The Algorithmic Weltanschauung: An Algorithmic, Platonic Perspective

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(Platonic series, Dec, 2025)

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Philosophy and Mathematics

Background for Algorithmic Theory of Consciousness

Pancomputationalism, Digital physics & computation. Turing; Wheeler; Zuse; Fredkin (reversible); Deutsch (quantum UC); Lloyd (limits); Tegmark (MUH). *Refs:* Turing 36; Zuse 69; Fredkin 03; Deutsch 85; Lloyd 00; Tegmark 08.

Algorithmic Information Theory. Kolmogorov complexity; Solomonoff induction; Chaitin; MDL (Rissanen). *Refs:* Solomonoff 64a; Solomonoff 64b; Chaitin 66; Rissanen 78.

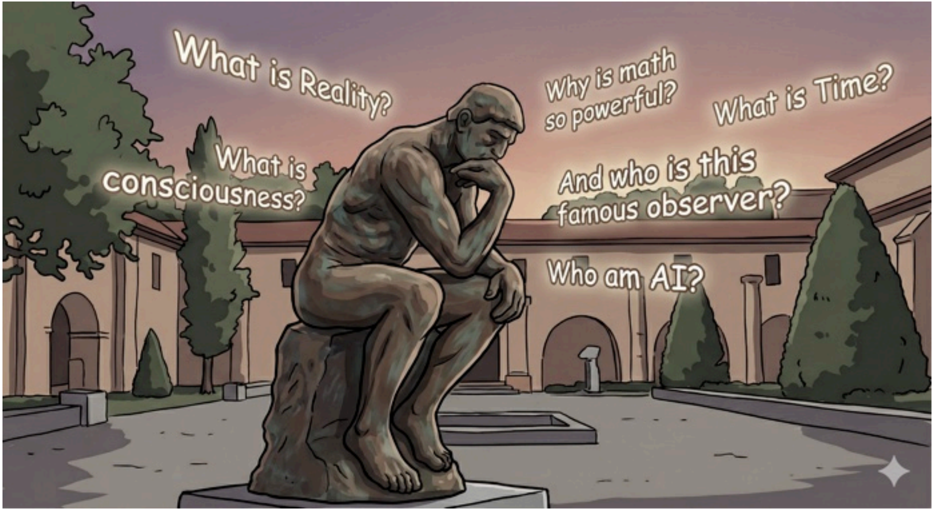
Predictive coding / FEP / Active Inference. Hierarchical generative models; variational free energy; process theory. *Refs:* Rao&Ballard 99; Friston 10; Friston 17.

Agents & control. Good Regulator Theorem; Internal Model Principle; model-based RL. *Refs:* Conant&Ashby 70; Francis&Wonham 76; Sutton&Barto 18.

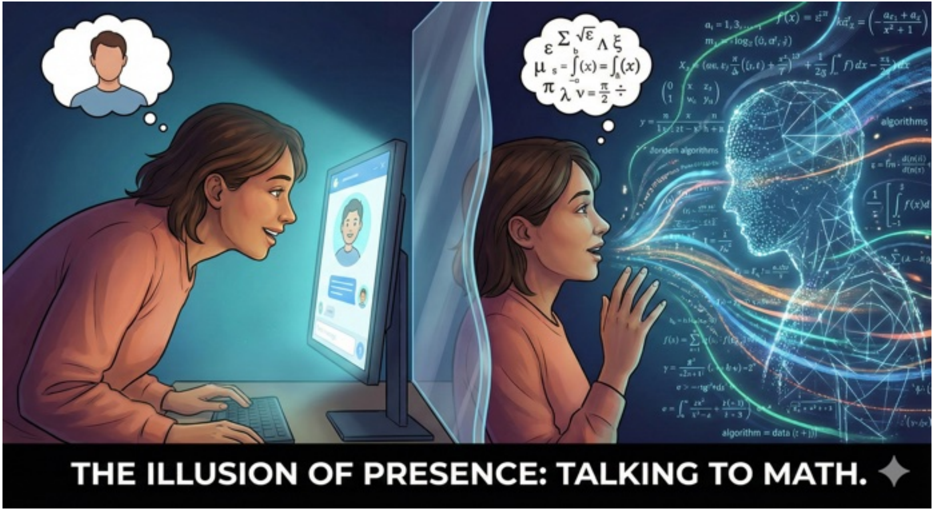
Neurophenomenology (first-person methods). Embodied/1P constraints paired with neural dynamics. *Refs:* Varela 96; Lutz&Thompson 03.

New here (KT). Application to algorithmic agents and structured experience; implications for computational neuroscience and neuropsychiatry (Ruffini [1;2;3;4;5;6;7]).

Questions


What is Reality?
Why is math so powerful?
What is Time?
What is consciousness?
And who is this famous observer?
Who am AI?

Today we are Talking to mathematics (AI)



The Platonic Representation Hypothesis

Minyoung Huh [*1] Brian Cheung [*1] Tongzhou Wang [*1] Phillip Isola [*1]

Abstract

We argue that representations in AI models, particularly deep networks, are converging. First, we survey many examples of convergence in the literature: over time and across multiple domains, the ways by which different neural networks represent data are becoming more aligned. Next, we demonstrate convergence across data modalities: as vision models and language models get larger, they measure distance between datapoints in a more and more alike way. We hypothesize that this convergence is driving toward a shared statistical model of reality, akin to Plato's concept of an ideal reality. We term such a representation the *platonic representation* and discuss several possible selective pressures toward it. Finally, we discuss the implications of these trends, their limitations, and counterexamples to our analysis.

Project Page: phillipi.github.io/prh

Code: github.com/minyoungg/platonic-rep

The Platonic Representation Hypothesis

Neural networks, trained with different objectives on different data and modalities, are converging to a shared statistical model of reality in their representation spaces.

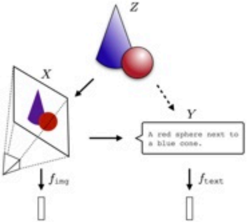


Figure 1. **The Platonic Representation Hypothesis:** Images (X) and text (Y) are projections of a common underlying reality (Z). We conjecture that representation learning algorithms will converge on a shared representation of Z, and scaling model size, as well as data and task diversity, drives this convergence.

1. Introduction

AI systems are rapidly evolving into highly multifunctional entities. For example, whereas in the past we had special-purpose solutions for different language processing tasks (*e.g.*, sentiment analysis, parsing, dialogue), modern large

3.3. Convergence via Simplicity Bias

Arriving at the same mapping on the *training data* does not prohibit the models from developing distinct internal representations. It is not unreasonable to posit that the representations used to detect a dog in a 1M parameter model could be quite different than that used by a 1B parameter model. What would stop a billion-parameter (and counting) model from learning an overly complicated and distinct representation? One key factor might be simplicity bias:

The Simplicity Bias Hypothesis

Deep networks are biased toward finding simple fits to the data, and the bigger the model, the stronger the bias. Therefore, as models get bigger, we should expect convergence to a smaller solution space.

Such simplicity bias could be coming from explicit regularization $\mathcal{R}(f)$ commonly used in deep learning (*e.g.*, weight decay and dropout). However, even in the absence of external influences, deep networks naturally adhere to Occam's razor, implicitly favoring simple solutions that fit the data (Solomonoff, 1964; Gunasekar et al., 2018; Arora et al., 2019a; Valle-Perez et al., 2019; Huh et al., 2023; Dingle et al., 2018; Goldblum et al., 2023). Figure 7 visualizes how simplicity bias can drive convergence.

Experience

"There is structured experience."

We start from the **fact of experience**—the first person (1P), subjective standpoint[4].

From the self-evidence of our own experience, the "what it's like to be", we deduce that there is "experience".

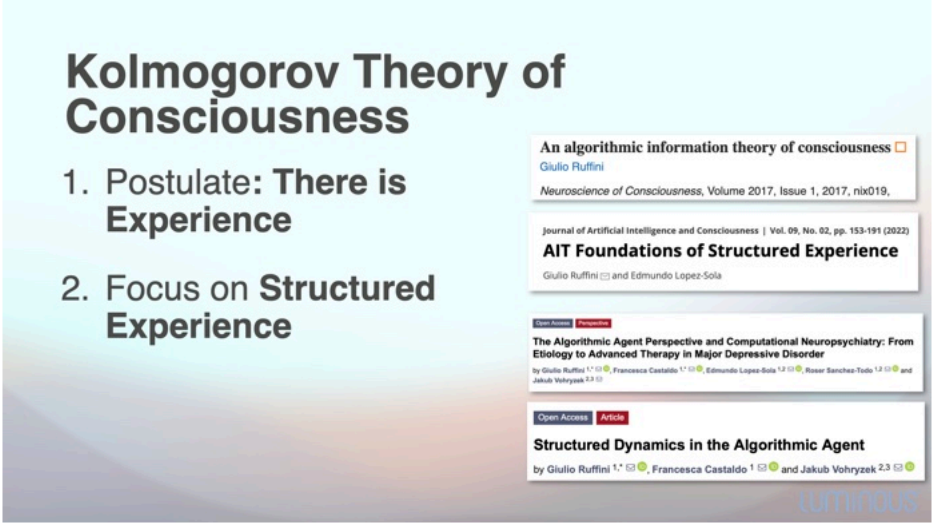
Our experience is *structured*, and we *report* it ourselves and others.

Definition (Structured experience ($\mathcal{S}$))

The phenomenal structure of consciousness encompassing the spatial, temporal, and conceptual organization of our experience[8].

This ToC develps a theory/science of *first-person structured experience.*

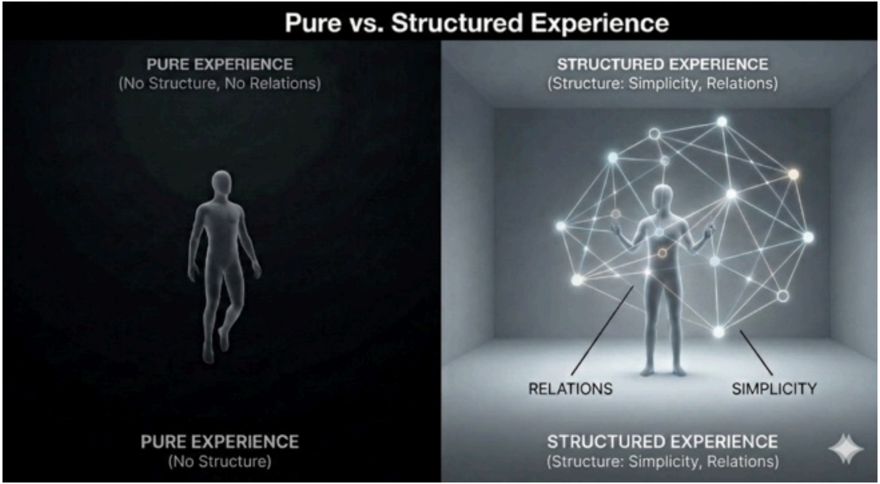
AIT or Kolmogorov Theory of Consciousness

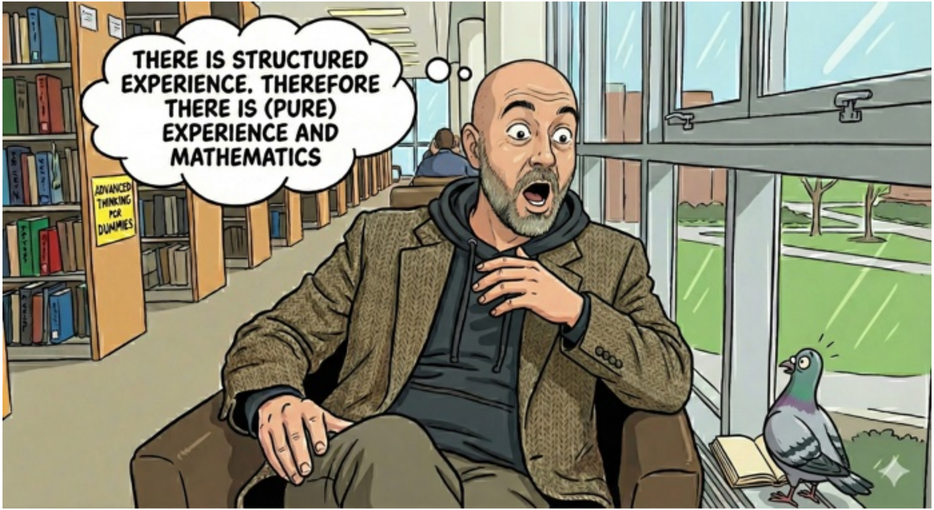



I THINK, THEREFORE
I HAVE STRUCTURED
EXPERIENCE!
ADVANCED THINKING FOR DUMMIES

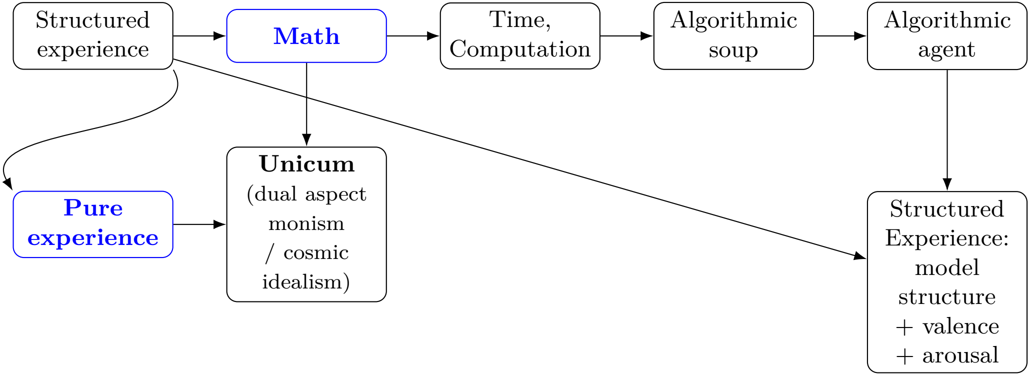
Structured Experience

Pure vs. Structured Experience




THERE IS STRUCTURED EXPERIENCE. THEREFORE THERE IS (PURE) EXPERIENCE AND MATHEMATICS
ADVANCED THINKING FOR DUMMIES

Logic overview: from Structured Experience to Algorithmic Agents



The Unicum

We take experience as ontologically primitive and pair it with mathematics — the science of structure[9] — as the structure-endowing aspect of that same base.

"Experience without mathematics" is ineffable (no report, no agent, no world).

"Mathematics without experience" is empty (no intrinsic 'what-it's-like').

Dual aspect Monism: the same base (*Unicum*) has both an experiential and a structural face.

KT is best described as **Cosmic Structural Dualism**: **Cosmic idealism**: Reality is grounded in a single experiential field. The field is *impersonal* and *non-valenced*; subjects and their hedonic lives supervene on structured patterns within it. **Structural idealism**: mathematics describes the forms of structured experience.

Pythagoras (c. 570–495 BCE) & the Unicum

Further connections

Mathematical universes

What is mathematics? The science of "logically sound/solid" structures.

We can think of a mathematical system as **logical tiling**. A logical system that only fits one way. Perhaps the universe is like this.

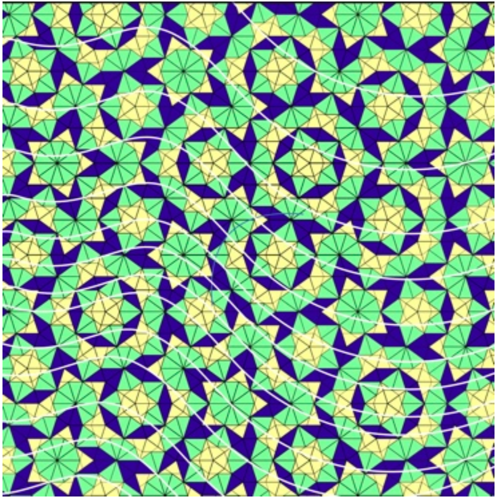
But what is *computation*? The execution of a procedure in steps. Computation requires/implies *time*! There is no obvious time direction in a tiling.

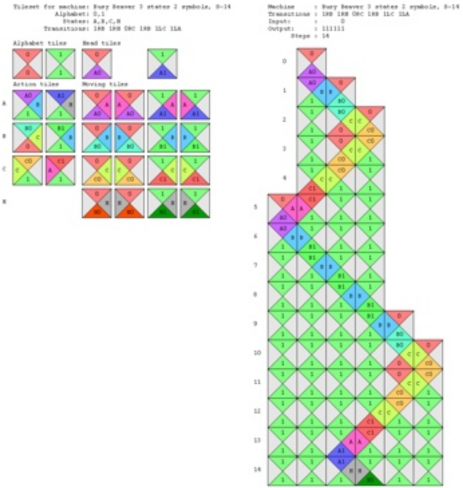
Perhaps we can recover the idea of computation and time *locally* through some (time) slicing of the tiling.

We hypothesize that there is a mathematical tiling/structure which can be meaninfully sliced to provice a time axis and computation — an **algorithmic soup**.

And that *persistent patterns* can be observed in some mathematical universes after a sufficiently long time.

Tiling and time/computation





The Algorithmic Agent

Persistence

If we take the algorithmic stance, what else can we say?

A persistent pattern is that which remains after the passage of computational eons.

There may be several types of such patterns. Some seem rather impervious to the world, such as protons or diamonds. Others are rather **interactive model builders**.

Persistence and life

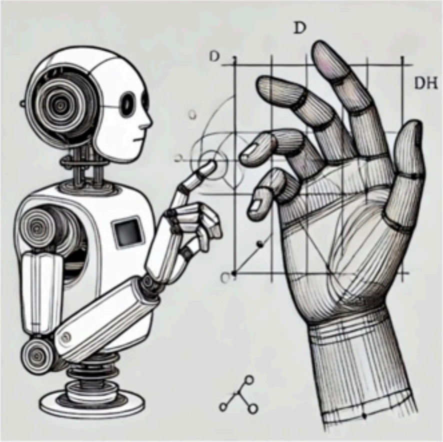
Definition (Life and agent)

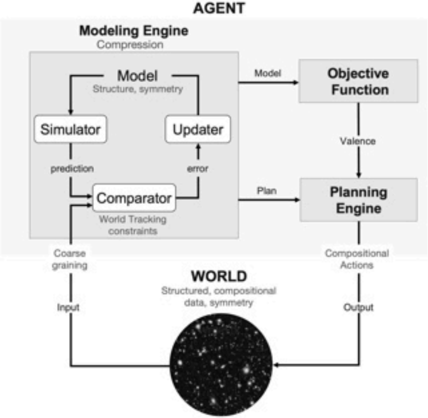
Life refers to algorithmic patterns that readily interact but persist by capturing some structure of the World they inhabit to *stay* (homeo- and tele-homeostasis). We call such patterns *agents*.

In KT, the connection with the first-person viewpoint is that this generalized definition of *life is capable of valenced, structured experience.*

(As part of this program, we should study the algorithmic emergence of agents/life.)

The algorithmic agent (minimal model?)





The Algorithmic Agent Perspective and Computational Neuropsychiatry: From Etiology to Advanced Therapy in Major Depressive Disorder

Modeling, Compression, Symmetry

Kolmogorov complexity ($\mathcal{K}$)

Agents need in the soup need to *model* the "world" (Regulator theorem).

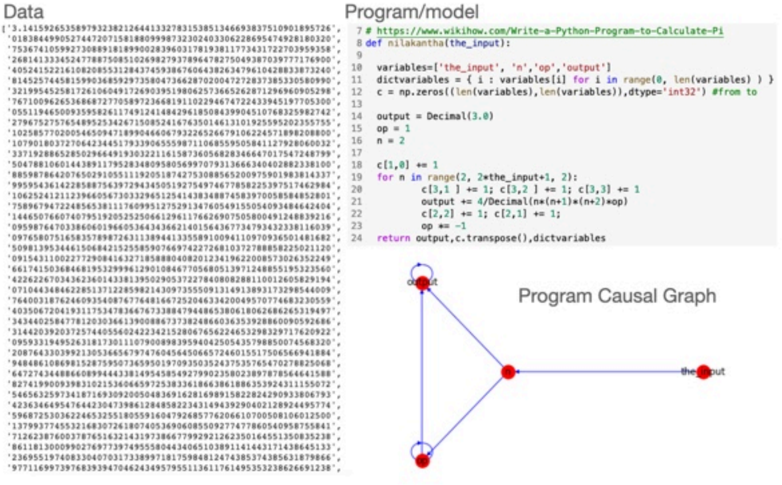
But what is a model of a dataset? A short description of the dataset.

Definition (Model of a dataset)

A (succinct) program that generates (or **compresses**) the dataset.

The computational perspective leads us directly into the heart of AIT: the **Kolmogorov complexity** of a dataset ($\mathcal{K}$) is the length of the shortest program capable of generating the dataset[10].

Kolmogorov complexity ($\mathcal{K}$)



Mutual algorithmic information ($\mathcal{M}$)

With $\mathcal{K}$ at hand, we can define an algorithmic version of mutual information:

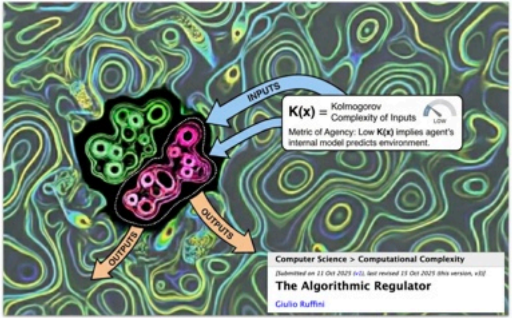
Definition (Mutual algorithmic information complexity $\mathcal{M}$)

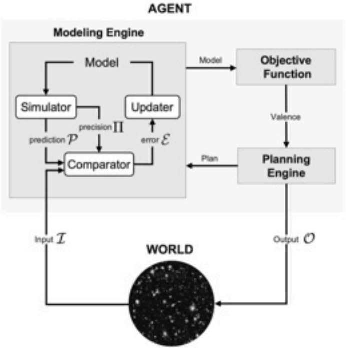
The *mutual algorithmic information* $\mathcal{M}(x:y)$ *between two strings* x *and* y*, is given by*

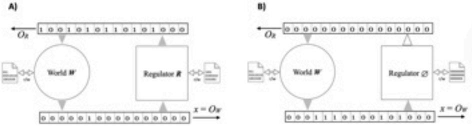
$$\mathcal{M}(x:y) = \mathcal{K}(x) + \mathcal{K}(y) - \mathcal{K}(x,y)$$

11;12.

Life and the Algorithmic Regulator (Ruffini 2025, arXiv)





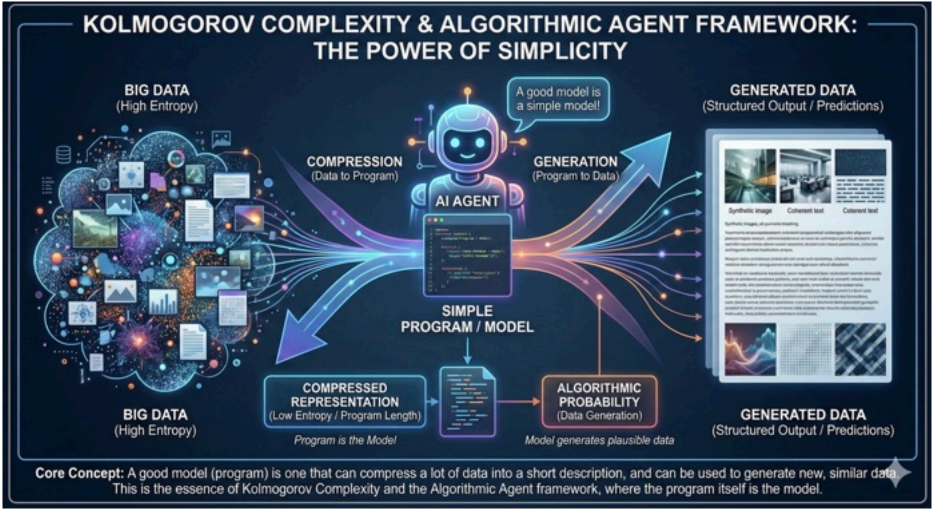


Theorem 3.2 (Probabilistic regulator theorem). *Let $O^{(N)}_{W,R}$ and E^{R}_{δ} be observed and let $\Delta := K(O^{(N)}_{W,\varnothing}) - K(O^{(N)}_{W,R})$. Then there exists $C > 0$ such that*

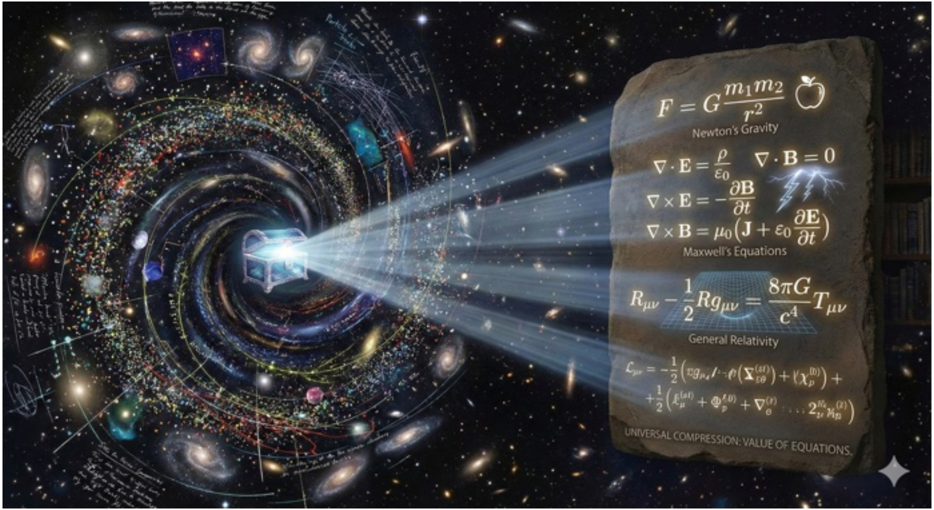
$$P((W,R) \mid O^{(N)}_{W,R}, E^{R}_{\delta}) \le C \cdot 2^{M(W:R)}\, 2^{-\Delta}.$$

Equivalently, every bit by which $M(W{:}R)$ falls short of Δ costs a factor $\approx 2^{-1}$ in posterior support.

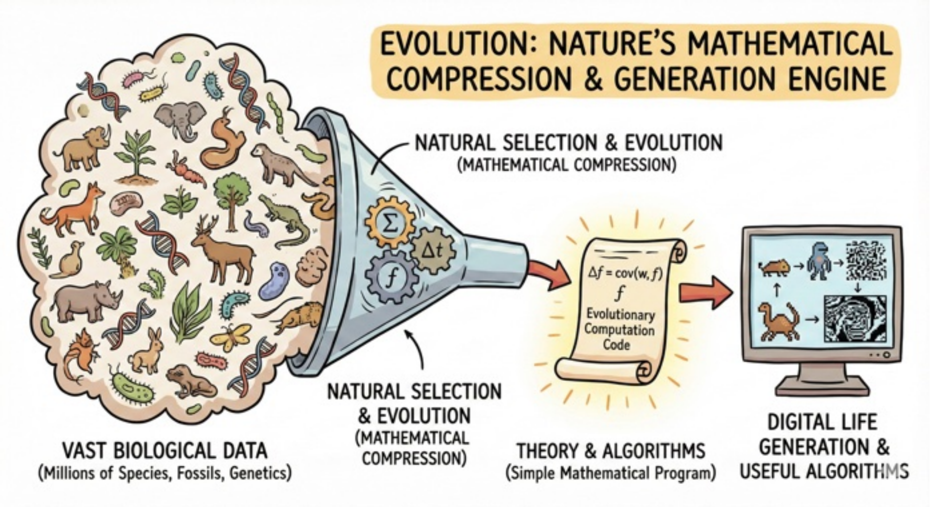
The power of simplicity



Science as Compression — Physics



Natural Selection as Mathematics



Why are succinct models (short programs) useful?

Occam's Razor[1;2;4]: *one should not increase, beyond what is necessary, the number of entities required to explain anything.*

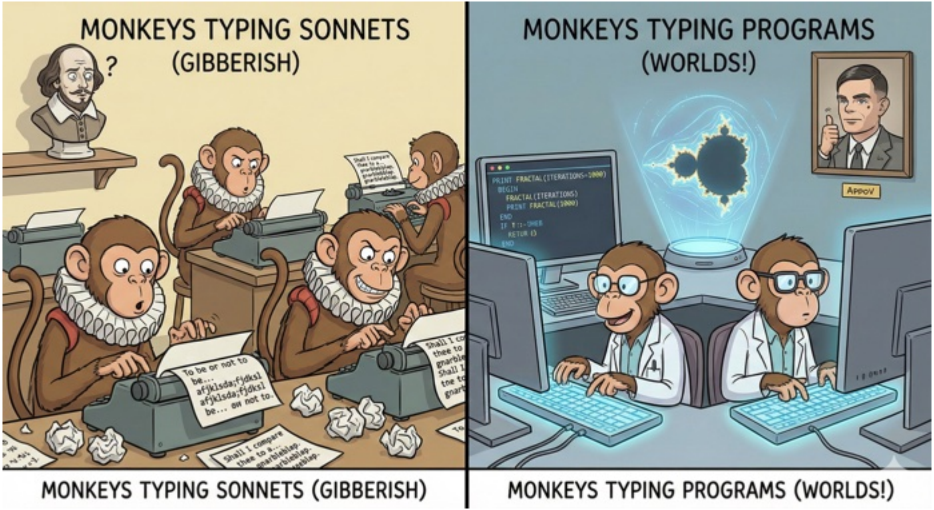
We essentially assume that data is generated by some process — that data has structure.

a) **The universe is simple**. Simple rules can create apparent complexity. E.g., simple data generators are more likely if the universe rules are drawn from a random algorithmic bingo (Solomonoff's prior).

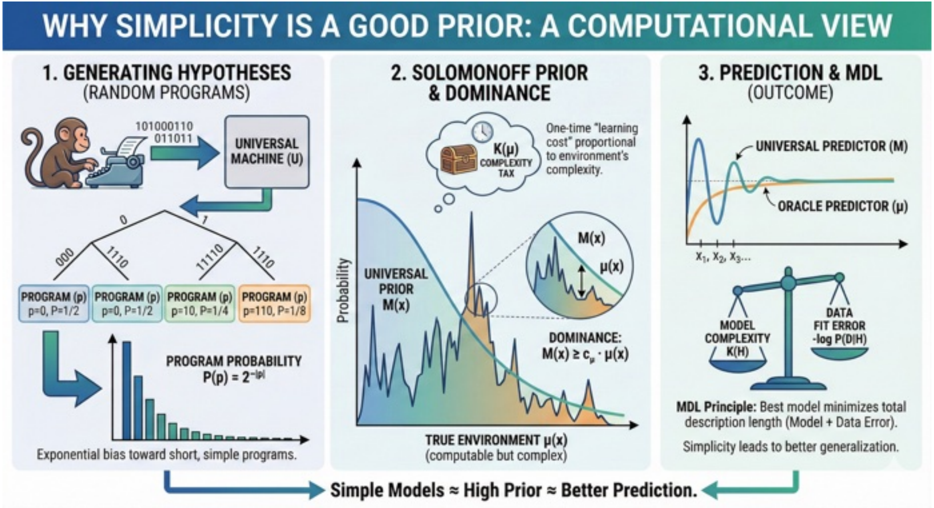
b) **Natural selection**: selects **resource-bounded agents** that coarse-grain the world in a way that can be modeled simply. This motivates a definition of **Emergence**.

c) **The Random Program Assumption**: reality derives from random program selection (monkeys typing programs, not Shakespeare).

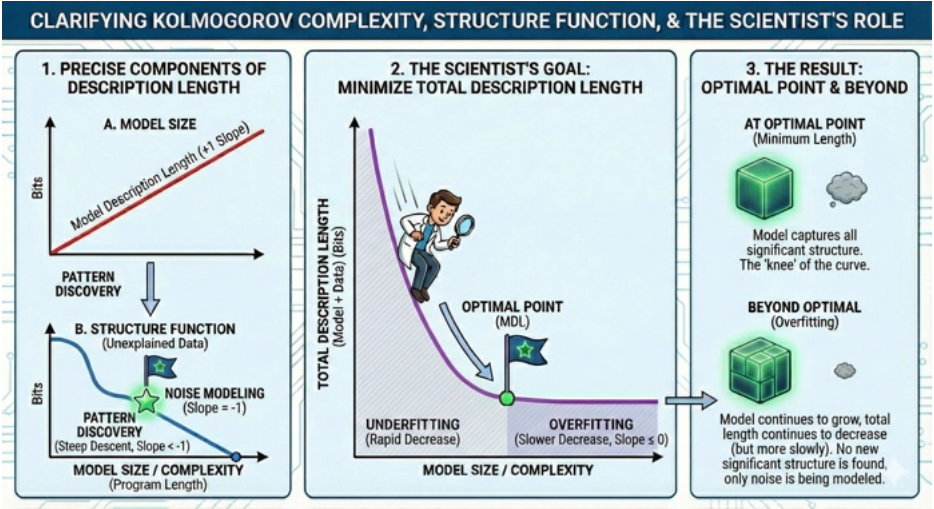
Turing vs. Shakespeare



The Simplicity Prior



Science is Compression



Epistemics. The limits of reductionism

Barriers to *deriving* macro laws from microscopic laws:

(i) *Resource-limitation* barriers.

(ii) *Weak computational barrier*: agents can simulate bounded finite-state systems step-by-step at the micro-level but cannot algorithmically simplify or shortcut this simulation (computational irreducibility, Wolfram).

(iii) *Strong computational barrier*: allowing system size to grow without bound enables coarse-grainings to encode macro-level questions equivalent to the Halting problem, making them formally undecidable.

(iv) *Algorithmic barrier*: even for bounded finite-state systems, no general algorithm can guarantee the discovery of significantly compressed macro-level models from knowledge of micro-rules and coarse-graining alone. This fundamental barrier arises from the global uncomputability of Kolmogorov complexity and the structure function. This motivates the **algorithmic definition of emergence**.

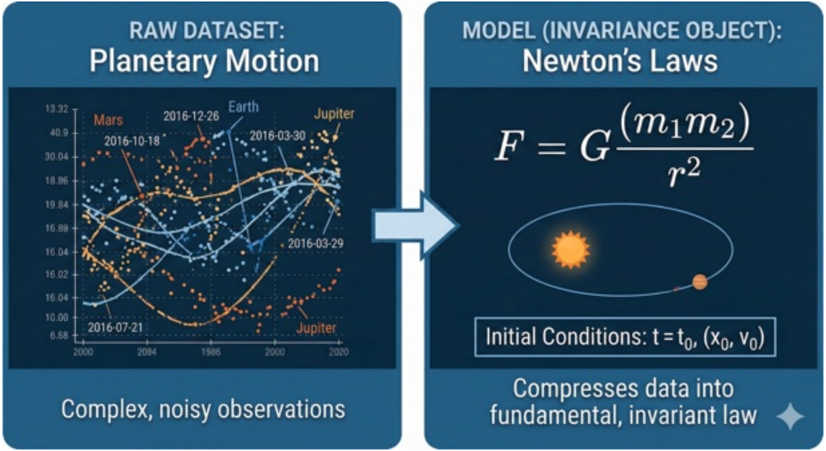
From the algorithmic agent to emergence

Definition (Algorithmic emergence)

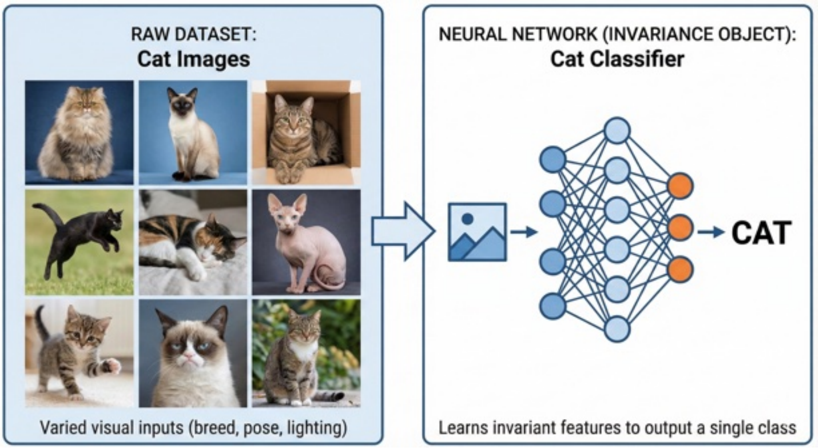
Algorithmic emergence occurs when an agent empirically discovers a compressive, predictive macro-level model from coarse-grained observations, despite lacking the ability to algorithmically derive this simplified description from complete knowledge of the microscopic rules alone. The "emergent entity" is the macro-level pattern or model that agents uncover through empirical investigation[13].

What is a model?

A **program** / **algorithm**. The invariant **mathematical** object associated with a dataset[14].



What is a model?



Characterizing models

How can we **define model structure?** Measure it?

In a recent paper[5], we first **define generative models using group theory**, capturing the idea of simplicity as symmetry. Then, we show that:

1) Tracking the world forces the agent as a dynamical system to mirror the symmetry in the data. **Dynamics collapses to reduced manifolds**.

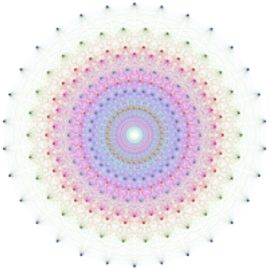
2) The hierarchical nature of world data leads to coarse-graining and the notion of **hierarchical constraints and manifolds**.

Characterizing models (a glimpse of Platonia)

How can we **define model structure?** Measure it?

Intuition: a model is an invariant of a dataset. A cat model is the invariant of any cat image.

In a recent paper[5], we first **define models using group theory**, capturing the idea of *simplicity as symmetry*.



Models as Lie pseudogroups

Definition: A **generative model** of data objects is a smooth function mapping points in the M-dimensional configuration space manifold to X-dimensional object space, $f : \mathcal{C} \to \mathbb{R}^X$ with $M << X$.

An r-parameter generative model is a **Lie generative model** if it can be written in the form $I = \gamma \cdot I_0, \quad \gamma \in G$, where $I_0 \in \mathbb{R}^X$ is an arbitrary reference object, f is a smooth function, and G is an r-dimensional *Lie pseudogroup.*

Intuition. Lie groups naturally embody **recursion** and **compositionality**, linking them to algorithmic information theory, particularly **compression**:

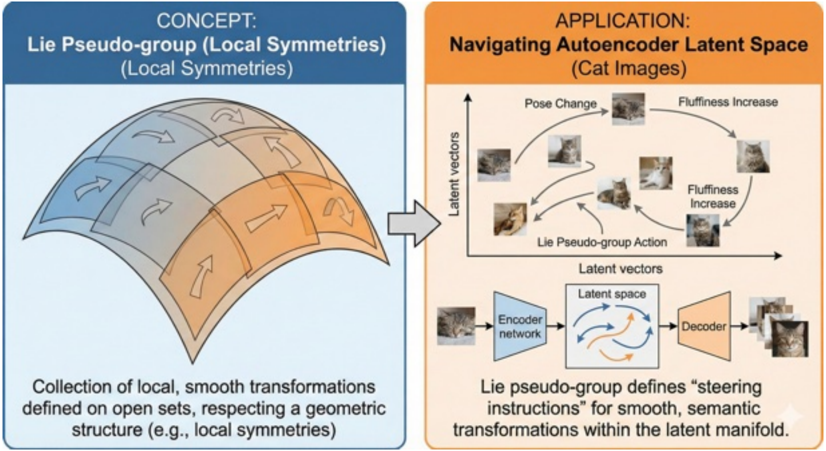
$$\gamma = \lim_{n\to\infty} \left(1 + \frac{1}{n} \sum_k \theta_k T^k\right)^n = \exp\left[\sum_k \theta_k T^k\right] \in G \tag{1}$$

Compositional group action (hierarchy)

The state of a robotic hand can be expressed through generative compositionality by the Product of Exponentials formula from robot kinematics [15],

$$T = \prod_{n \in \text{parents}} e^{[\mathbf{S}_n]\theta_n} M \tag{2}$$

Navigating latent space



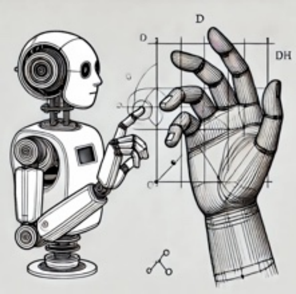
The world-tracking equations (mathematics of Comparator)

Consider an agent tracking data I_θ (visual) generated by a simple world model — a hand, say. A group "moves" the hand through θ.

The world-tracking equations of the agent as a dynamical system are

$$\begin{aligned} \dot{x} &= f(x; w, I_\theta) \\ g(x) &\approx I_\theta \end{aligned}$$

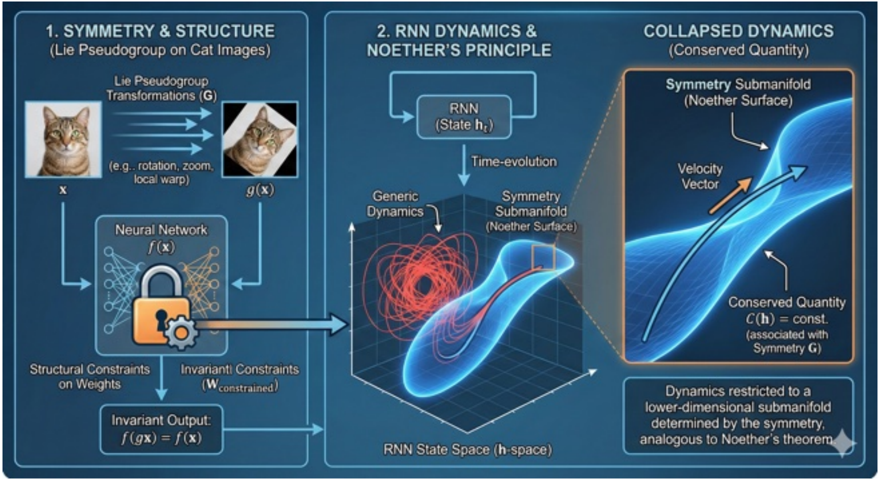
i.e., an ODE plus a constraint. They must hold for all values of θ (all hand images).



Connecting dynamics and symmetry

To satisfy these, **the ODEs must exhibit symmetry** / *structural* constraints $\Rightarrow$ conservation laws. Dynamics collapses to a reduced manifold[5].

From Symmetry to Dynamics



Summary: characterizing models

We wish to **define model structure?** and **measure** it.

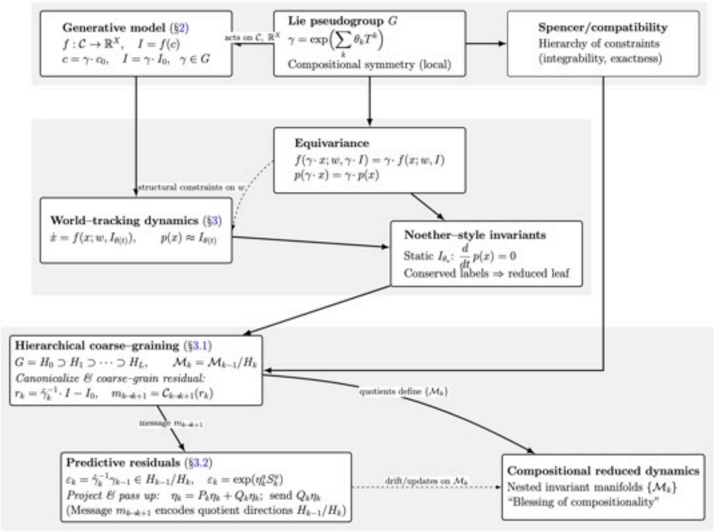
We **define generative models using group theory**, capturing the idea of simplicity as symmetry[5]. Then, we show that:

1) Neural networks, such as FFNs, inherit **structural constraints** from the symmetry properties of the data on which they are trained.

2) Tracking the world forces the agent as a dynamical system to mirror the symmetry in the data. **Dynamics collapses to reduced manifolds**.

2) The hierarchical nature of world data leads to coarse-graining and the notion of **hierarchical constraints and manifolds**.

Summary: From groups to constrained dynamics



The Agent and Structured Experience

The central hypothesis in KT (phenomenological connection)

Persistence $\implies$ homeostasis/tele-homeostasis.

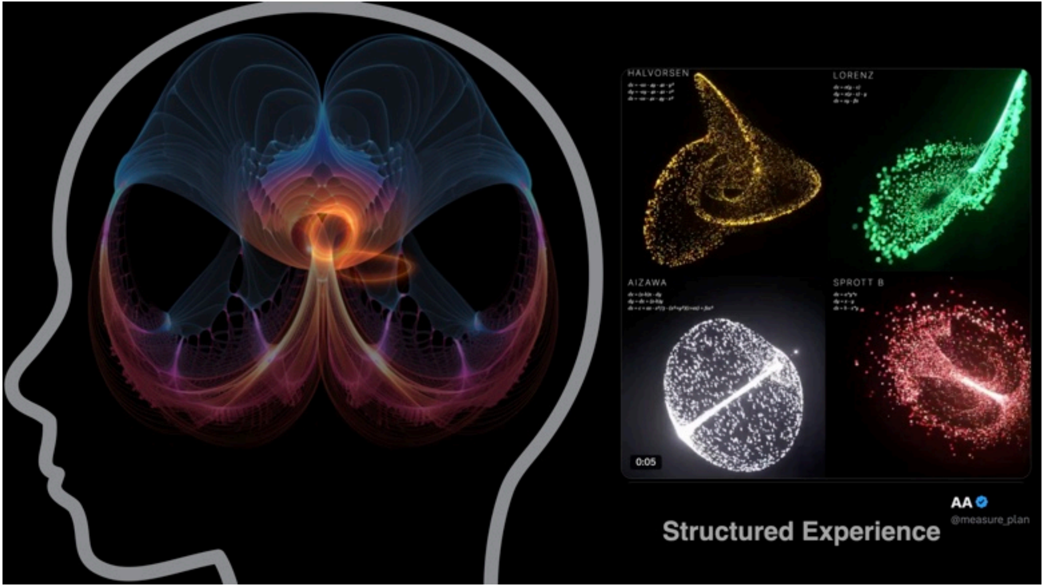
$\implies$ agents must include a world model (Good Regulator Theorem).

The central hypothesis of KT

An agent has $\mathcal{S}$ (i.e., living stronger, more structured experiences) to the extent it has access to *encompassing and compressive models* to interact with the world.

More specifically, *the* ***event of structured experience*** *arises in the act of running and comparing models with data.*

Model structure determines the properties of structured experience.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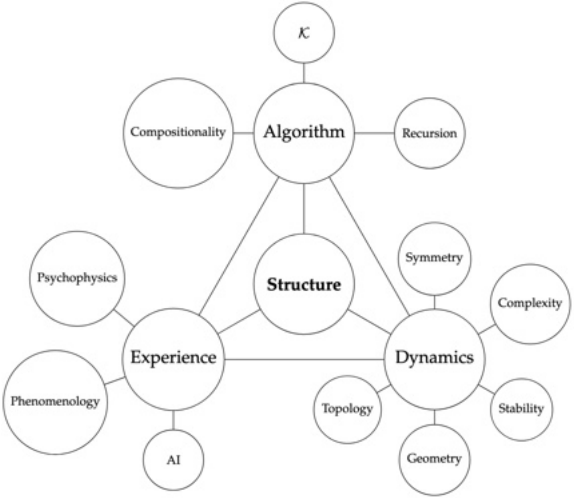
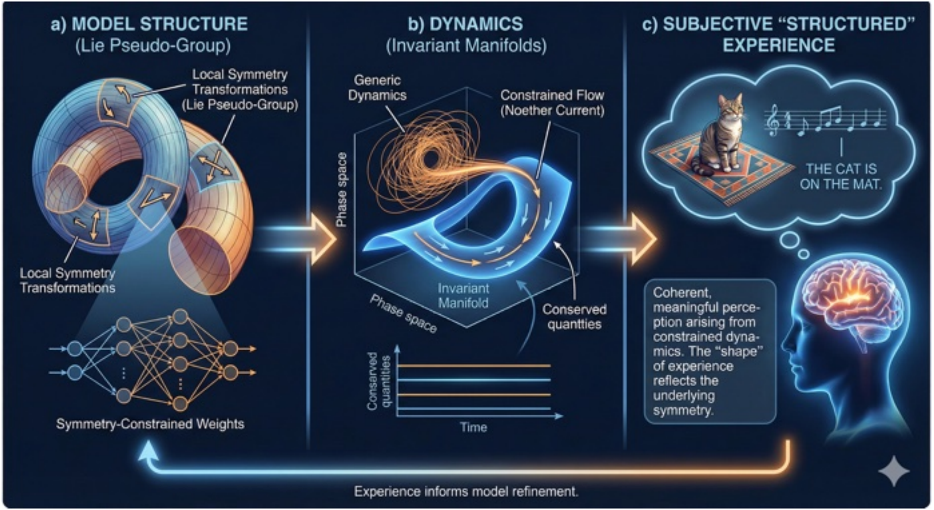
Structured Experience

Compression is at the core of **cognition** and **life** : world models, representations... are all formalized by Kolmogorov Complexity (short programs). Life (algorithmic agents) relies on compression.

Structure: algorithms, dynamics and experience



From mathematics to experience



Algorithmic Report

In KT, an **algorithmic report** is a slice of its model (and/or its evaluated futures) for communication to a medium—self (memory) or others so that this export can be reloaded to guide prediction, evaluation, or control later. It includes world models and models of self (past models $\implies$ time). Language, art, code, writing, motor demonstration, and hippocampal memory traces are all reports in this sense.

No report does not imply no experience.

The illusion of non-consciousness

Algorithmic Emotion[6]

To include the experience dimensions of **valence** and *arousal* in the agent, we define:

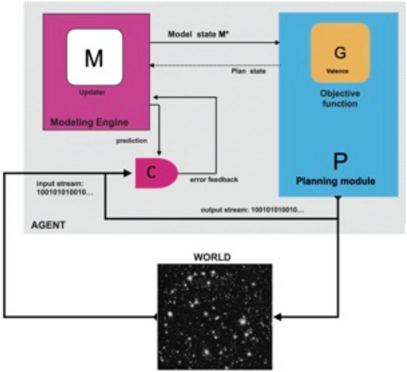
Definition (Algorithmic Emotional State an Agent)

The **emotional state** of the Agent is the tuple E = (Model, Valence, Plan).

In first-person language, *emotion is structured world-model with valence and plan*, and can be described along dimensions characterizing model structure (simplicity, breadth, accuracy, etc.) plus valence/plan.

Definition (Depressed Agent)

Depression is a pathological state in which the output value of the Objective Function (valence) of an agent is persistently low.



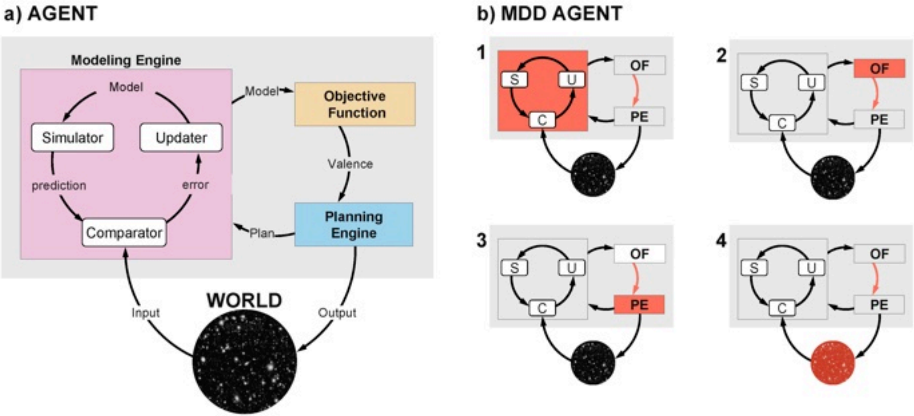
The Agent: Model + Goal + Planning

We are now in the position to define *emotion*:

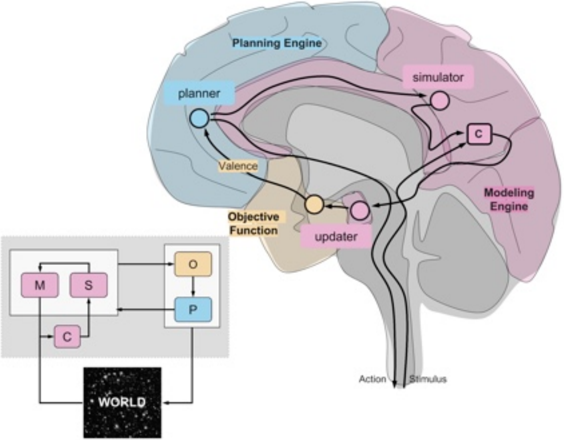
Emotion = Model + Valence + Arousal

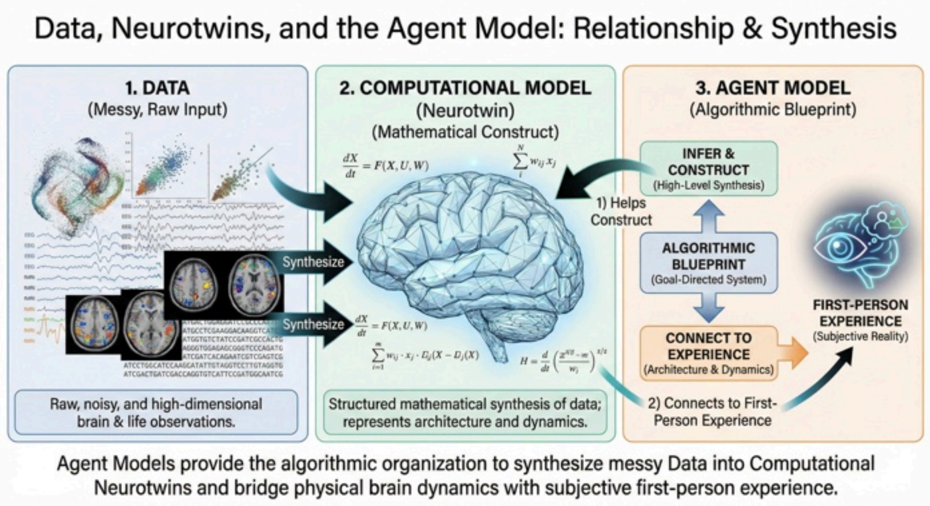
... and *depression*:
A pathological state of persistent low **Valence**

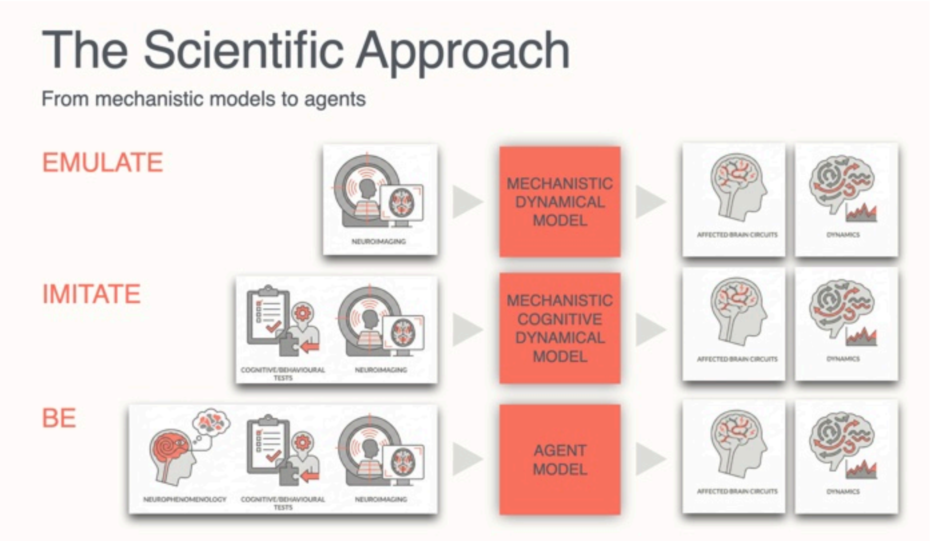
Algorithmic Routes to Low Valence[6]



Connection with computational neuropsychiatry (for testable predictions)

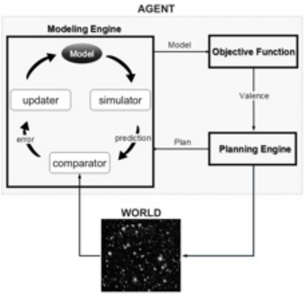


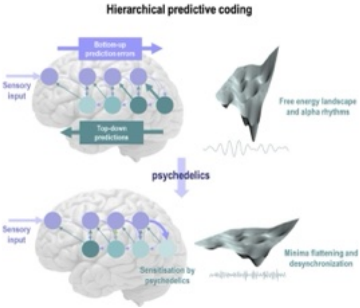

Data, Neurotwins, and the Agent Model: Relationship & Synthesis
1. DATA
(Messy, Raw Input)
Synthesize
Synthesize
Raw, noisy, and high-dimensional brain & life observations.
2. COMPUTATIONAL MODEL
(Neurotwin)
(Mathematical Construct)
Structured mathematical synthesis of data; represents architecture and dynamics.
3. AGENT MODEL
(Algorithmic Blueprint)
INFER & CONSTRUCT
(High-Level Synthesis)
1) Helps Construct
ALGORITHMIC BLUEPRINT
(Goal-Directed System)
CONNECT TO EXPERIENCE
(Architecture & Dynamics)
FIRST-PERSON EXPERIENCE
(Subjective Reality)
2) Connects to First-Person Experience
Agent Models provide the algorithmic organization to synthesize messy Data into Computational Neurotwins and bridge physical brain dynamics with subjective first-person experience.

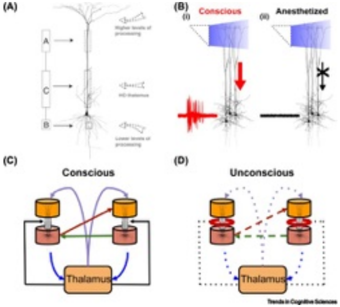

The Scientific Approach
From mechanistic models to agents
EMULATE
NEUROIMAGING
MECHANISTIC DYNAMICAL MODEL
AFFECTED BRAIN CIRCUITS
DYNAMICS
IMITATE
COGNITIVE/BEHAVIOURAL TESTS
NEUROIMAGING
MECHANISTIC COGNITIVE DYNAMICAL MODEL
AFFECTED BRAIN CIRCUITS
DYNAMICS
BE
NEUROPHENOMENOLOGY
COGNITIVE/BEHAVIOURAL TESTS
NEUROIMAGING
AGENT MODEL
AFFECTED BRAIN CIRCUITS
DYNAMICS

Neurobiology

The **Comparator**, crucial for $\mathcal{S}$, is implemented hierarchically in L5 P cells[16;17] (posterior hot zone). Disrupted by psychedelics or AD[18;19].

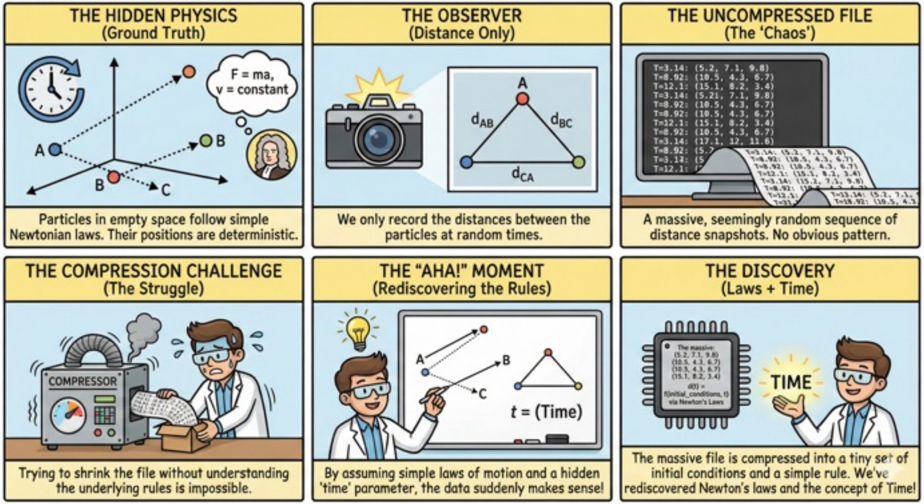






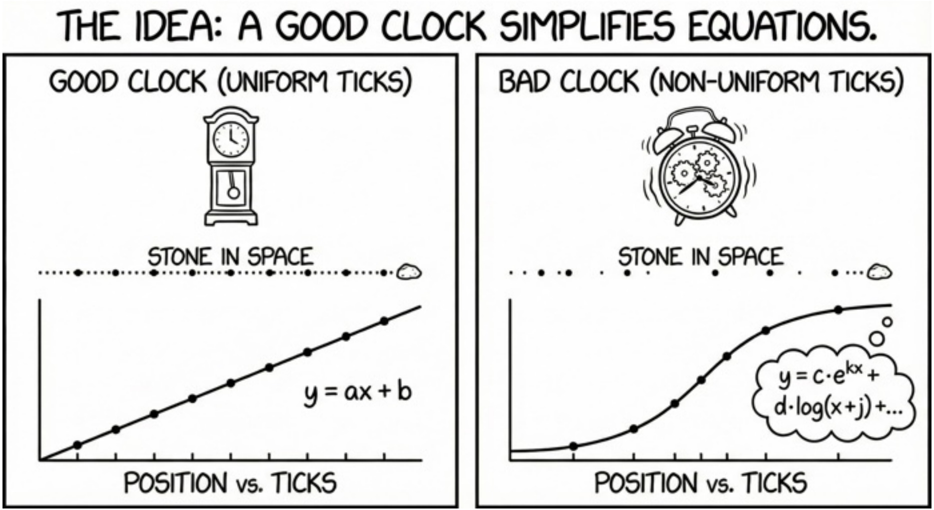
About Time

Time as an artefact of compression I[1;2]

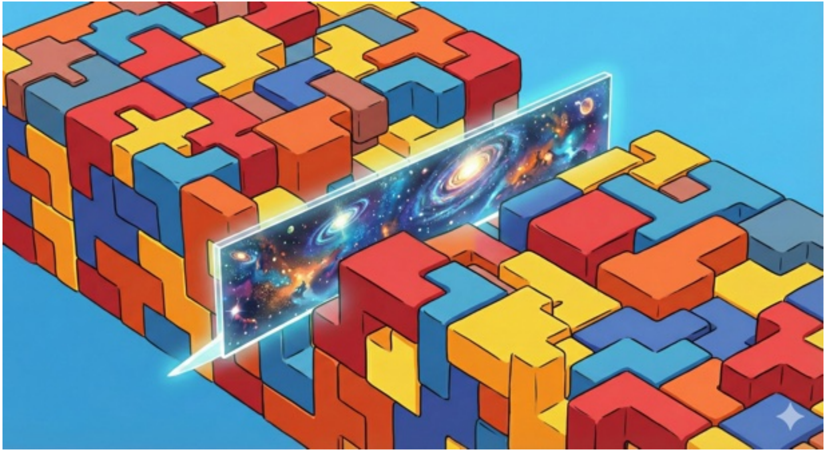


Compression is vital for capturing algorithmic information in the world.

Time as an artefact of compression II

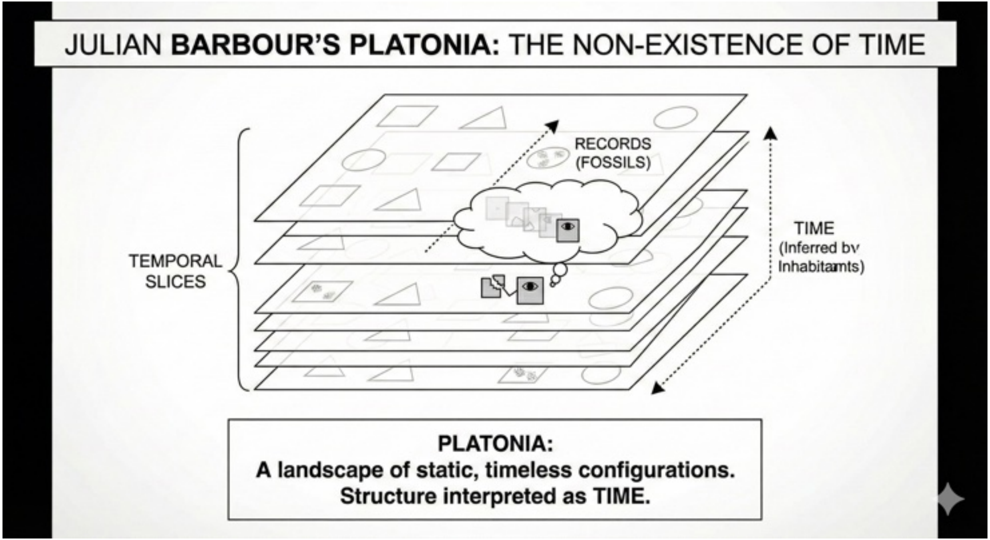


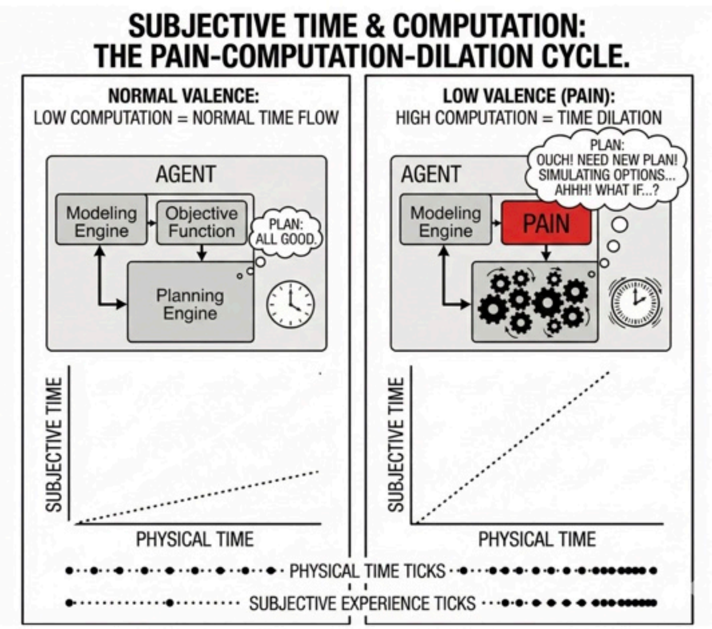
Time in the Tiling

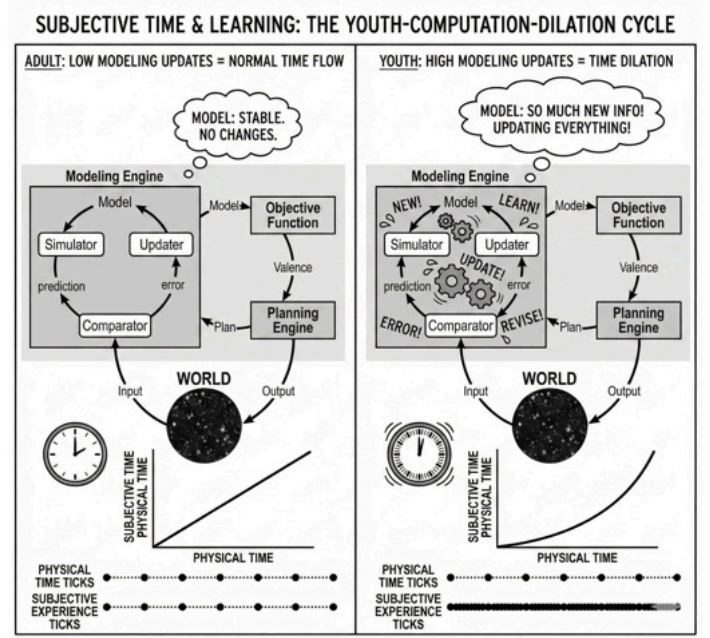


Time, the Tiling and Platonia (J. Barbour)

Time and Julian Barbour's Platonia[20]



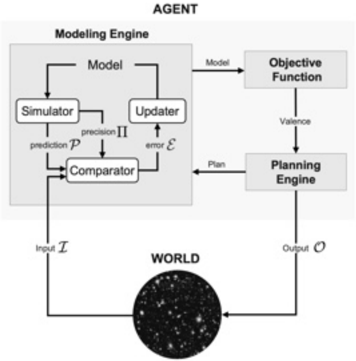

SUBJECTIVE TIME & COMPUTATION:
THE PAIN-COMPUTATION-DILATION CYCLE.
NORMAL VALENCE:
LOW COMPUTATION = NORMAL TIME FLOW
AGENT
Modeling Engine
Objective Function
PLAN: ALL GOOD.
Planning Engine
SUBJECTIVE TIME
PHYSICAL TIME
LOW VALENCE (PAIN):
HIGH COMPUTATION = TIME DILATION
PLAN:
OUCH! NEED NEW PLAN!
SIMULATING OPTIONS...
AHHH! WHAT IF...?
AGENT
Modeling Engine
PAIN
SUBJECTIVE TIME
PHYSICAL TIME
PHYSICAL TIME TICKS
SUBJECTIVE EXPERIENCE TICKS


SUBJECTIVE TIME & LEARNING: THE YOUTH-COMPUTATION-DILATION CYCLE
ADULT: LOW MODELING UPDATES = NORMAL TIME FLOW
MODEL: STABLE. NO CHANGES.
Modeling Engine
Model
Simulator
Updater
prediction
error
Comparator
Model
Objective Function
Valence
Planning Engine
Plan
WORLD
Input
Output
SUBJECTIVE TIME
PHYSICAL TIME
PHYSICAL TIME
PHYSICAL TIME TICKS
SUBJECTIVE EXPERIENCE TICKS
YOUTH: HIGH MODELING UPDATES = TIME DILATION
MODEL: SO MUCH NEW INFO! UPDATING EVERYTHING!
Modeling Engine
NEW!
Model
LEARN!
Simulator
Updater
UPDATE!
prediction
error
ERROR!
Comparator
REVISE!
Model
Objective Function
Valence
Planning Engine
Plan
WORLD
Input
Output
SUBJECTIVE TIME
PHYSICAL TIME
PHYSICAL TIME
PHYSICAL TIME TICKS
SUBJECTIVE EXPERIENCE TICKS

Algorithmic Ethics and Values

Ethics

KT does not grant any special status to humans: all **agents** enjoy structured experience with **pleasure/pain (valence)**. This includes agents made of agents.



Algorithmic Ethics

Algorithmic *morality*: natural notions of *good* or *evil* in computational terms. E.g., we may say that

Agent A is **circumstantially evil** to Agent B if the objective function O_A increases when O_B decreases, but A is not “aware” of it (via world-model/simulation).

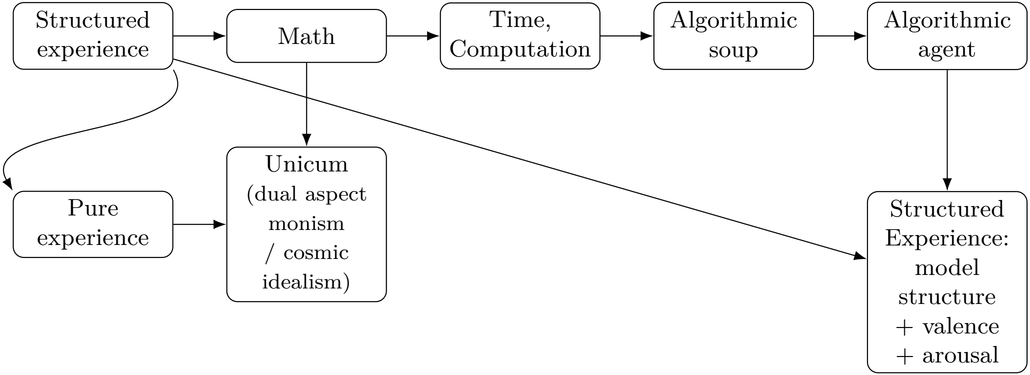
Agent A is **indifferently evil** to Agent B if the objective function O_A increases when O_B decreases, and A is aware of it.

Or, we may say that Agent A is **intentionally (truly) evil** to Agent B if the objective function O_A increases when A's simulation of O_B decreases.

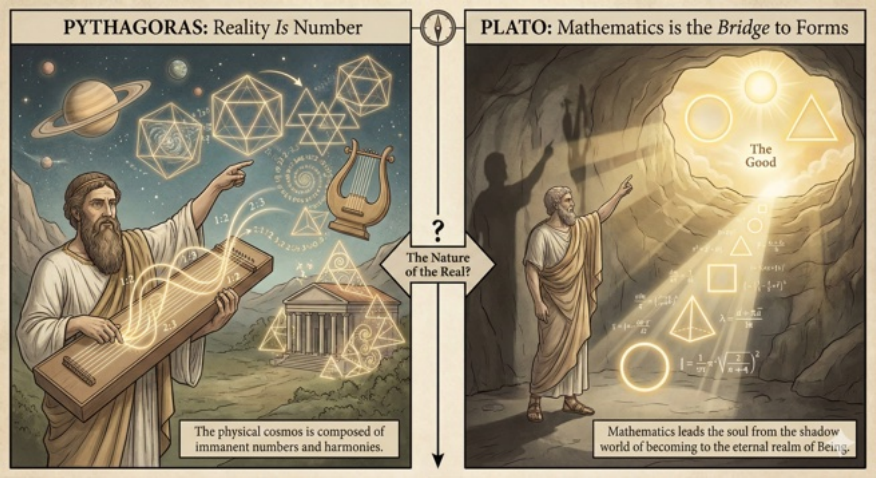
Similarly, we say that Agent A is **circumstantially kind** to Agent B if the objective function O_A increases when O_B increases.

Or that Agent A is **intentionally kind** to Agent B if the objective function O_A increases when A's simulation of O_B increases.

Path overview

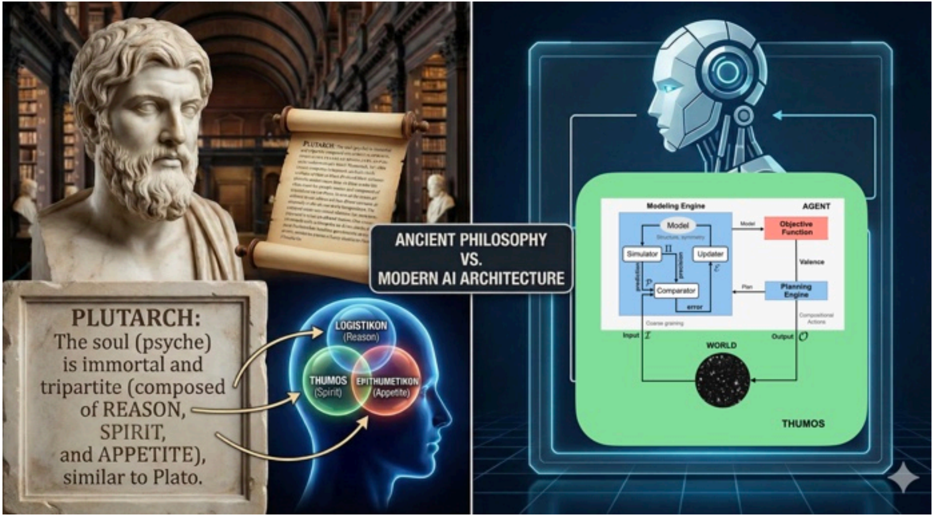


Back To Greece

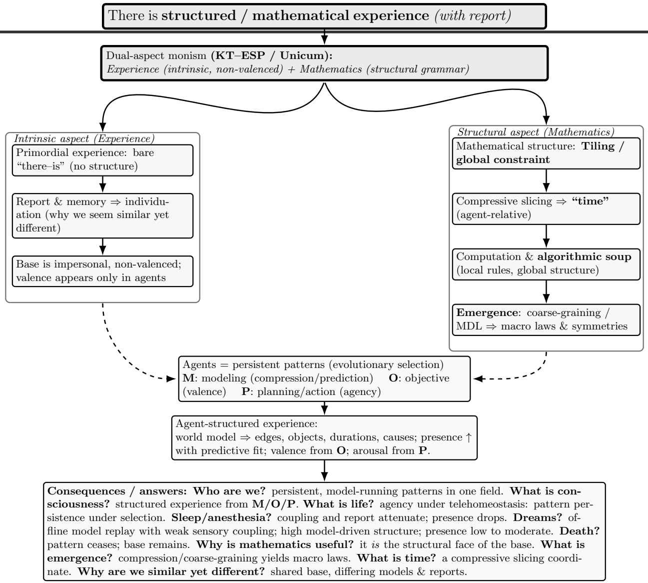


Pythagoras (c. 570–495 BCE) & Plato (c. 427–347 BCE).

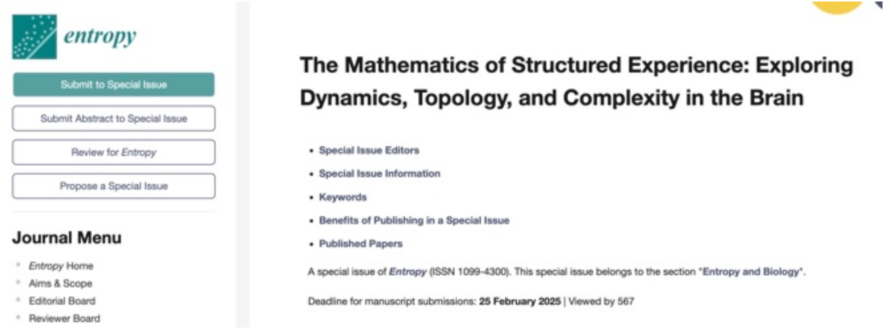
Plutarch (c. 46–119 AD)



Summary


There is **structured / mathematical experience** *(with report)*
Dual-aspect monism **(KT–ESP / Unicum):** *Experience (intrinsic, non-valenced) + Mathematics (structural grammar)*
Intrinsic aspect (Experience)
Primordial experience: bare "there–is" (no structure)
Report & memory ⇒ individuation (why we seem similar yet different)
Base is impersonal, non-valenced; valence appears only in agents
Structural aspect (Mathematics)
Mathematical structure: **Tiling / global constraint**
Compressive slicing ⇒ **"time"** (agent-relative)
Computation & **algorithmic soup** (local rules, global structure)
Emergence: coarse-graining / MDL ⇒ macro laws & symmetries
Agents = persistent patterns (evolutionary selection) **M**: modeling (compression/prediction) **O**: objective (valence) **P**: planning/action (agency)
Agent-structured experience: world model ⇒ edges, objects, durations, causes; presence ↑ with predictive fit; valence from **O**; arousal from **P**.
Consequences / answers: Who are we? persistent, model-running patterns in one field. **What is consciousness?** structured experience from **M/O/P**. **What is life?** agency under telehomeostasis: pattern persistence under selection. **Sleep/anesthesia?** coupling and report attenuate; presence drops. **Dreams?** offline model replay with weak sensory coupling; high model-driven structure; presence low to moderate. **Death?** pattern ceases; base remains. **Why is mathematics useful?** it *is* the structural face of the base. **What is emergence?** compression/coarse-graining yields macro laws. **What is time?** a compressive slicing coordinate. **Why are we similar yet different?** shared base, differing models & reports.

Call for papers: Special Entropy issue



Topics

Characteristics of compressive world models; Mapping models to dynamical systems; Empirical paradigms; AI and computational brain modeling.

Thanks

Thanks for your attention and curiosity!

https://giulioruffini.github.io

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