
Nature Based Functional Analysis ‘general intelligence’ and causality in science

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Abstract

1 This paper names structural fundamentals for general intelligence and for mapping
2 causality in science. Three scientific models are used to pose an empiric core,
3 beyond artificial intelligence’s statistics. The models are Boltzmann’s thermody-
4 namic entropy, Shannon’s signal entropy, and Darwinian natural selection, joined
5 to frame all of science-and-engineering with *general terms*. The paper thus names
6 ‘principles’ and ‘primitives’ for intelligence and intelligence building, along with a
7 dualist-triune (2-3) fractal pattern. It claims a *purely structural account* of the cos-
8 mos is possible, prior to adding other ‘detail’, as a multi-level Entropic/informatic
9 continuum with ‘functional degrees of freedom’—all as a mildly-modified view of
10 signal entropy’s structural aspects.

11 1 Introduction and background

12 Intelligence essentially means ‘having an idea’ (abstraction), variably ‘testing’ that idea (feedback),
13 and recalling results (memory), as acquired/applied knowledge toward survival. The role of *human*
14 *intelligence* (HI) in posing such ‘linked abstractions’ has a long, deep, and oft-debated history in the
15 creation of ‘science-and-engineering’ (hereafter *science*, a psychological artifact).

16 Science hinges foremost on ‘the informatics’ (primal abstractions, math, language, etc.) used to
17 depict science. In our modern ‘statistical era’ this was noted by Claude Shannon and Warren Weaver
18 [1] as a missing “real theory of meaning”, tied to statistical “signal entropy”¹ [2]. I suggest a *scientific*
19 ‘theory of meaning’ requires framing General Intelligence (GI) for all that is known-and-knowable,
20 across all time, for all matter and energy, in a simple-to-complex cosmos. Such a broad view seems
21 absurd, but volumes of already-won HI demand no less. Also, nature holds near countless adaptive
22 options, evident as diverse life, all of which makes GI or ‘*general science* modeling’ a daunting task.

23 To start, we sense that ‘a thing’ like GI drives HI’s creation of *science* in our vast techno-cultural
24 ecology. But with HI as our sole GI pathway, we see many HI types with instincts, emotions,
25 mixed cultures, and logical gaps. GI thus arises as HI factual-fantasies: factual as partly verified
26 science, born of fantasies (ideation) from a few ‘creative’ individuals. Detailing and navigating such
27 uneven individual↔social psychological facets gives GI modeling an ‘impossible aspect’—driving
28 today’s AI to its statistical methods, contrary to preferred scientific vistas. For example, within GI,
29 science aims to describe-and-explain, cause-and-effect, in a measurable-and-repeatable way, with
30 necessary-and-sufficient detail—as a well-ordered ‘agreed view’ (sociability) of material events.

31 2 General intelligence principles

32 A question thus lingers, ‘How can we usefully model GI?’ Statistical AI methods show ‘a type
33 of intelligence’ (inferred answers), but with unsure utility [3, 4]. Probing utility has us next ask

34 ‘What general models already exist to aid GI science?’ Foremost here, HI *survival* evokes Darwin’s
35 “evolution by means of natural selection” (EvNS), our most successful scientific model [5]. EvNS
36 intuits an initial account of ‘How things generally work and fall apart in the cosmos’, for all life.

37 Next, Shannon signal entropy¹ holds *informatic utility* as “the mother of all models” [6]. ‘Informatic
38 processing’ is life’s main **adaptive** path with genomic and behavioral facets. Also, signal entropy’s
39 X^n “logarithmic base” is infinitely scalable, akin to simple-to-complex nature and a ‘natural loga-
40 rithm’² [7]. Moreover, it holds ‘signal-versus-noise’, akin to Life/Death. Despite signal entropy’s
41 utility, ‘information’ is still an *abstraction* of direct material events, with encoded memories studied,
42 joined, and tested for adaptive gains—‘memory’ itself being a type of bare testable informatic model.

43 Lastly, Rudolf Clausius and Ludwig Boltzmann’s views of thermodynamic entropy and statistical
44 mechanics add more detail on ‘How things generally work and fall apart in the cosmos’, with
45 simple-to-complex ‘commonsense’ on things generally *falling-apart* (aka Death).

46 Each model here holds some key GI facet, but alone none fulfill ‘GI’. Still, each shows a ‘functional
47 dialectic’ often seen as Life/Death. They also jointly pose simple-to-complex roles. Lastly, they are
48 all ‘general models’, each applying to a general aspect of all matter-and-life. This all suggests a
49 unified GI view might arise from this broken three-part scientific base—if given a correct framing.

50 2.1 Material utility and ‘informatic intelligence’

51 For a correct framing I first contrast the fact that many ‘material intelligences’ already exist (verified
52 HI), versus futuristic/imagined GI. For example, models like the Standard Model of particle physics
53 and the periodic table mark specific ‘material contexts’ with detailed ‘material content’ (primitive
54 particles, atoms, etc.) Primitive materiality is thus a **1st GI Principle** (P1): materially verified
55 *context-and-content* underlie all informatic/scientific aims, with branching simple-to-complex levels,
56 where **utility** marks how much ‘intelligence’ is truly held. In short, informatic intelligence of various
57 types allows us (via genomics and behavior) to explore/exploit primitive materials—aka science.

58 2.2 Material primitives onto logical primitives

59 Next, for GI *context-and-content*, ‘logical primitives’ differ from P1 ‘material primitives’. For
60 example, ‘modeling as a discipline’ starts as abstractly intuited views (abduction [8], hypothesis
61 formation) of complex real-world events—versus P1 *observed* ‘structures and traits of matter’. GI
62 thus calls for ‘intuitive tools’ (*logical* sensibility, symbols, and rules) alongside P1, to aptly frame
63 material relations, akin to mathematic and linguistic *general* ‘symbols-and-rules’. For example,
64 beyond P1 ‘structures and traits of matter’ GI symbols/rules would **also** hold ‘how matter behaves’ as
65 *logic*, akin to biologist Stuart Kauffman’s “order for free” [9].

66 Grasping ‘material-logic relations’ (causality) is the core of GI, where *material primitives* are domain
67 specific, but *logical primitives* often cross domains (general). Alfred Korzybski [10], founder of
68 general semantics, and biologist Gregory Bateson [11] pointed to material-logic differentiation as a
69 key informatic task—where aptly mapping “levels of abstraction” evokes a **2nd GI Principle** (P2).
70 As such, GI aptly maps/gleans *logical* “levels of abstraction” (P2), for all of observed material reality
71 (P1)—an informatic skill already *partly* exhibited as ‘HI science’.

72 2.3 General intelligence and dual aspects

73 P2 **material-logic** initiates a ‘dual aspect’ akin to ‘body-mind’ and ‘separation’. For more on ‘dualist’
74 P2 *logical primitives*, consider mathematic and linguistic ‘symbol primitives’. Symbolic objects
75 (numbers, letters, signs, tokens, etc.) are **Fitted** via syntactic rules for semantic effects, refined by
76 eons of trial and error. Another GI rule thus arises: (O)bjects + (S)yntax³ = (S)emantics, or *testable*
77 (O)bject (S)yntax affords (S)emantic effects—for all of science, math, language, and signal entropy’s
78 “the mother of all models”. This equally shows in simple machines as *Fit-ness* between Nut-and-Bolt,
79 Hammer-and-Nail, etc. Here, (S)-Fits between (O)s is the key semantic aspect, which I abridge as

¹See Appendix A: Figures 1 and 2 for a brief description and discussion of signal entropy.

² $\ln(x)$: “...one of the most useful functions in mathematics, with applications to mathematical models throughout the physical and biological sciences.”

³Syntax is a more narrowly targeted aspect of otherwise ‘generic order’.

80 2-3 ‘O-S-O’ or **O-(S)**et Fit-ness. *Symbol*-based ‘S-O material-logic’ marks a **3rd GI Principle** (P3a)
81 as a formal *dual aspect theory* or initial ‘theory of meaning’ where (S)ubject-and-(O)bject equally
82 inhabit and detail all of P1 material reality.

83 Here, P3a extends P2’s partly-abstract material-logic, via fully-abstract (S)-and-(O) symbols. (S)-and-
84 (O) *synthetic logic* also echoes dialectics: ‘thesis + anti-thesis = synthesis’; while P1 ‘observed matter’
85 more closely details *analytic logic*. One can also say (O) covers ‘structures and traits of matter’, and
86 (S) covers ‘how matter behaves’—or it frames uniform (S)emantic *logic* for *diverse material* O-S-O
87 roles. Thus, from hereon I use (S)-and-(O) as joint *general* logical primitives to cover all GI, and to
88 aptly map ‘a science’ for diverse (simple-to-complex) roles and levels.

89 2.4 General intelligence and a “Theory of Meaning”

90 (S)-and-(O) may seem like forced roles but a new *general system* is being posed where no other
91 view (math, etc.) answers Shannon and Weaver’s call for a “real theory of meaning” [12]. Shannon
92 [2] initially claimed “semantic aspects . . . are irrelevant to the engineering problem”⁴, in targeting a
93 “logarithmic base”. But he also saw that this left a ‘meaning-full gap’ that must be covered [1, 13].
94 The issue now is that Shannon statistics and its ‘meaningful gap’ also inhabit AI roles.

95 But ‘material \rightleftharpoons dualist logic \rightleftharpoons symbolic S-O (S)teps’, with ‘ \rightleftharpoons ’ feedback (P1, P2, and P3a) initiate
96 commonsense *informatic principles*. Here, signal entropy statistics hold **quantitative** (O)bject aspects.
97 But we now target **qualitative** (S)emantic *complements*—with (S)-Fits between (O)bjects [O-S-O]
98 as a *joint* (S)emantic role, or a base ‘theory of meaning’ as a new scientific system of thought. For
99 example, (S)-Fits between the Standard Model (O) and periodic table (O) mark a (S)emantic shift.
100 The Standard Model maps protons, neutrons, and electrons, three ‘(O)bject based functional degrees
101 of freedom’ (DoF) that next recombine as 94 ‘primitive atomic’ DoF, for a periodic table. This
102 **simple-to-complex** (S)hift shows 3 DoF \rightleftharpoons 94 DoF that also extends to: 1) prior 3 leptons + 3 quarks
103 = protons and neutrons; and 2) ensuing 94 elements + 3 molecular bonds = countless molecules—for
104 *contiguous* ‘simple \rightleftharpoons complex mutability’, not yet covered by any of the above principles.

105 A **4th GI Principle** is thus ‘Simple \rightleftharpoons complex mutability’ (P3b)⁵ with many material-logic facets.
106 Foremost,

- 107 • It holds orderly \rightleftharpoons chaotic, destructive \rightleftharpoons constructive, and simple \rightleftharpoons complex ‘Entropic (S)hifts’,
108 to more clearly detail *synthetic logic*—with an Entropic S-O **creative continuum** key to GI modeling.
- 109 • All of which proceeds via discrete \rightleftharpoons continuous, minute \rightleftharpoons major, and ‘branching’ (S)teps/Fits.
- 110 • This incites causal (S)hift studies, with GI material-logic gleaned (trail-and-error) as knowledge.
- 111 • But if ‘causes’ are otherwise vague, S-O still affords a bare *structural account* of ‘the thing’ studied.
- 112 • Contiguous Entropic-ity as *signal* \rightleftharpoons *noise* also echoes Life \rightleftharpoons Death, to pose a key adaptive task.
- 113 • Finally, a 2-3 (dualist-triune) pattern⁶ arises, as a likely structural/informatic backbone, where
114 **qualitative** (S)hifts are **quantitatively** enumerated via DoF—a *joint* quantitative-qualitative vista.

115 The above frames a 2-3 GI material-logic *structure*, with DoF. These ‘principles-and-primitives’
116 initiate a GI model but much lies ahead, as this already incites much complexity. For example, aptness
117 in *uniformly* mapping *diverse* informatic aspects is key to GI modeling—with uniform-diversity
118 being paradoxical. Some may say this view confuses opposed (S)-and-(O) (early Shannon view),
119 largely echoing ‘art-versus-science debates’ [14]. But science mostly omits creativity while nature is
120 eternally creative. Conversely, 2-3 (S)-and-(O) frame reciprocal-interleaved GI creativity.

121 3 General intelligence modeling: synthetic analysis

122 To continue, I next ‘synthesize’ the three prior scientific models as one role, but first briefly cover
123 scientific **evidence-based** versus AI **experiment-based** views of ‘proof’. Science starts with observed
124 matter (P1) and proceeds from there, but AI statistics differ. Models like IBM Watson and ChatGPT
125 start with large databases, parsed via statistics, where more-massive databases are called ‘foundation
126 models’ (re *primitives*). AI proof-of-concept comes as a ‘statistical experiment’ (algorithm) with
127 outputs compared to material reality (our ‘expectations’), versus starting with P1. The problem here

⁴An actual *forced split*, as all ‘Engineering roles’ are innately meaningful.

⁵Not called P4 as P3b better notes the fact (S)-*qualitative* aspects are innately tied to (O)-*quantitative* aspects.

⁶Evident here in dual-three-part space-time, with SPACE as: height, width, and **depth** (2d simple/**3d realism**);
and TIME with: past, future, and **present** (2d imaginal/**3d realism**), shown here as further-nested 2-3-2 Fits.

128 is that this relies wholly on HI (with already noted snags), along with vague ‘black box problems’.
 129 Today’s AI thus inverts ‘inquiry’, replacing ‘material \rightleftharpoons dualist logic \rightleftharpoons symbolic S-O (S)teps’
 130 with ‘statistical analysis’. As such, the *evidence-based* P1 approach this paper suggests is often
 131 side-stepped or ignored by *experiment-based* AI traditionalists.

132 3.1 General intelligence and evidence based views

133 But evidence-based GI seems possible with three **already proven** models framed as complements.
 134 First, EvNS *structure* shows as evolutionary trees, food chains, resource webs and the like. A ‘tree
 135 analogy’ thus initiates GI structure, *uniformly* holding *diverse* roles, via 2-3 +divisive, +directional,
 136 and -purifying ‘selection forces’ driving branching/(S)hifting DoF patterns as ‘tree forms’.

137 Thermodynamic entropy next frames *temporal structure*; astrophysicist Arthur Eddington’s “arrow of
 138 time”. A Big Bang has an expanding ‘singularity’ driving early material events, first seen as cosmic
 139 microwave background. This continues onto today, all as a 2-3 *temporal continuum*⁶, alongside an
 140 evolving-contiguous simple-to-complex 2-3 ‘tree form’. We later expect a final max-disordered Big
 141 Freeze or ‘heat death’ in the cosmos. While current cosmology remains unsure, it still seems likely
 142 that everything falls under the *temporal sway* of general ‘Entropic-ity’.

143 ‘Myriad material events’ next evokes signal entropy as a “mother of all models”, with infinitely varied
 144 aspects (Appendix A: Figures 1 and 2). Signal entropy’s innately-recombinant “logarithmic base”
 145 holds ‘discrete \rightleftharpoons continuous’ and ‘minute \rightleftharpoons major’ (S)teps, tied to the specific values used in
 146 X^n . It thus again marks general Entropic-ity across simple-to-complex roles, along with selectable
 147 EvNS ‘realms of discovery’. But tying signal entropy to *meaningful* material reality is tricky, due to
 148 Shannon’s forced split⁴ where “semantic aspects” are held apart from an “engineering problem”.

149 That split defies *commonsense* ‘information’ as useful intelligence. Next, Shannon also saw chaotic
 150 ‘noise’ (Entropy) *contra* signals (entropy)⁷, but is mute on how these presumed opposites are joined—
 151 he omits an ($e \rightleftharpoons E$)ntropic *continuum* where one is implied. Physicist and computer scientist John
 152 Von Neumann saw like ‘confusion’ in the fact that no Unified Field Theory (UFT) yet exists [15].

153 Signal entropy was quickly adopted but also soon abused in being called ‘information theory’, beyond
 154 Shannon’s modest ‘communication model’. It was so bad that he enrolled mathematician and machine
 155 translation pioneer Warren Weaver to add clarity, calling parts of his work “disappointing and bizarre”
 156 and missing a “real theory of meaning” [1]. Seven years on he wrote *The Bandwagon* [13] on things
 157 “ballooned to an importance beyond its actual accomplishments” with “an element of danger”. Despite
 158 this, signal entropy still stands as a firm scientific model, although gaps remain to be addressed.

159 But with these models framed as contiguous complements, I claim necessary-and-sufficient **pre-**
 160 **proven** detail exists for GI modeling—to *uniformly* frame *diverse* material events. To continue
 161 GI/S-O development I now target Shannon and Weaver’s missing “real theory of meaning” (ToM).

162 4 A targeted S-O ‘Theory of Meaning’

163 Figure 1’s ($e \rightleftharpoons E$)ntropic continuum poses an S-O base as *initial* 2-3 GI ‘structural fundamentals’.
 164 But a ToM offers more-detail: EvNS as dialectic (s)-agents *contra* (S)-Nature, or ($s \rightleftharpoons S$)urvival.
 165 Here, ($s \rightleftharpoons S$)ubjective-intelligences arise via: diverse niches \Rightarrow diverse agents \Rightarrow varied eras/*contexts*
 166 \Rightarrow varied ($s \rightleftharpoons S$)urvival/*content*—tied to prior ($e \rightleftharpoons E$)ntropic-ity. Each (S)tep marks a Natural test
 167 (trial-and-error), within a simple-to-complex chain of material events, all with countless ‘discoverable
 168 options’ (exploit-ability).

169 EvNS/trial-and-error has many faces, first marked in P3b (4th GI Principle). As further detail,
 170 competition/cooperation *between and within* species, **and** with Nature exists. Such *generative*
 171 aspects **create** a *mutable* “order for free”. Even signal entropy’s X^n is *purely* generative/mutable.
 172 For mechanical generative (S)hifts one can also ask ‘Why do 94 specific atoms arise, why not more or
 173 fewer types?’. A ToM moves past generic ($e \rightleftharpoons E$)ntropic-ity to more-detailed ‘(s)-agent experience’,
 174 learning to ask ‘Can more than 94 atom types exist?’ In this, we begin to see something we might
 175 call willful super-intelligence (SI)—targeting ‘things’ beyond Nature’s/GI impulsive creativity. But
 176 throughout, trial-and-error, for (s)-agents, (S)-Nature, and ($s \rightleftharpoons S$)urvival hold a central role.

⁷From Greek *entropia*, which means “a turning toward”, “transformation”, or “metamorphosis”.

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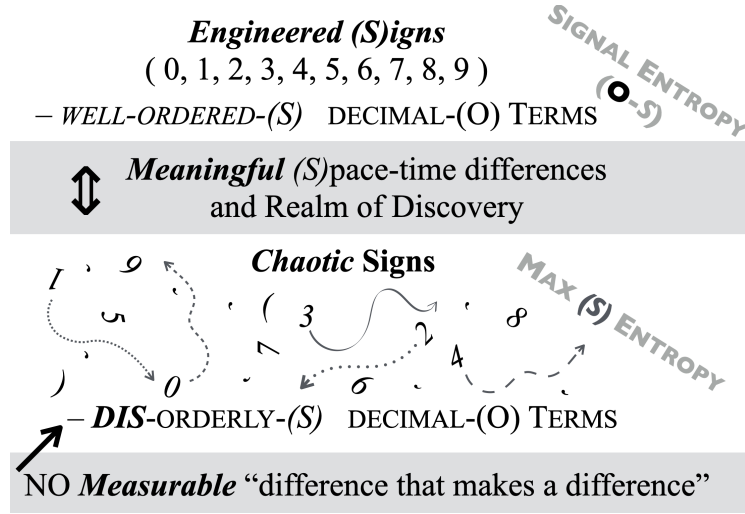


Figure 1: Engineered (S)igns, Entropic (S)teps, and min/max GI (S)tructure. Decimal primitives (top) show a *meaningful* agent-agreed **O-(S)**yntax as (S)pace-time Fits that all messages rely on. Next, Chaotic Signs lack (S)pace-time Fits (Max [S] Entropy). Between them lies mixed “order for free” as a Realm of Discovery, **and** supra-natural (super-intelligent) S-O options that build on (S)-discoverable order. This frames material reality as a dynamic ($e \rightleftharpoons E$)ntropic continuum of ‘knowledge’ and ‘gaps’, with countless options.

CAT	CCT	CTT	CCA	CAA	CTA	CTC	CAC	CCC
ACT	AAT	ATT	AAC	ACC	ATC	ATA	ACA	AAA
<u>TAC</u>	<u>TAT</u>	TCC	TTA	TAA	TCA	TTC	TCT	TTT

Figure 2: Scale-able and select-able signal entropy. C, A, and T (O)bjects are shown in X^n discoverable (S)pace-time Fits: an S-O volume of 3^3 signal entropy, or 27 *functional degrees of freedom* (DoF). CAT and ACT are (S)et English words, “what you *do* say”, others are (S)elect-able options “what you *could* say” [1] (emphasis added). For example, TAC and TAT hold ‘discovered meaning’ in new contexts (French, German, Old English). But all requires ‘agent agreement’ on inter-(S)ubjective (O)bject operation as en-cultured **O-S functioning**. Without **O-(S)**et roles, only ‘noise’ arises. Lastly, shifting X^n ’s values makes signal entropy infinitely (S)cale-able, (S)elect-able, and discoverable. The above thus shows ‘a type of intelligence’ simply in creating (S)electable recombinants, prior to functional analysis or ‘utility’.

B Conclusion: one problem, one thousand faces

Much remains to cover for $GI \Rightarrow S-O \Rightarrow ToM$, but this paper only targets structural fundamentals—‘atomic level’ (S)-and-(O) origination, operation, form, and utility behind humanity’s ‘remarkable adaptive feat’. Still, likely GI advantages are:

- *Synthetically* surpasses specialized domains, while retaining reductive *analytic* detail,
- Requires only minimal (S)-and- O input for initial informatic modeling,
- Allows joint (synthetic) mapping of knowledge alongside ‘gaps’, speculative $S-O$ proposals, acute voids, etc.
- Avoids imposing inadvertent anthropic biases (i.e., Nature based),
- Globally holds genomic-mechanical affordance, genomic-behavioral informatics, democratized information (‘culture’), and external memory (language, books, etc.), all toward “time-binding” [10] ‘human intelligence’.
- All surpassing AI statistical methods and ‘black boxes’.

But issues remain. Foremost, ‘Is any of this computable?’ For example, EvNS has no *key-equation* that produces ‘predictive outputs’, it instead offers a compelling intuitive Fit. Is this also true for GI modeling? Here, an odd ... 2-3-2... Fit seems to map a cosmic GI ‘informatic backbone’—with more-refined DoF detail *quantitatively*-enumerating-*qualitative* effects.

One next asks, ‘Okay, then where is that ToM equation?!’, raising three other issues: 1) more (S)-and-(O) and DoF mapping is needed for an equation, 2) that ‘equation’ likely shows *only* interpretive tendencies, as adaptive options amid widely differed contexts (nature does not hold just ‘one answer’), and 3) to blindly place such a likely-formidable equation in the public domain is simply naive.

The first issue calls for sharp redirection of AI investment, with fierce vested opponents [16]. The second means that the most GI/SI will likely offer is an ‘insight engine’ to aid human innovation and discovery. This also means ‘autonomous AI’ is unlikely to arise. Thirdly, issues of AI safety and ‘alignment’ remain vital, just as with eternal risks in our earliest discoveries and inventions—‘fire and handaxe use’. In general, tool use can never be taken for granted, always requiring careful consideration. But giving much attention to ‘safety’, far in advance of a useful GI/SI model, is nearly pointless as it lacks clear parameters.

Still, GI modeling merely poses a tool for ‘intelligent exploration’—where application of that tool ultimately requires much more work, while notably driving gains and risks. With that said, practical application can be quite demanding. For example, it is one thing to speak of posing 200 million protein structures, but it is a wholly different matter to actually produce and test the utility of 200 million proteins. As such, $S-O$ views likely support the “de-risking of science” [17].

For $GI/S-O$ alternatives, an AI neurologic view is often suggested. But here we see 10’s of neuron types with up to 75,000-100,000 neurons per cubic millimeter (about the size of a pin’s head), the operation of which we barely grasp. Neither do we know *when* or *if* we will ever see the technology needed to untangle and understand such neuronal masses.

On the side of today’s AI, our best work in typifying GI is “Intelligence measures an agent’s ability to achieve goals in a wide range of environments” [18], with scant detail. Moreover, AI’s only ‘intuitive fit’ is a Turing machine, plagued with an *eternally looping* (non-functional) ‘halting problem’. This places today’s AI on a very different ‘statistically inferred’ footing, apart from scientific methods. Science relies on self-evident functioning, while today’s AI has a ‘black box’ needing eternal functional verification by agents reviewing/verifying outputs. But with $S-O$ models of Nature as a base, GI modeling strikes directly at ‘foundations of science’ (natural philosophy), and all the reasons why this thing we call ‘intelligence’ even interests us—to improve human well being.