Integrating cognitive models into generative models of fMRI data: Computational parametric mapping

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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), an extension of the Bayesian population receptive field method (Zeidman et al., 2018), that allows fitting of cognitive models to neural data. CPM is exemplified on a simple reward learning task.

Our approach has **three advantages:**

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

Example questions for CPM:

- Do individual brain regions / voxels encode asymmetric learning for losses and gains?

Monetary Incentive Delay (MID) task

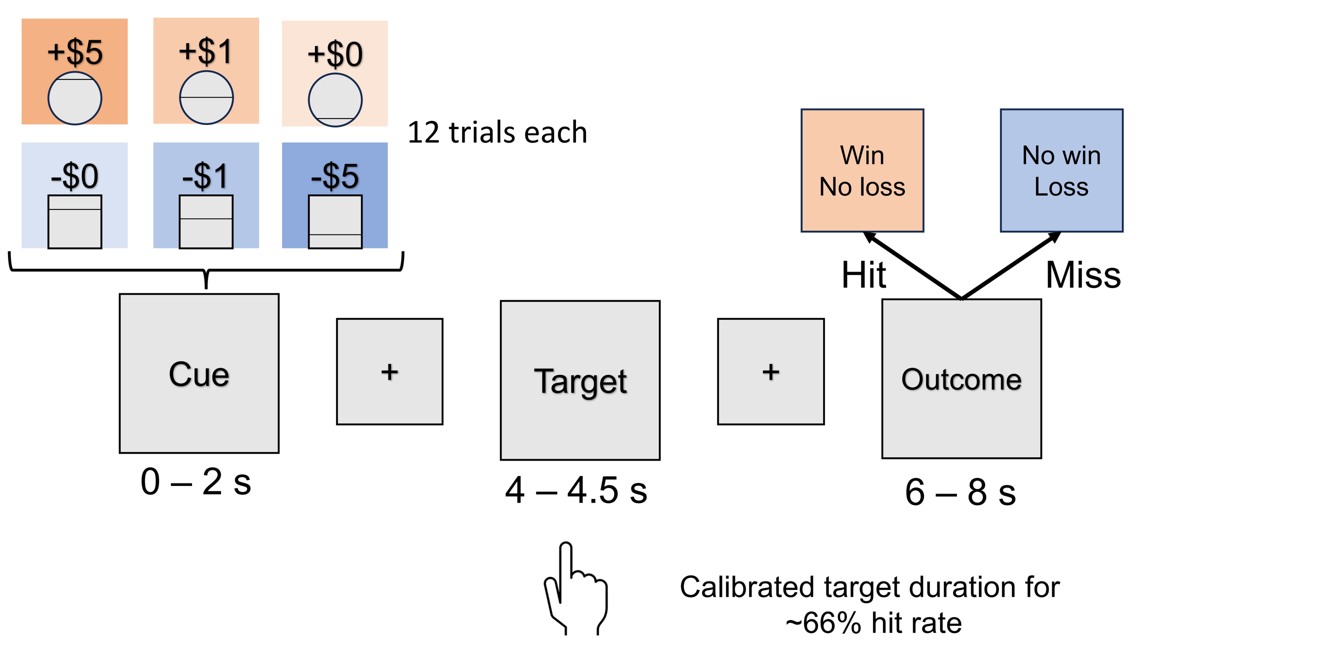

Fig. 1: We showcase CPM on the classic MID task using data collected by Srirangarajan et al. (2021), available at: openneuro.org/datasets/ds003858.

Cognitive Model

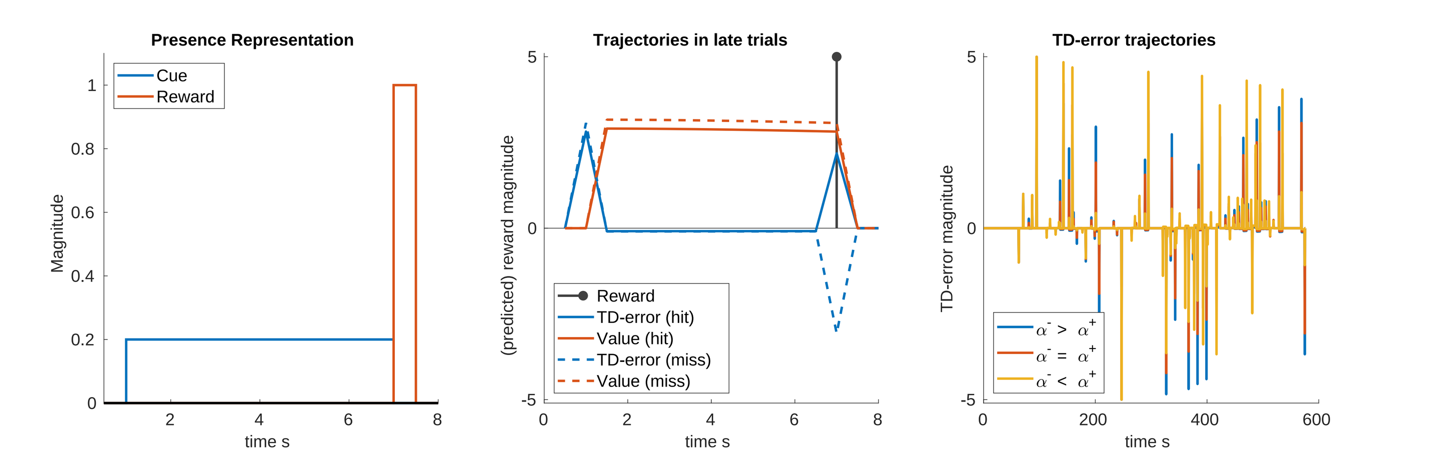

Fig. 2: Left, presence representation of a single trial; middle: RPE and value for a hit / loss trial; right: RPE trajectory for different learning rate asymmetries.

We use a TD(λ) model to estimate the trial-by-trial reward prediction error (RPE) trajectory and a presence representation of each trial (Ludvig et al., 2012).

$$\delta_t = R_{t+1} + \gamma W_t X_{t+1} - W_t X_t$$

$$W_{t+1} = W_t + \alpha \delta_t e_t$$

$$e_{t+1} = \gamma \lambda e_t + X_t$$

Simulations

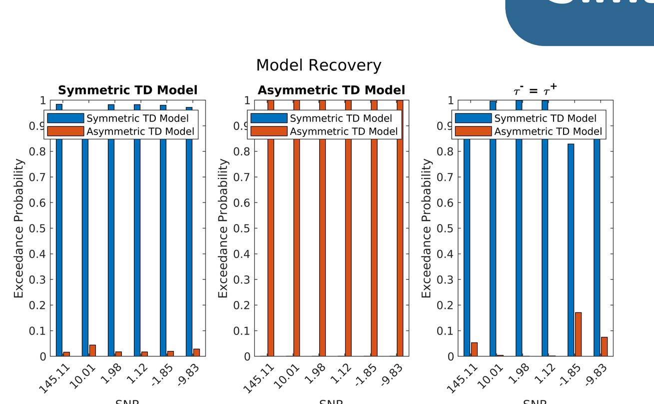

Fig. 3: Recovering the generative process.

We can recover whether data was generated by a single learning rate (τ) or an asymmetric learning rate model (τ^+, τ^-), even in the presence of noise. Furthermore, parameters can be estimated accurately.

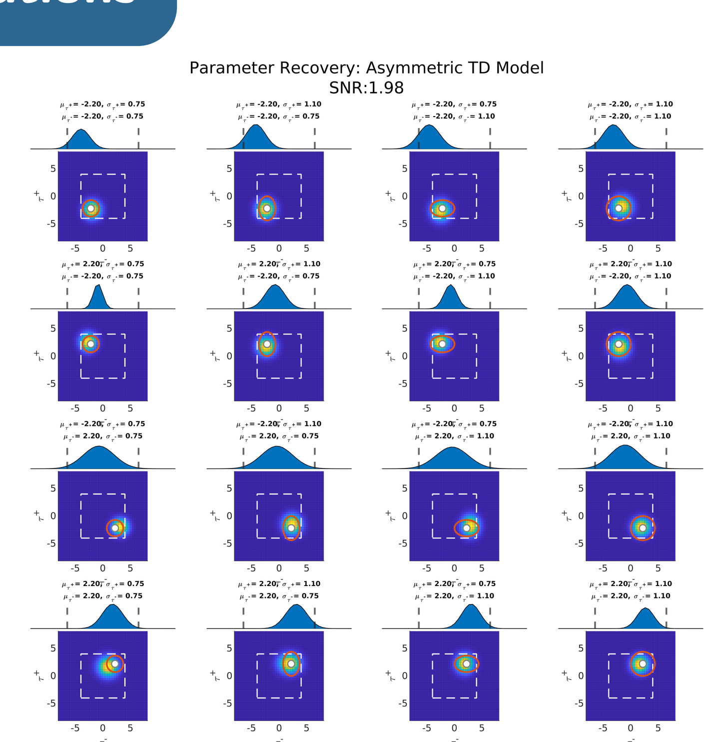

Fig. 4: Simulated voxels (red ground truth). Heatmaps: recovered cognitive field for an asymmetric learning model, above estimated 1-D cognitive field of the symmetric model

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CPM

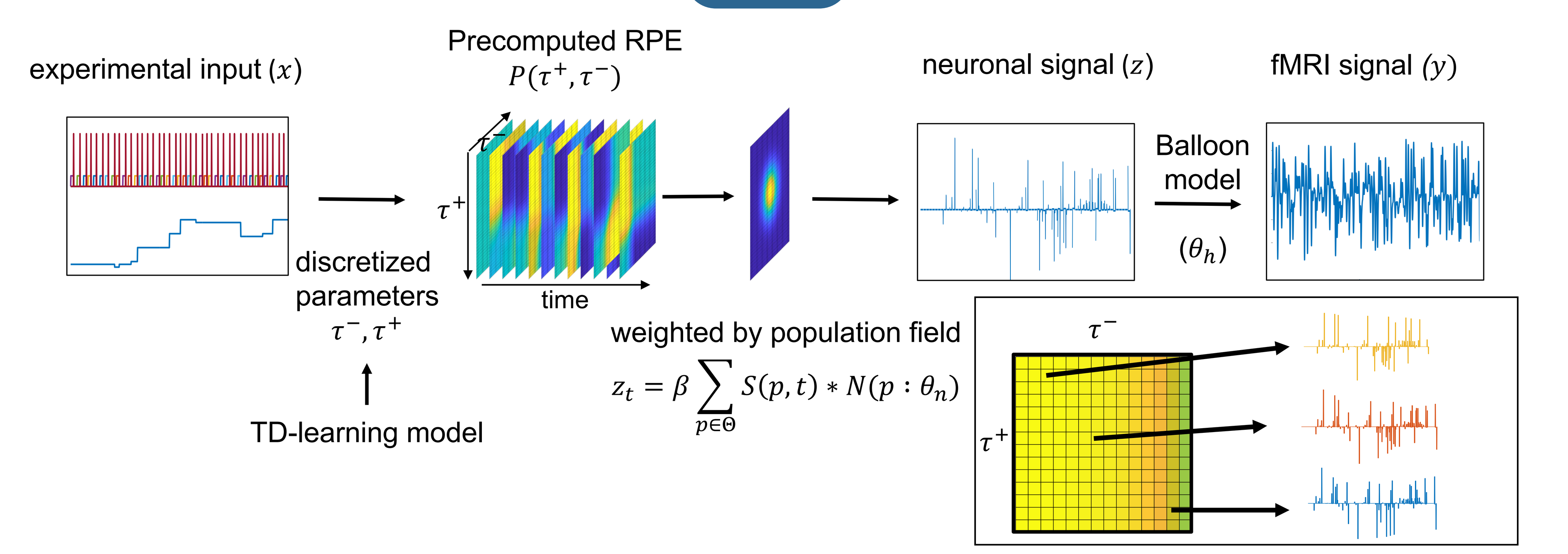

Fig. 5: Schematic overview over the CPM method. Note: $\frac{1}{1+e^{-\tau}} = \alpha$

- Outputs (latent states) of a cognitive model can be seen as neural responses generating parts of the BOLD signal in fMRI (e.g. model based fMRI, O'Doherty et al.,2007)
- Finding the parameters of the cognitive model that generates the most plausible response can be difficult.
- These parameters span a space (P), over which we can find a cognitive field, that explains the neural response in a voxel (z_t), by fitting the population response S which has unknown parameters Θ_n.
- In our case S is a Gaussian with location $\{\mu_{\tau^+}, \mu_{\tau^-}\}$ and spread $\{\sigma_{\tau^+}, \sigma_{\tau^-}\}$, that sums over a discretized subset of P.
- As the population response is akin to a population receptive field in visual neuroscience, we build on the BayesPRF toolbox by Zeidman et al. (2018) using Variational Laplace for inference (Zeidman et al., 2022).

Preliminary results

Group analysis

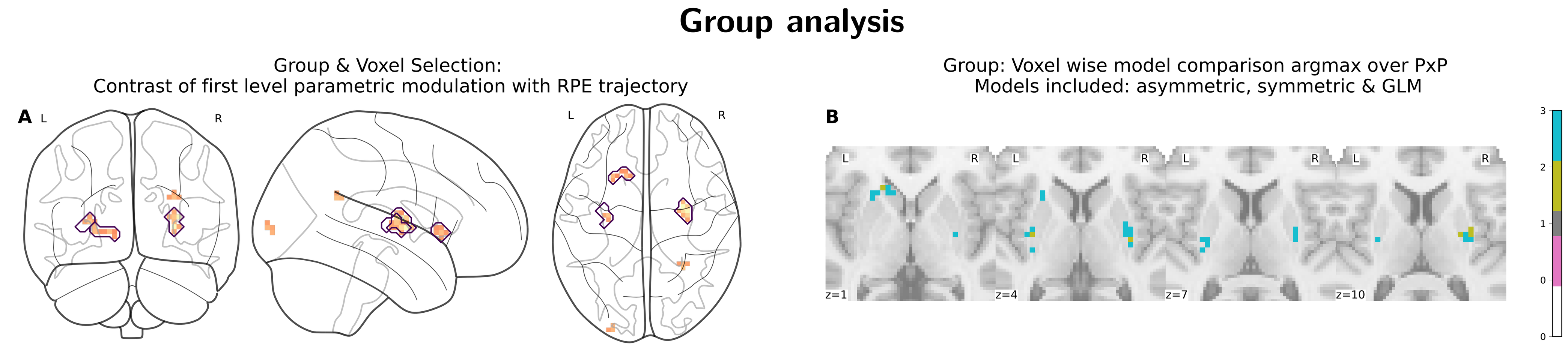

Fig. 6: A) group t-statistic of model based fMRI analysis, $p < 0.001$, cluster threshold=9. B) Model comparison over subjects, GLM is a scaled RPE trajectory ($\alpha = 0.5$)

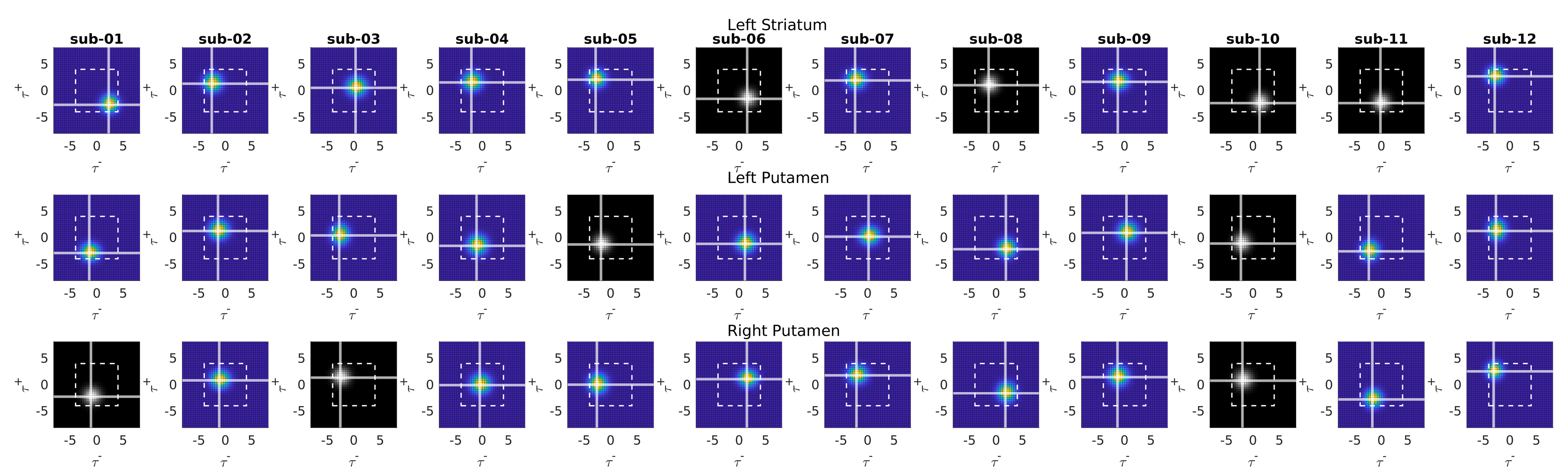

Fig. 7: Cognitive fields estimated by the asymmetric learning model, for the averaged time series in each region of interest. Dark plots do not exceed a BF>10 (comparison against null model, with fixed $\{\beta = -4\}$)

Subject level analysis

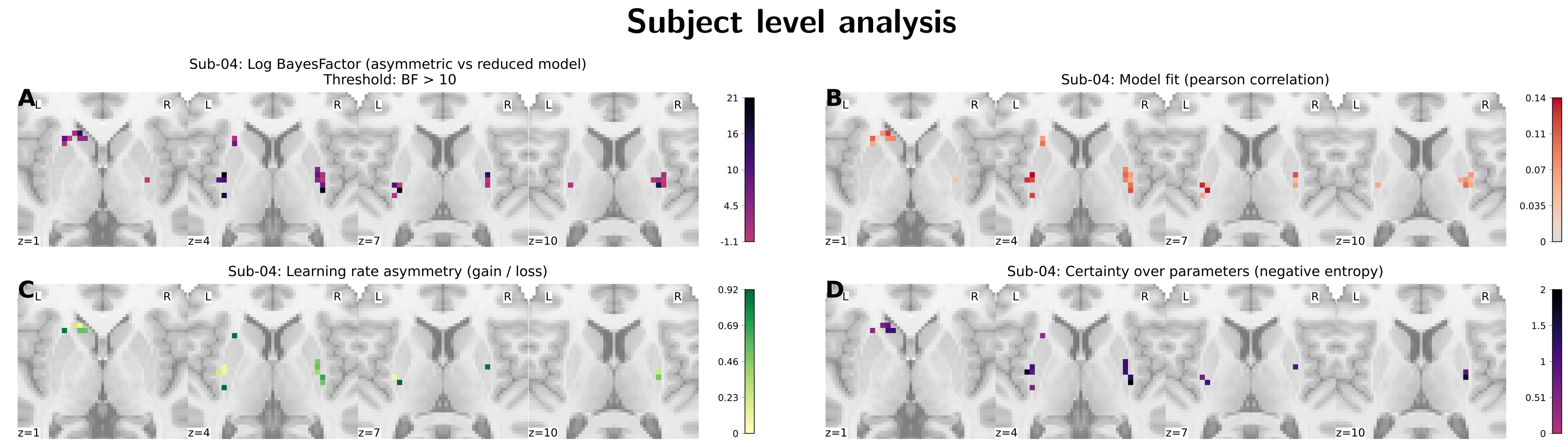

Fig. 8: For an example subject we see: A) BayesFactor as described above; B) Pearson correlation of the predicted vs the actual signal. C) The learning rate asymmetry $\frac{\alpha^+}{\alpha^+ + \alpha^-}$, higher values indicate larger asymmetry towards learning from gains. D) Negative entropy of the receptive fields' parameters (θ_n), as a measure of certainty over the parameters.

Conclusion

- CPM builds on receptive field models to map cognitive models onto brain.
- CPM is fast enough to apply to real neuroimaging data.
- Proof of principle analyses show robust model & parameter recovery in simulations.
- Application to real data, shows a first promising application of the method, further validations are necessary.

References

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