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What Would it Take to Teach a Computer to Think?

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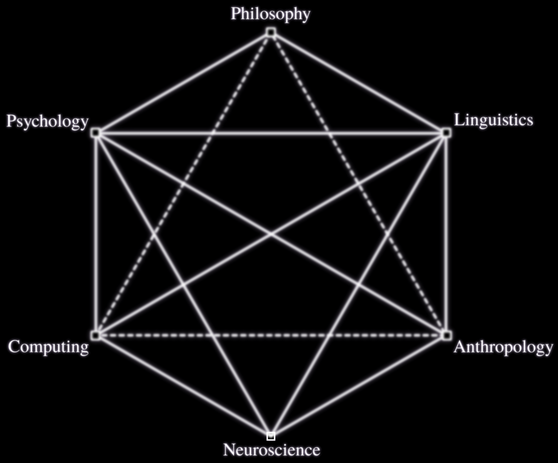
Carleton University

What Is Cognitive Science?



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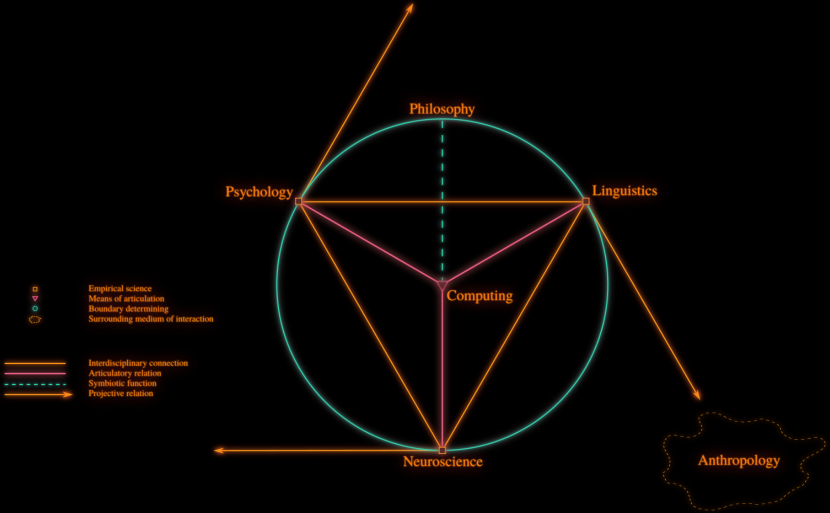

Mind as Machine

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- It describes how information-bearing states causally influence one another to change over time
- We can precisely test theories by making computational models that predict the causal structure mediating the states we measure
- So, artificial intelligence in cognitive science is a set of methodological tools we use to make our theories precise and testable

Learning's Kinda Like Searching Innit?

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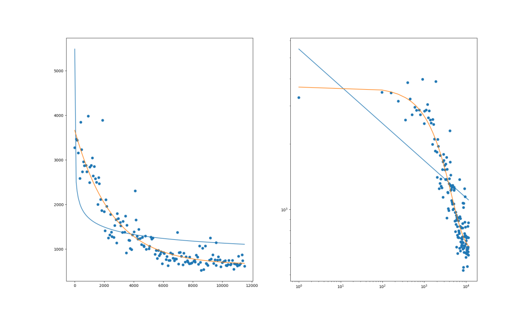

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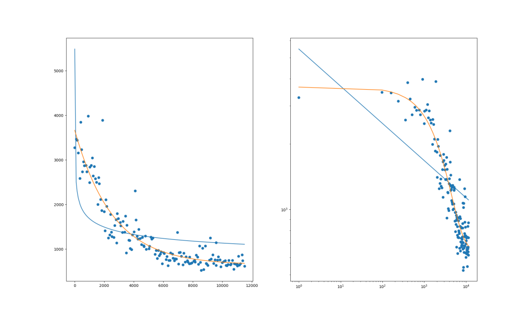
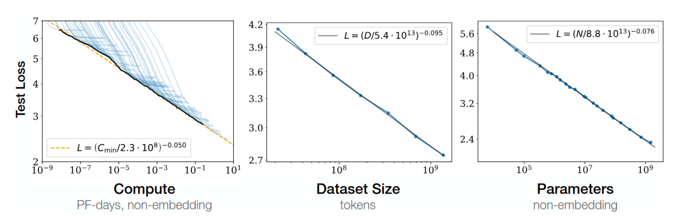


What do learning curves tell us about memory and skill acquisition?

What Doesn't It Work Like



Reproduced from Kaplan et al. (2020)

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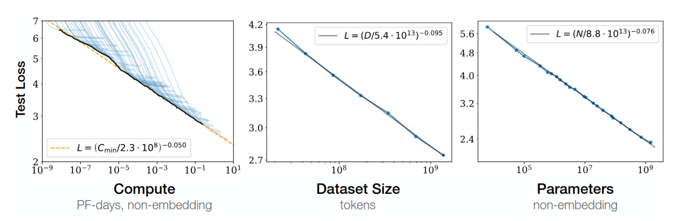

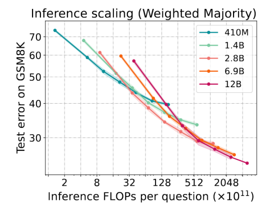

Reproduced from Kaplan et al. (2020) and Wu et al. (2025)

Search and Decision

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[1] Source of the graphic on slide 4

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    - describe the behaviour of an attractor neural network with small basins of attraction, and
    - an evidence accumulation process driving decision
- You explore through representations until you find the correct decision, and learn by finding better exploration strategies

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Characteristic Functions

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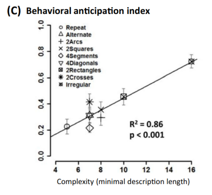
- So how is it that brains don't need to read the whole internet to learn anything?

Well, Maybe They Learn Programs



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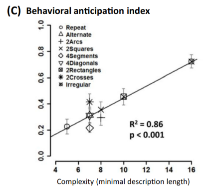

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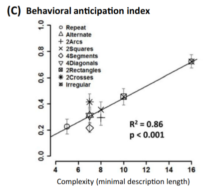

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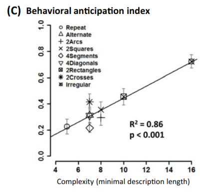

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- So, then, how can mental states be programs? Can we learn with them?

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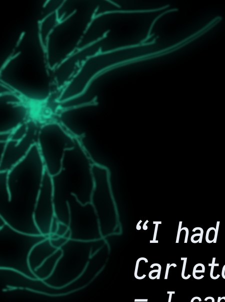
- Third, we need to show how the right representations can **constrain searching** to enable it to be efficient; we began working on this problem in Tomkins-Flanagan et al. (2025)
- Then, we need to build **brainlike networks** that are able to take advantage of our representation scheme to learn efficiently



"I had no idea this kind of cutting edge research was happening at Carleton!"
– I can't remember who said this

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