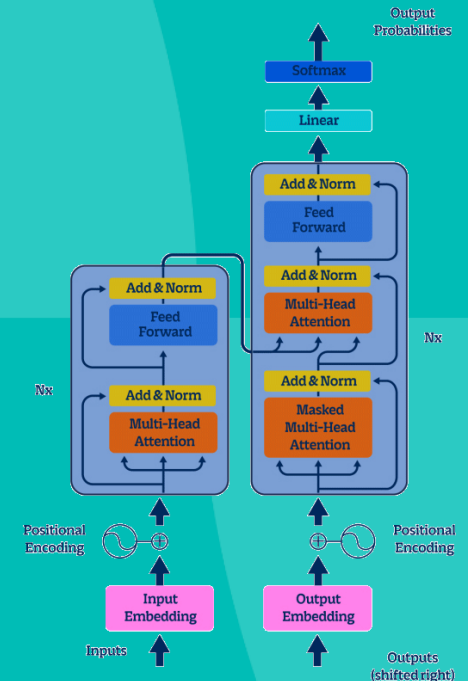


Building brains for the future: The neuroscience school leaders need now

Barbara Oakley, PhD, PE, FAAAS, FIEEE, FAIMBE
Coursera's Inaugural Innovation Instructor
Winner of McGraw Prize in Education (2023)
Distinguished Professor of Engineering
Oakland University, Rochester, Michigan
Oakley@oakland.edu







Philip Oakley

The transformer

Attention Is All You Need

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lukaszkaiser@google.com

Illia Polosukhin* ‡
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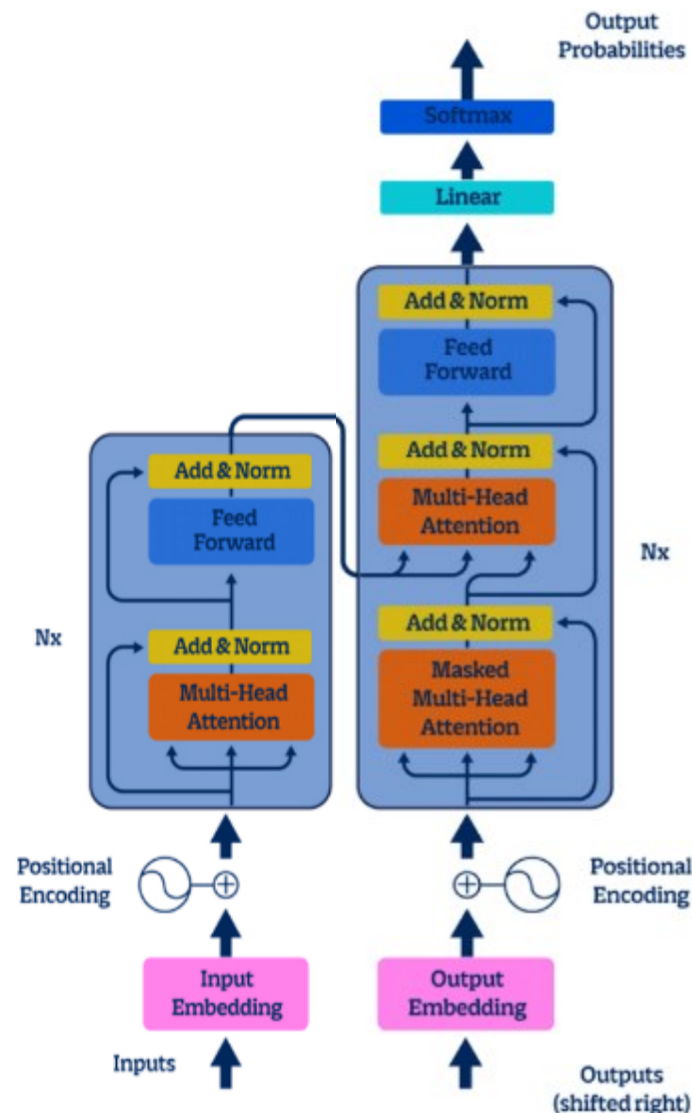
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.0 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature.

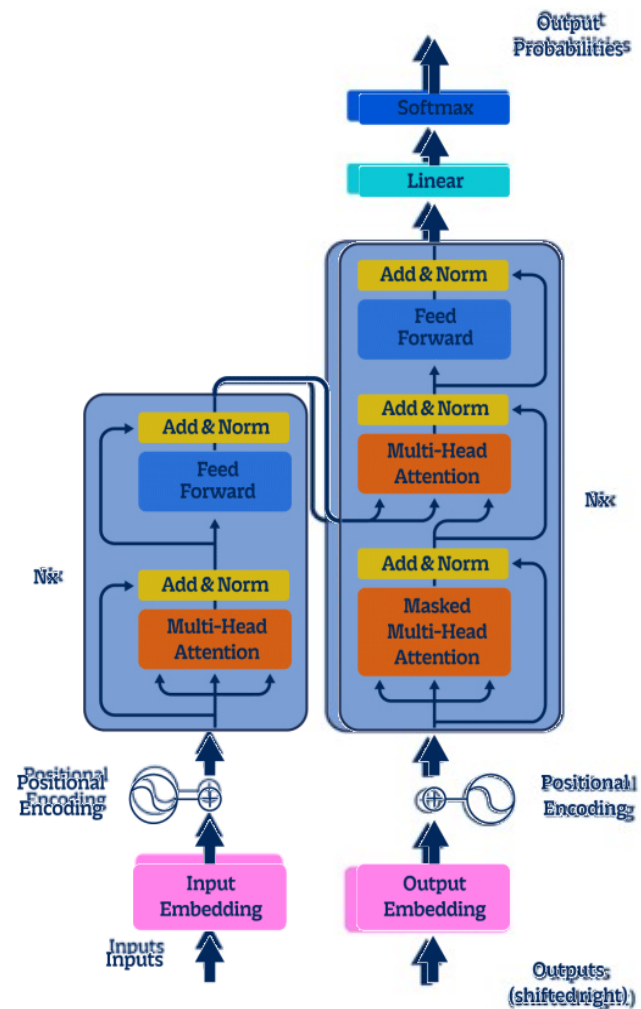
31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA.

Encoder

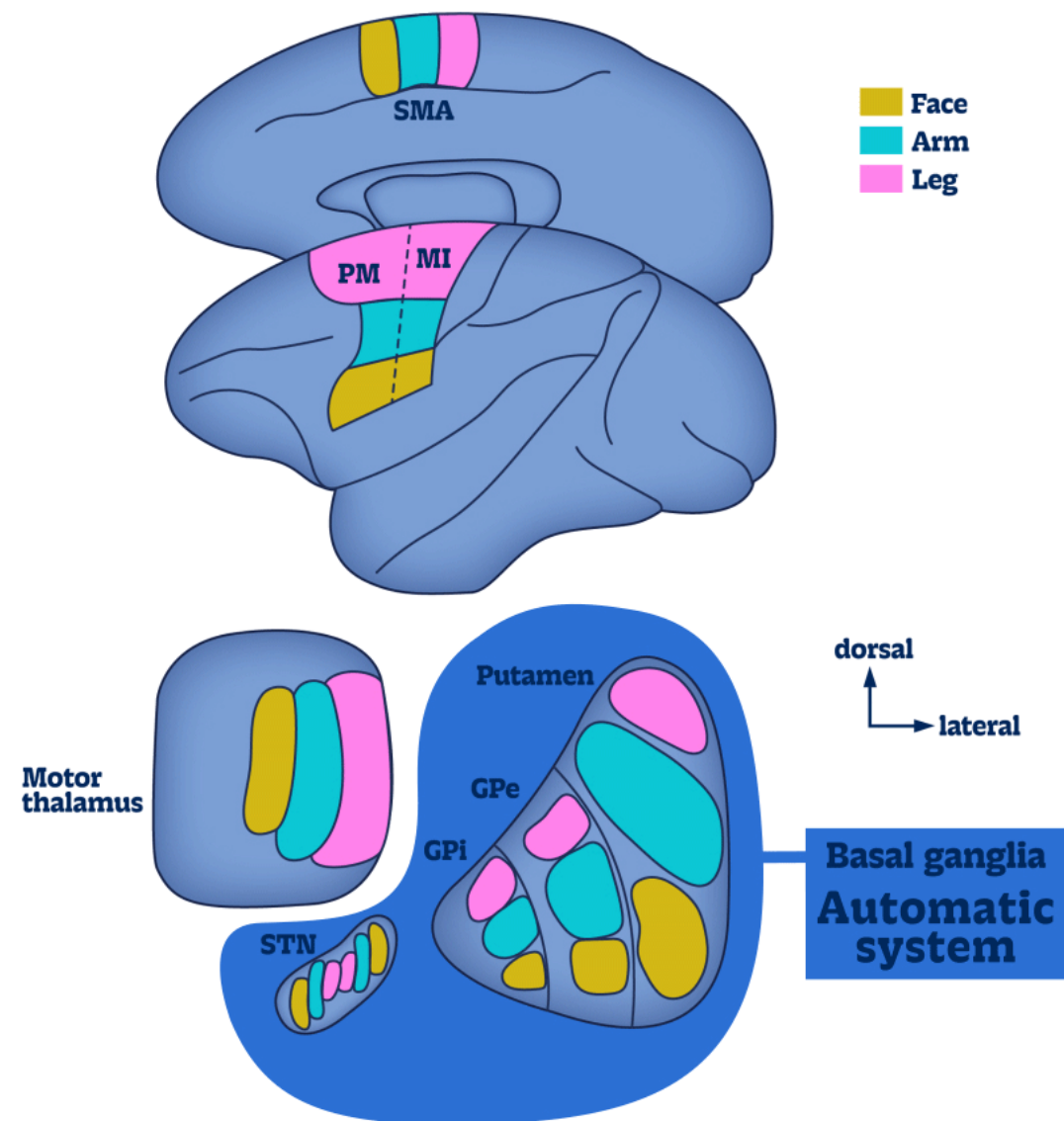
Decoder



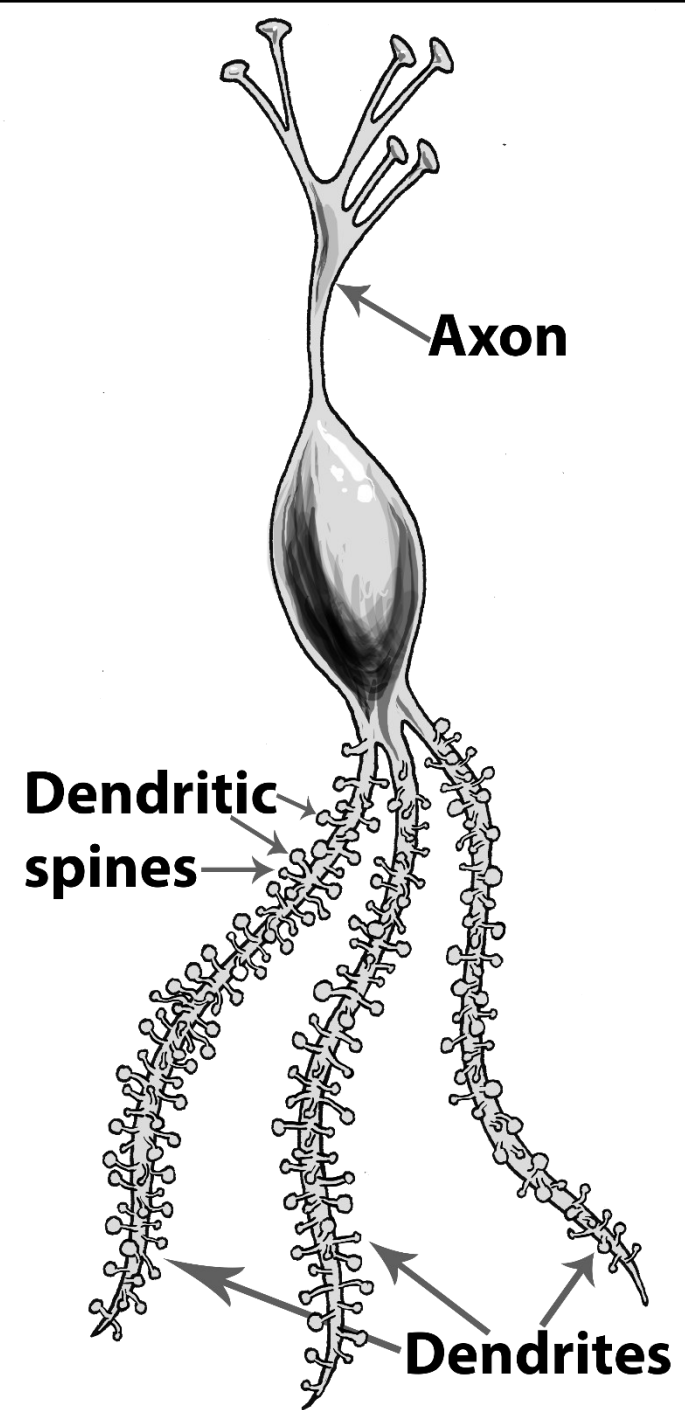
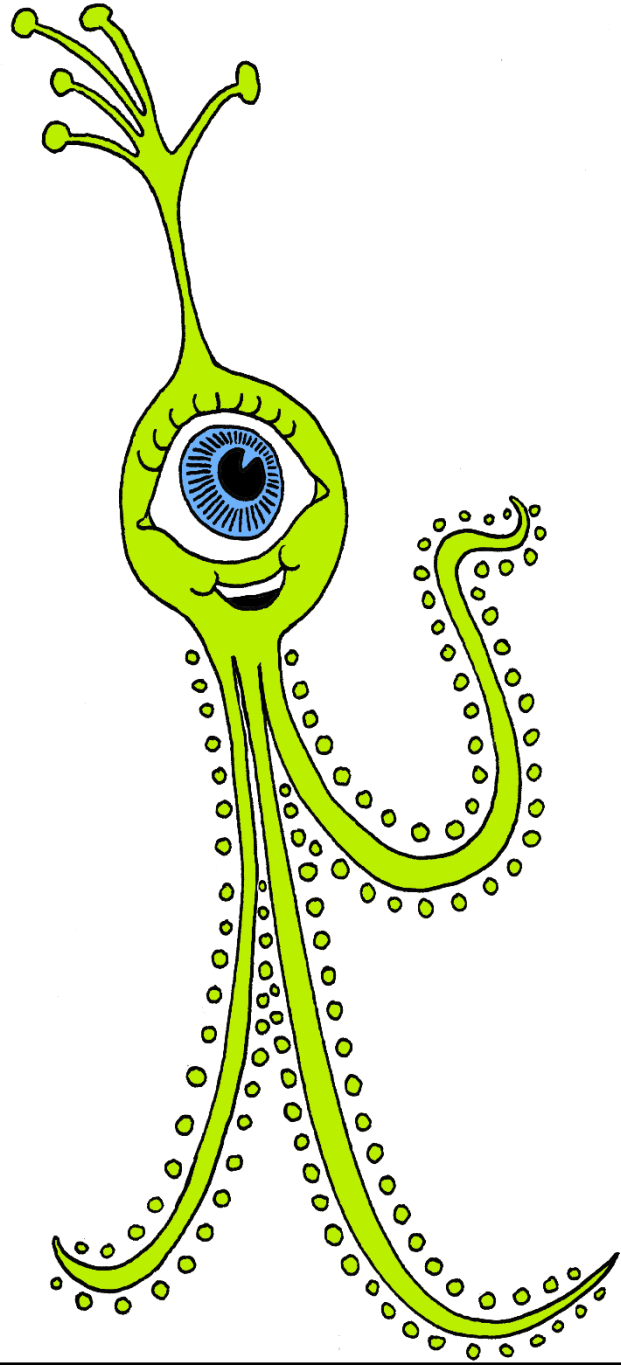
Flow of information through transformers in AI

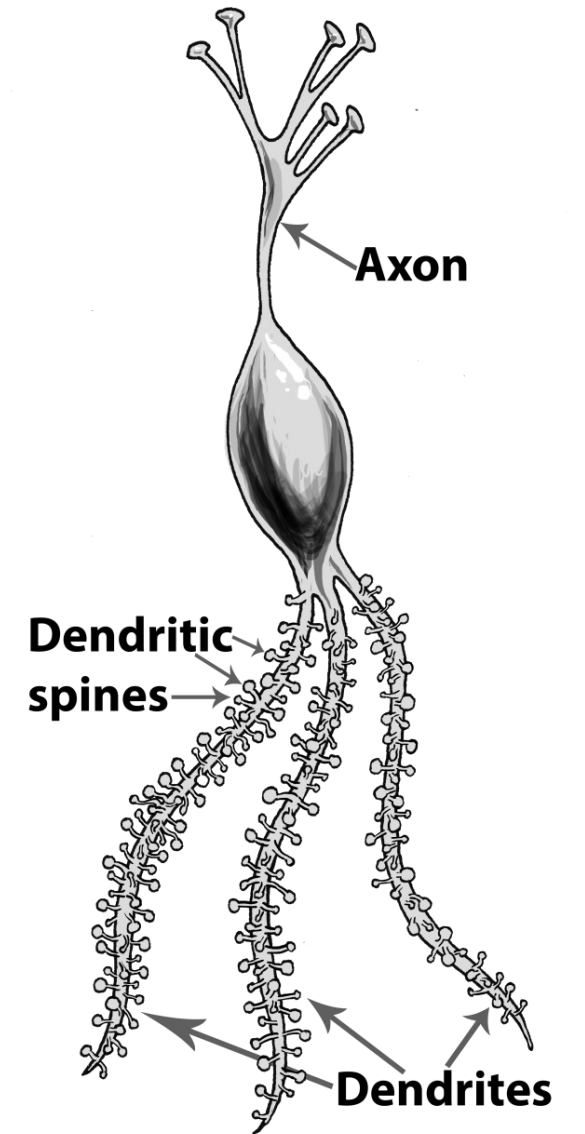
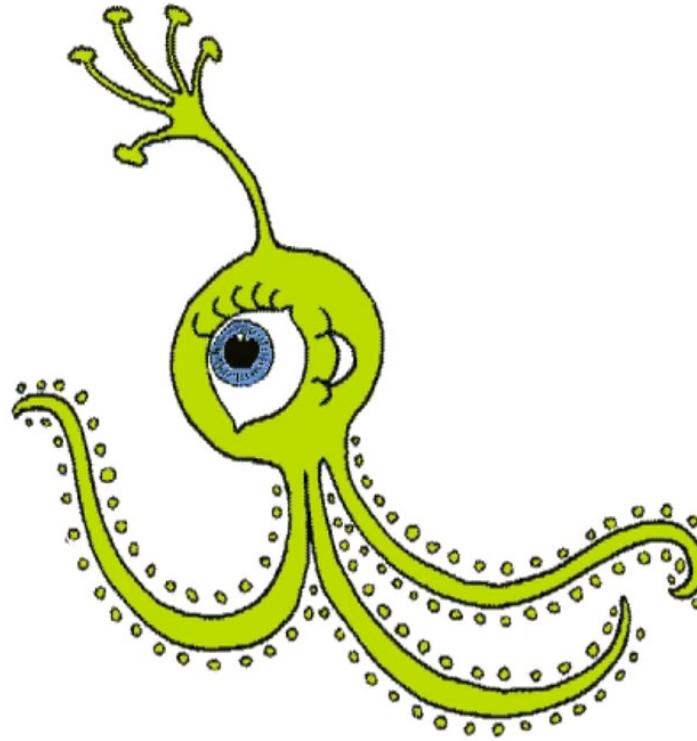
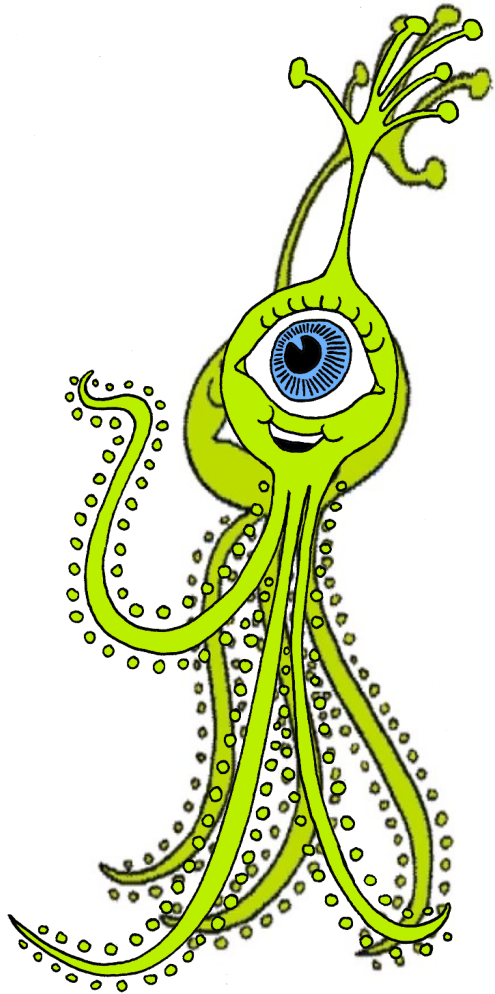


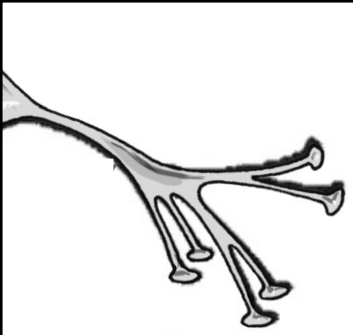
Flow of information in the brain



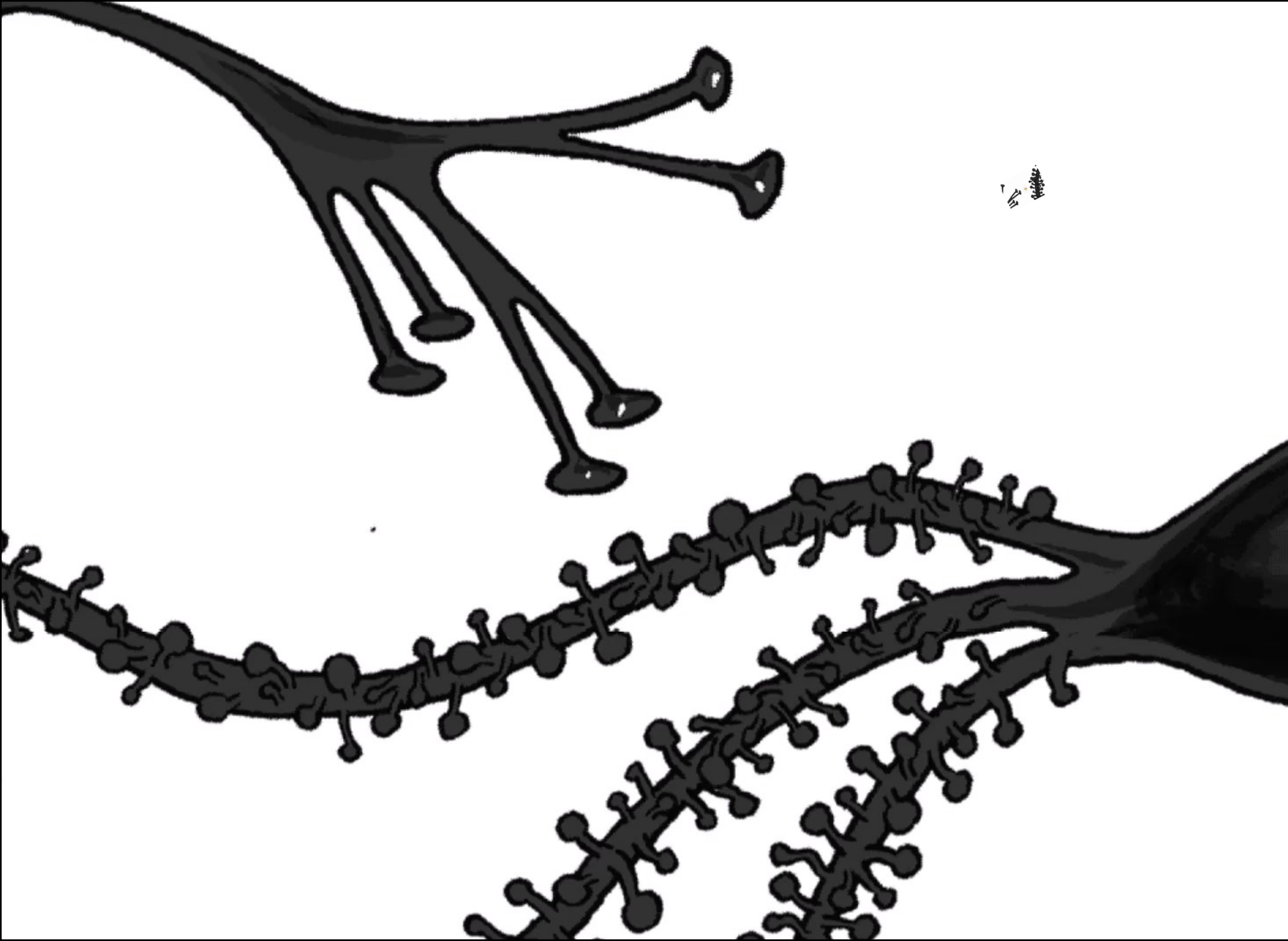






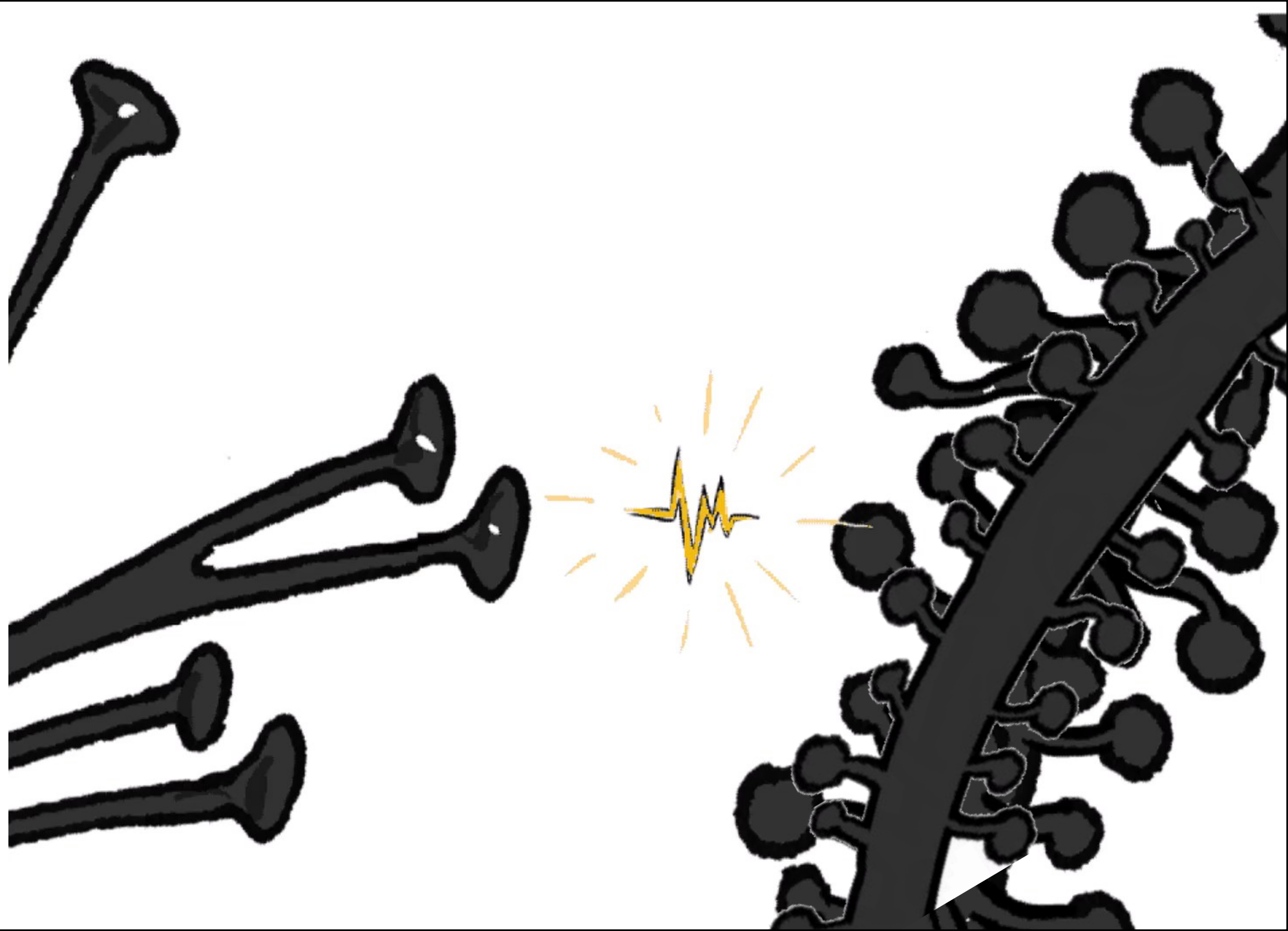


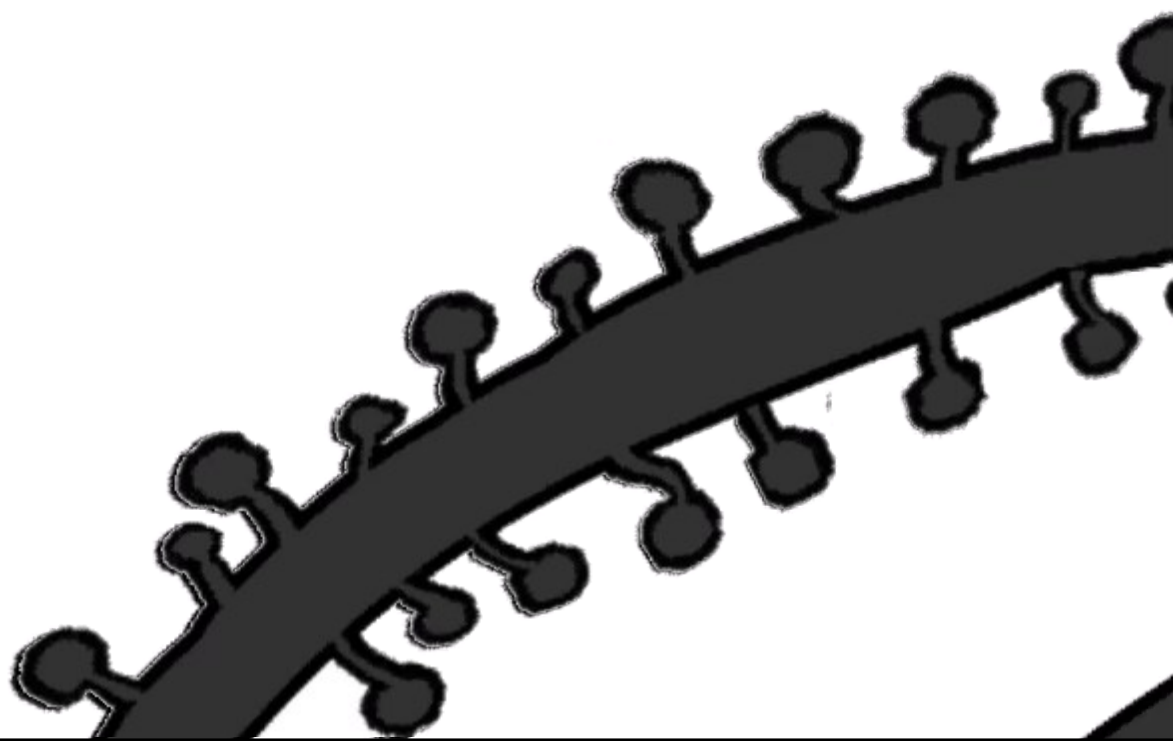
Neurons
send
signals

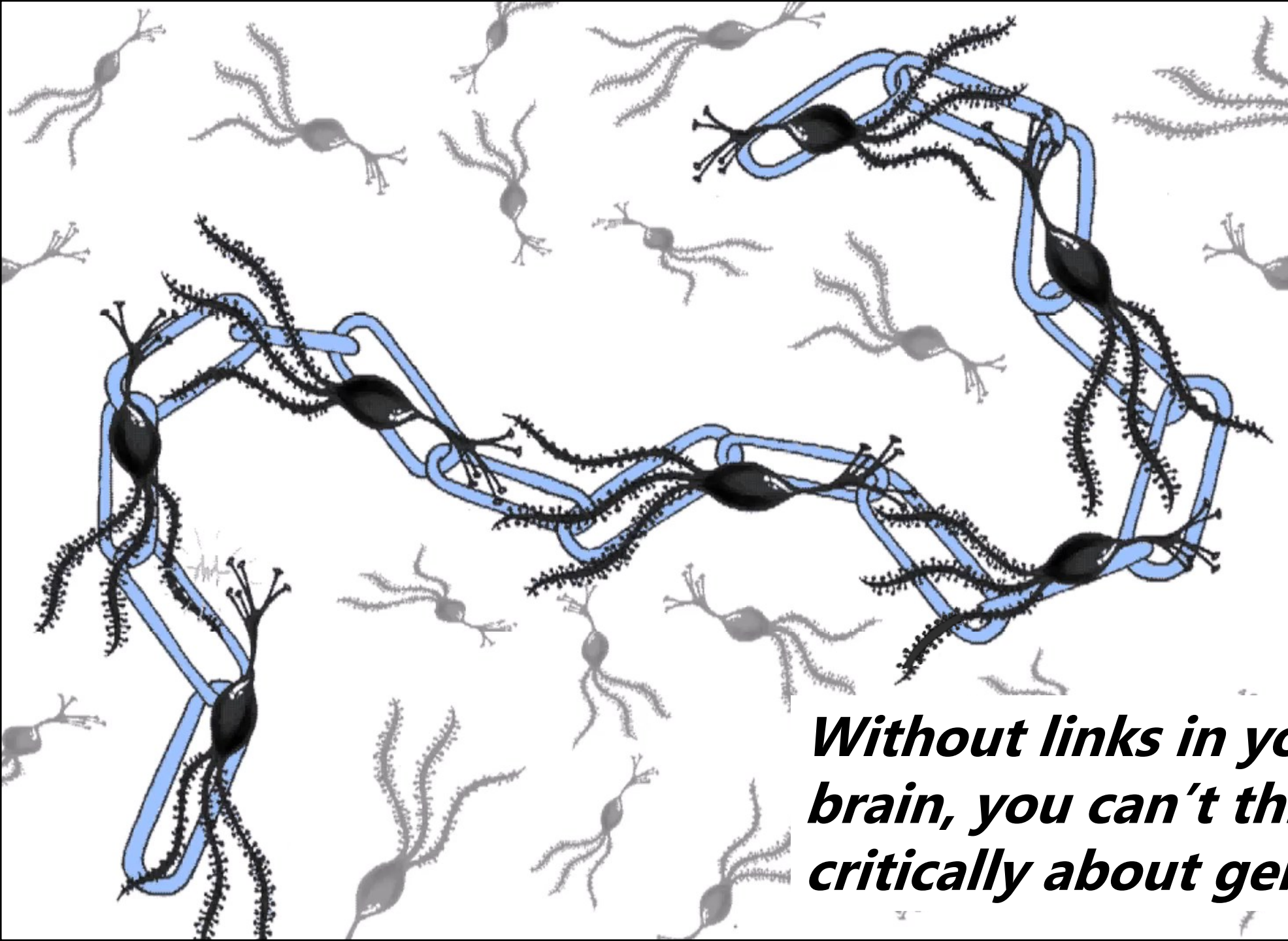


Neurons create
sets of links
when you learn
something.

Connections
strengthen
with practice







***Without links in your own
brain, you can't think
critically about genAI!***

Ray M. Dolby

3 June 1957

The Scientist and His Scientific Method

The scientist, through years of mental development, evolves within himself an operational technique which is designed to eliminate errors of irrational thinking. Such a method, a real necessity in the complexity of today's technology, has long been recognized as the easiest, surest, and fastest route to the solution of a scientific problem.

Francis Bacon's awareness of the need for better techniques in thinking is demonstrated in the "Novum Organum." Similarly, Newton recognized the essential features of logic in his "Rules of Reasoning in Philosophy," and, along with others, isolated the mechanics of scientific thinking, concluding that one must:

- A. be logical and objective
- B. be open-minded
- C. be thorough
- D. be conservative; never be absolutely sure about anything
- E. be willing to discard old ideas if they are no longer useful

The need for a method which assures clear thinking in all endeavors is truly as obvious today as it has ever been. And yet, what does the scientist do with this talent, developed only by considerable study and self-discipline, as soon as he leaves the laboratory? It is forgotten--left behind with his smock and his slide rule.

RAY M. DOLBY, 1957 · AGE 24

***Without links in your own
brain, you can't think
what YOU don't yet know well.
critically about genAI!***

Stanford | University Libraries



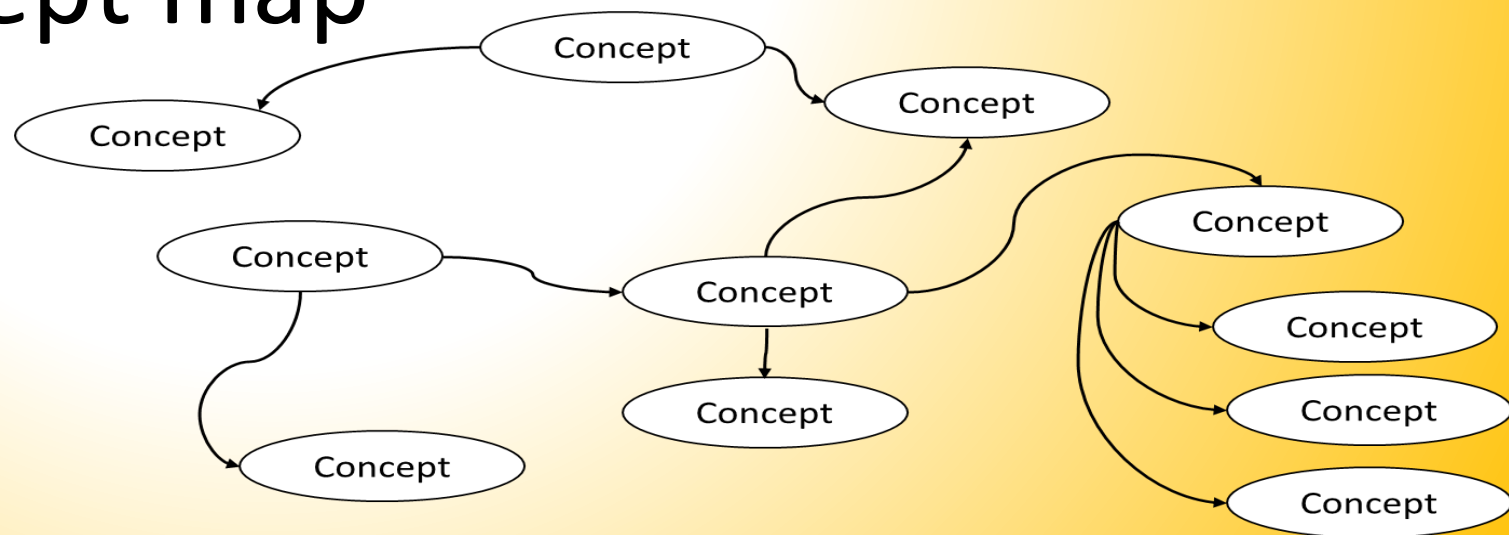
Archival Collections at Stanford

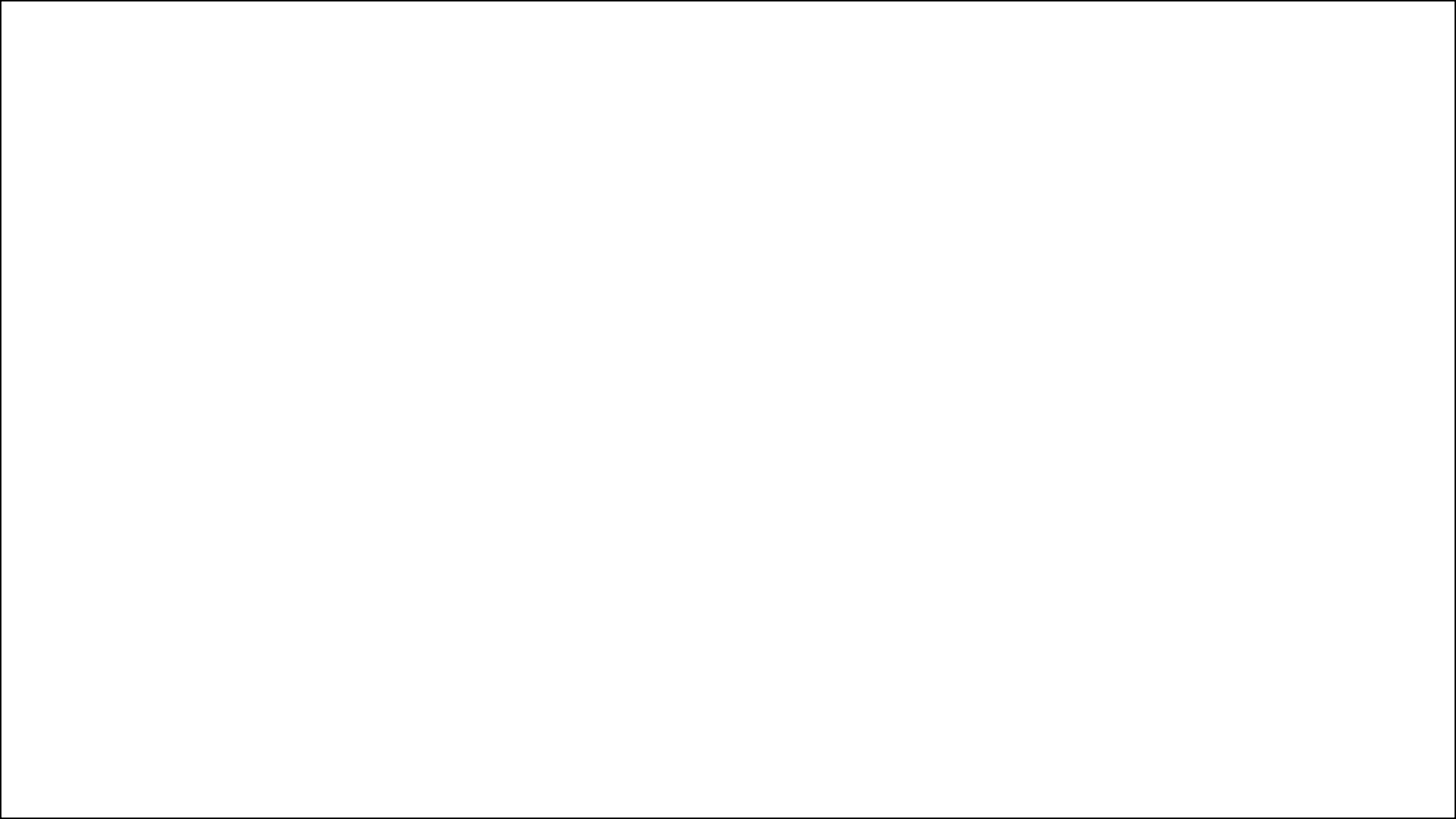


Ray Dolby papers, [c. 1940s - 2000s]

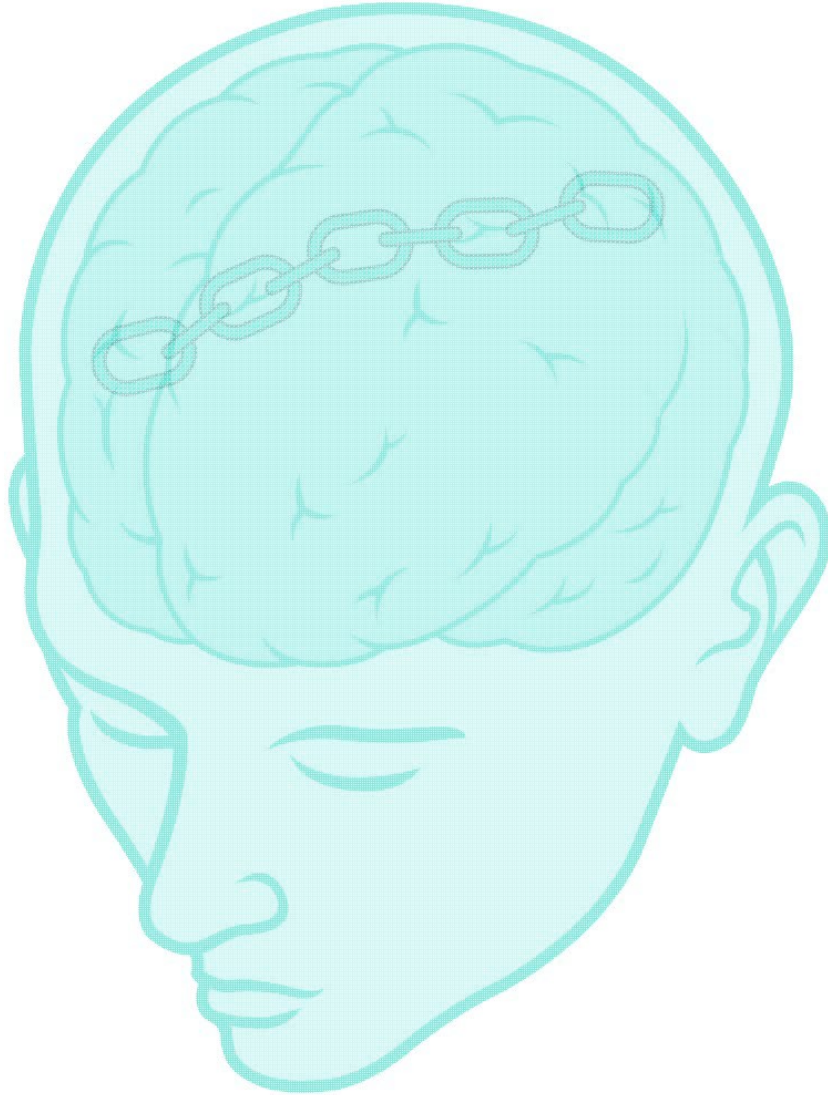
What is the most powerful technique to help students learn most efficiently?

- Reread
- Highlight or underline
- Retrieval practice (“recall”)
- Create a concept map

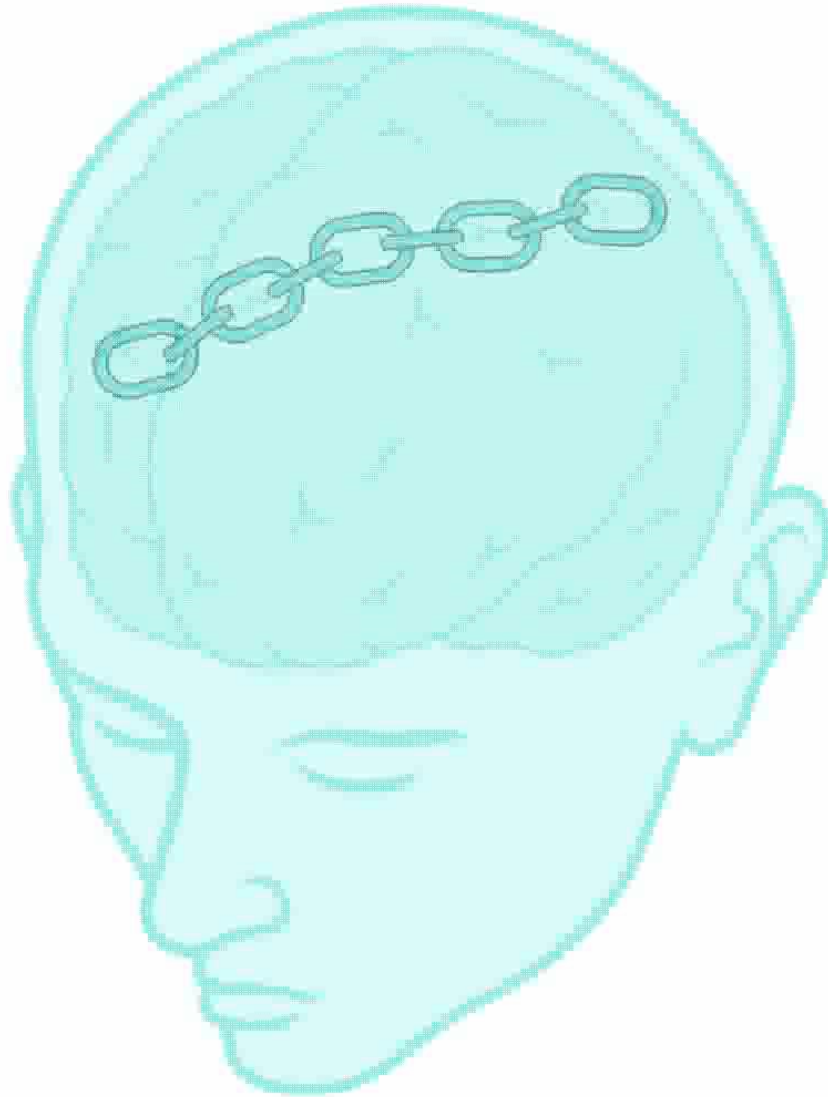




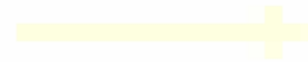
Retrieval Practice



Retrieval Practice



Initial learning



Mapping

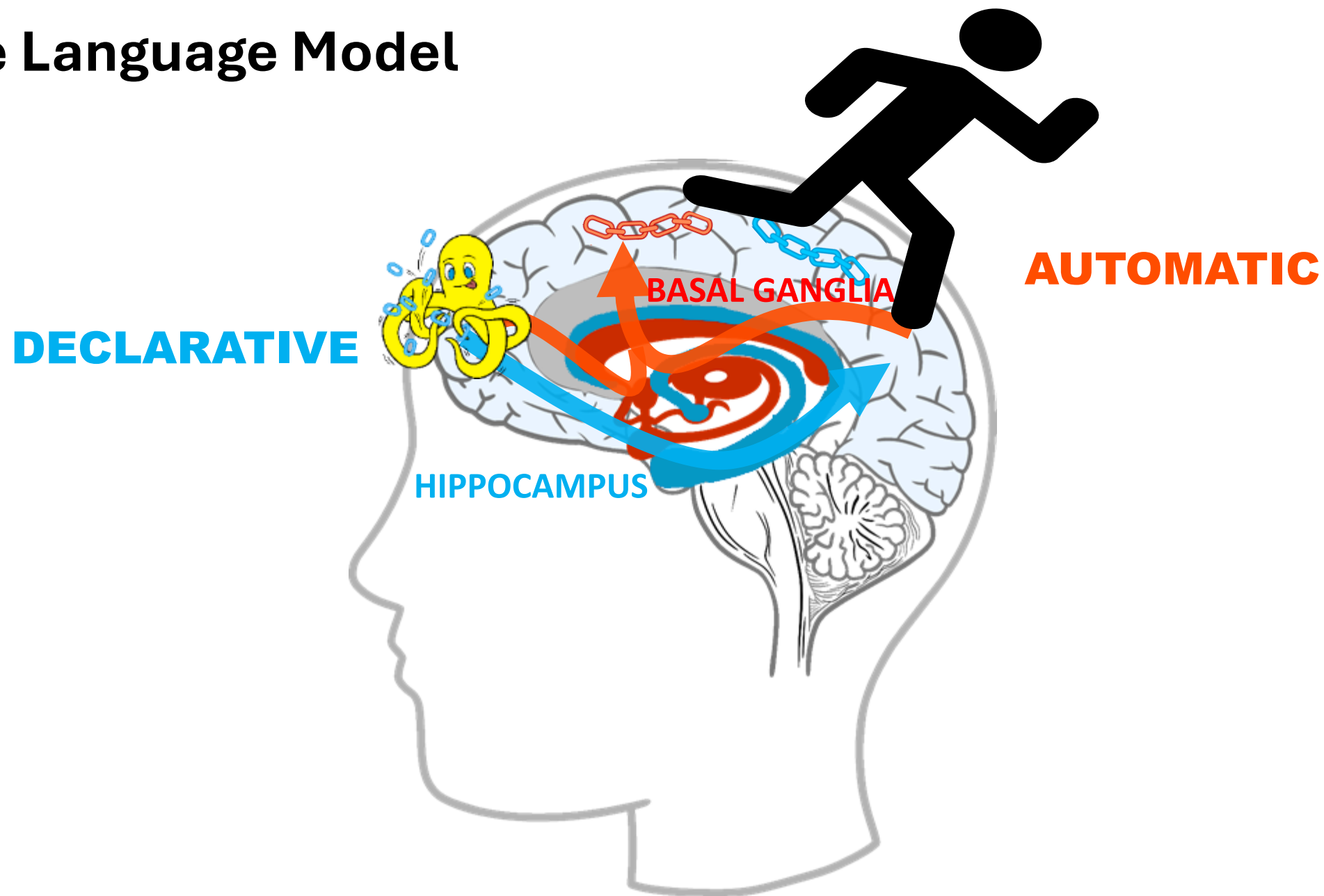
. Blunt

activities that encourage elaborative studying
practice retrieving and reconstructing knowledge
cticing retrieval produces greater gains in memory
cent mapping. The advantage of retrieval practice

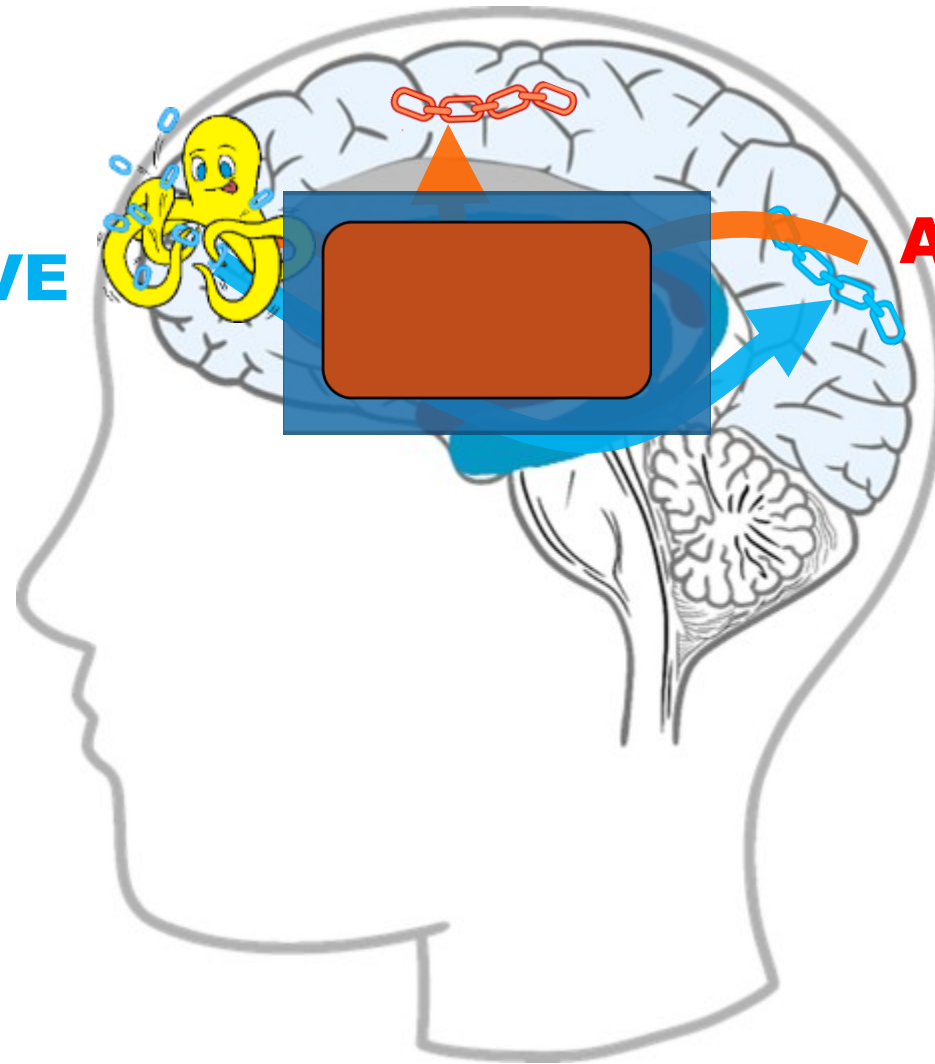
AI shows *But I'm the only one who KNOWS!*



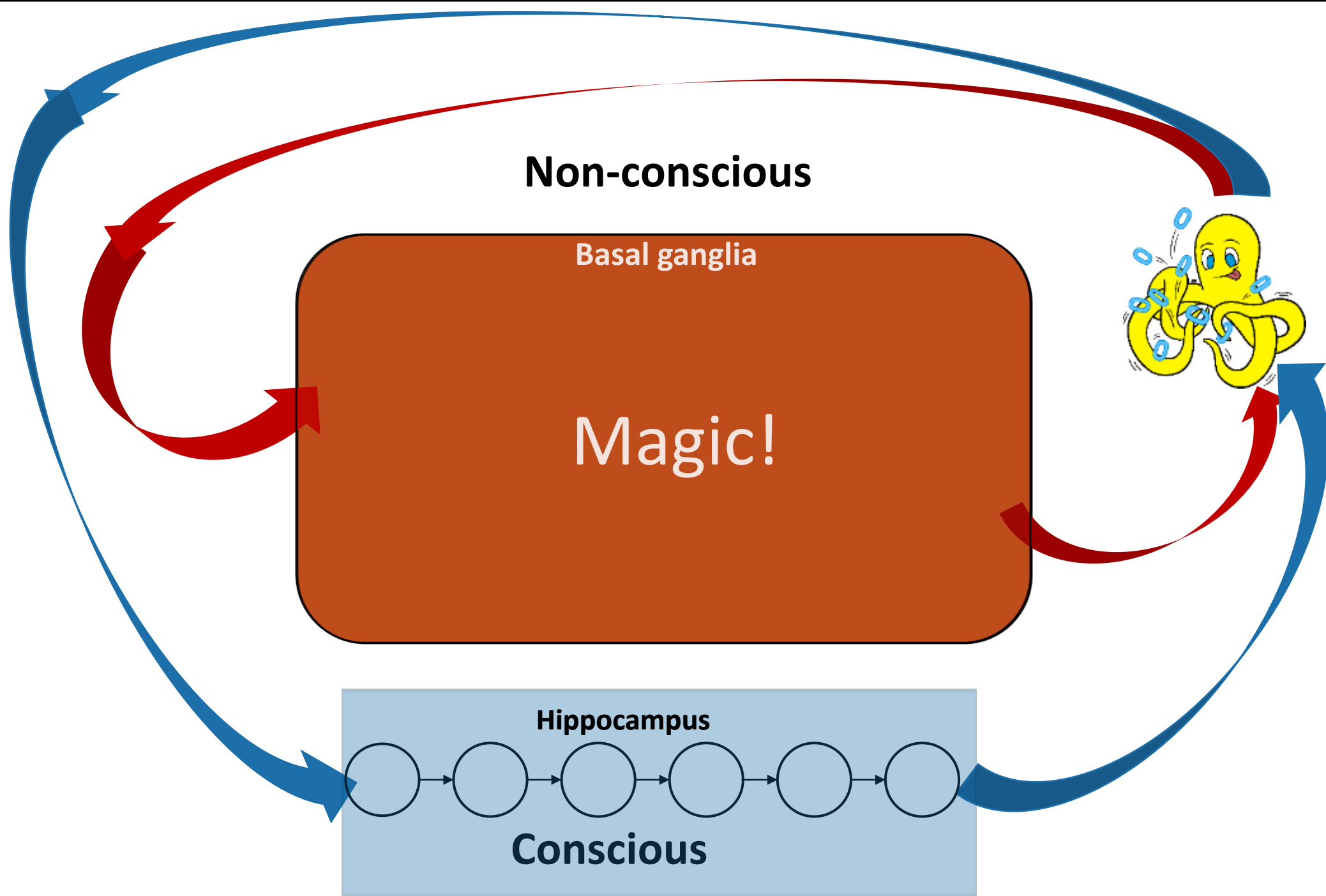
Large Language Model



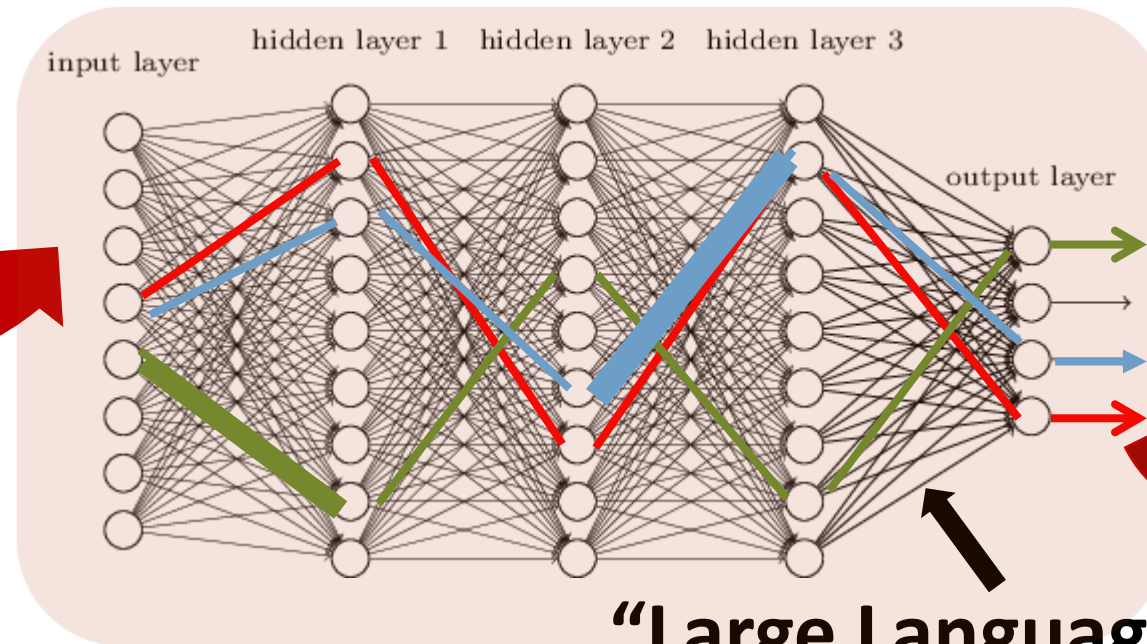
DECLARATIVE



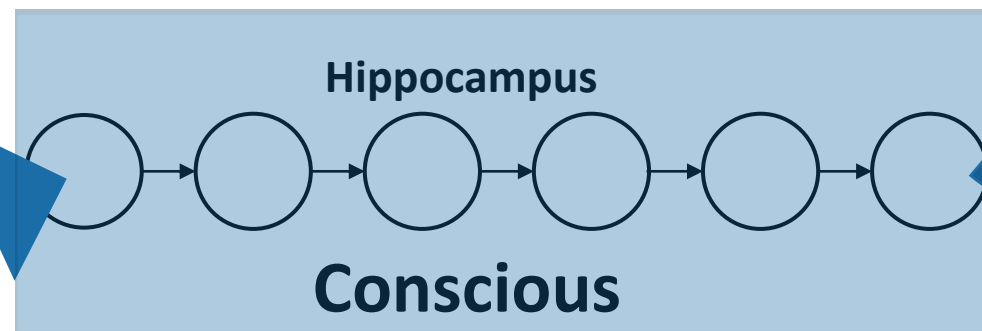
AUTOMATIC



Non-conscious



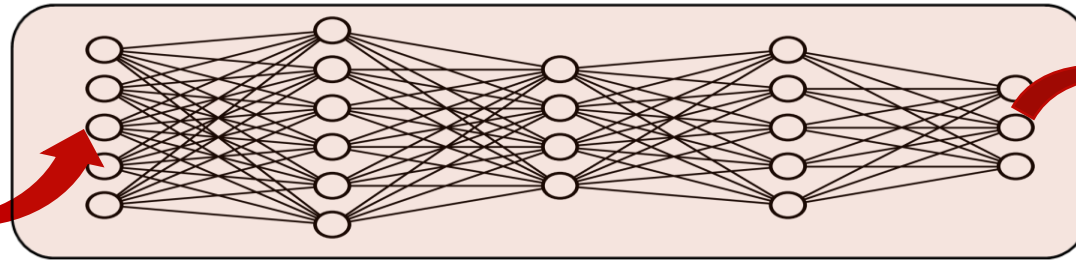
"Large Language Model"



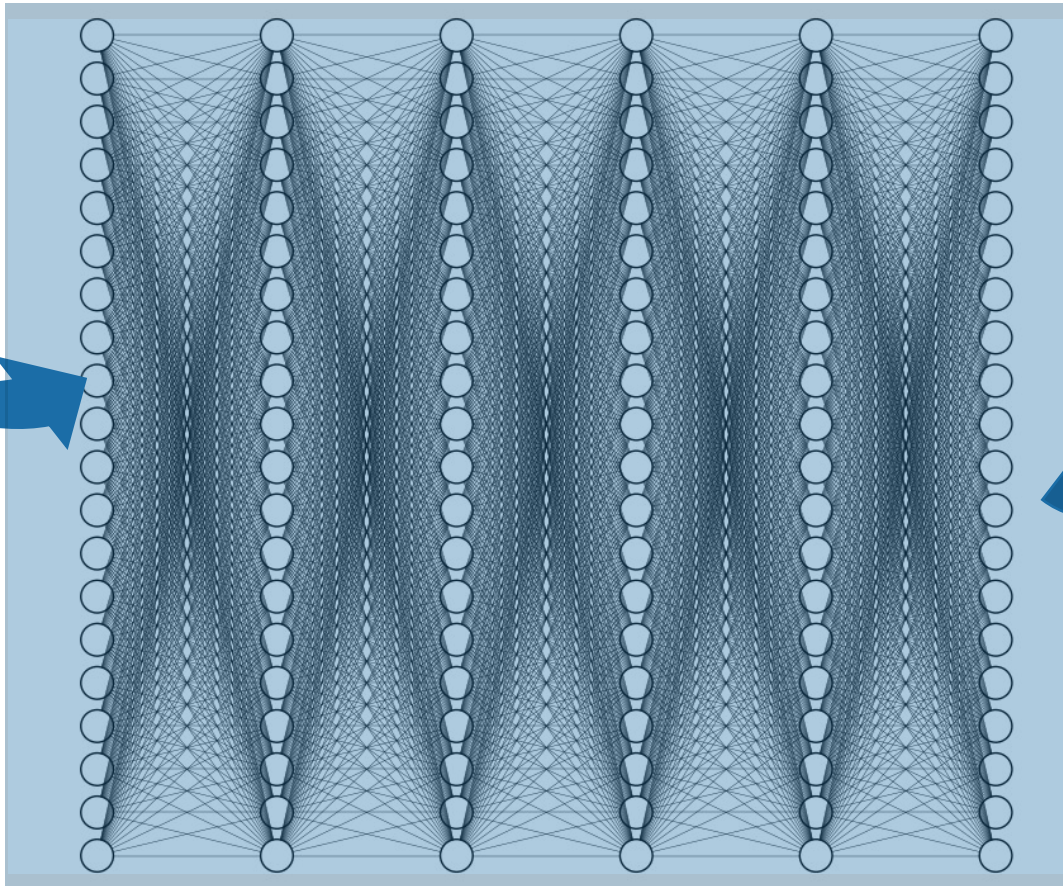
Conscious

Basal ganglia

Non-conscious



“Grokking”

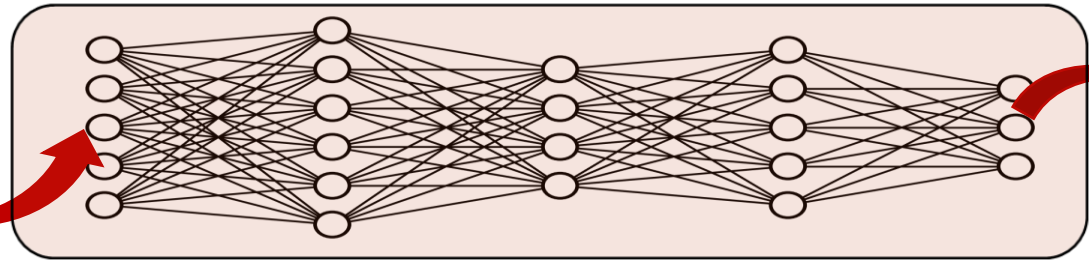


Hippocampus

Conscious

Basal ganglia

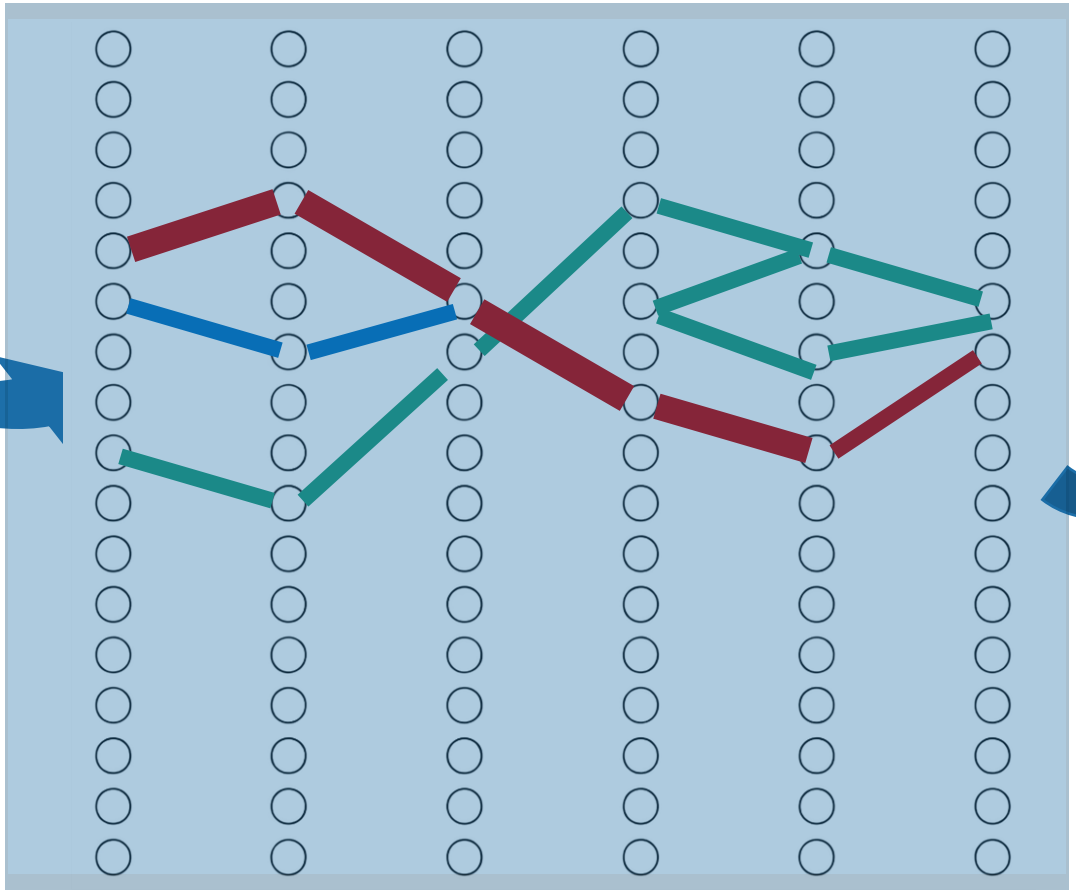
Non-conscious



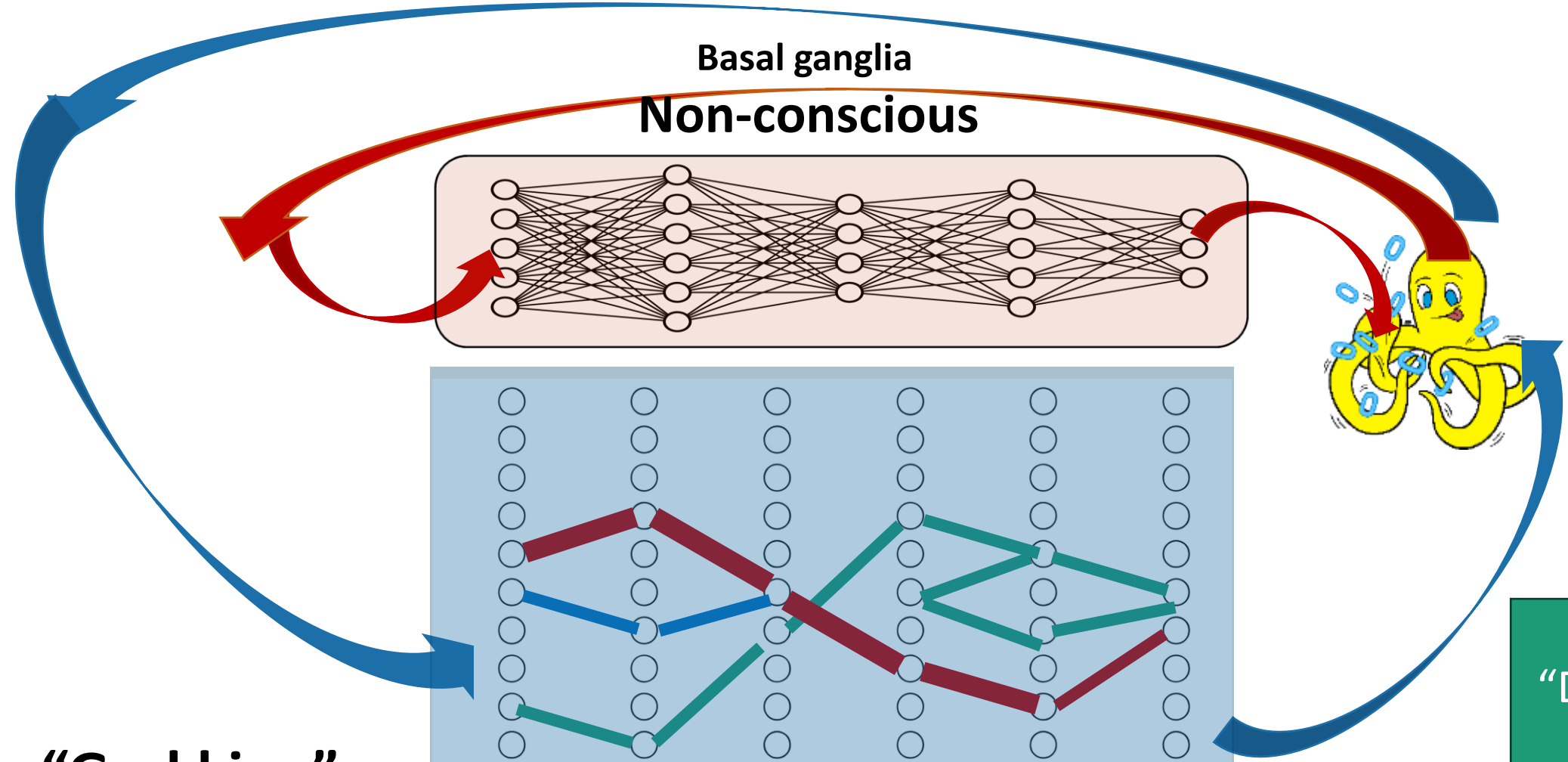
“Distillation”

Hippocampus

Conscious

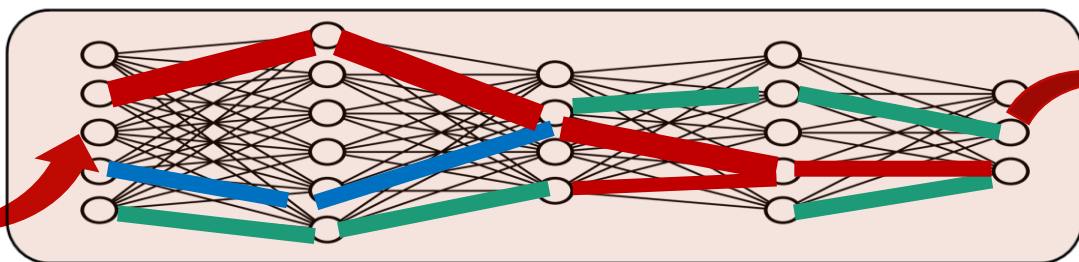


“Grokking”



Basal ganglia

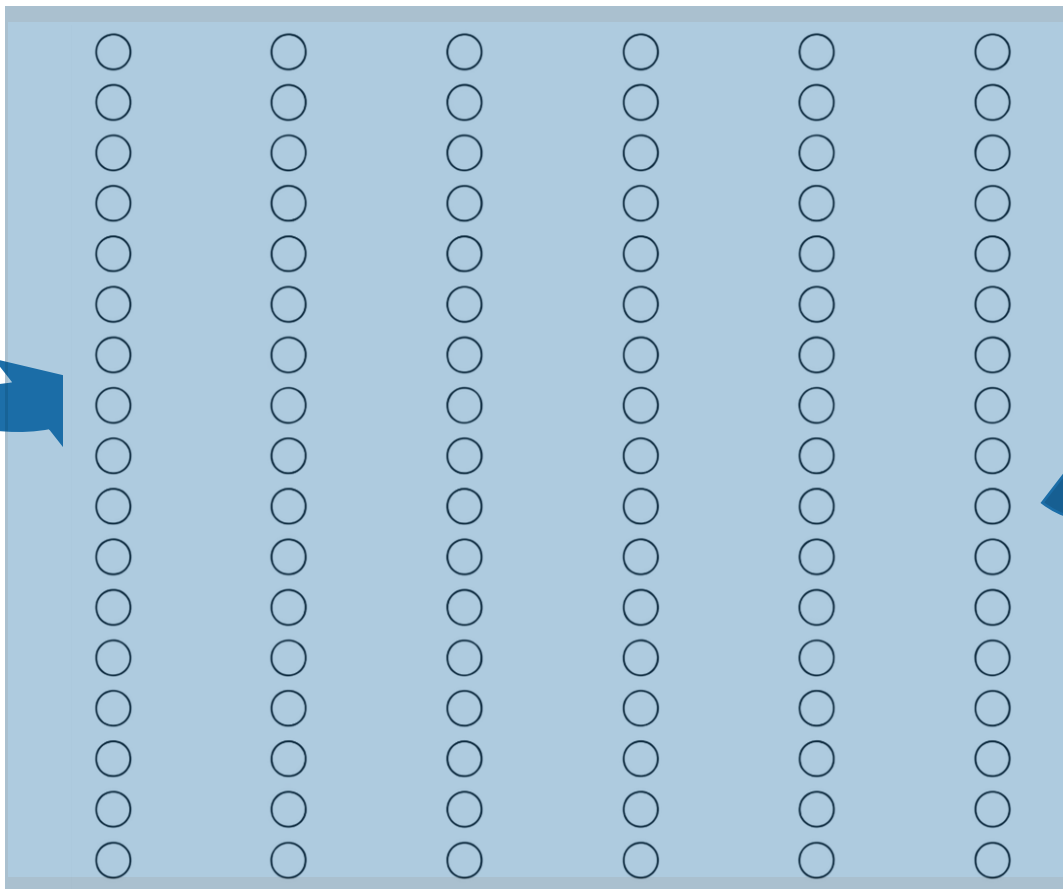
Non-conscious



“Distillation”



“Grokking”



Hippocampus

Conscious

(2019)10:4646

Let's look deeper at grokking

<https://doi.org/10.1038/s41467-019-12552-4>

OPEN

The **Eighty Five Percent Rule** for optimal learning

Robert C. Wilson^{1,2*}, Amitai Shenhav^{3,4}, Mark Straccia⁵ & Jonathan D. Cohen⁶

Researchers and educators have long wrestled with the question of how best to teach their clients be they humans, non-human animals or machines. Here, we examine the role of a single variable, the difficulty of training, on the rate of learning. In many situations we find that there is a sweet spot in which training is neither too easy nor too hard, and where learning progresses most quickly. We derive conditions for this sweet spot for a broad class of learning algorithms in the context of binary classification tasks. For all of these stochastic gradient-descent based learning algorithms, we find that the optimal error rate for training is around 15.87% or, conversely, that the optimal training accuracy is about 85%. We demonstrate the efficacy of this 'Eighty Five Percent Rule' for artificial neural networks used in AI and biologically plausible neural networks thought to describe animal learning.

Let's look deeper at grokking

- Power, A., Burda, Y., Edwards, H., Babuschkin, I. & Misra, V. (2022). *"Grokking: Generalization beyond overfitting on small algorithmic datasets."* arXiv:2201.02177.
 - **Original discovery:** neural networks suddenly generalize long after memorizing training data.
- Davies, X., Langosco, L. & Krueger, D. (2023). *"Unifying grokking and double descent."* arXiv:2303.06173.
 - **Three competing patterns** (memorization, fast heuristic, true understanding) with different learning speeds. Math behind the visualization.
- Fedorenko, E., Piantadosi, S. T. & Gibson, E. A. F. (2024). *"Language is primarily a tool for communication rather than thought."* Nature 630, 575–586.
 - **Language network is for communication, not thinking.** Thinking happens in separate brain networks. People with severe aphasia retain math, logic, causal reasoning. Language is always the surface layer.
- Ullman, M. T. (2020). *"The Declarative/Procedural Model: A neurobiologically motivated theory of first and second language."* In B. VanPatten et al. (Eds.), *Theories in Second Language Acquisition* (3rd ed., pp. 128–161). Routledge.
 - **Two memory systems:** hippocampal (declarative—fast, explicit, words and facts) and basal ganglia (procedural—slow, implicit, grammar and skills). Grammar shifts from declarative to procedural with extended practice. Strikingly parallel dynamic to grokking curves.
- Sundaram, S. et al. *"Teaching Models to Teach Themselves: Reasoning at the Edge of Learnability."* arXiv preprint arXiv:2601.18778 (2026).
 - **Models plateau** when problems exceed their learnability frontier. SOAR meta-RL framework: teacher generates synthetic stepping-stone problems, rewarded by student progress on hard datasets. Self-generated curricula unlock learning where direct training fails.

Grokking: From Memorization to Understanding

Training accuracy

ON

Accuracy Over Training dashed = train, solid = test



Grokking: From Memorization to Understanding

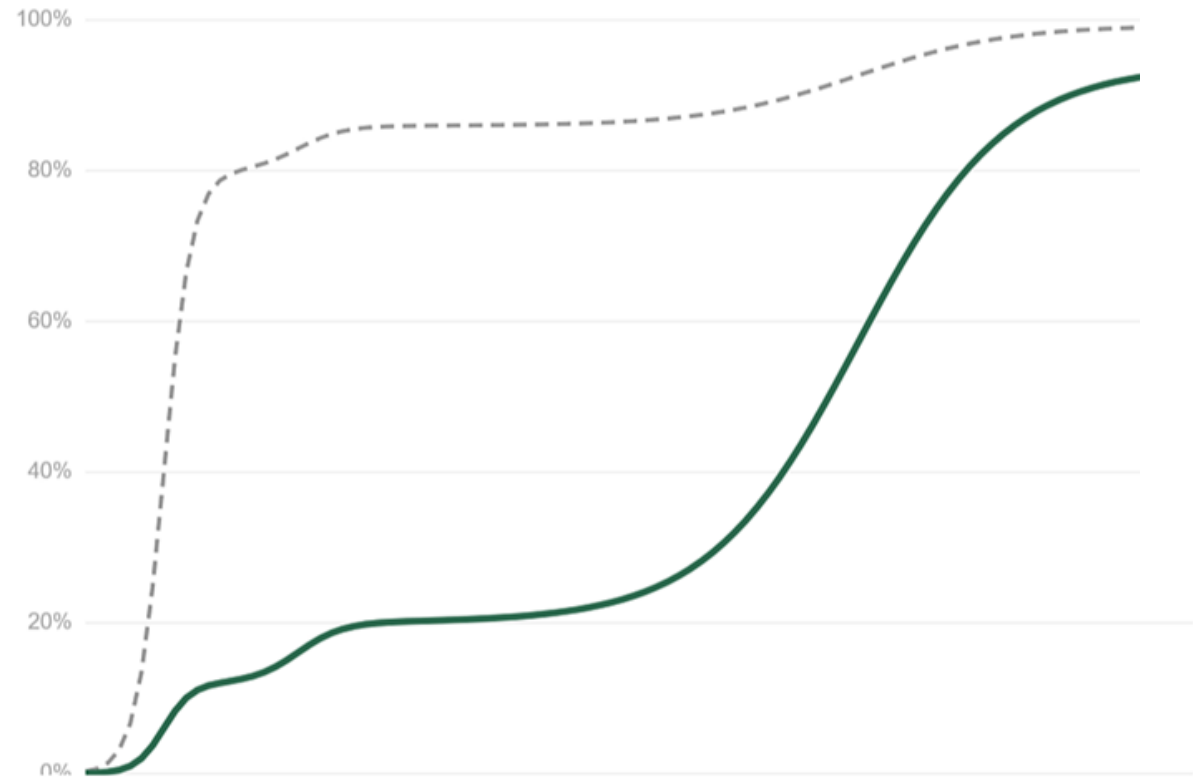
● Training accuracy

ON

● Test accuracy

ON

Accuracy Over Training dashed = train, solid = test



Grokking: From Memorization to Understanding

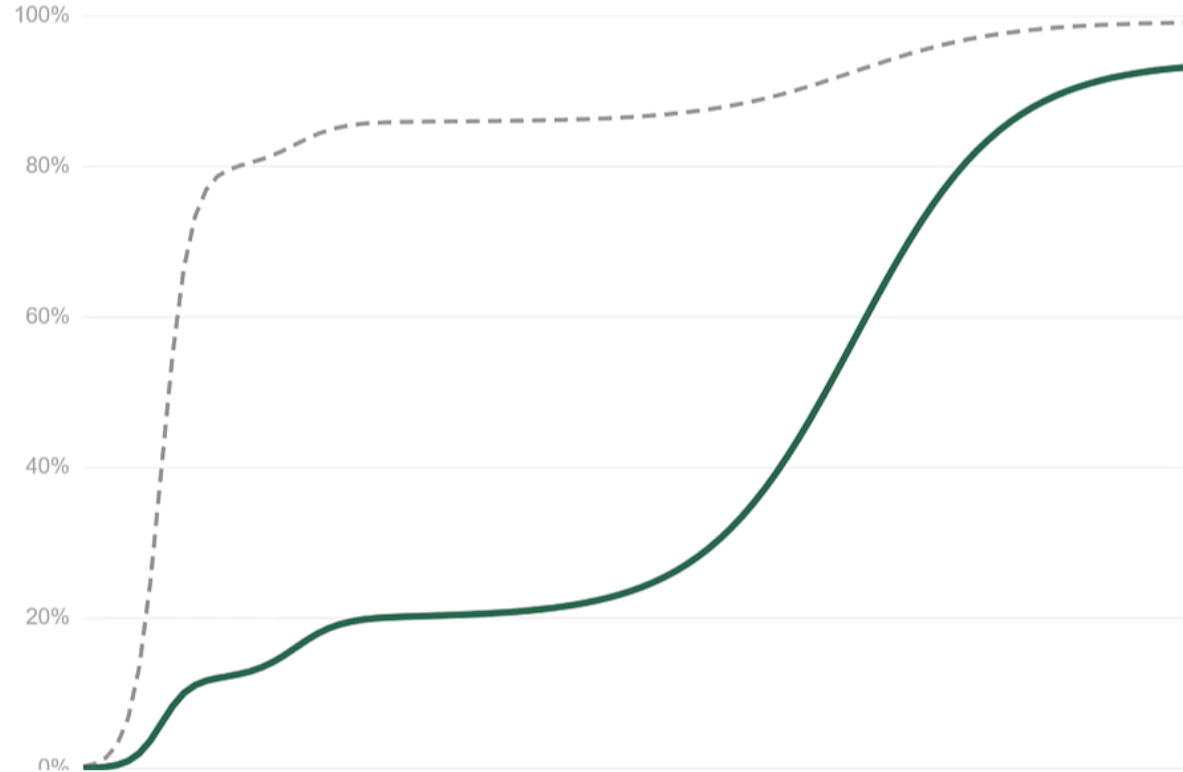
- ☒ Training accuracy ON
- ☒ Test accuracy ON
- ☒ Memorization ON
- ☐ Fast heuristic OFF
- ☐ True understanding OFF

Memorization

"How are you?"

reveal ▶

Accuracy Over Training dashed = train, solid = test



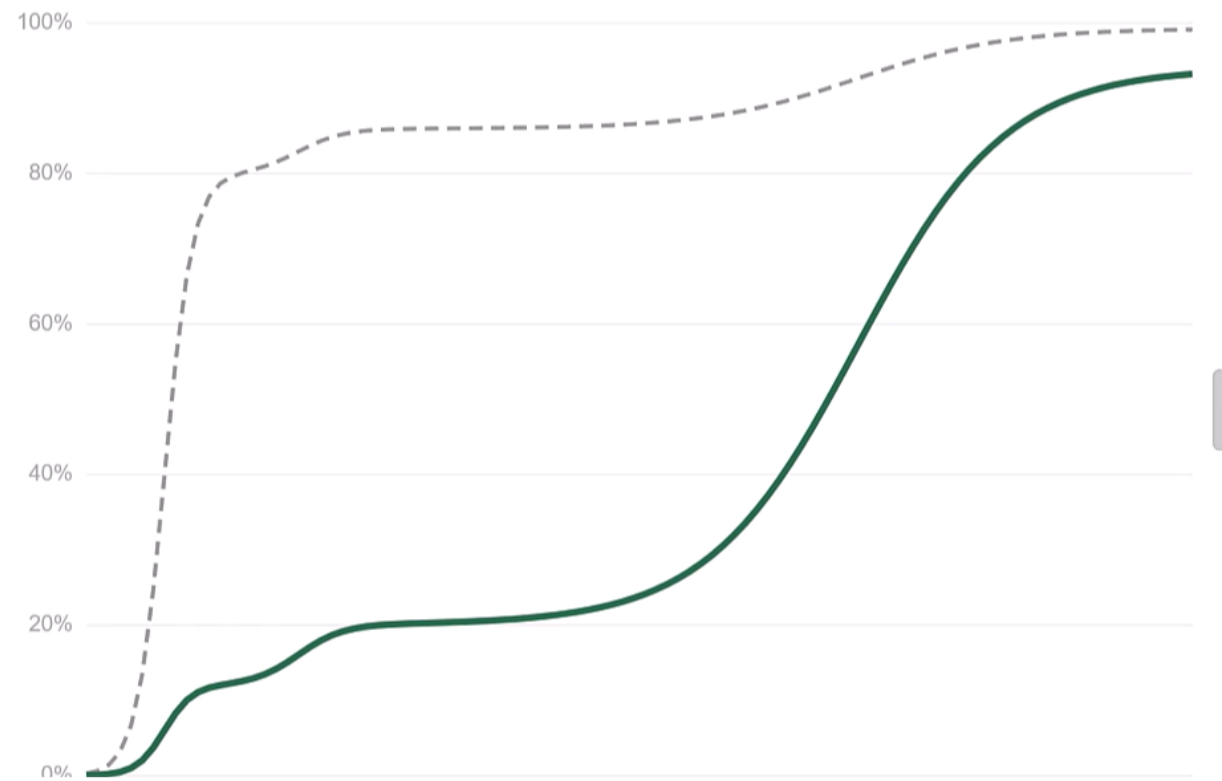
Grokking: From Memorization to Understanding

- ☒ Training accuracy ON
- ☒ Test accuracy ON
- ☒ Memorization ON
- ☐ Fast heuristic OFF
- ☐ True understanding OFF

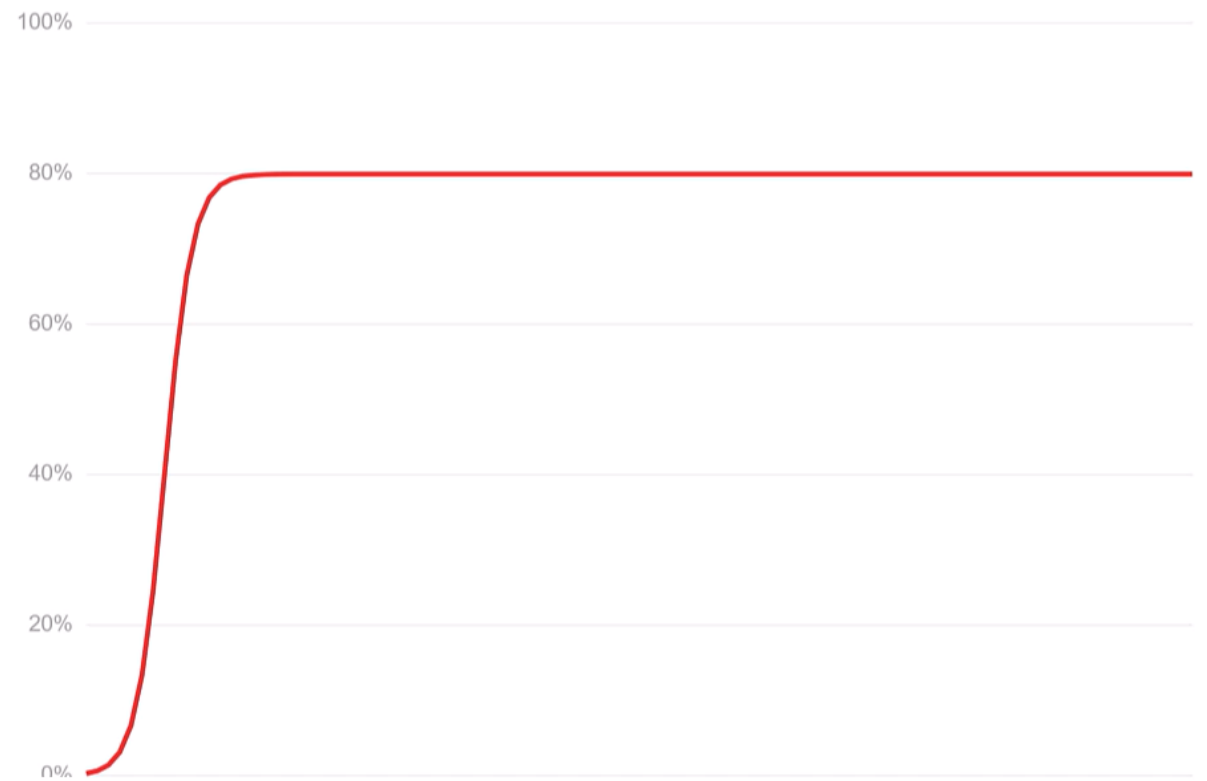
Memorization

"How are you?" *I am fine, thank you*
"How is your mother?" *Huh?*

Accuracy Over Training dashed = train, solid = test



Pattern Strength Over Training what's happening inside the learner?



Grokking: From Memorization to Understanding

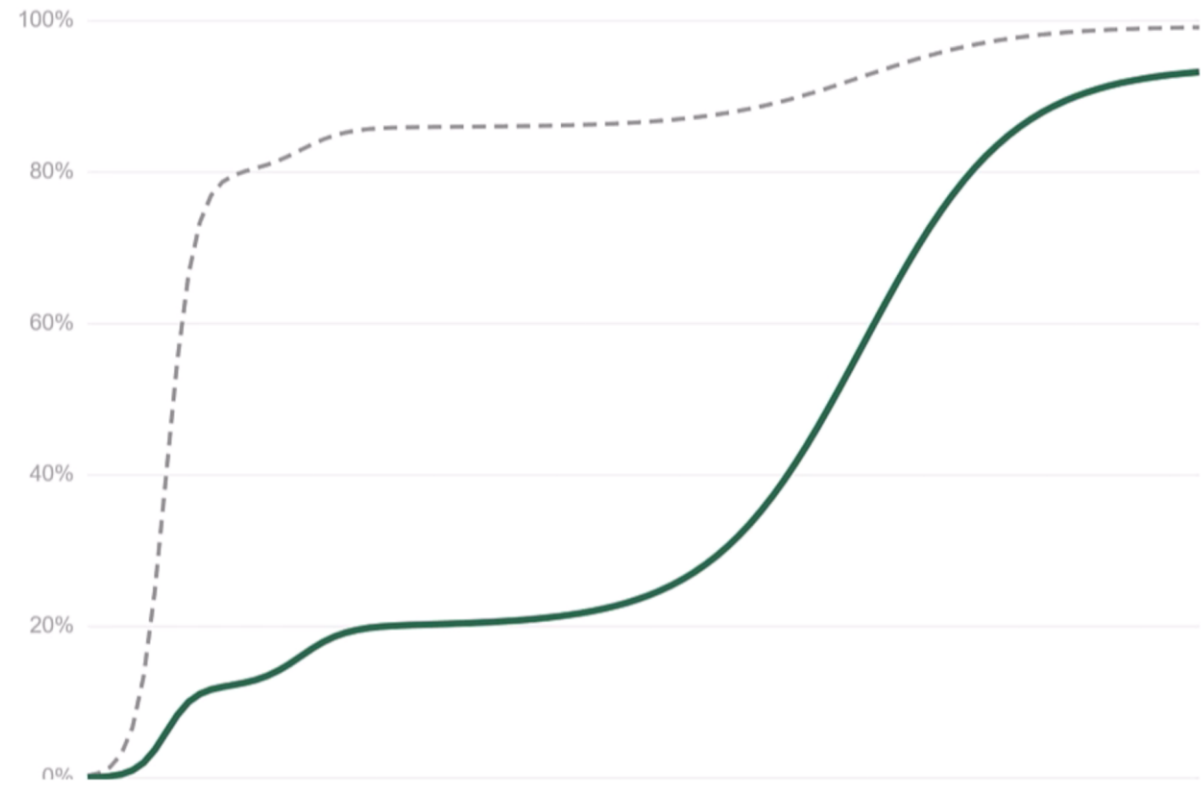
- ☒ Training accuracy ON
- ☒ Test accuracy ON
- ☒ Memorization ON
- ☒ Fast heuristic ON
- ☐ True understanding OFF

Memorization

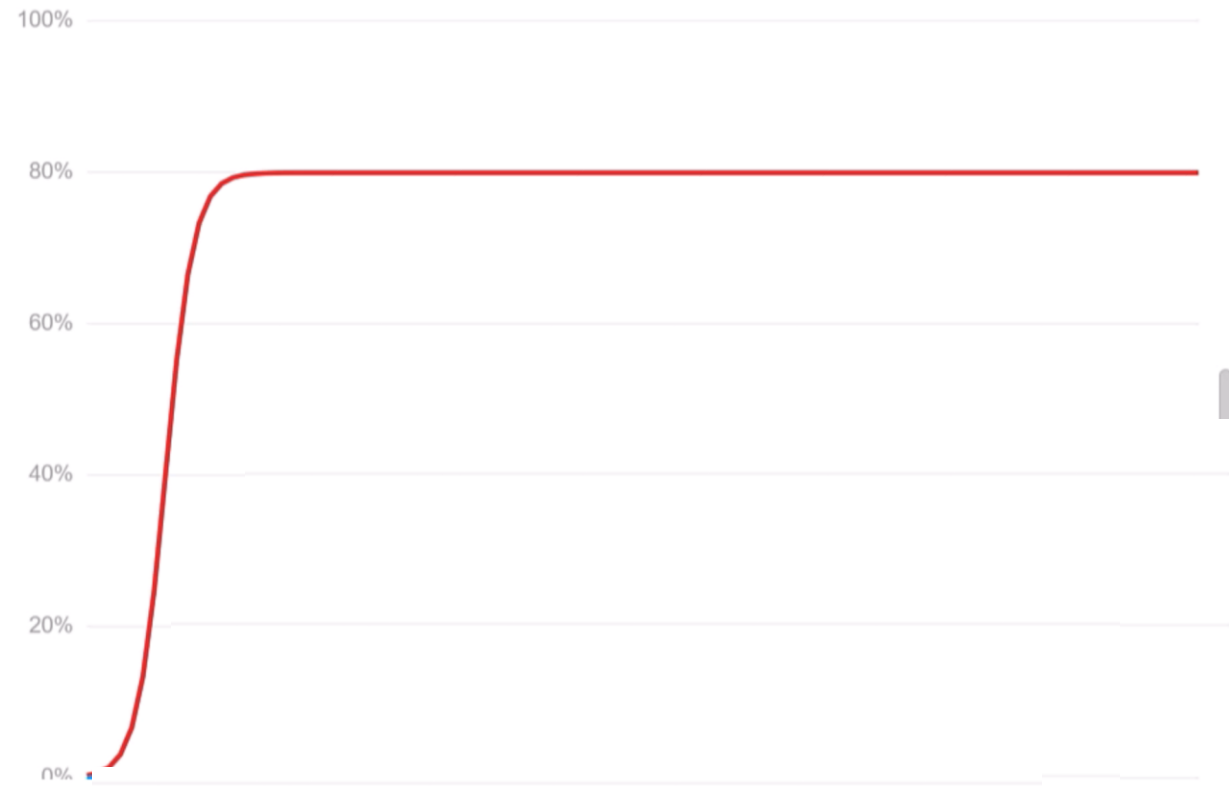
"How are you?" *I am fine, thank you*
"How is your mother?" *Huh?*

Fast Heuristic

Accuracy Over Training dashed = train, solid = test



Pattern Strength Over Training what's happening inside the learner?



Grokking: From Memorization to Understanding

☒ Training accuracy ON

☒ Test accuracy ON

☒ Memorization ON

☒ Fast heuristic ON

☐ True understanding OFF

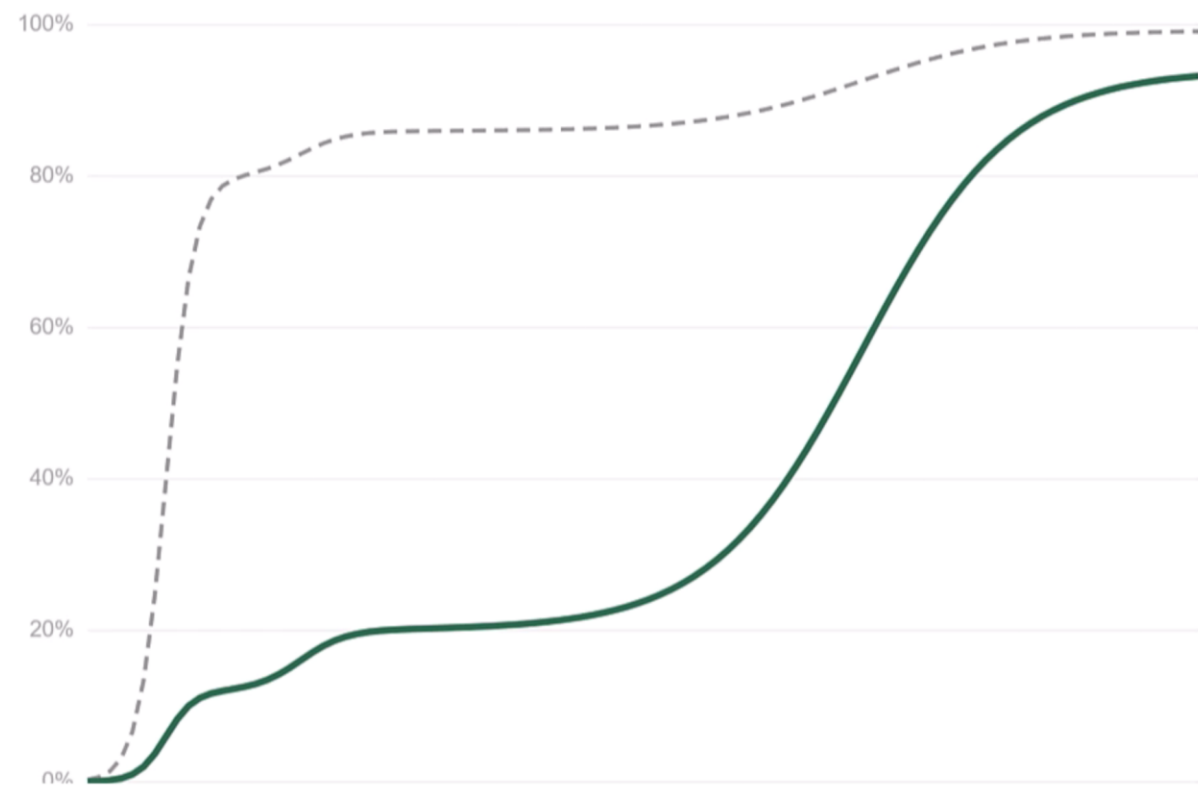
Memorization

"How are you?" *I am fine, thank you*
"How is your mother?" *Huh?*

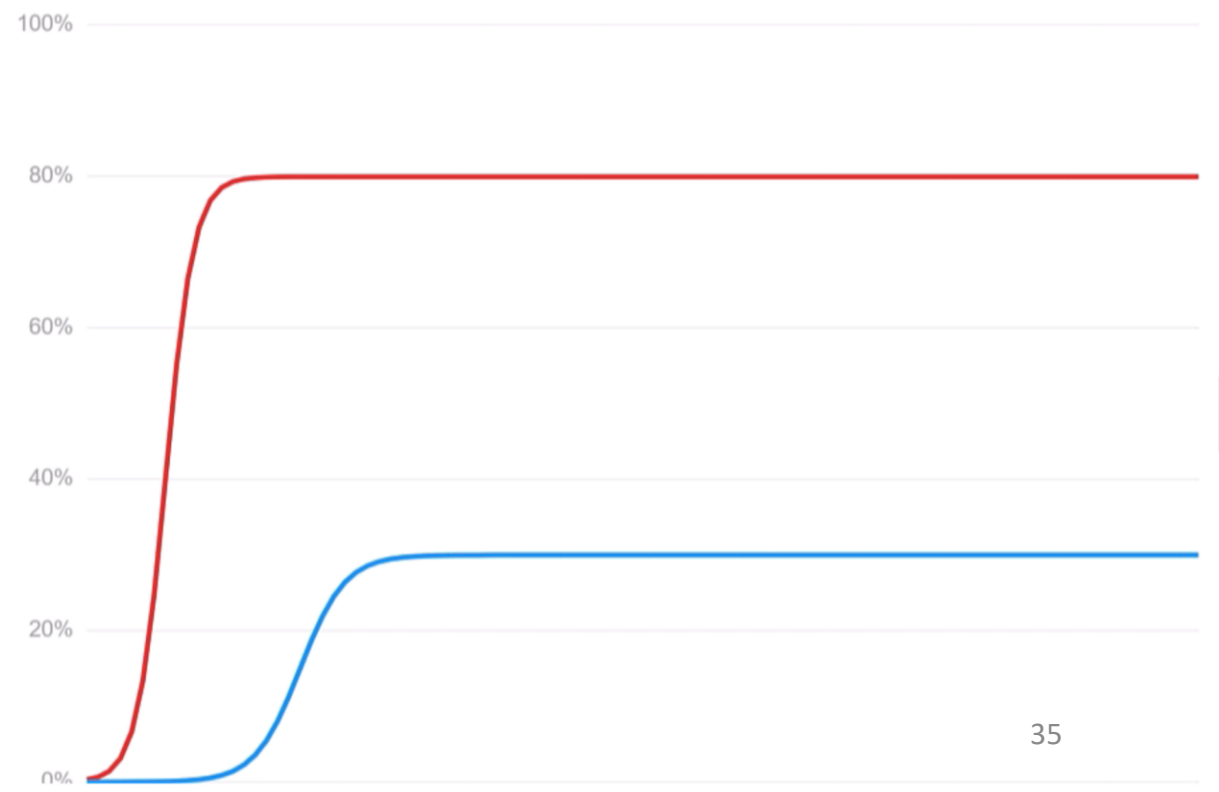
Fast Heuristic

Rule: add -ed for past tense walked, talked ✓
But: goed, runned ✗

Accuracy Over Training dashed = train, solid = test



Pattern Strength Over Training what's happening inside the learner?



Grokking: From Memorization to Understanding

● Training accuracy

ON

● Test accuracy

ON

● Memorization

ON

● Fast heuristic

ON

● True understanding

OFF

Memorization

"How are you?" *I am fine, thank you*
"How is your mother?" *Huh?*

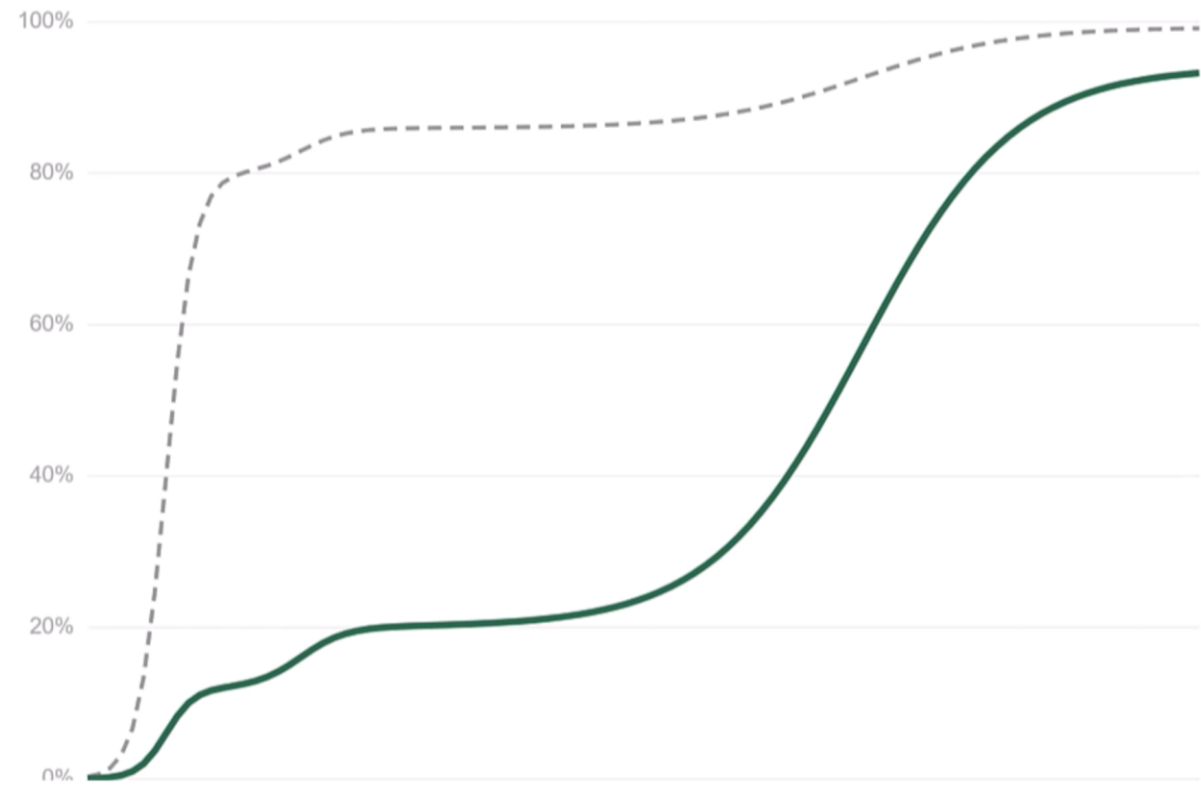
Fast Heuristic

Rule: add *-ed* for past tense walked, talked ✓
But: *goed, runned* ✗

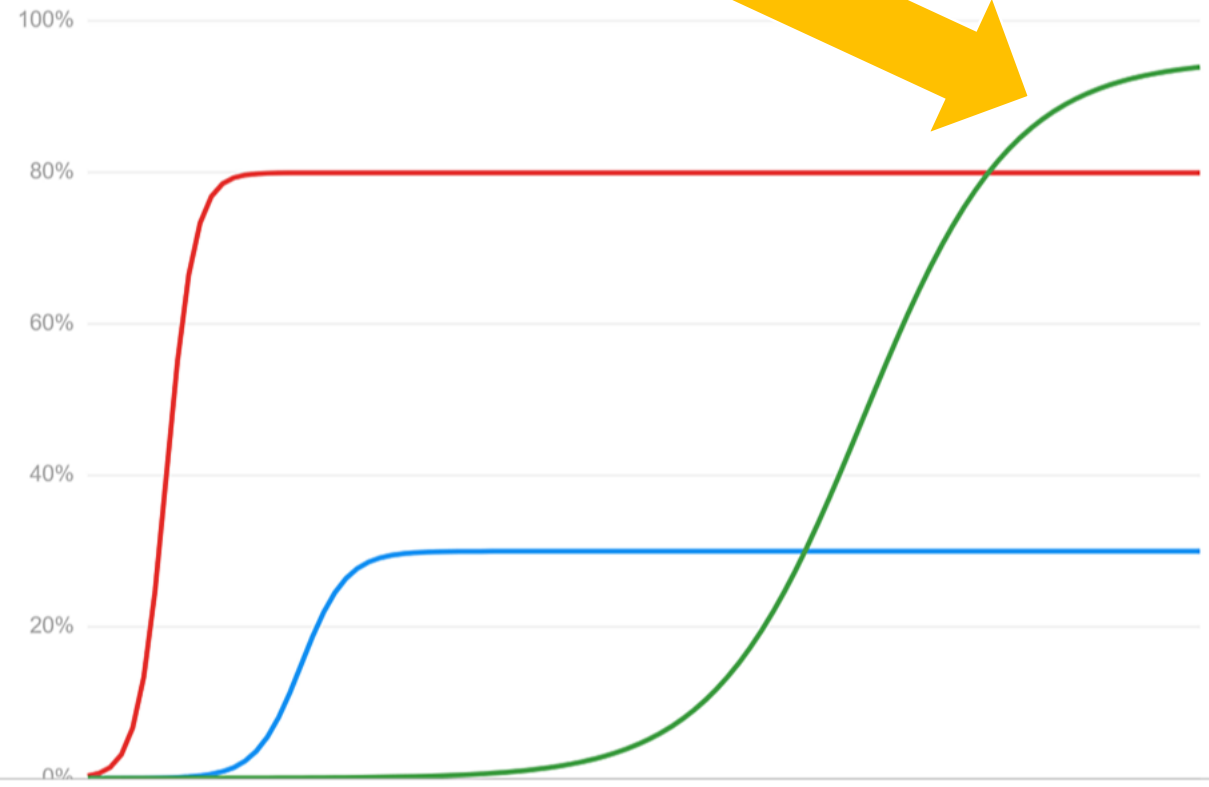
True Understanding

Handles anything new—even sentences never heard before

Accuracy Over Training dashed = train, solid = test



Pattern Strength Over Training what's happening is



Grokked!



Grokking: From Memorization to Understanding

☒ **Training accuracy** ON

● **Test accuracy** ON

● Memorization ON

● **Fast heuristic** ON

● **True understanding** ON

Well-scaffolded Teaching

100%

Memorization

"How are you?" *I am fine, thank you*

"How is your mother?" *Huh?*

Fast Heuristic

Rule: add -ed for past tense walked, talked ✓

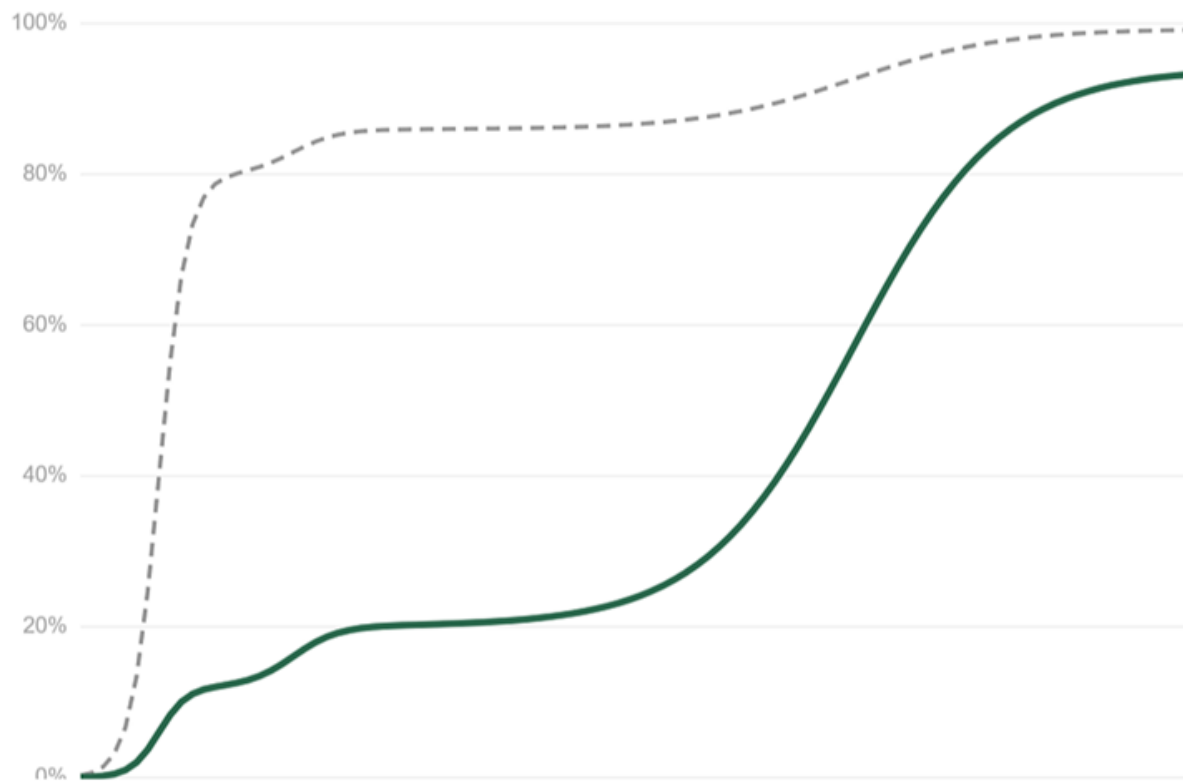
But: goed, runned X

True Understanding

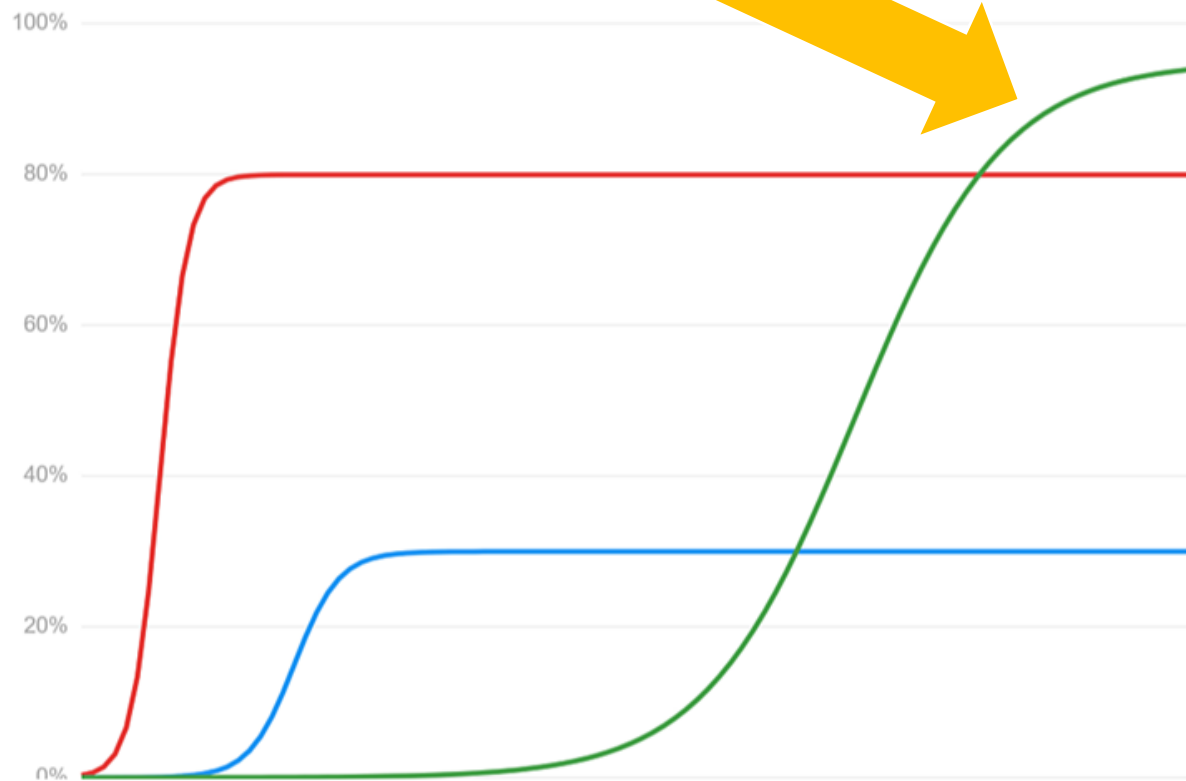
Handles anything new—even sentences never heard before

Accuracy Over Training

dashed = train, solid = test



Pattern Strength Over Training



Grokking: From Memorization to Understanding

- Training accuracy ON
- Test accuracy ON
- Memorization ON
- Fast heuristic ON
- True understanding ON



Memorization

"How are you?" *I am fine, thank you*
"How is your mother?" *Huh?*

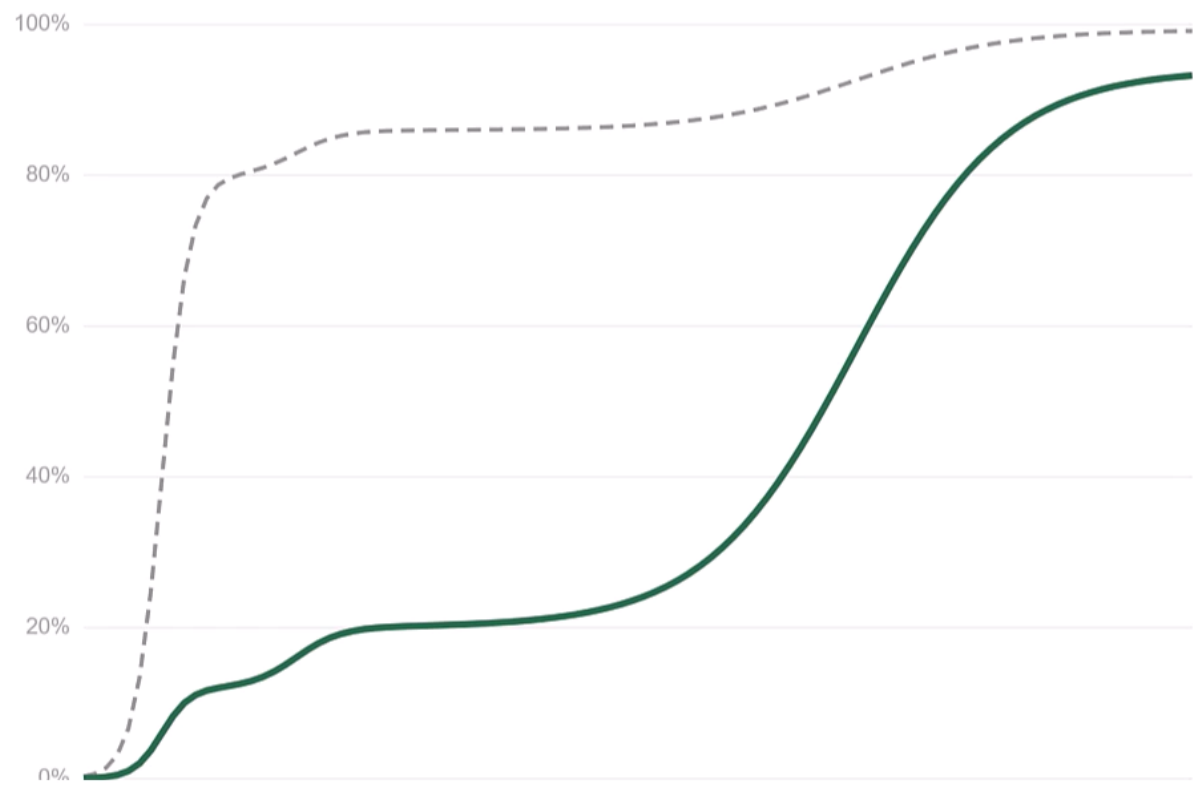
Fast Heuristic

Rule: add -ed for past tense walked, talked ✓
But: goed, runned ✗

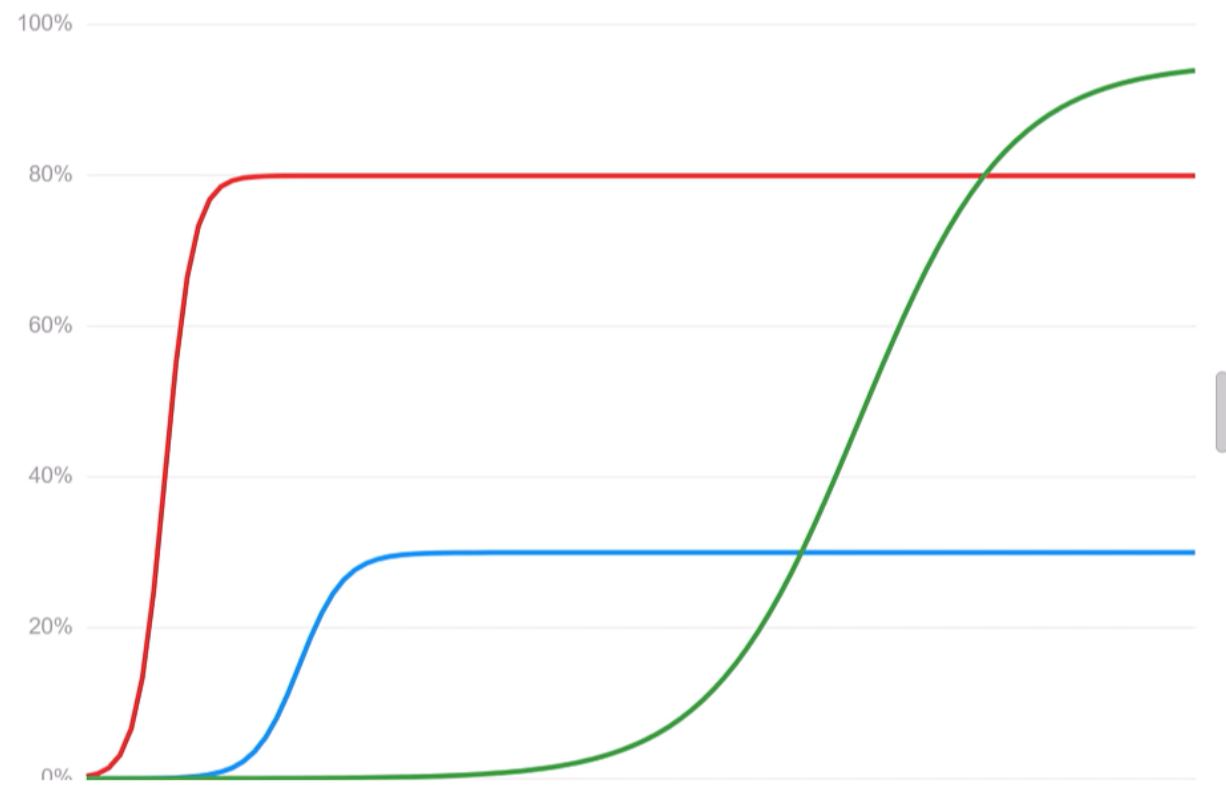
True Understanding

Handles anything new—even sentences never heard before

Accuracy Over Training dashed = train, solid = test



Pattern Strength Over Training what's happening inside the learner?



Grokking: From Memorization to Understanding

- ☐ Training accuracy ON
- ☒ Test accuracy ON
- ☒ Memorization ON
- ☒ Fast heuristic ON
- ☒ True understanding ON

Well-scaffolded Teaching

0%

Memorization

"How are you?" *I am fine, thank you*
"How is your mother?" *Huh?*

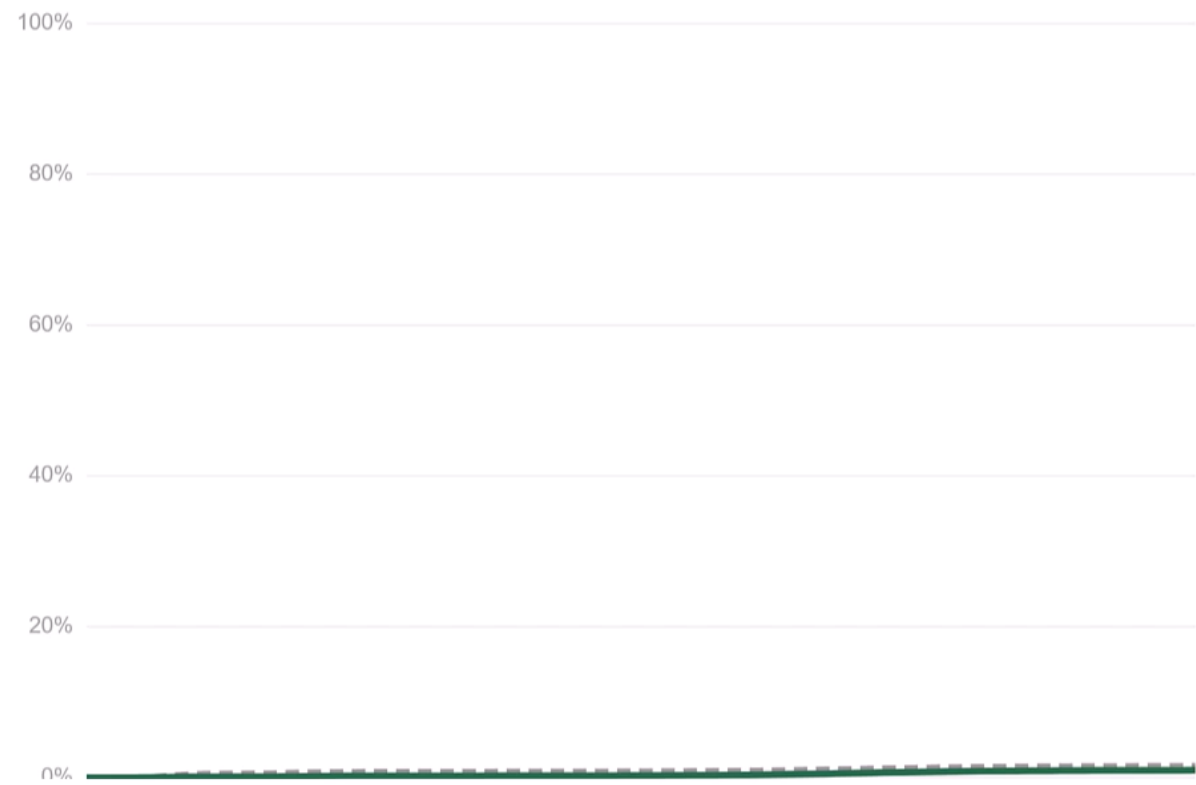
Fast Heuristic

Rule: add -ed for past tense walked, talked ✓
But: goed, runned X

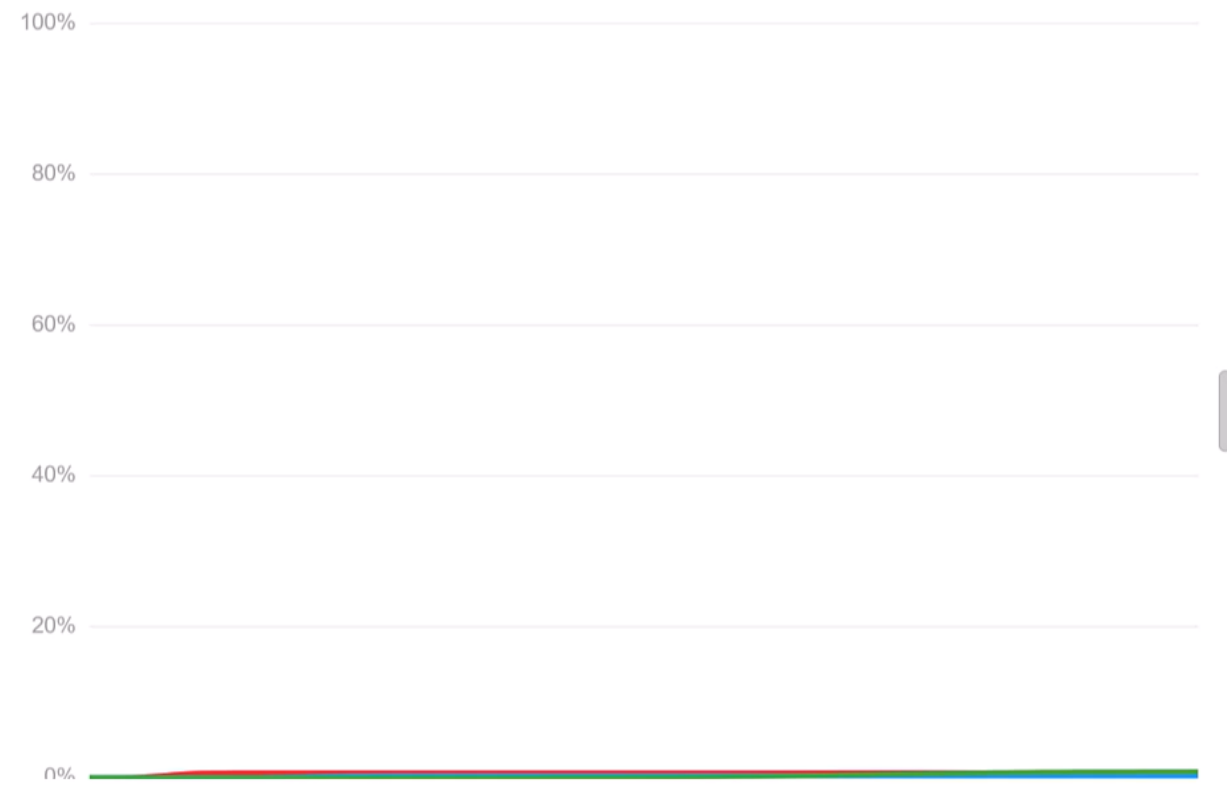
True Understanding

Handles anything new—even sentences never heard before

Accuracy Over Training dashed = train, solid = test

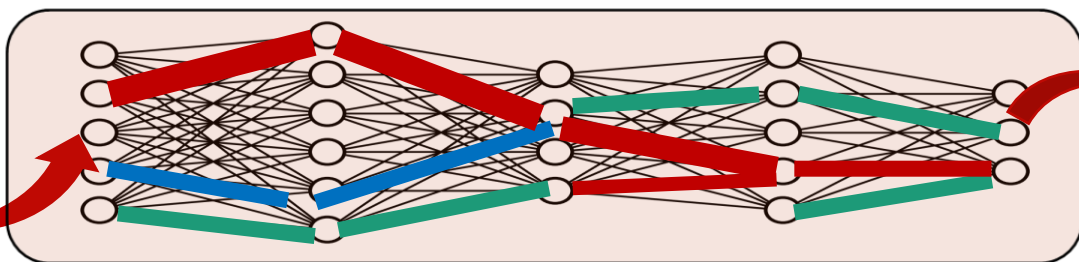


Pattern Strength Over Training what's happening inside the learner?



Basal ganglia

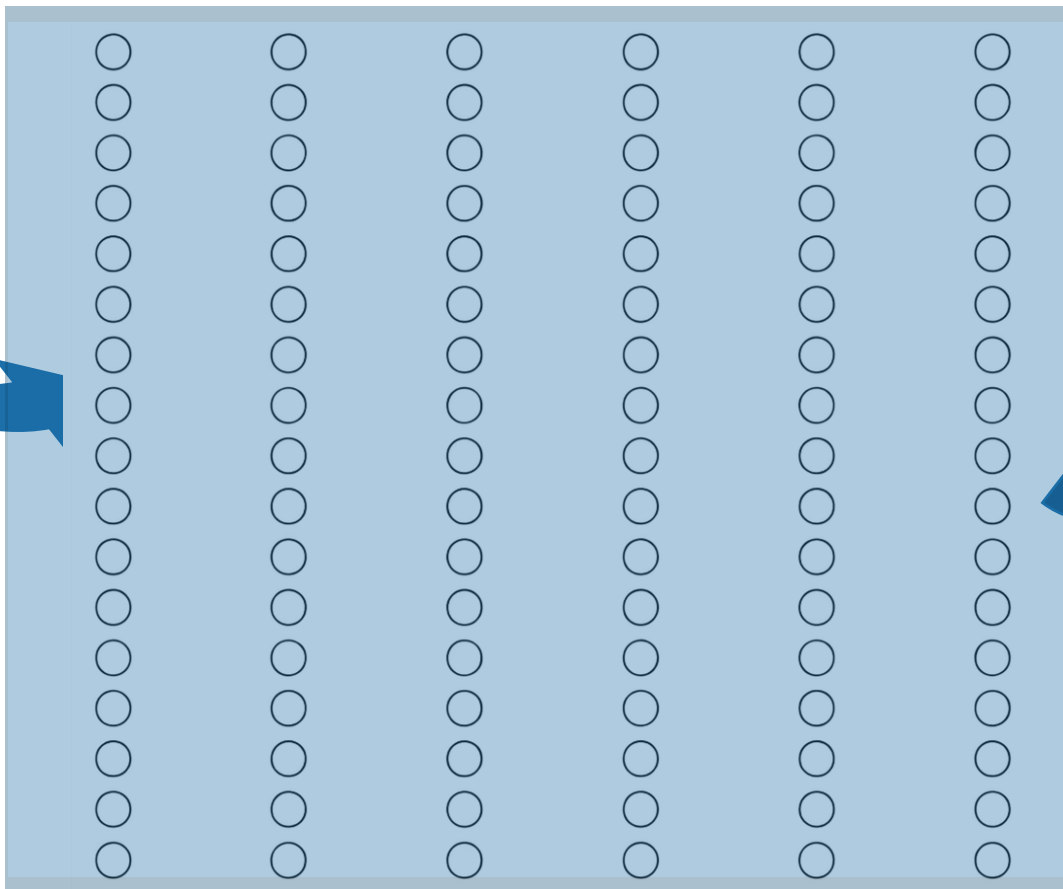
Non-conscious



“Distillation”



“Grokking”



Hippocampus

Conscious

Basal ganglia

Non-conscious

Active ("Student-centered")
Learning

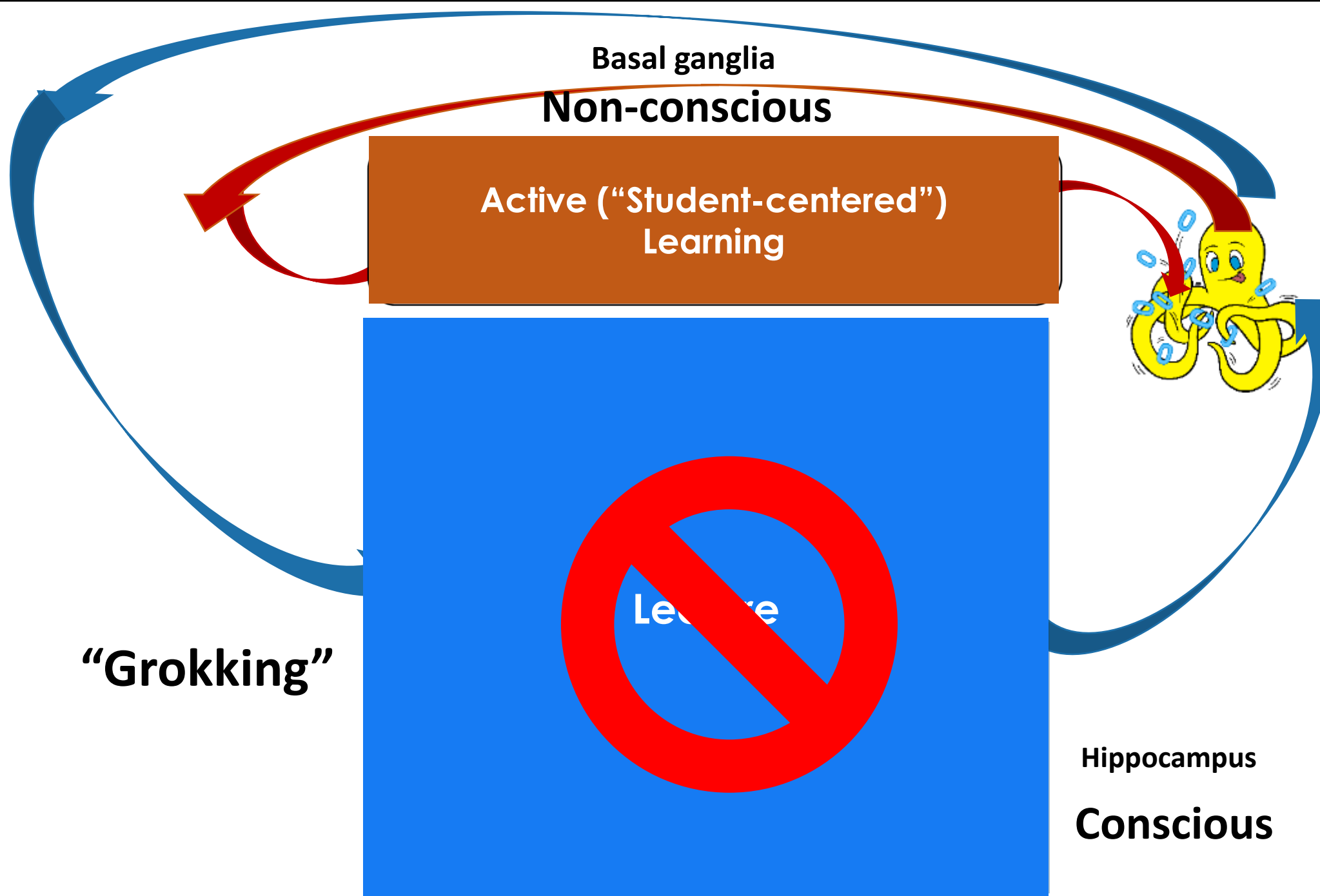


Lecture

"Grokking"

Hippocampus

Conscious



Active (“Student-centered”)
Learning



Lecture

Lecture

Active
Learning

Lecture

Active
Learning

Lec-
ture

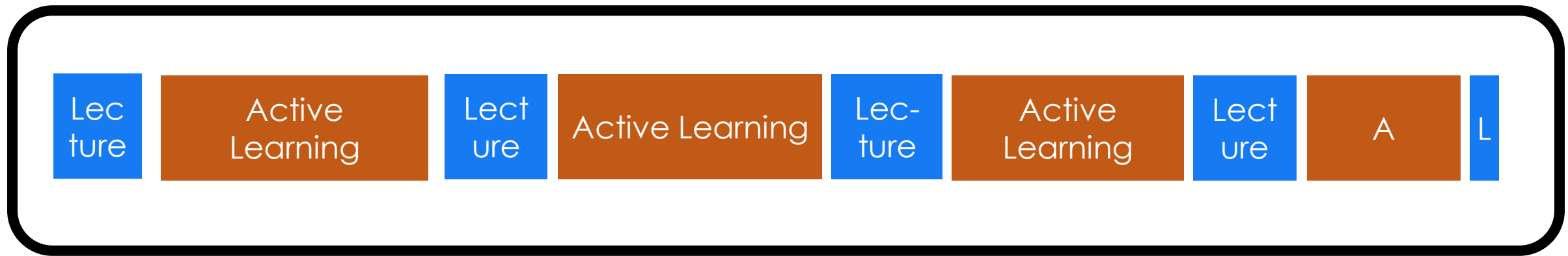
Active
Learning

Lecture

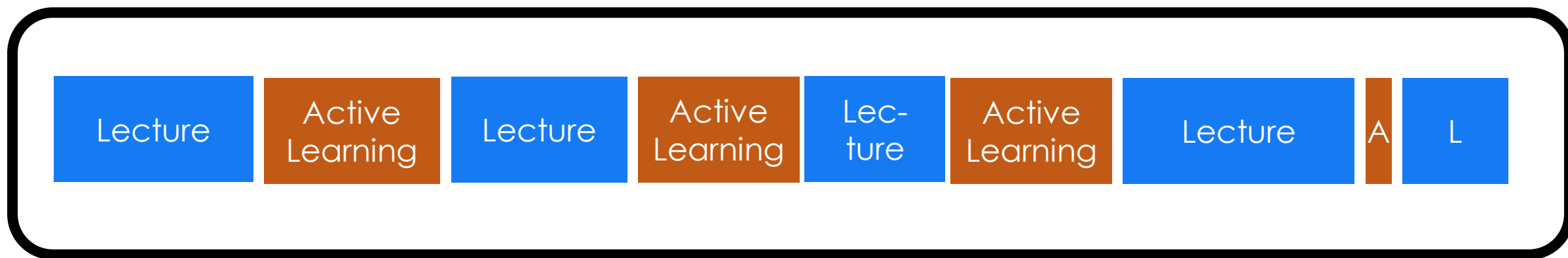
A

L

Direct instruction



Direct instruction



Direct instruction

The “Activity Ratchet”

Lect
ure

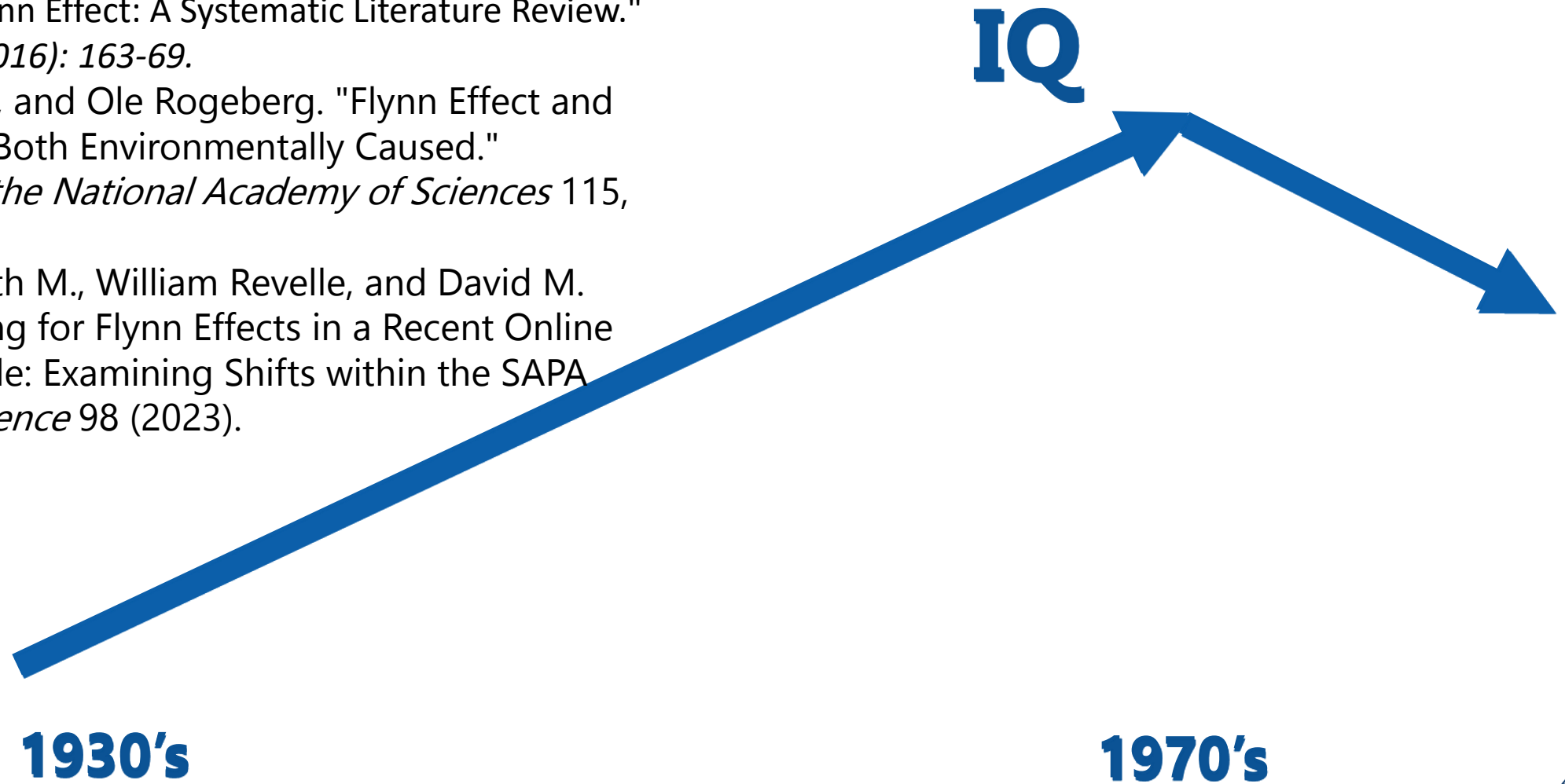
Active Learning

L

The Flynn Effect

Flynn, James R. "The Mean IQ of Americans: Massive Gains 1932 to 1978." *Psychological Bulletin* 95, no. 1 (1984): 29.

- Dutton, Edward, Dimitri van der Linden, and Richard Lynn. "The Negative Flynn Effect: A Systematic Literature Review." *Intelligence* 59 (2016): 163-69.
- Bratsberg, Bernt, and Ole Rogeberg. "Flynn Effect and Its Reversal Are Both Environmentally Caused." *Proceedings of the National Academy of Sciences* 115, no. 26 (2018):
- Dworak, Elizabeth M., William Revelle, and David M. Condon. "Looking for Flynn Effects in a Recent Online U.S. Adult Sample: Examining Shifts within the SAPA Project." *Intelligence* 98 (2023).



What will our future hold?

The Scientist and His Scientific Method

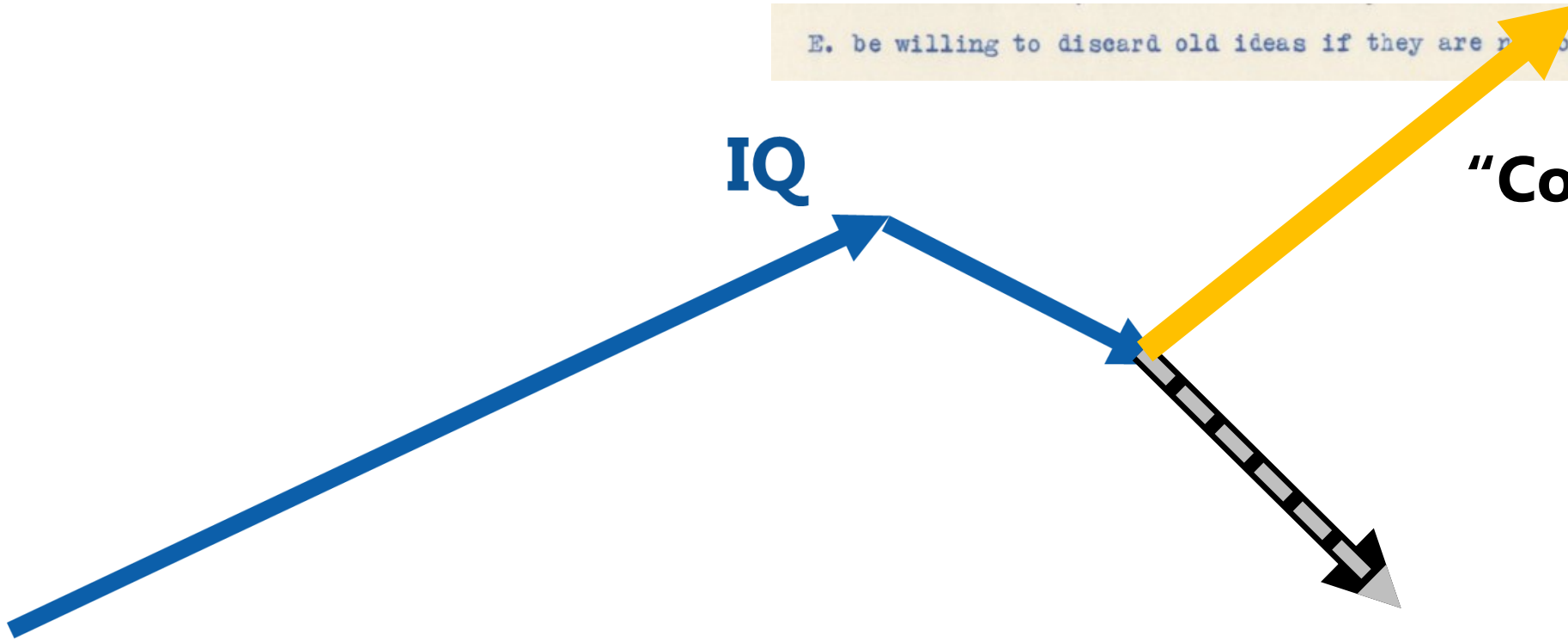
E. be willing to discard old ideas if they are no longer useful

IQ

"Cognitive realism"

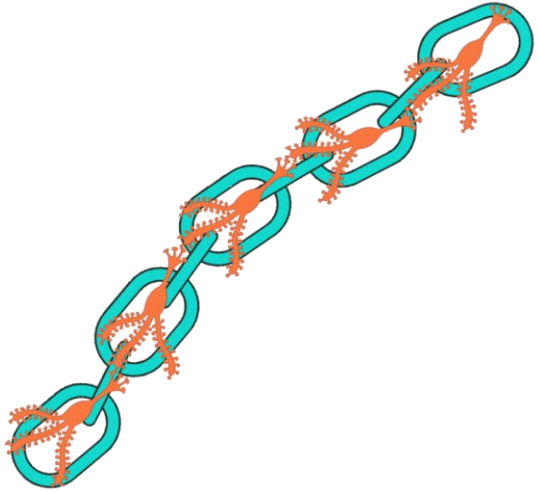
1930's

1970's



“Cognitive realism” tells us:

- **Build the links.** *Foundational knowledge is vital.*
- **Test frequently.** *Frequent low-stakes tests with no access to AI.*
- **Spice *enhances***—it can’t carry the meal

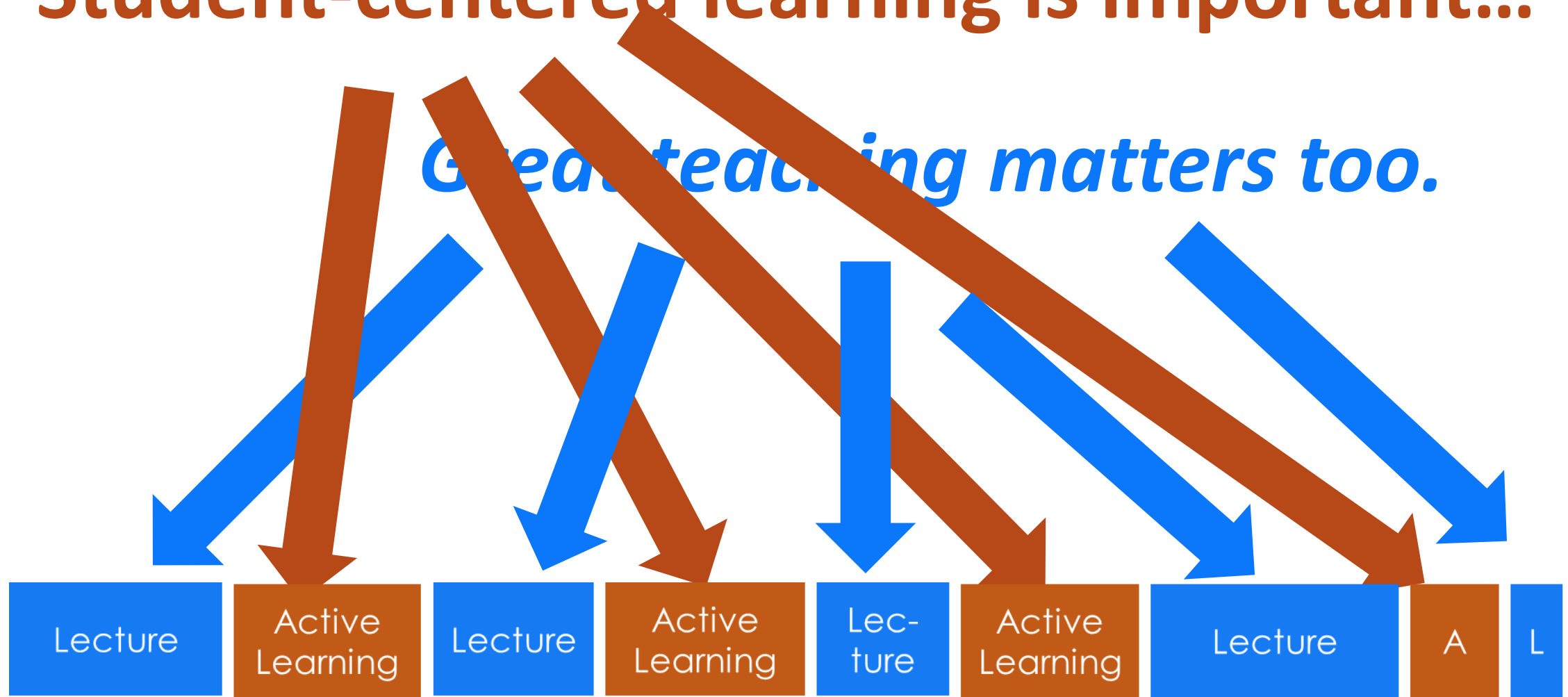


Carefully designed
explicit instruction
The main dish



Student-centered learning is important...

Great teaching matters too.



“Cognitive realism”