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(1) Decision making as sequential Bayesian inference

How do we combine information to make decisions? Assumption: infer a target stimulus G and context stimulus C from noisy evidence e^G, e^C ; $r(\cdot)$ defines mapping from posterior to a probability of response. Respond based on fixed threshold on response probability.



Background: from Bayesian inference to drift and diffusion

At time τ , infer identity of $g \in \mathcal{G}$, $|\mathcal{G}| = n$ drawn from G based on evidence e_τ^G :

$$P_\tau(G = g | e_\tau^G) \propto P(e_\tau^G | G = g)P_{\tau-1}(G = g | e_{\tau-1})$$

Decide when $\max_g(G = g) > \theta$, pick option
 $\arg \max_g(G = g) > \theta$.

If there are only two hypotheses:

$$\log Z_g^+ \triangleq \log \frac{P(e_\tau^G | G = g_0)P_{\tau-1}(G = g_0)}{P(e_\tau^G | G = g_1)P_{\tau-1}(G = g_1)}$$

$$= \log \frac{P_0(G = g_0)}{P_0(G = g_1)} + \sum_{t=1}^{\tau} \log \frac{P(e_t^G | G = g_0)}{P(e_t^G | G = g_1)}$$

In discrete form: Wald's Sequential Probability Ratio Test (SPRT): optimal test for two hypotheses (Wald 1947). In continuous form: Ratcliff's Diffusion Decision Model (DDM; Ratcliff 1978). In either form, emerging consensus theory of the behavioral/neural dynamics of simple decisions (Edwards, 1965; Gold & Shadlen 2002; Kira et al. 2015).

References: Braver (2012). TiCS, 16(2), 106–13; Edwards (1965) J. Math. Psych. 2, 312–329; Gold & Shadlen (2002). Neuron, 36(2), 299–308; Kira, Yang, & Shadlen (2015). Neuron, 85(4), 861–873; Ratcliff (1978) Psych. Rev., 85(2), 59–108; Servan-Schreiber, Bruno, Carter, & Cohen (1998). Bio. Psych., 43(10), 713–722; Wald, & Wolfowitz (1948). Annals of Math. Stat., 19(3), 326–339; Yu, Dayan, & Cohen (2009). JEP:HPP, 35(3), 700–717

Define $\delta t \triangleq$ duration of a single update, and look at the limit as $\delta t \rightarrow 0$:

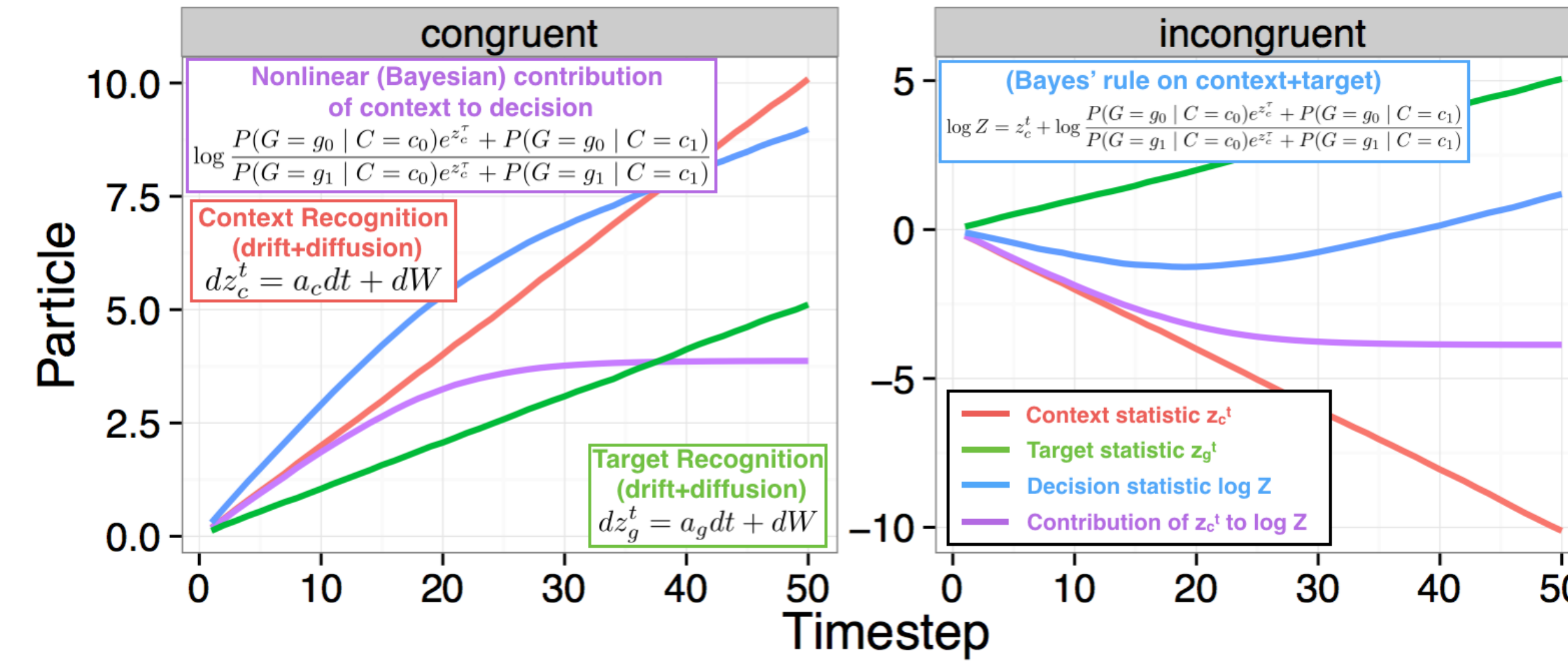
$$dz_g = z_g^0 + a_g dt + b_g dW$$

$$z_g^0 = \log \frac{P_0(G = g_0)}{P_0(G = g_1)}$$

$$a_g = \mathbb{E} \left[\log \frac{P(e_t^G | G = g_0)}{P(e_t^G | G = g_1)} \right]$$

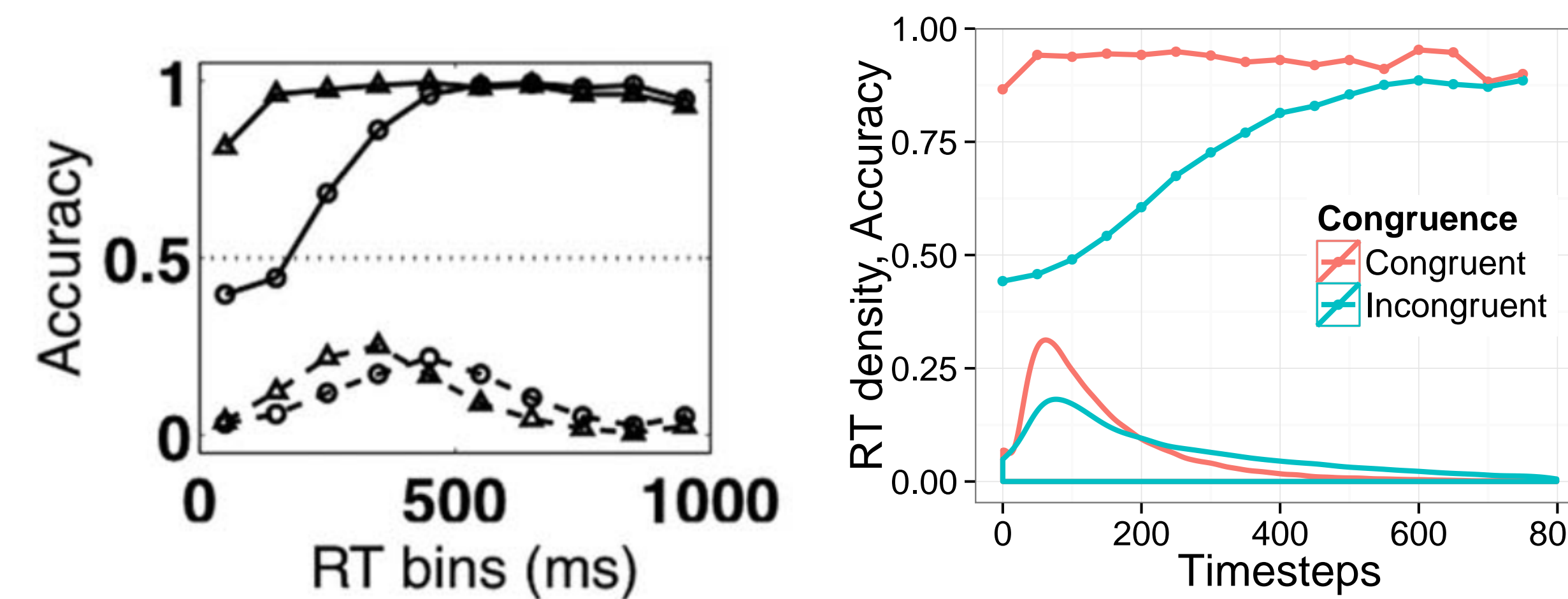
$$b_g^2 = \text{Var} \left[\log \frac{P(e_t^G | G = g_0)}{P(e_t^G | G = g_1)} \right]$$

(2) Generalizes previous model of Flanker task

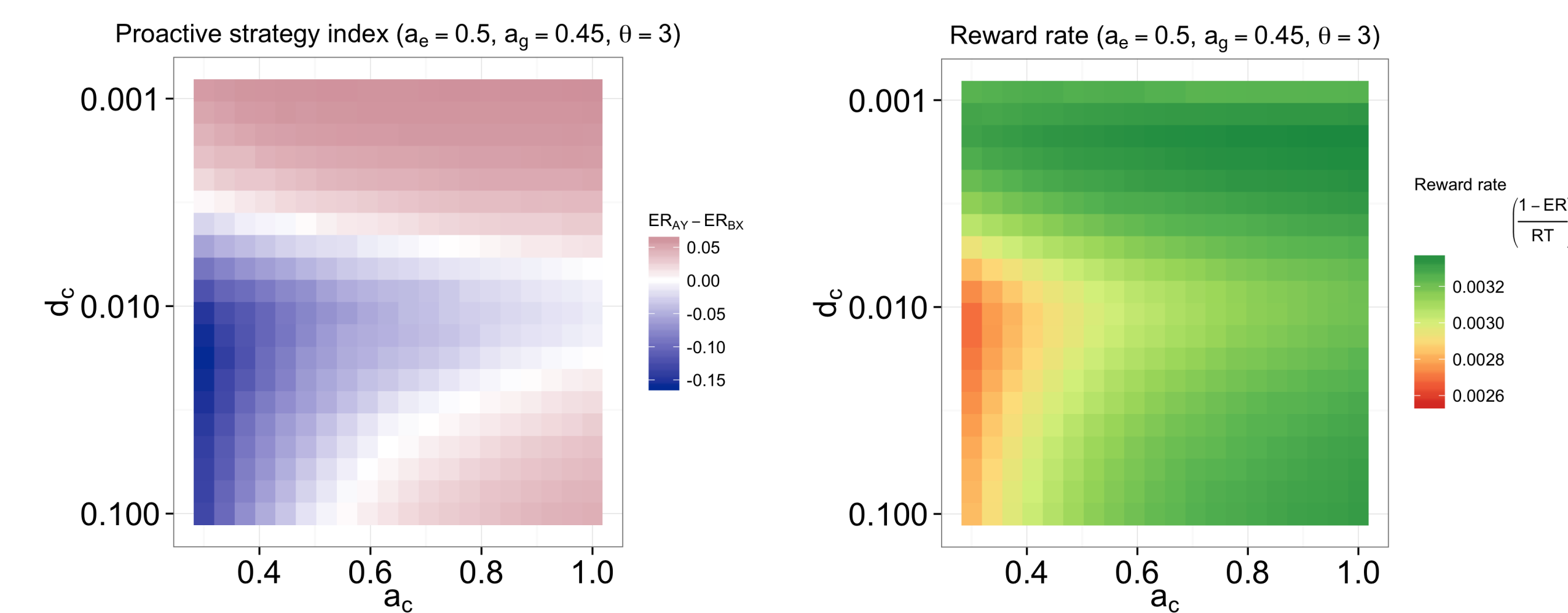


Average dynamics of model for congruent and incongruent Flanker trial. Notationally equivalent to a model by Yu, Dayan & Cohen 2009 after relabeling posterior events.

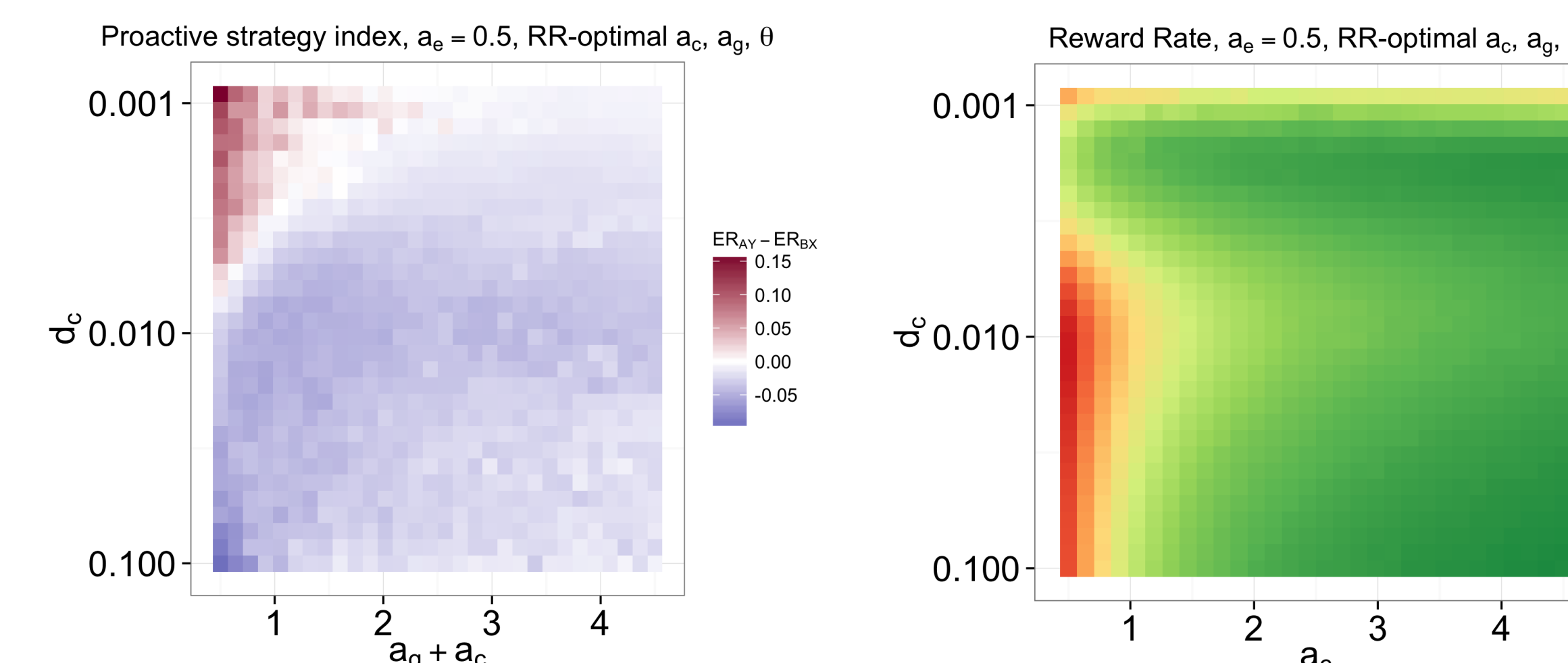
From Servan-Shreiber et al, 1998



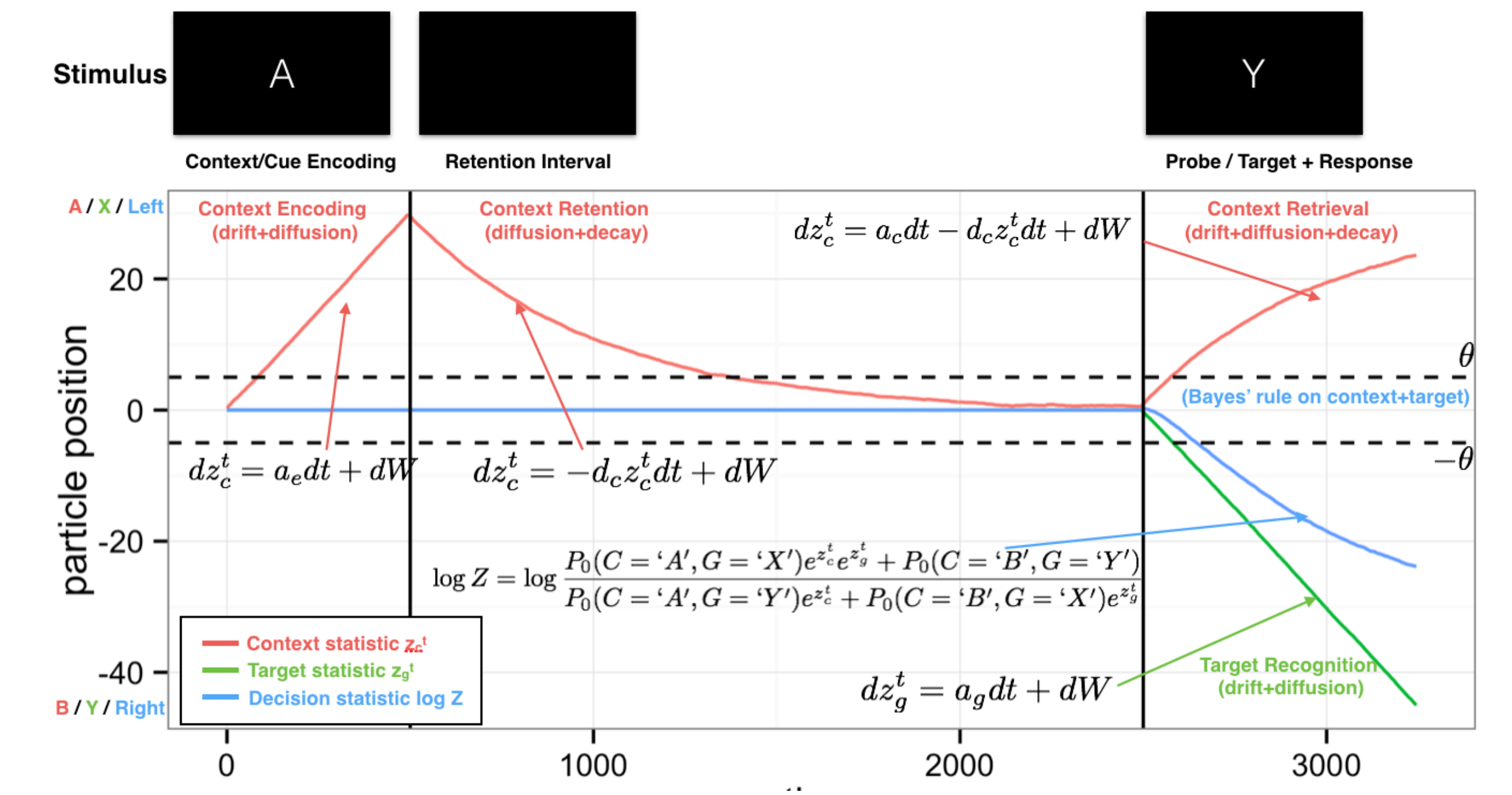
(4) Bounded optimal control in AX-CPT



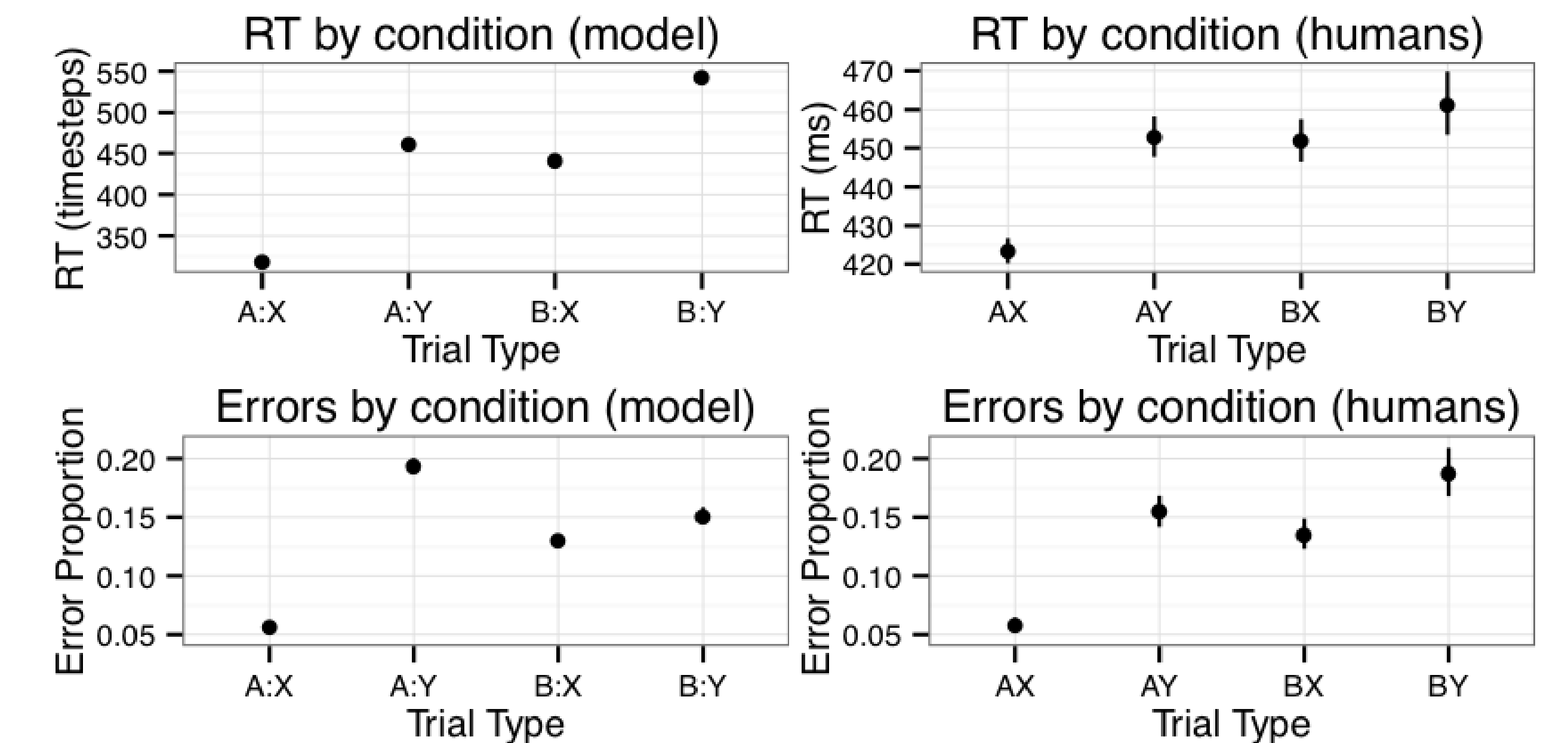
Above left: model recovers behavioral signature of both “proactive” and “reactive” control in AX-CPT (Braver 2012). **Above right:** increased reward rate with higher decay suggests a rational benefit of memory decay. **Below left:** proactive/reactive behavior index at reward-rate optimal setting of threshold, target and retrieval drift (a_c, a_g). Proactive behavior emerges when decay is low but so is total capacity. **Below right:** beneficial role of decay remains at reward-rate optimal strategy.



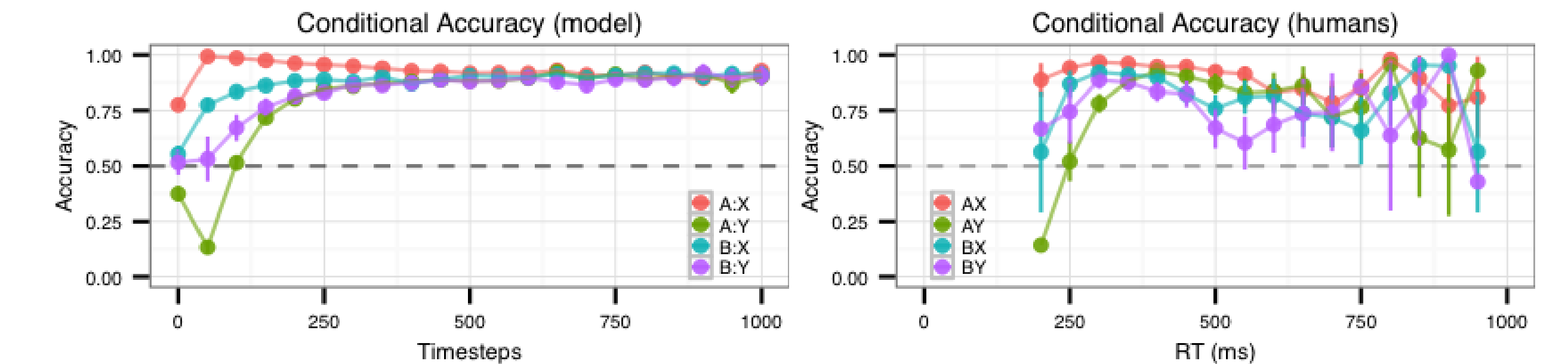
(3) Recovers AX-CPT Behavior under same parameters



Average dynamics of model for AY trial of AX-CPT.



Above: RT and error rate predictions (left) of model and comparison to humans (right) under same parameters as flanker task (taken from Yu et al. 2009); **Below:** accuracy by RT bin for the model (left) and humans (right). The model recovers the full pattern, with exception of overestimated BY RTs relative to the other RTs.



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