Task Preparation is Reflected in Neural State Space Dynamics

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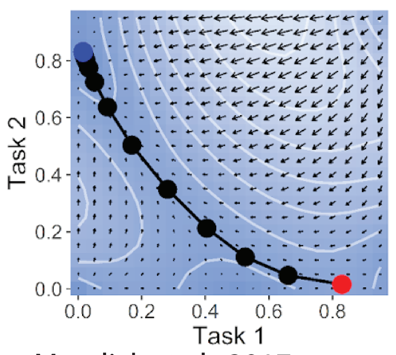
Introduction

Task sets define the mappings between our perception and our actions. **How does our brain transition between different task sets?**

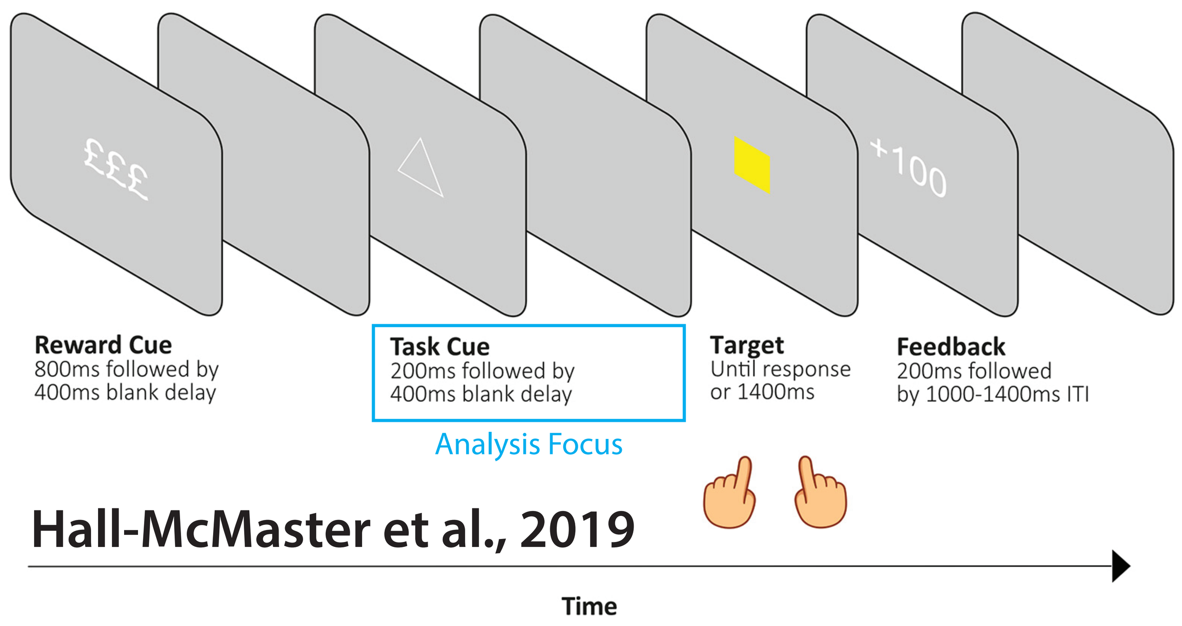
Computational cognitive theories have suggested that our transitions can be understood using dynamical systems theory, with neurally plausible process models. However, there is limited neural evidence support these dynamical models.



Musslick et al., 2017

Here, we re-analyzed a recent task-switching neuroimaing experiment to explicitly test the dynamical switching hypothesis. Using tools from systems neuroscience for estimating latent dynamical systems, we show the neural dynamics support task reconfiguration.

Task Design



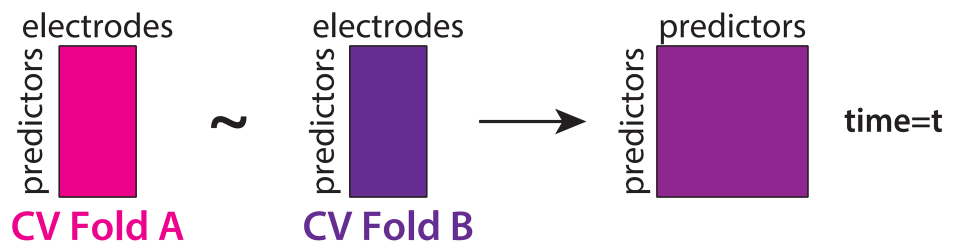
Human participants (n=30) performed a cued task-switching experiment during 61-channel scalp EEG. Participants responded to either shape color or shape identity, depending on pre-trial cue (50% switch rate).

Participants performed 10 blocks of 65 trials, excluding trials with errors, previous errors, or EEG artifacts (M=469 trials).

EEG Analysis

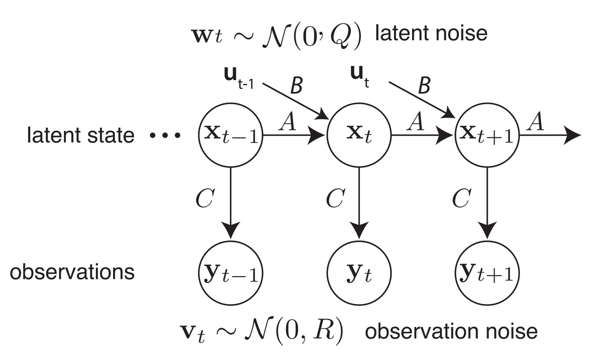
EEG data were preprocessed in the original experiment. We used regression baseline (300ms - 50ms before task cue onset).

Encoding Geometry Analysis: Linear encoding models were fit at each timepoint, separately for even and odd runs. Electrode regression weights were correlated across runs to test encoding reliability and alignment.



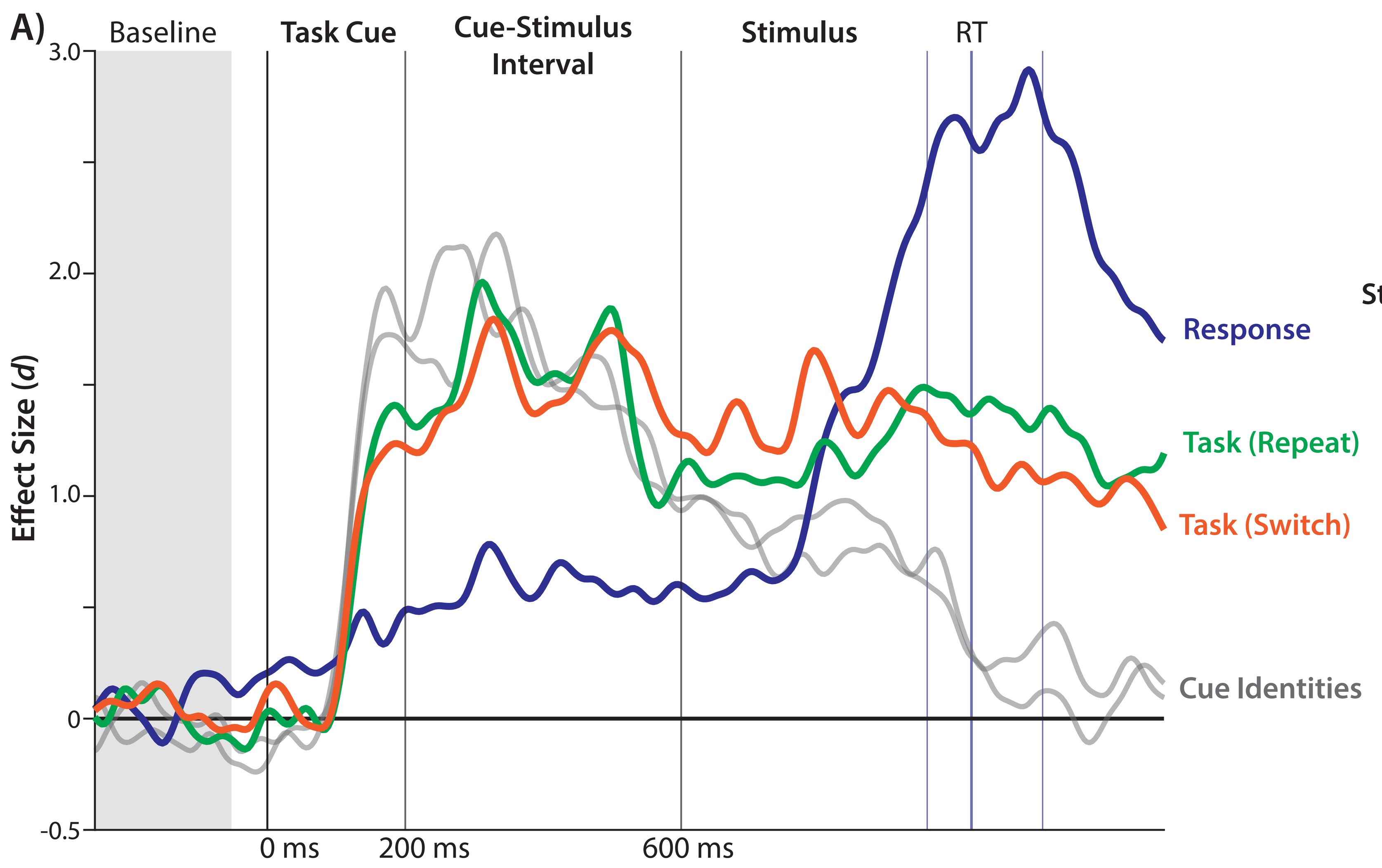
State Space Inference: We modeled the EEG activity as a latent dynamical system, mapping a latent system (***x***, e.g. neural sources) to an observed system (***y***, electrode voltage). Task conditions were inputs to the latent system. We used linear dynamics and observations with Gaussian noise.

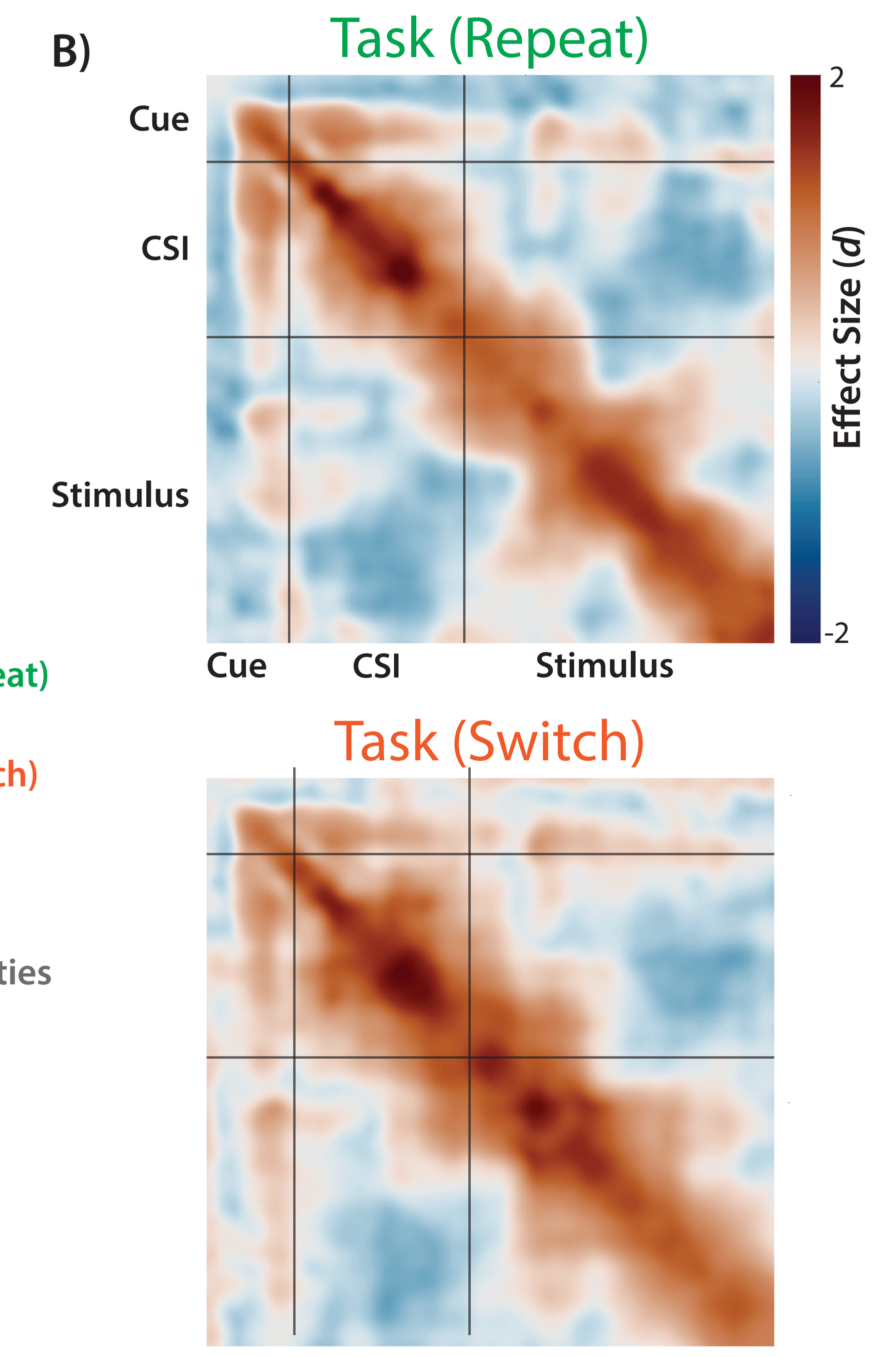
We estimated the system parameters using a custom Julia implementation of Expectation Maximization, which has efficient analytic methods for inferring linear-gussian systems.



$$x_{t+1} = Ax_t + B_t u_t + w_t$$
$$y_t = Cx_t + v_t$$

Dynamic Encoding





A) We replicated robust pre-stimulus task encoding, with different timecourse from value cue features.

B) Temporal generalization shows dynamic task encoding (e.g., relatively poor generalization from cue period to task period).

State Space Inference

C) Higher dimensional latent spaces fit held-out data better.

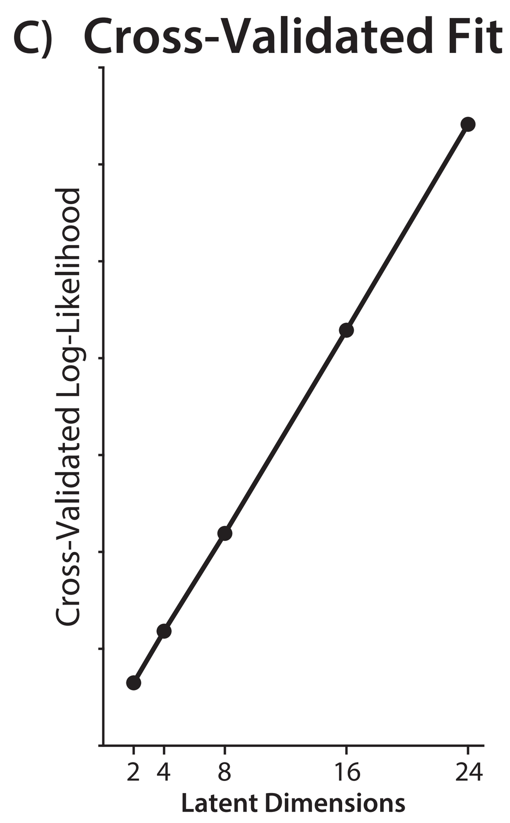
D) Our best-fitting model made good single-trial predictions for held-out data, using the standard methods of filtering test trials with estimated parameters.

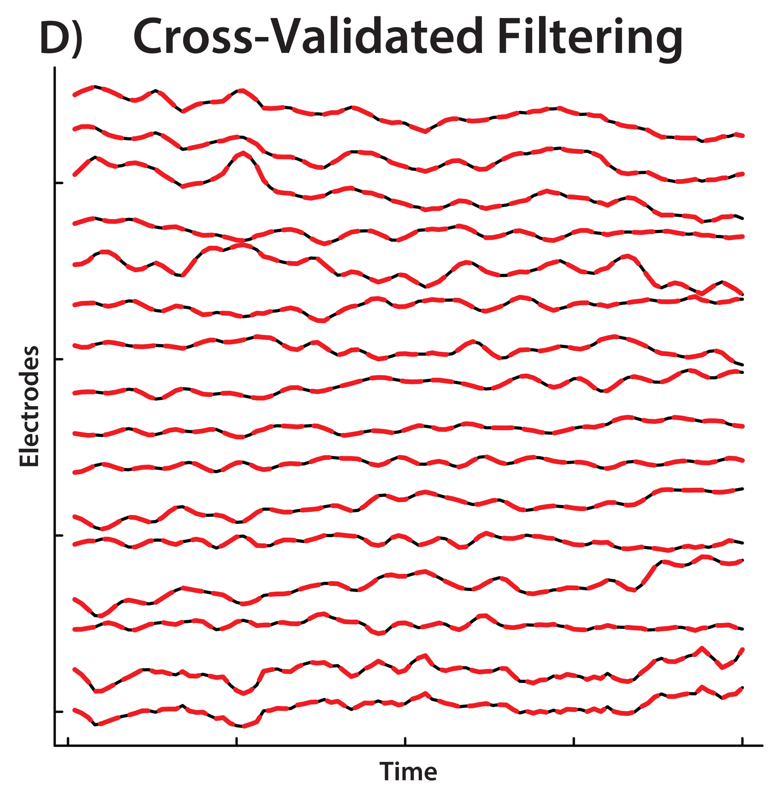
E) Input magnitude phasically increased during the cue period

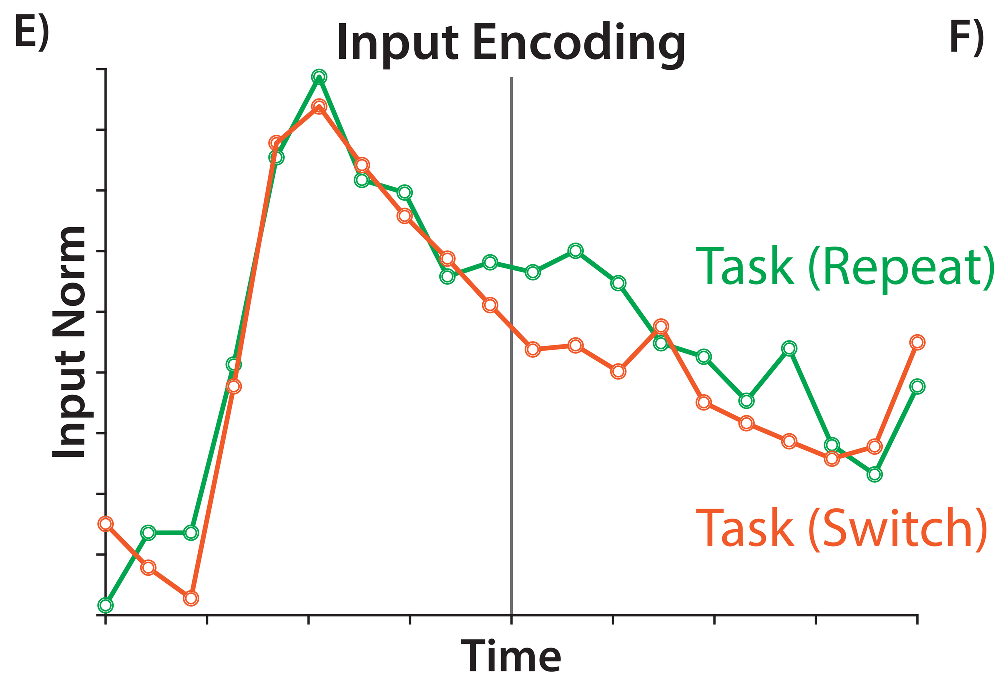
F) Temporal similarity of input dimensions consistent with periodic encoding

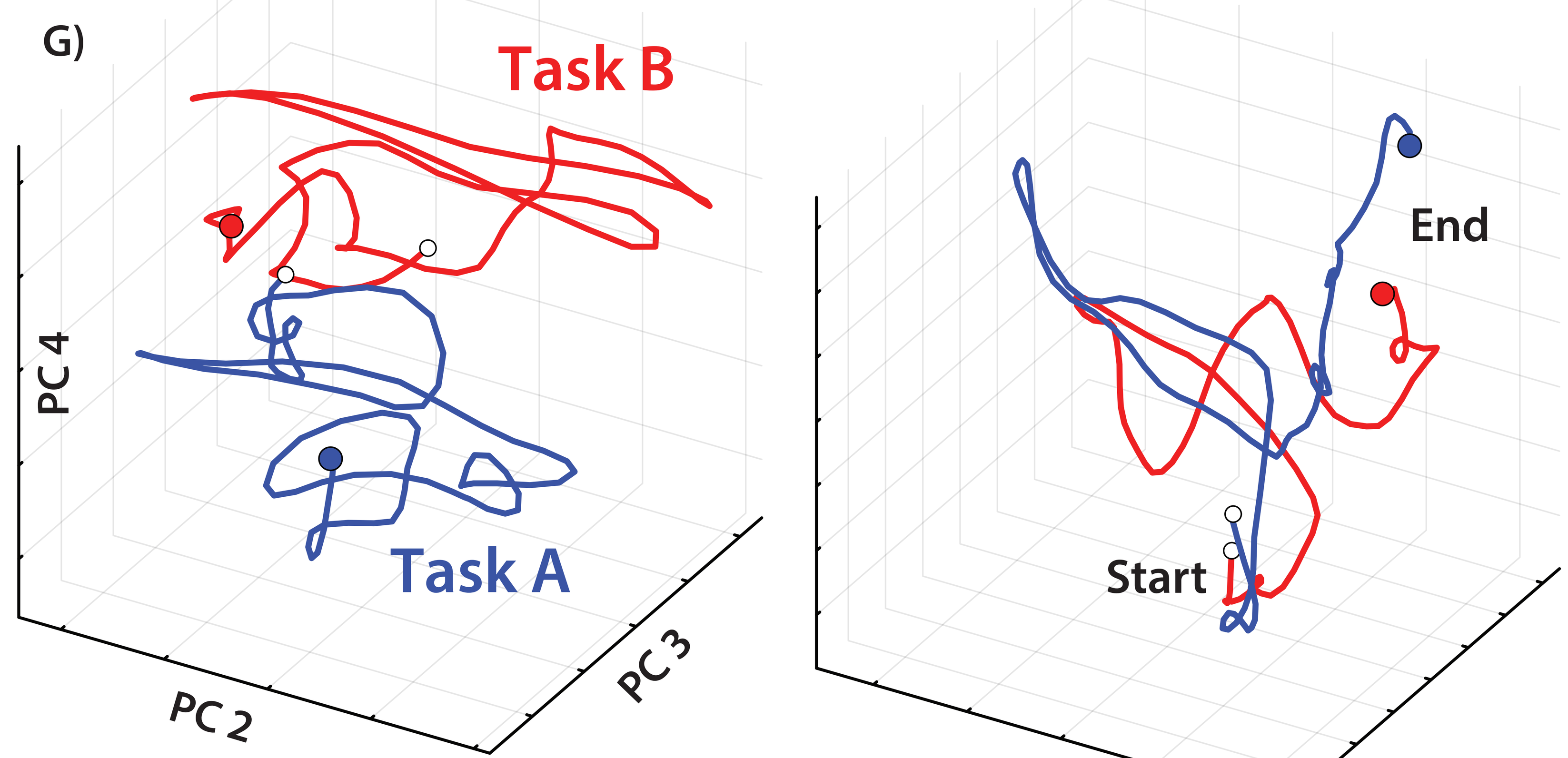
G) Average latent trajectories for two example participants, plotted on their principal components

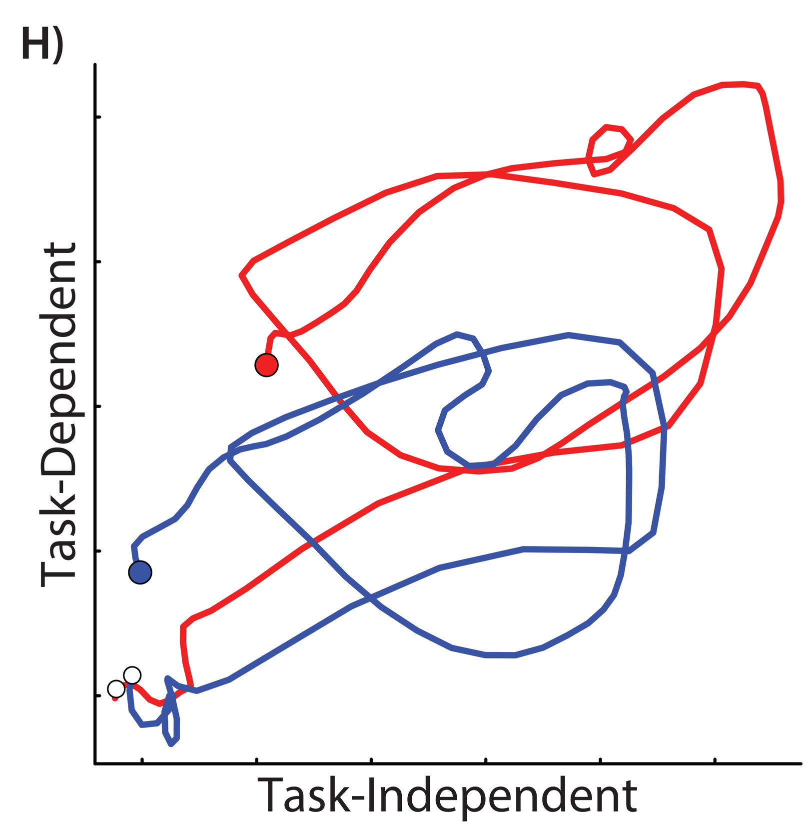
H) Average latent trajectory for a third participant, projected into the average task-invariant and task-encoding input dimensions







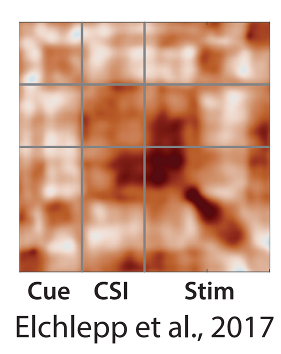




Discussion

- Task encoding dynamically evolves throughout preparation
- Dynamical systems models are a good fit to EEG data
- Task-dependent dynamics are non-stationary or periodic

Next Steps:
- Replicate in other task-switching datasets
- Measure neural correlates using MEG
- Test optimal control theories



Elchlepp et al., 2017

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