Rational Models of Cognitive Control

Michael C. Mozer

Institute of Cognitive Science and
Department of Computer Science
University of Colorado, Boulder

Sachiko Kinoshita
Macquarie University

Mike Shettel
University of Colorado

Shaun Vecera
University of Iowa

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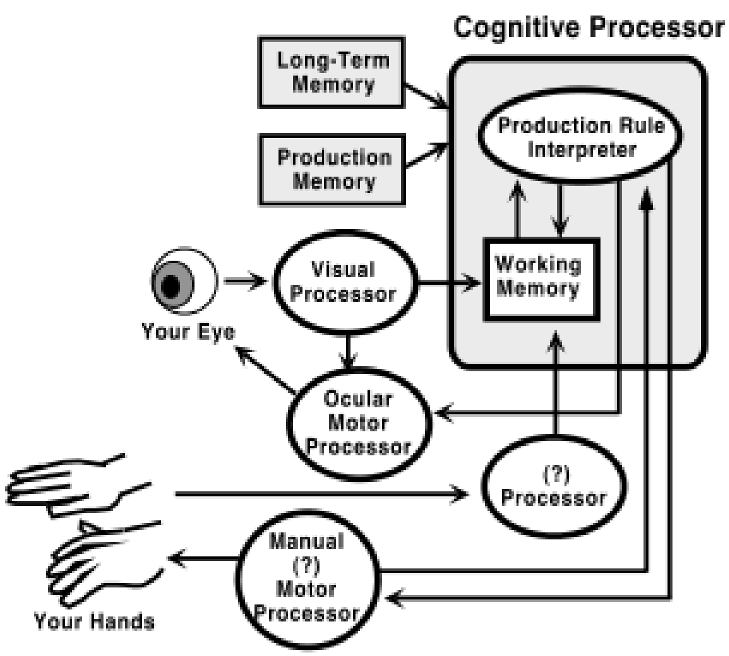
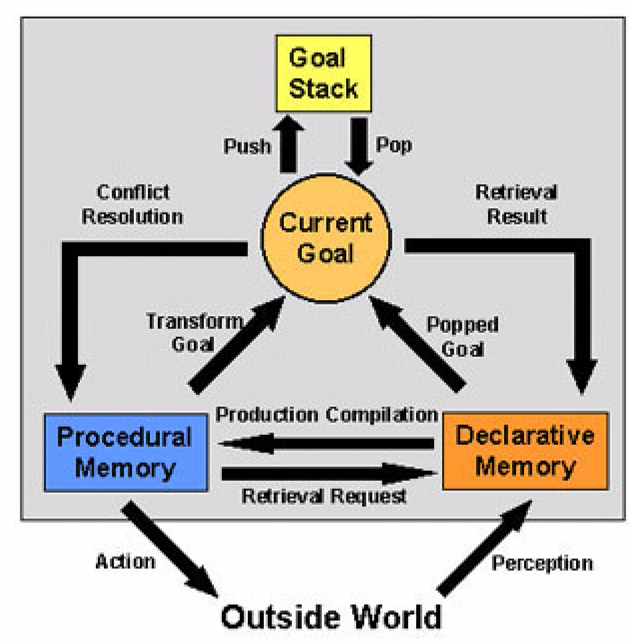
EPIC: Kieras & Meyer



ACT-R: Anderson



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Conventional perspective

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Our perspective

Cognitive control involves optimizing human performance to the task and to the structure of the environment.

Visual Search

Find the 20p coin in a handful of change.

Find your friend in a crowd.

Find a particular book in your library.

How is the visual system dynamically reconfigured to perform a remarkable variety of arbitrary tasks?

Control of Visual Attention

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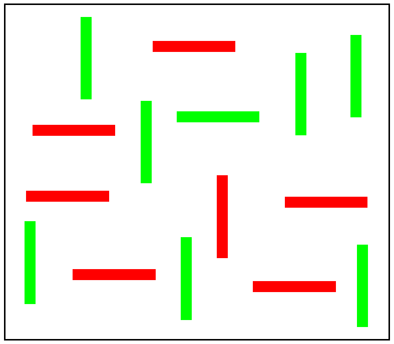
1. Focusing processing resources on task-relevant visual features and locations

e.g., find the red vertical bar



Control of Visual Attention

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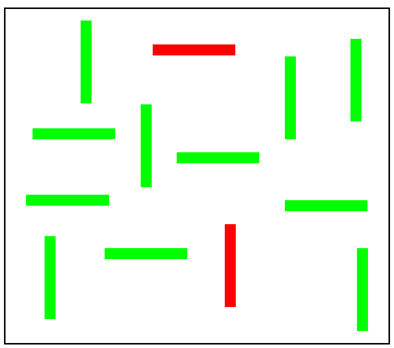

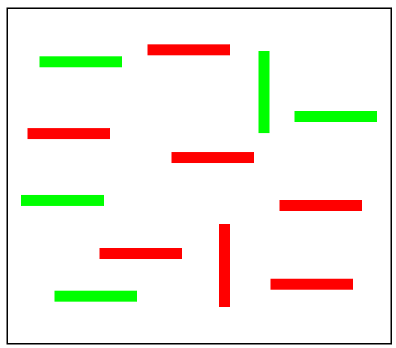

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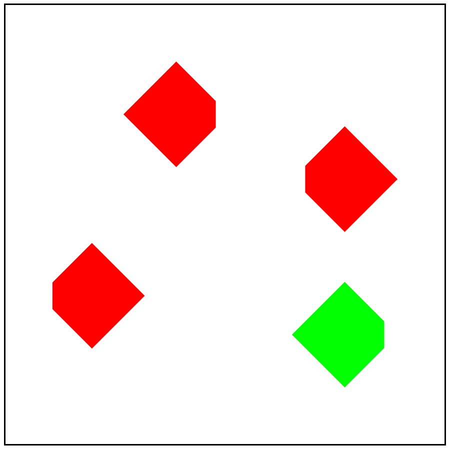
Two distinct problems?

Strategy: Study the latter to get a handle on the former

Attentional Adaptation
(Maljkovic & Nakayama, 1994)

Is odd colored diamond notched on the left or right?



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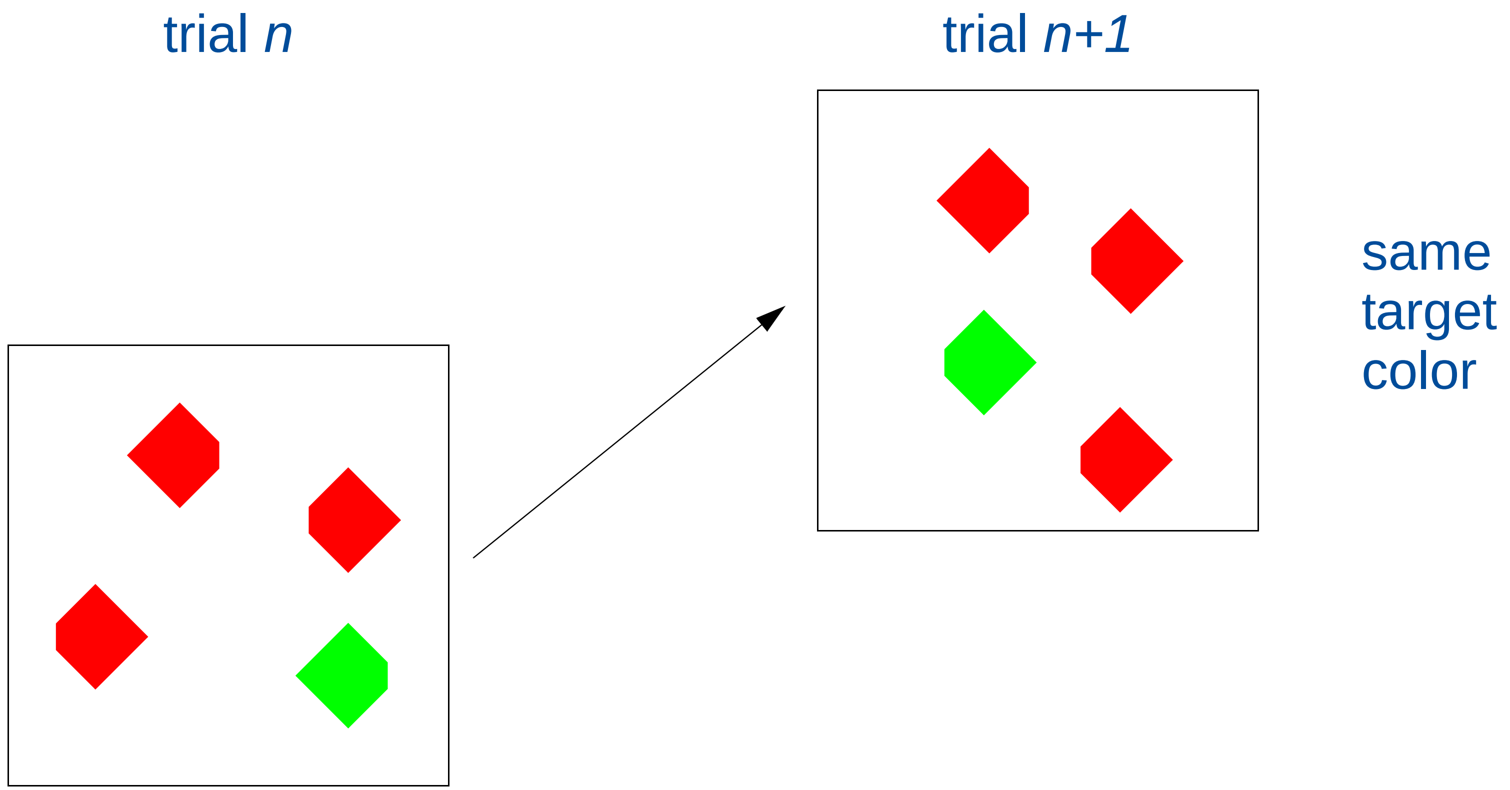

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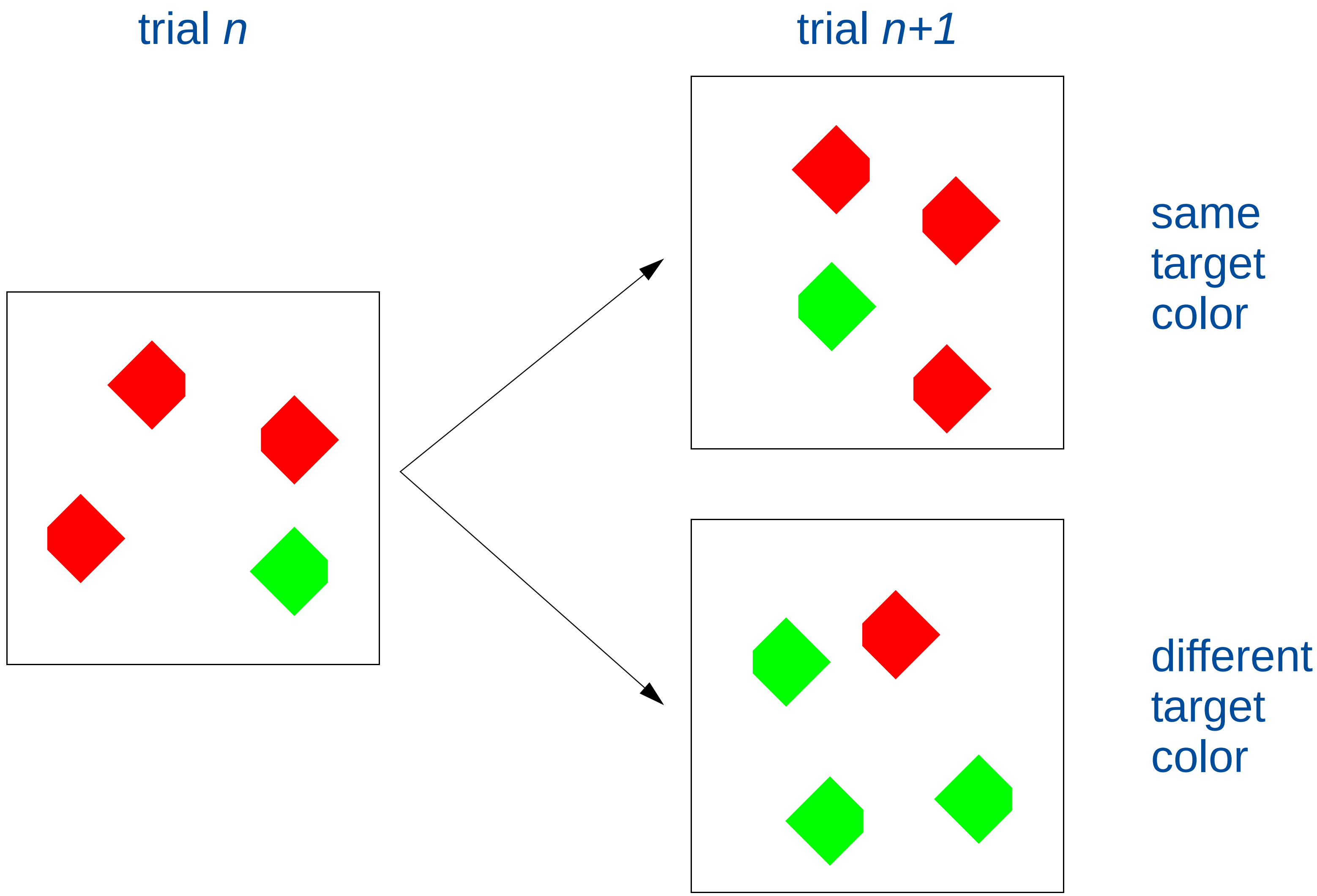

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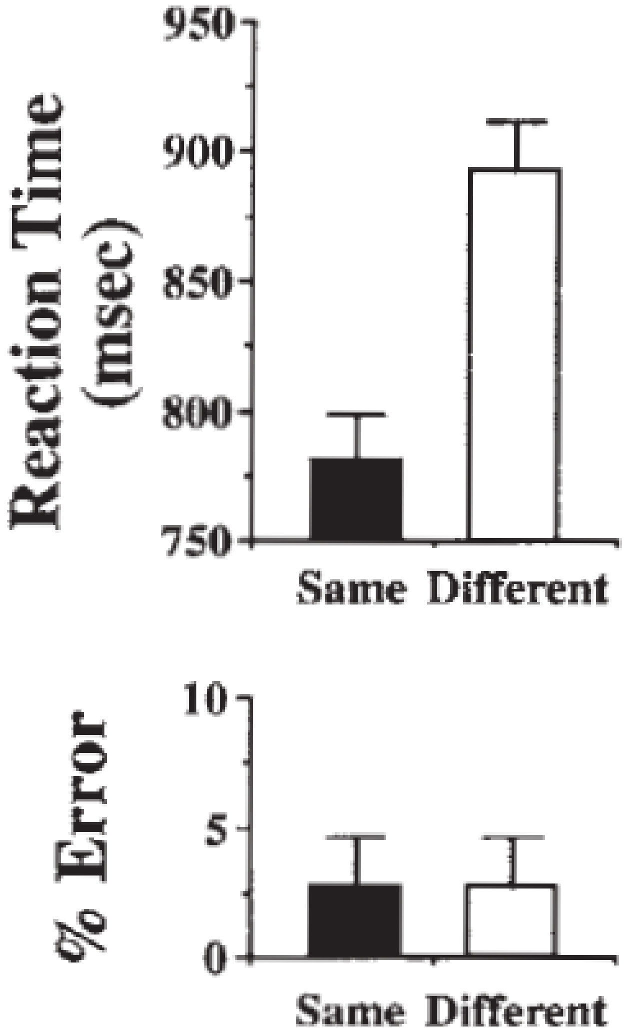

Why Does Repetition Facilitate Performance?

We view attentional control as optimizing performance to the environment in which an individual is operating.

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Two-Stage Process

1. Construct predictive (probabilistic) model of the environment based on past experience.
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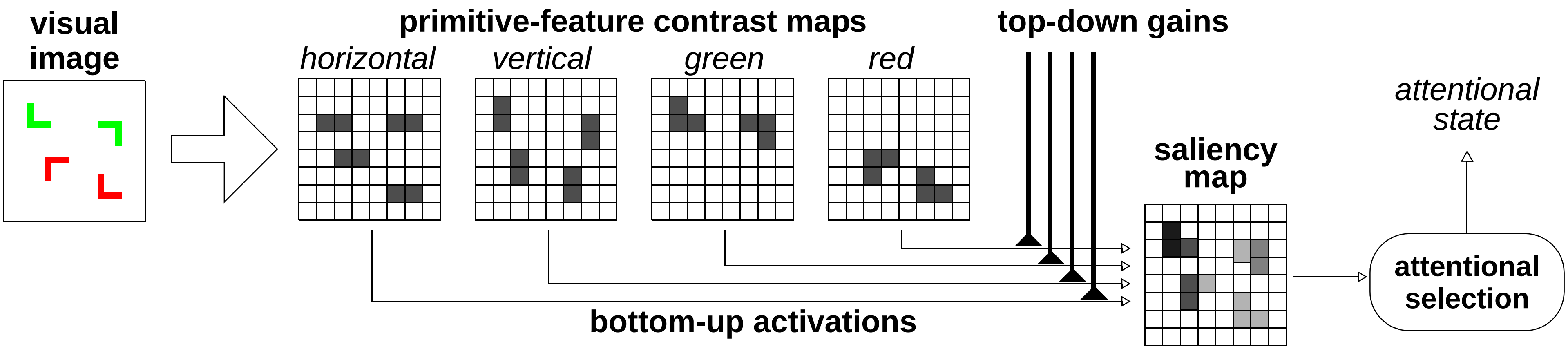
e.g., Itti et al. (1998); Koch & Ullman (1985); Mozer (1991); Wolfe (1994)



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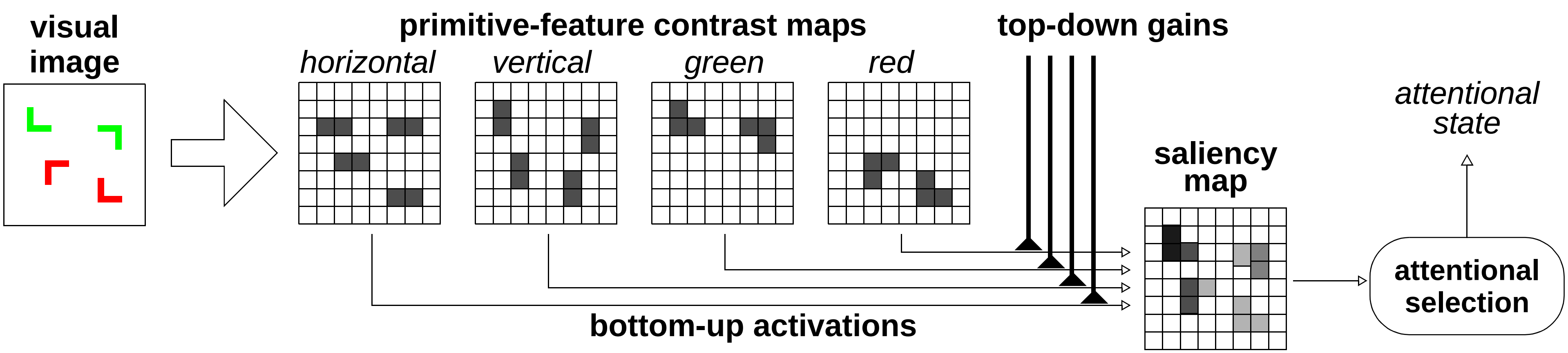


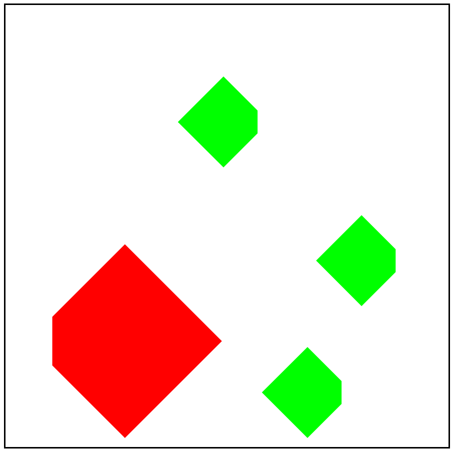
Modeling the Environment

Characterize environment via a probability distribution over configurations of target and distractor features

To simplify presentation, assume distractors are homogeneous.

Example

T_{color}=*red*
T_{size}=*large*
T_{notch}=*left*
D_{color}=*green*
D_{size}=*small*
D_{notch}=*right*



Model

$P(T_{color}, T_{size}, T_{notch}, D_{color}, D_{size}, D_{notch})$

Model 1: Independent Features

$P(T_{color}, T_{size}, T_{notch}, D_{color}, D_{size}, D_{notch}) =$

$$P(T_{color})\, P(D_{color})\, P(T_{size})\, P(T_{notch})\, P(D_{size})\, P(D_{notch})$$

Independence assumption is too strong to characterize natural environments.

Model 2: Full Joint Distribution

T_{color}	D_{color}	T_{size}	T_{notch}	D_{size}	D_{notch}	P(.)
red	*red*	*small*	*left*	*small*	*left*	
green	*red*	*small*	*left*	*small*	*left*	
red	*green*	*small*	*left*	*small*	*left*	
...	...	...	...	...	...	
green	*green*	*large*	*right*	*large*	*right*	

With 6 features, $2^6 - 1 = 63$ free parameters

Requires large amount of experience to obtain accurate probability estimates.

Model 3: Task-Based Architecture

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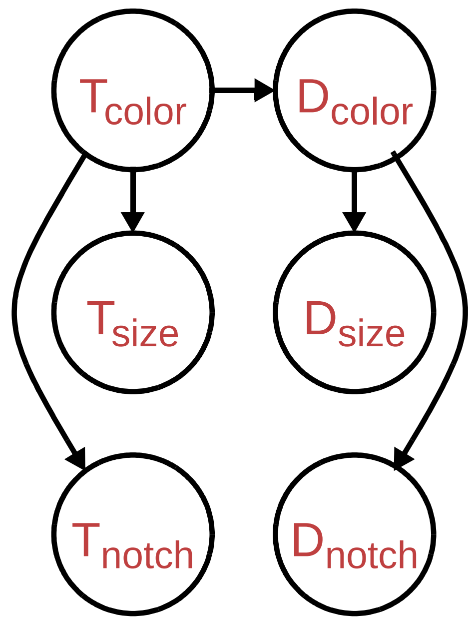
Bayes net

Efficient way of representing high-order probability distributions in terms of low-order distributions



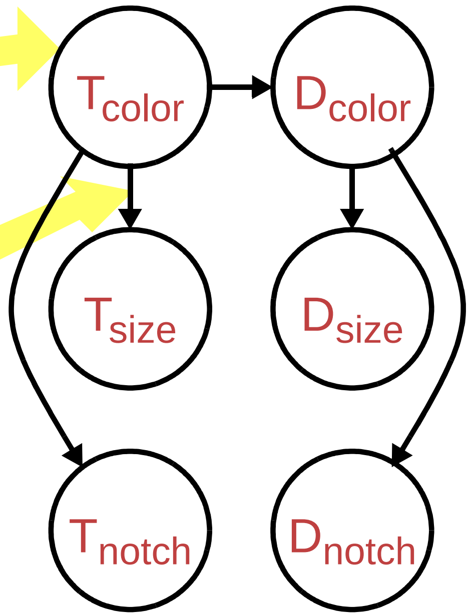
Model 3: Task-Based Architecture

Bayes net

Efficient way of representing high-order probability distributions in terms of low-order distributions

T_{color}	P
red	0.3
green	0.7

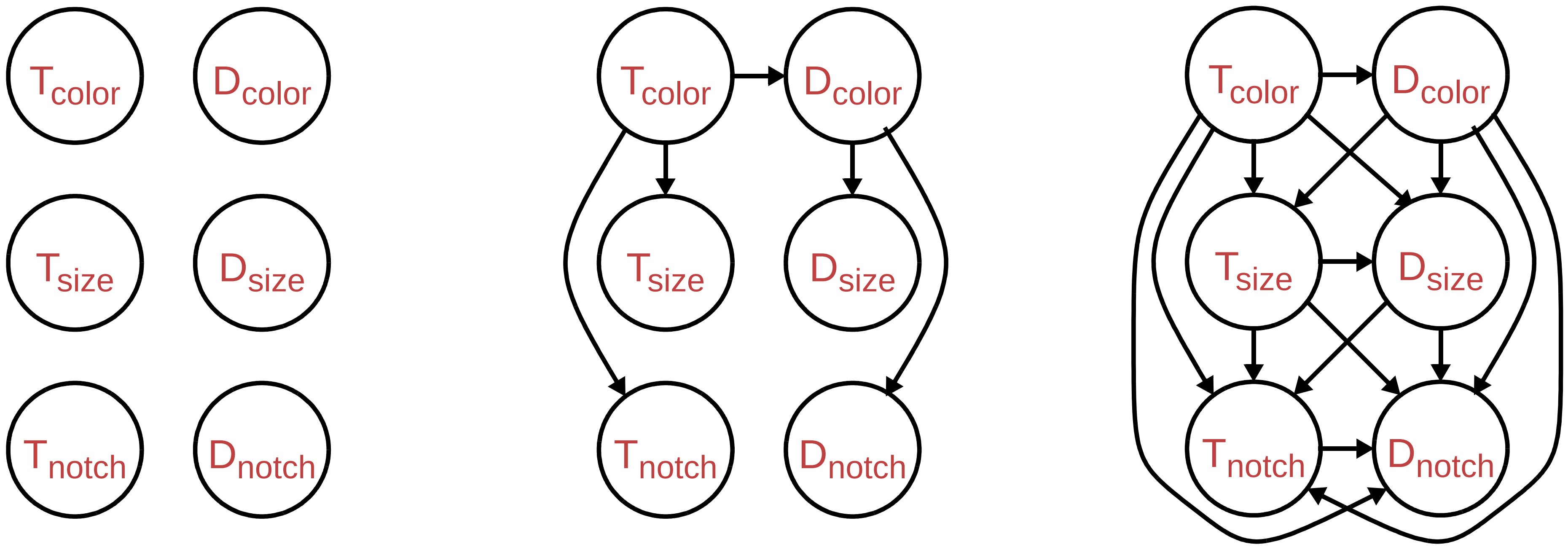
T_{size}	T_{color}	P
large	*red*	0.2
small	*red*	0.8
large	*green*	0.6
small	*green*	0.4



$$P(T_{color}, T_{size}, T_{notch}, D_{color}, D_{size}, D_{notch}) =$$

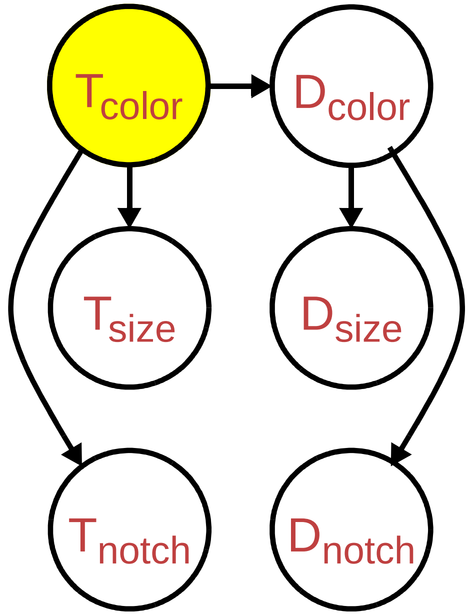
$$P(T_{color})\, P(D_{color} \mid T_{color})\, P(T_{size} \mid T_{color}) P(T_{notch} \mid T_{color})\, P(D_{size} \mid D_{color})\, P(D_{notch} \mid D_{color})$$

Comparing the Architectures



Independence Architecture	**Task-Based Architecture**	**Full Joint Architecture**
6 free parameters	**11 free parameters**	**63 free parameters**

Key Assumptions of Task-Based Architecture



- **Defining feature of target is root of tree.**

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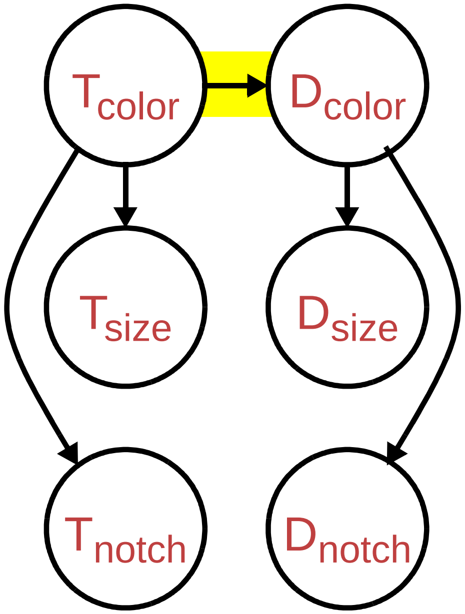

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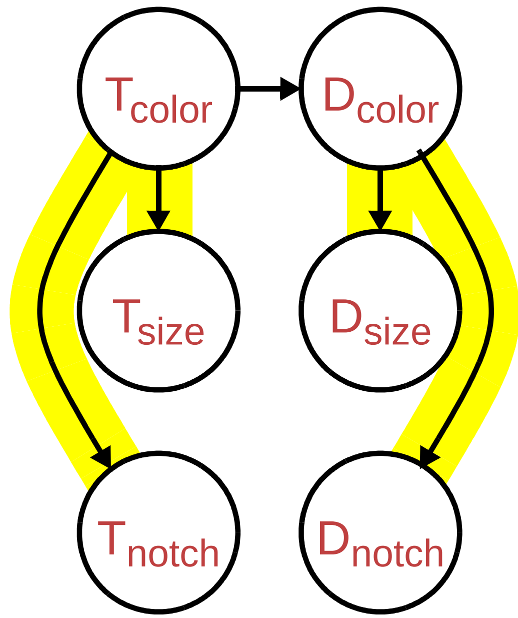

- Defining feature of target is root of tree.
- Defining feature of target dominates defining feature of distractor.
- **Defining feature of target dominates nondefining features of target, and likewise for distractors.**

Simulation of Attentional Adaptation Paradigms

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3. **Following each trial, update environment model.**

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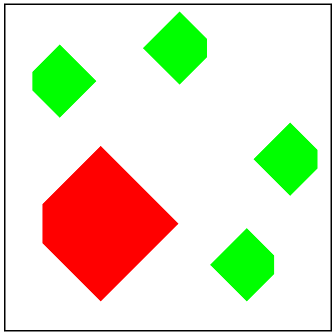

should increase

$P(T_{color} = \textit{red})$

$P(T_{size} = \textit{large} \mid T_{color} = \textit{red})$

$P(D_{color} = \textit{green} \mid T_{color} = \textit{red})$

$P(D_{notch} = \textit{right} \mid D_{color} = \textit{green})$ ...

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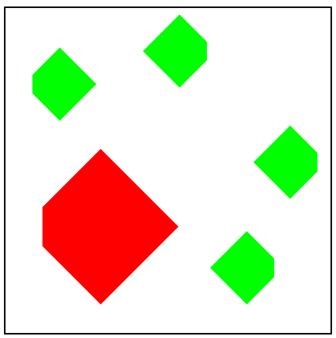

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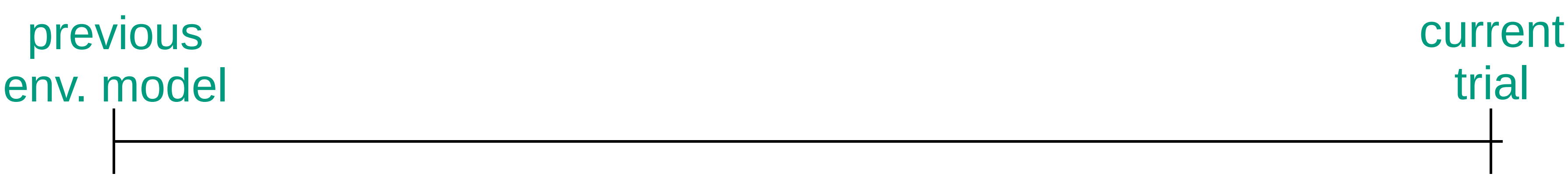
Simplest scheme: parameter interpolation



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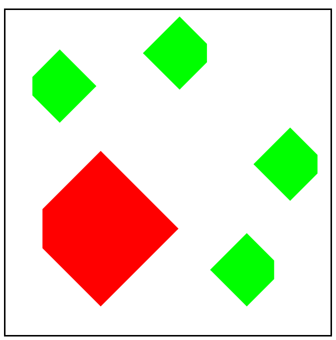

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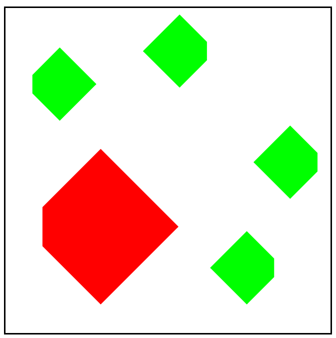

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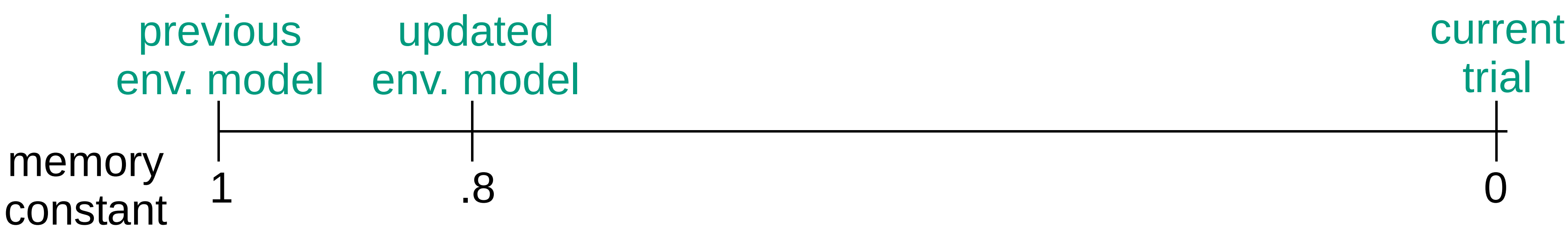


Simulation of Attentional Adaptation Paradigms

1. **Set up Bayes net for each experiment based on task description.**

2. **Generate trial sequence that replicates those used in experimental studies.**

3. **Following each trial, update environment model.**

4. **Following each update, optimize attentional control to the current environment model.**

   Rather than explicitly modeling this optimization process, we assume that it yields RTs that are faster to configurations that have higher probability.

   RT ~ –log[$P(T_{color}, T_{size}, T_{notch}, D_{color}, D_{size}, D_{notch})$]

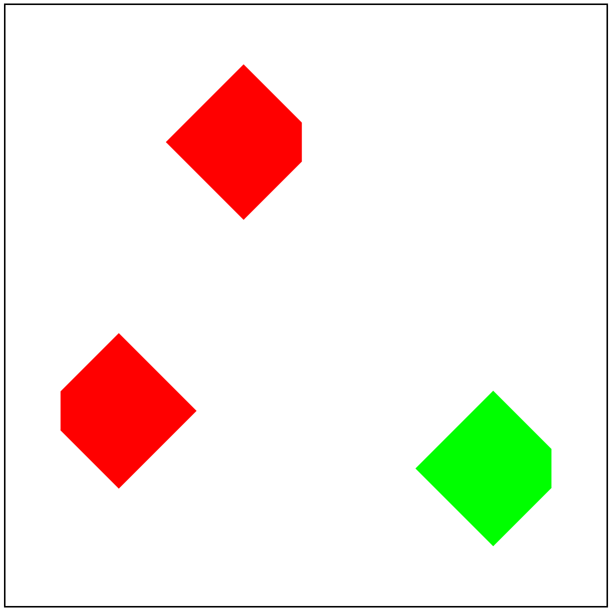
   Use this assumption to predict RT on a given trial.

Maljkovic and Nakayama (1994), Experiment 5

Task

Search for color singleton in display of red and green diamonds.

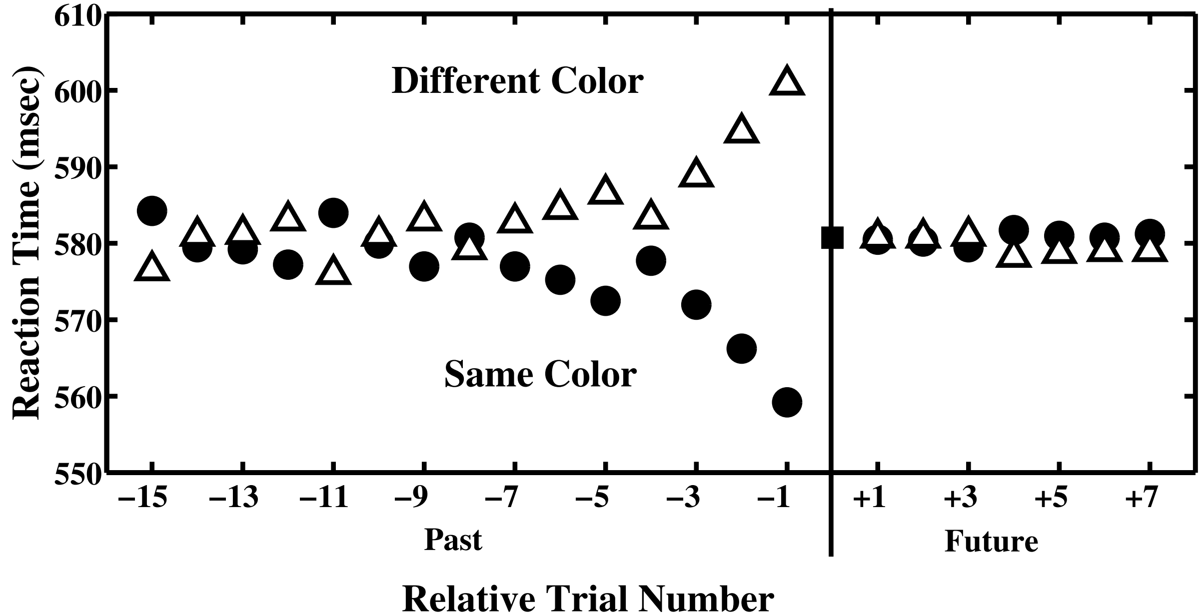
Report whether notch is on left or right.



How does color *k* trials back affect RT on current trial?

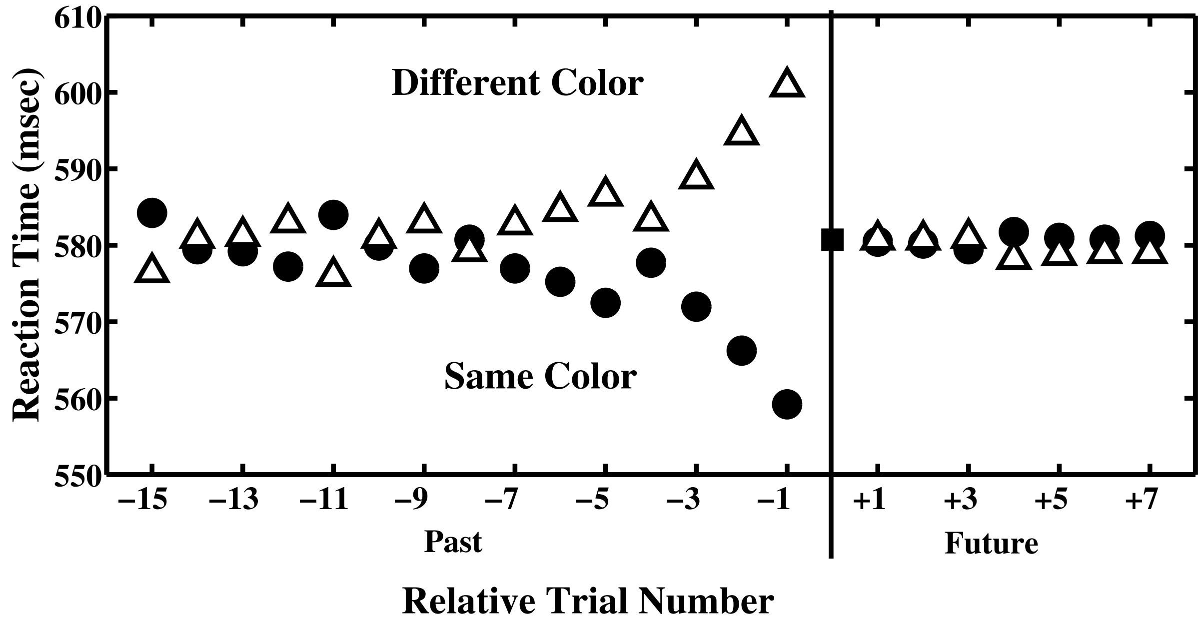
Maljkovic and Nakayama (1994), Experiment 5

Human Data

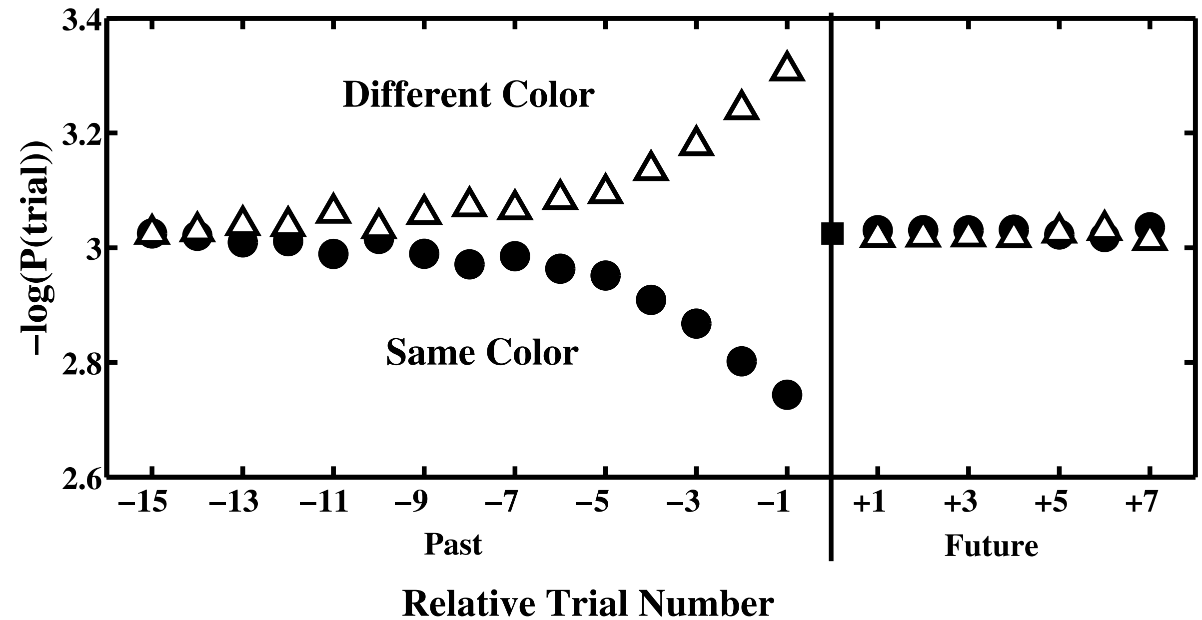


Maljkovic and Nakayama (1994), Experiment 5

Human Data



Simulation

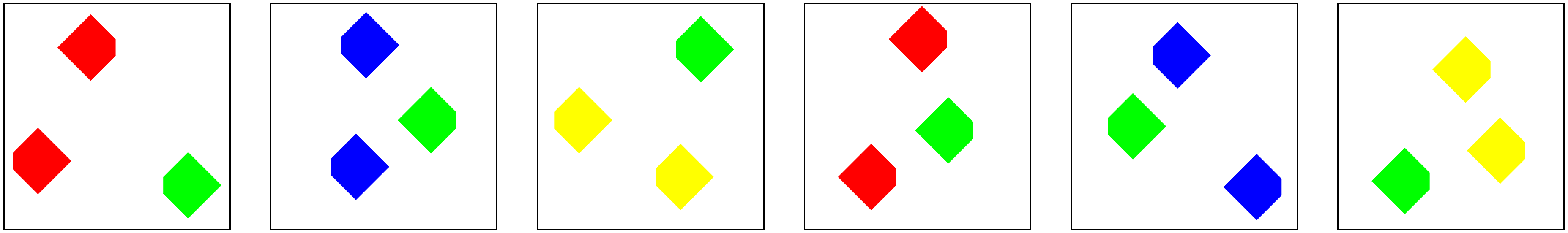


Maljkovic and Nakayama (1994), Experiment 8

In last experiment, facilitation could be due to repetition of either target *or* distractor color.

In this experiment, four distinct colors.

Repeat target color up to 6 trials, changing distractor color.



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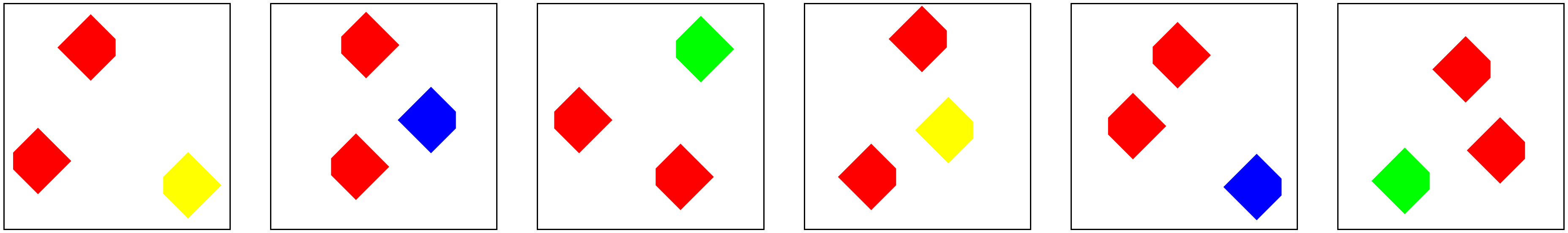

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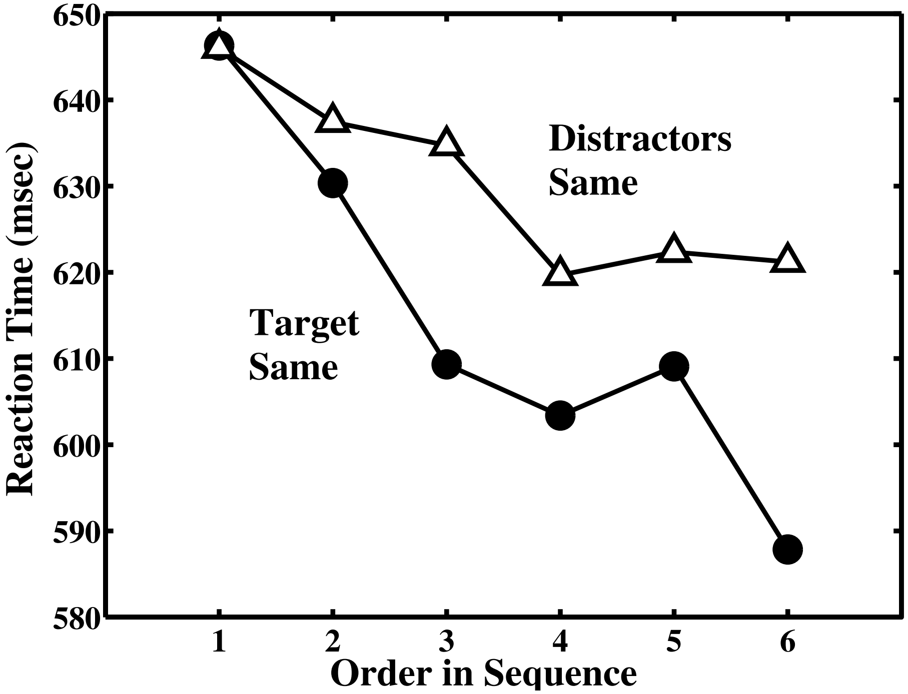

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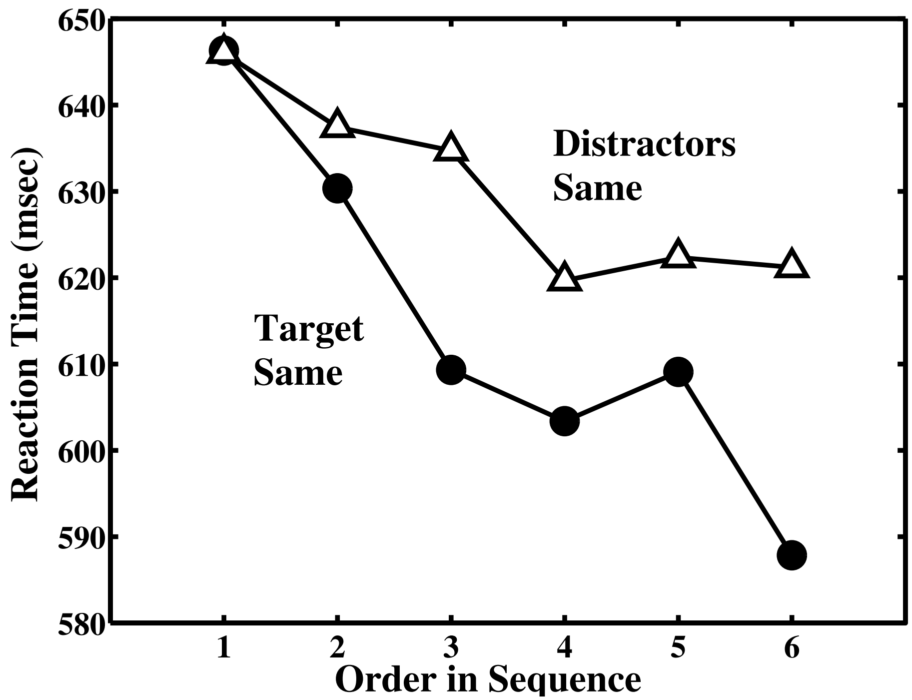

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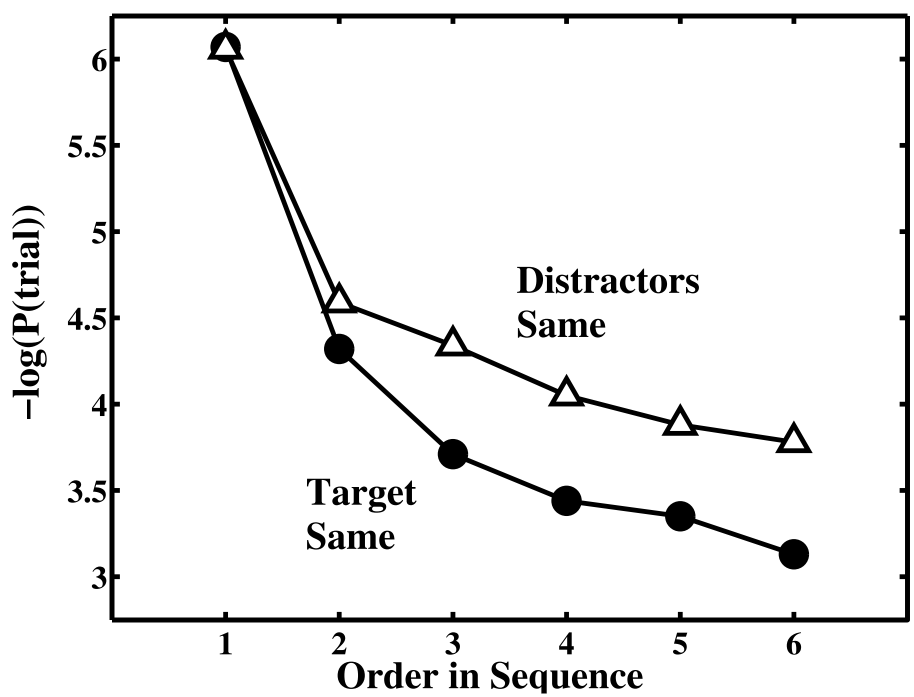


In model, greater effect for target repetition due to dominance of target over distractor.

Huang, Holcombe, and Pashler (2004)

Previous experiments studied only one feature dimension.

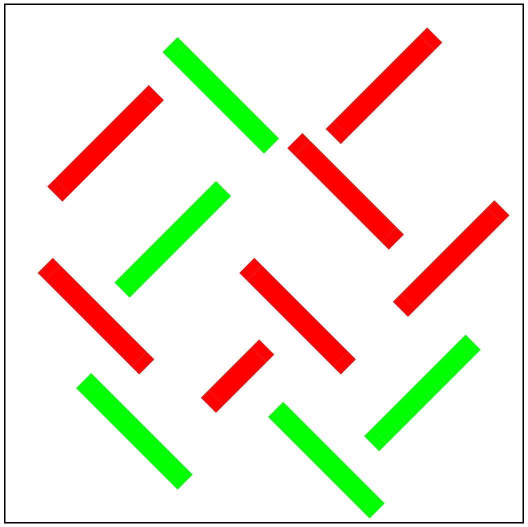
If stimuli vary on multiple dimensions, how do repetitions on one dimension interact with repetitions on another?

Task

Search for singleton in size.

Report slant (left or right).

Color and orientation uncorrelated with size.



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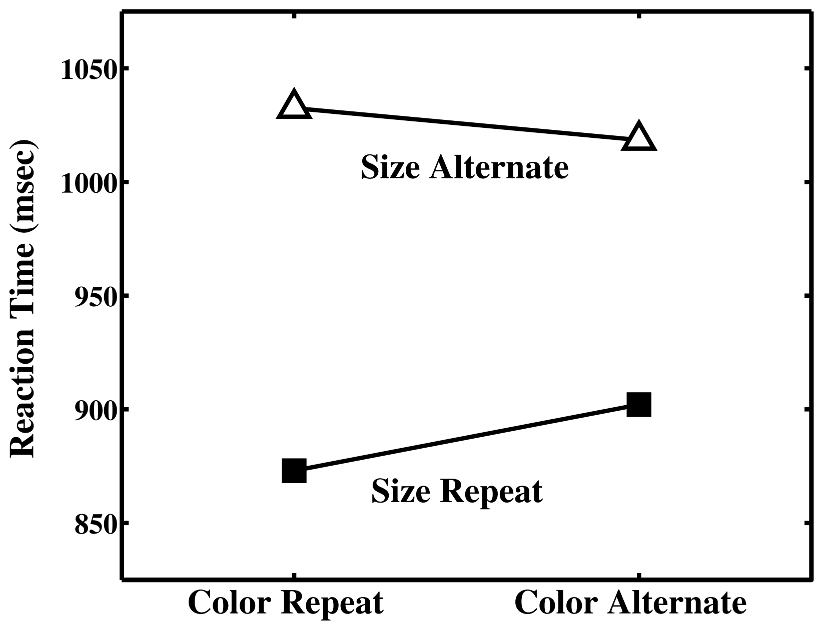

Repetition of defining feature (size) speeds response.

Repetition of nondefining feature (color) speeds response, but only if defining feature is repeated.

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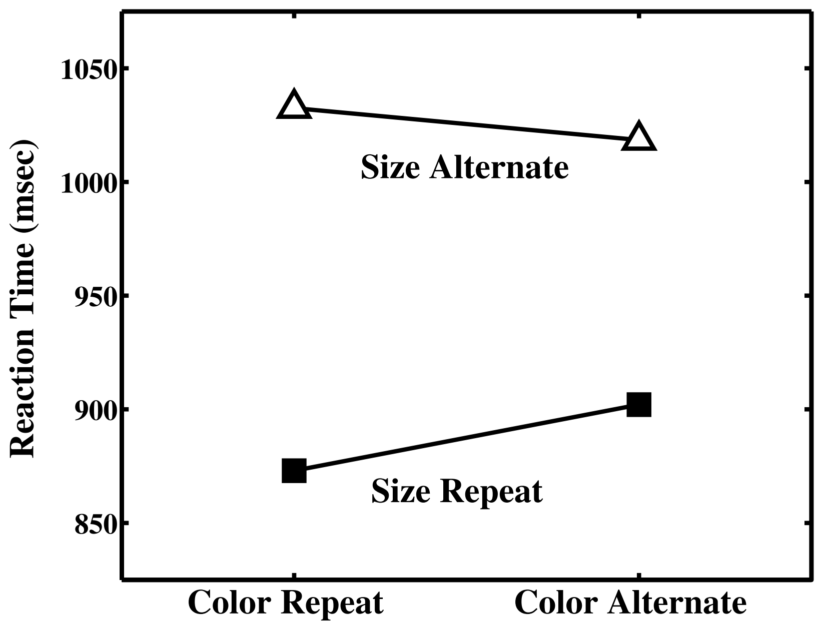

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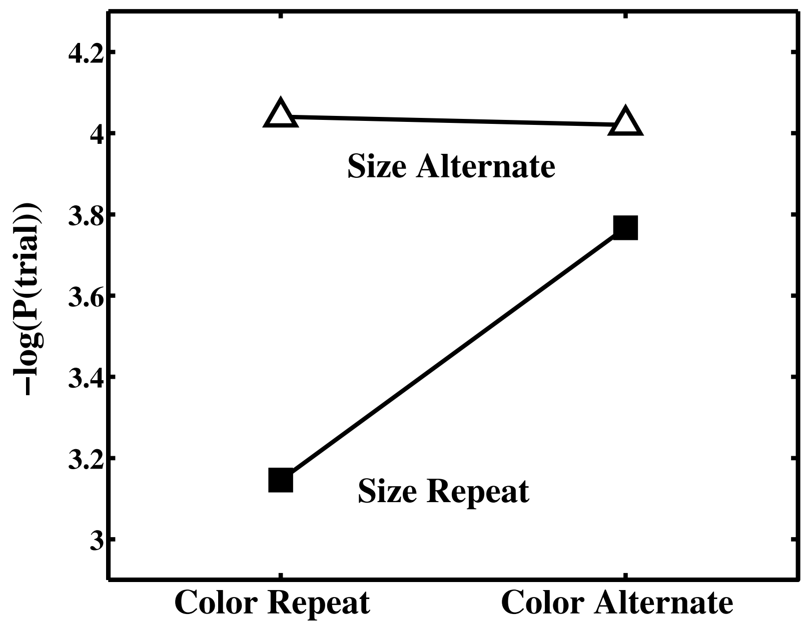

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In model, interaction due to dominance of defining feature over nondefining feature

Wolfe, Butcher, Lee, & Hyle (2003)

Task

Detect presence/absence of singleton in display of colored, oriented lines.

Blocks of trials, corresponding to environments of varying complexity.

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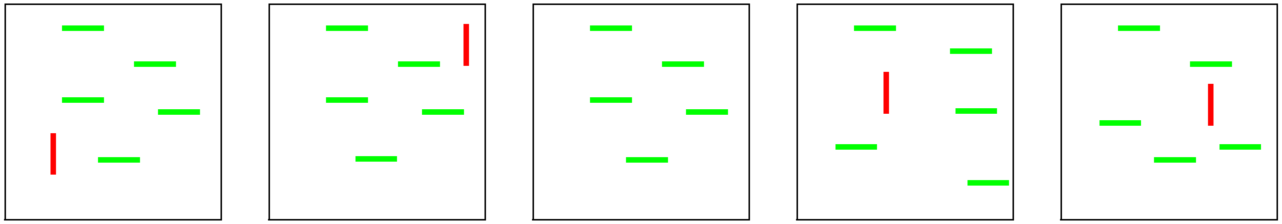

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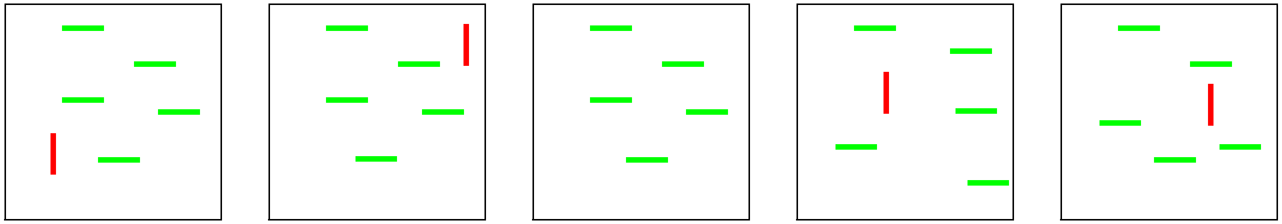

simple
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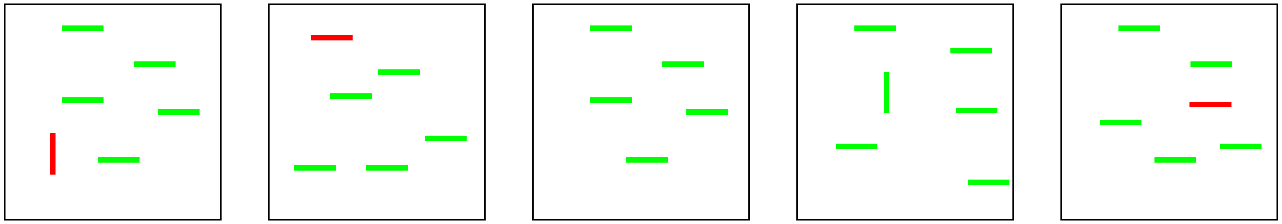

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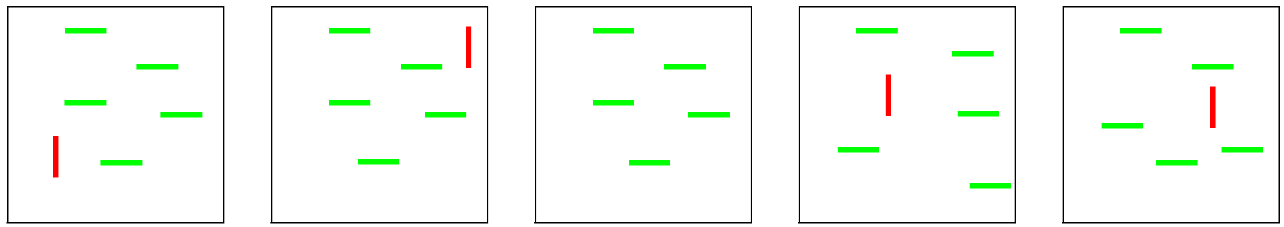
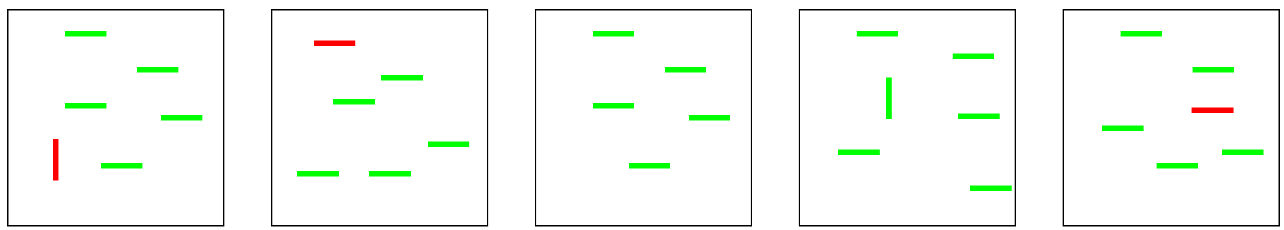
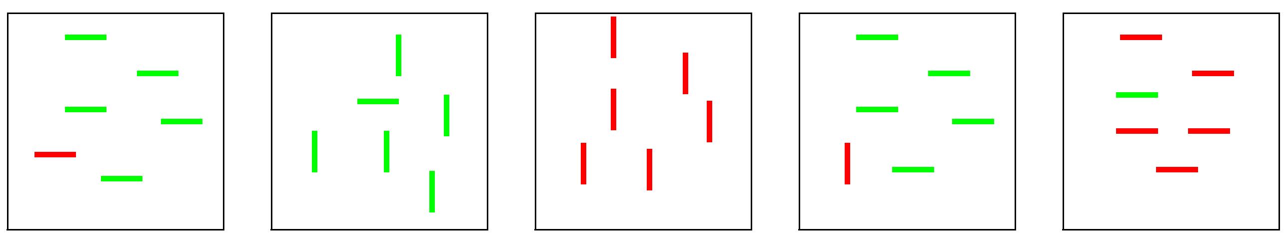


simple environment (red or vertical target)

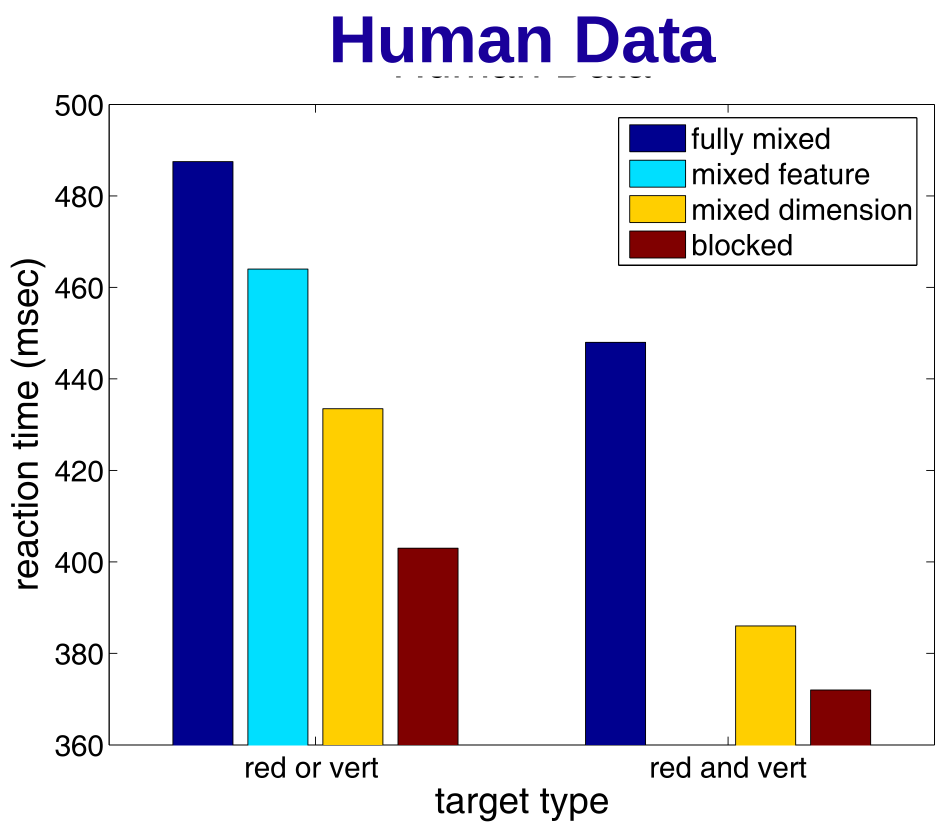


complex environment (target is odd item)



Measure RT on target-present trials.

Wolfe, Butcher, Lee, & Hyle (2003), Experiment 1



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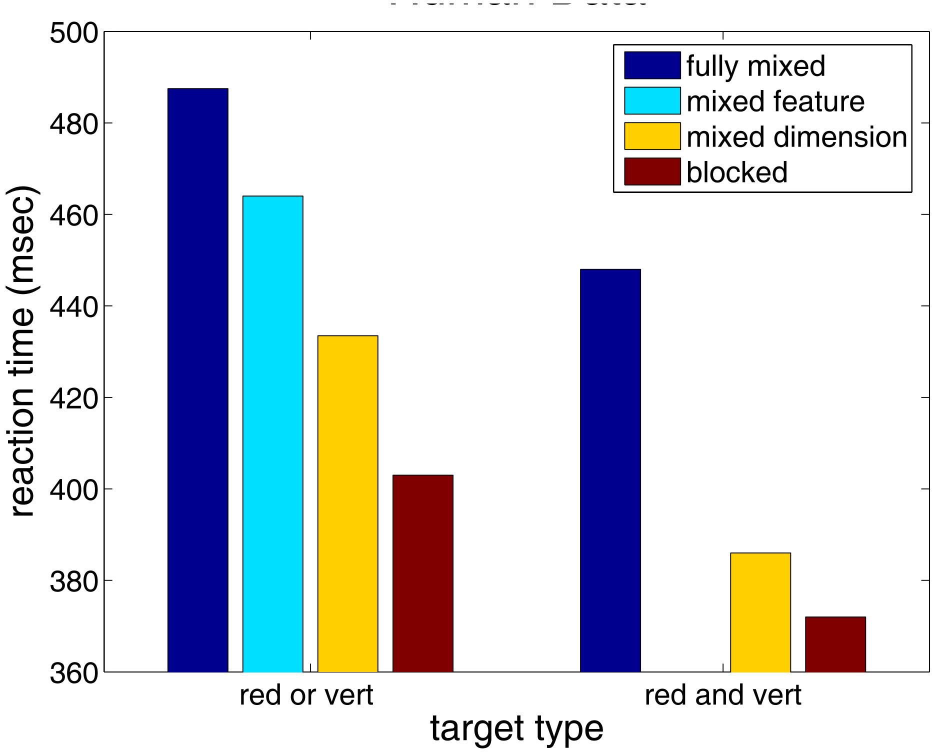
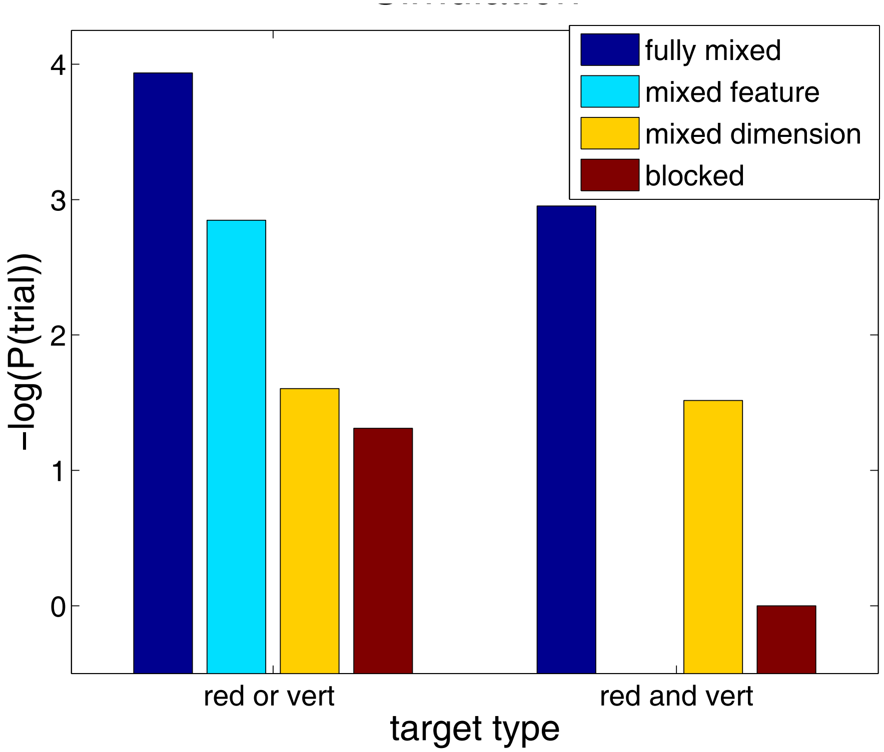


Simulation



Other Accounts of Attentional Adaptation

Feature-strengthening account (Maljkovic & Nakayama, 1994; Wolfe et al., 2003)

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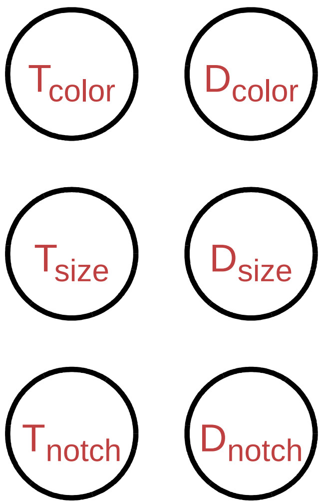
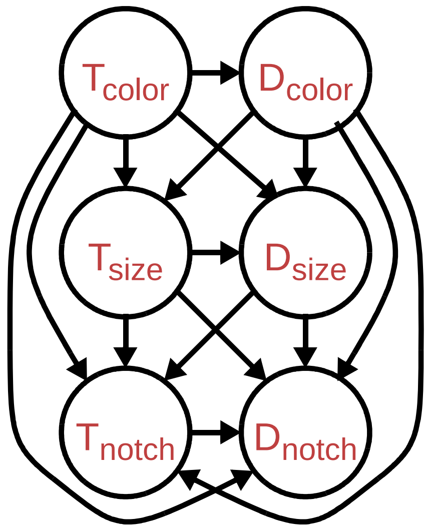


Independence Architecture

Episodic account (Hillstrom, 2000; Huang et al., 2004)



Full Joint Architecture

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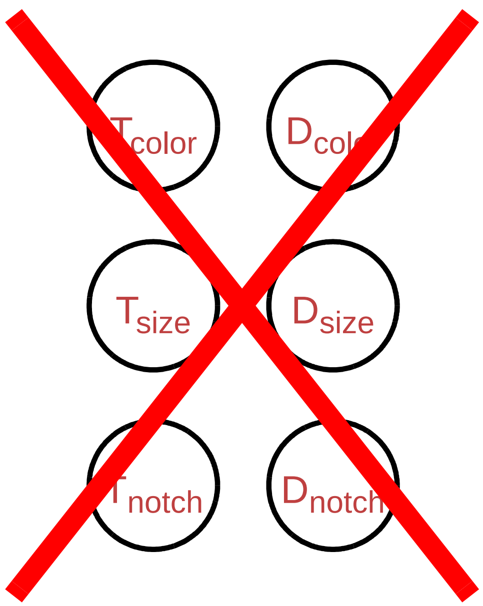

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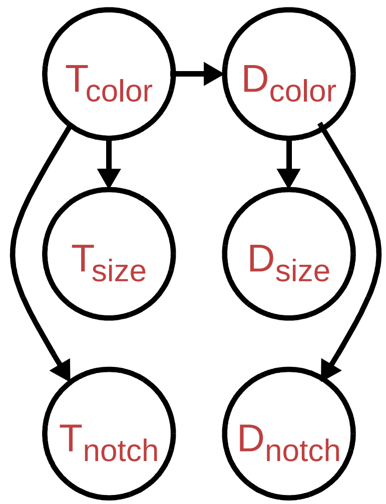
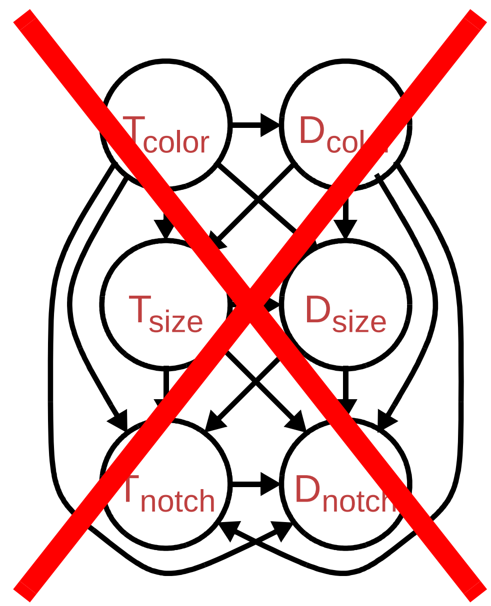


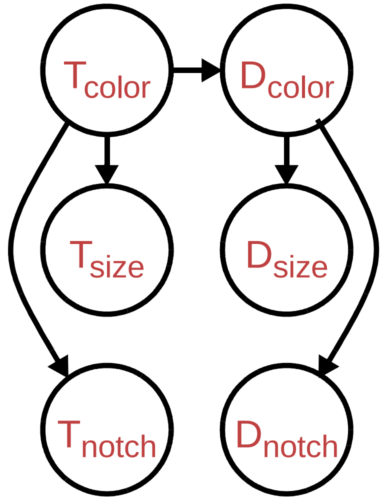
Task-Based Architecture



Full Joint Architecture

Neither is adequate to explain the range of data

Two Ways to View Architecture



- **model of the structure of the environment**
- **model of attentional control**

Rational account

Information processing is optimized to the structure of the environment.

Allows for limitations on information processing
(e.g., structural restrictions on architecture)

Pushing the Rational Account Further

Why does influence of past experience decay rapidly?

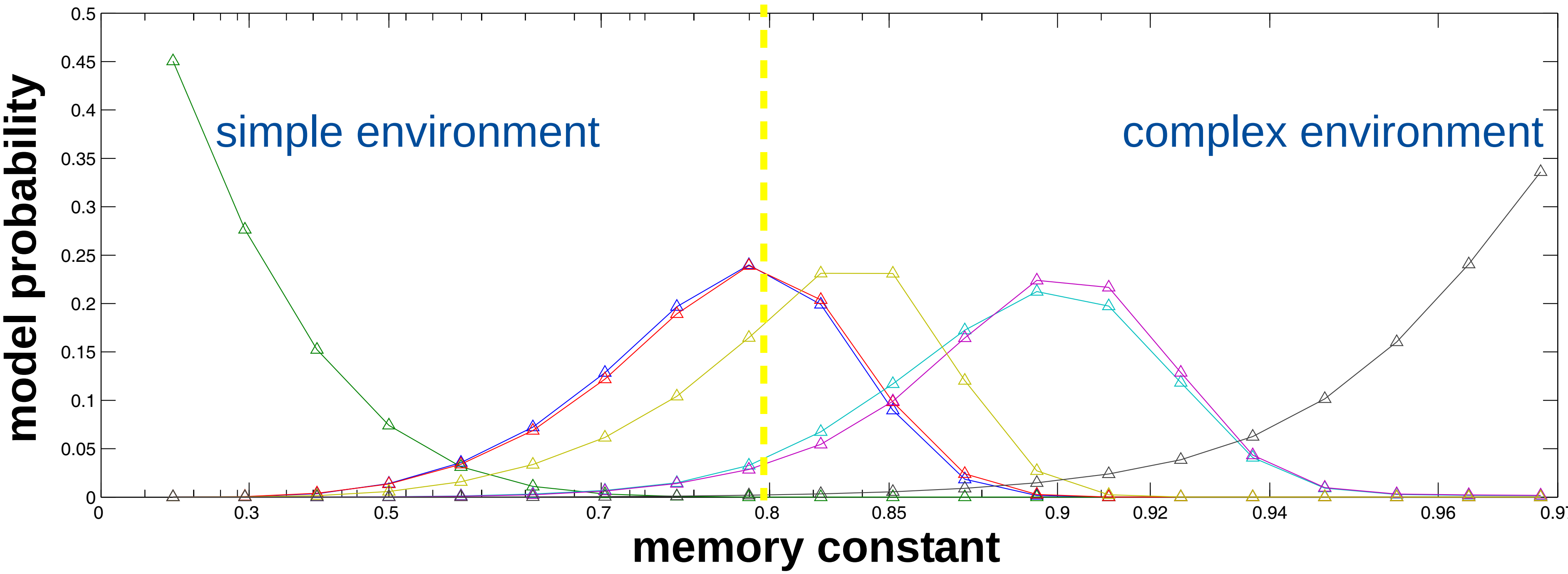
Pressures on duration of influence

- Adapting quickly to changing environment → short lived influence
- Capturing statistics of complex environments → long-lived influence

Is observed memory duration optimal?

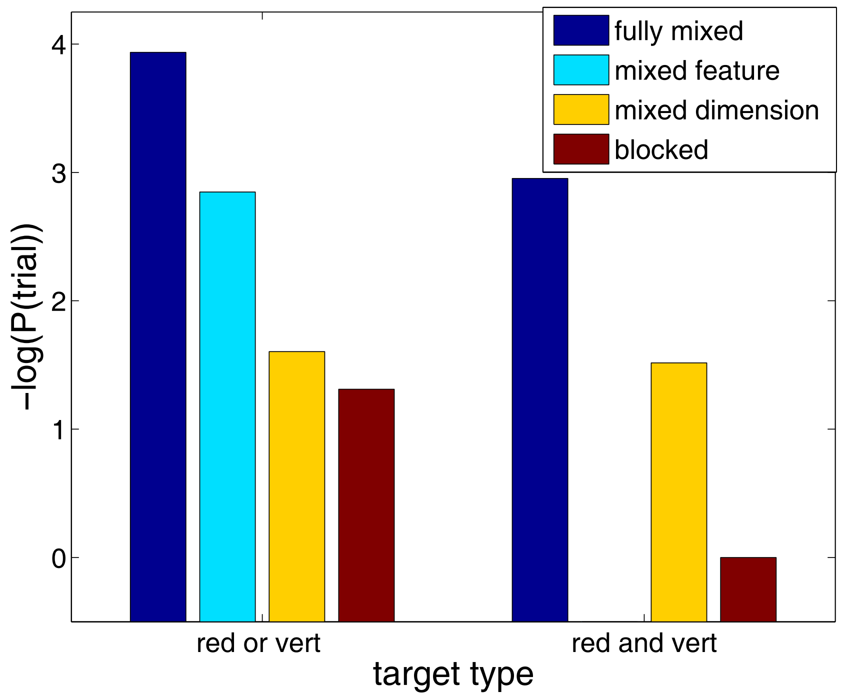
Use Bayesian model selection to determine appropriate memory constant in a given environment.

Posteriors on Memory Constant for Environments of Wolfe et al.

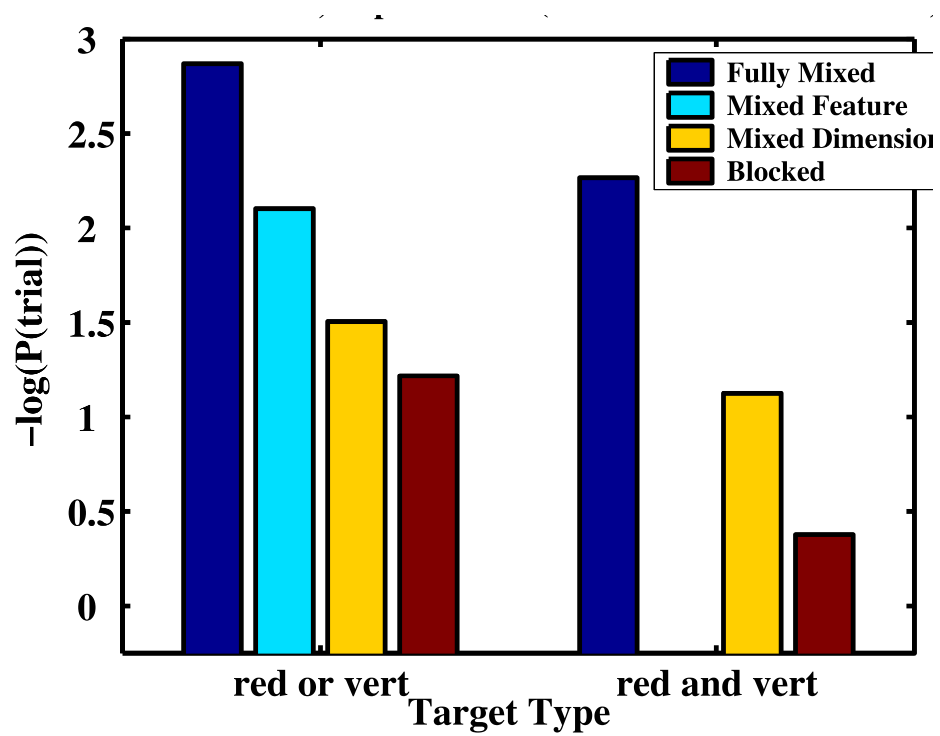


Prediction Via Model Averaging

original simulation



Bayesian model averaging



Eliminates the one free parameter of model

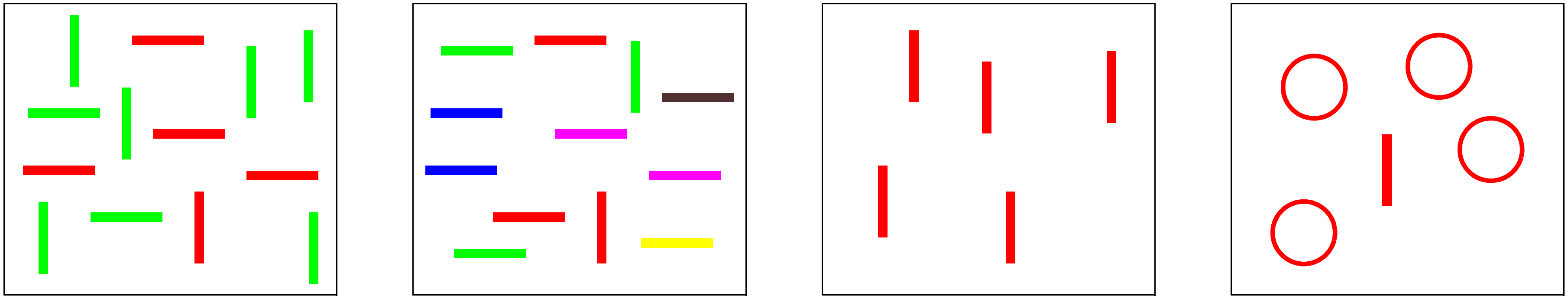
How Do Verbal Task Descriptions Influence Control of Attention?

How Do Verbal Task Descriptions Influence Control of Attention?

1. **Task provides a representational framework for encoding the environment.**

2 Task provides weak description of environment that can be used for determining initial control settings.

e.g., find the red vertical line



Control settings can clearly be refined once environment has been experienced.

Stimulus-Response Task

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E.g., simple addition problem

19 + 12

Task: name the sum of the numbers

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Control issue

When to initiate response?

Speed-accuracy trade off

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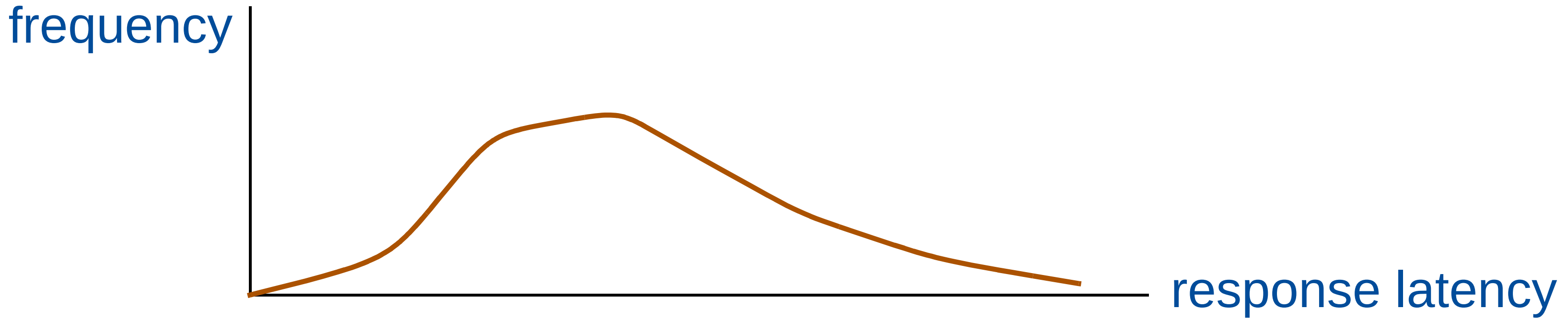
Response latency distribution



Can explain much response variability via sequence effects.

$$18 + 23$$

48 + 26

$$3 + 1$$

List-Composition Effect
(Lupker, Kinoshita, Coltheart, & Taylor, 2003)

Pure Easy Block	Pure Hard Block	Mixed Block
3 + 2	8 + 6	3 + 2
1 + 4	5 + 7	5 + 7
10 + 7	9 + 4	10 + 7
5 + 5	12 + 9	12 + 9

List-Composition Effect
(Lupker, Kinoshita, Coltheart, & Taylor, 2003)

Reaction Time

	Easy	Hard
Pure Block	635 msec	1059 msec

Error Rate

	Easy	Hard
Pure Block	0.3%	3.0%

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	Easy	Hard
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Mixed Block	0.0%	4.8%

List-Composition Effect
(Lupker, Kinoshita, Coltheart, & Taylor, 2003)

Reaction Time

	Easy	Hard
Pure Block	635 msec	1059 msec
Mixed Block	683 msec	1003 msec
Difference	+48 msec	–56 msec

Error Rate

	Easy	Hard
Pure Block	0.3%	3.0%
Mixed Block	0.0%	4.8%
Difference	–0.3%	+1.8%

List composition affects speed-accuracy trade off.

Cognitive Control

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We interpret cognitive control as optimizing performance to the environment in which an individual is operating.

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Mechanisms

1. construct predictive model of the environment
2. use predictive model to optimize performance

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List-composition effect reflects this control process at work.

Modeling List-Composition Effects

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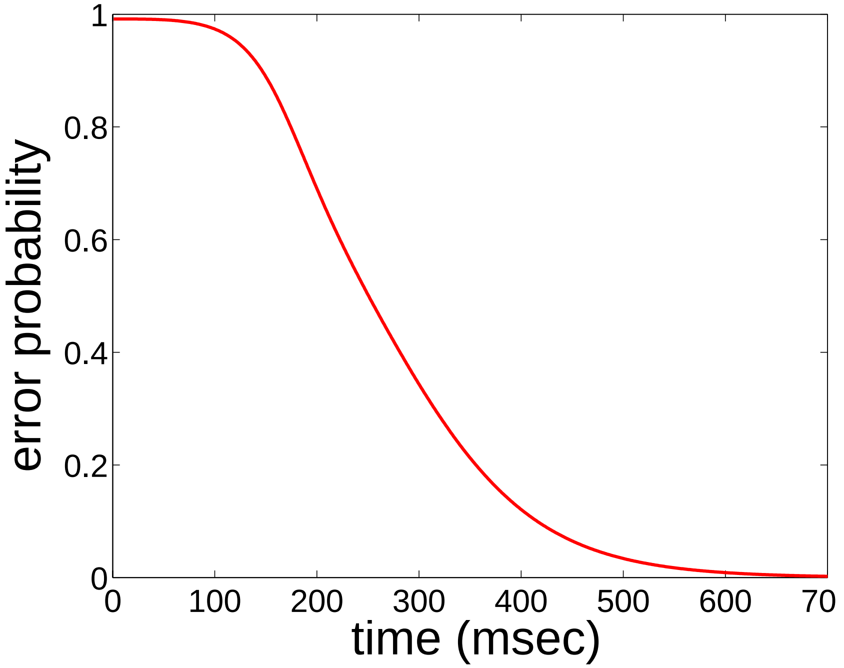
Assumptions

- At each instant of time during the processing of a stimulus, the cognitive system estimates the probability of producing an error if a response is made based on the available evidence.

  The estimate is used for deciding when to initiate a response.



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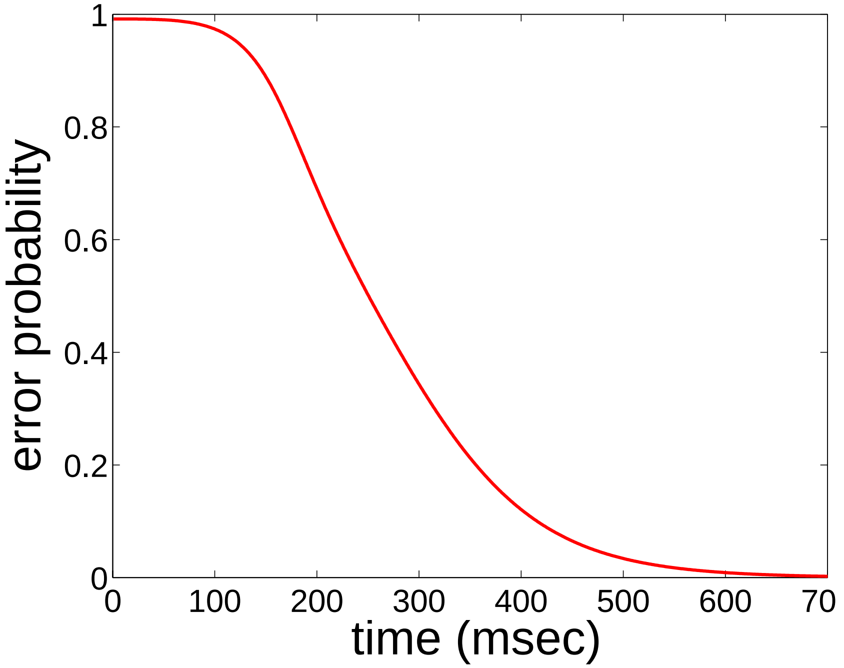
- The estimate is unreliable.



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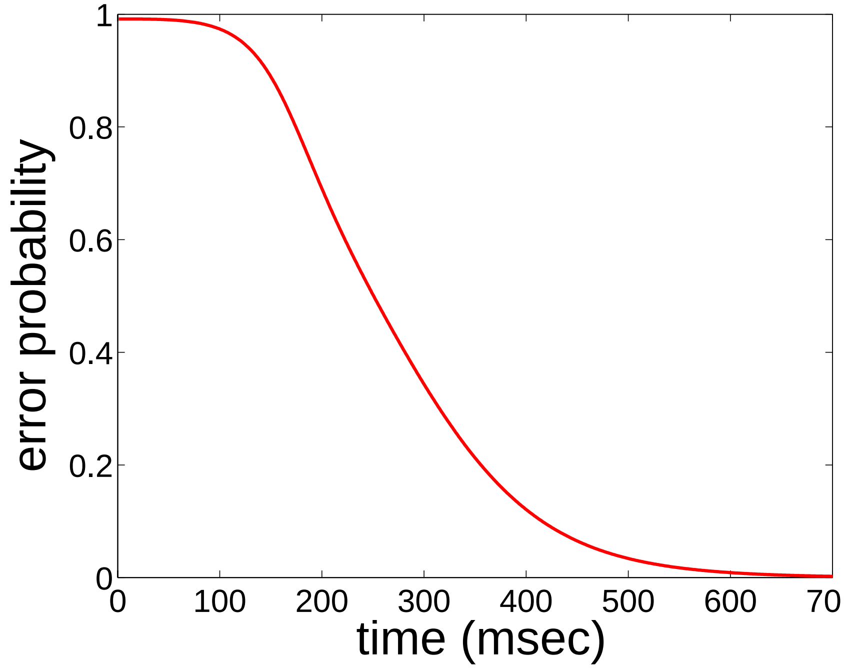
- Current trial is similar in difficulty to recent trials.



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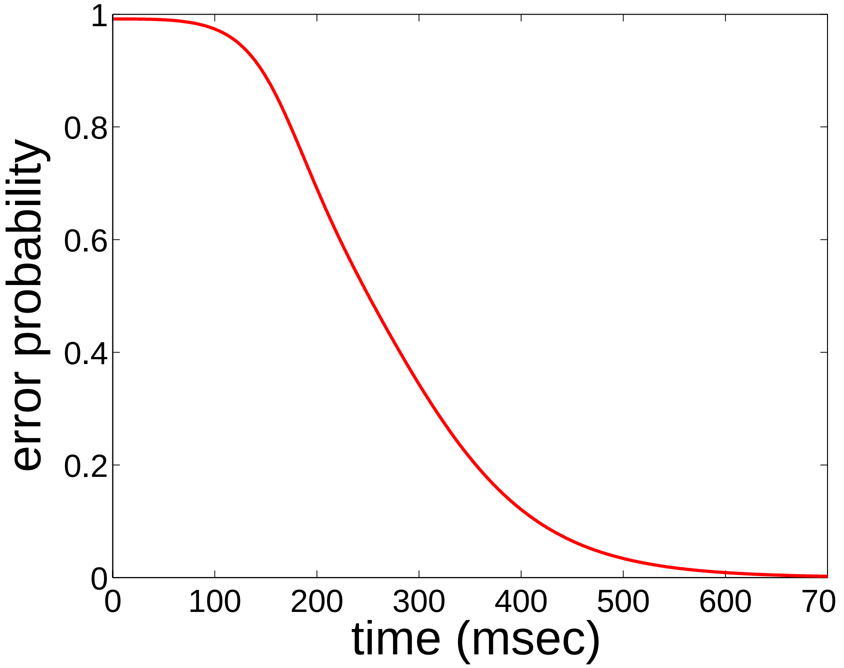


Under these assumptions, it is adaptive to use an error estimate based on current *and recent* trials.

Thus, recent trial history affects current trial performance.

Model Details

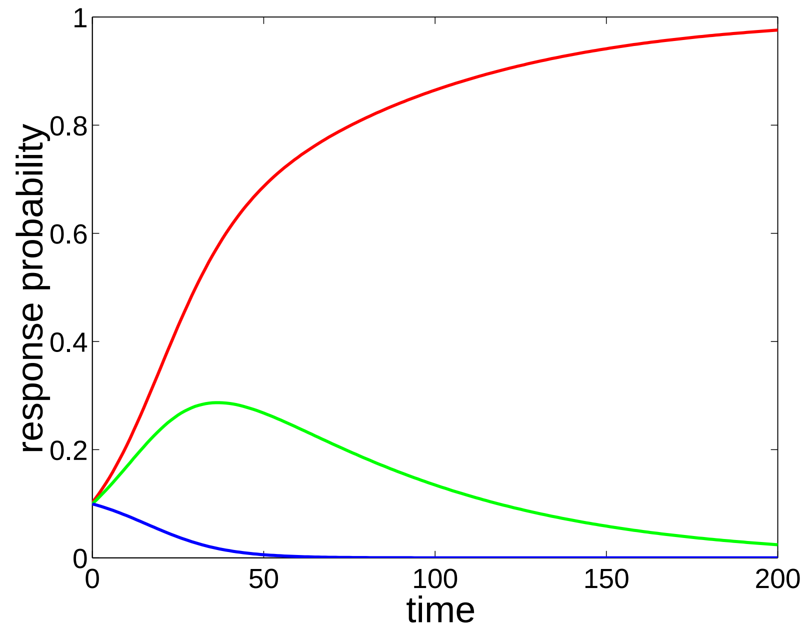
Probabilistic information transmission (PIT) framework of Mozer, Colagrosso, and Huber (2002, 2003)

Dynamic Bayes net

Generalization of sequential sampling models (random walk, diffusion, accumulator models)

PIT produces probability distribution over responses.

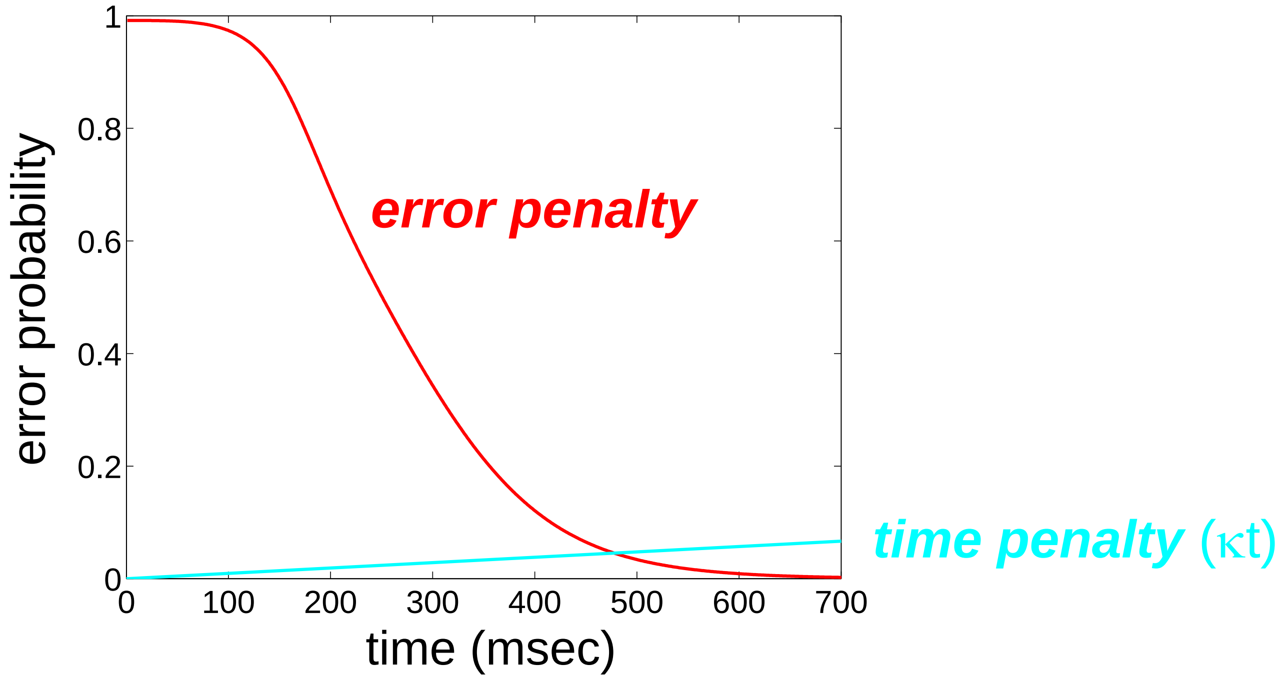
Error probability estimated from this distribution.



Other models of temporal dynamics work fine.

Model Details

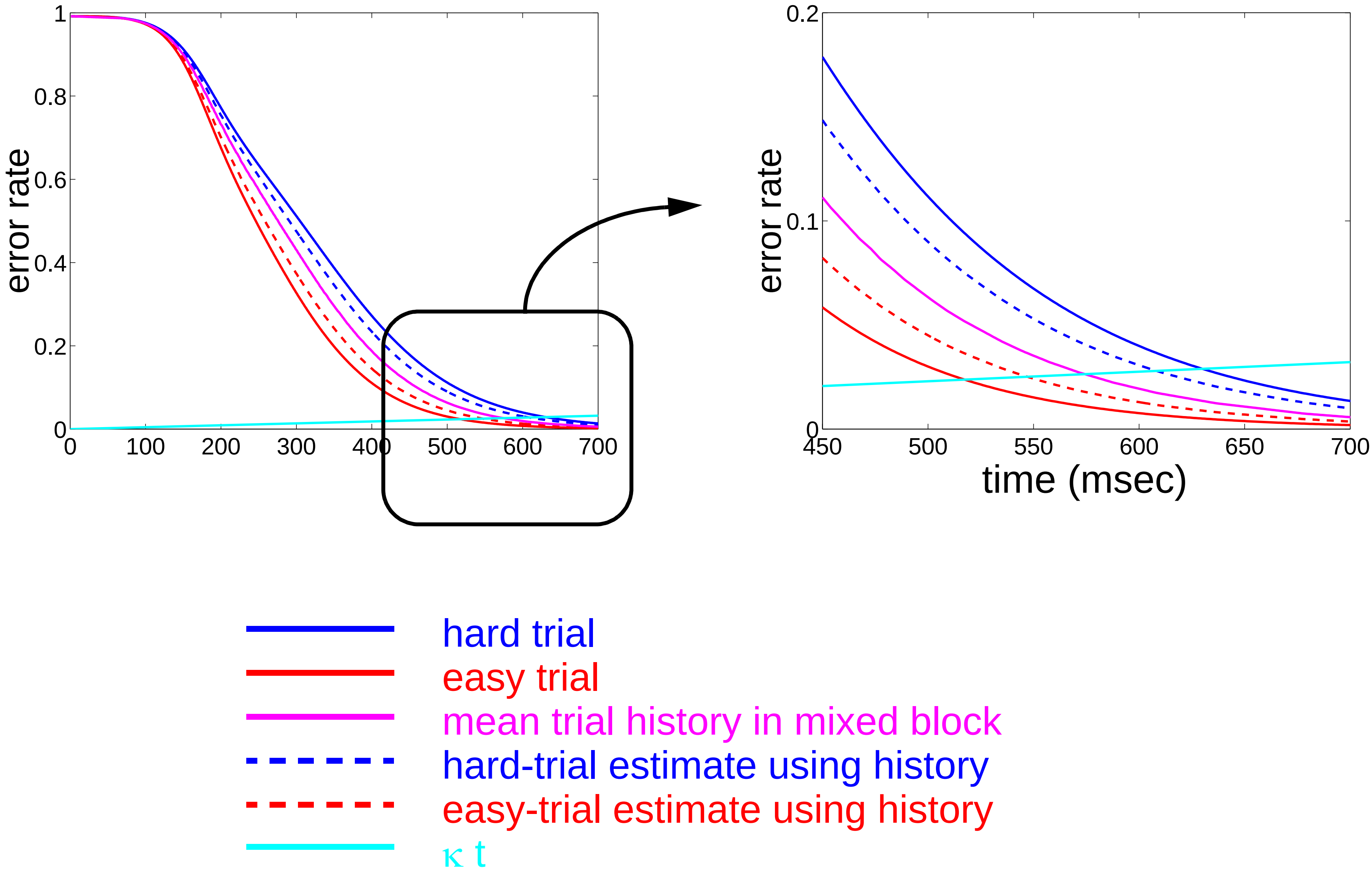
Initiate response when *error penalty* drops below *time penalty*



Can be cast in framework of maximizing expected utiliity.

Other decision rules work fine.

Model Operation



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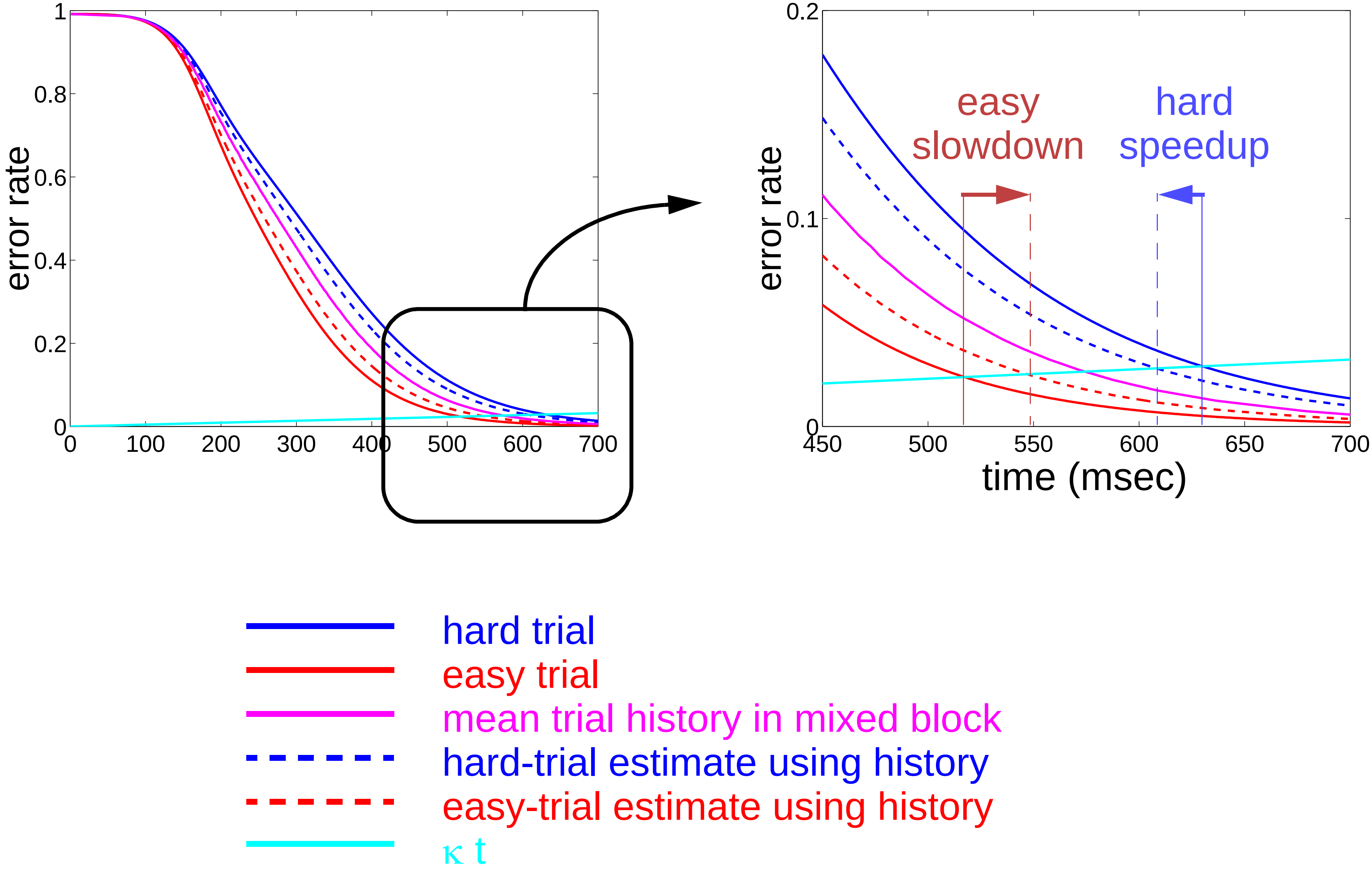
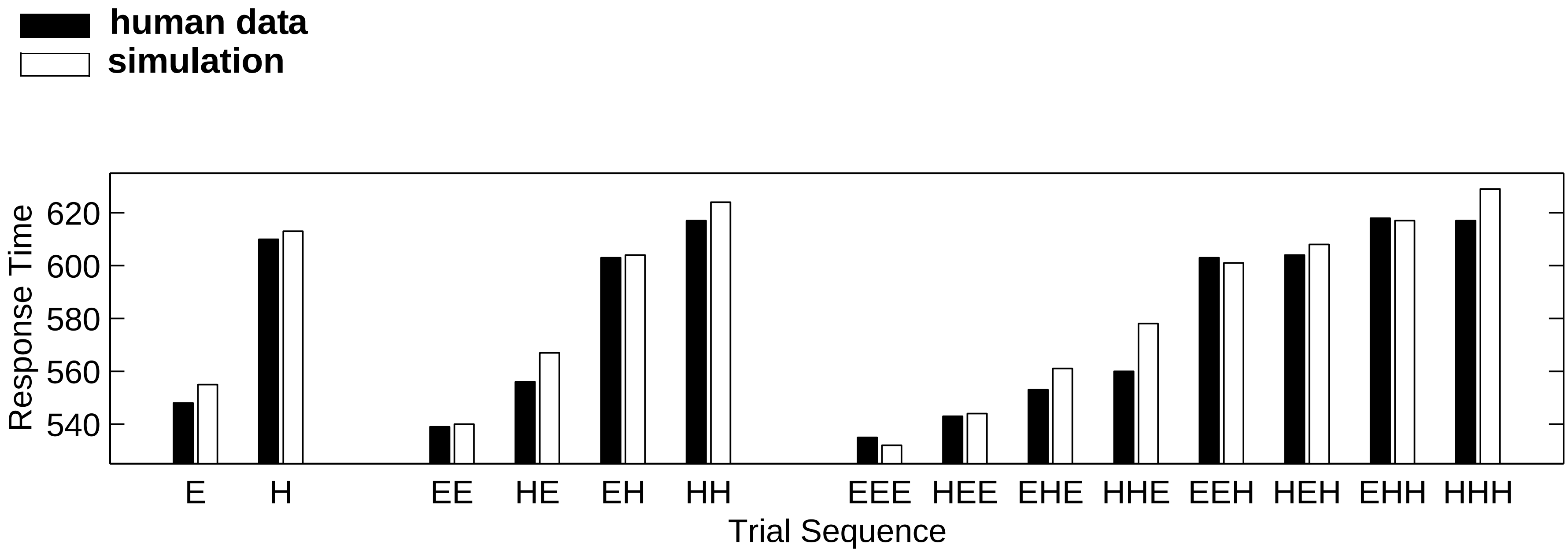


Taylor & Lupker (2001), Experiment 1

		Human Data		Simulation	
		Easy	Hard	Easy	Hard
RT	Pure	519 msec	631 msec	518 msec	630 msec
	Mixed	548 msec	610 msec	548 msec	610 msec
	Diff.	+29 msec	–21 msec	+29 msec	–20 msec

		Human Data		Simulation	
		Easy	Hard	Easy	Hard
Error Rate	Pure	0.6%	2.9%	2.3%	2.9%
	Mixed	0.7%	2.9%	1.6%	3.6%
	Diff.	0.1%	0.0%	–0.7%	0.7%

Taylor & Lupker (2001, Experiment 1)



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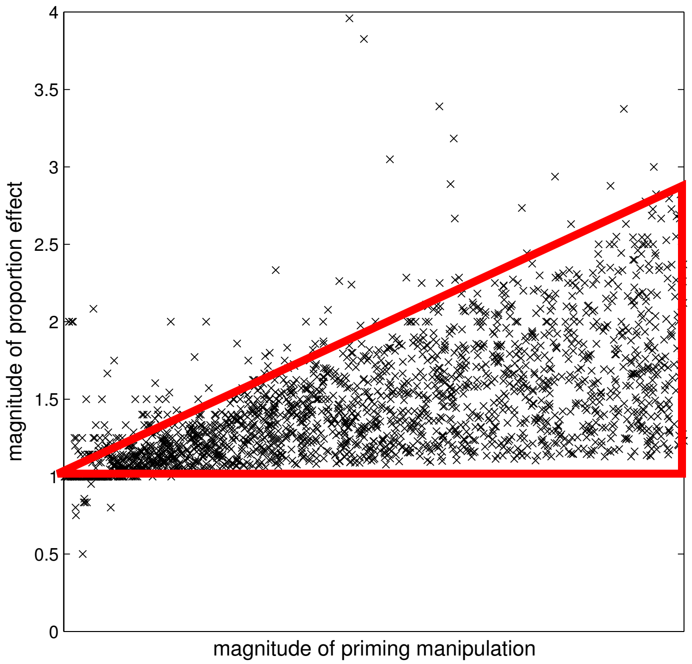
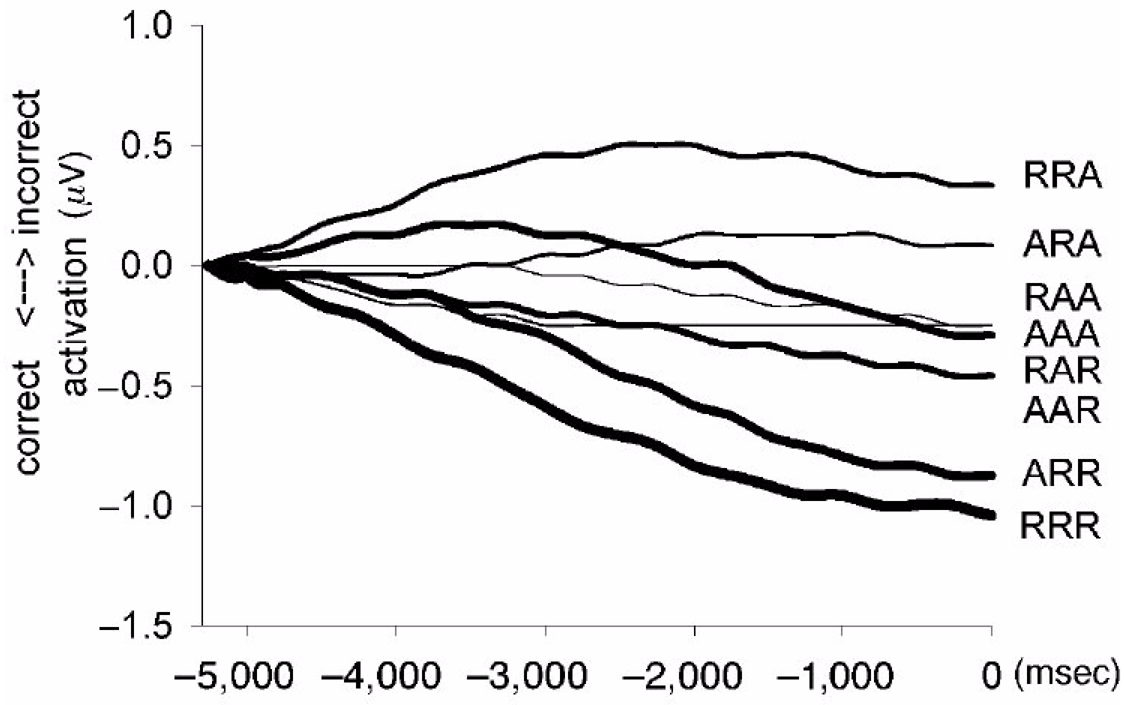
Model makes strong predictions.



LRP Data (Jentzsch & Sommer, 2002)



Conventional Perspectives on Cognitive Control

Control involves allocating a limited resource.

- Some tasks invoke more control than others (Wolfe et al., 2003)
- Accounts often imply homunculus that distributes resource.

Control involves loading a new program into the brain's CPU for each task.

***Explicit* mechanisms**

Our Unconventional Perspective

Much of what appears to be cognitive control can be interpreted as a consequence of optimizing performance to the ongoing stream of experience.

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Learning on a second-to-second time scale

Over a range of simple tasks, about five experiences are needed to tune performance. (No measurable speed up in performance beyond that.)

This tuning is obligatory each time the task or environment switches, *regardless of past experience with task or environment*.

Performing task is necessary: preparation is not sufficient.

Tuning can occur to abstract features (e.g., target color, stimulus difficulty)

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Our claim: Experience allows brain to build a model of the environment, which is used to optimize performance.

Even a rough model is very helpful.

Compared to direct reinforcement learning techniques, requires *much less* interaction with the environment for learning.

Explanations for List-Composition Effects

Many explanations have been proposed.

e.g., Kello & Plaut (2001); Meyer, Roelofs, & Levelt (2003); Perea, Carreiras, & Granger (2005); Rastle & Coltheart (1999); Strayer & Kramer (1994)

All have deficiencies.

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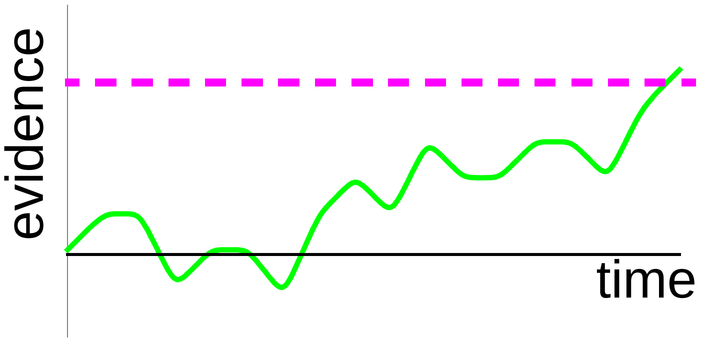
E.g., adjustment of response criterion

Diffusion model (Ratcliff, 1978)



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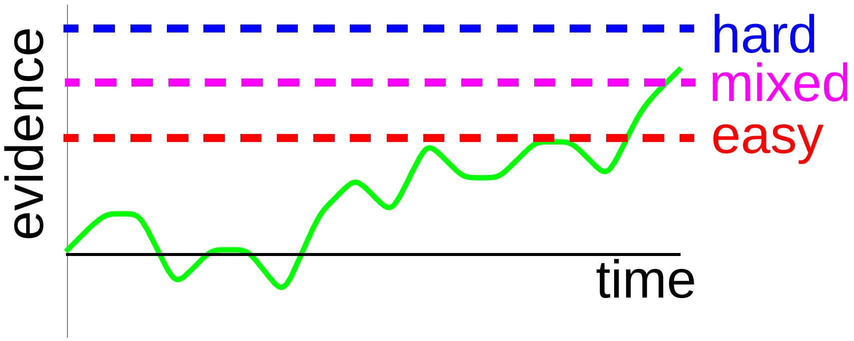

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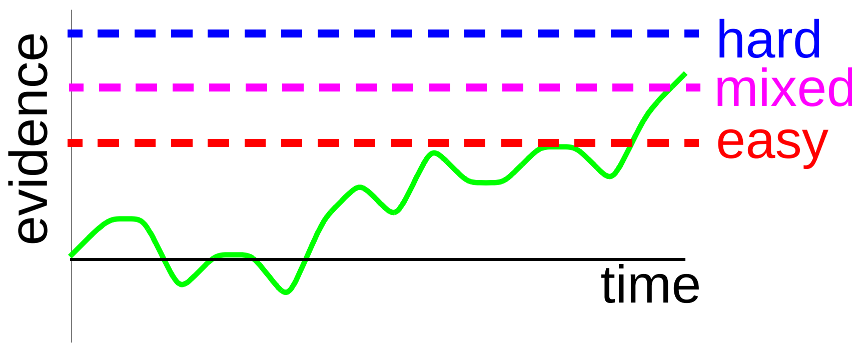


Experimental evidence contradicts criterion-adjustment accounts (Dorfman & Glanzer, 1988; Gold & Shadlen, 2003; Jentzsch & Sommer, 2002; Osman et al., 2000)

Sequential Dependencies

When executing a task repeatedly, experience on one trial affects performance on subsequent trials.

Performance = RT, accuracy, type of errors, interpretation of stimulus, etc.

Adaptation on the time scale of seconds

Robust and widespread across a range of tasks

Some varieties termed priming

Most are short lived (~ 5 trials)

Some are long lived (> 100 trials)

Sequential Dependencies

component of architecture			
perception			
stimulus-response mapping			
response initiation			
attentional control			

Sequential Dependencies

component of architecture	experimental paradigm		
perception	identification		
	intensity judgement		
	categorization		
stimulus-response mapping	task switching		
response initiation	word naming		
	choice		
attentional control	cued detection and identification		
	visual search		

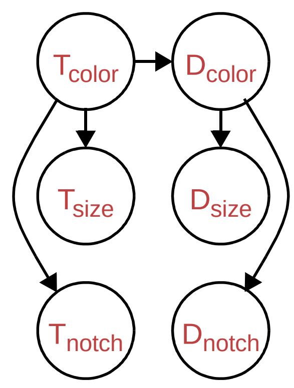
Sequential Dependencies

component of architecture	experimental paradigm	dimension of dependency	
perception	identification	stimulus shape and identity	
	intensity judgement	stimulus magnitude	
	categorization	stimulus features	
stimulus-response mapping	task switching	task set	
response initiation	word naming	stimulus difficulty	
	choice	response repetition	
attentional control	cued detection and identification	cue validity	
	visual search	stimulus features	
		global stimulus configuration	

Sequential Dependencies

component of architecture	experimental paradigm	dimension of dependency	example citations
perception	identification	stimulus shape and identity	Bar & Biederman (1997); Ratcliff & McKoon (1997)
	intensity judgement	stimulus magnitude	Lockhead (1984, 2004)
	categorization	stimulus features	Jones & Mewhort (2003); Stewart et al. (2002)
stimulus-response mapping	task switching	task set	Rogers & Monsell (1995)
response initiation	word naming	stimulus difficulty	Kiger & Glass (1981); Taylor & Lupker (2001)
	choice	response repetition	Jentszch & Sommer (2002); Jones et al. (2003)
attentional control	cued detection and identification	cue validity	Bodner & Masson (2001); Posner (1980)
	visual search	stimulus features	Maljkovic & Nakayama (1996); Wolfe et al. (2003); Huang et al. (2004)
		global stimulus configuration	Chun & Jiang (1998, 1999)

Fancy Version of Model



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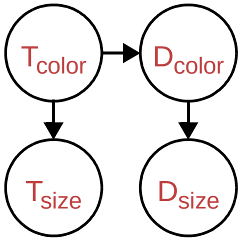

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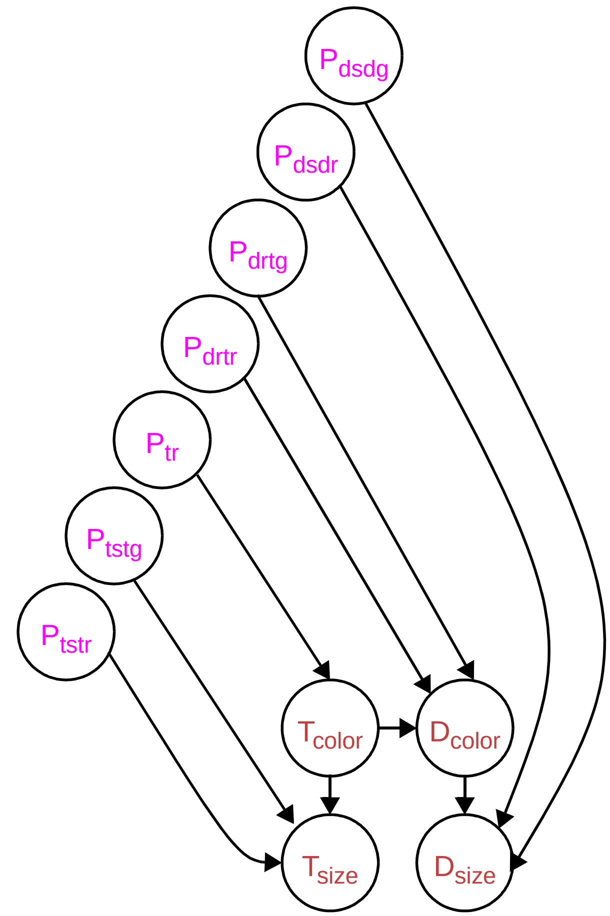

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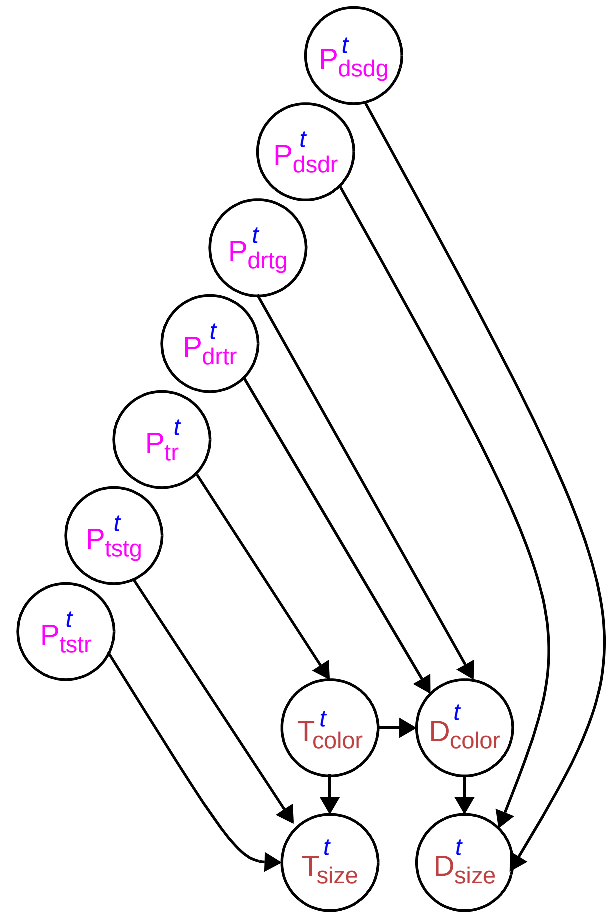

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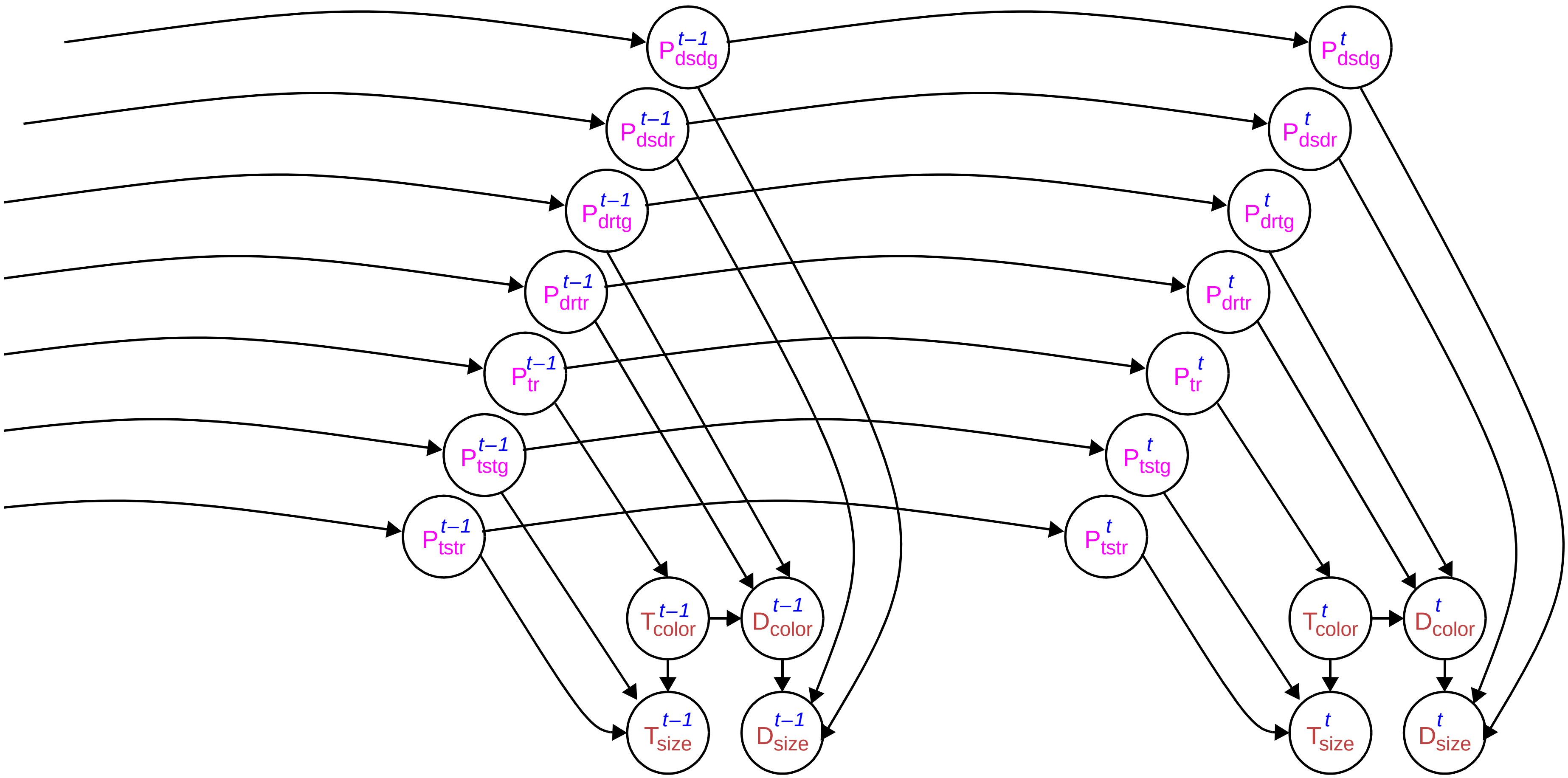

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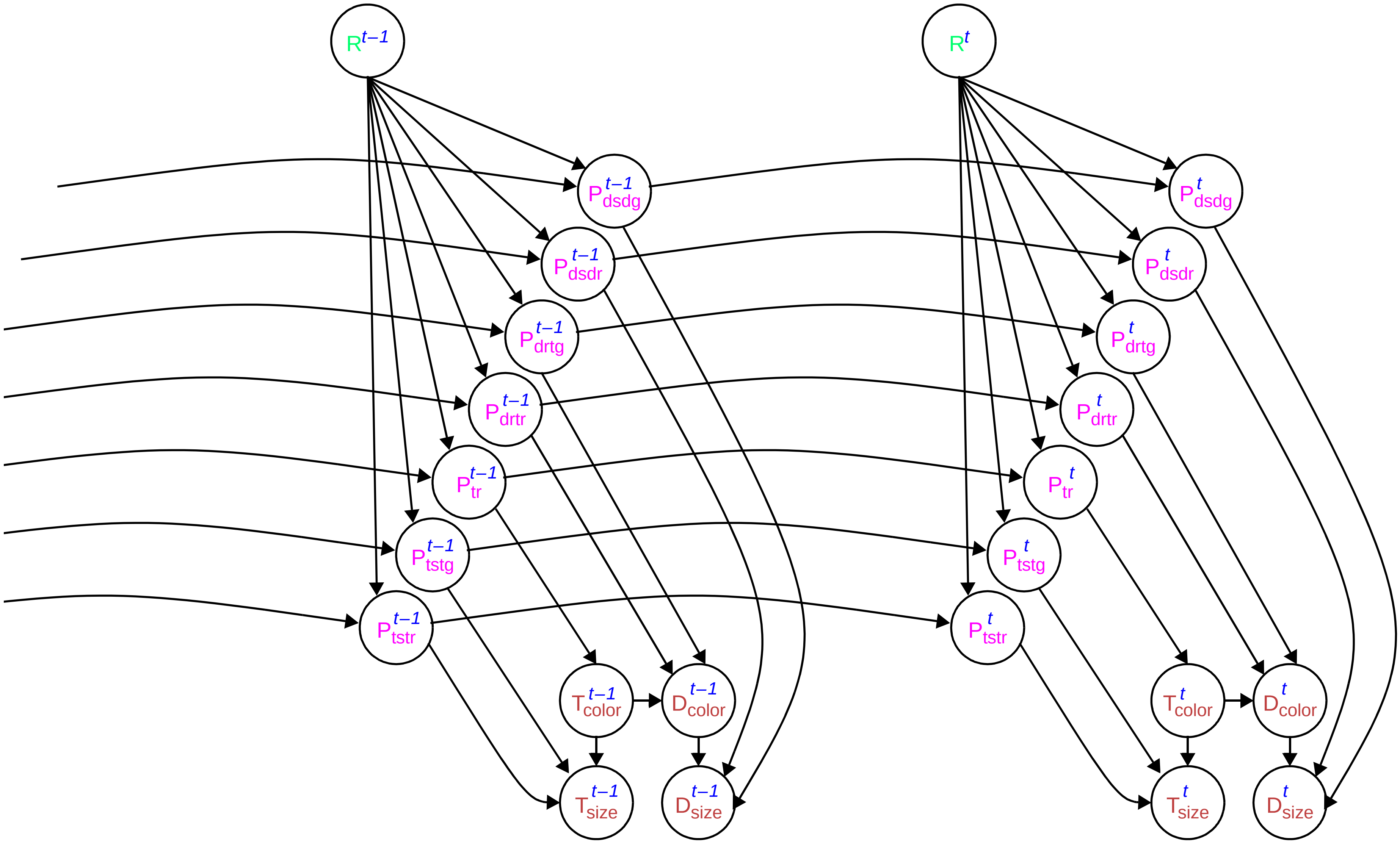

Summary

Two case studies

1. control of attention and the influence of recent stimulus displays

2. control of response initiation and the influence of recent stimulus difficulty

Sequential dependencies reflect adaptation to the ongoing stream of experience.

Implicit control

Trial-to-trial adaptation looks like control from the experimenter's perspective.

But not from the perspective of processing mechanisms