Dynamic Associative Memory: Connecting Short-term and Long-term Memory

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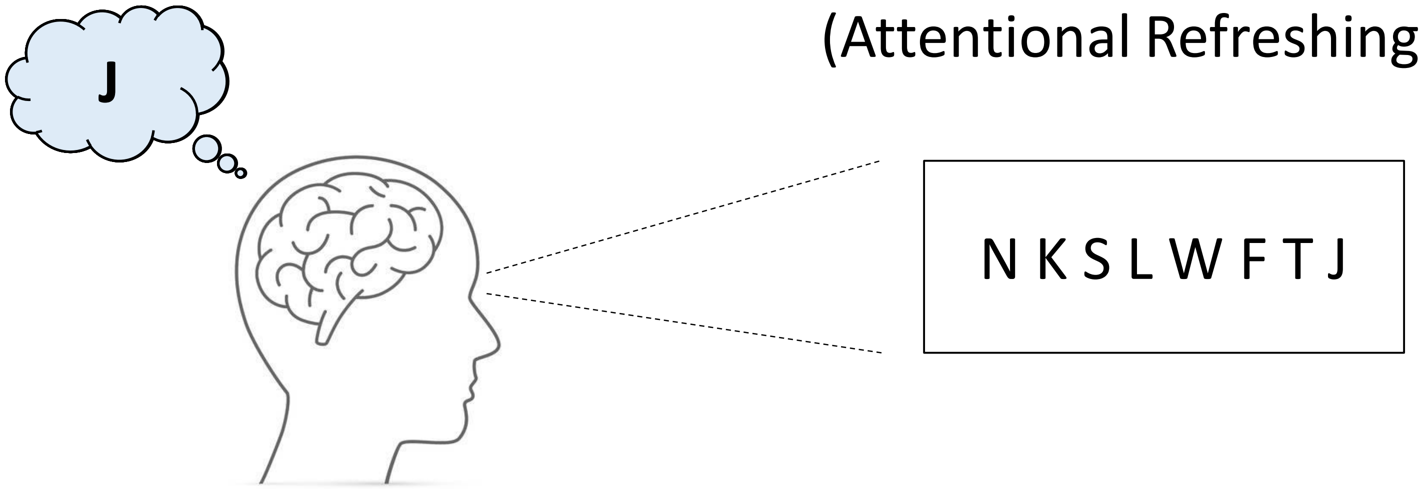
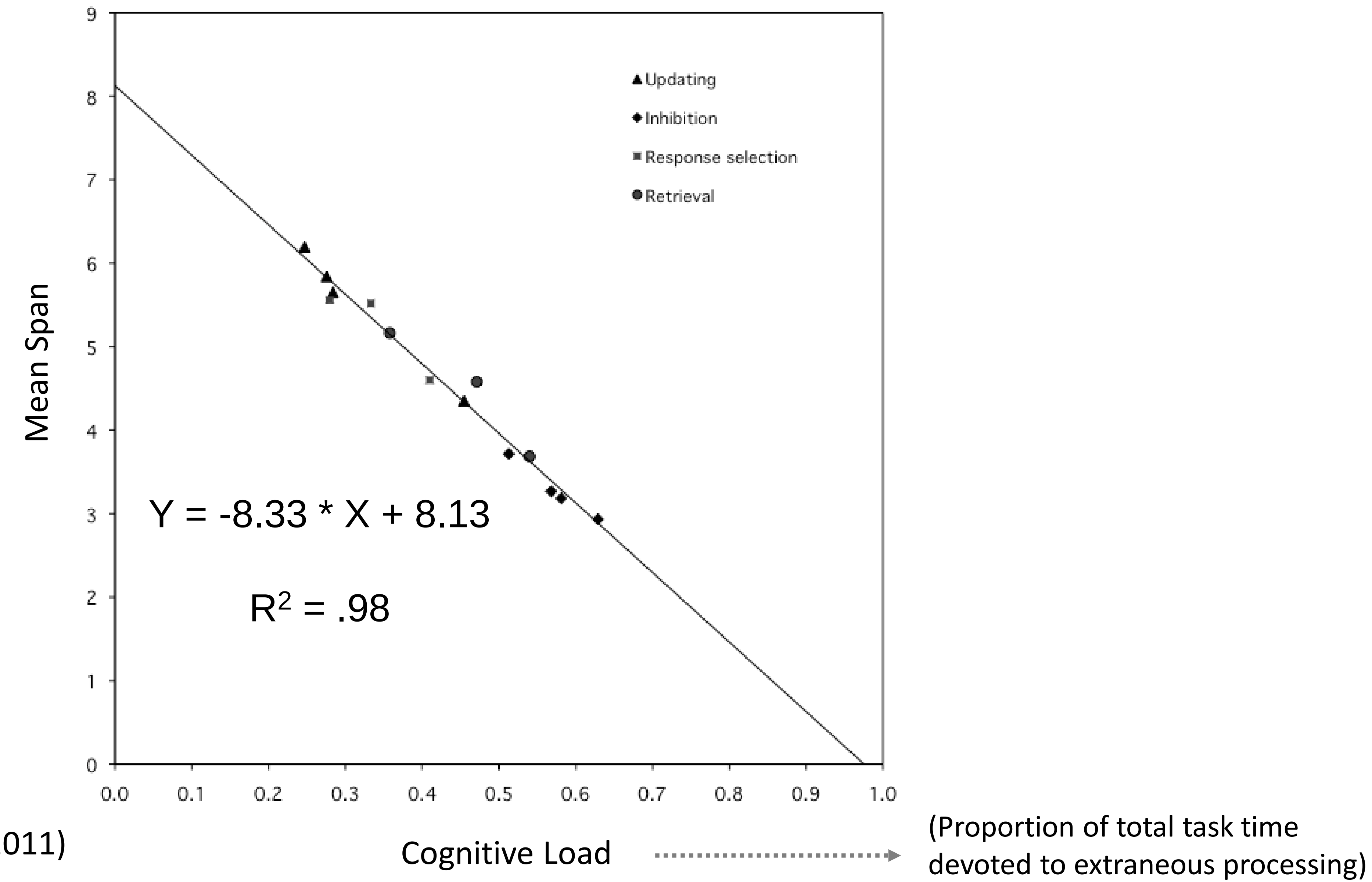
July 25, 2020

The Time-Based Resource-Sharing (TBRS) Model of Working Memory



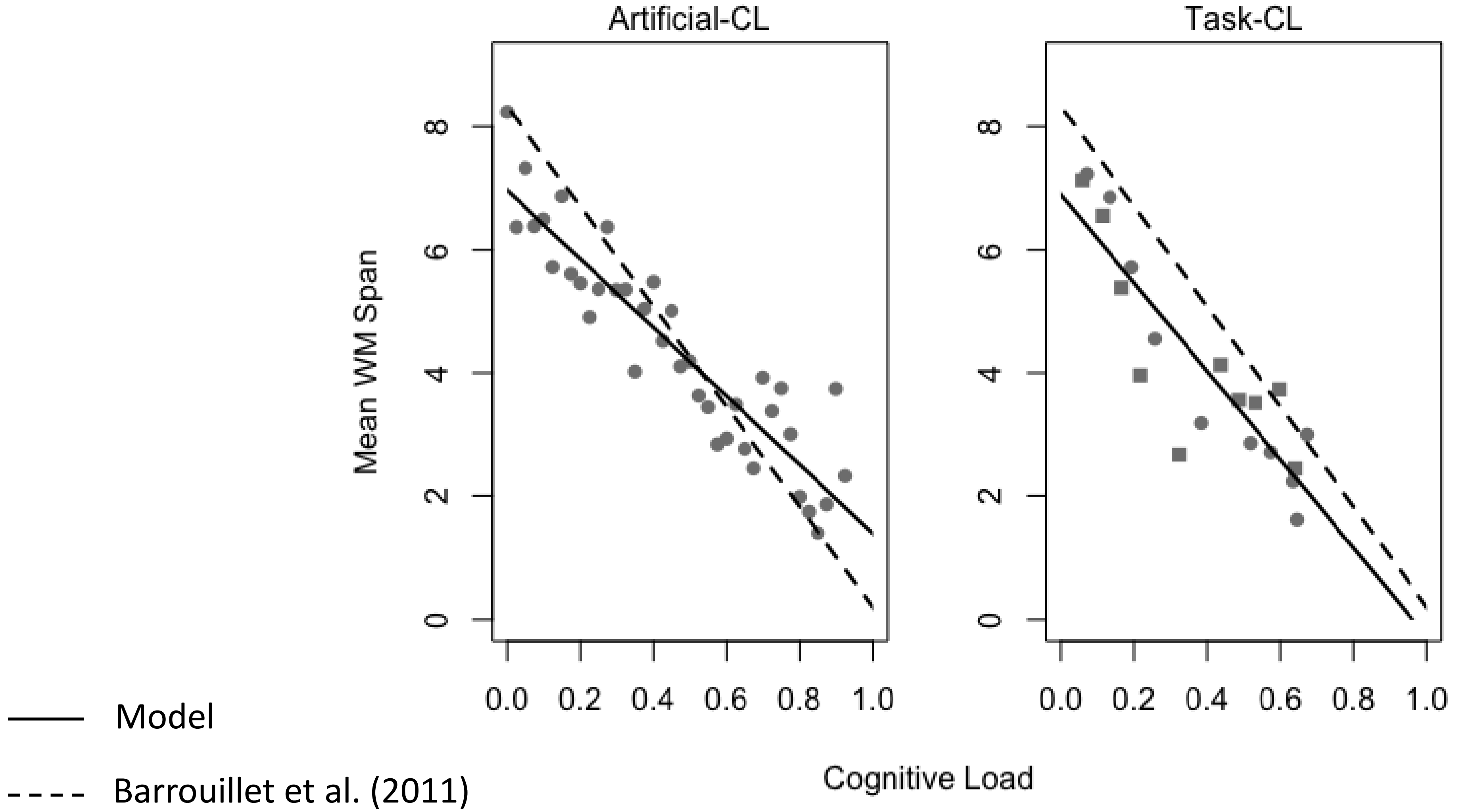
Working Memory Capacity is Constrained by Concurrent Processing



Barrouillet, Portrat & Camos (2011)

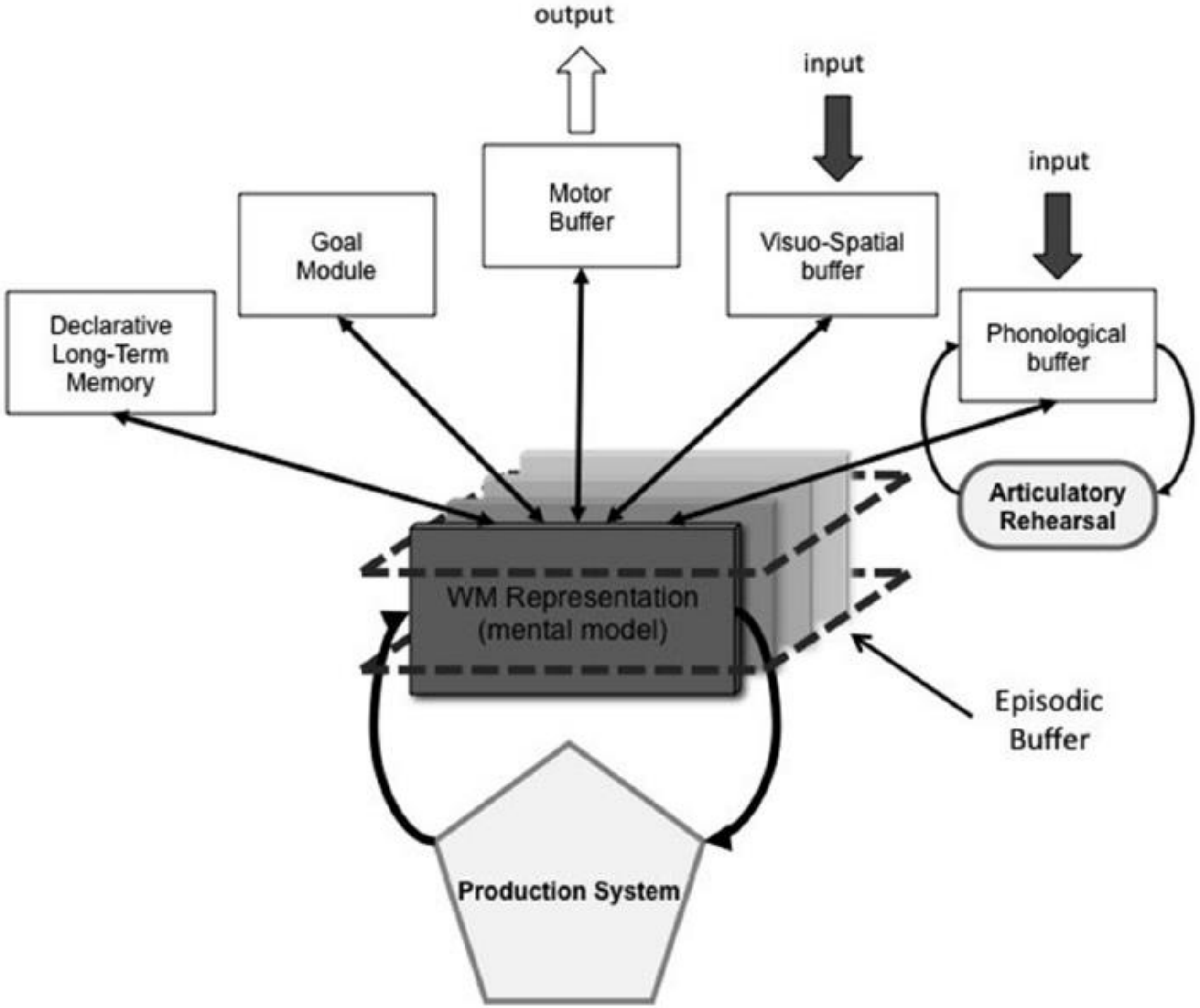
ICCM 2018

Glavan & Houpt (2018) An Integrated Working Memory Model for Time-Based Resource-Sharing



TBRS and ACT-R are Compatible

TBRS	ACT-R
Maintenance and processing require the same resource (attention)	Limited capacity buffers
Central bottleneck	Only one production may fire at a time
Attended items gain activation; all others undergo temporal decay	Power law learning and forgetting (base-level learning)
Rapid switching between maintenance and processing	Utility and production rule conditions to establish relative priority



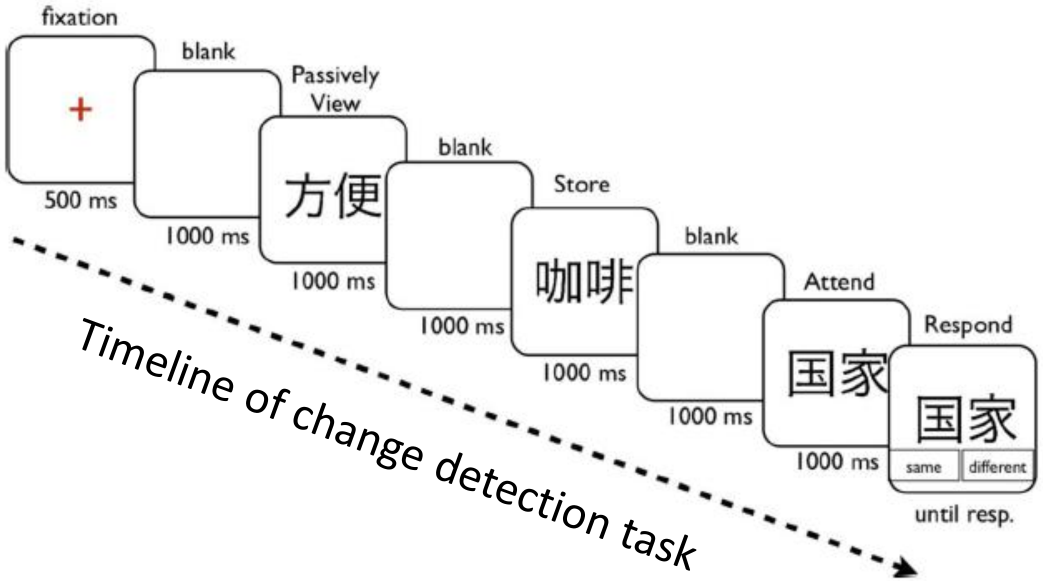
The Time-Based Resource-Sharing model architecture (Figure 6.1 in Barrouillet and Camos, 2015, p. 118).

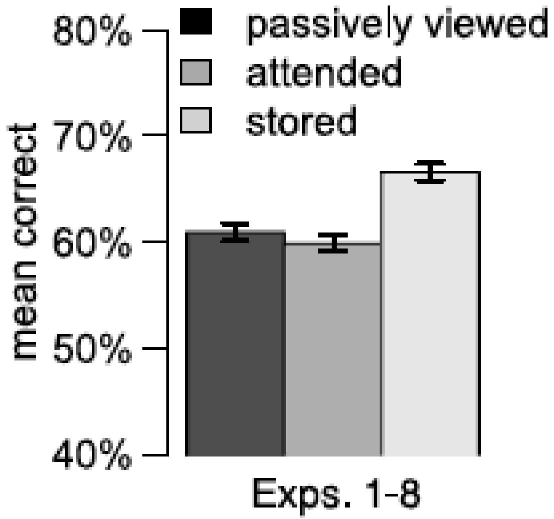
Why are some things quickly forgotten, and how do we retain other things seemingly indefinitely?

- Separate memory systems?
  - Working memory (WM) → shorter retention (seconds to minutes), under load
  - Short-term memory (STM) → shorter retention, generally without load
  - Long-term memory (LTM) → longer retentions (minutes to indefinitely)
- Studies traditionally focus on only one system (with exceptions)
  - Ignores the relevant factor of time
- Let's focus on the accessibility of knowledge as function of time and circumstance
  - What approaches have been taken to explain each system?
  - Which approaches can be integrated to improve our understanding of memory as a whole?

Evidence WM Maintenance Improves LTM

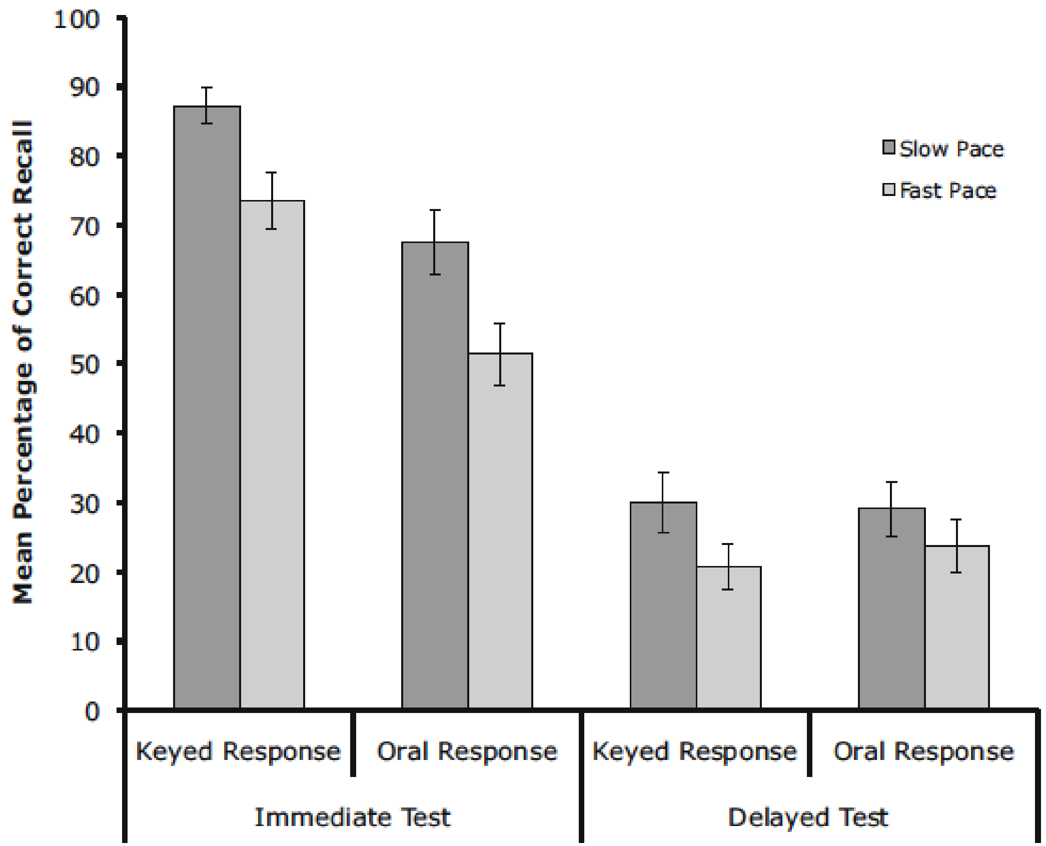
- Hartshorne and Makovski (2019) conducted a meta-analysis of 61 experiments in the literature
    - Increased time for maintenance improves accuracy in a subsequent LTM test
- Replicated this effect in 13 large-N studies of their own





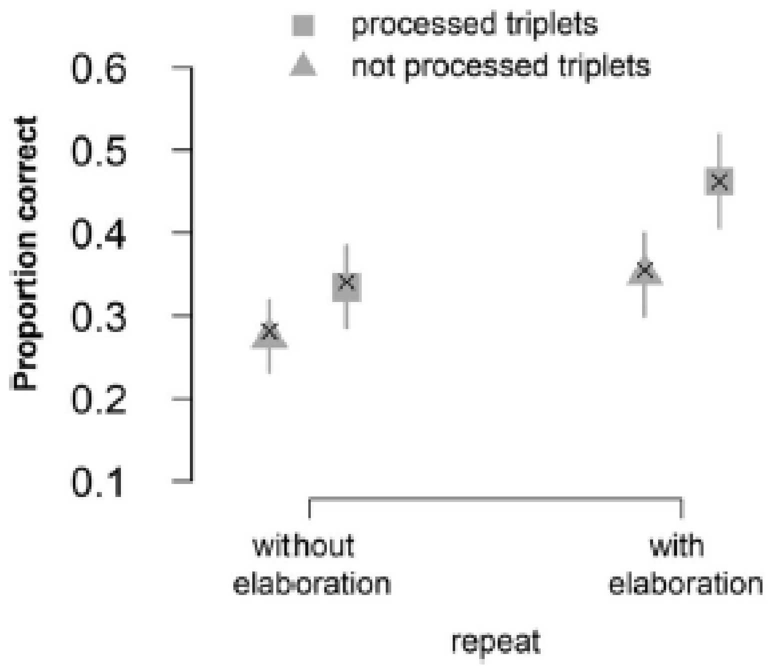
Mechanisms Implicated in WM/LTM

Attentional refreshing



(Camos & Portrat, 2015)

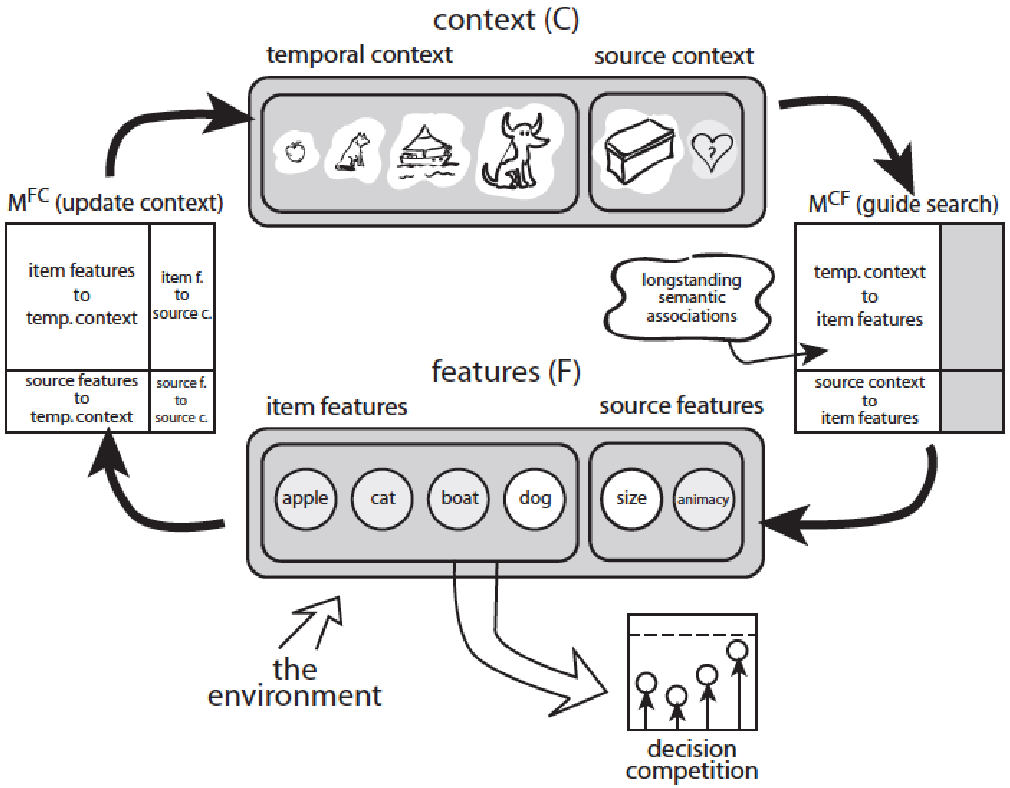
Elaboration



(Bartsch, Singmann & Oberauer, 2018)

Representations Implicated in STM/LTM

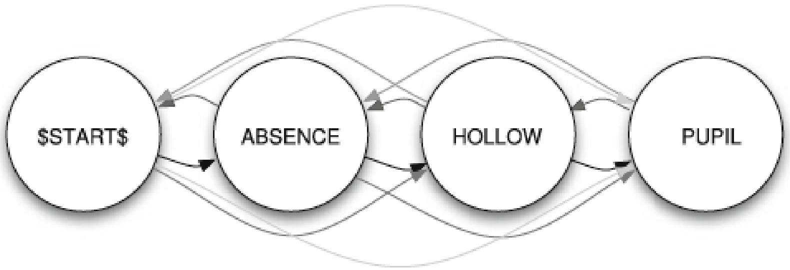
Item-to-Context Associations



(Polyn, Norman & Kahana, 2009)

Caplan (2015), Jonker & MacLeod (2017), Davachi and DuBrow (2015)

Item-to-Item Associations



(Solway, Murdock & Kahana, 2011)

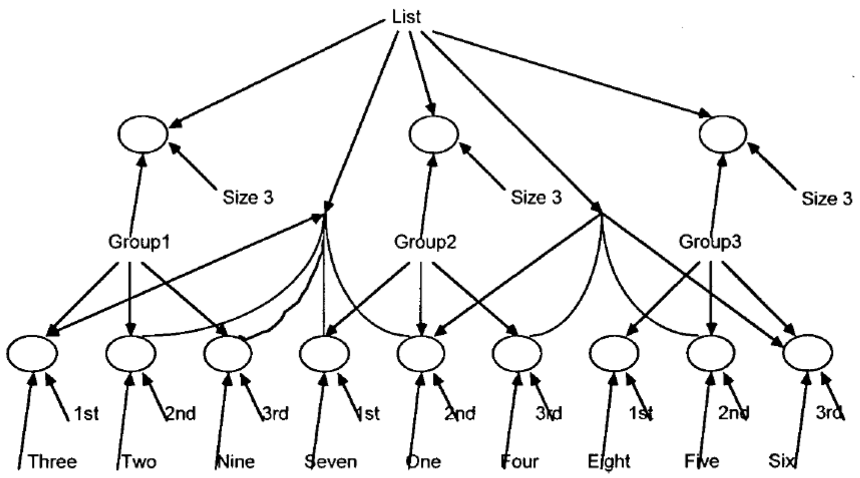


FIG. 2. A network representation of the chunk structure encoding the 9-element list "329 714 856".

(Anderson, Bothell, Lebiere & Matessa, 1998)

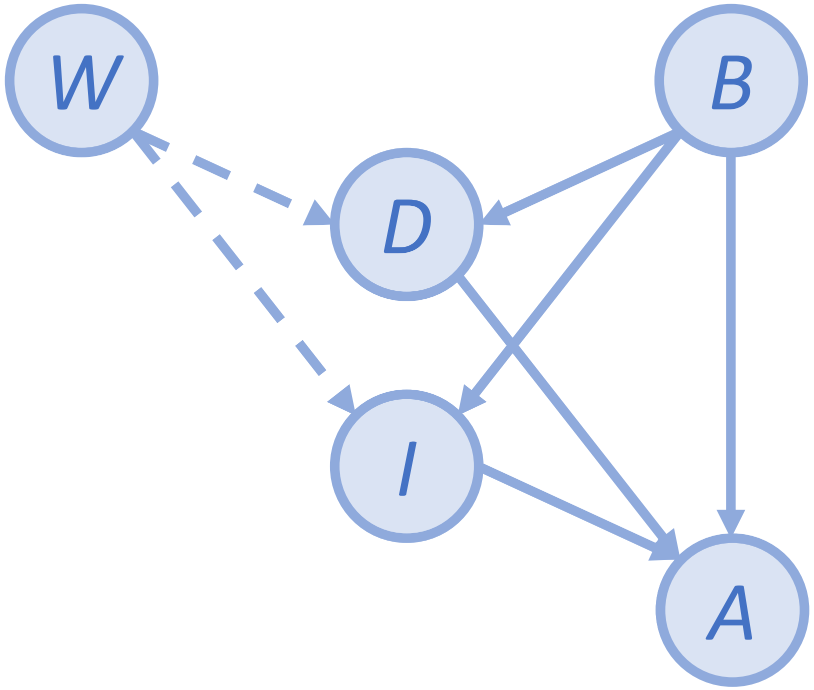
Proposed STM/LTM Transfer Theory

- Over the short-term, the strength of items' association with the current context temporarily elevates their accessibility. **Refreshing may keep the activation of these items above threshold** so long as attention can be devoted to them.
- With time, the shared temporal-context of the items becomes weaker, naturally reducing their accessibility. **The cognitive system must learn contextually-invariant associations between the items while they are still available in the short-term.**
- Items that have survived to long-term have superior connectivity in declarative memory, **allowing them to be cued/accessed more efficiently.**

Proposed Modifications to the Architecture

- Adopt attentional refreshing as standard
- Modify spreading activation and partial matching calculations
  - Direct Associations – symbolic, similar to the existing fan mechanism
  - Indirect Associations – subsymbolic, based on relative similarity

$$A_i = B_i + .5 \cdot I_i + .5 \cdot D_i\,) \cdot D_i$$



- Allow chunks in declarative memory to serve as sources of spreading activation in addition to buffers
  - Treat the retrieval request as spreading activation
- Associative learning process to create new *relation* chunks that link associates

The Dynamic Associative Memory Module

- Implements automatic attentional refreshing
- Overrides default activation calculations
  - For tractability, only new chunks created by the imaginal module get to participate in activation spreading
- Tracks association strengths and merges a new relation chunk when above threshold

```
821.053   PROCEDURAL        CONFLICT-RESOLUTION
821.053   DAM               start-attentional-refreshing
821.053   PROCEDURAL        CONFLICT-RESOLUTION
821.299   DAM               REFRESHED-CHUNK RELATION2211
821.299   PROCEDURAL        CONFLICT-RESOLUTION
821.299   DAM               start-attentional-refreshing
821.299   PROCEDURAL        CONFLICT-RESOLUTION
821.299   DAM               REFRESHED-CHUNK CHUNK26-0
821.299   PROCEDURAL        CONFLICT-RESOLUTION
821.299   DAM               start-attentional-refreshing
821.299   PROCEDURAL        CONFLICT-RESOLUTION
821.526   DAM               REFRESHED-CHUNK CHUNK32-0
821.526   PROCEDURAL        CONFLICT-RESOLUTION
821.526   DAM               start-attentional-refreshing
821.526   PROCEDURAL        CONFLICT-RESOLUTION
821.536   DAM               REFRESHED-CHUNK CHUNK20-0
821.536   PROCEDURAL        CONFLICT-RESOLUTION
821.536   DAM               start-attentional-refreshing
821.536   PROCEDURAL        CONFLICT-RESOLUTION
821.548   DAM               REFRESHED-CHUNK CHUNK14-0
821.548   PROCEDURAL        CONFLICT-RESOLUTION
821.548   DAM               start-attentional-refreshing
821.548   PROCEDURAL        CONFLICT-RESOLUTION
821.560   ------            Stopped because time limit reached
821.560   VISION            SET-BUFFER-CHUNK VISUAL-LOCATION VISUAL-LOCATION163 NIL
821.560   VISION            visicon-update
821.560   PROCEDURAL        CONFLICT-RESOLUTION
821.610   PROCEDURAL        PRODUCTION-FIRED ATTEND
821.610   PROCEDURAL        CLEAR-BUFFER VISUAL-LOCATION
821.610   PROCEDURAL        CLEAR-BUFFER VISUAL
821.610   PROCEDURAL        CONFLICT-RESOLUTION
821.610   PROCEDURAL        CONFLICT-RESOLUTION
821.626   DAM               REFRESHED-CHUNK CHUNK26-0
821.626   PROCEDURAL        CONFLICT-RESOLUTION
821.626   DAM               start-attentional-refreshing
821.626   PROCEDURAL        CONFLICT-RESOLUTION
821.668   VISION            Encoding-complete VISUAL-LOCATION163-0 NIL
821.668   VISION            SET-BUFFER-CHUNK VISUAL TEXT163
821.668   PROCEDURAL        CONFLICT-RESOLUTION
821.718   PROCEDURAL        PRODUCTION-FIRED ENCODE-CENTER
821.718   PROCEDURAL        CLEAR-BUFFER VISUAL
821.718   PROCEDURAL        CLEAR-BUFFER RETRIEVAL
821.718   DECLARATIVE       start-retrieval
821.718   PROCEDURAL        CONFLICT-RESOLUTION
821.718   PROCEDURAL        CONFLICT-RESOLUTION
821.795   DECLARATIVE       RETRIEVED-CHUNK RECALL
821.795   DECLARATIVE       SET-BUFFER-CHUNK RETRIEVAL RECALL
821.795   PROCEDURAL        CONFLICT-RESOLUTION
821.845   PROCEDURAL        PRODUCTION-FIRED BEGIN-RECALL
```

Base-level Activation

- Implements the refreshing and decay assumptions of TBRS
  - Produces recency and frequency effects
- Includes base-level (temporal) inhibition
  - Temporarily penalizes more recently retrieved items to avoid perseveration
- Free intercept parameter

$$B_i = \log\left(\sum_{j=1}^{n} t_{ij}^{-\delta}\right) - \log\left(1 + t_{in}^{-\gamma}\right) + \beta$$

Direct Associative Process (DAP)

- Based on symbolic, all-or-nothing relations
- Two chunks *i* and *j* are *directly associated* if and only if either *i* is in a slot of *j* or *j* is in a slot of *i*

$$\delta_{ji} = \begin{cases} 1 & \text{if } j \text{ and } i \text{ are directly related} \\ 0 & \text{otherwise} \end{cases}$$

$$D_i = \underbrace{W_R \cdot \sum_{j \epsilon R} \frac{\delta_{ji}}{\sum_{l \epsilon \mathcal{M}} \delta_{jl}}}_{\text{Retrieval Request}} + \underbrace{\sum_{b \epsilon B} \left(W_b \cdot \sum_{j \epsilon b} \frac{\delta_{ji}}{\sum_{l \epsilon \mathcal{M}} \delta_{jl}} \right)}_{\text{Buffer Spreading}} + \underbrace{\sum_{m \epsilon \{\mathcal{M} \setminus i\}} \left(B_m \cdot \sum_{j \epsilon m} \frac{\delta_{ji}}{\sum_{l \epsilon \{\mathcal{M} \setminus i\}} \delta_{jl}} \right)}_{\text{Declarative Spreading}}$$

Indirect Associative Process (IAP)

- Based on continuous similarity relations
  - Regularized gamma function is a reasonable candidate
- Here, *k* is a slot-type common to chunks *i* and *j*
  - *E.g., temporal-context*

$$\Psi_k(k_i, k_j; s_k, r_k) = \frac{\Gamma(s_k, r_k|k_i - k_j|)}{\Gamma(s_k)}$$

Indirect Associative Process (cont.)

- Activation from retrieval request spreads by normalized geometric mean of its similarity to each item in memory
  - Represents the specificity of the request
- Buffers spread their source-activation (*W*)
- Items in memory spread their base-level activation (*B*)

$$I_i = W_R \cdot \frac{\left[\prod_{k_{Ri}} \zeta_k \cdot \Psi_k(k_R, k_i)\right]^{\frac{1}{K_{Ri}}}}{\sum_{l \epsilon \mathcal{M}} \left[\prod_{k_{Rl}} \zeta_k \cdot \Psi_k(k_R, k_l)\right]^{\frac{1}{K_{Rl}}}}$$

$$+ \sum_{j \,\epsilon\, \mathcal{B}} \left(W_j \cdot \frac{\sum_{k_{ji}} \Psi_k(k_j, k_i)}{\sum_{l \epsilon \mathcal{M}} \sum_{k_{jl}} \Psi_k(k_j, k_l)} \right)$$

$$+ \sum_{j \epsilon \{\mathcal{M} \setminus i\}} \left(B_j \cdot \frac{\sum_{k_{ji}} \Psi_k(k_j, k_i)}{\sum_{l \epsilon \{\mathcal{M} \setminus i\}} \sum_{k_{jl}} \Psi_k(k_j, k_l)} \right)$$

Associative Learning Process (ALP)

- When an item is retrieved, the model updates its estimates of the *causal power* of other items to have caused that retrieval
  - The causal power of x on y is the probability x causes y when x is present
- Once a power estimate exceeds some threshold, a new item representing the direct association between the two items is created
- The new relation chunk may now participate in refreshing and spreading activation processes

Associative Learning (cont.)

- Power PC theory of causal induction (Cheng, 1997)

$$\rho_{xy} = \frac{P(y|x) - P(y|\neg x) - \rho_{ay}[P(a|x) - P(a|\neg x)]}{1 - \rho_{ay} \cdot P(a|x)}$$

- If all candidate causes can be assumed to occur independently

$$\rho_{xy} = \frac{P(y|x) - P(y|\neg x)}{1 - P(y|\neg x)}$$

Associative Learning (cont.)

When chunk *y* is retrieved, update the following arrays:

$$P_t(y|x) = \alpha \cdot \mathcal{L}_y(t) + (1-\alpha) \cdot P_{t-1}(y|x)$$

for any chunk x currently in the causal set, and

$$P_t(y|\neg x) = \alpha \cdot \mathcal{L}_y(t) + (1-\alpha) \cdot P_{t-1}(y|\neg x)$$

for any chunk x not currently in the causal set, where

$$\mathcal{L}_y(t) = \left[1 + \exp\left(-\frac{A_y(t) - \tau}{s_\varepsilon}\right)\right]^{-1}$$

Associative Learning (cont.)

- Update the following to learn strength of associations

$$S_{xy}(t) = \alpha \cdot \rho_{xy}(t) + (1 - \alpha) \cdot S_{xy}(t - 1)$$

- When S_{xy} is computed to be above some threshold (free parameter), create a new chunk representing the association between x and y

Hypotheses and Predictions

- Model should predict
  - Cognitive load effect
  - Semantic and temporal clustering
    - Greater for delayed than immediate recall
    - Greater with repetition
  - Elaboration instructions give associative learning a “head start”
  - Primacy within-list, primacy and greater recency between-lists
- New module allows to adjudicate some debates in the literature
  - Fixed or variable attentional refreshing rate?
  - Is attentional refreshing covert?
    - Should it be subjected to a retrieval threshold?

Discussion

- Dynamic Associative Memory theory
  - A process-level, computational account of
    - how memories are formed and maintained in the short-term
    - how memories reinforced to remain accessible in the long-term
  - Unites pre-existing theories of WM, STM, LTM, learning, and reasoning
- Work in progress (thanks COVID-19!)
  - Module/model fully coded, in testing
  - Simulation study on deck, human study planned
- “A good model is useful.”
  - These amendments are computationally costly.
  - We probably don’t want to enable them for every model.
  - Current ACT-R may be at a more useful level of abstraction for some tasks.

Thank you!

- All feedback is appreciated
- Happy to answer any questions