

A Processing Ghost in a Tank Machine

Mario Fifić

Grand Valley State University Michigan

Air Force Research Laboratory, Cognitive Lunch Brown Bag, November, 2013

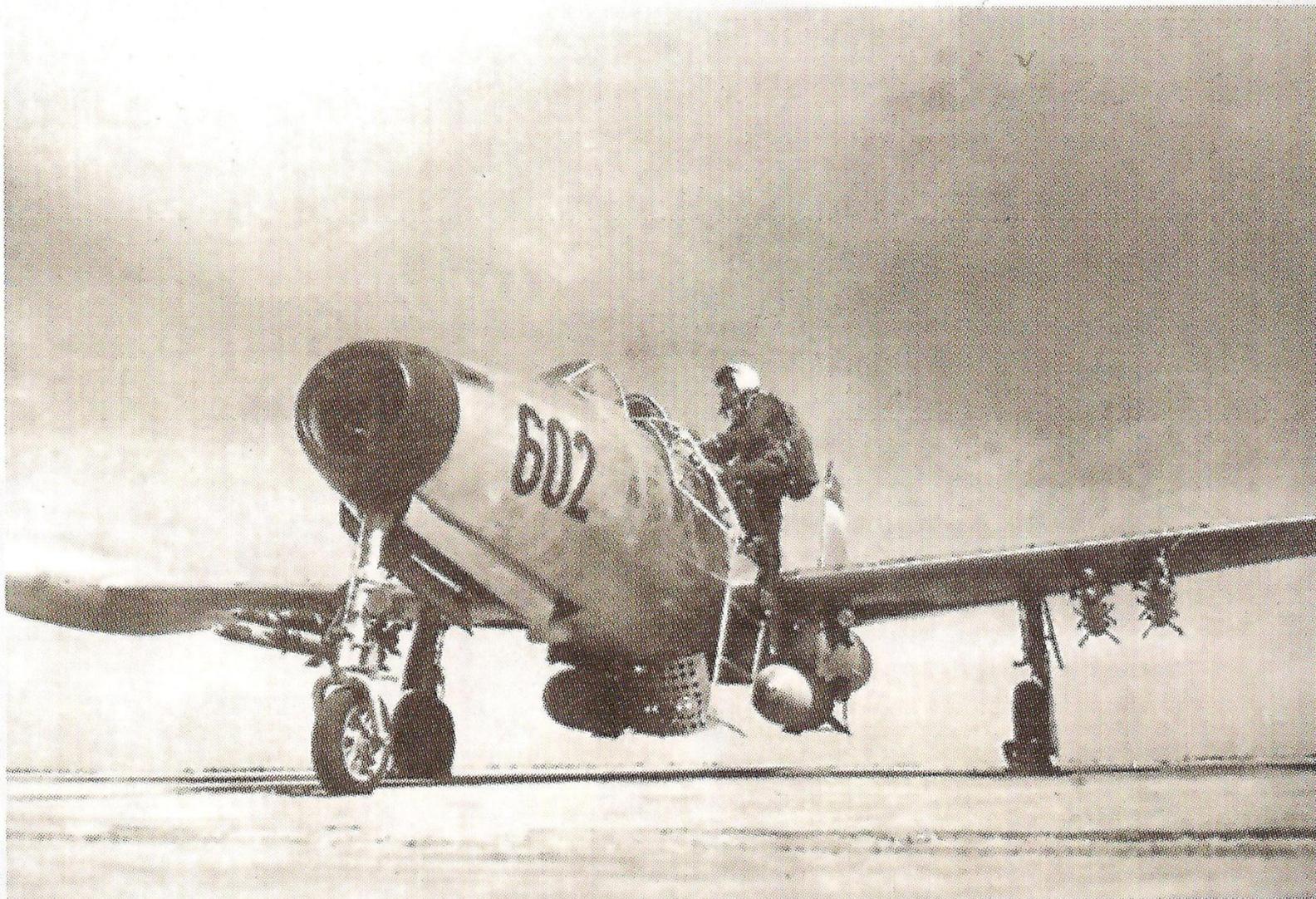
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Research Perspectives

Mario Fifić

Grand Valley State University, MI

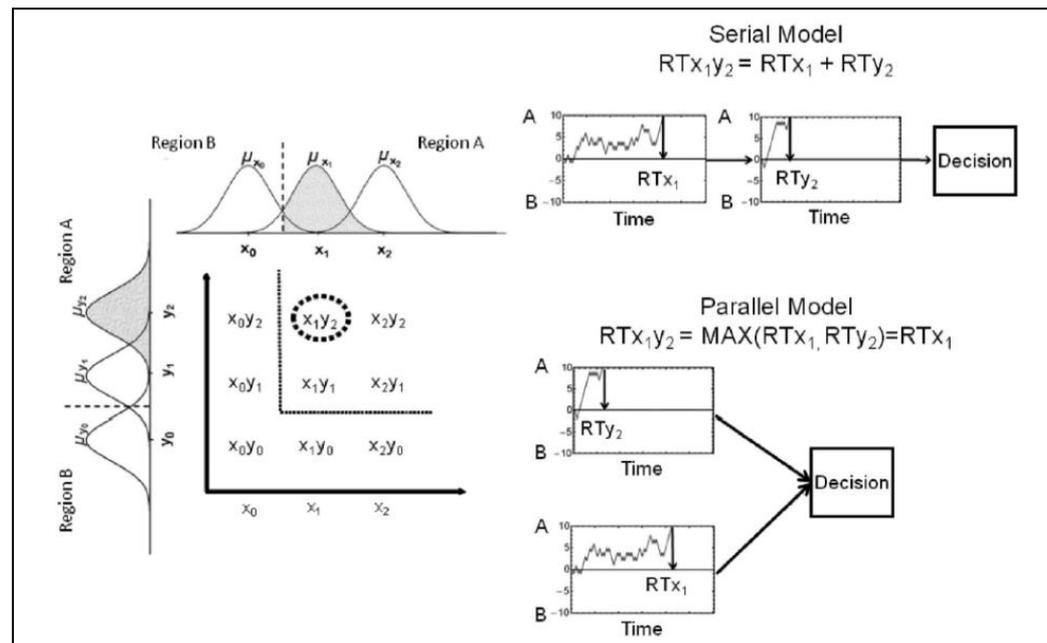
- My research interests center on developing a process-tracing approach that allows for precise determination of the fundamental properties of the mental processes that underlie cognitive actions.

Theoretical advances

Logical-Rule Models of Classification Response Times: A Synthesis of Mental-Architecture, Random-Walk, and Decision-Bound Approaches

Mario Fific
Max Planck Institute for Human Development

Daniel R. Little and Robert M. Nosofsky
Indiana University, Bloomington



A magnifying glass on human cognition

Journal of Experimental Psychology:
Learning, Memory, and Cognition
2010, Vol. 36, No. 5, 1290–1313

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0278-7393/10/\$12.00 DOI: 10.1037/a0020123

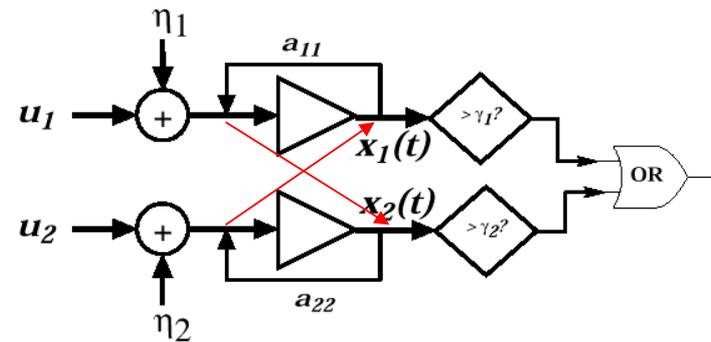
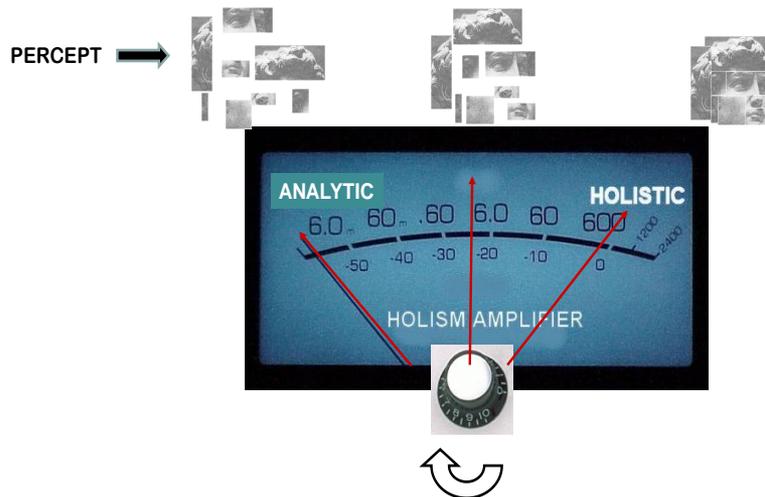
Information-Processing Alternatives to Holistic Perception: Identifying the Mechanisms of Secondary-Level Holism Within a Categorization Paradigm

Mario Fifić

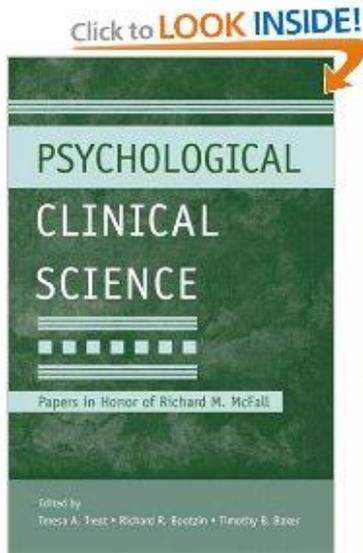
Max Planck Institute for Human Development

James T. Townsend

Indiana University Bloomington



The applications

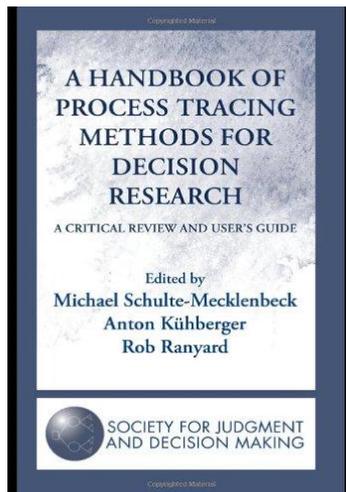


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Assessment of Mental Architecture in Clinical/Cognitive Research

James T. Townsend and Mario Fifić
Indiana University

Richard W. J. Neufeld
University of Western Ontario



Part III: Methods for Tracing Physiological, Neurological, and Other Concomitants of Cognitive Processes

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6 Analyzing Response Times to Understand Decision Processes

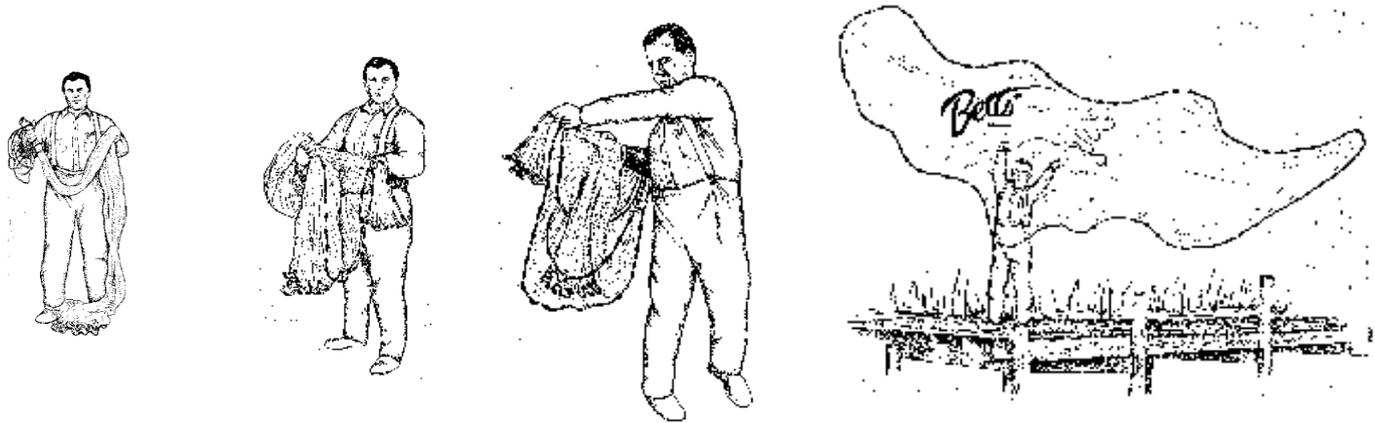
141

Wolfgang Gaissmaier, Mario Fifić, and Jörg Rieskamp

Motivation

- Understanding mind's cognitive mechanism
- Understanding the brain's neural mechanisms
- Assessment of individuals with application in Clinical, Personality, Developmental Psychology

Stopping Rule Selection (SRS) Theory Applied to Deferred Decision Making



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Marcus Buckmann

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NSF (SES-1156681)



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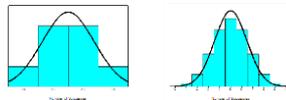
[Air Force Research Laboratory](#), November, 2013

Working memory (WM) under consideration

- Processing order
- Capacity status
- Subdivision by modalities
- Dual or one system
- Status of mental representations & resource allocation

Resource allocation models of WM

- The discrete-slot model proposes that WM operates on the **ALL-OR-NONE** principle: holding only high-resolution item representations stored in a limited number of memory slots.
 - The slots+averaging model is variant of the discrete-slot model assuming that more than one slot could be allocated to a single item representation
- the variable-resources model WM operates on the **ALL-GET-SOME** principle: a pool of limited resources is dynamically allocated across a set of memorized items representations.



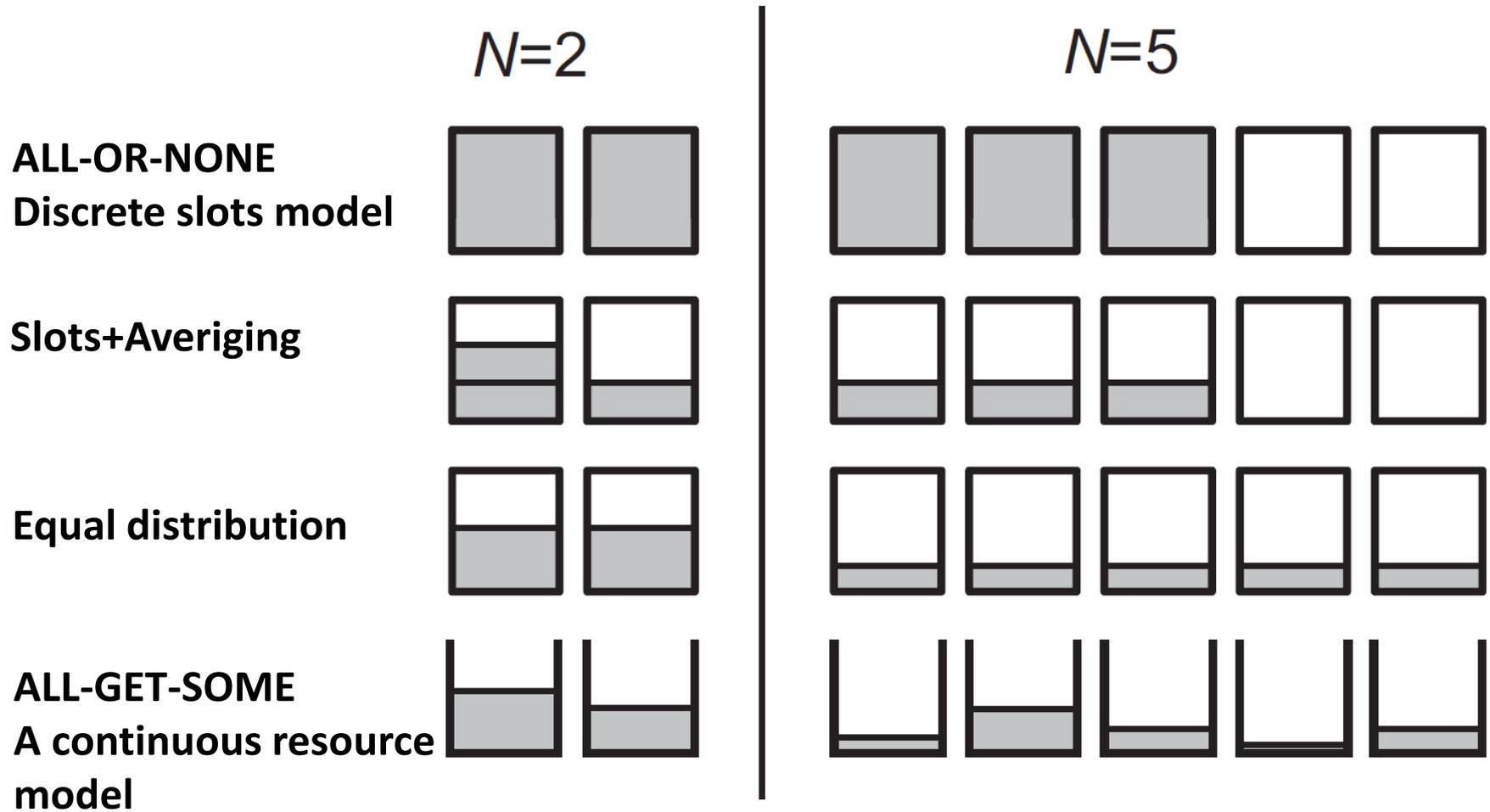
$\lim_{n \rightarrow \infty} f(x)$



Why status of mental representations?

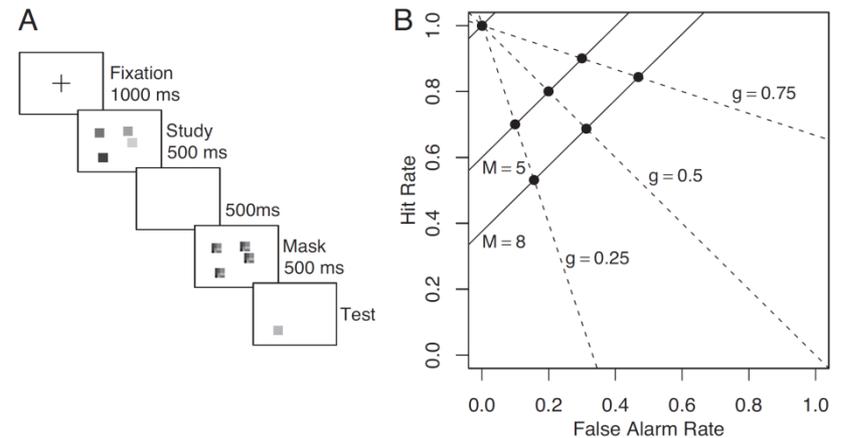
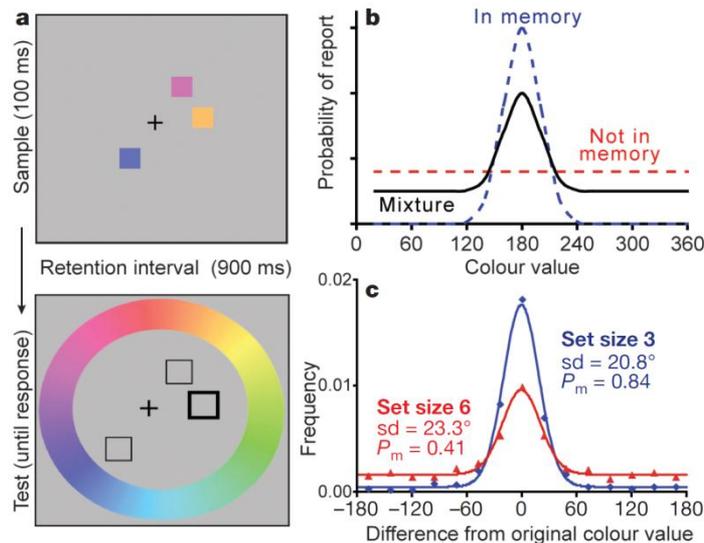
- Resource allocation.
- If representations are ALL-OR-NONE, and the system's capacity is limited, then when there is information overload an operator must guess.
- Sophisticated guessing?
- Neural system's implications.

Resource allocation in model of WM



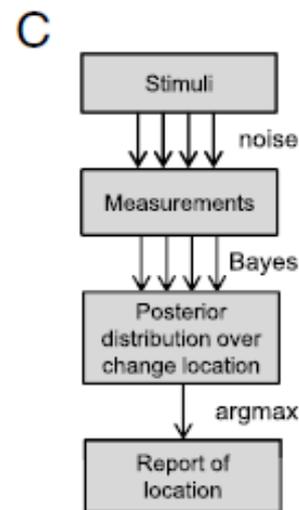
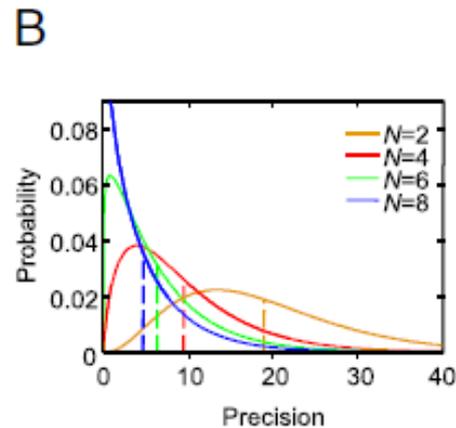
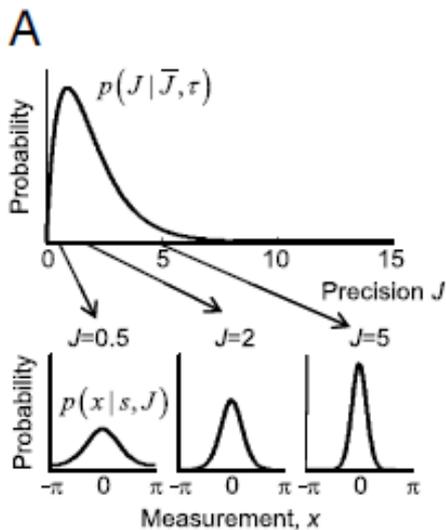
Evidence supporting Discrete Slots Model

- Zhang & Luck 2008
- Cowan (2001) The magical number 4 in short-term memory
- Rouder, Morey, Cowan, Zwilling, Morey, & Pratte (2008).
- Donkin, Nosofsky, Gold, & Shiffrin, (in press 2013).



Evidence supporting the Variable-resource model

- van den Berg, R., Shin, H., Chou, W.C., George, R., & Ma, W.J. (2012)
- Bays & Husain (2008)



van den Berg, et al. (2012). Appendix..

ments $\mathbf{x} = (x_1, \dots, x_N)$ and $\mathbf{y} = (y_1, \dots, y_N)$, we use a Bayesian-observer model. The Bayesian observer computes a probability distribution over the location of the change, $p(L | \mathbf{x}, \mathbf{y})$, and then reports the location with the highest probability. The posterior distribution over L is proportional to the joint distribution, $p(\mathbf{x}, \mathbf{y}, L)$, which in turn is evaluated as an integral over the remaining variables, namely Δ , θ , and φ ,

$$\begin{aligned} p(\mathbf{x}, \mathbf{y}, L) &= \iiint p(\mathbf{x}, \mathbf{y}, \theta, \varphi, \Delta, L) d\Delta d\theta d\varphi \\ &= \iiint p(L) p(\Delta) p(\theta) p(\varphi | L, \theta) p(\mathbf{x} | \theta) p(\mathbf{y} | \varphi) d\Delta d\theta d\varphi, \end{aligned}$$

where in going from the first to the second line we have used the structure of the generative model in Fig. S1B. Substituting distributions and evaluating the integral over φ gives

$$p(\mathbf{x}, \mathbf{y}, L) = \frac{1}{N} \left(\frac{1}{2\pi} \right)^{N+1} \int \prod_{i=1}^N \left(\int p(x_i | \theta_i) p(y_i | \varphi_i = \theta_i + \Delta \delta_{L,i}) \right) d\Delta, \quad \text{[S16]}$$

where $\delta_{L,i} = 1$ when $L = i$ and 0 otherwise. Because we are interested only in the dependence on L , we can freely divide by the L -independent product $\prod_{i=1}^N (\int p(x_i | \theta_i) p(y_i | \varphi_i = \theta_i))$, leaving only integrals pertaining to the L th location:

$$p(\mathbf{x}, \mathbf{y}, L) \propto \frac{\iint p(x_L | \theta_L) p(y_L | \varphi_L = \theta_L + \Delta) d\theta_L d\Delta}{\int p(x_L | \theta_L) p(y_L | \varphi_L = \theta_L)}. \quad \text{[S17]}$$

that is among the encoded ones. In analogy to Eq. S16, this probability is

$$\begin{aligned} (L \text{ encoded}) p(\mathbf{x}, \mathbf{y}, L) &= \frac{1}{N} \left(\frac{1}{2\pi} \right)^{K+1} \\ &\times \int \prod_{i=1}^K \left(\int p(x_i | \theta_i) p(y_i | \varphi_i = \theta_i + \Delta \delta_{L,i}) \right) d\Delta. \end{aligned} \quad \text{[S19]}$$

Now we evaluate the joint probability of \mathbf{x}, \mathbf{y} and that the change occurred at a location L that is not among the encoded ones. This probability is equal to

$$\begin{aligned} (L \text{ not encoded}) p(\mathbf{x}, \mathbf{y}, L) &= \iint p(\mathbf{x}, \mathbf{y}, \theta, \varphi, L) d\theta d\varphi \\ &= \iint p(L) p(\theta) p(\varphi | L, \theta) p(\mathbf{x} | \theta) p(\mathbf{y} | \varphi) d\theta d\varphi \\ &= \frac{1}{N} \left(\frac{1}{2\pi} \right)^K \prod_{i=1}^K \left(\int p(x_i | \theta_i) p(y_i | \varphi_i = \theta_i) \right). \end{aligned} \quad \text{[S20]}$$

As one would expect, this probability does not depend on L . Because we are interested only in the location L for which $p(\mathbf{x}, \mathbf{y}, L)$ is largest (i.e., the argmax), we divide both Eqs. S19 and S20 by Eq. S20. Then, in analogy to Eq. S17, we have to take the argmax of

$$\begin{cases} (L \text{ encoded}) & \frac{1}{2\pi} \frac{\iint p(x_L | \theta_L) p(y_L | \varphi_L = \theta_L + \Delta) d\theta_L d\Delta}{\int p(x_L | \theta_L) p(y_L | \varphi_L = \theta_L)} = \frac{1}{2\pi \int p(x_L | \theta_L) p(y_L | \varphi_L = \theta_L)} \\ (L \text{ not encoded}) & 1. \end{cases}$$

Unresolved question(s)

(what's under the all-or-none carpet)

- (1) We argue that the above research advances have been downplaying the experimental approaches to directly manipulate the allocation of resources across item representations held by WM.
- Our study showed that, when instructed, subjects adaptively allocated a limited amount of resources and shared them across memorized item representations.

Unresolved question(s) (what's under the carpet)

- (2) The exact mechanism of resource allocation has not been specified.

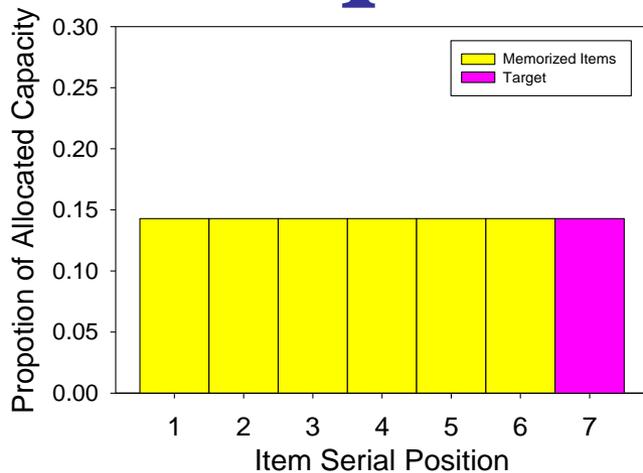
Specific Research Questions

- ❑ How are the resources allocated in WM? (Half-Half rule)
- ❑ What is the status of mental representations in WM?

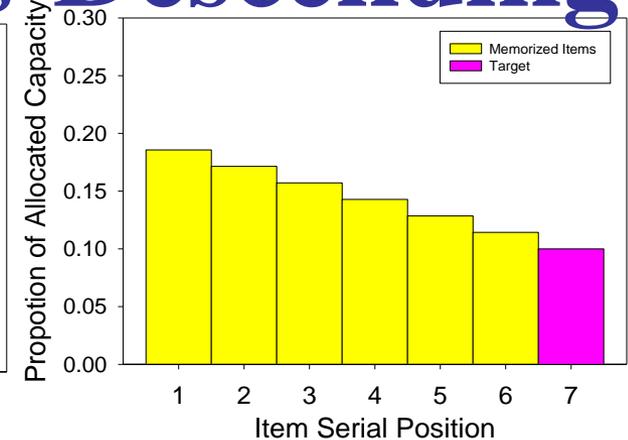
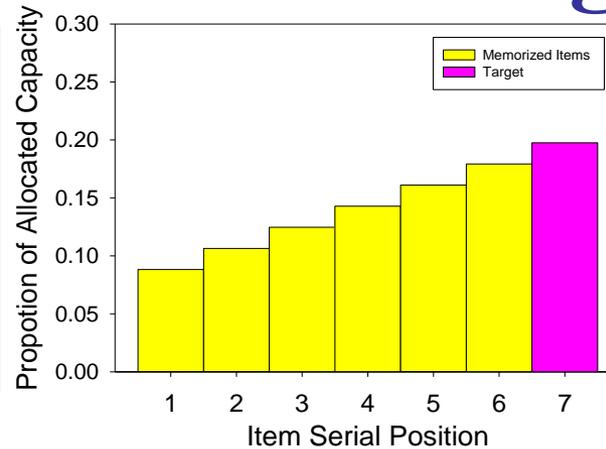
How are the capacity resources allocated?

Attentional gating function in STM

Equal



Ascending Descending



How are the capacity resources distributed?

The Half-Half Optimal Rule

- The optimal solution for allocation of a limited amount of resources: one Half of resources should be allocated to memorized items and another Half to a target.

$$\arg \max_{\text{Target}} \left[\sum_i^{N-1} \text{Target} \cdot \text{Item}_i \right]$$

$$\sum_i^{N-1} \text{Target} \cdot \text{Item}_i = \text{Target} \sum_i^{N-1} \text{Item}_i = \text{Target} (\text{TotalCapacity} - \text{Target}) =$$

$$\text{Target} \cdot \text{TotalCapacity} - \text{Target}^2$$

$$\frac{d}{d\text{Target}} [\text{Target} \cdot \text{TotalCapacity} - \text{Target}^2] = \text{TotalCapacity} - 2 \cdot \text{Target}$$

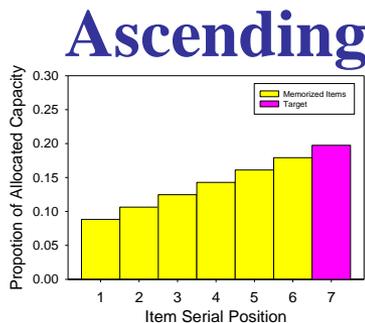
$$\text{TotalCapacity} - 2 \cdot \text{Target} = 0$$

$$\text{Target} = \frac{1}{2} \text{TotalCapacity}$$

The Target Locking Hypothesis

- Implication for non-optimal strategies, after the Half-Half rule →

Attentional gating should aim to allocate more capacity resources to the target than to memorized items.



The model

The Exemplar-Based STM Retrieval Model EBRW and the Item-Target Product Rule

**Capacity
Distributed via
Attentional Gating**

N = number of items stored in STM + Target

$$\text{Item Capacity}(\text{Target Capacity}) = f(N) = -\frac{2(\text{Intercept} \cdot N - \text{TotalCap})}{N(1+N)}$$

$$\text{Assuming limited capacity} = \int_N f(N, \text{Intercept}) = \text{TotalCap}$$

Distance

$$d_{ij} = \left[\sum_{k=1}^K w_k |x_{ik} - x_{jk}|^r \right]^{\frac{1}{r}}, \quad \text{EBRW}$$

d_{ij} = fixed value distance (free paramter)

$d_{ij} = 0$, on positive match

Activation*

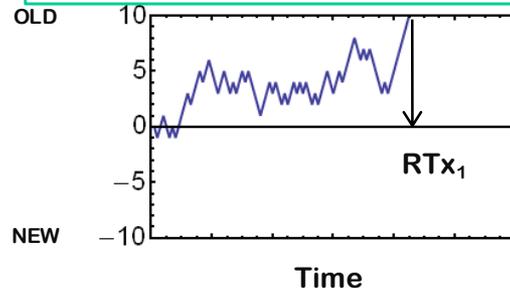
$$s_{ij} = \exp(-c \cdot d_{ij}) \cdot \text{Item Capacity}_i \times \text{Target Capacity}_j$$

Similarity Capacity via Attentional Gating

**Stepping
Probability**

$$p_i = \frac{\sum s_{i,old}}{\sum s_{i,old} + \beta}$$

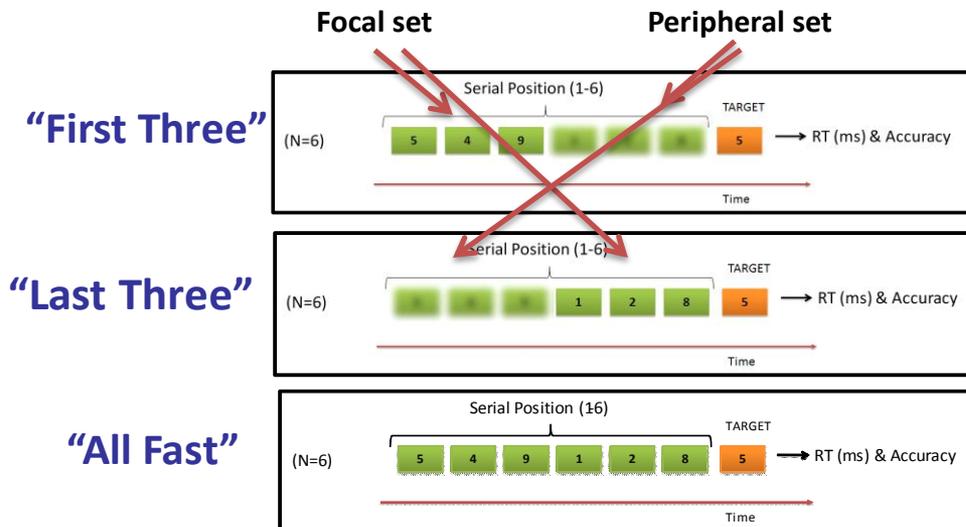
**Random
Walk**



New Method

The attention-to-position paradigm

- Rapid short-term memory paradigm
- **Focal set** : To pay special attention to certain item positions in the memorized list, called a “focal set”. This means that if a target item was a member of a focal set, a response decision had to be extremely fast, and accurate
- **Peripheral set**: The rest items not contained in a focal set.



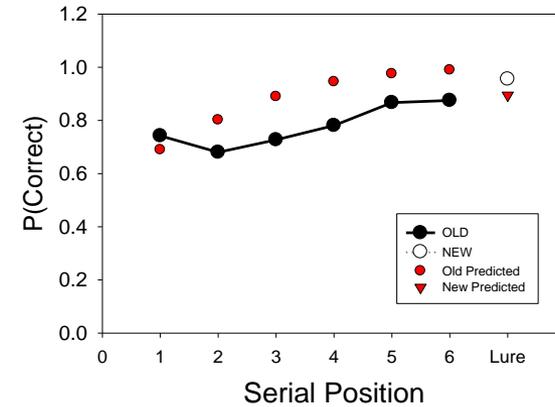
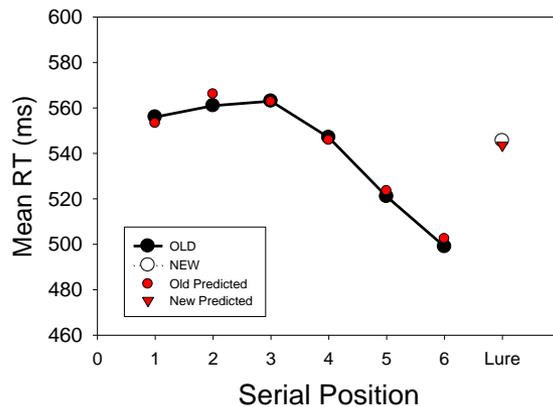
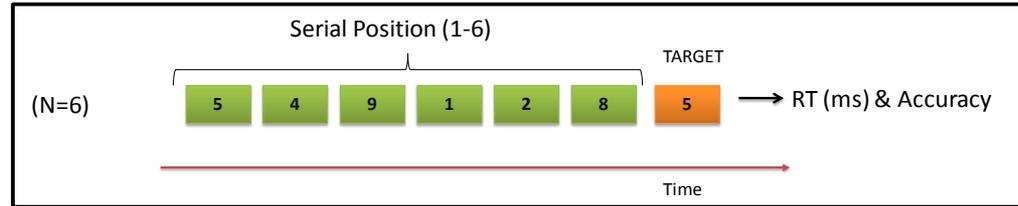
New Method

The attention-to-position paradigm

- To prevent interference of extraneous variables with the process of resource allocation the subjects were instructed to pronounce each item in a set, without accentuation, and with a monotonic prosody
- Two measures: mean response time (RT) and accuracy.

The data

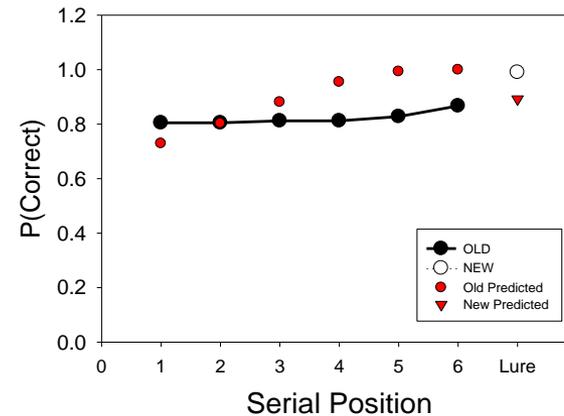
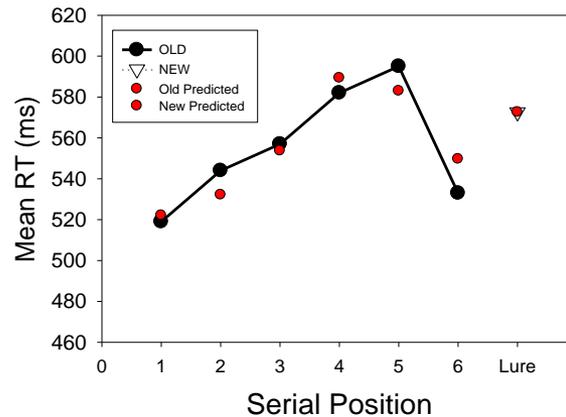
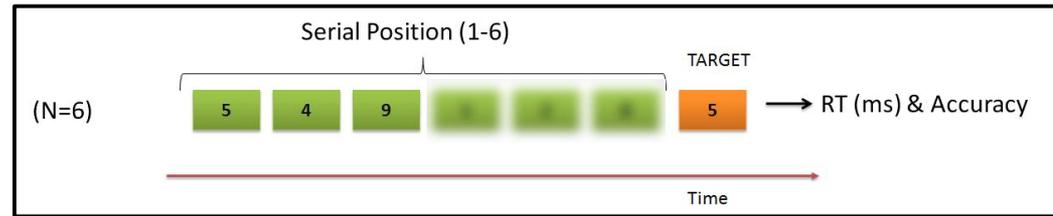
“All Fast”



- This is a typical RT pattern observed in the STM research, the primacy and recency
- ~~(1) Equal-precision~~
- ~~(2) ALL OR NONE~~
- (3) The decay-representation WM model
- (4) Fluid-resource model
- (5) Slots+averaging model

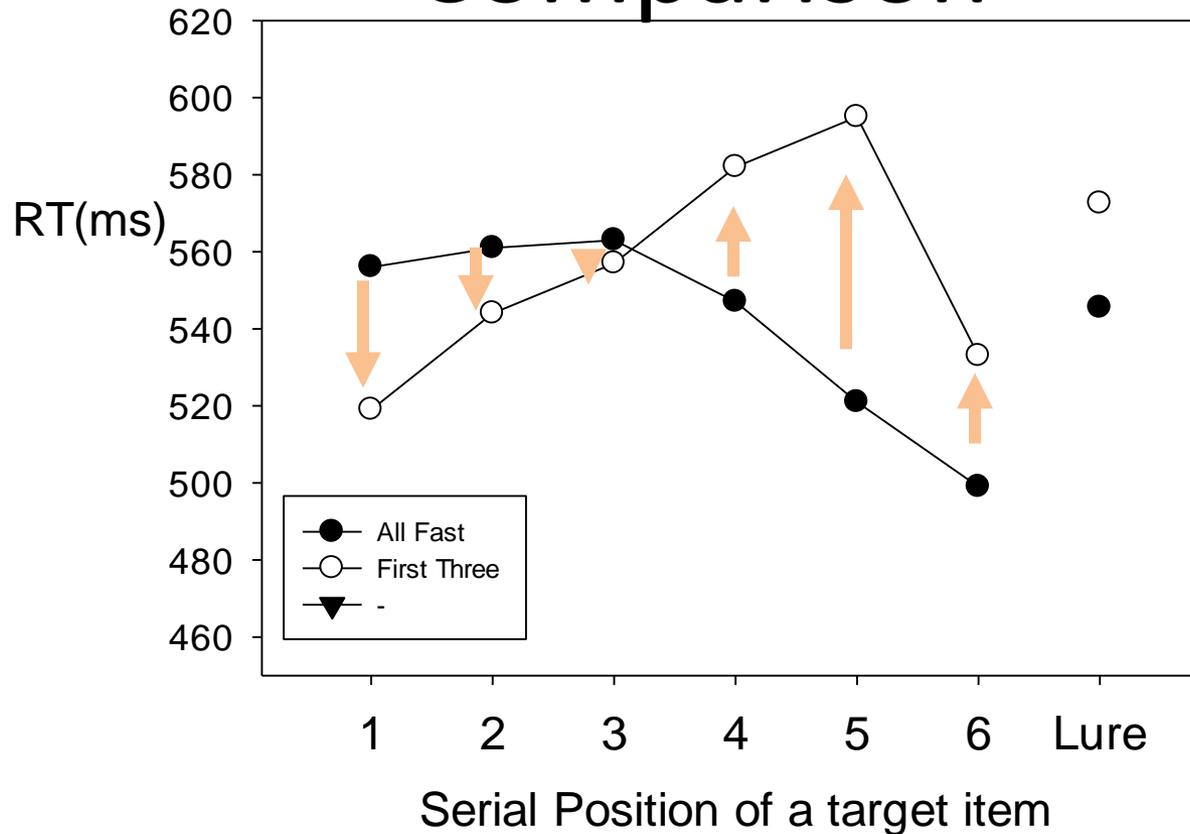
The data

“First Three”



- This is a typical pattern observed in the STM research, the primacy and recency
- ~~(1) Equal precision~~
 - ~~(2) ALL OR NONE~~
 - ~~(3) Decay representation WM model~~
 - (4) Fluid-resource model
 - (5) Slots+averaging model

Comparison

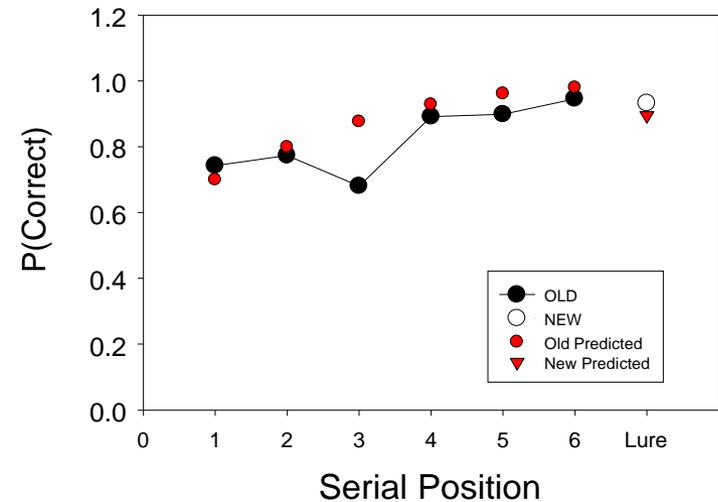
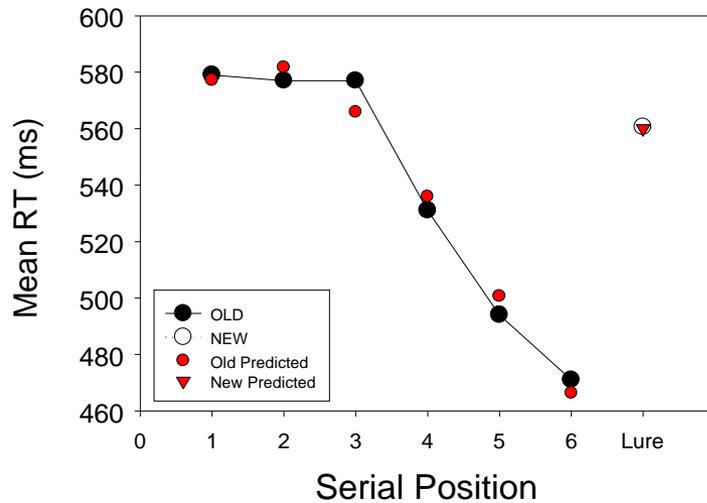
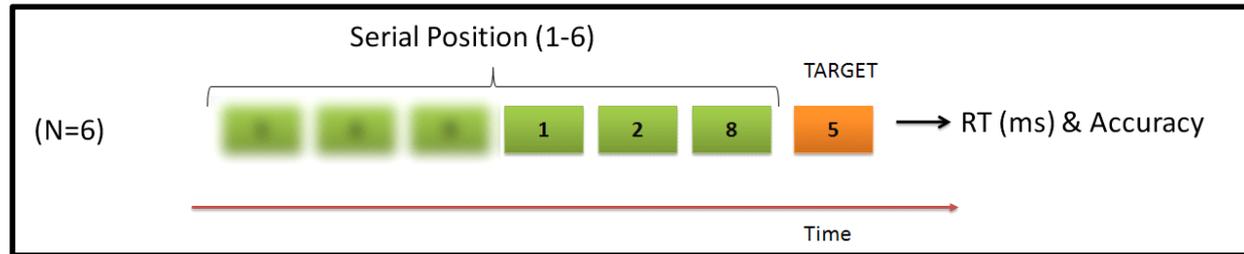


- Implications

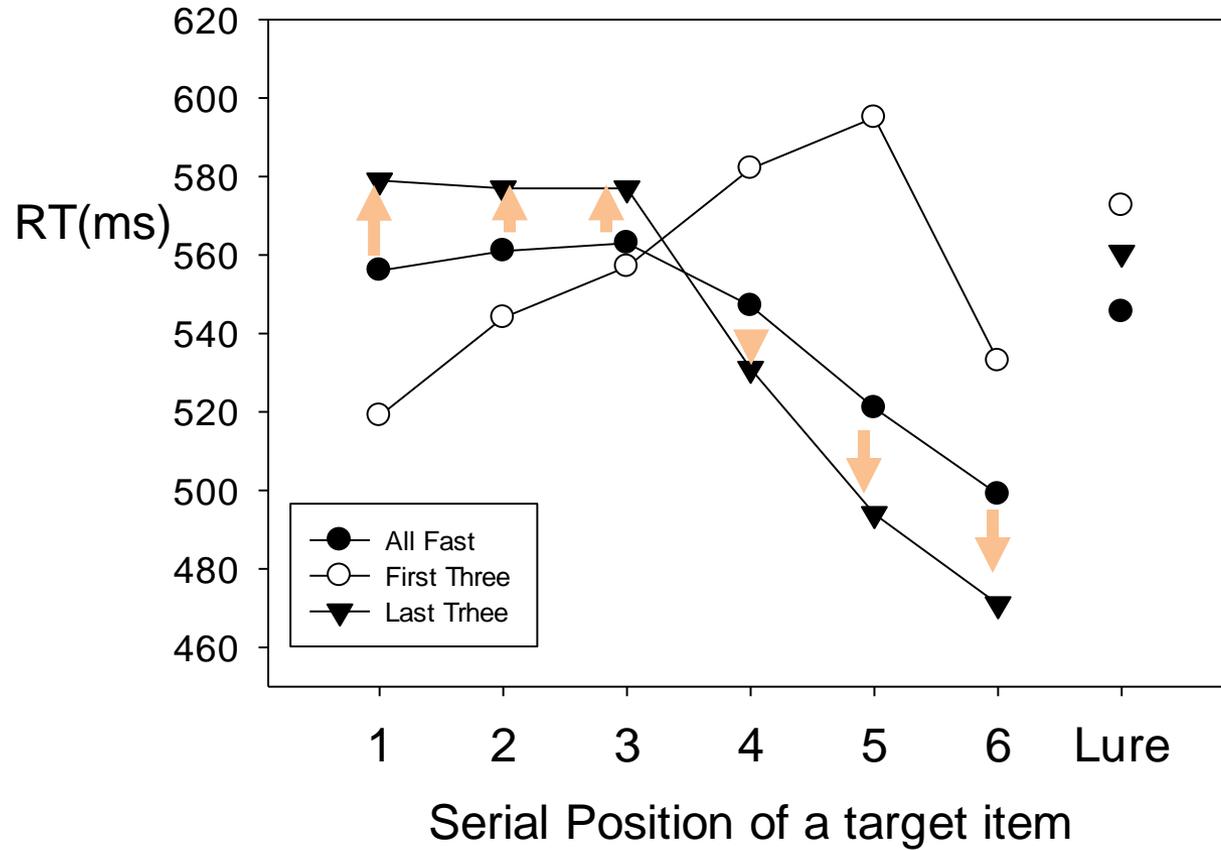
- A discontinuous serial position effect -> Dual WM systems
- The principle of resource conservation-> Strictly fixed capacity

The data – further validation of resource allocation

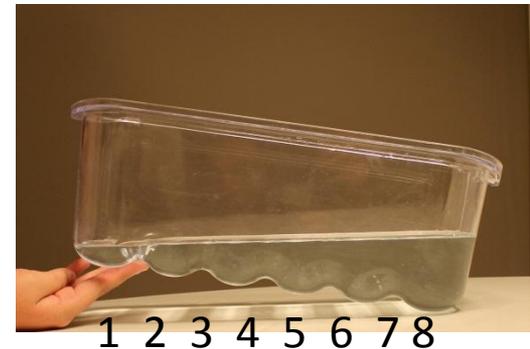
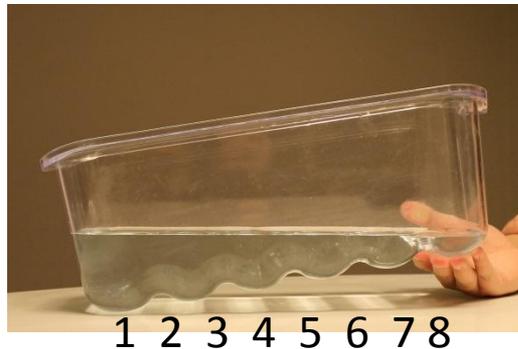
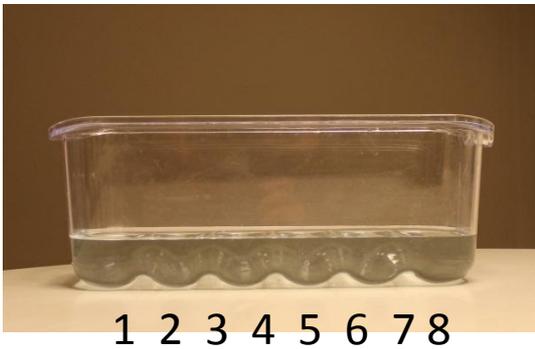
“Last Three”



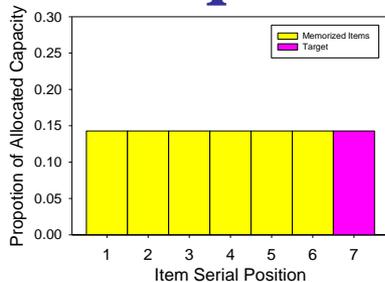
Comparison



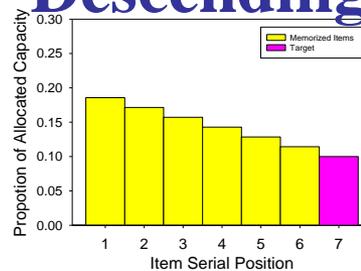
The proposed resource allocation model :The Tilted Water Tank



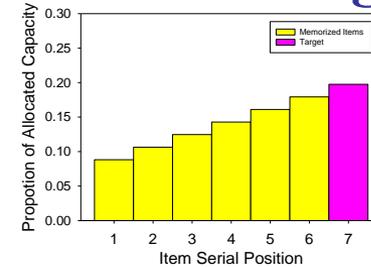
Equal



Descending



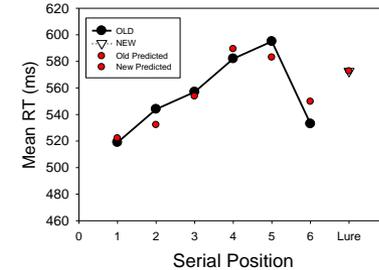
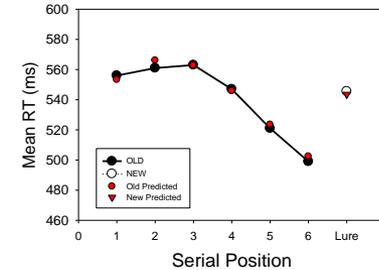
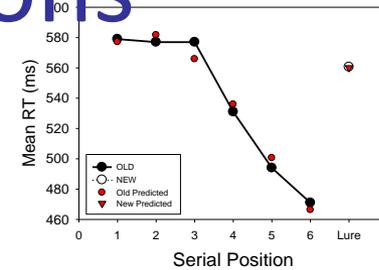
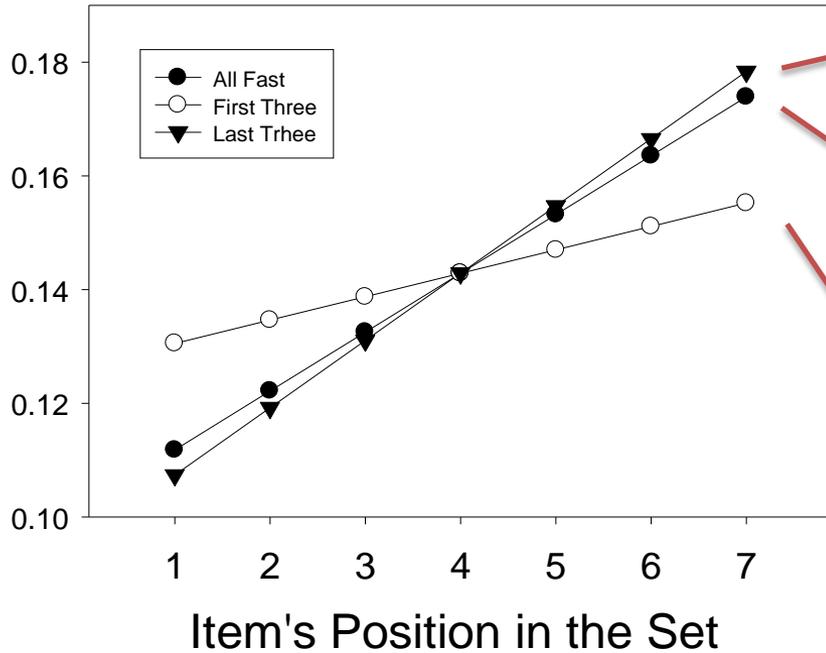
Ascending



Model fitting: the linear distribution function of resource allocation

Estimated Capacity Allocations

Capacity Proportion Allocated



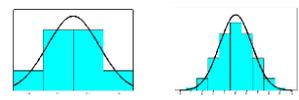
discrete-slot
model



slots+averaging
model



variable-resources
model



$\lim_{n \rightarrow \infty} f(x)$



How many boxes?

- Conduct data fitting of the EBRW model that can freely allocate fixed amount of resources across memorized items, including the parameter which defines a number of possible memory slots (boxes).
- In other words: find the number of possible resource allocation units (slots, boxes) that maximizes the goodness of fit of the model for resource allocation.

How many boxes?

	Free resource parameter-EBRW mode		
Params	All Fast	First Three	Last Three
c	0.959	2.383	1.6
acrit	2.52	3.556	11.378
bcrit	3.936	43.592	17.164
scale	44.706	4.576	1.901
mu	175.816	137.859	256.035
listbase	0.175	0.261	0.42
dscale	2.705	0.979	0.65
m1	0.145	0.161	0.128
m2	0.131	0.166	0.131
m3	0.132	0.167	0.128
m4	0.161	0.170	0.176
m5	0.201	0.172	0.208
m6	0.231	0.164	0.229
boxes	801	670	711

$\sum_{mi=1}^6$

$\sum_{mi=1}^6$

$\sum_{mi=1}^6$

Conclusions

- New method for testing WM, attention by instruction
- Support for the variable-resources model WM, all-get-some
- Falsification of all-or-none approaches, discrete representations
- We specified a likely mechanism of resource allocation (Target locking) and provided rationale
- The ghost is likely to reside in a tilted tank!

Further Implications:

- Linear distribution function of resources could serve as a proxy to the Attentional Gating mechanism.
- Falsification of Dual system WM view: the last item position advantage
- A joint fit of mean RT and choice probabilities.[EBRW]
- A STM capacity resources are strictly limited (the conservation of resources principle)

Free allocation of fixed capacity model

2D Graph 1

