How the Tail Wags the Dog in Task Switching – Response Selection May Interfere with Task Selection

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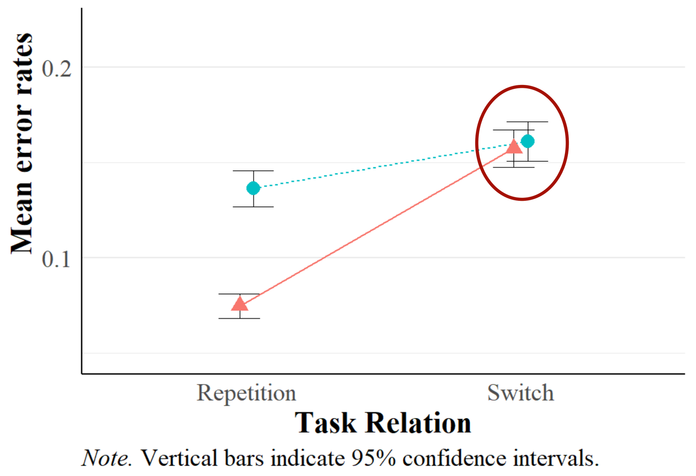
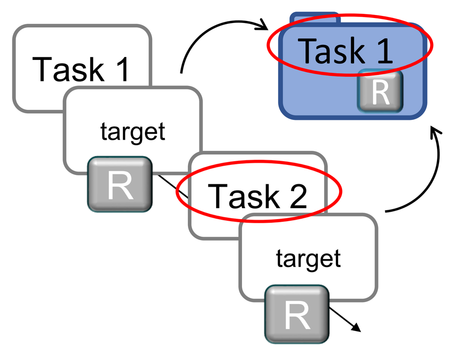
The Response Repetition (RR) Effect in Task Switching

Task switching (see Kiesel et al., 2010 for a review) used to study cognitive control in multitasking settings, but performance is also affected by features binding and episodic retrieval processes (e.g., Koch & Allport 2006).

For example, we often observe response repetition benefits in task repetitions that *disappear* or become *costs* in task switches. Different accounts exist that can explain this effect, one of them is task-response binding and retrieval account (Altmann, 2011; Koch, Frings & Schuch, 2018).



Note. Vertical bars indicate 95% confidence intervals.

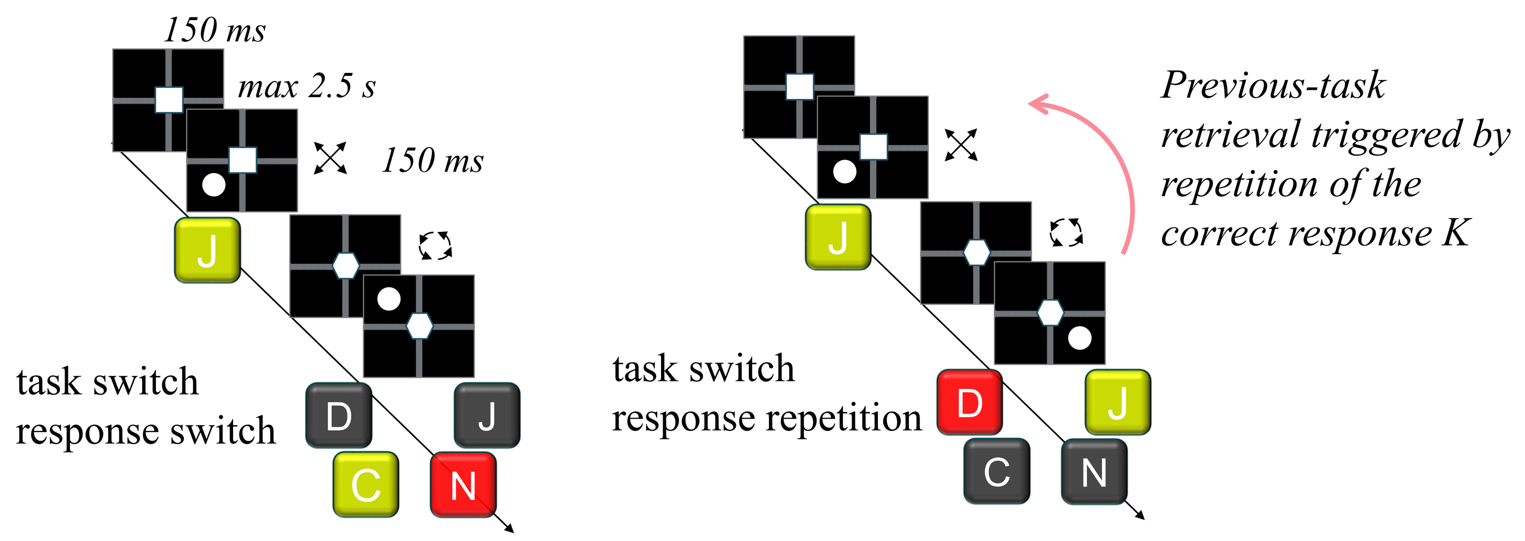


The task and the response are bound in each trial. When the response repeats, it retrieves the n-1 task, which is wrong in task switches.

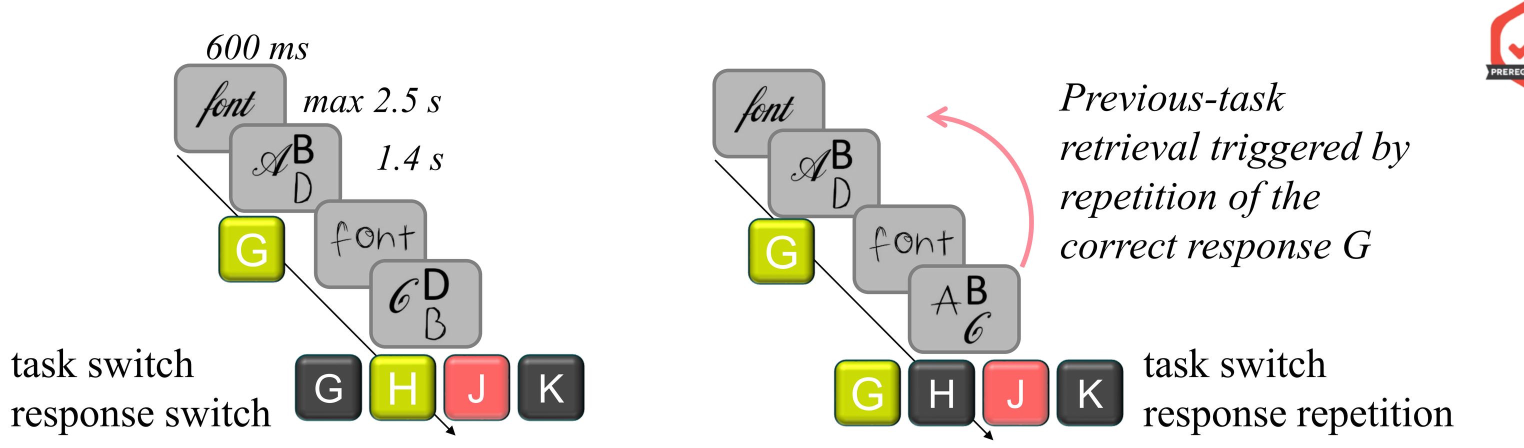
Research Question: Does repeating the correct response induce retrieval of the previous task?

The Datasets: A Re-Analysis of Grange (2023) and a New Study

Re-analysis of Grange, 2023. Participants switched between three tasks (mentally move the dot in the correct quadrant) with four responses (D, C, J, or N) mapped on the spatially compatible responses. Once the effect of interest was found in the **N=255** participants, these were subsampled to estimate the minimum number of observations necessary for detecting the effect with > 80% power in the new study.



New Study. Participants switched between three tasks (detect the letter in the cued font), with four responses (A, B, C, or D mapped on G, H, J and K, respectively). According to the power analyses, **N=96** granted enough observations to find the effect of interest in 80% of the cases.



G is correct, but J may be erroneously pressed if the n-1 task is retrieved and performed.

We could distinguish correct responses from n-1 task confusion errors, third task-confusion errors and response confusion errors.

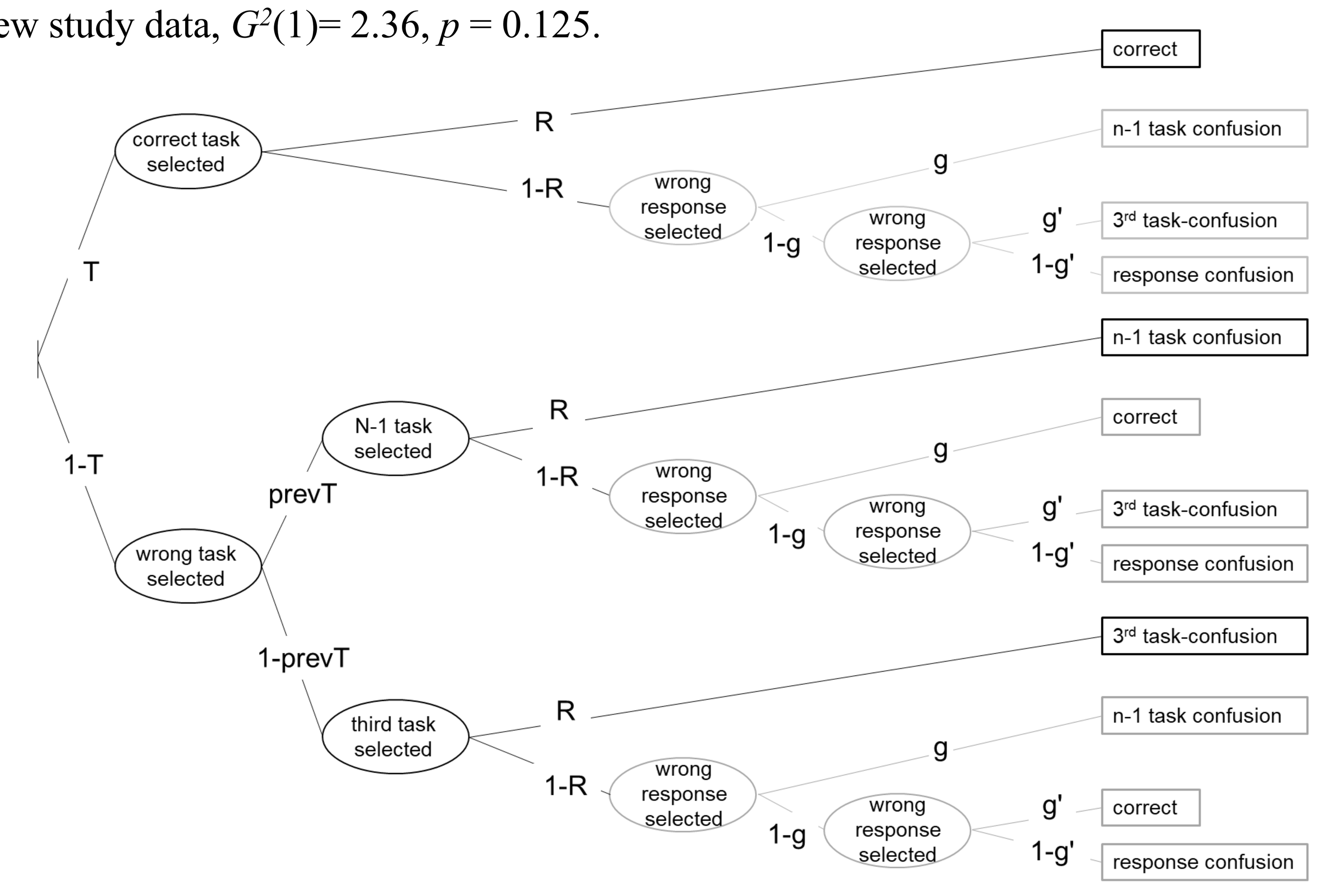
Operational Hypothesis: In response repetitions, higher probability of n-1 task confusion errors than in response switches, due to response-triggered retrieval of the n-1 episode.

Classical MPT Analyses: Aggregate Data Across Participants

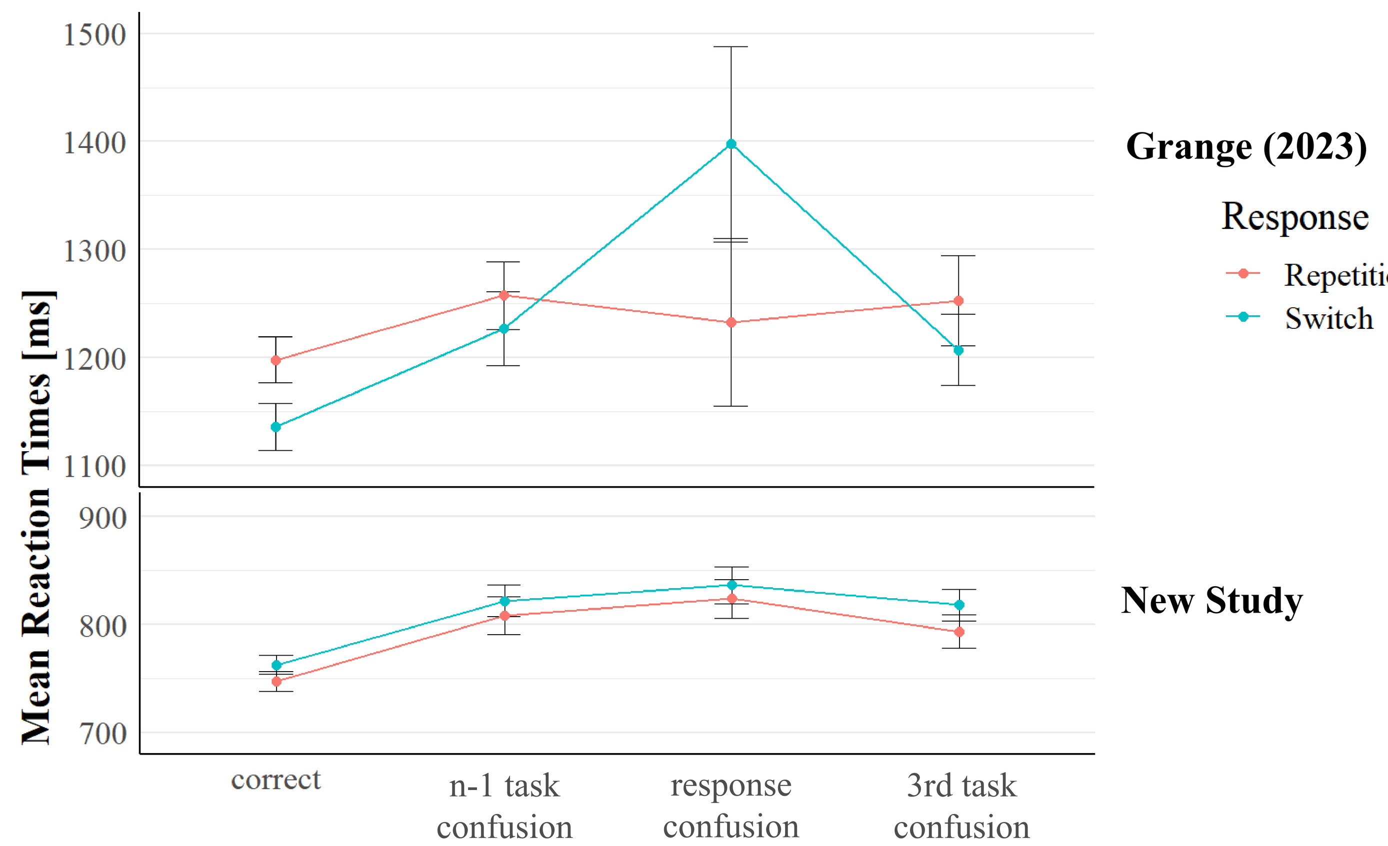
Descriptives. We looked at the % of each error type over the total number of errors, pooling data from all participants in the new study and in Grange (2023). In both cases, the % of n-1 task confusions was higher in response repetition than switches.

		% of Errors Pooled	
Response	**Category**	**New Study**	**Grange, 2023**
Response Repetition	N-1 task confusion	**32.62%**	**45.80%**
	Response confusion	28.74%	6.44%
	Third task confusion	38.64%	47.76%
Response Switch	N-1 task confusion	**29.19%**	**36.01%**
	Response confusion	27.76%	6.93%
	Third task confusion	43.05%	57.06%

Preregistered analyses. We designed the Multinomial Processing Tree Model (MPT, Batchelder & Riefer, 1999) below, with 8 categories, 6 free categories and 6 free parameters (0 df). The *T* parameter indicates selection of the correct task, *prevT* selection of the n-1 task, and *R* selection of the correct response for the selected task. g and g' were constant and equal to .33 and .5, respectively. We predicted the $prevT_{\text{response repetition}}$ parameter to be higher in response repetitions than switches. Thus, a model in which $prevT_{\text{response repetition}} = prevT_{\text{response switch}}$ should misfit the data. This was the case for Grange (2023) data, $G^2(1) = 45.87$, $p < .001$, but not for the new study data, $G^2(1) = 2.36$, $p = 0.125$.



Reaction times by response type. Mean RTs in the different response categories. In both Grange (2023) and the new study, the different errors were numerically slower than the correct responses. We had no hypotheses about that, but slower errors speak against fast guesses and in favour of time-consuming processes that might reflect the need to solve interference, e.g., triggered by the initial response selection that may be capable of interfering with task selection.



Note. Vertical bars indicate standard errors of the means.

(Work in Progress) Latent-Trait Hierarchical Bayesian MPT Analyses

We used the TreeBUGS R package (Heck et al., 2018) to fit latent-trait hierarchical MPT models on the new study and Grange (2023) data with n.iter = 50000, n.burnin = 10000, n.adapt = 3000, n.thin = 3, and changing the default priors as follows:

prevTprior = "dnorm(0,1)" # default precision and mean (= 0.5).

Tprior = "dnorm(1.96,1)" # default precision, but mean = 0.975

Rprior = "dnorm(1.2,1)" # default precision, but mean = 0.885

(without doing so, the three MCMC did not converge for many parameters and several R-hat were > 1.05).

Model selection. In the new study, the best model was the one including only T as a free parameter. The best model whereby prevT was a free parameter included also R as a free parameter. In Grange (2023), the best model was the full model.

New Study			Grange, 2023		
Free Parameters	**DIC**	**PPP**	**Free Parameters**	**DIC**	**PPP**
T	2784.74	0.432	*full_model*	*5397.49*	*0.505*
T+R	2791.22	0.388	T+prevT_model	5402.27	0.01
R+prevT	*2793.06*	*0.484*	T+R_model	5446.15	< 0.01
All	2793.51	0.431	T_model	5448.18	< 0.01
prevT	2796.98	0.166	R+prevT_model	5559.23	< 0.01
R	2798.92	0.025	R_model	5591.5	< 0.01
None	2800.03	0.011	prevT_model	5636.49	< 0.01
T+prevT	5318.93	0.317	null_model	5684.34	< 0.01

Parameters Estimates. Work in progress, no test was conducted to test parameters difference.

	Classical MPT				traitMPT Estimates			
	New Study *full model* (df = 0)		Grange 2023 *full model* (df = 0)		New Study *R+prevT*		Grange 2023 *full model* (df = 0)	
Parameter	**Estimate**	**95% C.I.**	**Estimate**	**95% C.I.**	**Mean**	**SD**	**Mean**	**SD**
prevT	**0.31**	(0.14, 0.47)	**0.48**	(0.46, 0.52)	**0.286**	0.108	**0.488**	0.016
prevTs	**0.12**	(0.01, 0.24)	**0.36**	(0.35, 0.39)	**0.088**	0.057	**0.362**	0.012
R	0.89	(0.88, 0.9)	0.99	(0.99, 0.99)	0.896	0.008	0.995	0.001
Rs	0.88	(0.88, 0.89)	0.99	(0.99, 0.99)	0.888	0.008	0.996	0.001
T	0.98	(0.96, 0.99)	0.96	(0.95, 0.96)	0.975	0.004	0.963	0.002
Ts	0.97	(0.96, 0.98)	0.97	(0.97, 0.98)	-	-	0.977	0.001

Summary & Discussion

We provided some evidence for retrieval of the N-1 task upon repetition of the N-1 response in trial N (i.e., the correct, but eventually not executed keypress).

- With classical pooled-data MPTs, we found evidence for such a retrieval in the re-analysis of Grange (2023), and a non-significant trend in the new study.
- With latent-trait hierarchical bayesian models, the parameters estimates were consistent with the classical MPT results in both studies.

Caveats: (i) The default priors of traitMPT functions were changed for the T and R parameters to priors centered on the classical-MPT estimates (otherwise, the MCMC did not converge). The results were the same when the priors were centered on 0.6 for either T or R, but the MCMC again did not converge when *both* T and R were centered on 0.6. (ii) No test on the prevT and prevTs parameters was run yet.

Next steps: (i) Can model selection be hypotheses-informed? (ii) Find out why MCMC do not converge, (ii) understand how to specify correct/meaningful priors (iv) use MPT-RT (Reaction Times) models.

Relevant References

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Link to the poster: https://github.com/ele-ben/Posters