

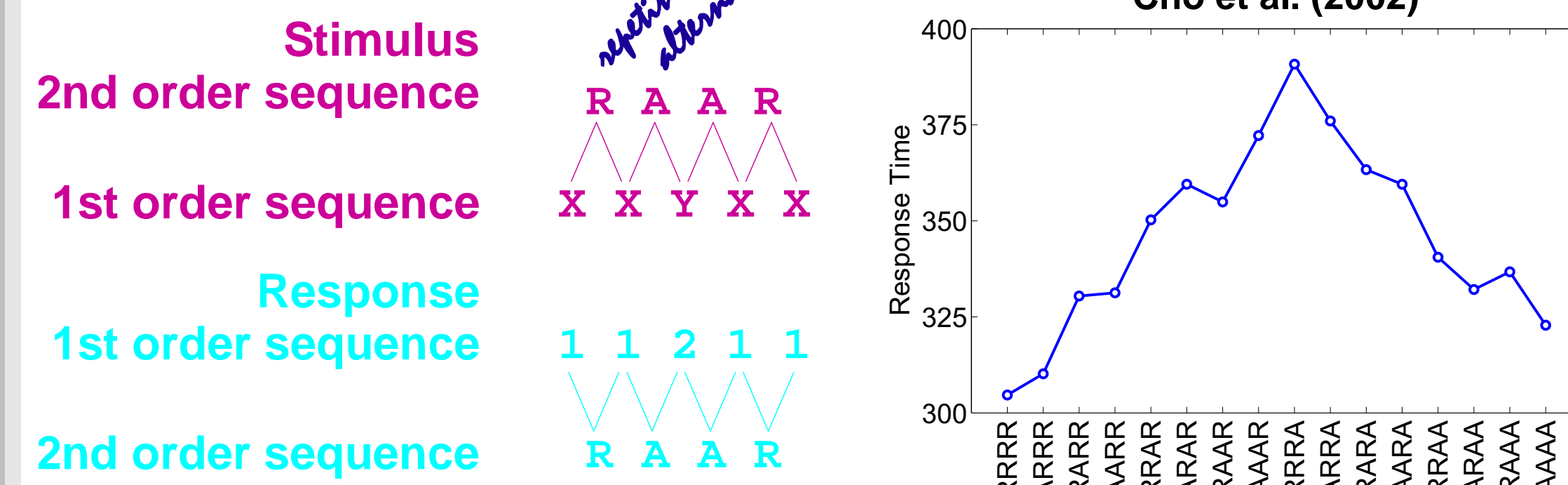
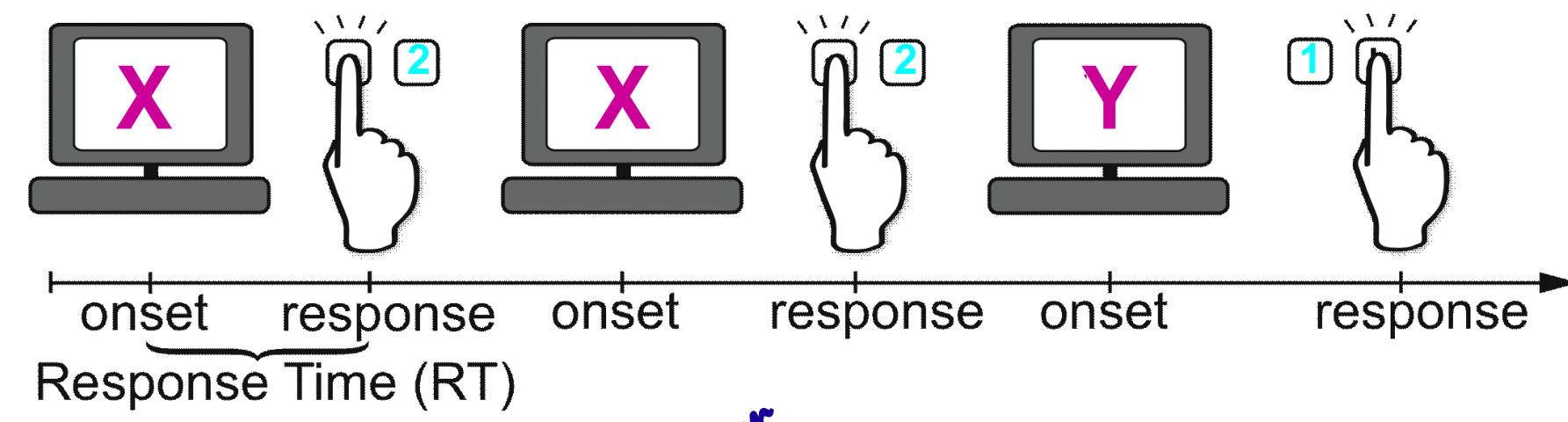
Predicting Temporal Patterns In The Environment: Toward Primitive Mechanisms Of Learning, Memory, And Generalization

Matt C. Jones*, Tim Curran*, Michael C. Mozer*, Matthew H. Wilder+
Institute of Cognitive Science*, Departments of Psychology* and Computer Science+, University of Colorado

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Predicting What Comes Next

Individuals develop strong expectations of upcoming events in environment based on recent experience.
Expectations illuminate brain's encoding of sequences.
E.g., two choice task



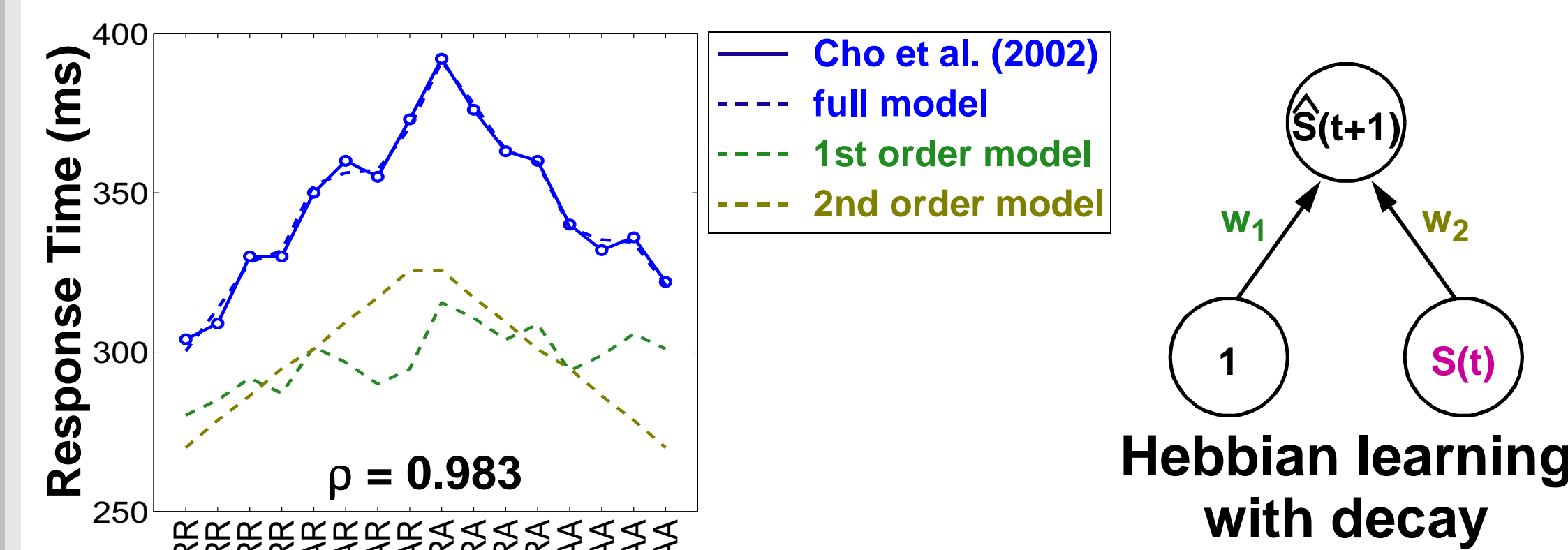
Dual Priming Model (Wilder, Jones, & Mozer, 2009)

Brain predicts what will happen next based on history, which is captured in two memory traces.

- First-order trace — YXXXX
 $w_1(t) = (1 - \phi)w_1(t-1) + \frac{\phi}{2}S(t)$ (stimulus on trial t, X = +1, Y = -1)
- Second-order trace — ARRA
 $w_2(t) = (1 - \gamma)w_2(t-1) + \frac{\gamma}{2}S(t)S(t-1)$

Prediction combines both traces
 $\hat{S}(t+1) = w_1(t) + w_2(t)S(t)$

Response time is fast if next stimulus matches prediction



Experiment Objectives

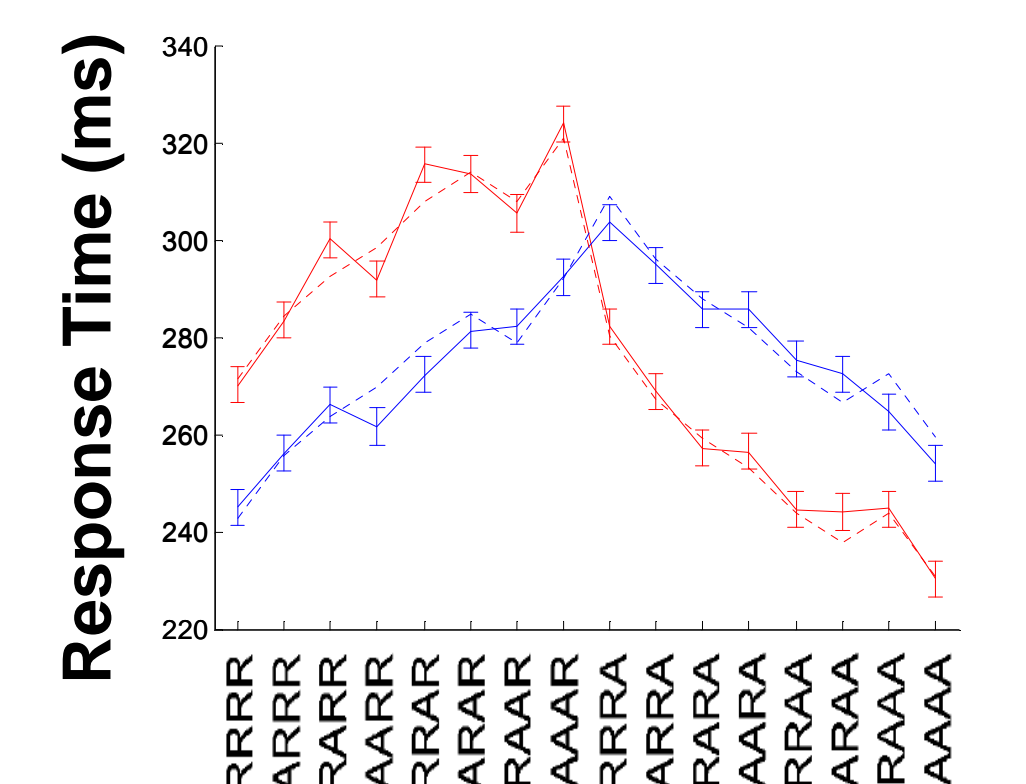
- Further test dual priming model
- Use EEG to tease apart stimulus and response priming
- Examine long-term learning of environmental statistics via two conditions

positive autocorrelation (2/3 repetition rate)
X Y X X X X X X X Y Y X X Y Y X X X
negative autocorrelation (1/3 repetition rate)
Y Y Y X Y X Y X X X X Y X Y X Y X

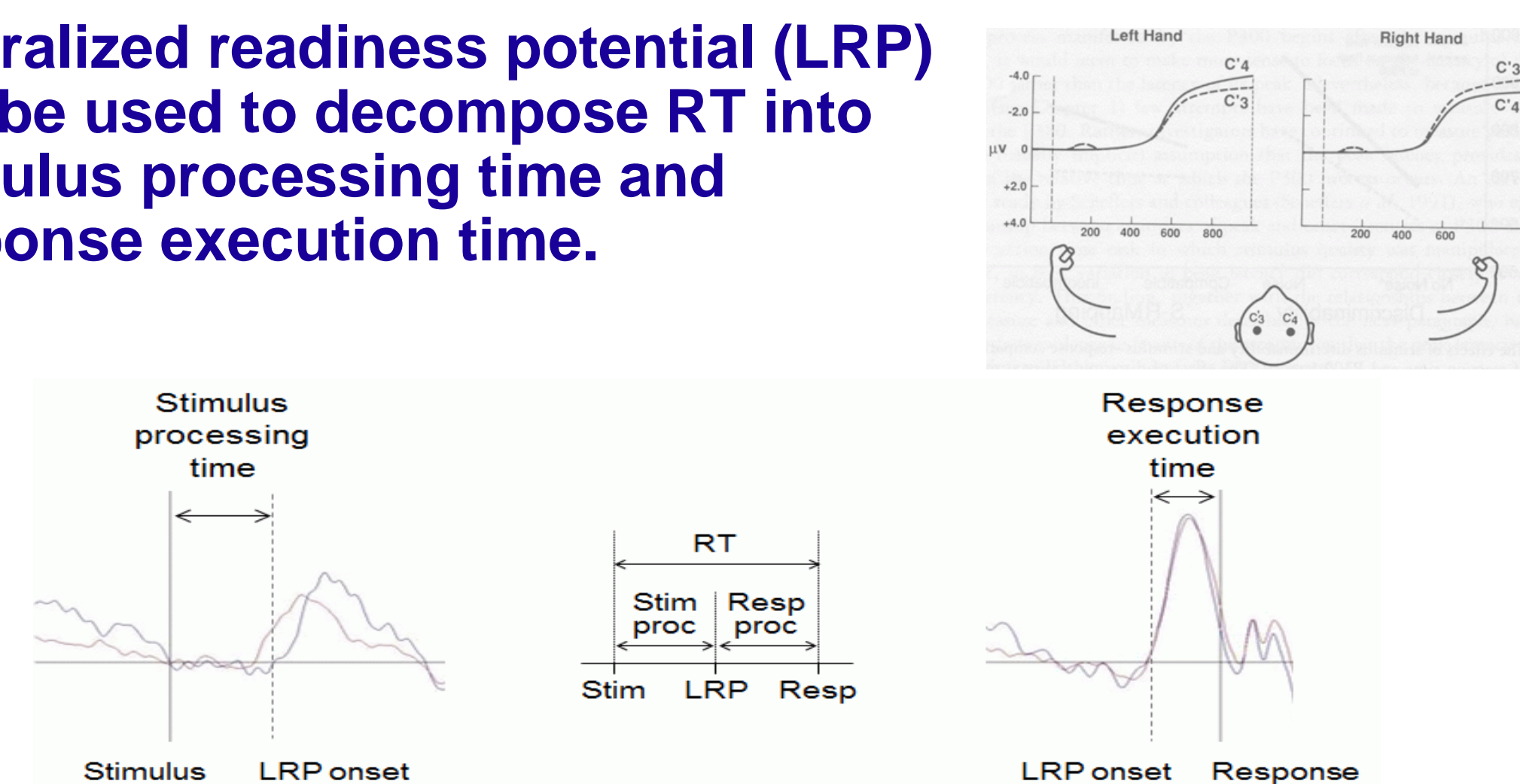
Reaction Time Analysis

Dual-priming model predicts human RTs in the two autocorrelation conditions.

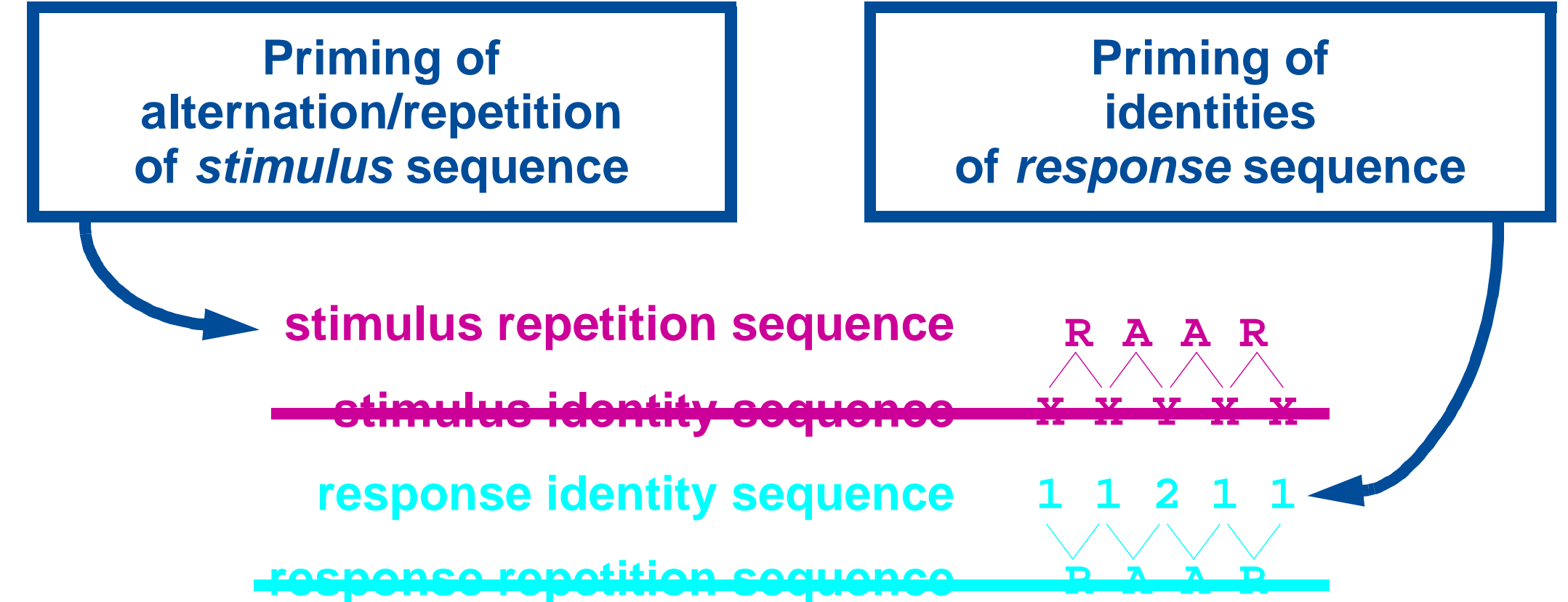
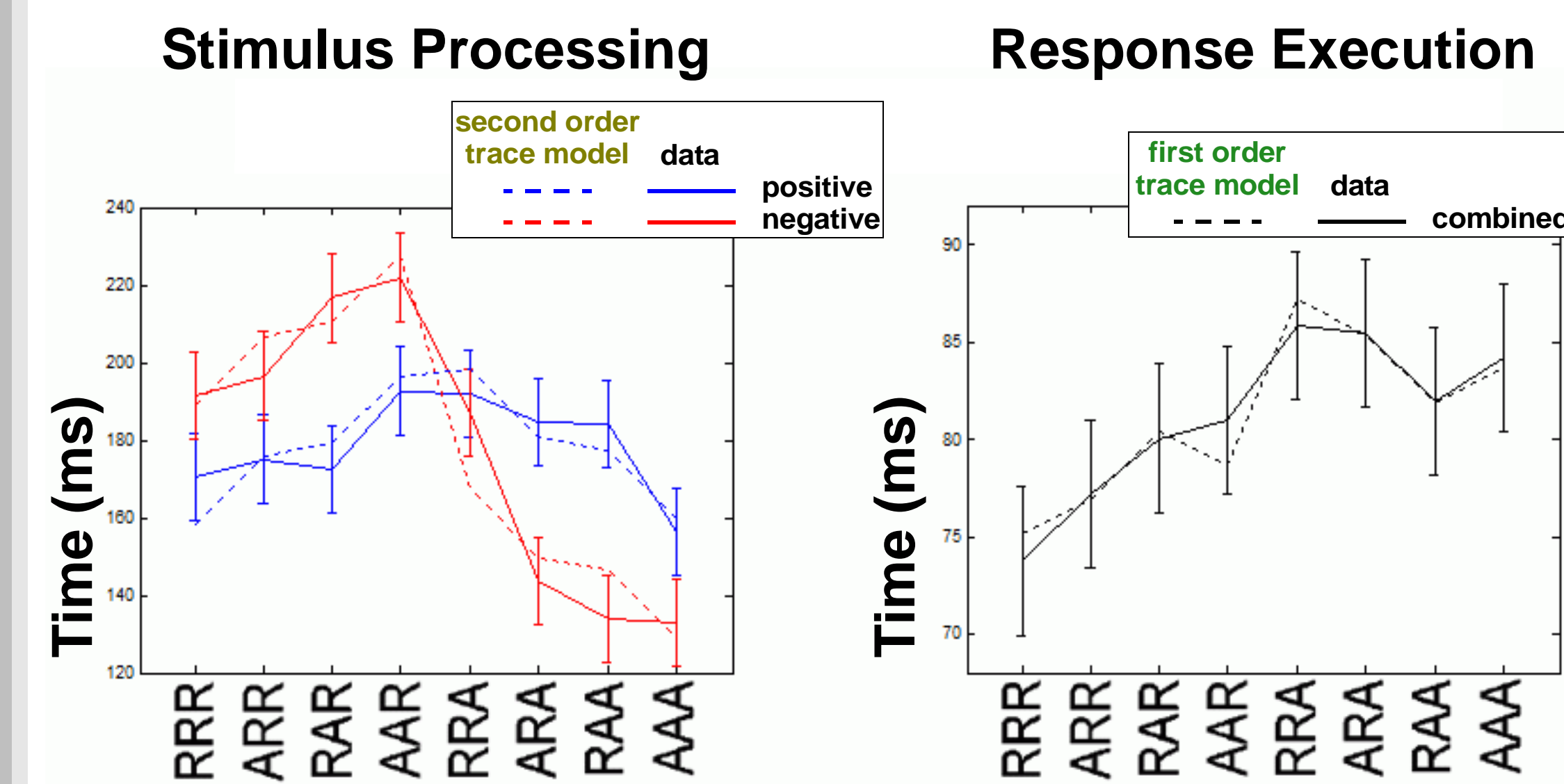
model data
- - - - - positive
- - - - - negative



Lateralized readiness potential (LRP) can be used to decompose RT into stimulus processing time and response execution time.



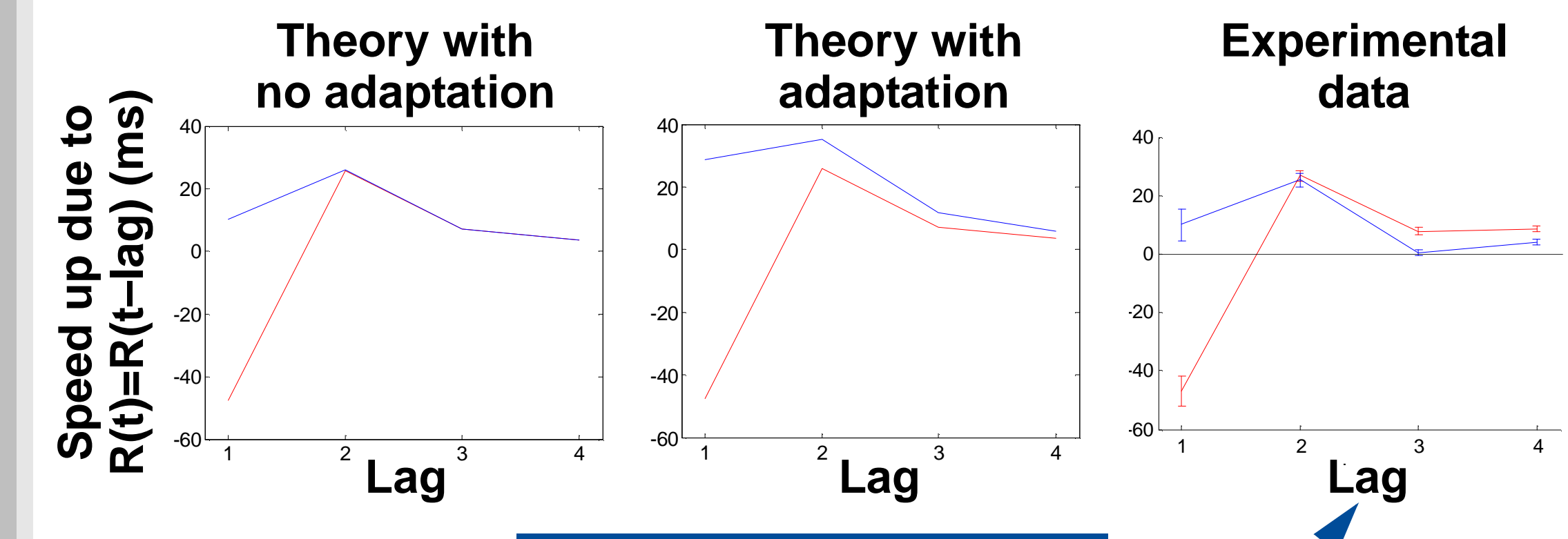
Model's two memory traces dissociate into stimulus processing and response execution stages.



Adaptation To Environment

If individuals adapt to long-term structure of environment, response identity priming should be stronger in positive autocorrelation condition than negative.

Positive lag	X	X	X	X	X
Negative lag	X	Y	X	Y	X

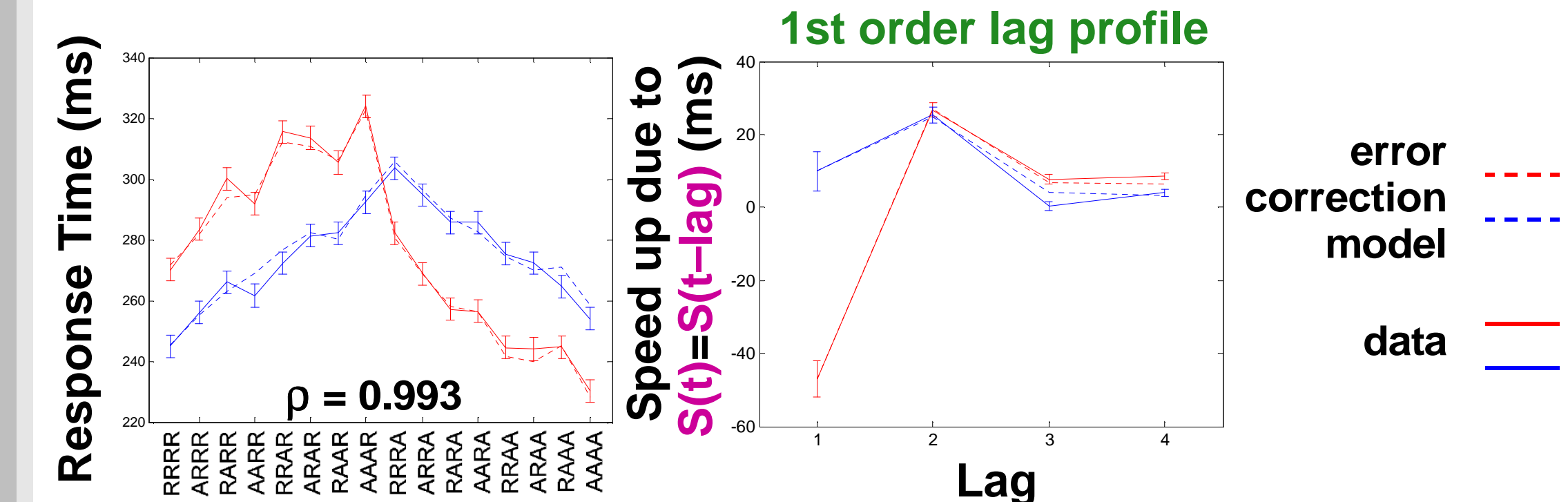
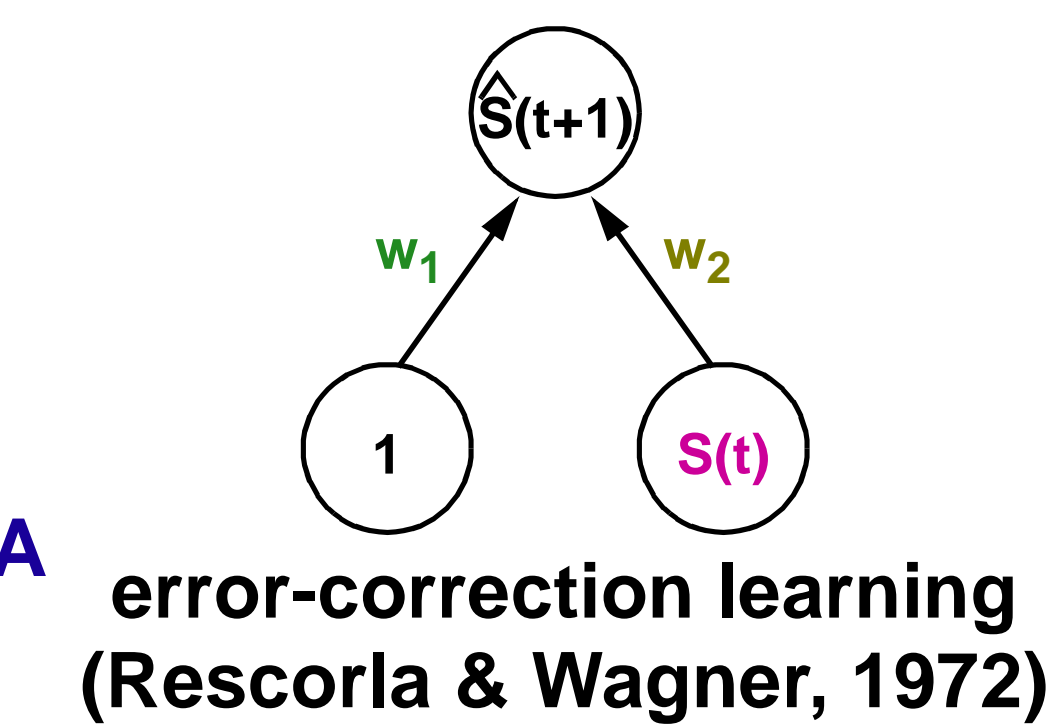


Cue Competition And Error-Correction Learning

Inverse adaptation effect is explained by replacing Hebbian learning with error-correction learning.

Model prediction as before
 $\hat{S}(t+1) = w_1(t) + w_2(t)S(t)$

- First-order weight — YXXXX
 $\Delta w_1(t) = \phi(\hat{S}(t) - S(t))$
- Second-order weight — ARRA
 $\Delta w_2(t) = \gamma(\hat{S}(t) - S(t))S(t-1)$



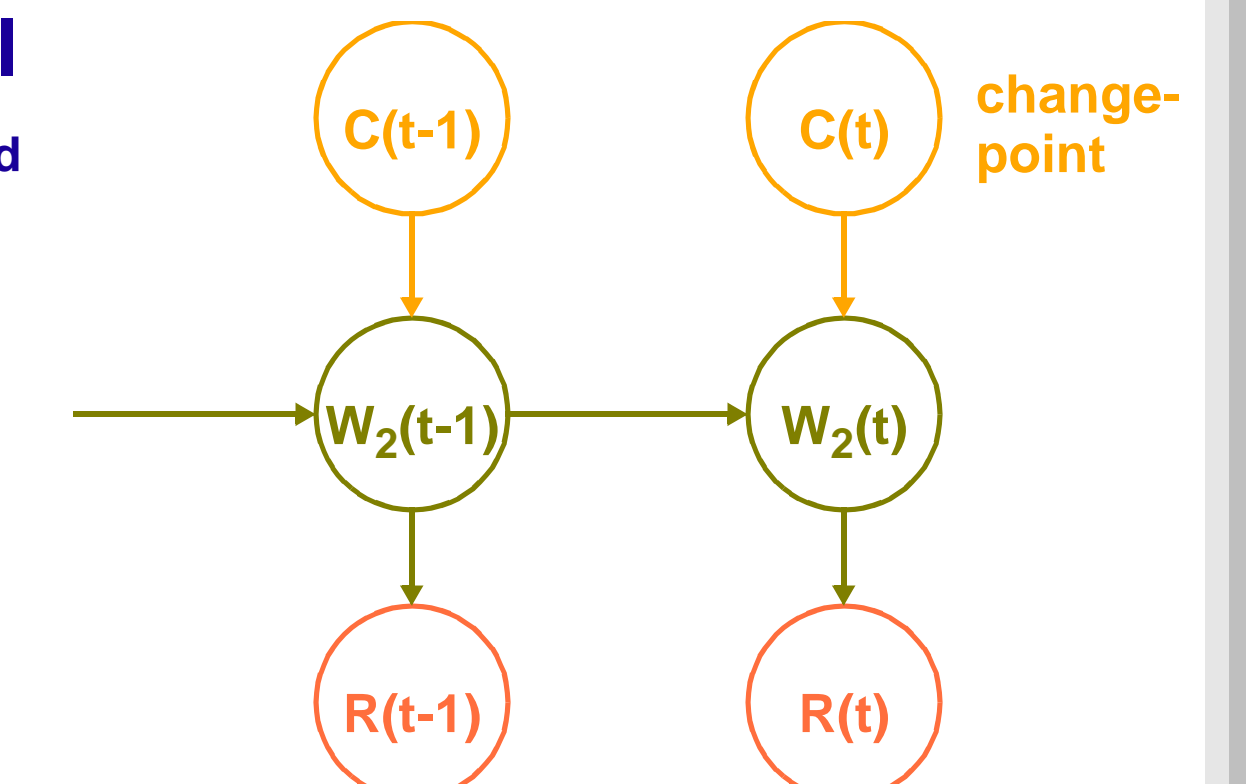
Error contributed by $w_2(t)$ pushes $w_1(t+1)$ in opposite direction \Rightarrow inverse adaptation effect

Toward A Normative Account

DBM: Dynamic Belief Model

Jones and Sieck (2003); Mozer, Kinoshita, and Shettle (2007); Yu and Cohen (2009)

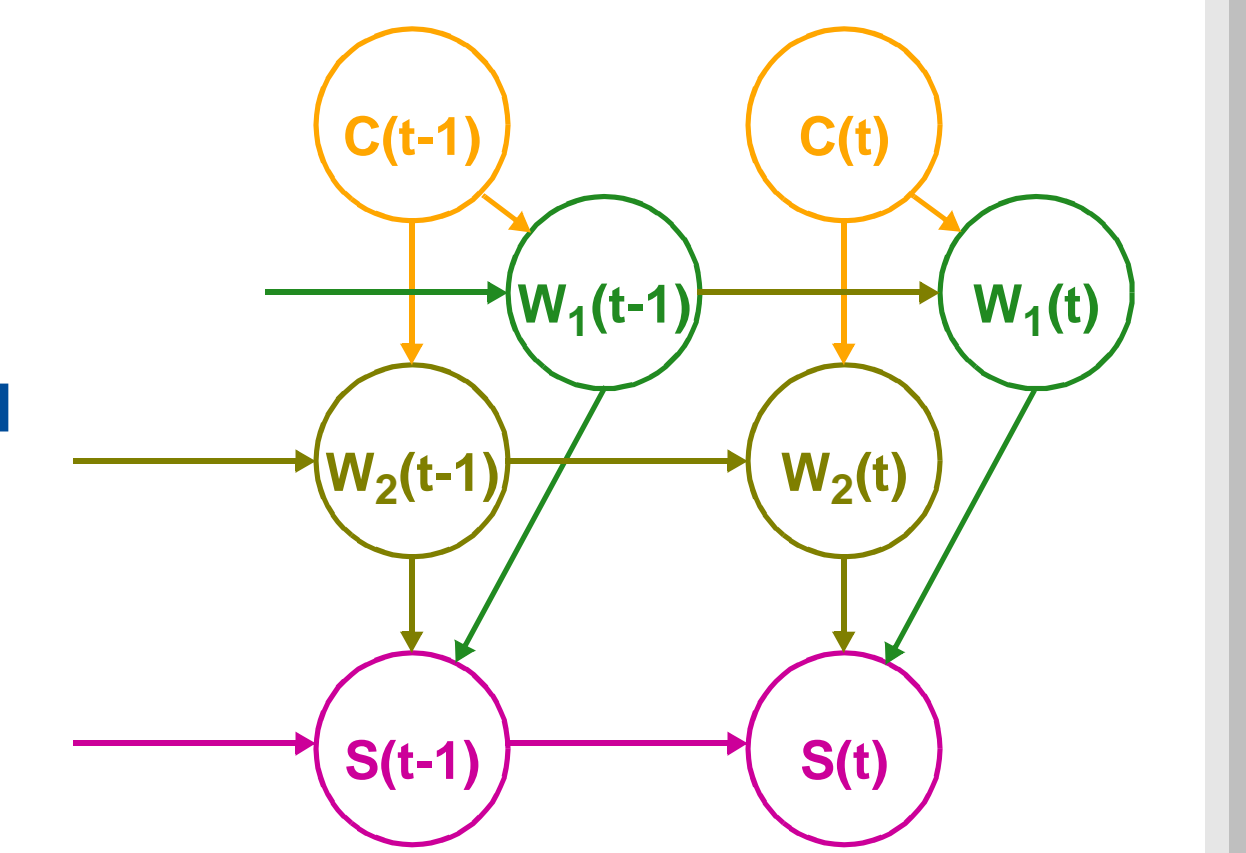
Assumes repetition probability (W_2) is fixed for runs, with occasional changepoints (C)
Predicts repetition or alternation (R)



DBM2: Dynamic Belief Mixture Model

Wilder, Jones, and Mozer (2009)

Assumes stimulus (S) distribution is a Bernoulli mixture based on identity and repetition/alternation
Predicts stimulus/response identity

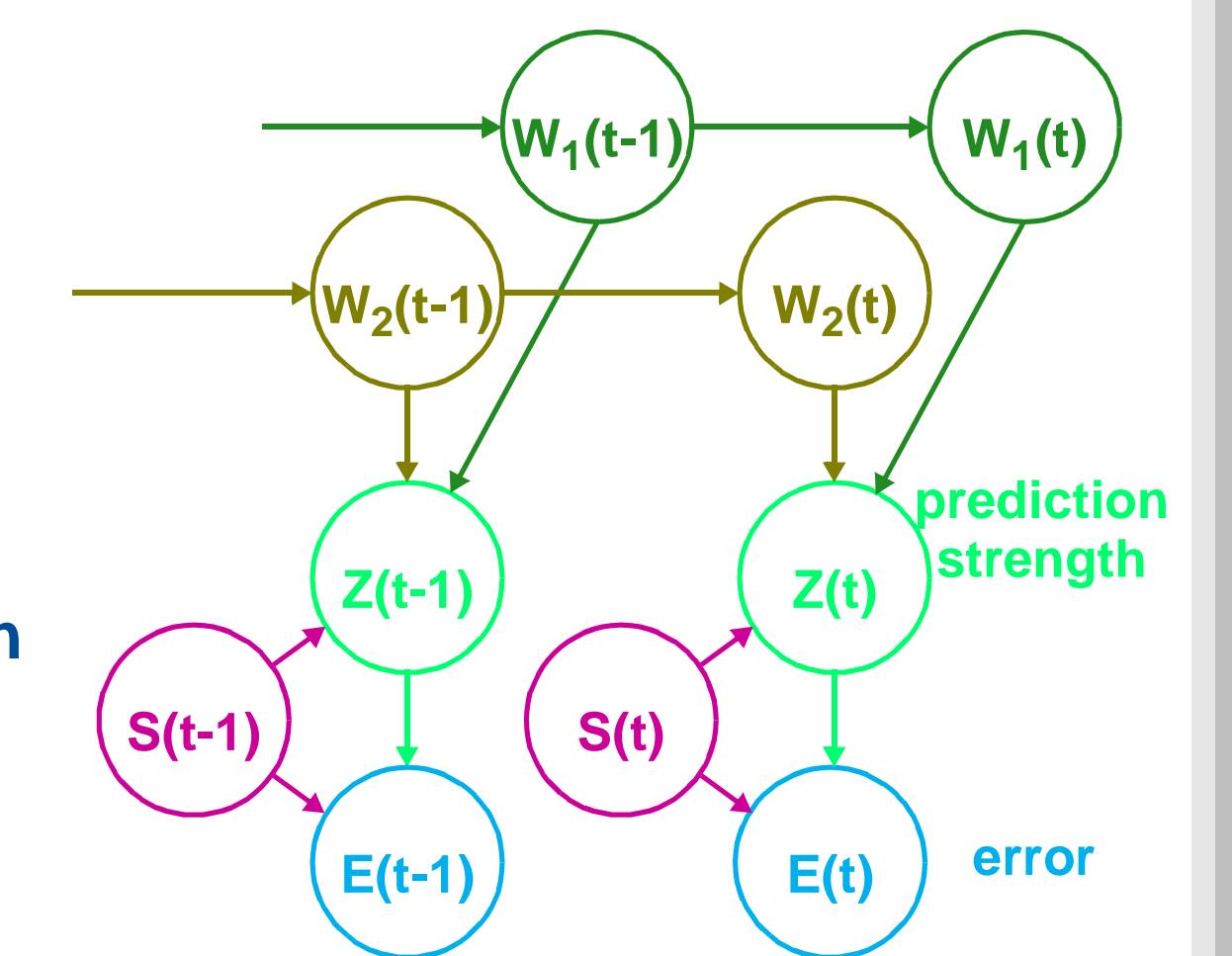


Dual priming model is a good approximation to DBM2

Kalman Filter Model

Instead of changepoint dynamics, assumes continuous fluctuation in first- and second-order probabilities

Produces updates in which the two cues (W_1, W_2) compete to predict stimulus



Toward A Neural Account

Cascaded diffusion processes

Relative processing speed of each stage can

- explain alternation bias
- amplify or attenuate first- and second-order effects

Tested in second experiment in which we manipulated

- ease of stimulus processing (random dot kinetogram coherence)
- ease of response processing (one button press vs. sequence)

