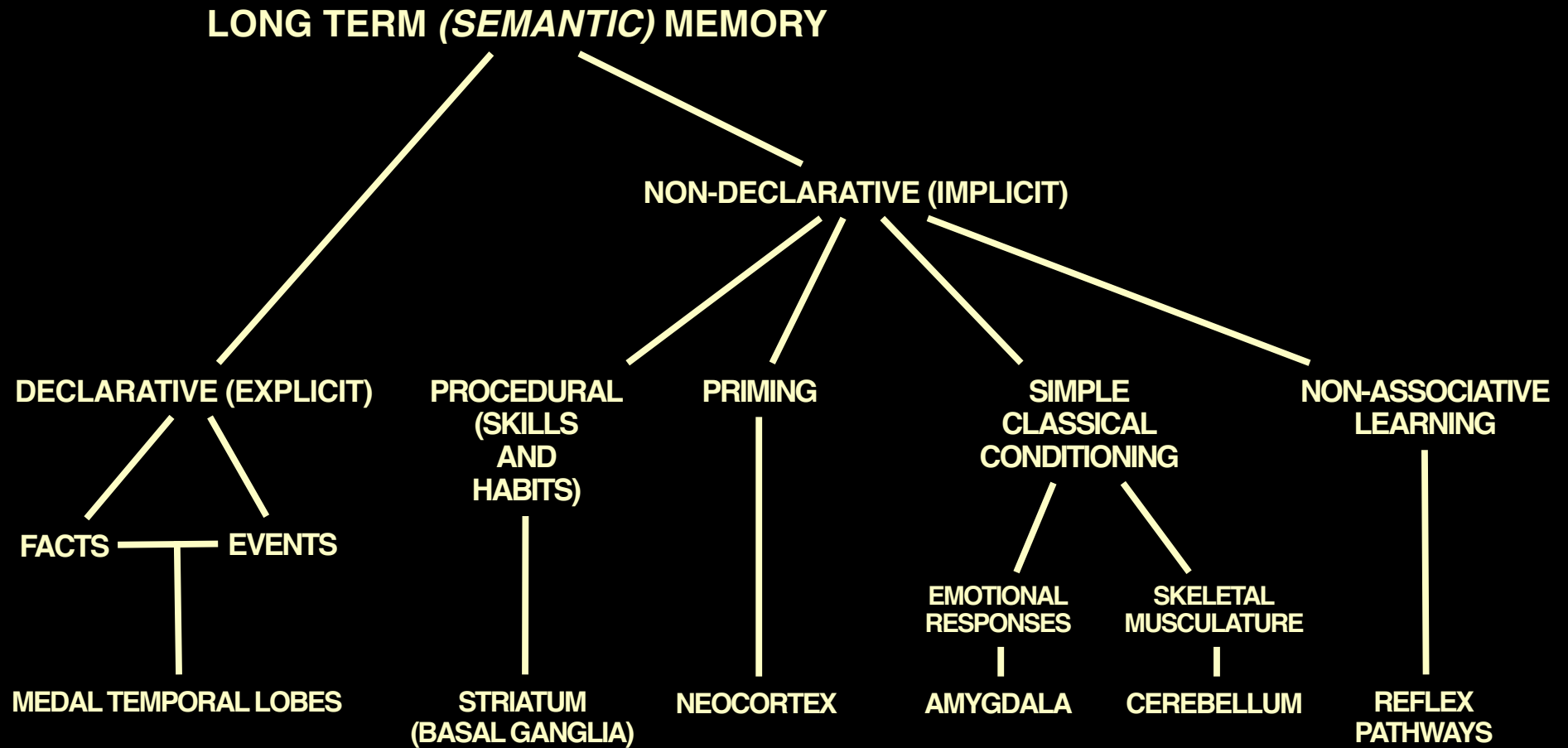


**Episodic Memory
and the
Complementary Learning Systems (CLS)
Hypothesis**

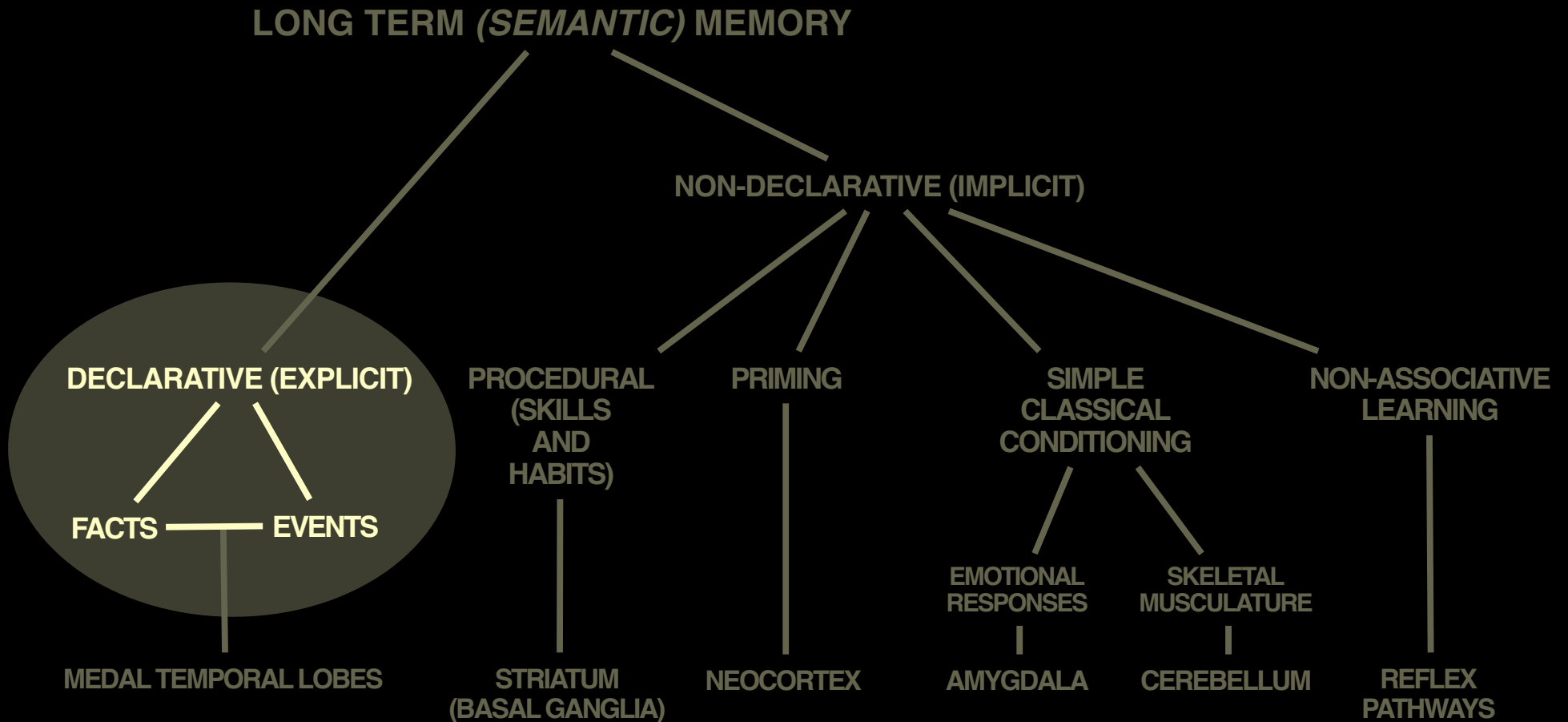
Classic Taxonomy

Squire & Zola-Morgan (1988)



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Memory

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- **Memory = any persistent effect of experience**
(not just memorization of facts, events, names, etc.)
 - ***State-based* memory** (active maint., “short term” memory)
- vs.
- ***Weight-based* memory** (long-term memory):
 - **associative learning:**
gradual, integrative cortical learning, and priming effects

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- but what about one-shot learning / rapid memorization?

there's a fundamental problem...

Paired Associates (AB-AC) Learning

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- **AB-AC paired-associates learning paradigm:**

Paired Associates (AB-AC) Learning

– first learn set of paired associates (AB):

(AB)

window-reason

bicycle-garbage

Paired Associates (AB-AC) Learning

– then learn new associate for 1st member of each old pair (AC)...

(AC)

window-telephone

bicycle-desk

Paired Associates (AB-AC) Learning

– then test on both sets of associations:

(A)
window-
bicycle-

Paired Associates (AB-AC) Learning

– then test on both sets of associations:

(A)	(B)
<i>window-</i>	<u>?</u>
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Paired Associates (AB-AC) Learning

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(A)	(B)
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Paired Associates (AB-AC) Learning

– then test on both sets of associations:

(A)
window-
bicycle-

(C)
?
?

Paired Associates (AB-AC) Learning

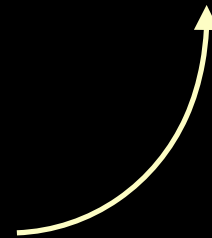
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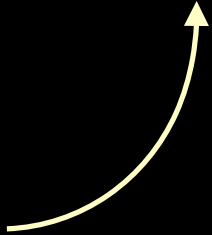
(C)
telephone
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Paired Associates (AB-AC) Learning

- **Human performance:**
 - “retroactive” interference:
get *some* loss of memory for AB association

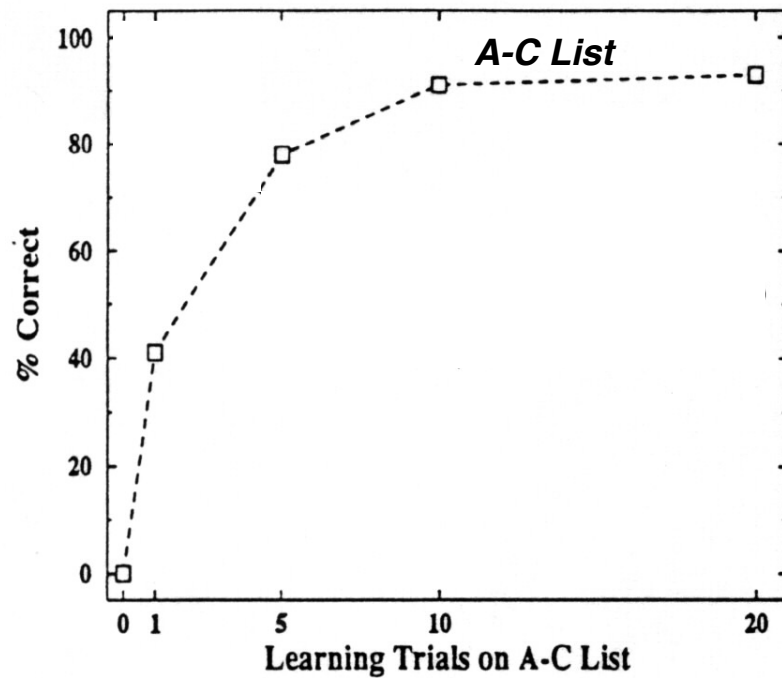


Paired Associates (AB-AC) Learning

- **Human performance:**
 - “retroactive” interference:
get *some* loss of memory for AB association
 - however, loss is modest and gradual (“graceful” degradation)...
- 

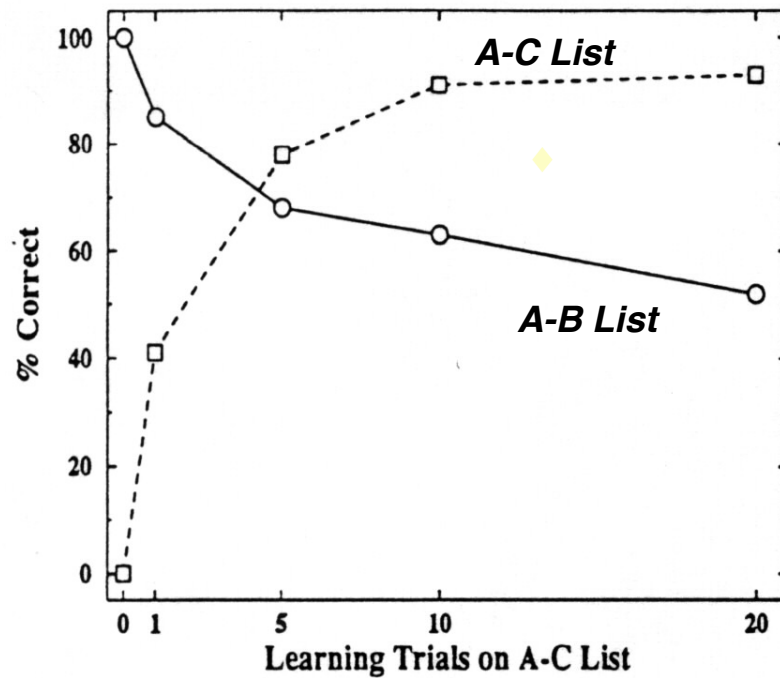
Paired Associates (AB-AC) Learning

a) AB-AC List Learning in Humans



Paired Associates (AB-AC) Learning

a) AB-AC List Learning in Humans



Model of AB-AC List Learning

McCloskey & NJ Cohen (1989)

- **Simple pattern associator**

- **input:**

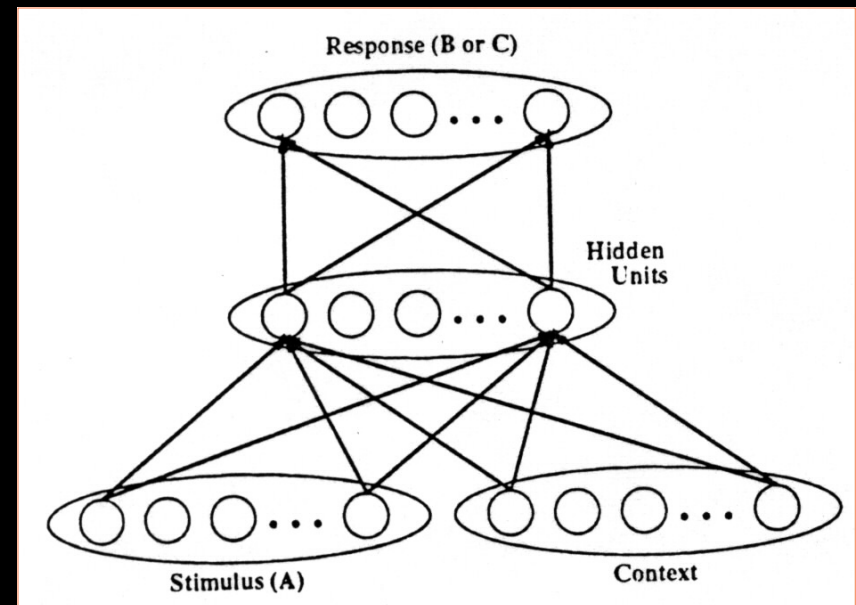
- “A” stimuli
 - Context units (list label)

- **output:**

- “B” or “C” associate
(depending upon context)

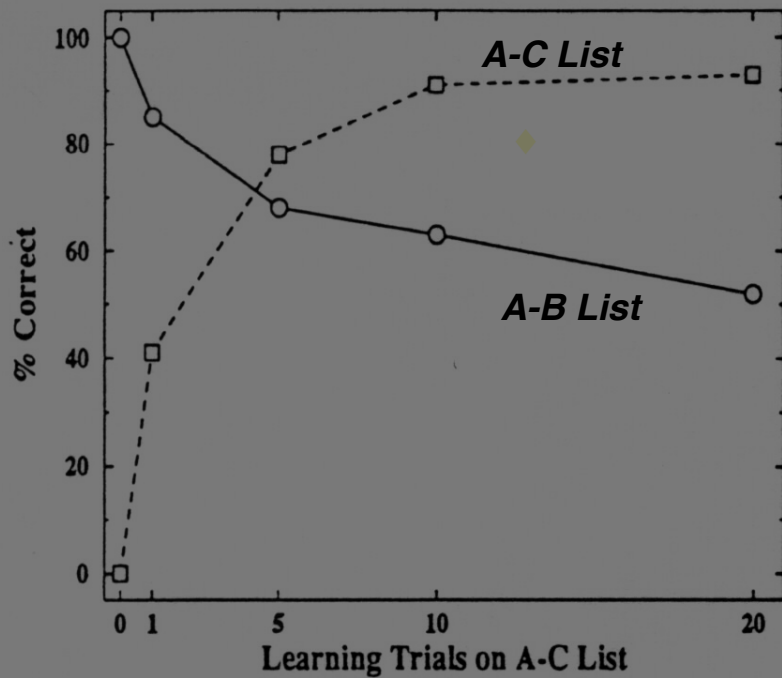
- **trained with backprop**

- **Model finding...**

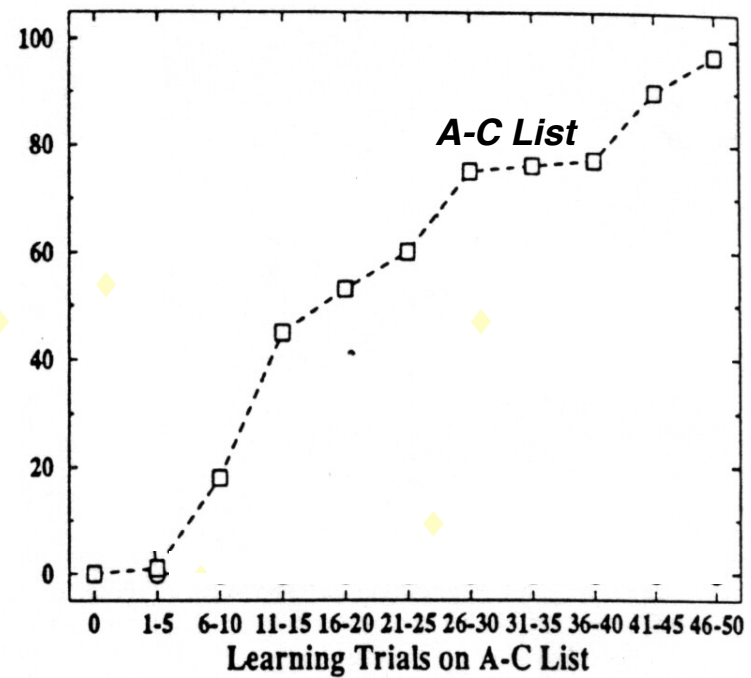


Model of AB-AC List Learning

a) AB-AC List Learning in Humans

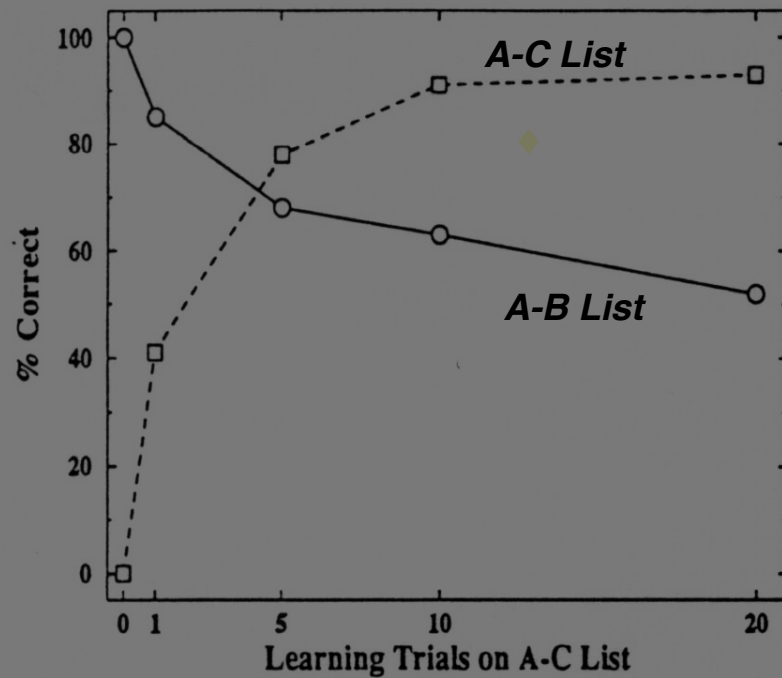


b) AB-AC List Learning in Model

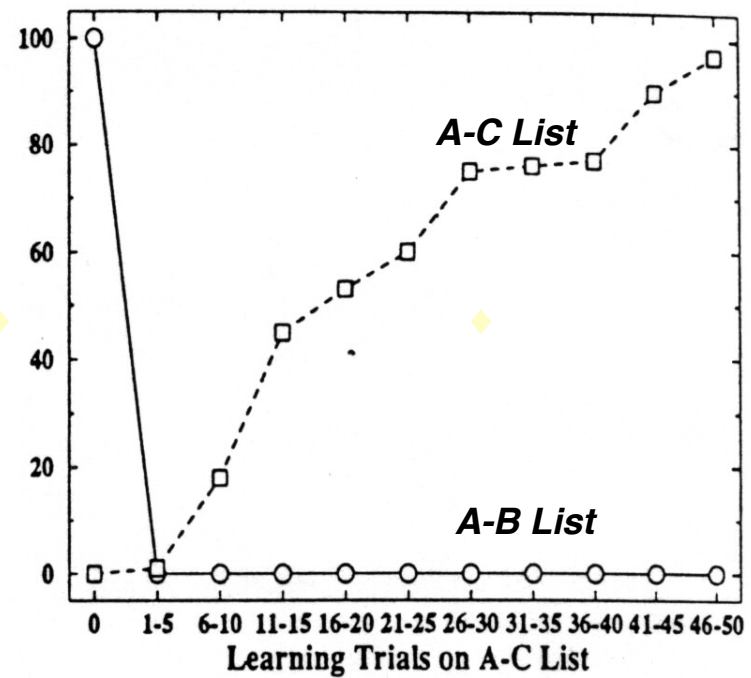


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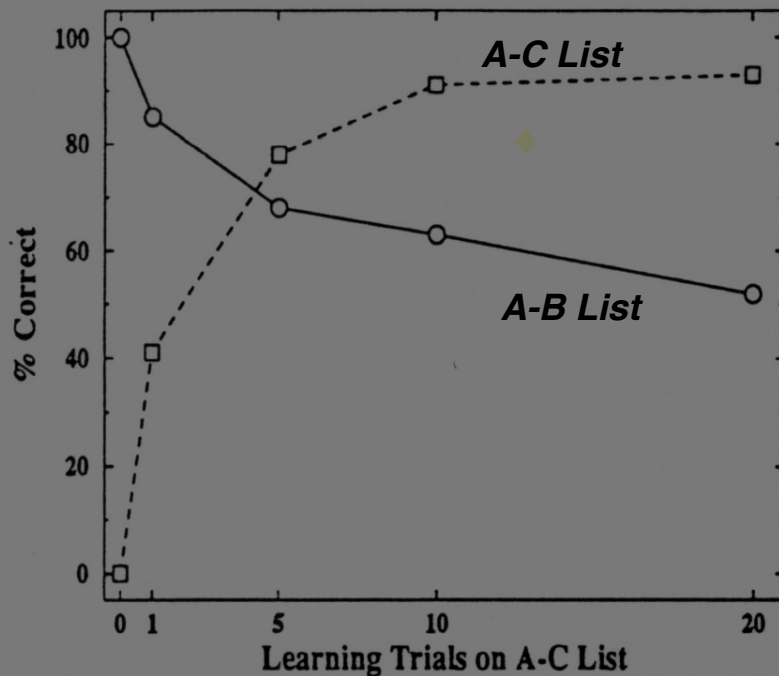
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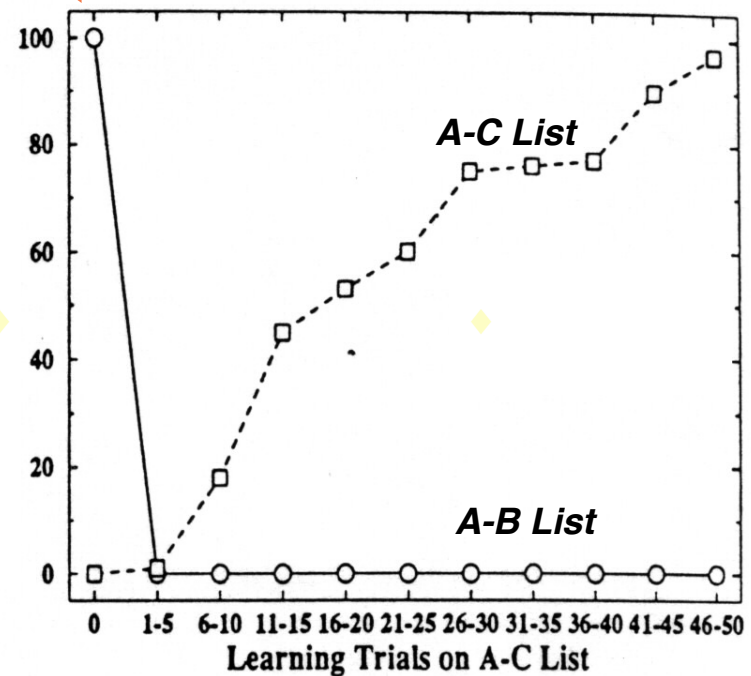
Model of AB-AC List Learning

- Learned first set of paired associates (AB) without any trouble

a) AB-AC List Learning in Humans



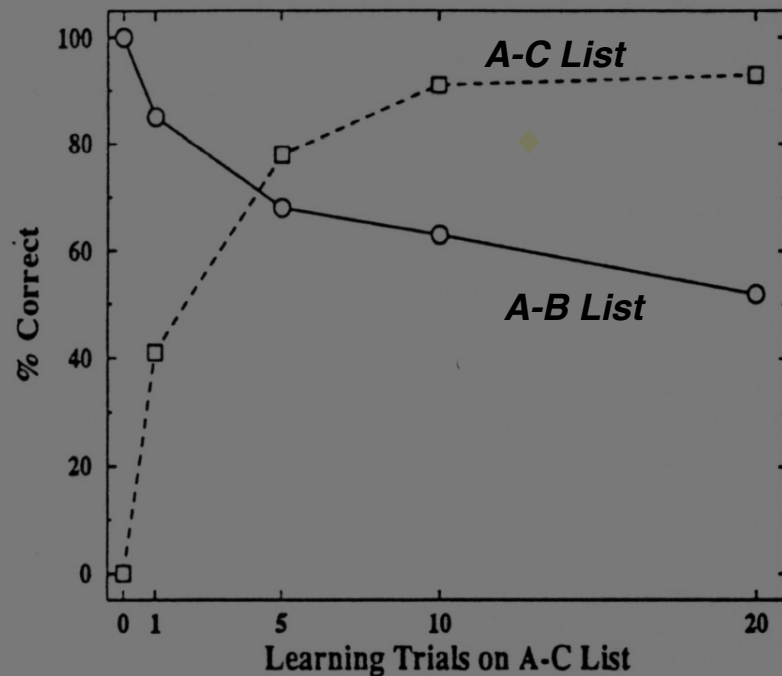
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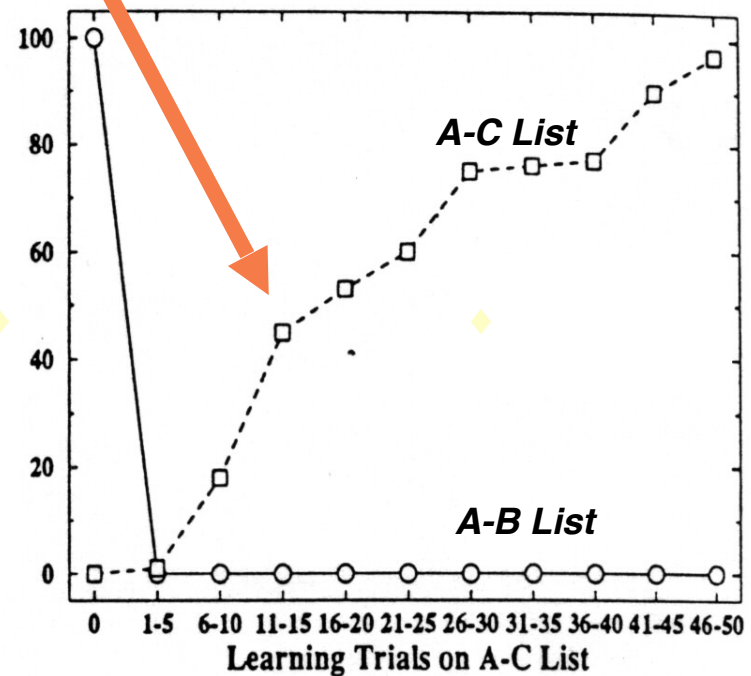
Model of AB-AC List Learning

- Took a bit longer to learn the second set (AC), but do could so pretty well; but...

a) AB-AC List Learning in Humans



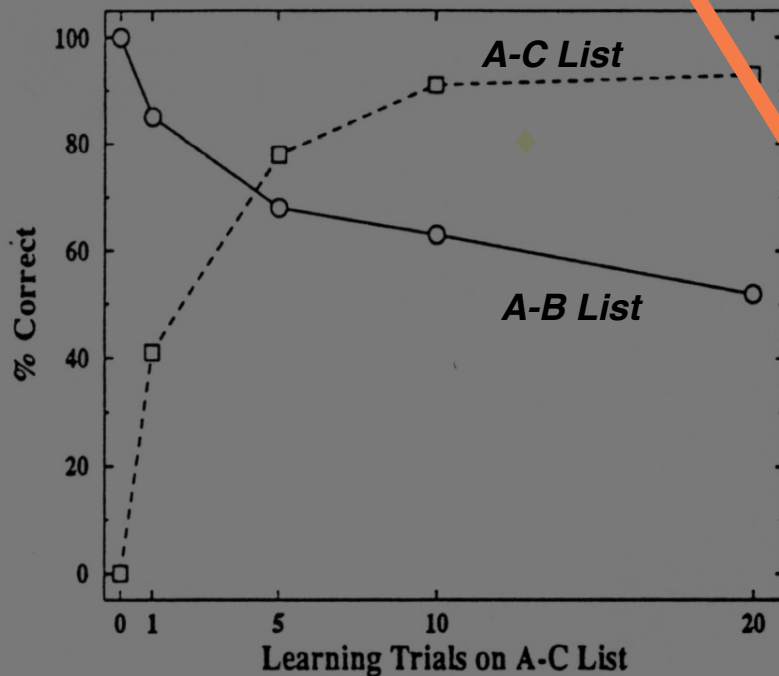
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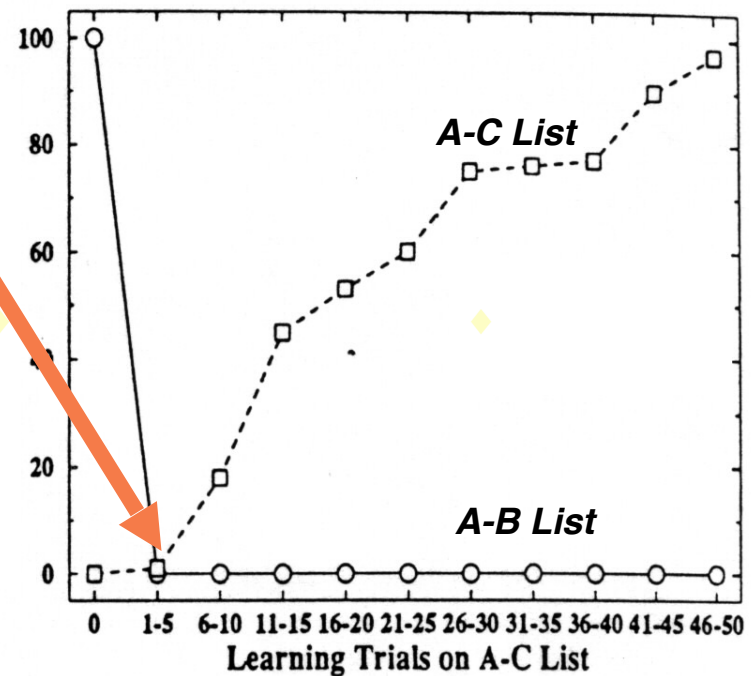
Model of AB-AC List Learning

- *Network loses AB association even before it even begins to learn AC:
Catastrophic interference!*

a) AB-AC List Learning in Humans



b) AB-AC List Learning in Model



Episodic vs. Semantic Memory

Episodic vs. Semantic Memory

- Distinction between:
 - memory for *actual details* of an item or event (“*episodes*”)
 - ♦ *acquired quickly*;

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(*anyone remember the word I asked you to spell last class?*)

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 - “flashbulb memories”: where were you on Nov. 5, 2024?
 - even when they are not very important
 - (*anyone remember the word I asked you to spell last class?*)
- **But usually not for very long** (*maybe days, but not months...*)

Episodic vs. Semantic Distinction

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- **Episodic** (*Tulving, 1972*):
 - memory for events and/or details: “**episodes**”
 - “one trial learning”

Episodic vs. Semantic Distinction

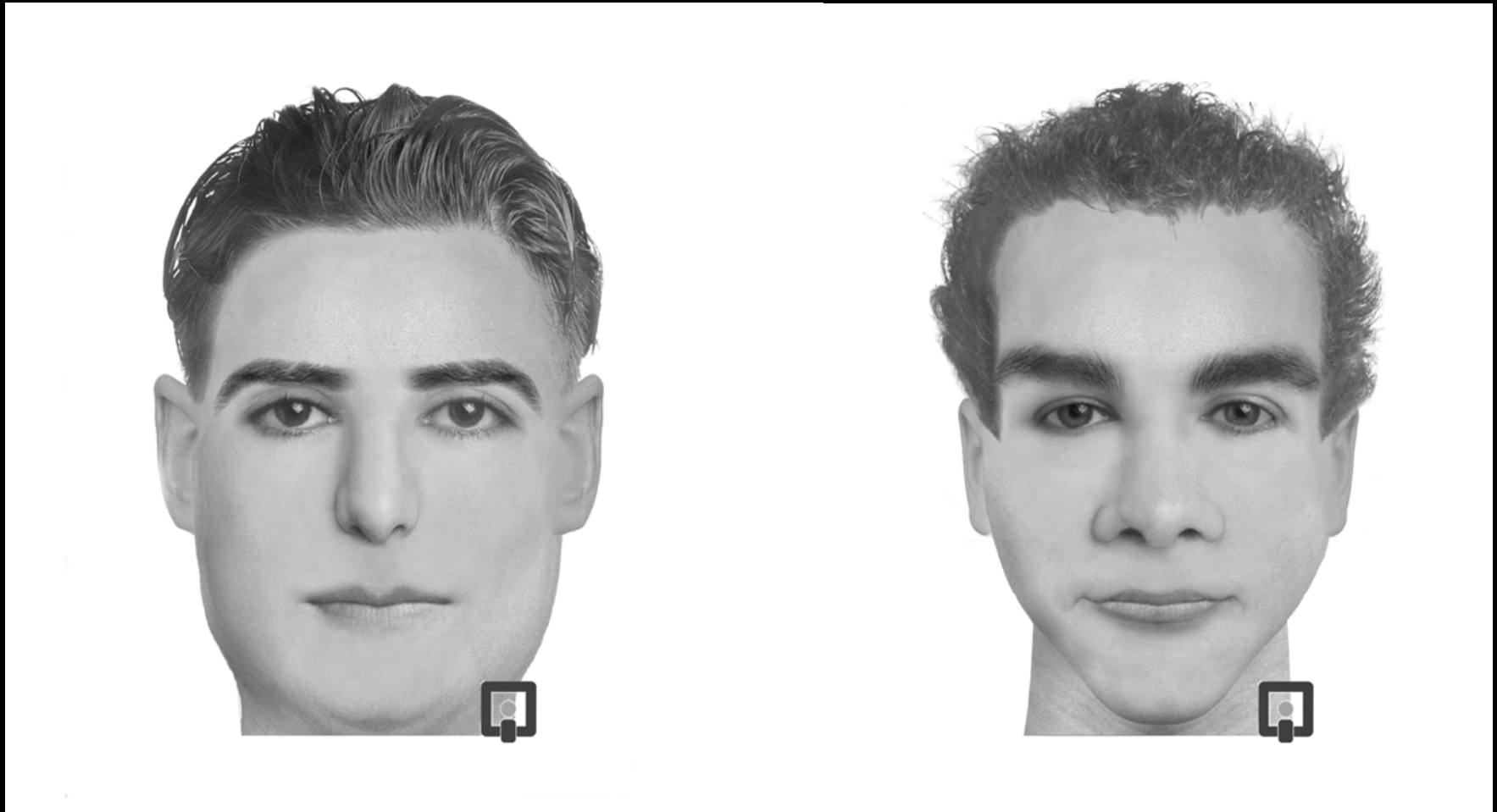
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Observe these faces...





Which one did you see before?

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- examples:
 - *where is the most popular place to park?*
 - *meanings of words...*

Observe these words...



**Respond yes if you saw *exactly*
the following words...**

rats















Episodic vs. Semantic Memory

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- **Task** (*Hintzman et al., 1992*):
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- we can even quickly learn *exceptions* to statistical regularities:

- a penguin is a bird that *can't* fly...

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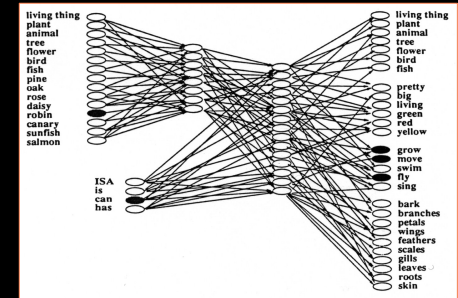
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- **Another potential solution:**

- interleaved training...

Interference in Semantic Networks

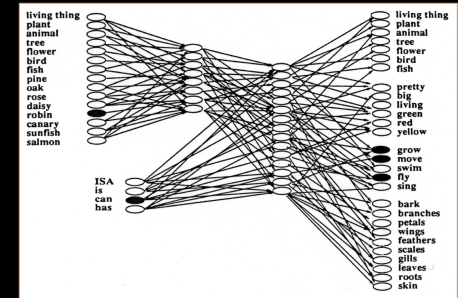
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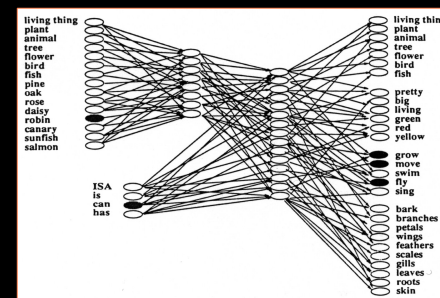
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 - penguin: bird that swims but doesn't fly



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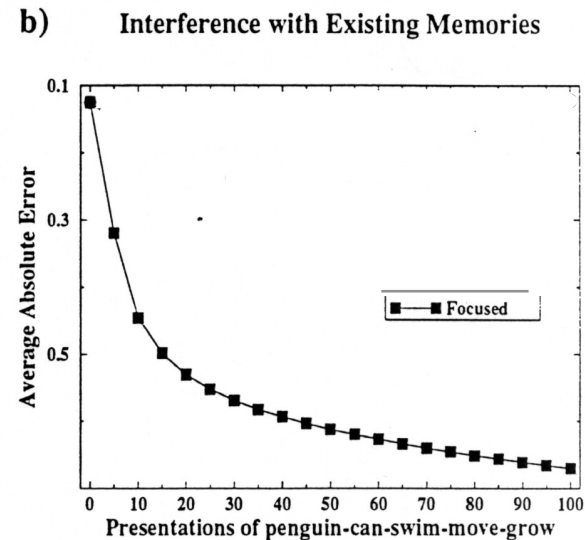
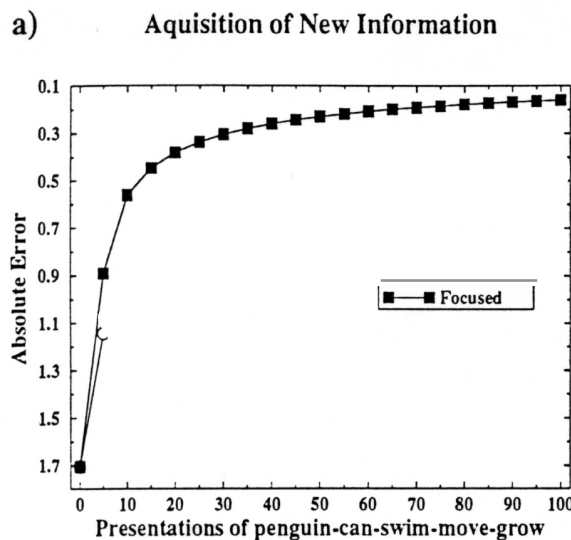
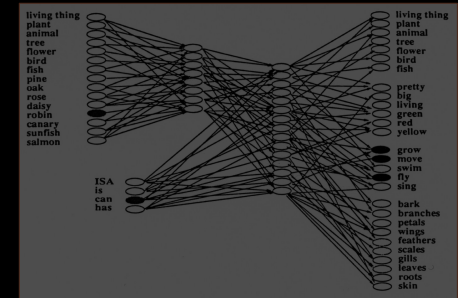
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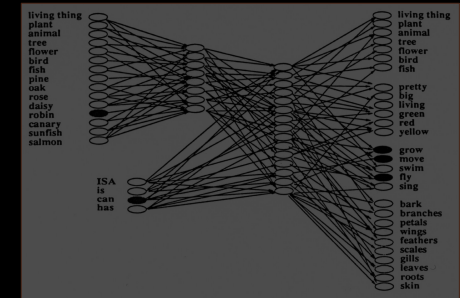
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 - however, it interferes with old knowledge: **catastrophic interference**
begins to think all birds swim and don't fly!

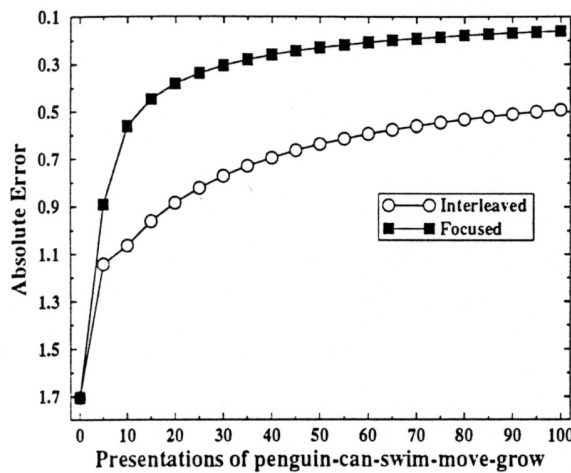


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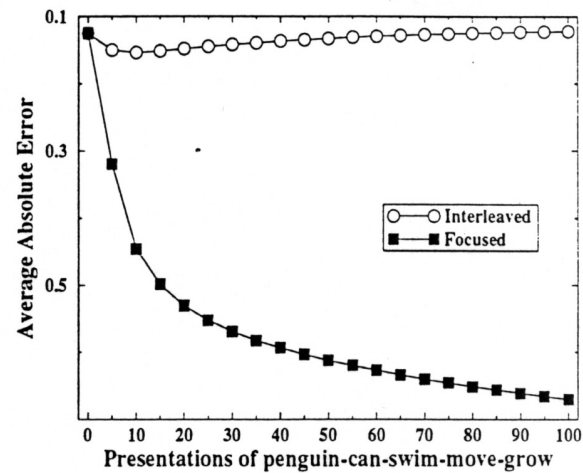
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a) Acquisition of New Information



b) Interference with Existing Memories



Interference in Semantic Networks

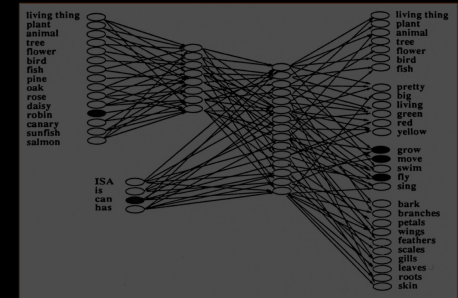
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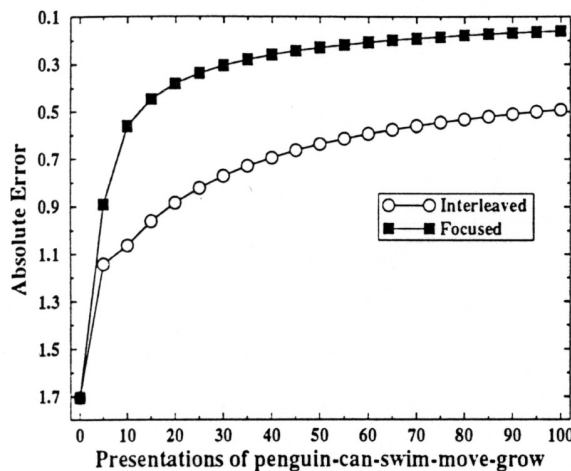
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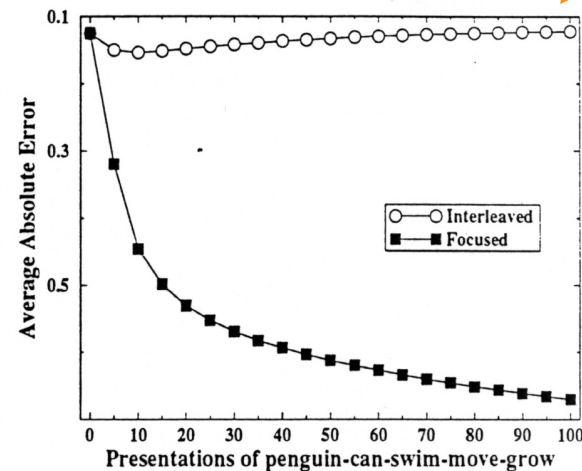
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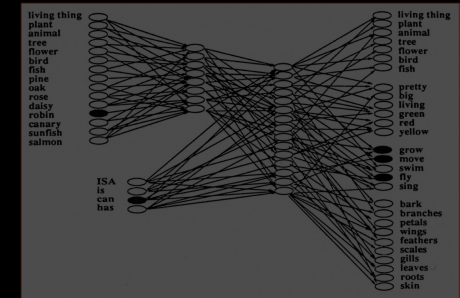
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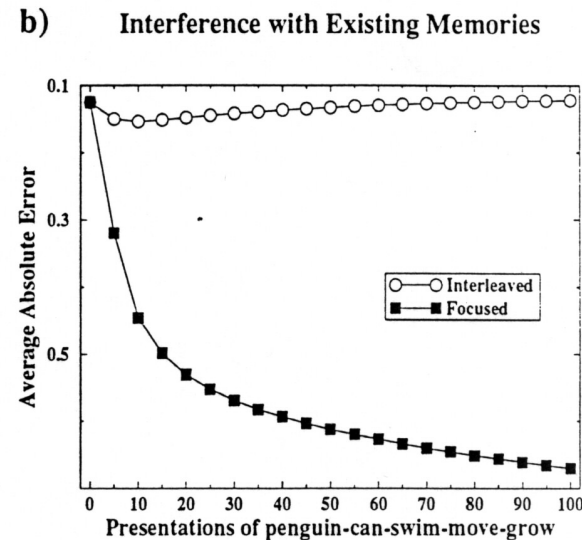
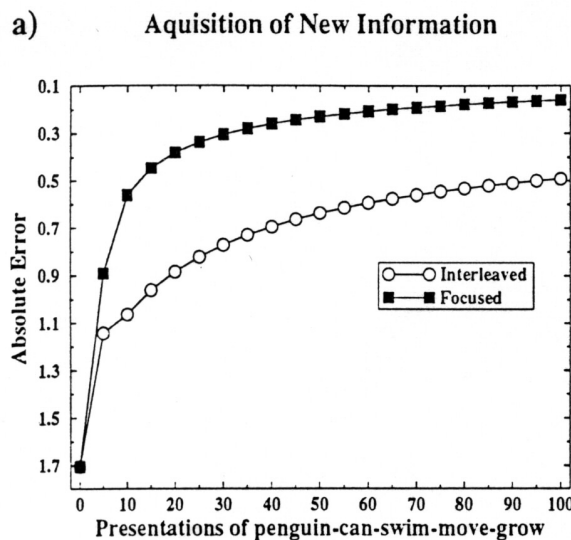
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- **Interleaved Training:**

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 - “carves out space” for penguin without disturbing other birds
- however, still can't explain rapid (one-shot) learning



Interference in Semantic Networks

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- learn slow (*semantic*)

- acquire “statistical” knowledge (*consistent relationships*)

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Two Incompatible Goals

Remember Specifics

e.g., Where did I park today?

Goal: Avoid interference

Extract Generalities

e.g., Where do I usually park?

Goal: Accumulate experience

Two Incompatible Goals

Remember Specifics

e.g., Where did I park today?

Goal: Avoid interference

Solution:

separated representations
(*e.g., keep days separate*)



Extract Generalities

e.g., Where do I usually park?

Goal: Accumulate experience

Solution:

overlapping representations
(*integrate across days*)



Division of Labor

Remember Specifics

e.g., Where did I park today?

Goal: Avoid interference

Solution:

separate representations
(keep days separate)



System: *Hippocampus*

Extract Generalities

e.g., Where do I usually park?

Goal: Accumulate experience

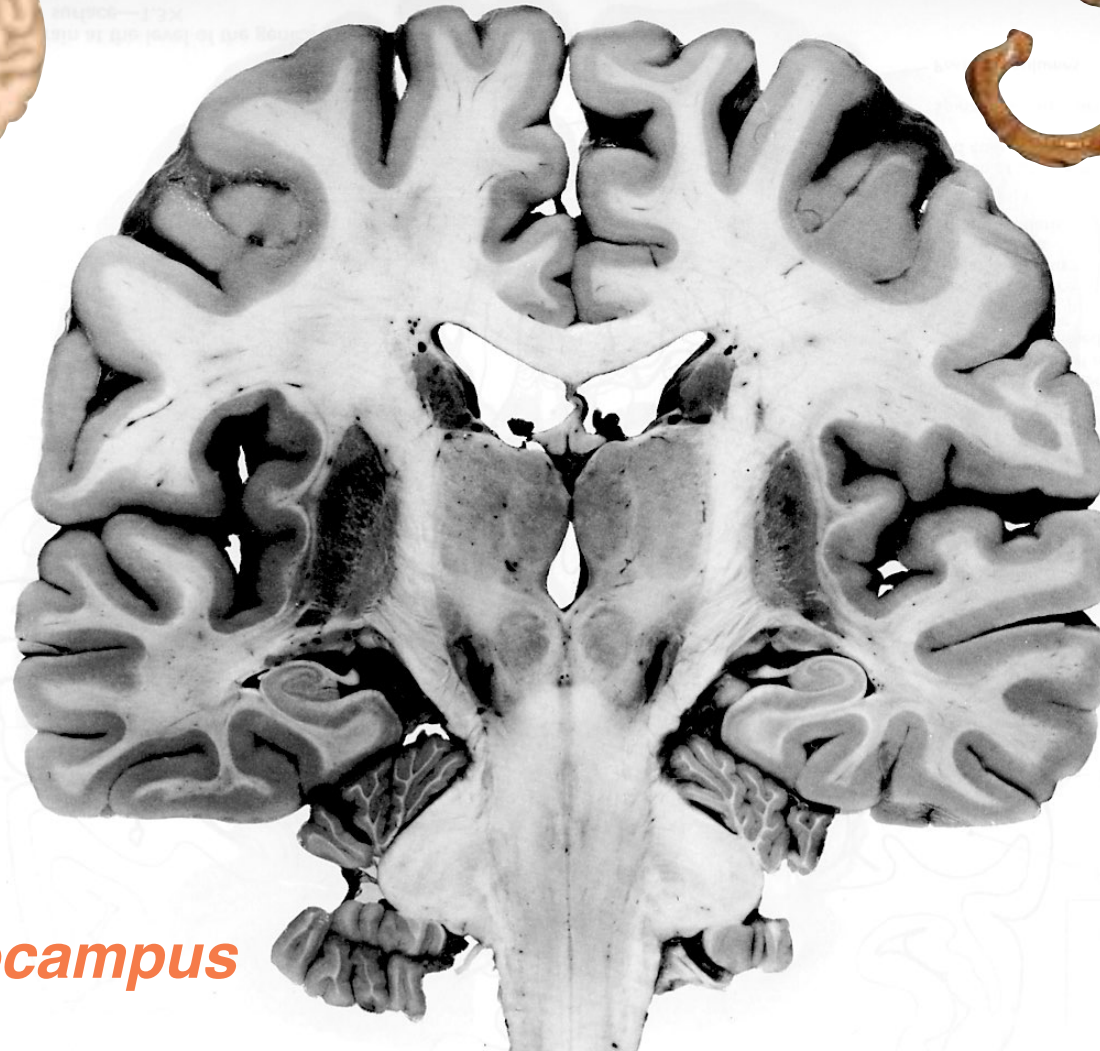
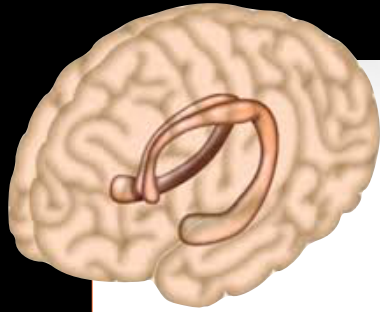
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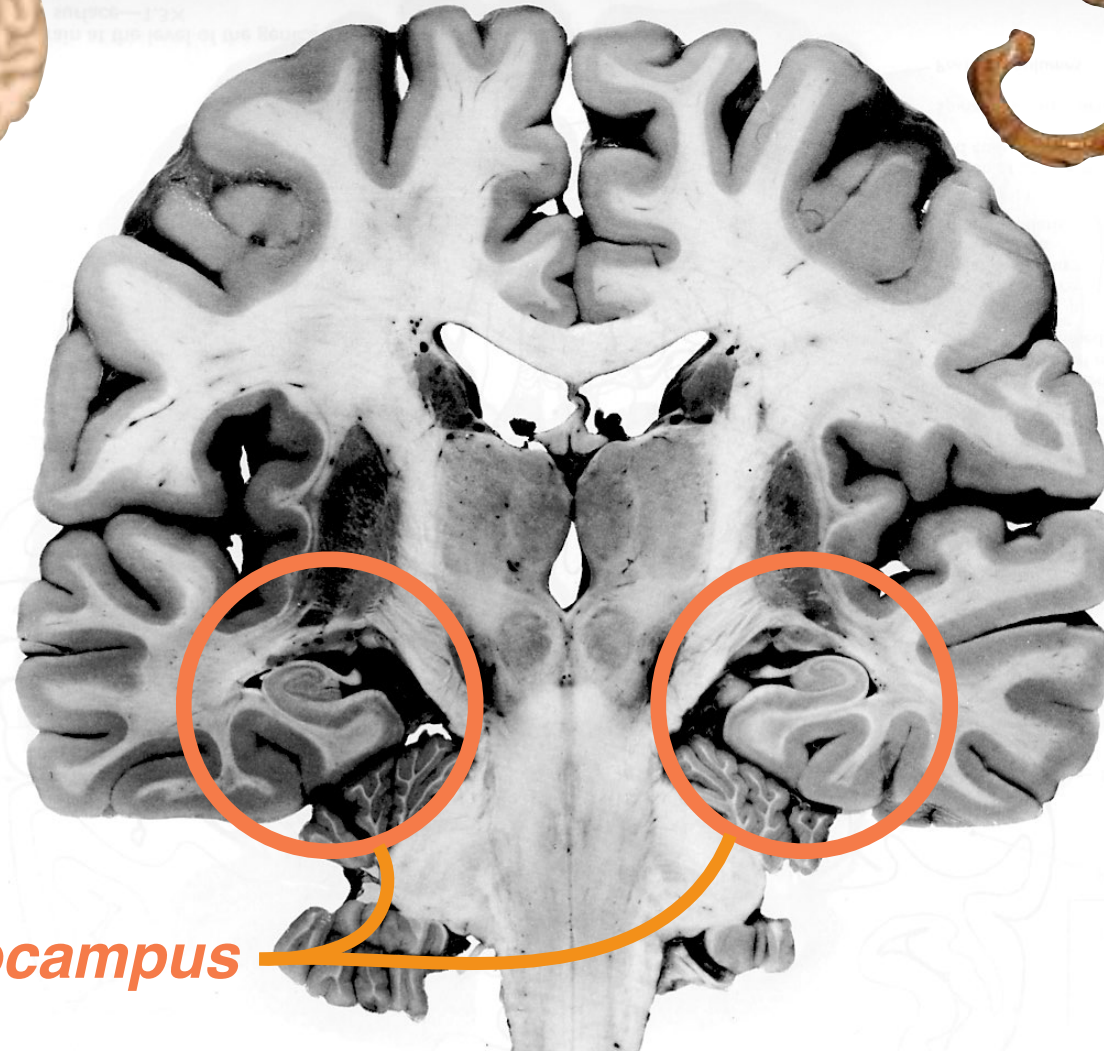
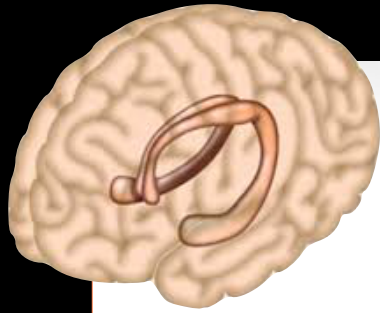
System: *Neocortex*

The Hippocampus



Hippocampus

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hippocampus



- The other learns slowly, aggregates, and stores semantic information

neocortex



Functions of Hippocampus

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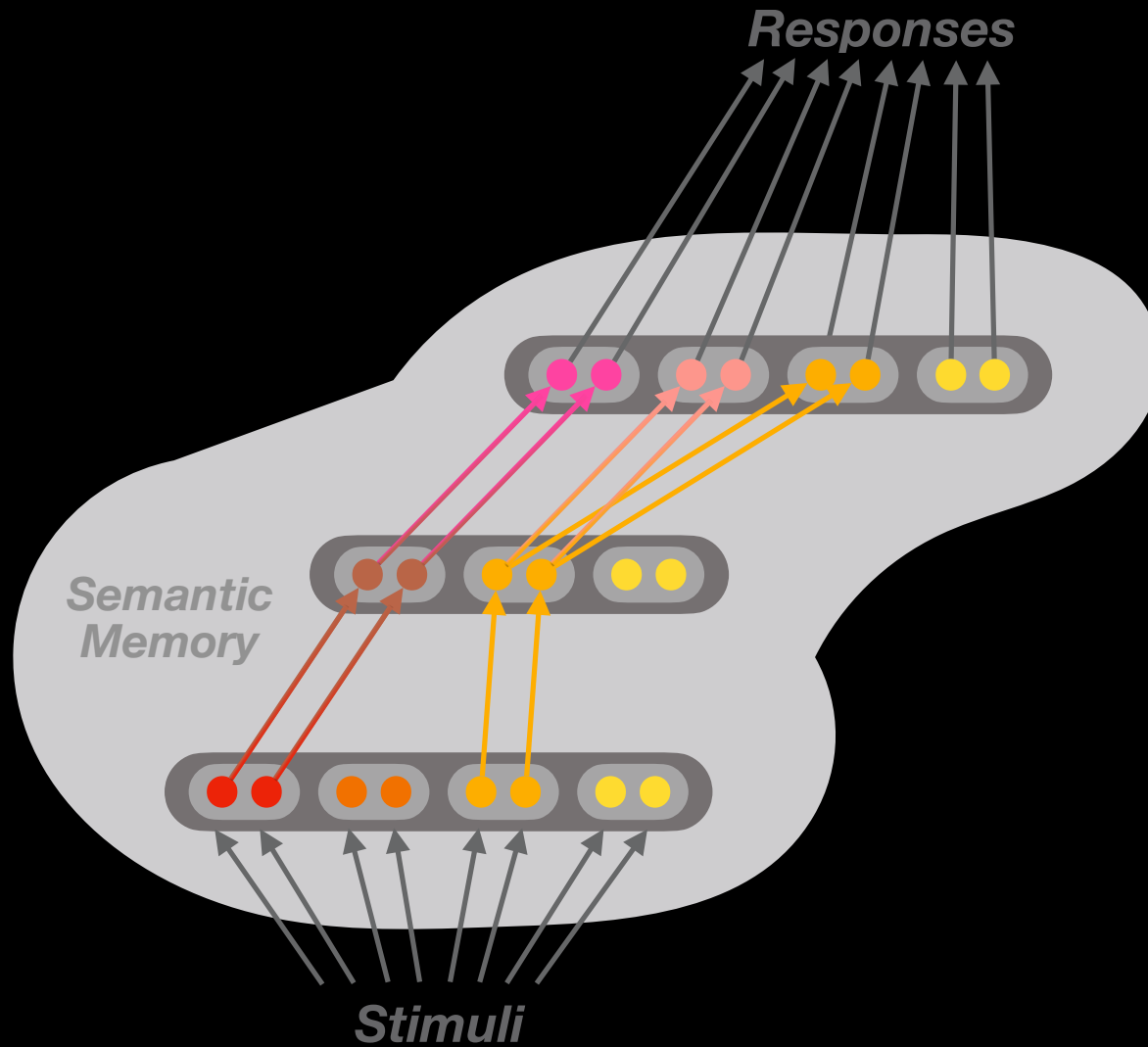
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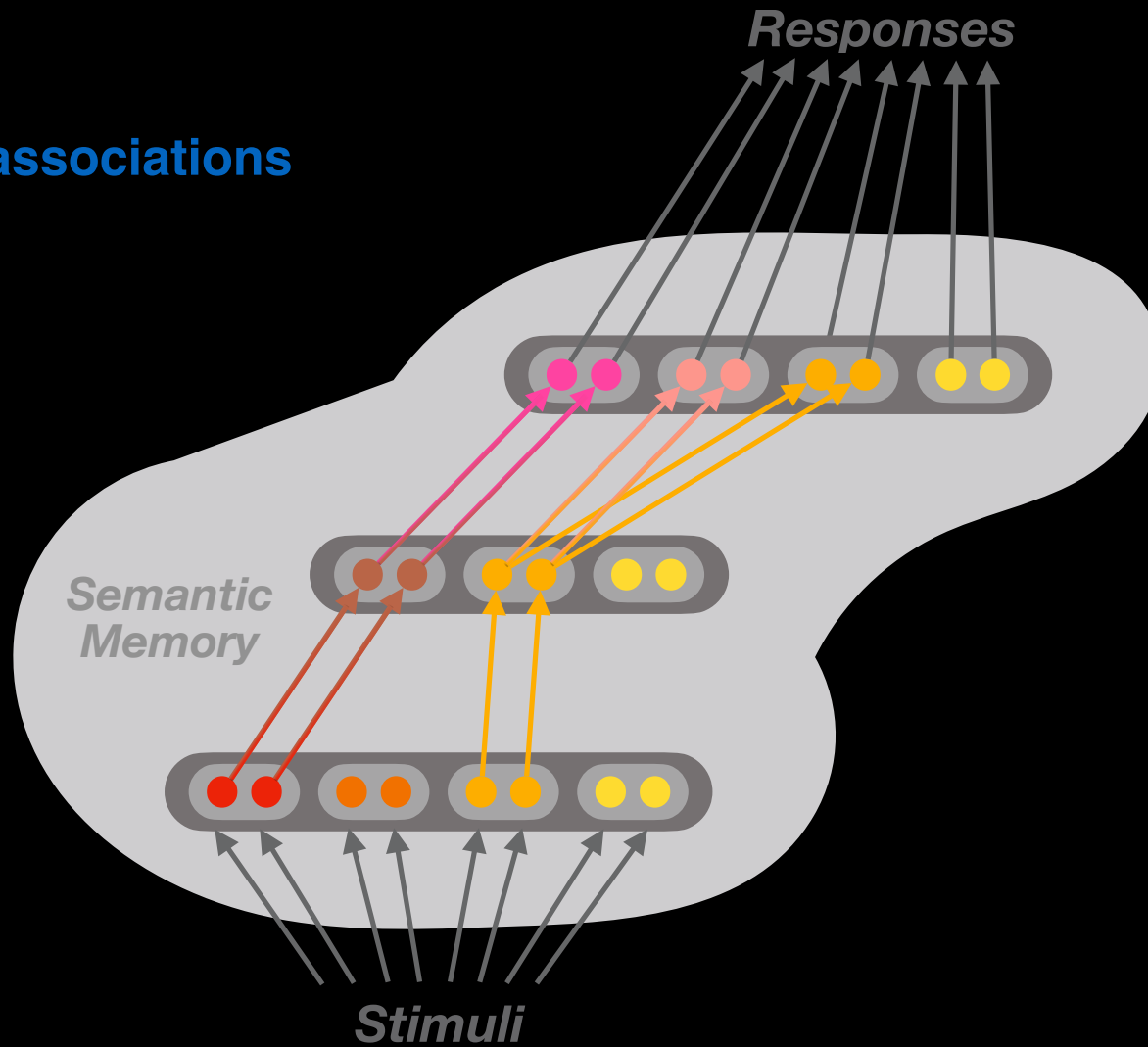
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 - **why must it be slow?**
 - ensure it is relevant
 - minimize disruption of existing knowledge

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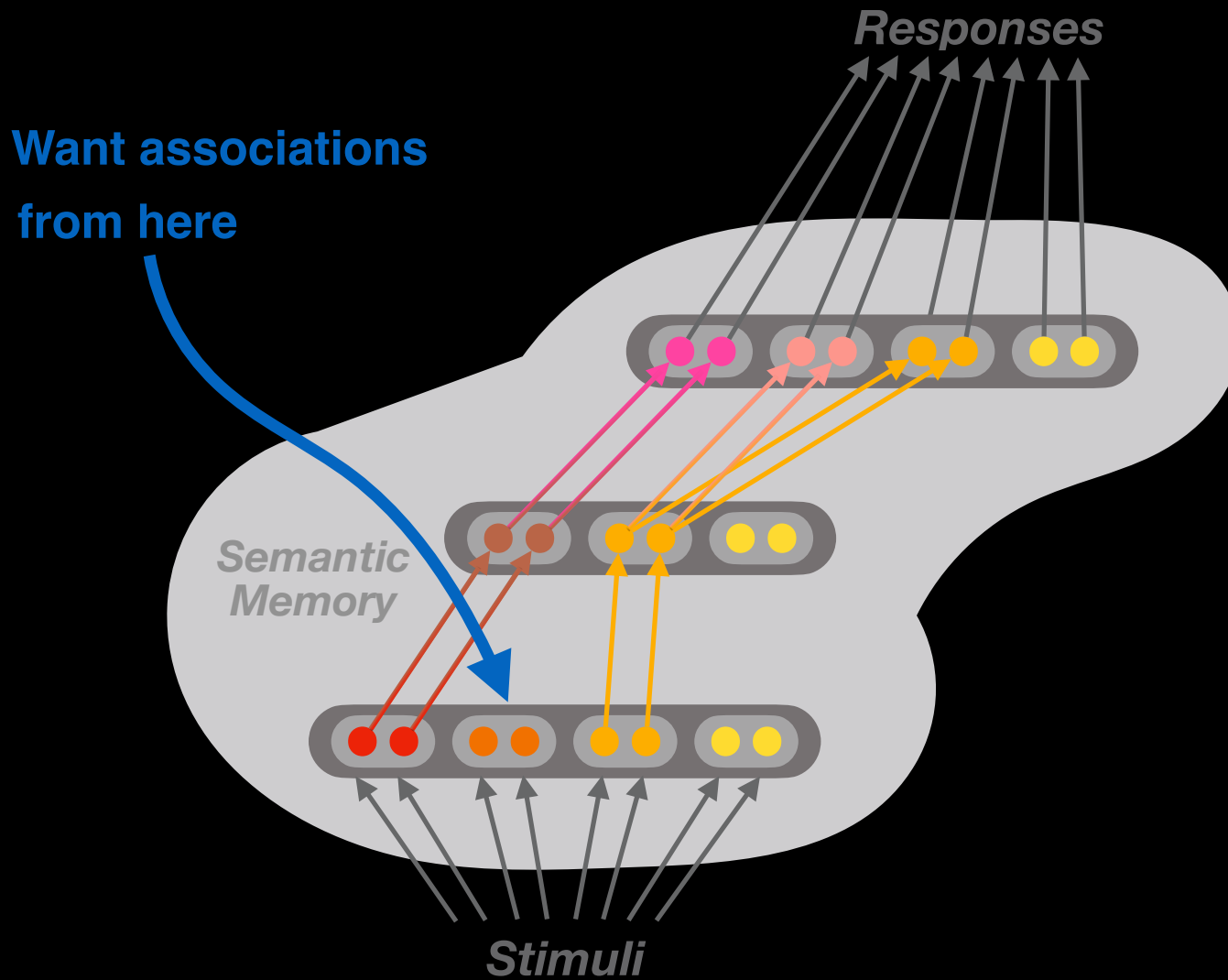


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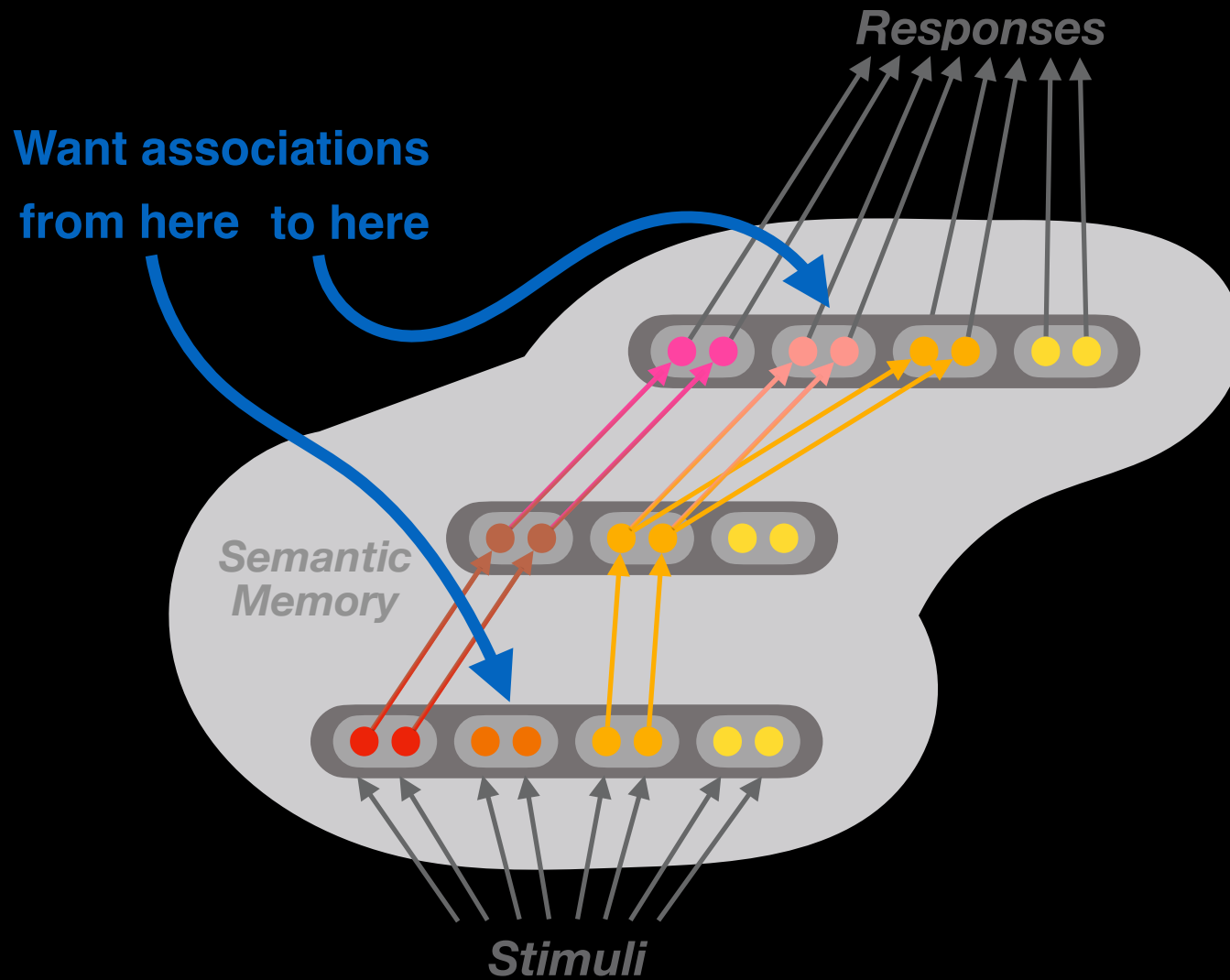
Want associations



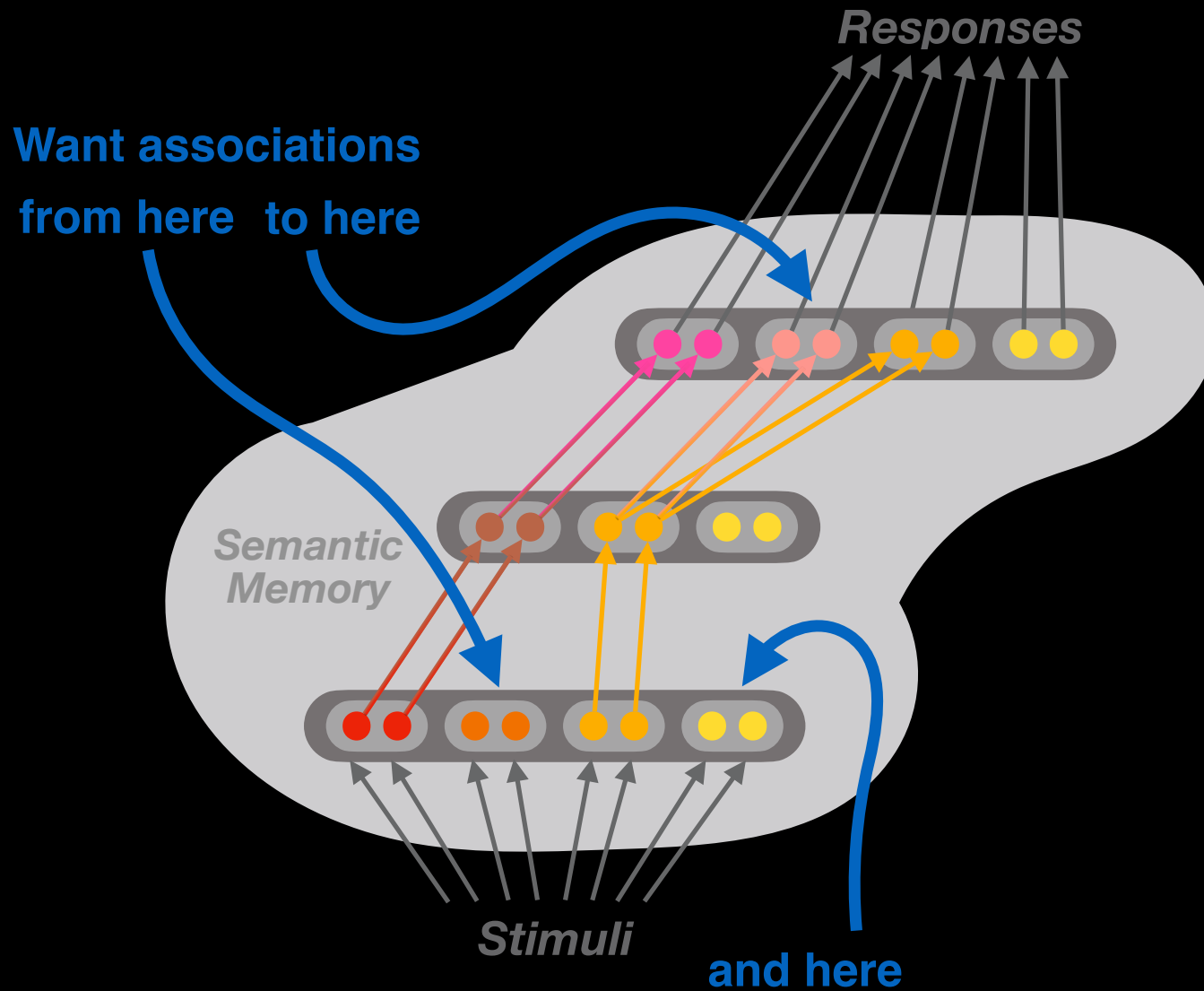
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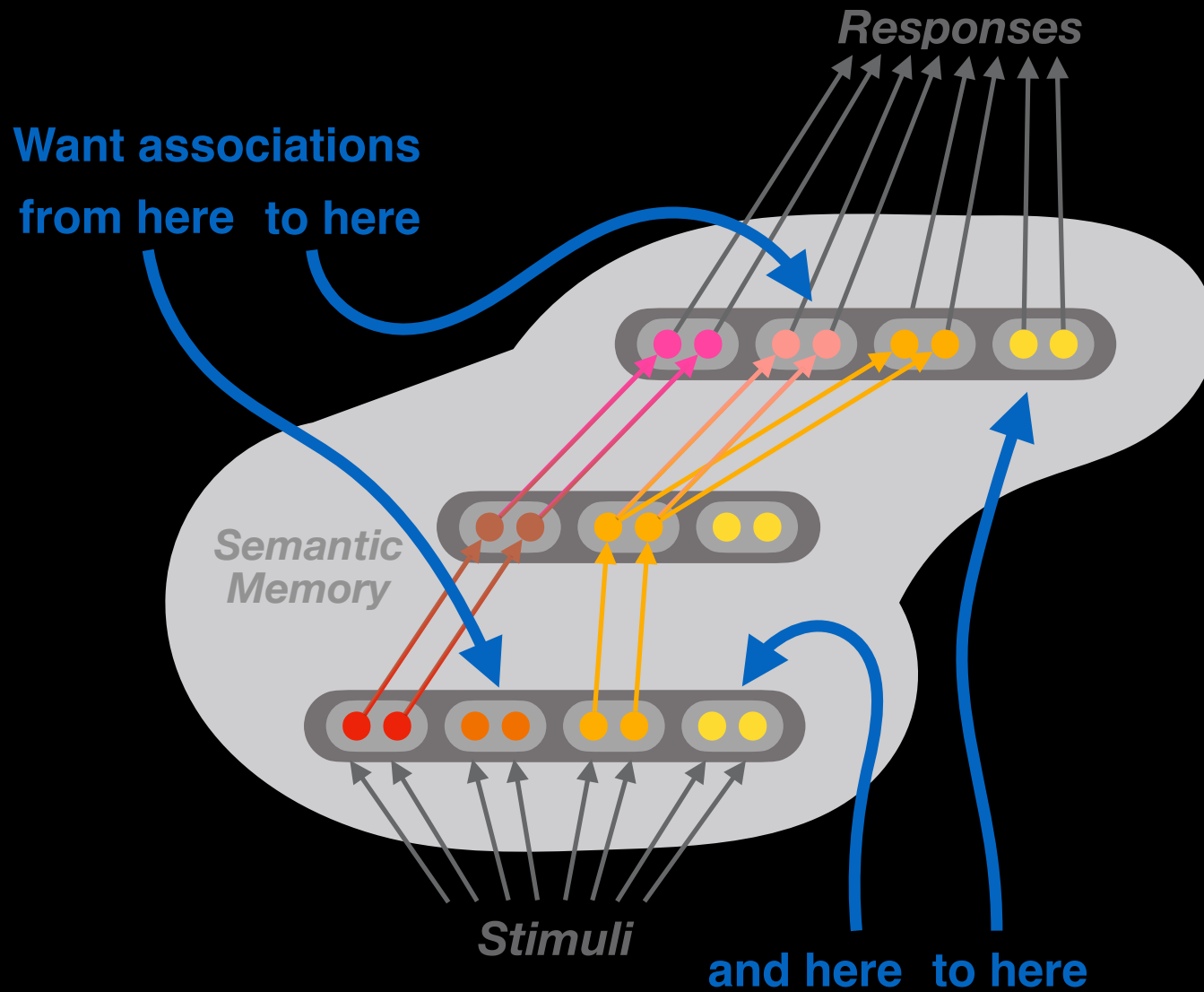
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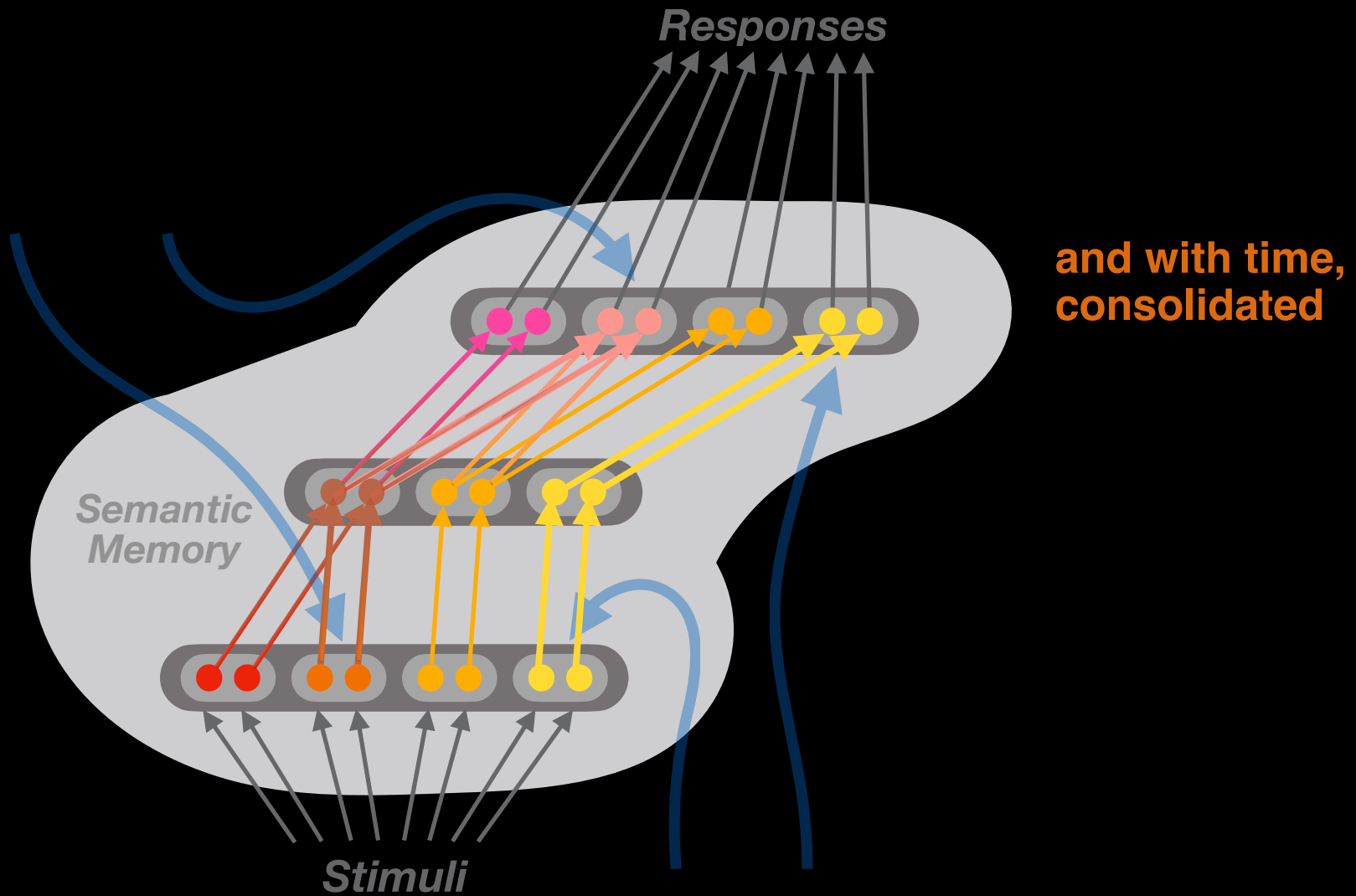
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- **Simulated effects of consolidation in animal studies**

For example...

Memory Consolidation in Rodents

(Kim & Fanselow, 1992)

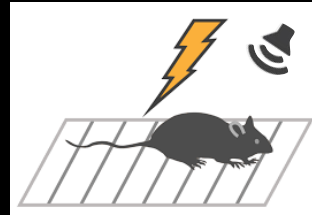
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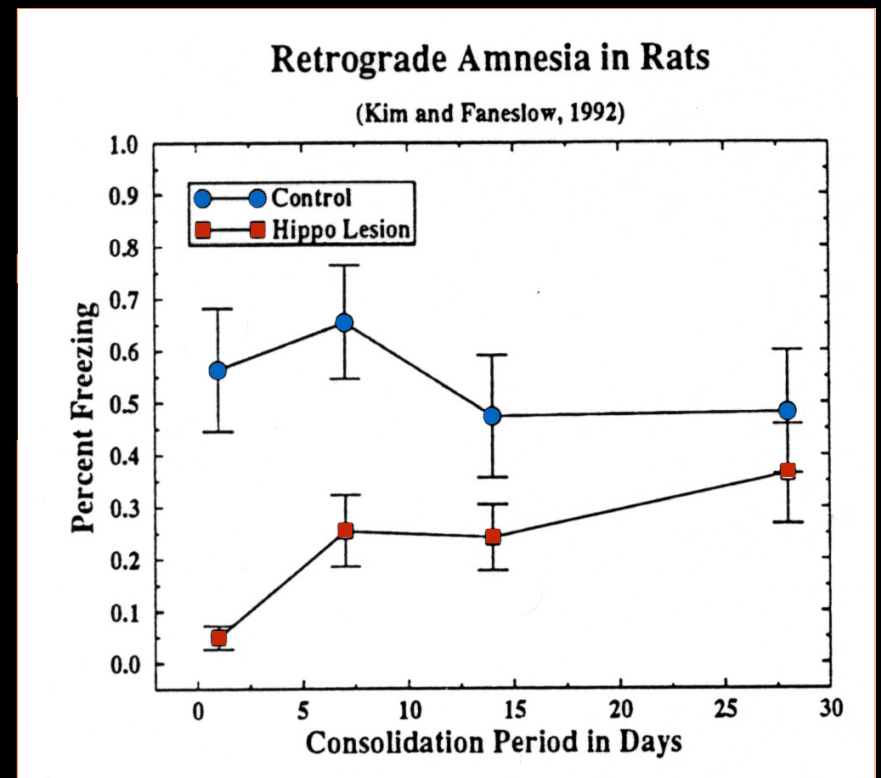
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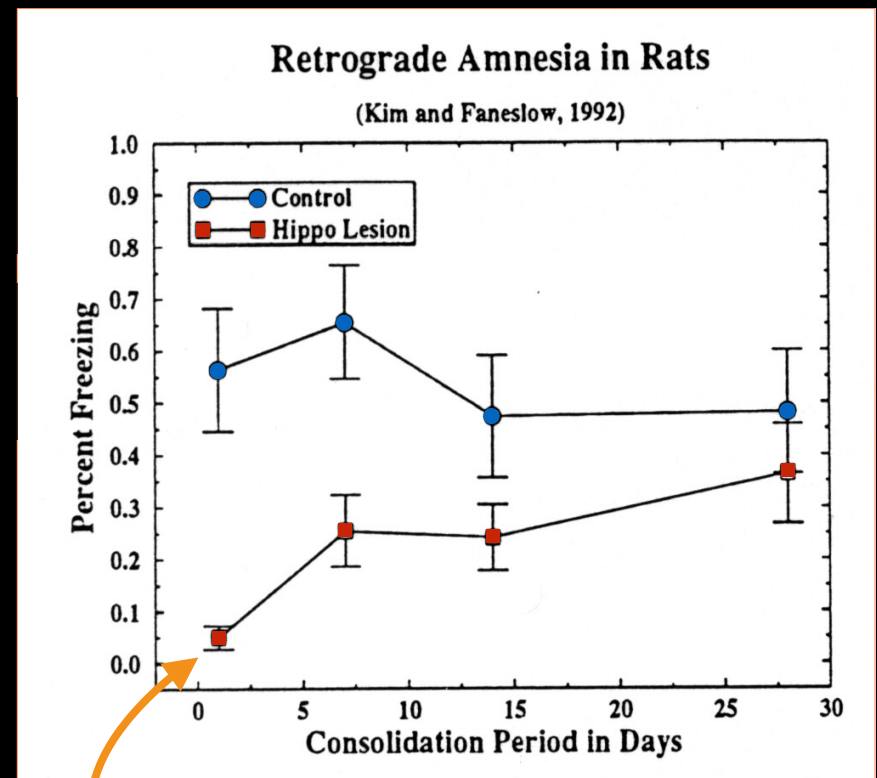
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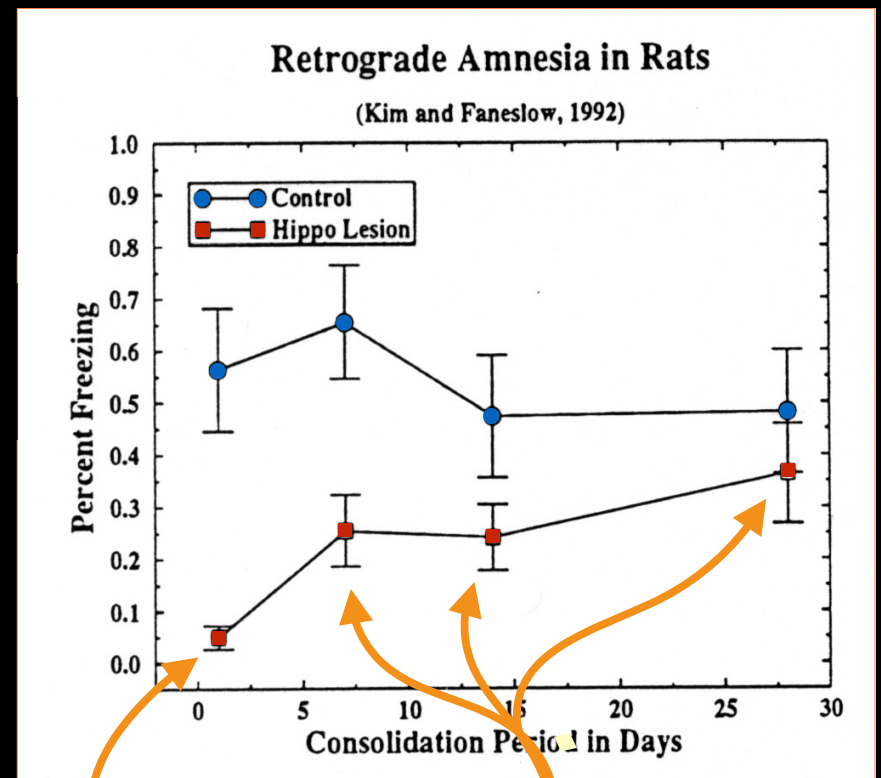
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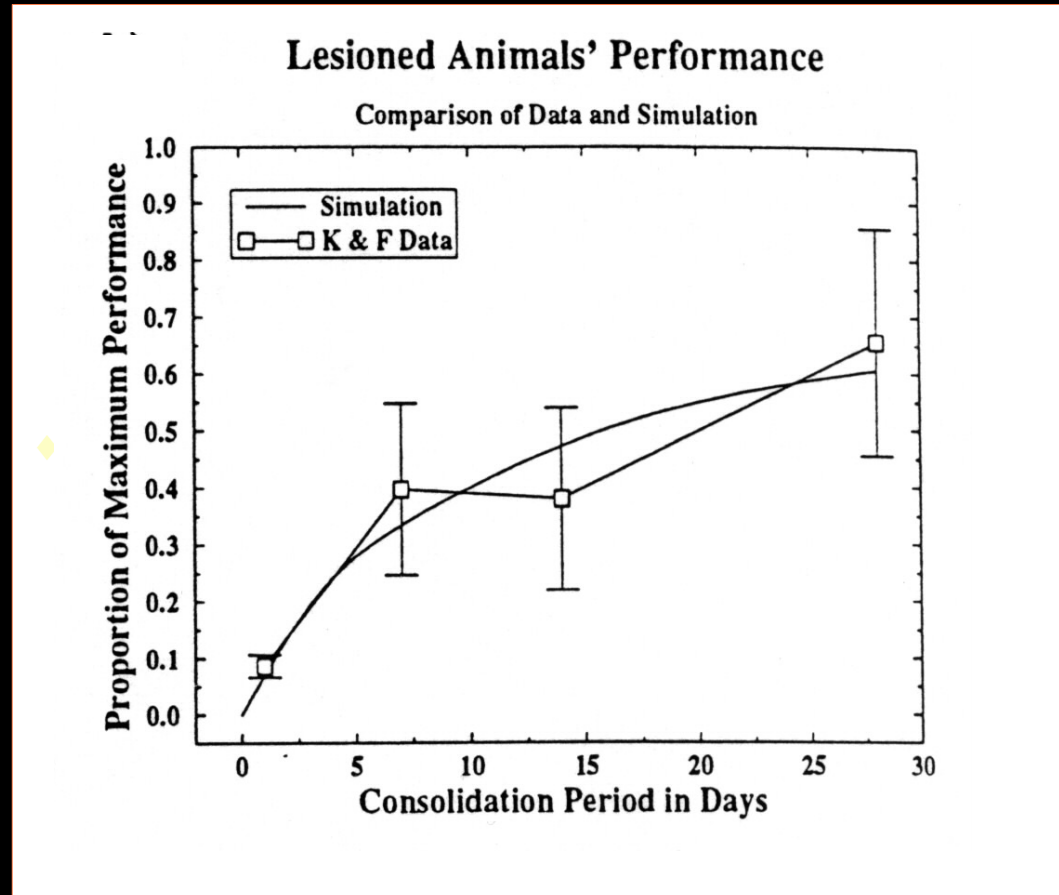
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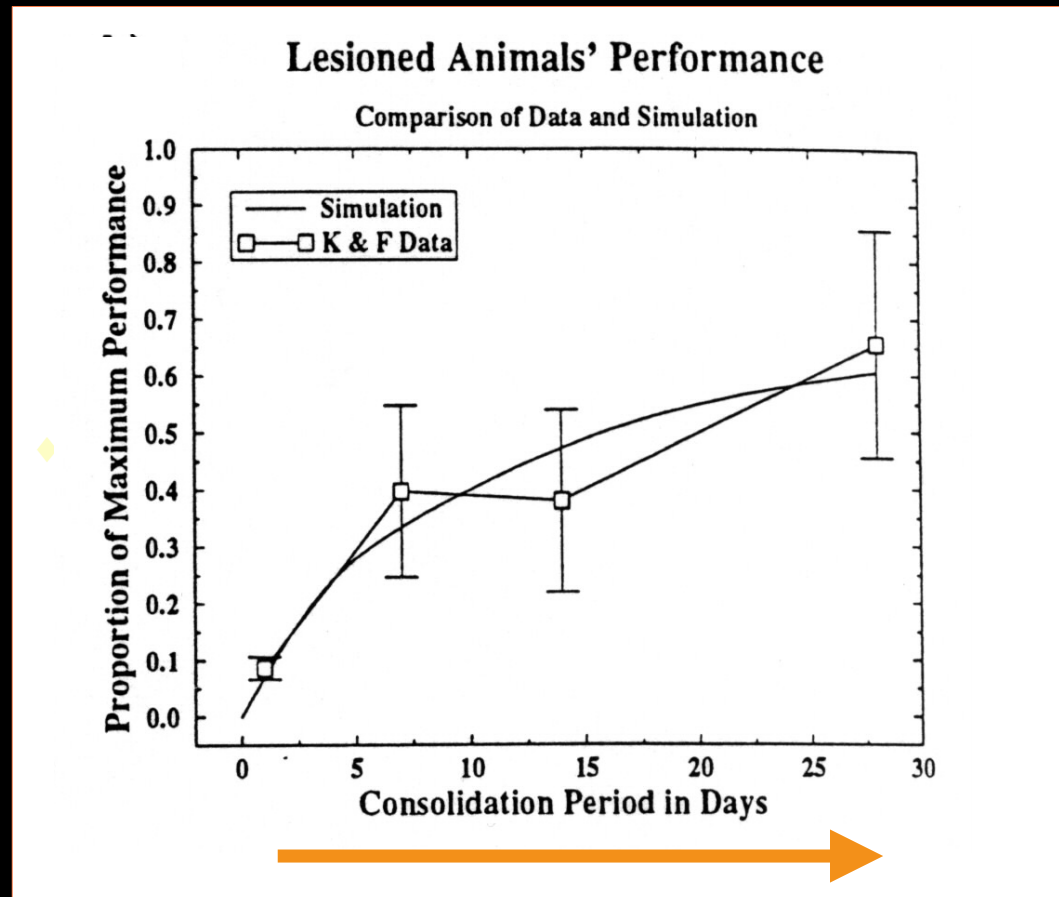
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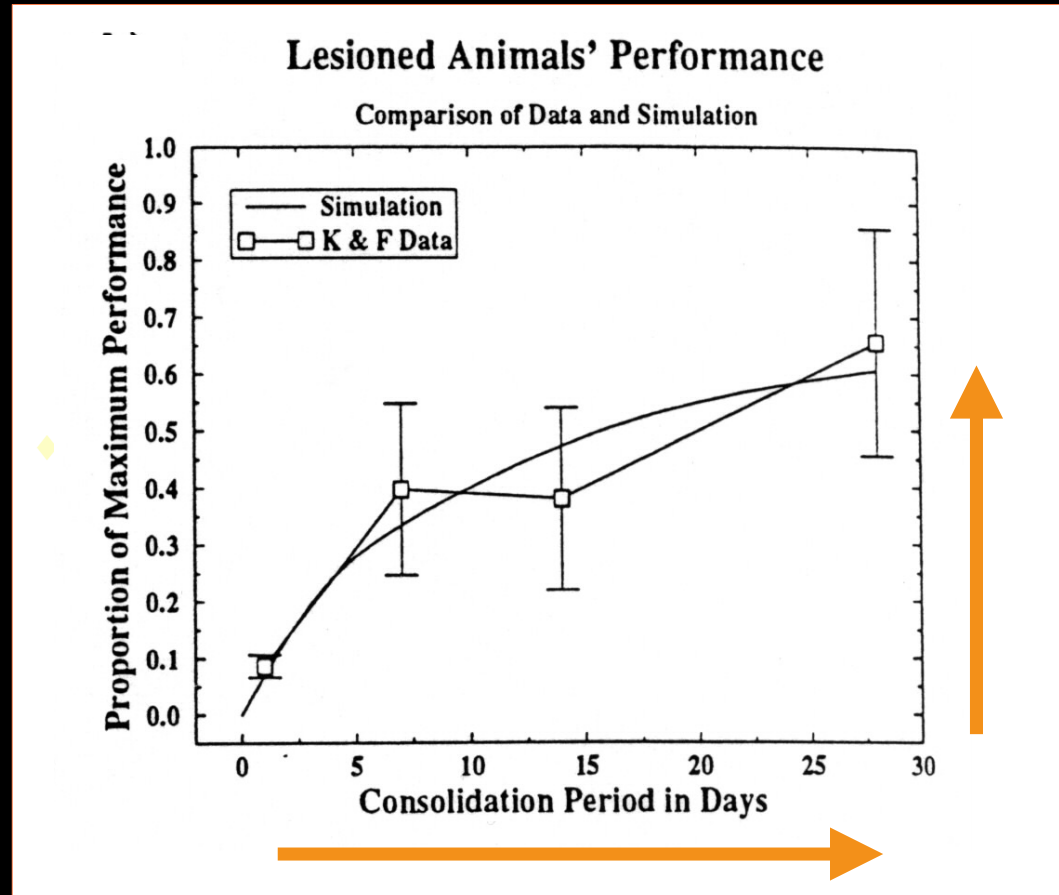
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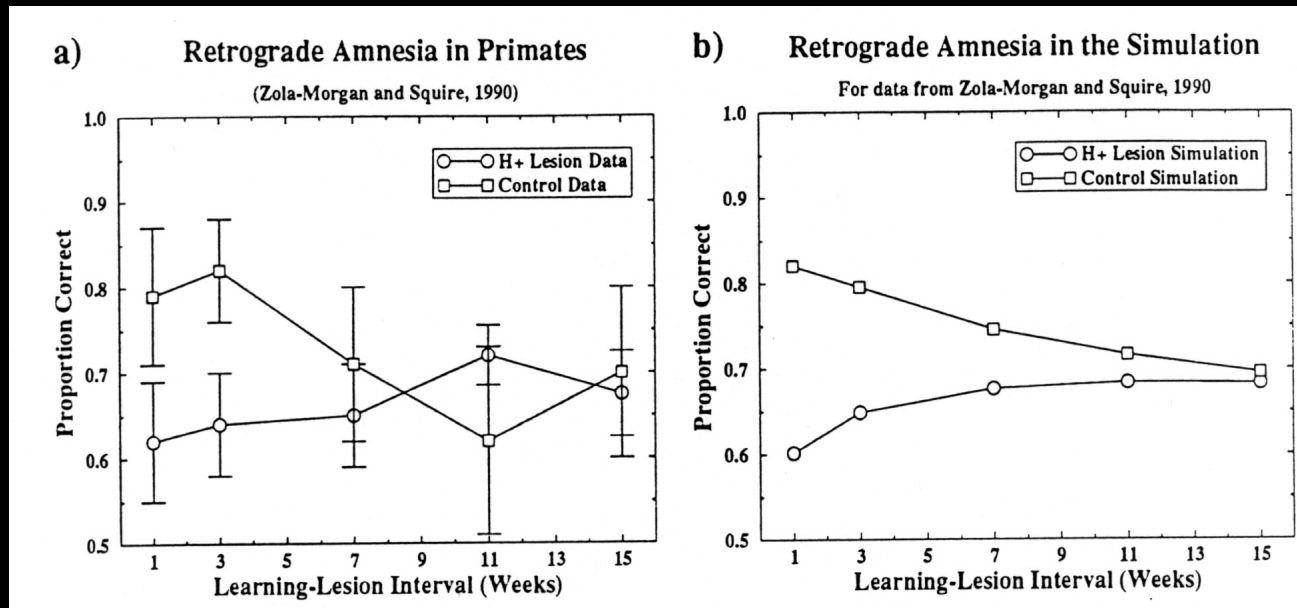


the better
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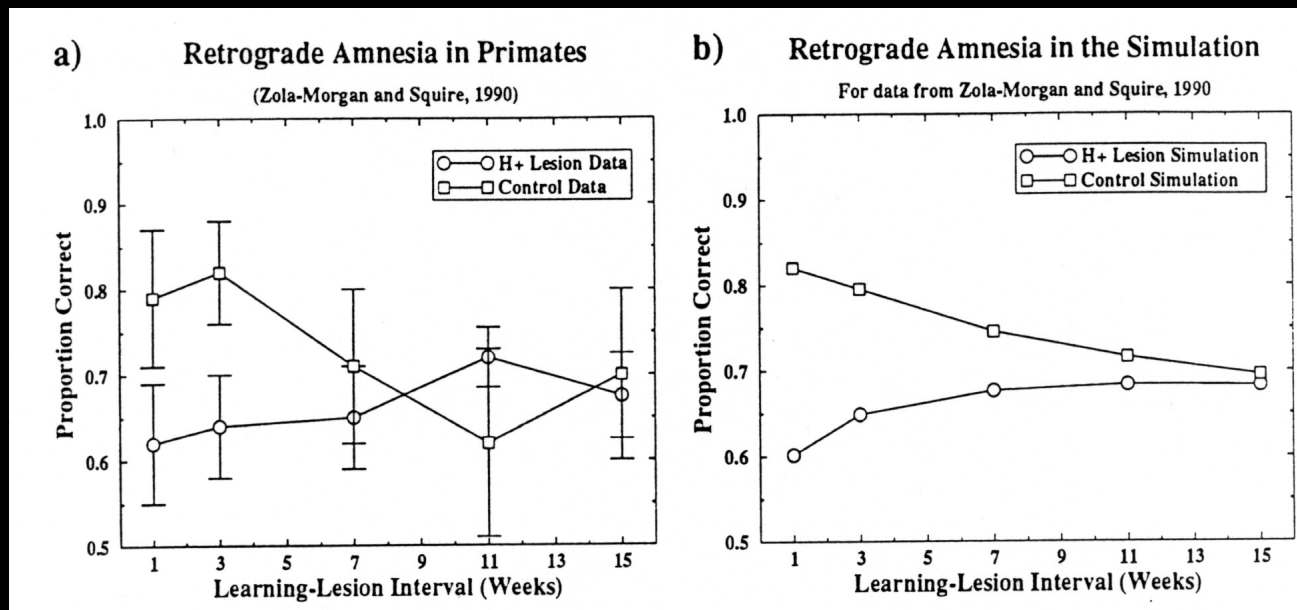
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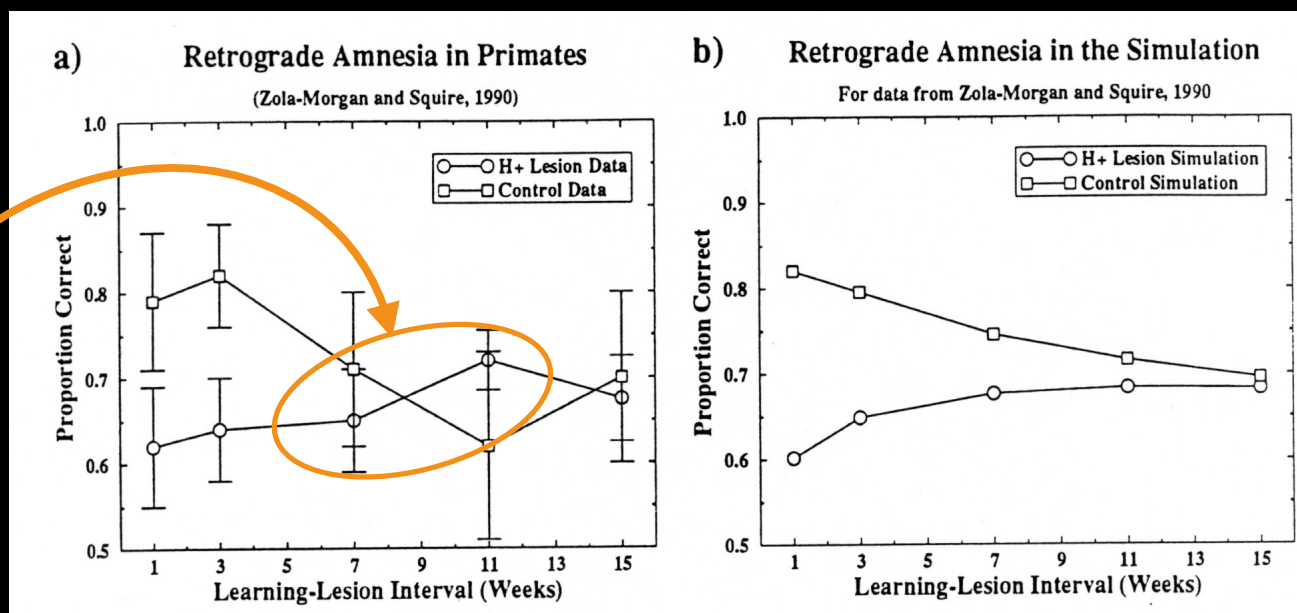
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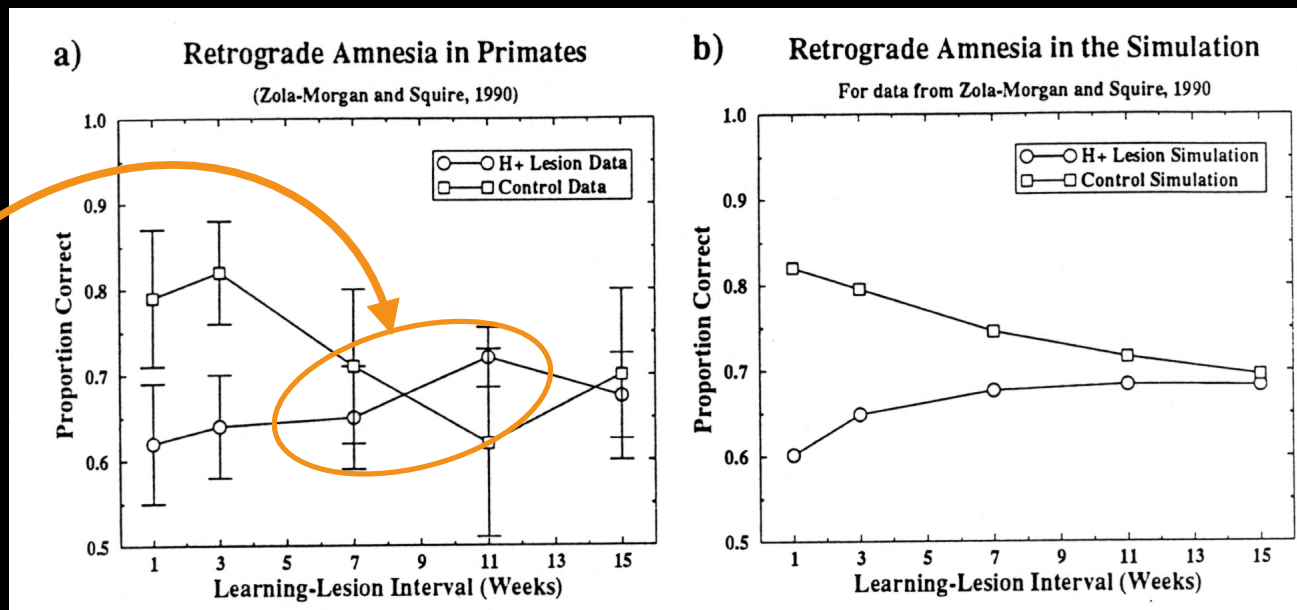
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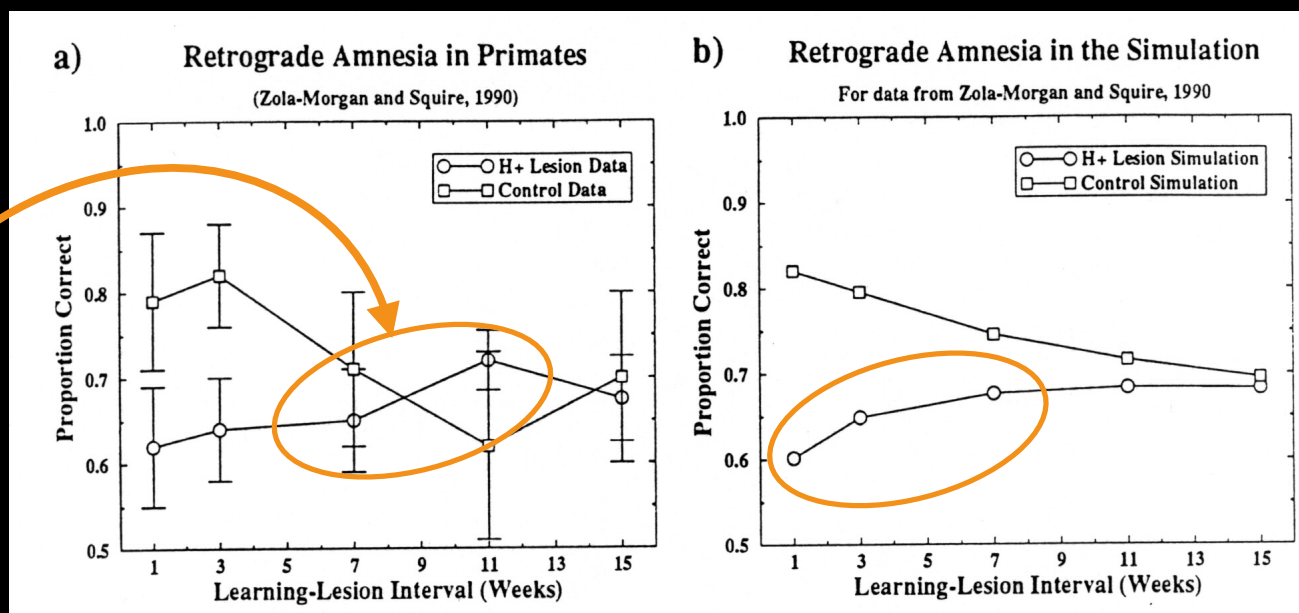
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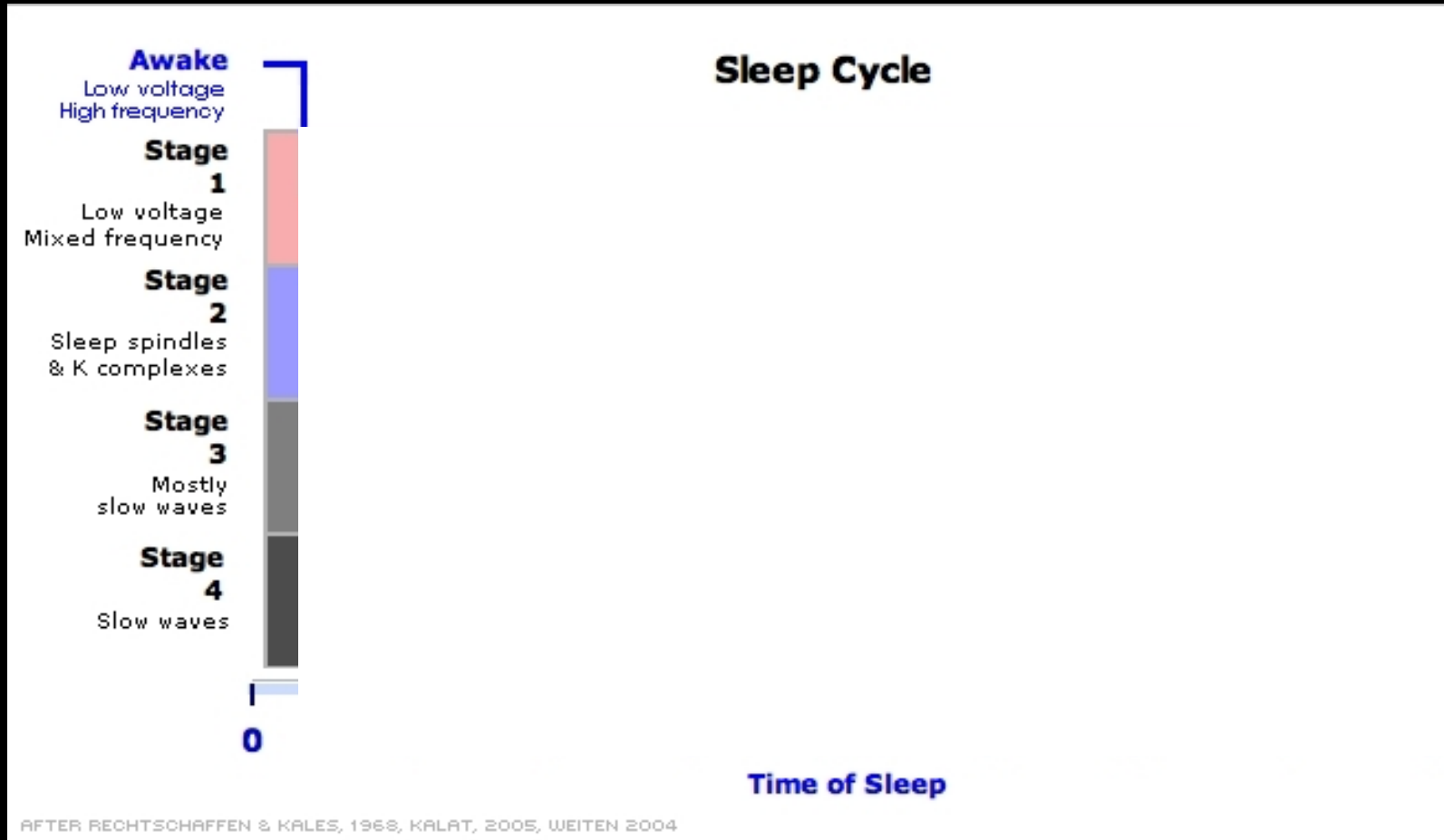
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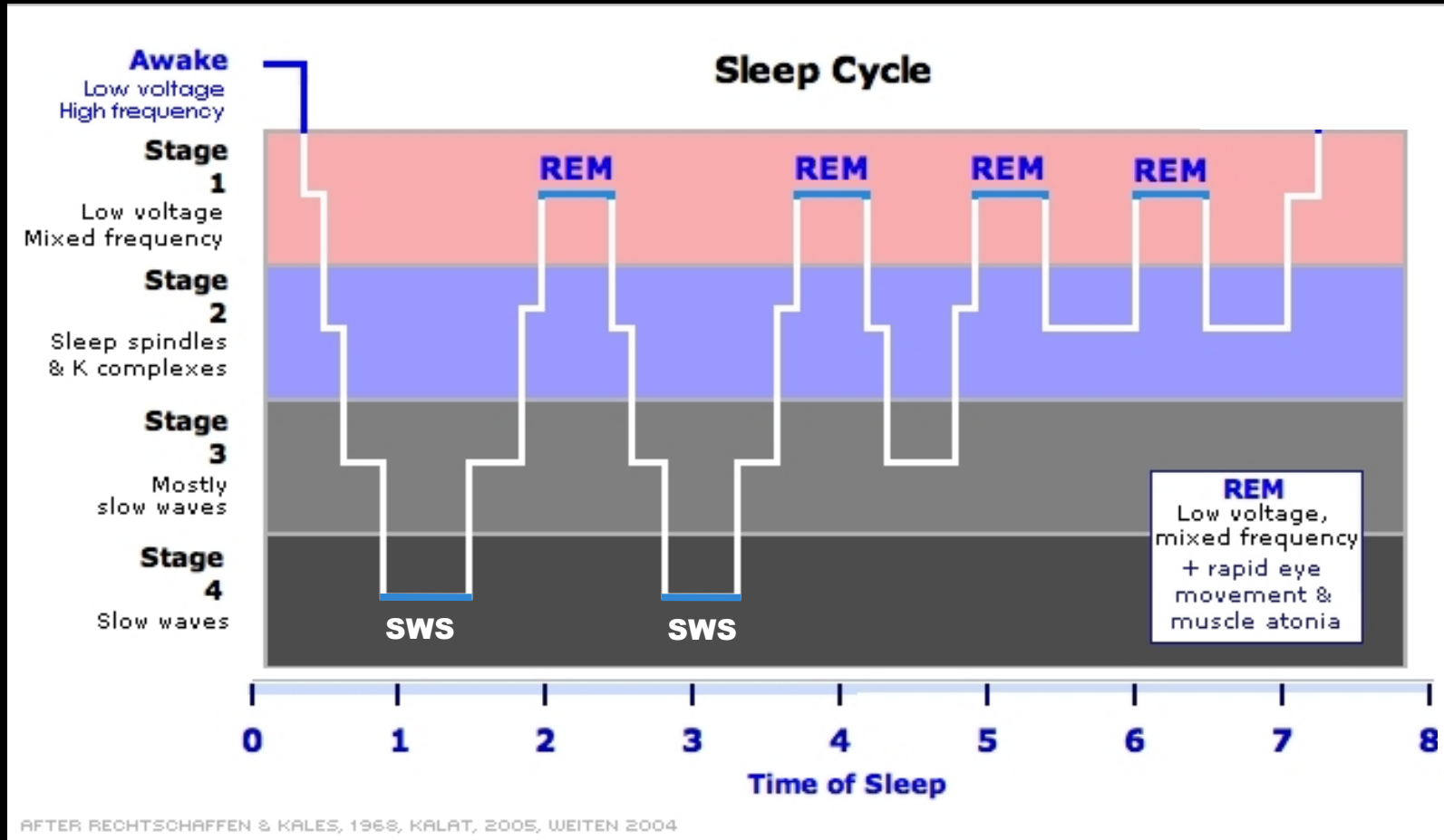
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- **sleep...**

Sleep



Sleep



Sleep and Dreaming

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Sleep and Dreaming



Sleep and Dreaming



Sleep and Dreaming



Why?

