Continuous and Discrete Transitions during Task-Switching

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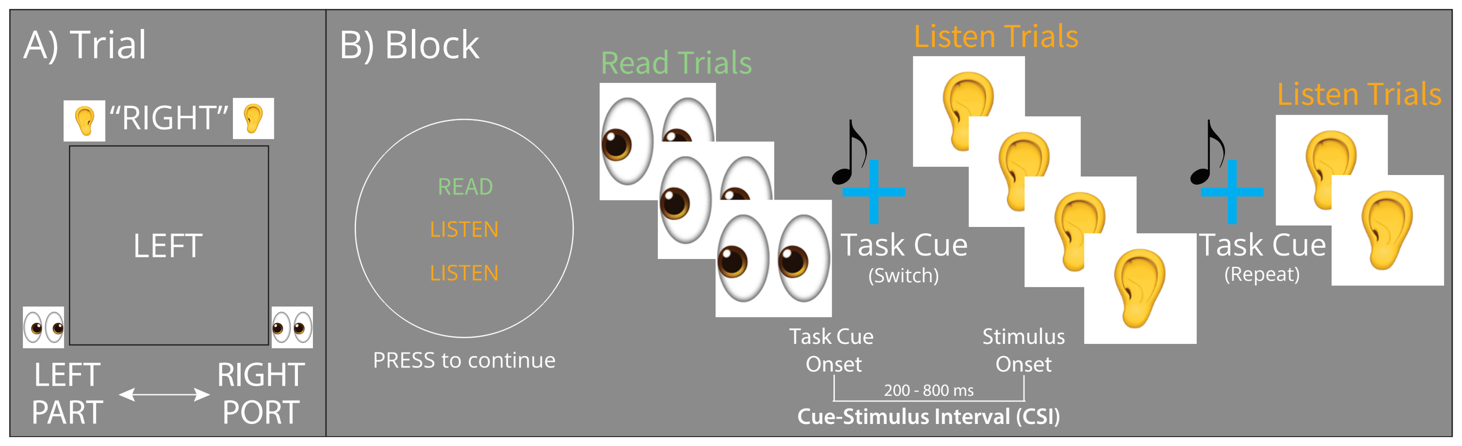
Research Question

Task sets define the mappings between our perception and our actions. **How do we purposefully transition between different task sets?**

Previous work has suggested that our transitions can be understood using dynamical systems theory. However, continuous dynamics rely on a continuum of task sets between two settings, an idea that has been challenged based on seemingly discrete shifts in performance.

Here, we developed a novel task to maximize reconfiguration demands, and used trial-level modeling to characterize the functional form of task-set reconfiguration.

Task Design



A) In each trial, participants saw a word and heard a word, responding to the relevant dimension. B) At the beginning of each block, participants read a task list, instructing the order in which to perform the reading and listening tasks. They then performed each task over the course of a random-duration mini-block, switching to the next task on the list when they received a generic Task Cue. The preparation time for the next task randomly varied across task transitions (most common range: 200 - 800 ms).

Participants (n=59) responded to an audio-visual stimulus, either reading the text or listening to the speech.

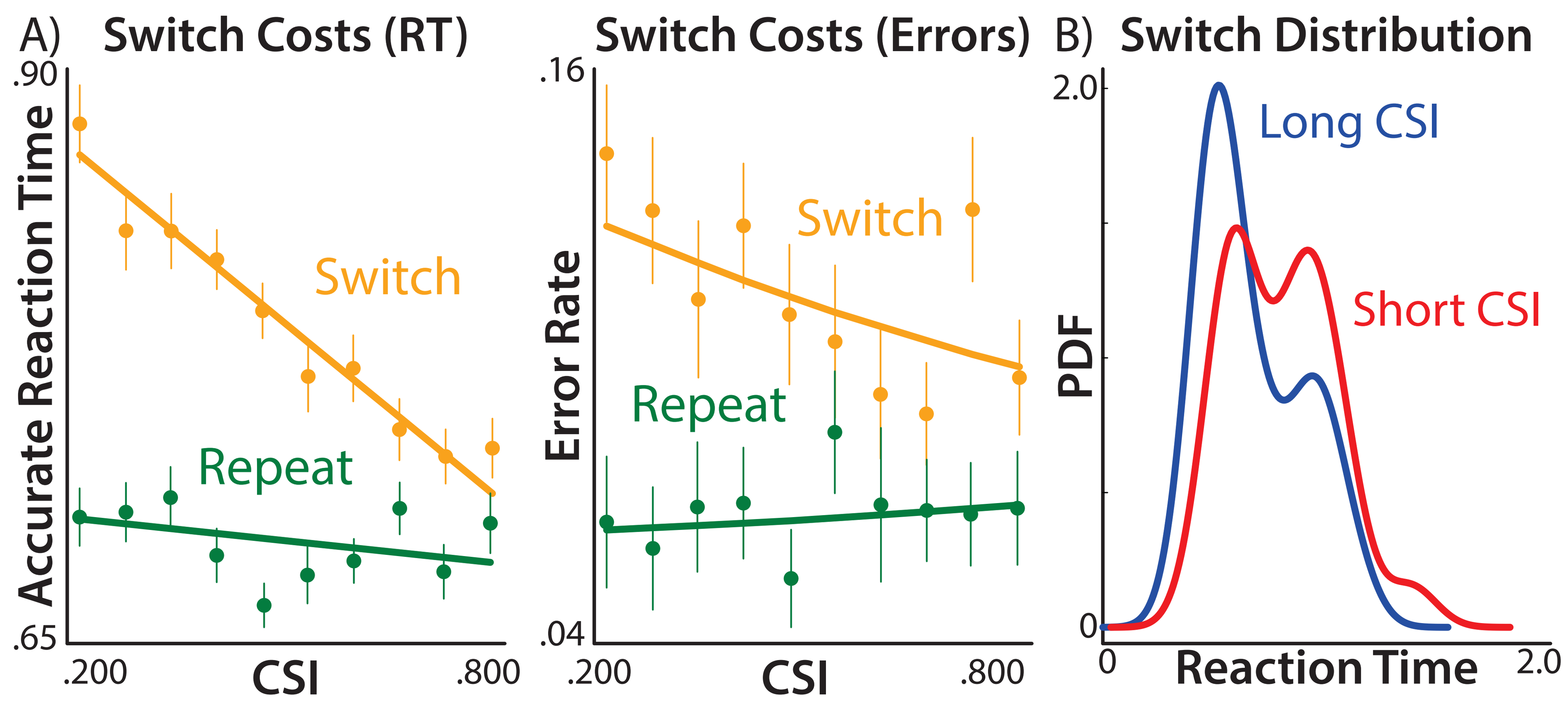
At the start of each block, participants were given a list of three tasks (e.g., read, listen, listen). In each mini-block of trials, they had to do the corresponding task. Transitions between mini-blocks were signaled with a task-agnostic cue (blue fixation cross + tone), forcing participants to recall the upcoming task.

To measure the dynamics of reconfiguration, we uniformly sampled task cue duration (cue-stimulus interval; CSI) at each mini-block transition, measuring how the first trial after a transition depended on preparation time.

Results

Performance improves with preparation time
As expected from previous work, people performed worse when they switched tasks than when they repeated tasks. Also consistent with previous work, people reduced these switch costs with more preparation time (CSI).

However, the post-switch RT distribution revealed that performance was bimodally distributed, inconsistent with the vanilla version of the dynamical systems account.



A) Longer cue-stimulus intervals (CSI) reduced participants switch costs. On switch trials (orange), participants were faster (left) and made fewer errors (right) with longer CSIs, whereas CSI had a much weaker influence on repeat trials. CSI is binned for visualization. Error bars reflect within-subject standard error; trend lines are predictions from mixed effects regression. B) Post-switch reaction time distributions from an example participant. 'Long CSI' are the longest 25% of CSIs (> 600 ms), 'Short CSI' are the shortest 25% of CSIs (< 334 ms).

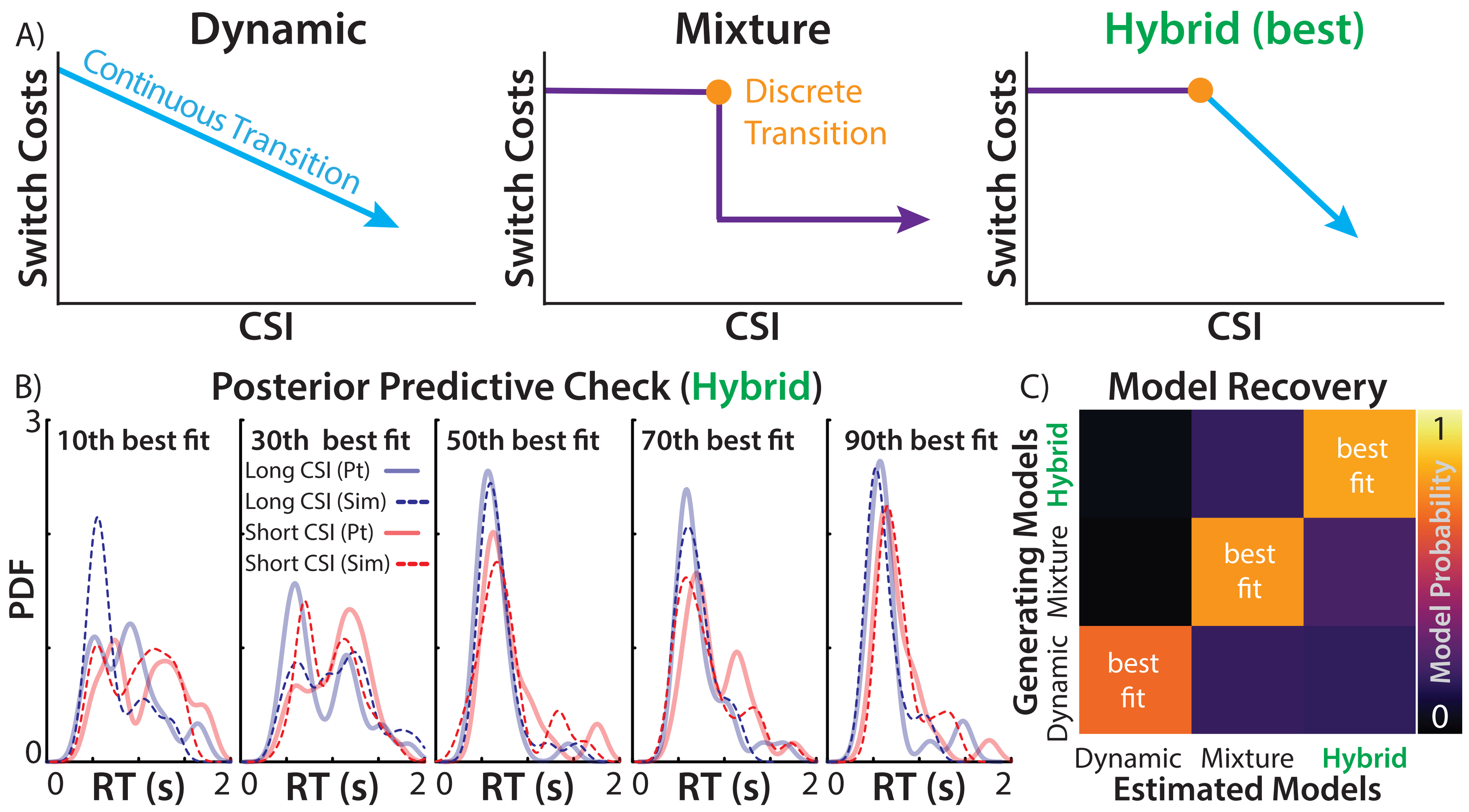
Participants show discrete and continuous transitions
To understand these dynamics, we fit trial-level models to post-switch RTs using hierarchical EM.

Dynamic models assume gradual dynamics: (logRT ~ CSI)

Mixture models assume discrete transitions. RTs come from two distributions, with a mixture that depends on CSI:
($\log RT \sim wN(\mu_1, \sigma) + (1-w)N(\mu_2, \sigma)$; $w \sim CSI$)

Hybrid models assume that participants transition between two different dynamical regimes. Mixtures and means depended on CSI:
($\log RT \sim wN(\mu_1, \sigma) + (1-w)N(\mu_2, \sigma)$; $w, \mu_1, \mu_2 \sim CSI$)

Hybrid models fit best (likelihood on held out participants). In the best-fitting variant, the first regime was static (no dynamics), and the second regime improved over time.



A) There were three classes of models: models with continuous transitions ('Dynamic'), models with discrete transitions ('Mixture'), and models with both continuous and discrete transitions ('Hybrid'; best-fitting). Note that the discrete transition onset is random across trials. B) Behavior simulated from the best-fitting Static-Dynamic Hybrid model approximated participants' RT distributions. Participants are sorted according to their average model likelihood (left to right, worst to best fitting). Simulations reflect a single draw from the model to avoid over-smoothing. B) Model recovery demonstrated that the ground-truth model could be selected by our fitting and comparison procedures. Specific models are 'Dynamic', 'Static Mixture', and 'Static-Dynamic Hybrid'. Model fits are posterior model probabilities on cross-validated likelihoods.

Discussion

Unlike the predictions of continuous and discrete transition models, we found that a 'switching dynamical system' was the best explanation for participants behavior.

This kind of system suggests that there are at least two distinct processes involved in task switching. Consistent with this idea, it has been proposed that discrete dynamics during task-switching reflect the recall of task information from episodic memory. In our task, these demands are elevated due to the uninformative cue and the block-varying task list.

Ongoing work suggests that reducing memory demands shifts behavior closer to the continuous hypothesis, consistent with this memory account.