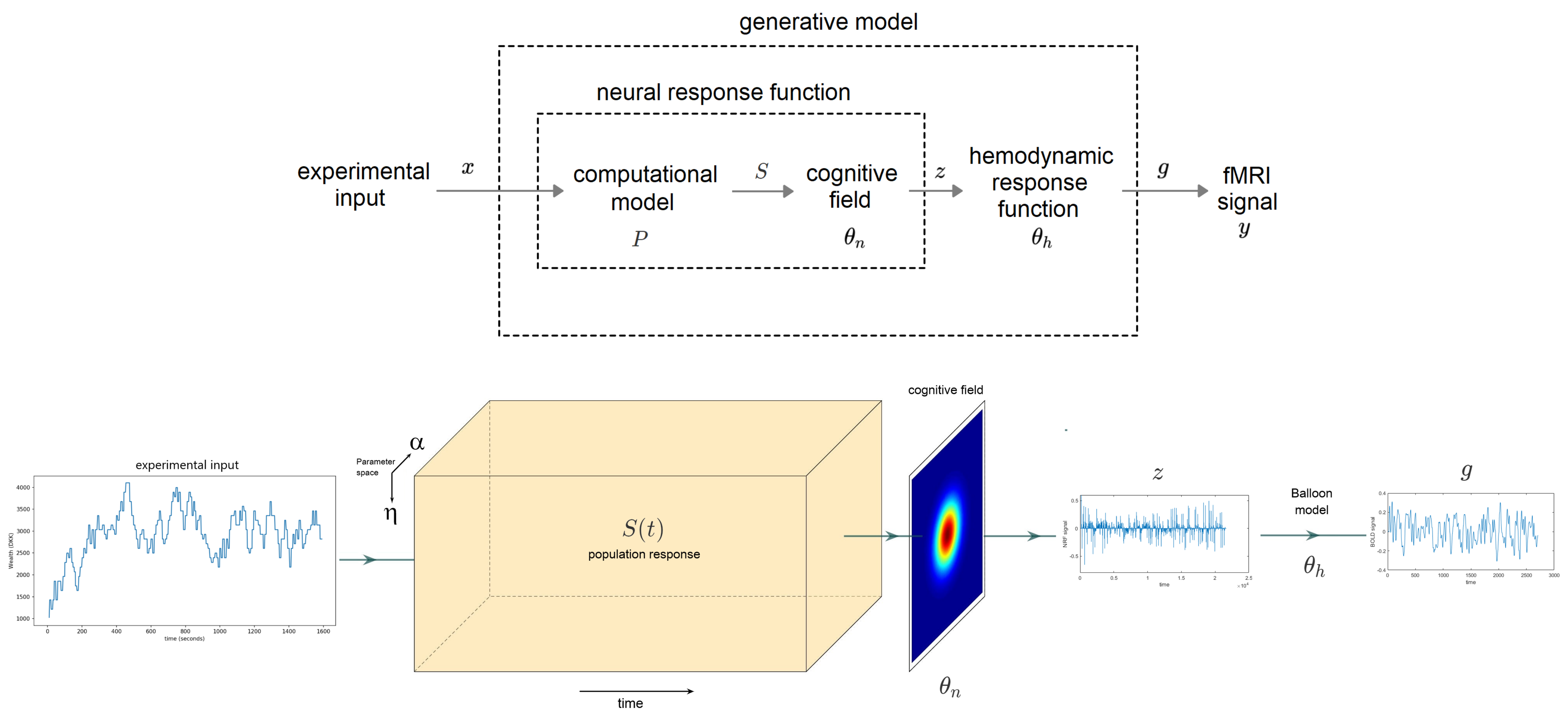
Introduction

- To understand the neural basis of cognition, cognitive models have to be incorporated into the modelling of neural data.
- We introduce computational parametric mapping (CPM), which allows cognitive model to be fitted directly to neural data.
- CPM builds on and generalizes the Bayesian population receptive field frameworks[1].

Three advantages:

1. Circumvents need for behavior
2. Allows topographic mapping of cognitive parameters and model comparisons
3. Fast enough for extensive neural systems

CPM



The neural response function z(t) is a population receptive field model[2,1], that uses the parameter space, P, of a cognitive model, as an analogy to the visual space used in retinotopy. The neural response function $z(t)$, thus maps experimental inputs x to a neuronal population response z, parametrized by unknown neural parameters θ_n

$$z(t) = \beta \sum_{p \in \Theta} S(p,t) * N(p : \theta_n)$$

To calculate $z(t)$ it is necessary to calculate the population response S, which is the cognitive model's response over (Θ), a discrete subset of the parameter space P. In our case, the cognitive field — analogous to a receptive field — is a Gaussian function N defined by location $\{\mu_\alpha, \mu_\eta\}$ and standard deviation $\{\sigma_\alpha, \sigma_\eta\}$. In essence, $z(t)$ is the sum of population responses S, weighted by a cognitive field N. This generative model is fitted to fMRI data y by using the variational Laplace method[3].

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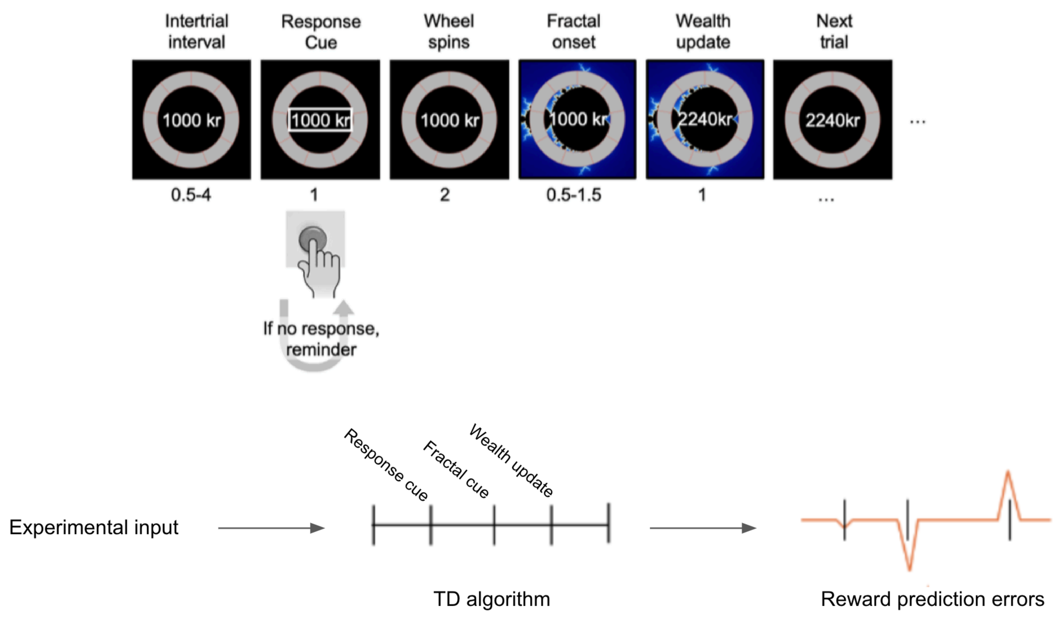
Simulations

Simulation of Experiment



Participants learn to associate images with a fixed change in their wealth.

We model a classic learning task using a TD-learning algorithm — with complete serial compounding[4] — using changes in utility for the estimation of the reward prediction error:

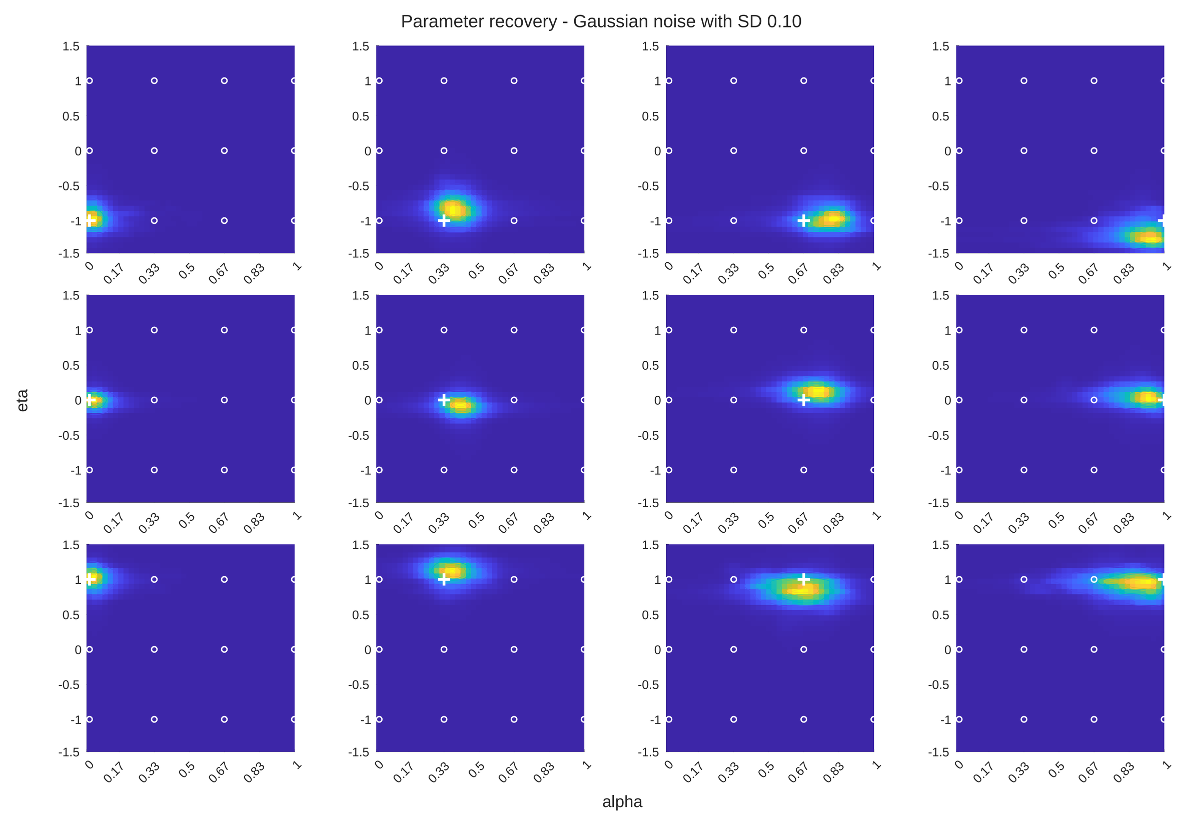
$$U_{t+1} = u(C_{t+1}, \eta) - u(C_t, \eta)$$

where u is an isoelastic utility function and C_t is the current wealth level. The learning rule is:

$$\delta = U_{t+1} + \gamma W_t X_{t+1} - W_t X_t$$
$$W_{t+1} = W_t + \alpha\delta$$

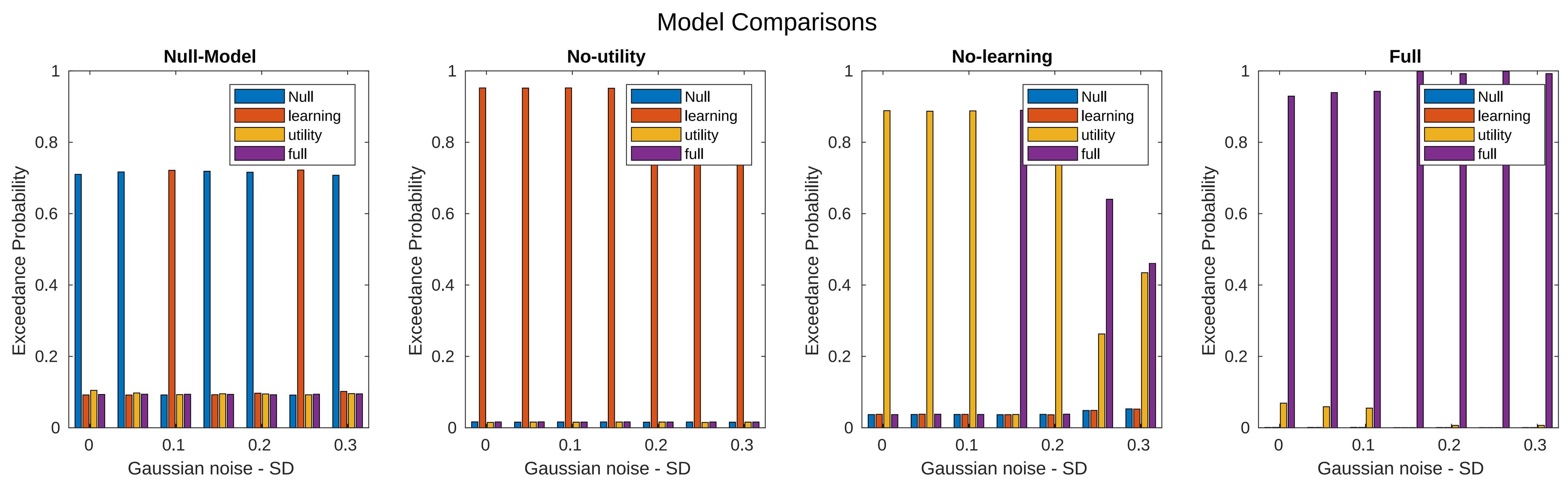
Here, we are interested in mapping learning rate (α) and utility (η) parameters to the human reward system, constituting the parameter space P in CPM. Our simulation consisted of artificial "voxels" that represent different data generation processes using combinations of learning rates $\alpha = \{0.0, 1/3, 2/3, 1.0\}$ and utility parameters $\eta = \{-1.0, 0.0, 1.0\}$, at different noise levels. We performed parameter and model recovery using Bayesian model reduction.

Parameter Recovery



→ Relatively good parameter recovery

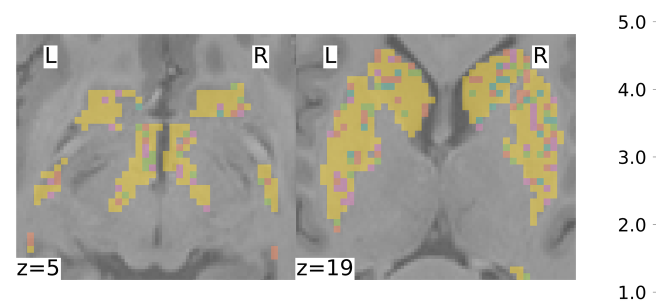
Model Recovery



→Generally good model recovery at low noise

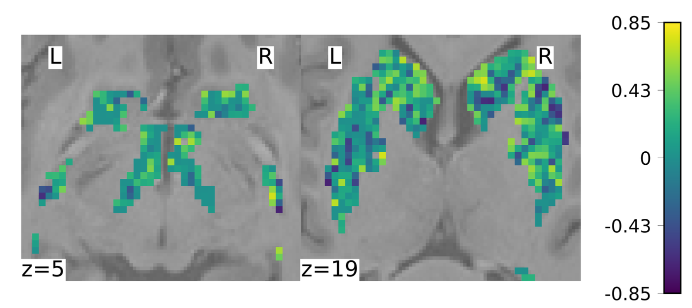
Example Outputs

Map of model comparisons



Index of winning model (winner takes all).

Map of cognitive parameters



Map over utility parameters η.

Conclusion

- CPM builds on receptive field models to map cognitive models onto brain.
- Proof of principle analyses show robust model & parameter recovery.
- CPM is fast enough to apply to real neuroimaging data.