Levels of Intelligence in Artificial and Biological Systems

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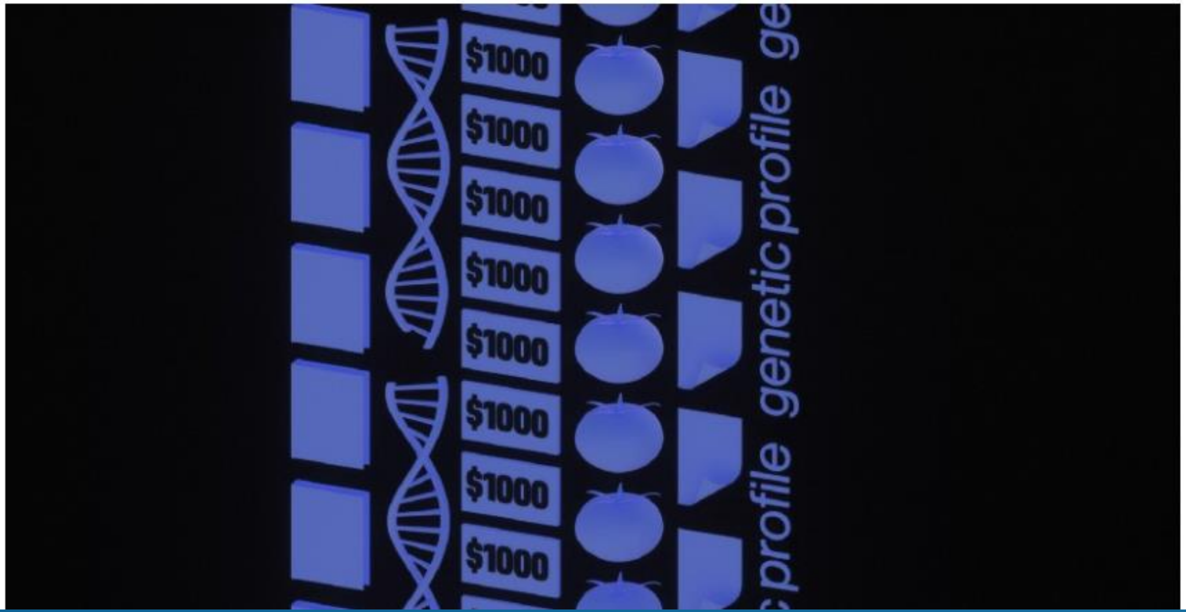
AI/AGI IS FILLED WITH MUCH EXAGGERATION COMPARED TO ACTUAL ACHIEVEMENTS

The New York Times 24K Followers About Follow

What Ever Happened to IBM's Watson?

IBM's artificial intelligence was supposed to transform industries and generate riches for the company. Neither has panned out. Now, IBM has settled on a humbler vision for Watson.

The New York Times Jul 19 · 10 min read ★



WHAT IS HEAVIER – A PENCIL OR AN OVEN?

How do these intelligences compare?

- **Neural Network** – phenomenal image processing and reinforcement learning
- **Child** – phenomenal causal learning with few examples (eg, Gopnik)

→NEED TO **MEASURE** SOME **QUANTITY** WHICH REFLECTS WHAT WOULD BE A REASONABLE ASSESSMENT OF A SYSTEM'S **"INTELLIGENCE"**

LEGG & HUTTER (2007) "UNIVERSAL INTELLIGENCE":

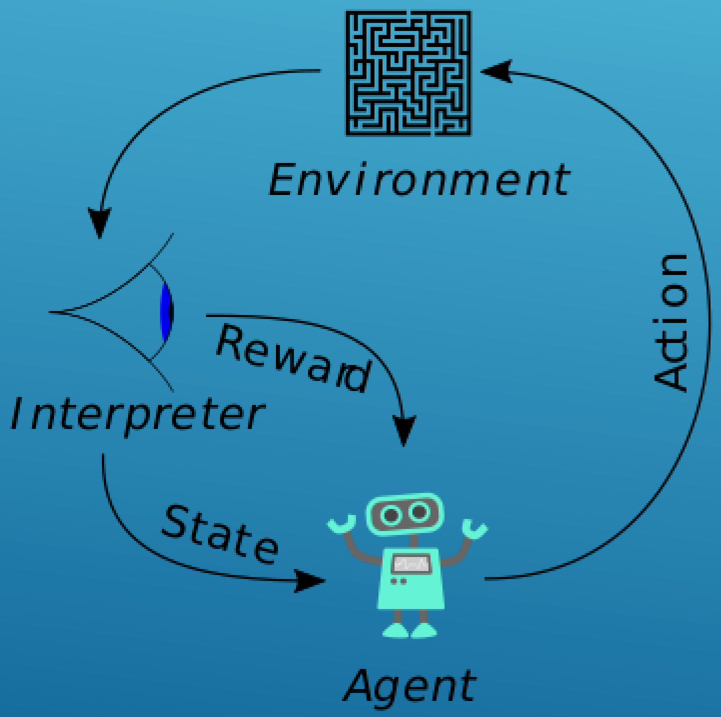
$$\Upsilon(\pi) := \Sigma_{\mu \in E}\, 2^{-K(\mu)}\, V^{\pi}_{\mu}$$

expected performance Υ of agent π

→ "universal intelligence"

LEGG & HUTTER (2007):

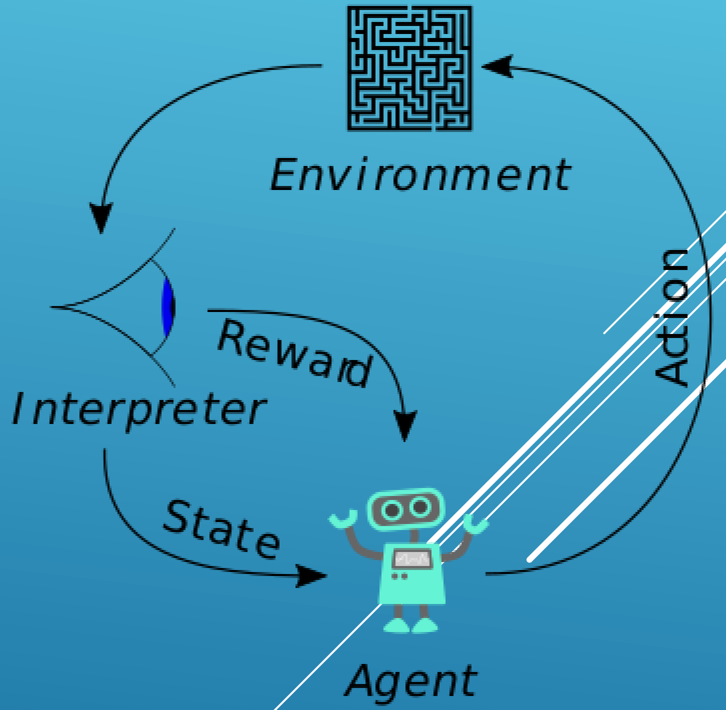
expected performance Υ of agent π



LEGG & HUTTER (2007):

expected performance Υ of agent π

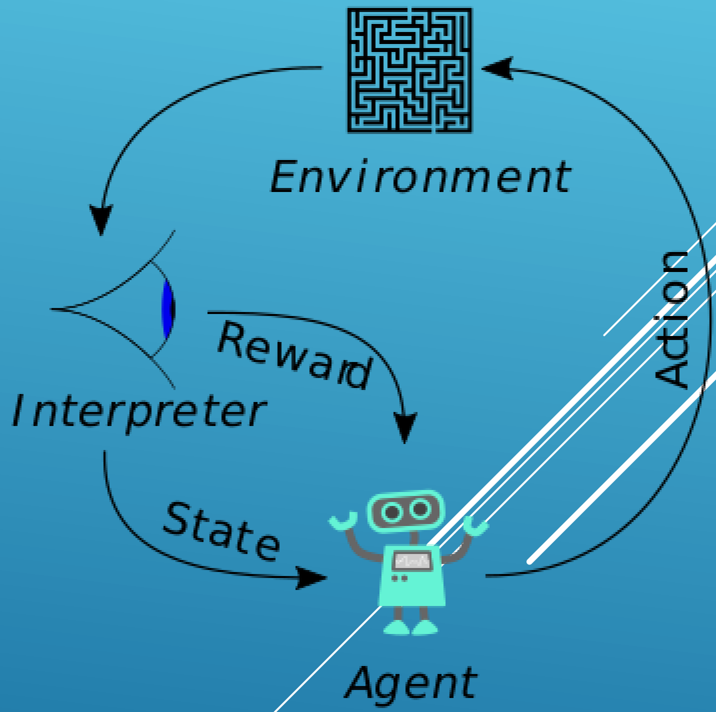
Neural Network



LEGG & HUTTER (2007):

expected performance Υ of agent π

Child



LEGG & HUTTER (2007) "UNIVERSAL INTELLIGENCE":

$$\Upsilon(\pi) := \Sigma_{\mu \epsilon E}\, 2^{-K(\mu)}\, V^{\pi}_{\mu}$$

algorithmic probability distribution of the space of environments $2^{-K(\mu)}$ times the value function V of agent π operating in environment μ

LEGG & HUTTER (2007) "UNIVERSAL INTELLIGENCE":

$$\Upsilon(\pi) := \Sigma_{\mu \epsilon E} 2^{-K(\mu)} V^{\pi}_{\mu}$$

-μ is one environment in the set of E all environments that could exist

LEGG & HUTTER (2007) "UNIVERSAL INTELLIGENCE":

$$\Upsilon(\pi) := \Sigma_{\mu \epsilon E} 2^{-K(\mu)} V^{\pi}_{\mu}$$

-V value function is equal to expected total reward for an agent

LEGG & HUTTER (2007) "UNIVERSAL INTELLIGENCE":

$$\Upsilon(\pi) := \Sigma_{\mu \epsilon E}\, 2^{-K(\mu)}\, V^{\pi}_{\mu}$$

Problem - K is Kolmogorov complexity function – not computable for real world

LEGG & HUTTER (2007) "UNIVERSAL INTELLIGENCE":

$$\Upsilon(\pi) := \Sigma_{\mu \epsilon E} 2^{-K(\mu)} V^{\pi}_{\mu}$$

-Schmidhuber (2011) workaround to compute equation

LEGG & HUTTER (2007) "UNIVERSAL INTELLIGENCE":

$$\Upsilon(\pi) := \Sigma_{\mu \epsilon E} 2^{-K(\mu)} V^{\pi}_{\mu}$$

-Goertzel (2010) – in real world cognitive animal may not function well in *all* possible envr'ts but function very well in some

Mapping the Landscape of Human-Level Artificial General Intelligence

- **Sam Adams** IBM
- **Itmar Arel** University of Tennessee
- **Joscha Bach** Humboldt University of Berlin
- **Robert Coop** University of Tennessee
- **Rod Furlan** Quaternix Research, Inc.
- **Ben Goertzel**
- **J. Storrs Hall** Independent Researcher and Author
- **Alexei Samsonovich** George Mason University
- **Matthias Scheutz** Tufts University
- **Matthew Schlesinger** Southern Illinois University, Carbondale
- **Stuart C. Shapiro** University of Buffalo, State University of New York
- **John Sowa** VivoMind Research, LLC

Mapping the Landscape of Human-Level Artificial General Intelligence

C1. The environment is complex, with diverse, interacting and richly structured objects.
C2. The environment is dynamic and open.
C3. Task-relevant regularities exist at multiple time scales.
C4. Other agents impact performance.
C5. Tasks can be complex, diverse and novel.
C6. Interactions between agent, environment and tasks are complex and limited.
C7. Computational resources of the agent are limited.
C8. Agent existence is long-term and continual.

Characteristics for AGI Environments, Tasks, and Agents.

Mapping the Landscape of Human-Level Artificial General Intelligence

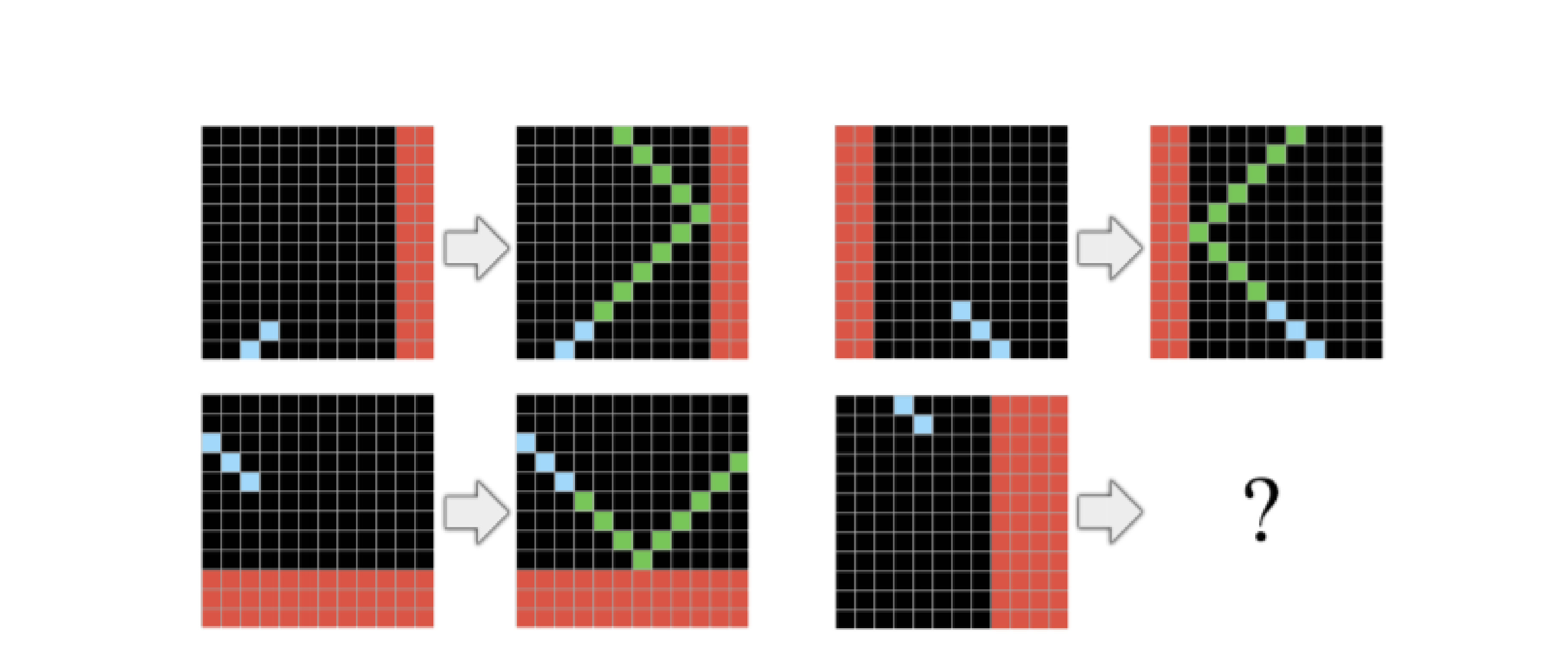
R1. Realize a symbol system
Represent and effectively use:
R2. Modality-specific knowledge
R3. Large bodies of diverse knowledge
R4. Knowledge with different levels of generality
R5. Diverse levels of knowledge
R6. Beliefs independent of current perception
R7. Rich, hierarchical control knowledge
R8. Meta-cognitive knowledge
R9. Support a spectrum of bounded and unbounded deliberation
R10. Support diverse, comprehensive learning
R11 Support incremental, online learning

Cognitive Architecture Requirements for AGI

Wozniak Test
-Robot can walk into unfamiliar house
-Robot can then make a cup of coffee

Steve Wozniak

Chollet (2019) ARC
"On the measure of intelligence"

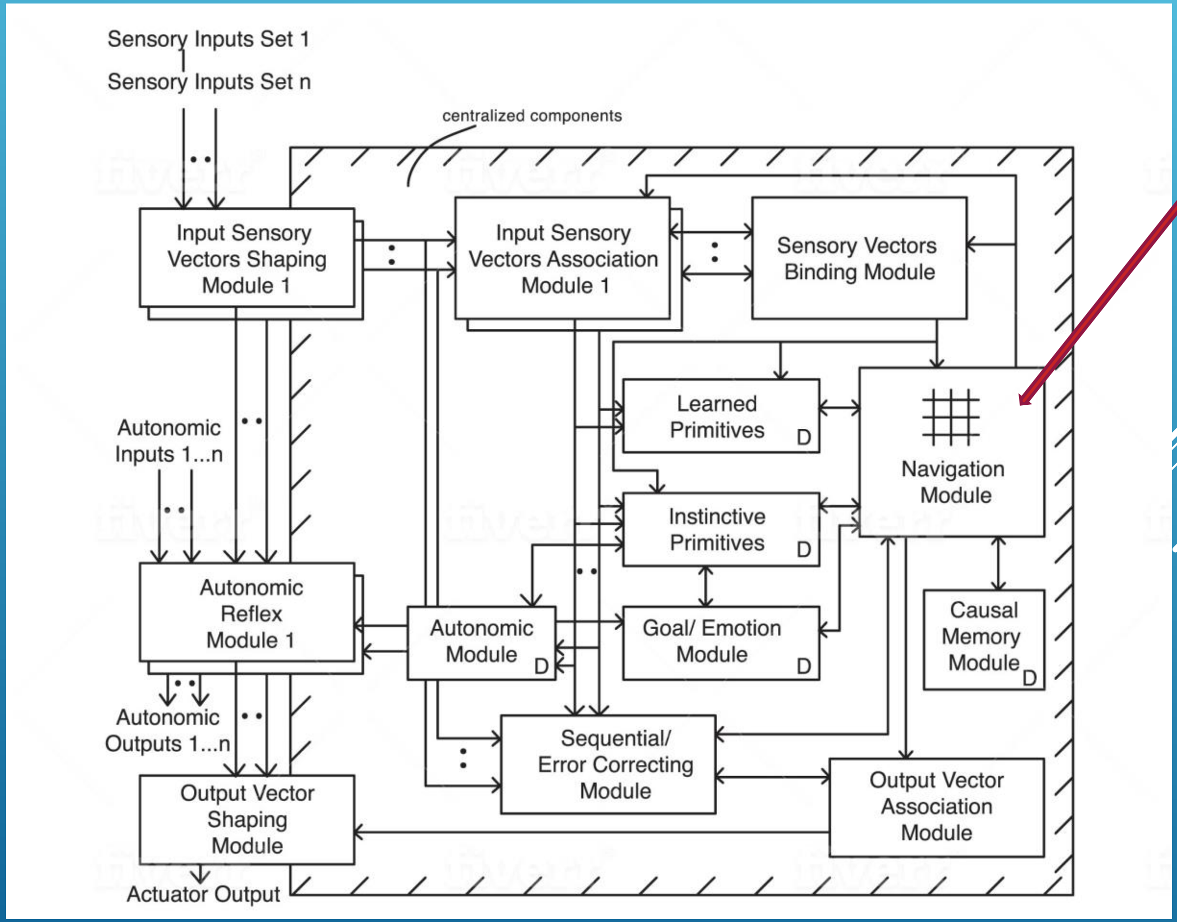


"abstraction and reasoning corpus"

Schneider (2021) – Two-Dimensional Rating Scale for Levels of Intelligence

-based on Causal Cognitive Architecture (Schneider 2018-2021)

CCA1 adds a Navigation Module
Lots and lots of small maps
Simple operations on these maps



-based on Causal Cognitive Architecture (Schneider 2018-2021)
-use of **navigation maps** for system of intelligence which can allow:

- **Association Behavior**
- **Pre-Causal Behavior**
- **Fully Causal Behavior**

Deep Learning Neural Network	3 Year Old Human Child
Pattern Recognition →Recognize the World	Model Building +also Pattern Recognition →Explain the World
Need 1000's examples for learning	A few examples enough

The solution: *Ability to Generate Causal Behavior*

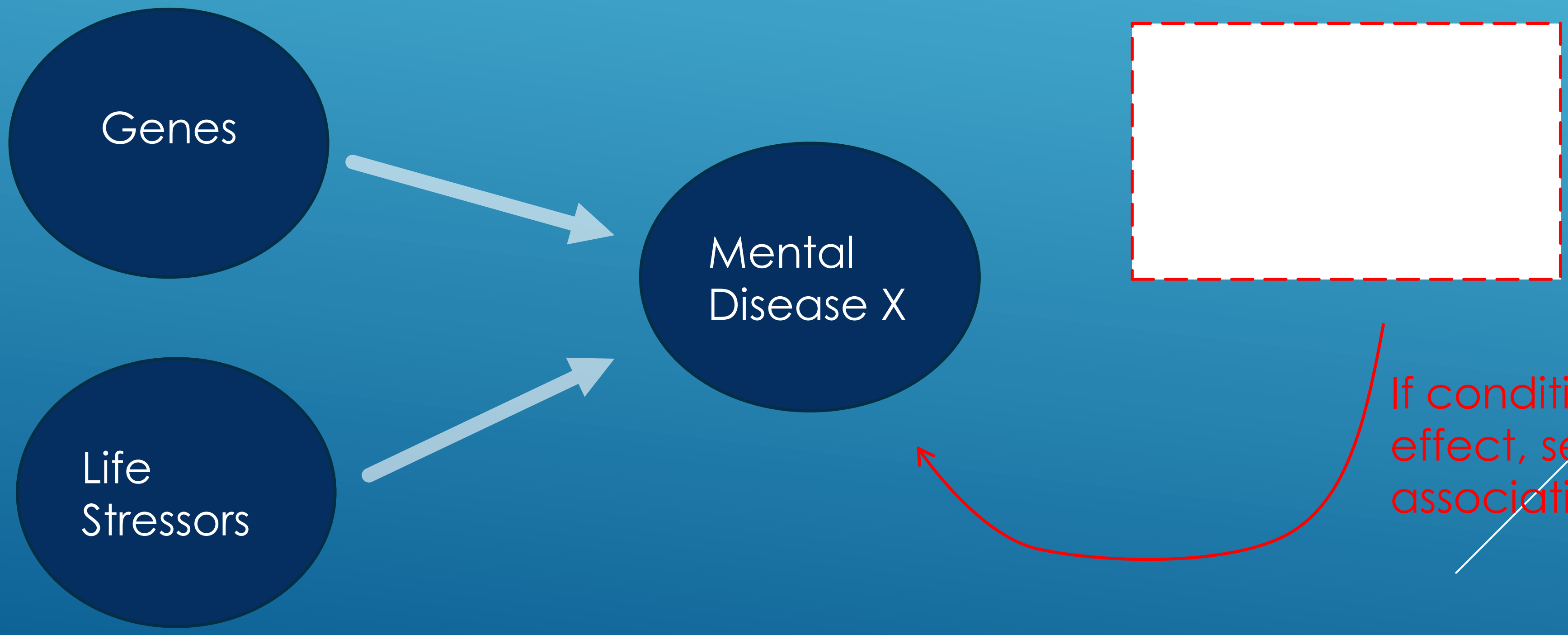
'Reptilian' and 'Mammalian' Brain – Associative Functioning

'Human' Brain, AGI – Causal Functioning

Directed Acyclic Graph (‘Causal Graph’) Counterfactual Theory

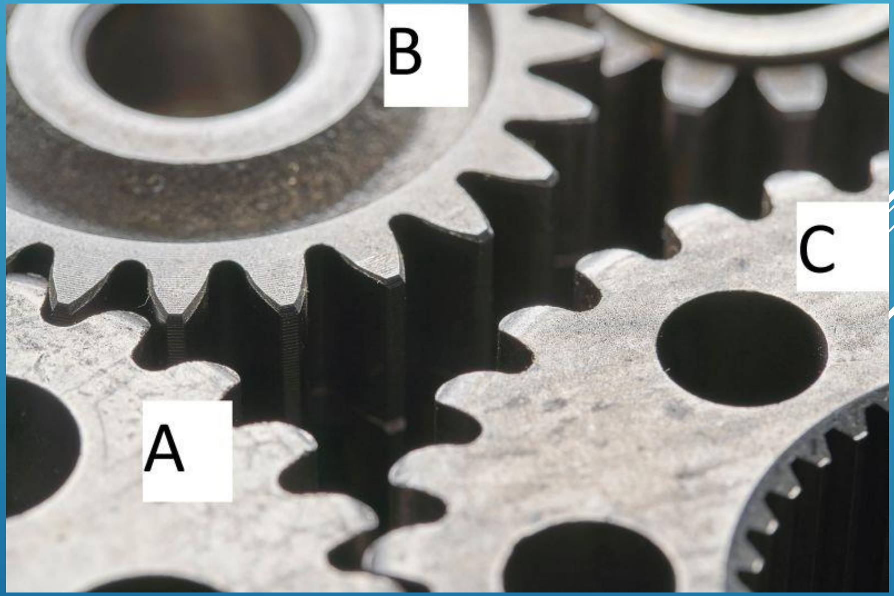
-- Useful for ***Analyzing*** Causality, eg, epidemiologists

-- Less Useful for ***Generating*** Causality, eg, AGI



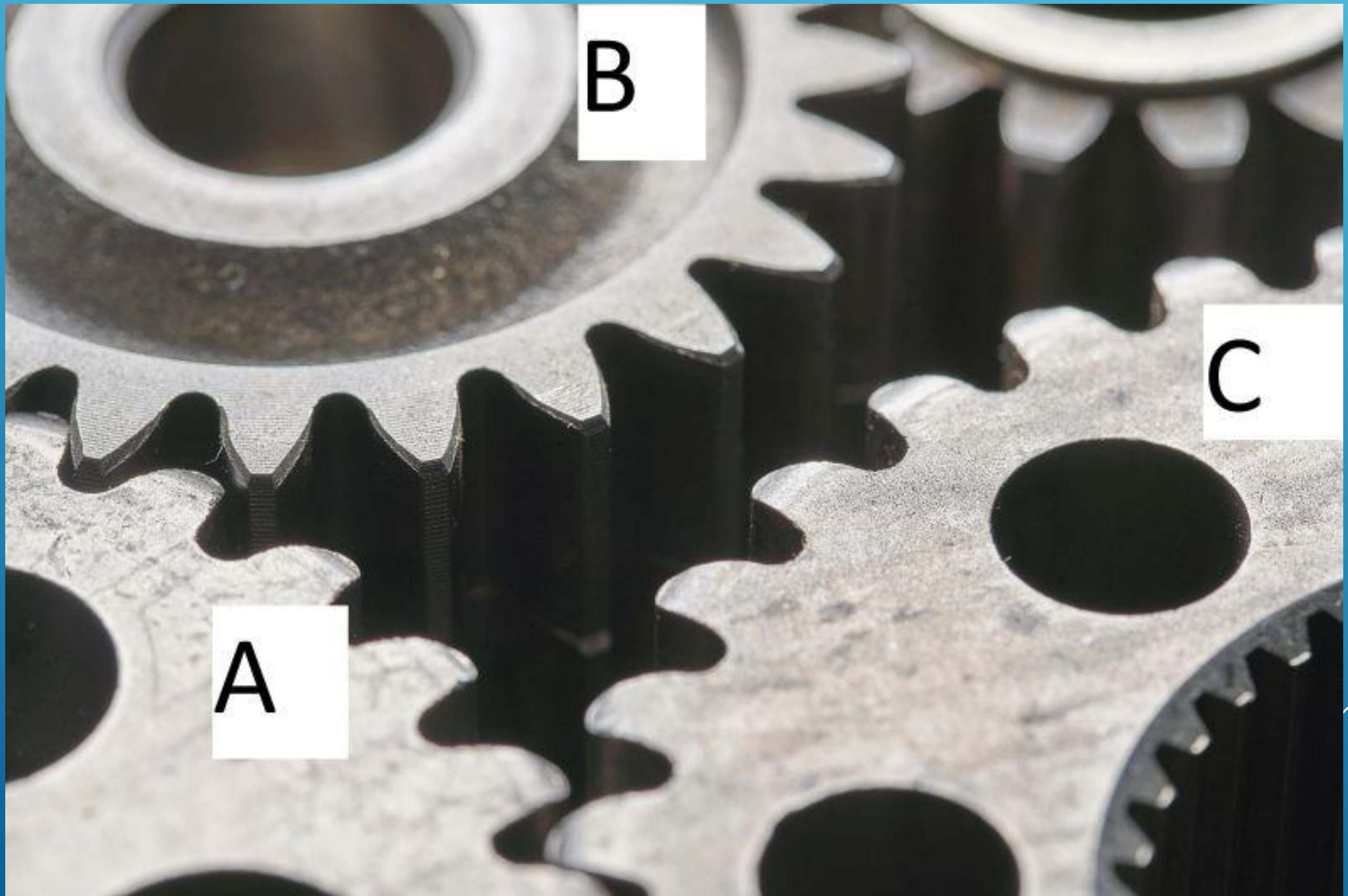
If condition on common effect, see confusing associations

We want a mechanism for generating causal behavior in the real world



-Agent (AGI, cognitive architecture, etc) has never seen the machine below (or even a similar machine).

-If Gear C is turned, what happens to Gear B?



-Child has never put green and pink block together before, and he has never put them at an angle.

-With no previous examples can he do this now?

-Rescue robot goes out into rain forest, and wants to cross this river. Noisy and fast flow. Never saw river like this before.

-Should it cross?

No.

Kaieteur Falls, Guyana

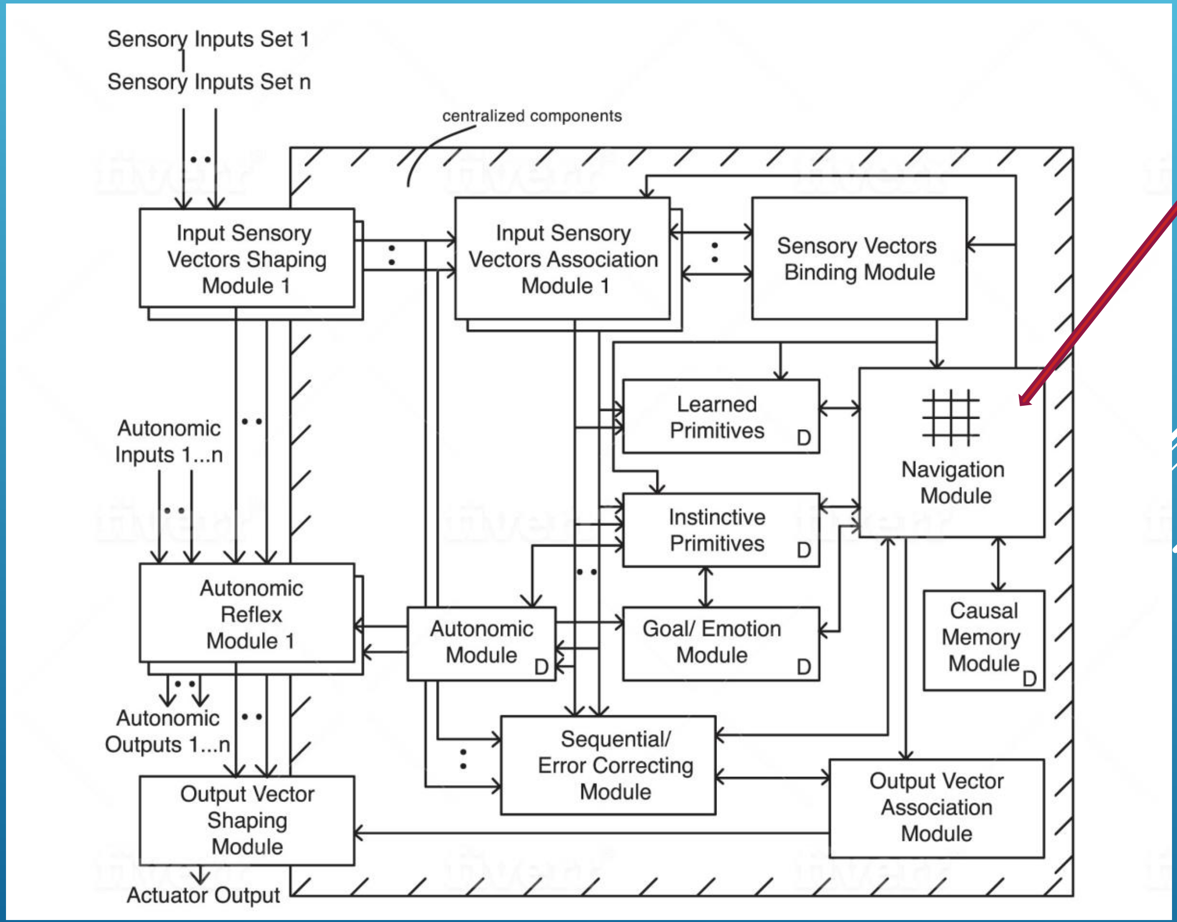
Causal Cognitive Architecture 1 (CCA1)

- ***Generates* Causal Behavior**

- Mesoscopic brain inspired cognitive architecture – good balance of low/mid level and high level components and features

- A pragmatic solution to the neural-symbolic problem

CCA1 adds a Navigation Module
Lots and lots of small maps
Simple operations on these maps



-based on Causal Cognitive Architecture (Schneider 2018-2021)
-use of **navigation maps** for system of intelligence which can allow:

- **Association Behavior**
- **Pre-Causal Behavior**
- **Fully Causal Behavior**

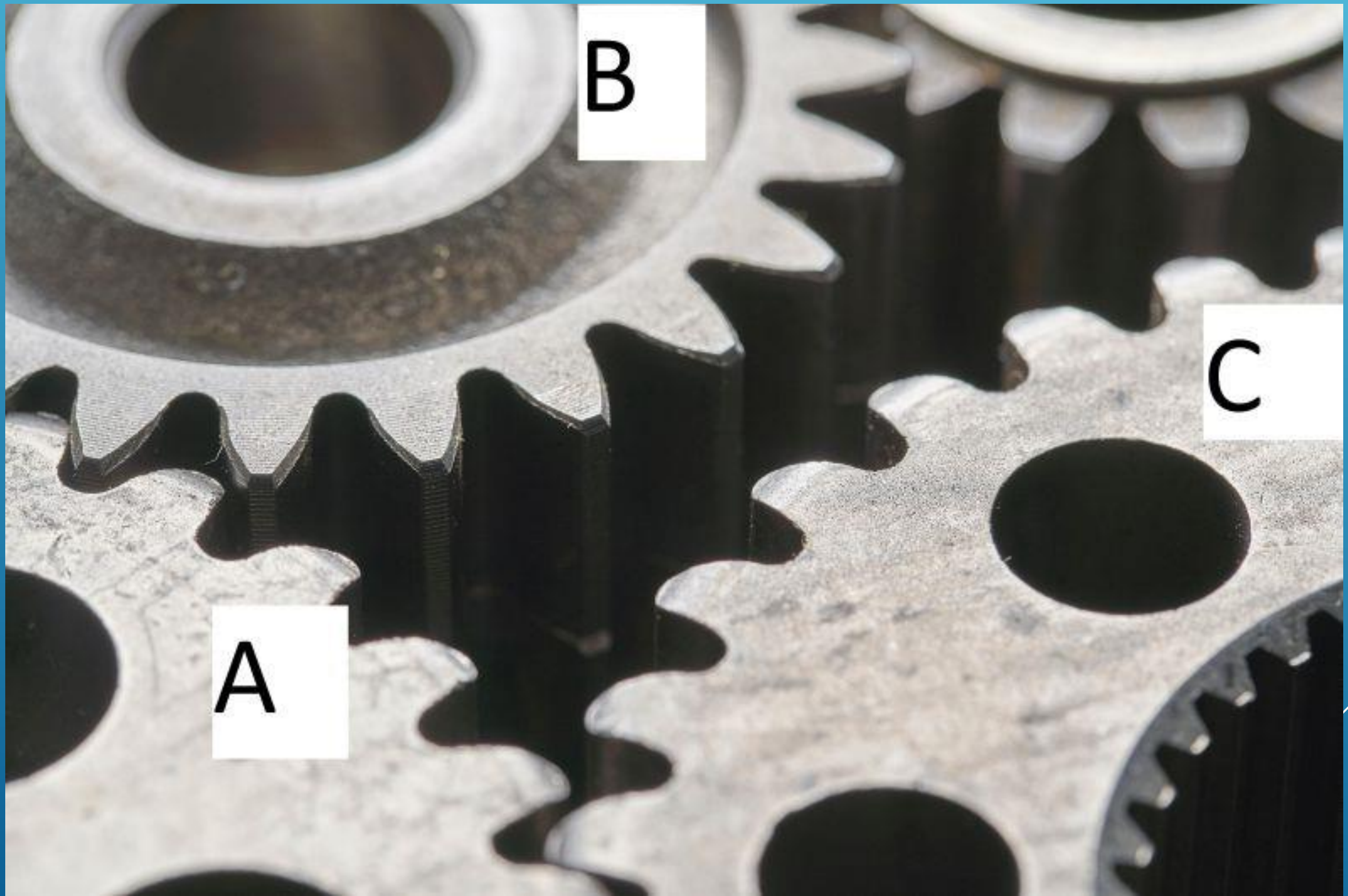
Choose pre-causal functioning of CCA1

Command Prompt - cca1_2020

```
Please choose type of "hippocampus"/"brain" which, of course,
 only loosely approximates the biological equivalent:
1. Lamprey hippocampal/brain analogue
2. Fish hippocampal/telencephalon analogue
3. Reptile hippocampal/pallium analogue
4. Mammalian hippocampus - note: meaningfulness, precausal
5. Human hippocampus - note: meaningfulness plus full causal features
6. Augmented Human level 1 - simultaneous multiple navigational threads
7. Augmented Human level 2 - algorithm center in each navigational module
Please make a selection:
```

-Agent (AGI, cognitive architecture, etc) has never seen the machine below (or even a similar machine).

-If Gear C is turned, what happens to Gear B?

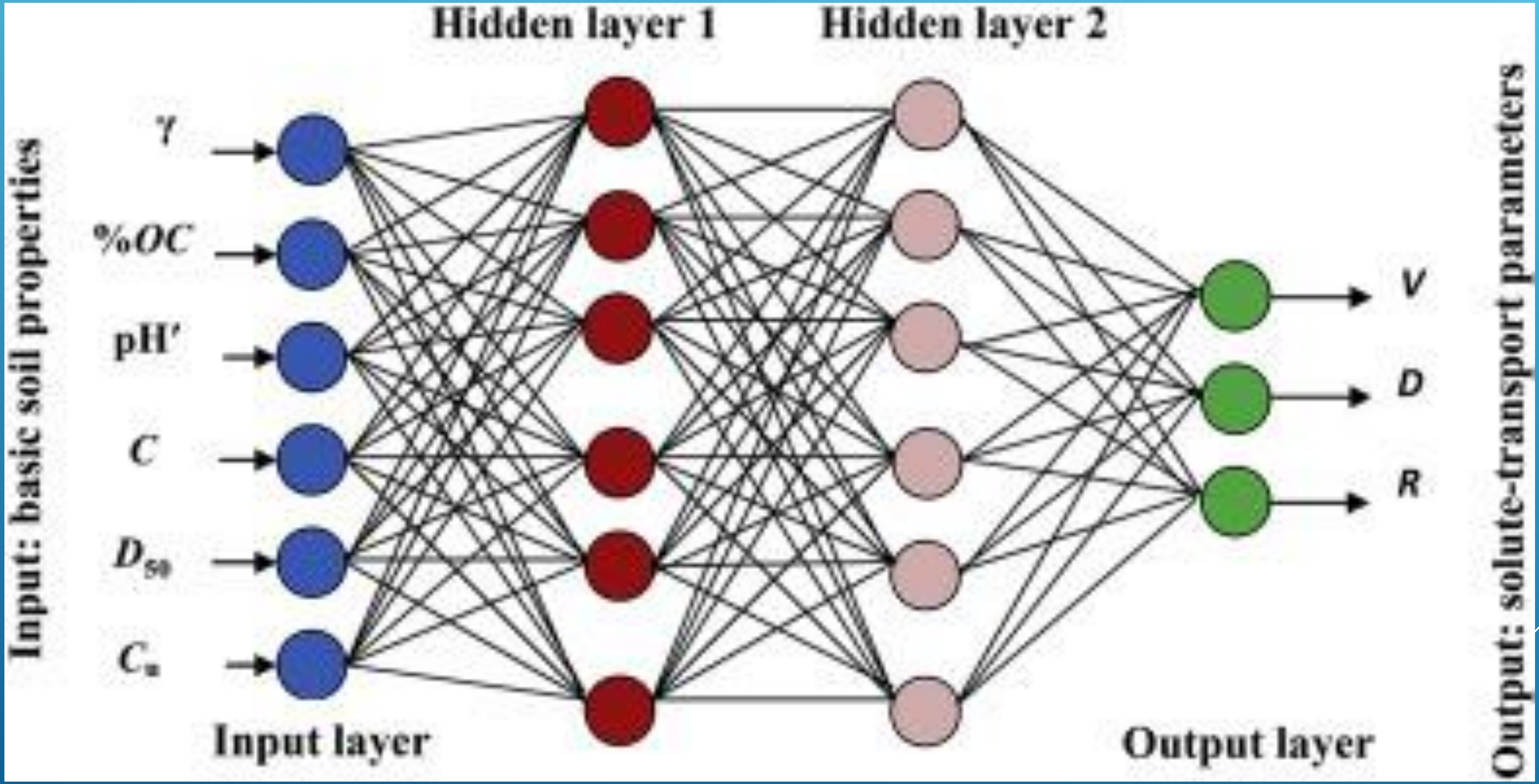


-Cannot fully repair a machine with 100’s of parts by associations only (unless very common reasons for the breakdowns)

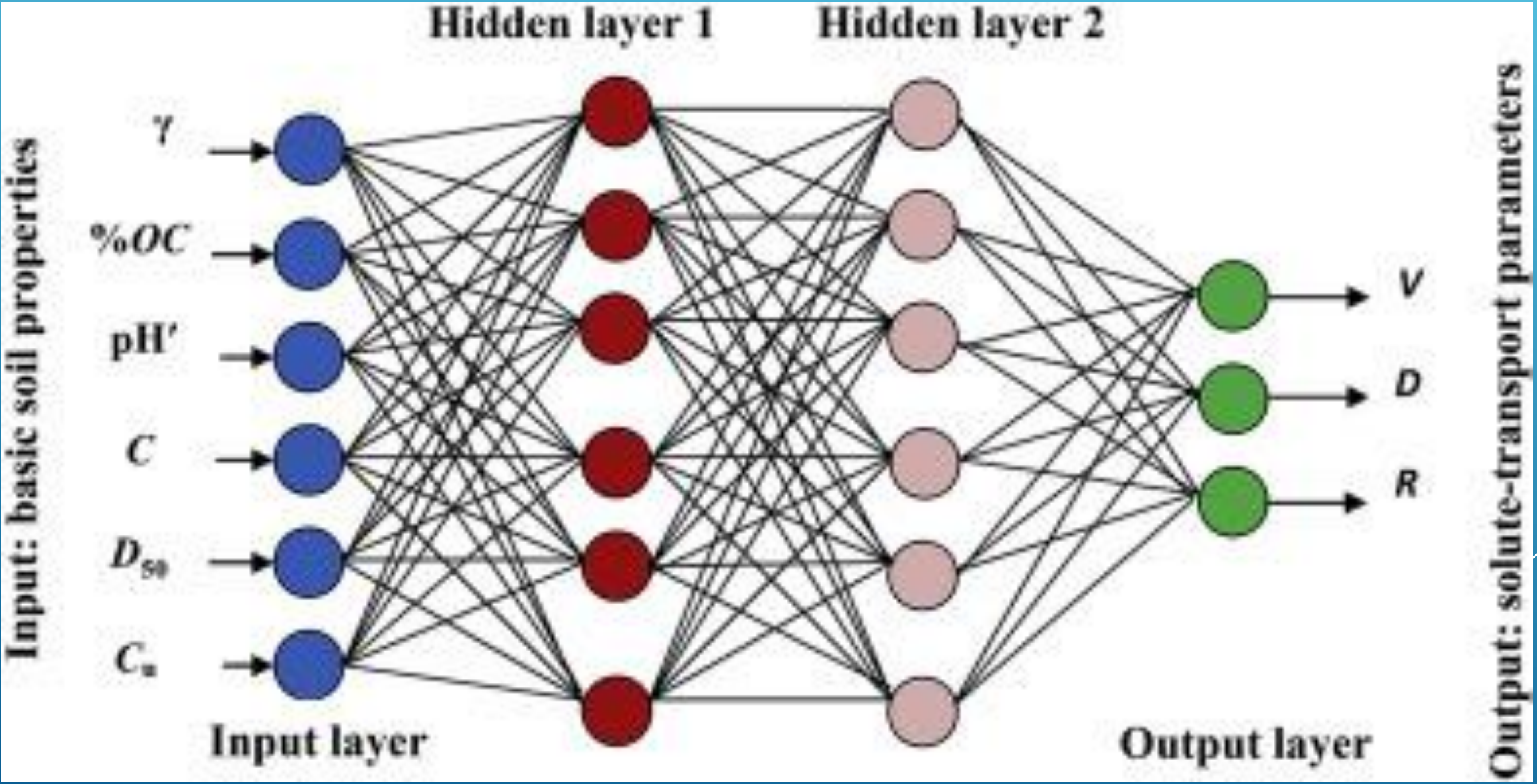
– even if only move a few parts there are millions and millions of combinations that need to be tried and learned by association ->simply not possible/practical

Causality allows repairing a machine the CCA1 has never seen before.

Deep Learning Neural Network great for many recognition and prediction tasks….



….but if something different than its training data…. it cannot predict how to fix machine never saw before



Schneider (2021) – Two-Dimensional Rating Scale for Levels of Intelligence

Axis I: “Level of Intelligence”
Axis II: “Benchmark Value”
(=$\log_{10}$(raw data processing))

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Natural Example: **Spores blowing in wind**

Level 0 – no or few organized associations
Benchmark 1 -- 10^1 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Artificial Example: **Digital clock**

Level 0 – no or few organized associations
Benchmark 2 -- 10^2 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Natural Example: **Bacterial chemotaxis**

Level 1 – reflexive associations
Benchmark 4 -- 10^4 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Artificial Example: **Data lookup table with one billion entries**

Level 1 – reflexive associations
Benchmark 5 -- 10^5 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Natural Example: **Fish simple behaviors**

Level 2 – complex associations
Benchmark 5 -- 10^5 processing power

I: “Level of Intelligence” (0 → 7)
II: “Benchmark Value” (=$\log_{10}$(raw data processing))

Artificial Example: **Convolutional Neural Network can recognize 1 million faces**

Level 2 – complex associations
Benchmark 5 -- 10^5 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Natural Example: **Fish complex behaviors**

Level 3 – complex associations with specialized processing centers
Benchmark 6 -- 10^6 processing power

I: “Level of Intelligence” (0 → 7)
II: “Benchmark Value” (=$\log_{10}$(raw data processing))

Artificial Example: **Generative Pre-Trained Transformer Neural Network with 175 billion parameters**

Level 3 – complex associations with specialized processing centers
Benchmark 7 -- 10^7 processing power

I: “Level of Intelligence” (0 → 7)
II: “Benchmark Value” (=$\log_{10}$(raw data processing))

Natural Example: **Reptile**

Level 4 – complex associations plus some pre-causal associations
Benchmark 6 -- 10^6 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Artificial Example: **Experimental eg, Causal Cognitive Architecture (Schneider, 2021)**

Level 4 – complex associations plus some pre-causal associations
Benchmark 1 -- 10^1 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Natural Example: **Mammal**

Level 5 – fully pre-causal associations
Benchmark 7 -- 10^7 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Artificial Example: **Experimental, eg, Causal Cognitive Architecture (Schneider, 2021)**

Level 5 – fully pre-causal associations
Benchmark 1 -- 10^1 processing power

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Natural Example: **Human**

Level 6 – pre-causal plus some cause-and-effect logic
Benchmark 5 -- 10^5 processing power
(Human := 5)

I: "Level of Intelligence" ($0 \rightarrow 7$)
II: "Benchmark Value" ($=\log_{10}$(raw data processing))

Artificial Example: **not available**

Level 6 – pre-causal plus some cause-and-effect logic
Benchmark n/a -- $10^{n/a}$ processing power
(Human := 5)

I: "Level of Intelligence" (0 → 7)
II: "Benchmark Value" (=$\log_{10}$(raw data processing))

Natural Example: **not available**
Artificial Example: **not available**

Level 7 – fully cause-and-effect mechanisms
Benchmark n/a -- $10^{n/a}$ processing power

Level of Intelligence	Natural Example	Artf'l Example	Benchmark Art Ex
Level 0 – No or Few Organized Associations	Spores blowing in the wind	Digital clock	**2**
Level 1 – Reflexive Associations	Bacterial chemotaxis	Data lookup table 1B entries	**5**
Level 2 – Complex Associations	Fish simple behaviors	CNN 1M faces	**5**
Level 3 – Complex + Spec Proc Centers	Fish complex behaviors	GPT-3 175B parameters	**7**
Level 4 – Complex +some Pre-Causal Associations	Reptile	Experimental [e.g., CCA]	**1**
Level 5 – Fully Pre-Causal Associations	Mammal	Experimental [e.g., CCA]	**1**
Level 6 – Pre-Causal +some Cause-and-Effect	Human	not available	human := **5**
Level 7 – Fully Cause-and-Effect	not available	not available	**n/a**

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