CogPonder

Towards a Computational Framework of General Cognitive Control

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INTRODUCTION

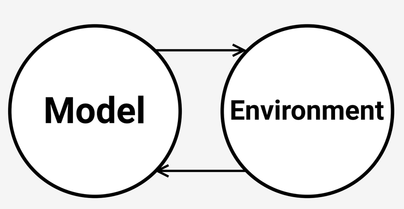
Background

- Cognitive control is a complex construct whose meaning lacks consensus.
- One of its key properties is that it regulates cognitive processes to to achieve particular outcomes. This regulation of processes has a measurable impact on response times (control is effortful and takes time).
- Psychological models are often unable to perform complex tasks and generalize. Developing computational models of CC that replicate human RT remains a significant challenge. Machine learning agents perform complex tasks but often ignore critical cognitive constraints such as response time.

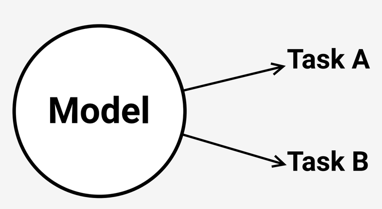
Objective

Develop a computational cognitive control framework that addresses limitations in psychology and machine learning and fulfills the following desiderata:

AGENCY
being able to perform the task at hand



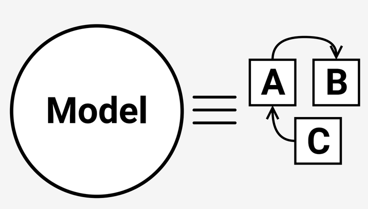
VERSATILITY
perform a wide range of tasks under a common framework



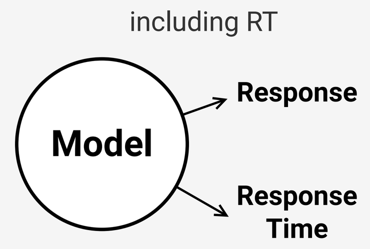
LEARNABILITY
integration into deep learning frameworks

$$Q_t \leftarrow Q_{t-1} + \dots$$

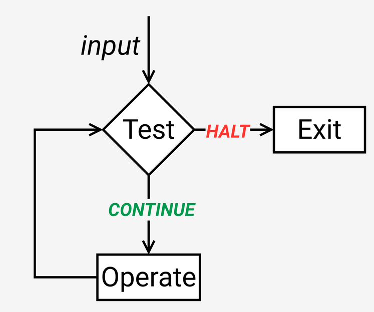
MODULARITY
flexibility and interpretability of the architecture



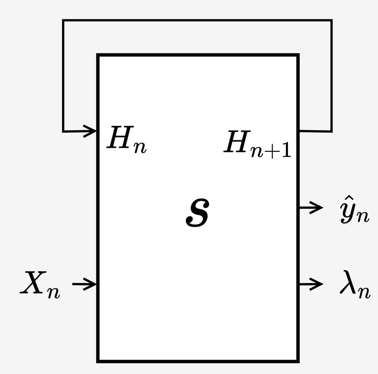
COMPLETENESS
account for all measured behaviors, including RT



KEY IDEAS



TOTE is a cognitive model [Miller1960], in which computations unfold in cycles with tests evaluating specific criteria and determining whether to halt or continue the process.

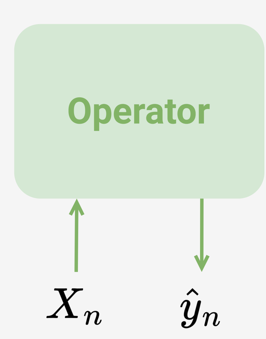


PonderNet is a more recent deep learning architecture [Banino2021] that adjusts the computational complexity of a neural network based on the complexity of the task and inputs, allowing the network to use fewer computational steps for simpler tasks.

CogPonder = TOTE + PonderNet

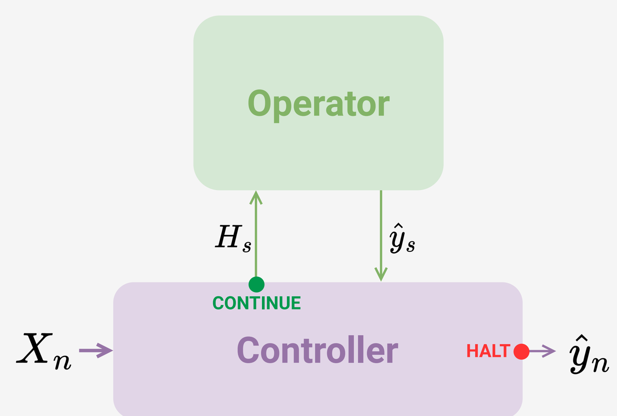
THE COGPONDER FRAMEWORK

Base Model



$$L = \mathcal{L}(\hat{y}_n, y_n)$$

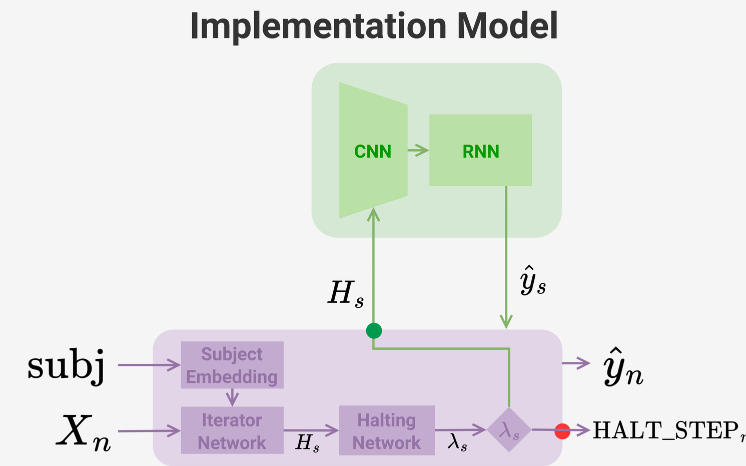
Augmented Model



$$L = \sum_{s=1}^{S} \mathcal{L}(\hat{y}_s, y_n)p_s + \beta \mathrm{KL}(p_s || d_{1..N})$$

$$p_s = \lambda_s \prod_{i=1}^{s-1} (1 - \lambda_i)$$

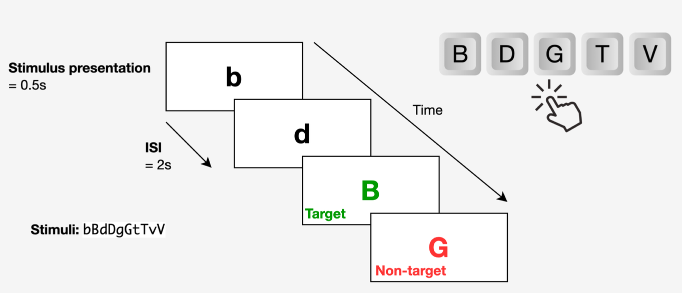
Implementation Model



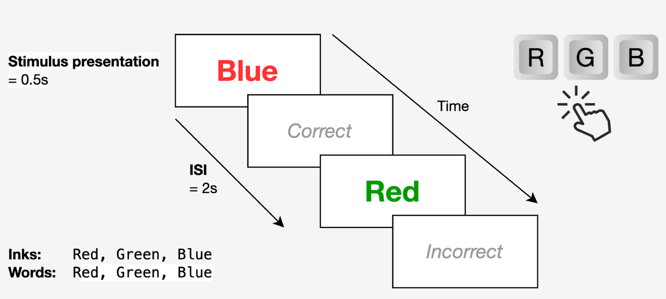
$$\hat{y}_n = \hat{y}_{s=\mathrm{HALT\_STEP}_n}$$

TESTING COGPONDER

- To demonstrate the value of the framework, we trained separate instances of CogPonder for Stroop and N-back tasks and aligned model's output to the human response and RT.
- **Data:** Self-Regulation Ontology dataset [N=521, 75%/25% train/test trials; Eisenberg2019]. We focused on participants who completed the Stroop and 2-back tests.

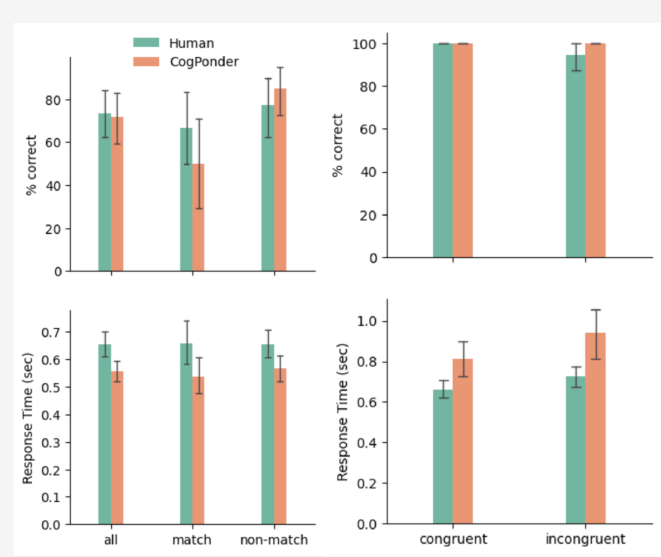


2-back



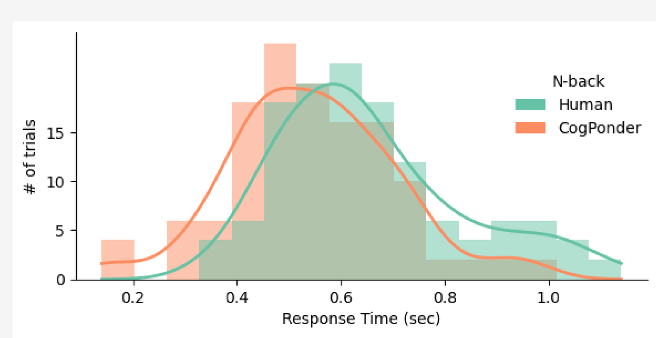
Stroop

CogPonder replicates behavioral patterns of humans in the Stroop and N-back, using the same architecture.



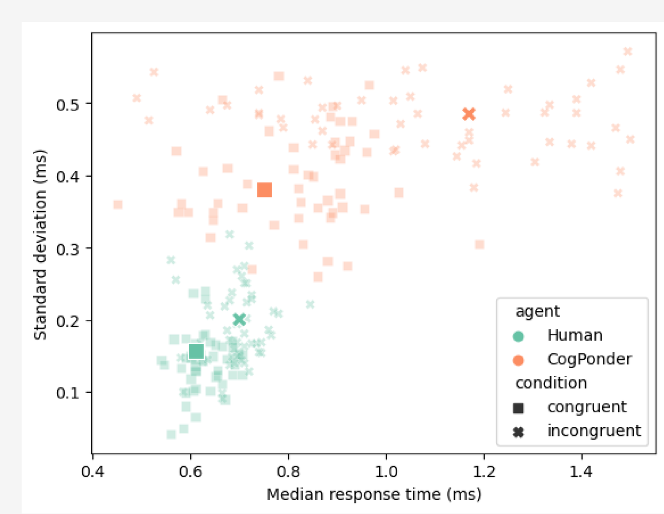
2-back **Stroop**

CogPonder generates RT distributions that are indistinguishable from those of humans.



2-back

CogPonder reproduces task-specific cognitive effects, e.g., the Stroop effect and the Match-vs-NonMatch difference in the N-Back task.



Stroop

CONCLUDING REMARKS

- It's possible to have a model that satisfies the desiderata. CogPonder is an interoperable scalable architecture that functionally separates the act of control from the controlled act, and can generate response/RT similar to human, demonstrating the potential to ground cognitive control in tractable computations.
- The ability of PonderNet and TOTE to adapt computational resources connects RT in experimental psychology with deep learning, and supports the design of computational models that perform complex cognitive tasks.

FUTURE WORKS

- Obviously the results are limited in a number of ways, but there is a value in having a shared account of human cognition and artificial agents that bridge cognitive disciplines.
- We are currently exploring the following directions for future work: multi-task implementations for a battery of cognitive tests and hierarchical structures for complex tasks.

Miller, G., Galanter, E., & Pribram, K. (1960). Plans and the Structure of Behavior.
Banino, A., Balaguer, J., & Blundell, C. (2021). PonderNet: Learning to Ponder.
Eisenberg, I. W., Bissett, P. G., Zeynep Enkavi, A., Li, J., MacKinnon, D. P., Marsch, L. A., & Poldrack, R. A. (2019). Uncovering the Structure of Self-Regulation through Data-Driven Ontology Discovery.

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