Is a Biological Organism a Computer?

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Roadmap

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Motivation

Some foundational questions:

- ✧ Why does the classical realm *work*?
- ✧ How does the natural world *do stuff*?
- ✦ What are the *mechanisms* behind *doing stuff*? ⇐ addressing today

Background I

There are many sectors of computing:

- ✧ Classical (laptops, phones, supercomputers, ...)
- ✧ Quantum (analog, annealing, universal, ...)
- ✧ Chemical (probabilistic, reaction-diffusion, ...)
- ✦ **Biological** $\Leftarrow$ addressing today

Disclaimer: I am not a biologist

🥸

Background II

Qualifications for a "simple" computer?

- ✧ Reads input from environment
- ✧ Utilizes input for:
  - ✦ Processing (short term memory)
  - ✦ Storage (long term memory)
  - ⇒ Both are interconnected (*processed input*)
- ✧ Processed input is utilized for output:
  - ✦ Observed decisions (calculations, movement, ...)
- ✧ Notion of *programmability* (ability to be modified)
  - ✦ e.g. computer programs are modified via code.

More on this later.

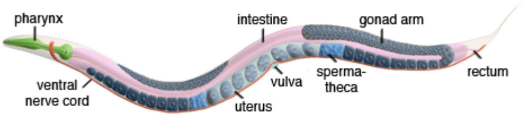
Ideal Biological Computing Candidate?

Caenorhabditis elegans

What is C. elegans? I: Why?

- ✧ Entire neural network visualized and mapped [2].
- ✧ Canonical example for many ongoing studies in various fields
  - → Biology, neuroscience, etc.
- ✧ Exhibits stochastic behavior with few parameters [4].
- ✦ Simple, accessible subject for studying.

What is C. elegans? II: Essential Anatomy



- **Head** Contains neurons connected to nervous systems
  - → sensory input from environment
- **Pharynx** Feeding organ
  - → energy input from environment
- **Intestine** Processes energy input
- **Ventral nerve cord** Processes sensory input

What is C. elegans? III: Simplified Anatomy

Summarizing, *C. elegans* will encounter:

- ✧ Input (light, heat, gradient changes, ...)

and exhibit:

- ✧ Output (decisions $\rightarrow$ movement, ...)

Concisely forming a *configuration alphabet* of *C. elegans* (*agent*):

$$\begin{aligned} \mathcal{A}_{\text{config}} &= \{\text{sensors reading environment, sensors controlled by decisions}\} \quad (1) \\ &= \{S_{\text{env}}, S_{\text{dec}}\} \quad (2) \end{aligned}$$

where $S_{\text{env}} \equiv \{\text{photoelectric, temperature}\}$, and $S_{\text{dec}} \equiv \{\text{actuators}\}$

Constructing the Agent I: Photoelectric Sensor

How would the photoelectric sensor work? Simplified, logic-based:

Environmental input to sensor	Red (R)	Green (G)
Output to actuators	0	1

Define function $f : \mathcal{A}_{\text{color}} \mapsto \mathcal{A}_{\text{info}}$ such that

- $\mathcal{A}_{\text{color}} = \{\texttt{R}, \texttt{G}\}$ $\equiv$ alphabet corresponding to environmental colors
- $\mathcal{A}_{\text{info}} = \{0, 1\}$ $\equiv$ alphabet corresponding to the photoelectric processed information

$\Rightarrow$ relayed to actuators.

Assign $f(\texttt{R}) = 0$, $f(\texttt{G}) = 1$ (bijective)

Constructing the Agent II: Temperature Sensor

Same logical construction as photoelectric sensor, but for $T < \tilde{T}$ or $T > \tilde{T}$:

Environmental input to sensor	$T < \tilde{T}$	$T > \tilde{T}$
Output to actuators	0	1

Analogous alphabets and functions can also be formulated.

Constructing the Agent III: Actuators

Next, how will the agent move in an environment?

Define $g : \mathcal{A}_{\text{info}} \mapsto \mathcal{A}_{\text{output}}$ where $\mathcal{A}_{\text{output}} \equiv$ alphabet of agent's *shape (movement) basis*
$\rightarrow$ set of corresponding elements of agent's generated behavior.

Posit the shape basis $\mathcal{A}_{\text{output}} = \{\texttt{forward}, \texttt{right}, \texttt{halt}\}$, where
$\texttt{reverse} = (\texttt{forward})^{-1}$, $\texttt{left} = (\texttt{right})^{-1}$, while `halt` has no "inverse".

Agent Interactions II: Initialization

Suppose $\frac{\mathrm{d}T}{\mathrm{d}t} = 0$, while color is varied in a closed environment.

Assign

- ✦ $g(0) = g(f(\texttt{R})) = \{\texttt{halt}\}$
- ✦ $g(1) = g(f(\texttt{G})) = \{\texttt{forward}, \texttt{right}\}$

where environmental colors (via a light shown onto the agent's environment) ultimately dictate the agent's movement with some probability.

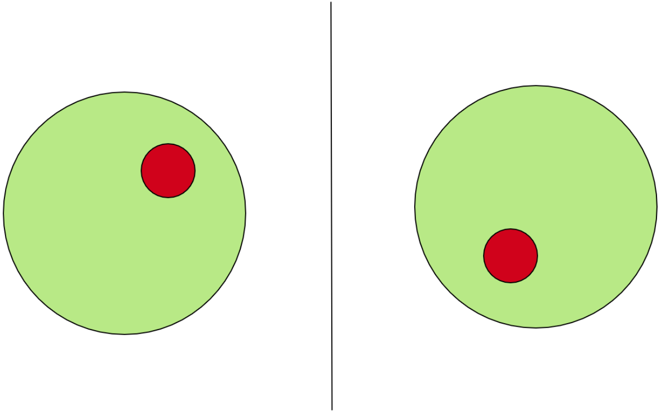
Note: Probability can be adjusted for ideal cases, e.g. $\Pr(\texttt{halt}|g(0)) = 1$
as well as non-ideal cases, e.g. $\Pr(\texttt{halt}|g(0)) = \varepsilon \Rightarrow \Pr(\texttt{halt}|g(1)) = 1 - \varepsilon$

Agent Interactions III: Experiments

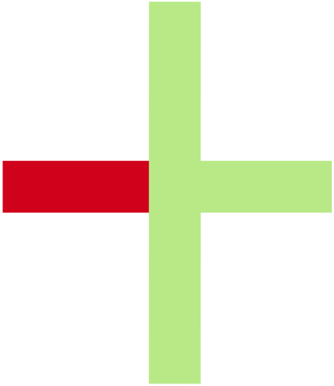
From this, simple experiments can be constructed to demonstrate:

- Decision making
- Learning?
- ...

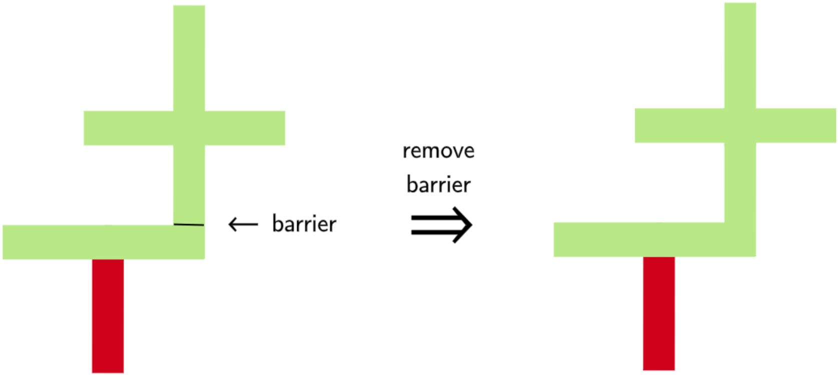
Agent Interactions III: Experiment 1



Agent Interactions III: Experiment 2



Agent Interactions III: Experiment 3



Summary

What can be concluded so far? The agent can

- ✦ Satisfy pre-programmed probabilistic criteria
- ✦ ...

How could this be improved?

- ✧ Is the agent *learning?* No.
- ✧ If not, what is the agent *doing?*

But this is what we've concluded!

Reconstructing the Agent I: What is missing?

How could an agent "learn"? Create two functions which optimize for:

- ✦ *Survival*
- ✦ *Reward*

The agent would then utilize these functions to interact with processed data, in the intermediary stage of relaying processed data $\rightarrow$ actuators.

Reconstructing the Agent II: Information Flow

Input $\rightarrow$ Process $\rightarrow$ Output

vs.

Input $\rightarrow$ Process $\rightarrow$ Optimization $\rightarrow$ Output

Reconstructing the Agent III: What else is missing?

However, these functions would not always work as intended.

- e.g. One agent eats bad food and dies. Another agent observes this, but eats bad food anyways.
- e.g. One agent eats good food. Instead of eating more of the good food, agent migrates away in search of something else.
- ...

so these functions are performing an *optimization* for some *probabilistic potential* which is *not ideal*.

Reconstructed Agent Interactions IV: Causality

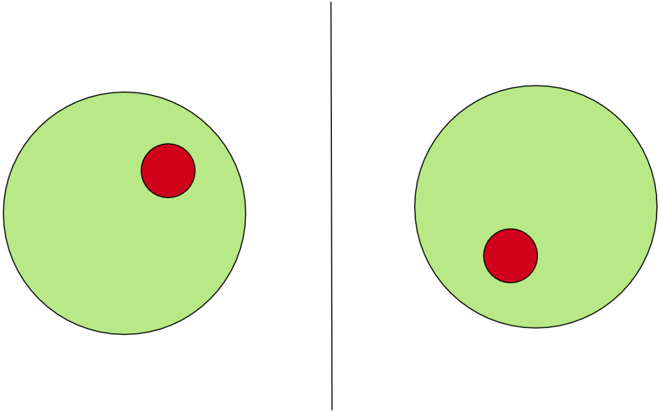
If the agent associates *causality* with these functions $\Rightarrow$ form of *learning*

e.g. after some time in its environment, if agent associates causal states:

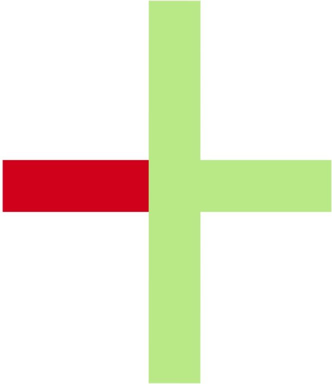
- ✧ $\mathcal{S}_0 \mapsto$ (halt in red zone to obtain food)
- ✧ $\mathcal{S}_1 \mapsto$ (move in green zone to search for food)

then the agent has "learned" i.e. actively optimized its probabilistic potential for survival and reward.

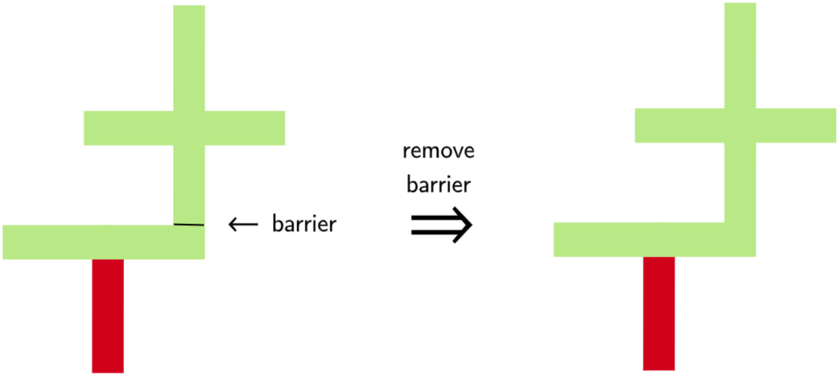
Reconstructed Agent I: Experiment 1, Take 2



Reconstructed Agent I: Experiment 2, Take 2



Reconstructed Agent I: Experiment 3, Take 2



Related Work I

This project essentially constructed a framework of *reinforcement learning (RL)*.

- Mori et al. utilizes a *mixture density recurrent neural network (MDN-RNN)* to model *C. elegans* stochastic behavior, and a *Deep-Q neural network* [3] to implement RL [4].

Related Work II

Movement (posture) of *C. elegans* has been described by an *eigenworm basis* [1] [5] as opposed to a *shape basis*.

- Ahamed et al. utilizes eigenworm projections to study movement in state space [1].

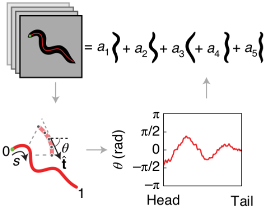


Figure: From [1]

Conclusions

Next steps:

- Simulate “toy” experiments
  - Various methods and experiment variations could be implemented.
  - Compute computational mechanics quantities and information theory measures

Thank you

- T. Ahamed, A. Costa, and G.J. Stephens. "Capturing the continuous complexity of behavior in *Caenorhabditis elegans*". In: *Nature Physics* (2021).
- S.J. Cook et al. "Whole-animal connectomes of both *Caenorhabditis elegans* sexes". In: *Nature* (2019).
- V Mnih et al. "Playing Atari with Deep Reinforcement Learning". In: *arXiv* (2013). arXiv: `1312.5602v1 [cs.LG]`.
- K. Mori et al. "Probabilistic generative modeling and reinforcement learning extract the intrinsic features of animal behavior". In: *Neural Networks* (2021).
- G.J. Stephens et al. "Dimensionality and Dynamics in the Behavior of *C. elegans*". In: *PLOS Computational Biology* (2008).