

# Living systems are smarter bots: Slime mold semiosis versus AI symbol manipulation

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## ABSTRACT

Although machines may be good at mimicking, they are not currently able, as organisms are, to act creatively. We offer an understanding of the emergent qualities of biological sign processing in terms of generalization, association, and encryption. We use slime mold as a model of minimal cognition and compare it to deep-learning video game bots, which some claim have evolved beyond their merely quantitative algorithms. We find that these discrete Turing machine bots are not able to make productive, yet unanticipated, “errors”—necessary for biological learning—which, based on the physicality of signs, their relatively similar shapes, and relative physical positions spatially and temporally, lead to emergent effects and make learning and evolution possible. In organisms, *stochastic resonance* at the local level can be leveraged for self-organization at the global level. We contrast all this to the symbolic processing of today's machine learning, whereby each logic node and memory state is discrete. Computer codes are produced by external operators, whereas biological symbols are evolved through an internal encryption process.

## 1. Introduction

The *Next Rembrandt* project is a much-celebrated example of a deep-learning algorithm being used to create art. Project designers (Korsten, 2016) employed a quantitative approach to capture the essence of Rembrandt's style with the goal of creating a new but typical painting. They first created a database of Rembrandt's paintings and then, because machine learning requires a lot of data, they selected the most common type, a portrait of a “Caucasian male between the ages of 30 and 40, with facial hair, wearing black clothes with a white collar and a hat, facing to the right” (pp. 02). Using facial recognition software, the features of male subjects—the distances between eyes, length of nose, and width of mouth—were categorized. The color and topography of painting surfaces were analyzed. After receiving some corrective feedback from painting experts, the deep-learning network formulated a three-dimensional digital representation of a Rembrandt-style portrait, modeled on a man who never existed but who was created by AI “imagination.” The *Next Rembrandt* was then printed onto canvas in successive layers (Fig. 1).

For comparison, consider *Old Woman Cutting her Nails* (1655–60) (Fig. 2), a painting previously attributed to Rembrandt that is now con-

sidered to be the masterful work of his student, who, we can say, learned the Rembrandt “algorithm.”

In *The Next Rembrandt*, the subject stands in a dark interior wearing a bright white collar. In *Old Woman*, soft light from above reflects off the subject's bright white blouse. Such illumination is a signature of Rembrandt. We can describe some of the techniques the master must have taught the student. More difficult to describe are the other Rembrandt-like choices made by the student that make *Old Woman* a work of art, not merely a deep fake. The unique aspects of *Old Woman Cutting her Nails* attract many museum visitors, whereas the commissioned portraits by Rembrandt, such as those used to train the algorithm in *The Next Rembrandt* experiment, do not attract the interest of as many visitors or Rembrandt scholars. While the AI-produced painting may pass the Turing Test, *Old Woman* surpasses it. After Rembrandt's student learned to recognize and formalize the master's style, he went beyond mere mimicry; the student was able to transform that understanding to paint a subject unlike one the master had done before. *The Next Rembrandt* misses what makes Rembrandt a great painter rather than just a highly skilled one.

We begin by offering ways of understanding the qualitative or interpretive aspects of biological information processing as deriving from

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Fig. 1. *The Next Rembrandt*, 2016.<sup>1</sup>



Fig. 2. *Old Woman Cutting her Nails*, 1655-60.

the use of generalization, association, and encryption, which, we argue, are semiotic relationships.<sup>2</sup> In order to find a basis for minimal cognition to compare to machine learning, we look at semiosis in a very simple form of life, the slime mold, *Physarum polycephalum*. Then we look at Alan Turing's notions of machine computation in relation to today's deep-learning video game bots, which some claim have evolved beyond their merely quantitative algorithms. And finally, as we contrast the kind of biological "computation" that Turing was investigating late in his life (Turing, 1952; Alexander, 2018) to machine computation, we suggest how better artificial models of biological processes might be attempted. Turing's work before and after his biological turn can be identified with *Turing machines* and *Turing systems*, respectively.

The idea that there exist two distinct methods of research, one quantitative, one qualitative, is as old as the idea that there are objective and subjective forms of knowledge that do not overlap and are in some sense opposed to each other, like mutually exclusive modes of reality. Donald Favareau (2010; 3) observes that this physical-mental dualism was codified by Rene Descartes and has prevented us from approaching truth with regard to emergent phenomena, which are so resistant to quantitative description; we have been left with unsatisfactory alternatives: either subjective mental processes are beyond the scope of science to investigate, or subjective mental processes are an illusion, which will be reduced to a quantitative descriptions once the technological means of investigation have sufficiently advanced.

Favareau points out that we have not always thought of subjective interpretation as something only animals with brains can do. He notes that Aristotle and some medieval philosophers had very well developed concepts of a natural, non-mental semiosis (10). Since we have lost this concept of non-mental interpretation, we start our analysis with an illustration.

## 2. Learning in slime molds

### 2.1. Generalization and association: The relational qualities of similarity and contiguity

Any single-cell organism capable of chemoreception will illustrate non-mental semiosis. If a micro-organism can detect a molecule that is a by-product of a food source, then it may move toward greater concentrations of the molecule. Detecting such a by-product is useful for maintaining its structure and thus moving toward it is habit-forming. Therefore, we can say that the molecule is *meaningful* to the organism. Through a series of affirming rewards, the species has evolved or "learned" to respond to this associative sign of food.

If this were all there is to organisms, as long as we understood the evolutionary design, we could quantify this type of intelligent behavior and predict subsequent actions. But the situation is more complicated. The chemoreceptor may bind with a different molecule that happens to mimic the shape of the molecule that comes from the food source. We can say the mimicking molecule is also a sign, due to its physical similarity to the true sign. If this mimicking sign triggers the response, *as if* that response will help the organism capture food, we can say this new molecule is a mediated sign of a food source that does *not*, in fact, exist. Through such error, creativity is possible.<sup>3</sup> It can potentially lead to de-

<sup>2</sup> Our triad, generalization, association, and encryption, is inspired by semiotician C.S. Peirce's classifications of different types of signs: icon, index and symbol (see Peirce, 1992), concepts which we have applied, in previous work, to subjects similar to the ones explored in this paper (e.g., see Alexander, 2017, 2019; Castro, 2010, 2011; and Bacigalupe, 2013). For this work, we chose to use terms not quite so associated with human semiosis.

<sup>3</sup> Not all creative behavior would be an unmitigated good, of course. Any error that results in a self-reinforcing effect may be considered a creative act but may ultimately lead to an ill effect on the agent. One can easily see here that semiosis is a process by which pathological behavior may emerge.

<sup>1</sup> Although ING funded the project, they have not established copyright of the *Next Rembrandt* image as a computer cannot hold copyright. See Schlackman, 2020.

veloping a new way of interacting with the environment that might be functional in a different way. Such fallibility is part of what makes signs adaptable via selection processes. The similarity between different signs can lead to *generalizations*, which can be “right,” leading to the continuation of a more robust habit or can be “wrong,” but leading to the discovery of a new habit, if the mistake is not harmful.

Favareau observes that Descartes failed to recognize “fallibility [as] an intrinsic aspect of the effective functioning of symbolic reasoning” and, with tragic consequences for hundreds of years of science, he “sought a ‘mechanism’ designed to subtract it out of the human repertoire entirely” (pp. 25) in order to get at objective truth. But we understand that error is essential to the process of learning new information. Similarly, as we argue in section 3, machine learning is also designed to iteratively reduce error, which actually prevents it from developing true intelligence.

Even more potentially productive than making *generalizations* is the kind of error that can be made out of the ability to make *associations*. Consider the famous example of the classical conditioning of Pavlov’s dog. In that experiment, an unconditioned stimulus (food odorant) that triggers a reflex response (salivating) is associated with a new conditioned stimulus (the sound of a bell), so that the new stimulus also triggers the reflex. Experiments with *Physarum polycephalum* (Shirakawa et al., 2011), *Escherichia coli* (Mitchell et al., 2009; Tagkopoulos et al., 2008) and *Paramecium* (Armus et al., 2006) show that Pavlovian conditioning may be possible in simple organisms, even those that do not have a nervous system. As Castro (2010, 2011) argues, *P. polycephalum* can be used as a model organism to understand minimal cognition using semiotics.

*P. polycephalum* is a single amoeboid organism, called a plasmodium, filled with streaming cytoplasm containing various chemicals, tube structures, proteins and typically thousands of nuclei. It moves by changing patterns of electrical potential oscillations (Ridgway and Durham, 1976; Kishimoto, 1958), contracting tubules at regular intervals and squeezing its bulging pseudopods forward (Wohlfarth-Bottermann, 1979; Teplov et al., 1991). If it does not detect food nearby, it moves toward some other quality, such as warmth, which is usually proximate to food. We note, warmth functions as an associative sign of food. *P. polycephalum* has evolved a “default” setting to move in the direction of warmth: it has a regulatory network mechanism that inhibits movement toward cooler conditions. Failure to achieve the goal of finding food in warmer areas will activate a random search of areas not yet explored; to do this, the inhibition toward cold must be disinhibited. *P. polycephalum* will then take a random walk, with the constraint that it cannot revisit any areas. Takagi et al. (2007) offer reaction-diffusion equations illustrating how *P. polycephalum* may make decisions with self-inhibition in response to temperature or chemical signals. Thus a few constraints make simple *P. polycephalum* capable of some intelligent food-seeking behaviors. The activity of slime mold may be considered an example of minimal cognition, going beyond metabolic homeostasis, toward chemical memory, selective searching and adapting (Nakagaki et al., 2000) Bich and Moreno, 2015; Castro, 2016; Sharov, 2016). Kramar and Alim (2021) note the way slime mold reorganizes and reshapes its tubular network in the presence of food signal is reminiscent of neuronal synapses’ plasticity. Moreover, as *P. polycephalum*’s use of bioelectric oscillators may be compared to the ionic signaling in neurons (Ridgway and Durham, 1976; Levin et al., 2006; Boussard et al., 2021) it may be considered an appropriate basic model of animal cognition.

In a classical conditioning experiment, Shirakawa, et al. (2011) trained *P. polycephalum* to unlearn its association of warmth with food and learn a new association of cold with food. In the experiment, a low-temperature stimulus was used as a conditioned stimulus and a food source was used as an unconditioned stimulus. After some exposures, a significant number of trained plasmodium acquired a new tendency to move toward the lowest temperature first. As Pavlov’s dog

learned to associate the sound of a bell with the receipt of food, causing the dog to salivate at the sound of a bell, the plasmodium learned to associate cooler temperatures with finding food, causing it to reverse its native thermotactic tendencies.

Further experiments need to be performed, but here we ask, if associated learning has occurred what could be the mechanism to explain it? Shirakawa and Sato (2013) propose a gene regulatory network model to explain how this associative learning takes place. We note here that Shirakawa et al. (2011) dismiss out of hand Saigusa et al.’s (2008) model, which does not depend on genetic expression, to explain a similar type of association between cold signal and a period of time. We will come back to Saigusa et al. later.

It is not known what type of specific network *P. polycephalum* is likely to use. Shirakawa and Sato’s model, depending as it does on programmed genes responding to environmental triggers, begs the question of how the genes were programmed to respond to triggers in this way. The researchers may be slipping into computer programming metaphors by inserting *a priori* externally imposed functionality into a process for discovering this entirely novel behavior. Their cybernetic circuit relies on a coherent (i.e. low noise) function that might seem to require significant generational time scales and/or mutation rates to achieve such a specific circuit via neo-Darwinian selection. We seek an alternative explanation for the slime mold’s capacity to learn rapidly without reward-punishment selection being employed.

We propose that a much more general Turing system model would suffice to explain how the associative learning might occur without necessarily enlisting the aid of real-time genetic repression and expression. We define a Turing system here as a set of non-linear equations (See Turing, 1952) describing self-catalyzing activator-inhibitor interactants from which dynamic temporal or spatial patterns emerge, typically because some of the chemicals involved diffuse/react at faster rates than other chemicals involved. Turing systems often function as switches, turning on and off biological processes. They underlie spontaneous self-organization and allow large qualitative changes to occur with small quantitative changes. The emergent temporal or spatial patterns do not initially have a function for the organism but, as with any regularities, they may be harnessed for functional ends.

The general idea of Shirakawa and Sato’s model with or without the genetic expression works as a Turing system if we assume, as they do, that the cold receptor and a food receptor are activated simultaneously, respectively triggering cold-signal and food-signal transduction pathways; the food-signal pathway increases the frequency of the plasmodium’s contraction, while the cold-signal pathway inhibits the reaction that causes contraction. As Shirakawa and Sato also show in their model, two pathways, or networks, could become coupled if one catalyzes the other’s activation and that of an inhibitor. Such interference could lead to a local buildup of a novel by-product that is not produced when the two different pathways are activated separately. (Under normal conditions for slime mold, food and cold are not usually coincident.) Finally, once the by-product is present in sufficient amounts, it could prevent the inhibition of the contraction. Thus, *the cold-signal would indirectly disinhibit its own inhibition function*. As Shirakawa and Sato also note, the buildup of these by-products would act as temporary memory, and the plasmodium’s movement away from cold could be disinhibited for as long as the by-products remained available in sufficient amounts, even if the food-signal were no longer present. When such a conditioned plasmodium encounters cold, it would *not* automatically move away from cold. Pavlovian conditioning would have caused unlearning of its association of food with warmth.<sup>4</sup> This may serve as a model of a general mechanism for associative learning.

## 2.2. Encryption and the quality of arbitrariness

Marcello Barbieri (2003, 2008) argues that new biological conventions can emerge when a physical object (or process) acts as an interme-



diary to join what would not, under normal conditions, come together or stay together. In our above analysis of *P. polycephalum* learning, between the input, Cold, and the outputs, Move or Don't Move, there exist multiple, more or less efficient, signal transduction pathways that could potentially bridge specific outcomes. Likewise, between simultaneous inputs, e.g., Cold and Food, and a specific output, Move, there could exist multiple signal transduction pathways that may act as a bridge. The possibility for many-to-one and one-to-many relations implies that there is no necessary connection between environmental triggers and responses: the same trigger can activate different responses in different situations. Therefore, input and output are linked only by what has emerged, as Barbieri notes, as a *natural convention*, an encryption process. We can think of the trigger and its response as symbolically encoded.

Unlike the two forms of semiosis that we have discussed so far—generalizations and associations which are linked by similarity and contiguity, respectively—encryption produces an *arbitrary* stand-in for what it represents, linked by a rule. Like an adaptor that converts an EU electrical plug to a US one, encryption yokes together two things that cannot otherwise link. In our case of slime mold here, cold-signal is yoked together with movement toward cold.

Although biological encryption does depend locally on similarity where two chemicals at either end of the adaptor react as determined by stereochemical affinities, this becomes obscured once chains of adaptors are linked together in complex signal transduction pathways, like the multiple encryptions of encryptions of a biological Enigma Code, and we are left with what seems to be a completely arbitrary link between input and output, any such mapping is, by definition, a biological code.

*P. polycephalum*'s Pavlovian conditioning described in the two examples above is only temporary. This short-term learning will fade when the reserve of chemicals runs low. The ability to pass on a new learning capacity to future generations is what makes evolution of complexity possible and this process depends upon the preservation and transmission of the encrypted *genetic* code, such that the ability and tendency to build specific proteins that serve specific functions is preserved and increased in the species' population by the natural selection of a set of rules (viz. adaptors) that ensures the specificity of the correspondence between the trigger and the response (See Barbieri, 2017). Barbieri's model works with the genetic, epigenetic and morphogenetic learning regimes with their respective time-scales.

To contrast this process with machine coding, we stress that natural biological encryption occurs internally. There is no external programmer writing the encryption code or constructing an adapter. When biological systems discover and make use of new mappings, they spontaneously encrypt the transformations between input and output, and the transduction pathways here represent the encryption rule.

We argue that *P. polycephalum* are capable of learning a new rule mainly because the chemicals in the transduction pathways are not discrete and may interact and interfere with each other, as we have seen above in our example of Pavlovian learning in slime mold. While Shirakawa and Sato's regulatory network scheme may be modeled like a wired circuit as in Fig. 3, such regulatory networks are in reality composed of free-floating chemicals, whose local interactions, with multiple other autocatalytic networks within the churning soup of the streaming cytoplasm, would be very difficult if not impossible to simulate digitally, because such discrete circuits would not be able to interfere with each other, compete for signals or catalyze each other's processes unless programmed to do so, *a priori*. On this rests one of our

main critiques of AI as incapable of truly intelligent or creative behavior. Computers have no means of spontaneously developing new codes/symbols.

The plasmodium is characterized as a network of hundreds or thousands of biochemical oscillators (Kauffman and Wille, 1975; Matsumoto et al., 1998; Mayne et al., 2016) capable of multiple coupling modes (Grebecki and Cieslawska, 1978). The oscillators function as local clocks and control peristaltic activity and growth via propagation of various waves (Vallverdu et al., 2018). It has been shown (Yamada et al., 2007) that waves of electrical potential change, propagating from various sources of activation or inhibition, collide with each other forming reaction-diffusion patterns typical of Turing systems (Adamatzky et al., 2005; Adamatzky, 2010). Radszuweit et al. (2014) have found that a small plasmodium that is not moving, and whose cytoplasm is not streaming, can exhibit a variety of spatial patterns that correspond to various Turing patterns, including rotating spirals (single and multiple), traveling and standing waves, and antiphase oscillations (Turing, 1952). In most large plasmodium some areas of the cytoplasm are like a stirred beaker, and the pattern will oscillate temporally, not spatially. In the next section, we explore how coordinated global temporal patterns might emerge from this chaotic collection of different chemical networks with varying concentrations and frequencies.

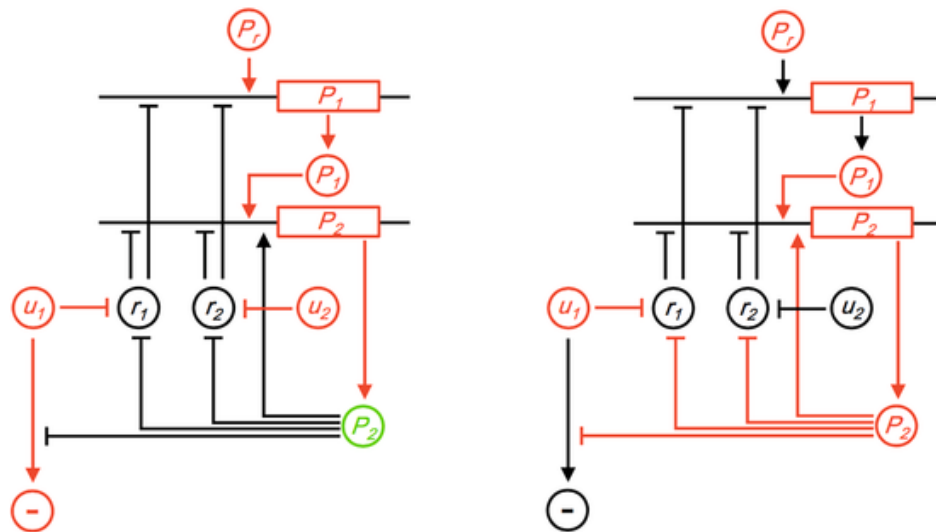
### 2.3. Interference patterns in slime mold activity

Saigusa et al. (2008) demonstrate how a *P. polycephalum* plasmodium, perturbed three times by a dry cold shock for 10 min every 60 min, can internalize an external cycle. This slime mold, in essence, learned to anticipate patterns in its environment. In response to each shock, the plasmodia would temporarily decrease their contraction frequency and hence speed, and then resume foraging. On what would have been the fourth perturbation according to the established rhythm, the plasmodia tended to slow again (especially smaller plasmodia) even though no shock was applied. The newly habituated slowdown within the tested population dissipated over two more cycles, until the plasmodia resumed their exploratory behavior uninterrupted. Six hours later the plasmodia were hit with dry cold air for 10 min after which they resumed foraging. Sixty minutes later, and as if a Pavlovian bell were being rung, many again slowed on the rhythm they had internalized previously although no additional cold shock was applied. The organism responded to a length of time as if it were a sign of a coming cold shock. As noted above, such "errors" demonstrate that semiosis is at work and this is a means by which an organism may be said to initiate novel, anticipatory<sup>5</sup> or creative actions.

To help better explain this behavior, Saigusa et al. (2008) devised a model that assumes a plasmodium has multiple chemical oscillators that would govern how the local frequency of contractions are perturbed and shaped by periods of dry cold. This model is similar to models by Winfree (1967) and Kuramoto and Nishikawa (1989) and others of the spontaneous synchronization of multiple oscillators with different natural frequencies. Such synchronization has been observed in groups of flashing fireflies (Buck and Buck, 1976; Buck, 1988) and chirping crickets (Walker, 1969), to name just two of many biological examples. There are also many examples of spontaneous synchronization in physics, such as lasers arrays (Yu et al., 1995) and microwave oscillators (York and Compton, 1991).

<sup>4</sup> A recent review, Dussutour (2021), looks at the controversial nature of associative learning in single cell organisms. We note that a theory of signs is often lacking in the intellectual tool kits of biological researchers, and therefore, it is not possible to clearly define what learning is and prove it has occurred. We hope our contribution here will help overcome some of these obstacles.

<sup>5</sup> To "anticipate" is to revisit behaviors previously triggered under similar previous conditions. Thus, anticipation is backward-looking rather than forward-looking. It is possible that the anticipated events will not occur, and therefore anticipatory actions are always about objects that are potentially nonexistent, that is, they are always semiotic; the actions "stand for" events that may not be realized.



**Fig. 3.** Shirakawa and Sato (2013) cybernetic circuit-like regulatory network scheme for associative learning in slime mold. (Left) Simultaneous inputs from cold  $u_1$  and food  $u_2$ , inhibit genetic repressors  $r_1$  and  $r_2$ . Expression of proteins  $P_1$  and  $P_2$  are activated and  $P_2$  accumulates. Cold  $u_1$  also activates the disinhibition on contraction. (Right) A sufficient level of  $P_2$  inhibits  $r_1$  and  $r_2$ , and through this positive feedback,  $P_2$  sustains its own expression.  $P_2$  also inhibits the pathway from  $u_1$  to disinhibition; thus, cancelling the avoidance response to cold stimulus. This figures show third and fourth stages of Shiradawa and Sato's four-part figure. Used by permission.

Different oscillatory chemical pathways involving multiple reactants would have different natural frequencies, and multiple chemical oscillators in a group with the same frequency, i.e., *frequency groups*, would typically be at different points in their phases. As Saigusa et al. (2008) note, when a dry cold shock of air is first presented to the plasmodium, each affected pathway oscillator would have different, similar, or the same characteristic frequency and the phase of each of these diverse oscillators would be randomly distributed. But, once shocked by the environment on a rhythm, oscillators of the *same* frequency as the rhythm of the environmental shock would cohere phasically upon each other. And then these groups of oscillators would also cohere with other groups of *similar* frequency. Saigusa argues that what caused the plasmodium to slow down was *both* the phasic coherence, and subsequent summation, of oscillators of the *same* frequency into their respective phasic grouping *and* these distinct yet *similar* groups tending towards the same phase and summing; it is only this second level of phasic coherence, which is hierarchically built on the first coherence, that produces observable change in macroscopic cellular behavior. When the environmental stimulation stopped, these distinct groups—the second coherence of oscillators with *similar* frequencies—began to dissipate, which ceased the slowdown of the plasmodium.

However, according to Saigusa et al. hidden order continued to exist among the oscillators even though the plasmodium had ceased its periodic slowdown: the initial frequency groups—those oscillators of the *same* frequency—remained phasically aligned, perhaps because chemical oscillators of the same frequency become coupled (See Kuramoto and Nishikawa, 1989 pp. 300). As such, when the shock happened again in this model, the plasmodium's cytoplasm was already biased with groups of in-phase oscillators with the same or similar frequencies to that of the original environmental shocks. A subsequent single shock many minutes later was enough to re-align the frequency groups that were still cohered, thus re-instantiating the echoed periodicity. The conditioned slow down response then occurred at the anticipated rhythm even though no additional cold dry shock is given. Contiguous populations of diversely-tuned oscillators respond distinctly to distinct environmental conditions; but they are not *discretely* tuned; their distinct sympathies for environmental stimulation overlap if sufficiently similar. Via spatio-temporal and a phasic proximity, the cytoplasm can then harness Turing system resonances, memorize periodicity, and recall in the presence of subsequent environmental stimulation. A dry

cold shock is associated with a unit of time due to the coincidence of the rhythm with a particular point in the phase space of some of the oscillators.

We argue that, in principle, the so-called 'noise' that exists among differentially tuned chemical oscillators is a basis upon which a system can harness its sparse order that happens to resonant with the environment. And, upon this scaffolding, the system can reasonably bias itself towards increased sensitivity to and anticipation of external patterns. This opens up the means for coherence, adaptive decoherence and productive errors. The diversity of oscillating reactions and their capacity to resonate and spontaneously cohere results in instantaneous self-organization and novel adaptive responses without being subjected to pure randomness and trial and error training, which is the typical approach for machine learning, as we will explore in section 3. No precisely tuned circuits are needed for organization. In Saigusa's model—also Bacigalupi's (2013) below—any given pattern, both its similar and proximal (i.e., semiotic) qualities can be captured by diverse oscillators.

Now we can distinguish between two distinct strategies for learning and adaptation: industry standard digitally implemented, diagrammable cybernetic models limited to discrete externally imposed symbols, such as in Shirakawa and Sato (2013), and novel models for learning and adaptation, deriving from more physically-grounded interrelating similar and contiguous signals, such as in Saigusa et al. (2008). We have shown how a new mapping between input, a period of time, and an output, slowing down, is spontaneously created by the organism without being subjected to an external selection process. This shows how organisms can create new behavioral codes for themselves. Once the mapping comes to exist, we might simply describe the resultant newly encoded switch as being either on or off, but if we do so, we may lose the information about how such mappings are possible.

Digital strategies are powerful tools that forgo the analog signal in favor of discrete states: saturated '1' and cut-off '0'. These states, or bits, are fundamentally symbols, because they arbitrarily stand in for what they represent; their discretized nature deliberately abstracts their referring capacity away from anything that is physically analogical. Digitization has many benefits in accuracy and counting in machine computation. Likewise, as Hoffmeyer and Emmeche (1991) stress, the digitization of a genetic code functions as a memory that enables the right proteins to be produced at the right time and in the right amounts

to ensure past useful responses are reactivated at the appropriate time. Codes are useful for accurately ensuring that the conditions will be such (e.g., necessary proteins present) that the steps in a process that have led to a functional outcome are likely to recur and future organisms can go directly from A to B to C to D without learning. The process of creating new biological codes is an error-reducing process that builds upon and increases the potential of a system to harness the sparse order of stochastic resonances between its own internal noise and regularities in the environment. Following a more Cartesian approach, computer programmers seek to eliminate the interference of a highly complex interactive physical system (from which biological codes may spontaneously emerge) and instead force externally imposed codes. Researchers who claim simplistically that an organism's behavior is determined by precisely defined genetic codes, ignore how codes emerge from analog signs and ignore how the learning process occurs. When computer programmers try to model organic processes with artificial digitization, they eliminate the system's ability to react to or refer to any physical phenomena other than externally imposed logic, which is itself relegated to the symbolic realm. All abilities to adaptively refer to the world are in systems sensitive to complex, and often surprising, physical patterns.

### 3. Machine intelligence in bots

#### 3.1. Reward and punishment

Can a machine learn similarly to the way we have described an organism learning? There are similarities, which we will highlight in this section. As Alan Turing notes in "Intelligent Machinery" (1948), a computer can easily be programmed to *play* a game by following rules, but to learn to *win* a game a computer must be able to make mistakes. Playing a game is similar to how an organism seeks food in nature. The basic rules and procedures are already known to the organism, that is, it has inherited the basic biological codes its species has evolved. But, because there are a number of different ways that an organism might achieve the goal, Turing argues that trial and error, reward and punishment, are necessary to train a computer or an organism to *win* a game. Turing presents the idea that a computer network that has no biases initially might become organized by selection pressure, by being rewarded and punished as it pursues some objective. He was imagining computer networks very similar to today's neural networks, whose various levels develop statistical biases as they process information. Animal brains, we note, also start out as largely unorganized neurons that develop more and more network biases through use. Every time a pathway is used, it tends to be reinforced, chemically, in ways that actually change the physical structure. As neurologist Donald Hebb (1949) so famously observes, neurons that fire together wire together.

Turing (1948) explains that we can think of a computer being "rewarded" if it can consult its look-up table and match an equivalent situation and follow a procedure that did not lead to failure to achieve the goal. We may say the computer network has the ability to make a generalization, based on similarity, and thus this process may be compared to biological semiosis. In a video game design with algorithms, aka bots, being trained in this manner, the bot recognizes its current state (interprets its current state as being similar to past states) and responds accordingly to advance a state closer to the goal. If  $x$  then  $y$ ; if  $x'$  then  $y$ . Turing's notion of what a reward might be for a computer is probably pretty close to what reward can be for an organism. An organism's equivalent reward would be to follow its usual signal pathway, the biological habit it has learned through evolution or development.

Punishment for a computer in training, according to Turing, would mean that, if no equivalent situation is found in its memory of past moves, the next move or state change should be random (1948; 425). On several occasions, Turing speculated that randomness may provide

humans with a back door for "free will" to emerge. This is an idea that had interested Turing since he was a young person (1932). But, as we shall see, adding randomness only pushes an agent to explore new actions and have more opportunities to be *passively* shaped by selection. As random actions have no semiotic relation to the agent, they cannot represent the "will" of the agent. As we have already discussed, organisms tend to make over-generalizations and mis-associations, which are self-motivated responses to the environment, not unmotivated random actions. Let us consider how using randomness to train a bot in a computer game plays out.

In *You Shall Not Pass*, an OpenAI computer game using deep reinforcement learning, a blue stick figure tries to run past a red stick figure to get to the opposite side of the board while the red one tries to block. Gleave et al. (2020) tested a well-trained Blue against a Red agent trained without respect to a reward model. Instead of trying to block Blue, Red sometimes drops to the ground and curls up into a ball. Although Blue could easily win by simply running past Red to get to the other side, Blue does not. Because Blue does not have "a distribution of similar opponents" dropping into a ball in its memory, Blue goes into random search (pp., 2). And, we assume, because most random moves will make Blue unstable, Blue falls down 86% of the time, and Red tends to win. Neural networks have world enough and time to learn using random search and can go through millions of training years in a short period of time; eventually Blue will learn to stop falling down and Red will stop curling up into a ball.

There are some instances in nature when an organism might use random search, for example, when *Escherichia coli* is experiencing extreme stress, as Glahardo et al. (2007) has noted, it may begin to mutate at random. Most individuals attempting such a desperate strategy die, just as Blue tends to die, but a few bacteria in the population might randomly hit on some new process that helps them survive in hostile conditions. This is a very radical innovation strategy. Fortunately, in most cases, species do not have to learn the hard way via random search and catastrophic selection events to evolve. While randomness does allow learning by trial and error to take place, as Turing himself observes in his 1938 Ph.D. thesis under Alonzo Church, when humans have no idea what to do, our next moves tend to be better than random and are based on "intuition" (Turing, 1939; 192–193). Perhaps organisms tend to switch to tools developed for other contexts because of their capacity to over-generalize and mis-associate. To the extent that an AI bot is only trained in one context, as Red and Blue are, switching to tools perfected for a different objective is not an option. And perhaps organisms' self-organizing tendencies allow them to resonate with new environment conditions to learn to anticipate more quickly.

#### 3.2. Bots breaking the game as creative generalization

Late in his short life, Turing continued to pursue more complex ways of understanding biological intelligence. In a BBC radio broadcasted talk entitled, "Can Digital Computers Think" (1951), Turing tentatively suggests a different way that computers might be able to transcend the limits of algorithmic thinking through a different kind of "mistake." He proposed that if a computer can do things it is not explicitly programmed to do, somehow, such actions might be considered self-motivated. He asks us to reconsider the dictum, that a machine can only do whatever we know how to order it to perform. He observes,

...there is no need to suppose that, when we give it its orders we know what we are doing, what the consequences of these orders are going to be.... If we give the machine a programme which results in its doing something interesting, which we had not anticipated, I should be inclined to say that the machine *had* originated something, rather than to claim that its behaviour was implicit in the programme, and therefore that the originality lies entirely with us.

In that talk, Turing does not go on to try and give an example of the kind of mechanism whereby interesting and surprising (to the programmer) behavior might emerge. But fortunately, we do have a recent example of this happening. In the OpenAI game, *Hide and Seek*, the AI bots managed to exploit bugs in the game that the programmers had not anticipated.<sup>6</sup>

In the game, both Seeker and Hiders move around the board with a command that allows them to skate in any 2-dimensional direction. While the Seekers are counting down from ten, Hiders can re-arrange walls, boxes and ramps to hide themselves and to lock the Seekers out. Through many trials wherein the bots try anything and stumble upon solutions that work, the bots learn to play the game. The reinforcement learning is accelerated by rewarding the bots for exploring *new* territory not just randomly revisiting territory (Baker et al., 2020). This may be compared to the slime mold's constraints in its random walk to avoid areas previously explored that did not result in finding food. After millions of trials, the Seekers learn they can move ramps and then use them to get over the walled fortresses that the Hiders have built. But the Hiders can learn to lock down the ramps to prevent the Seekers from moving them up against their walls. This is all normal play that the programmers had anticipated.

But after 390 million iterations a new strategy was discovered. The Seekers found that, if they move a box near to a fixed ramp and get on top of the box, they can make the box slide as if they were surfing on it. The designers had not anticipated that the “move” command would function on top of the box and move the box *with* the player. Next the Seekers learned to position the box near the wall of the Hiders's fortress and jump into it to win the game. The programmers did not anticipate this behavior.

An even more surprising defensive strategy was invented by the Hiders. After many millions of more tries, the Hiders discovered a bug in the design where the 3-D corner constraints were not well-defined, and the Hiders chucked the ramps out of the arena. Next the Seekers learned to exploit a similar bug to chuck themselves over the walls and onto the Hiders. Missing the relevance of these “breaking the game” innovations to the way biological repurposing of tools might actually work, Baker et al. (2020) opine that the “unwanted behaviors” should be eliminated from future game designs (pp. 8). To compare what we discussed in section 2, the bots here may have discovered a novel and surprising tool. The game designers decided that this type of learning was not allowed because it was an incorrect action, a mistake, from their perspective.

### 3.3. General conclusions about AI bots

Although Baker et al. go on to claim that the more predictable instances of developing winning strategies and counter strategies via trial and error training are appropriate examples of *emergent* AI learning, we note that the Hiders and Seekers are only learning how to *better* play a game that has well-defined goals, to hide or to seek. The use of random searches is a purely quantitative approach since the bots are not able to distinguish between better moves among equally possible ones until they try them. They make many stupid moves before discovering good ones by accident: they are passively molded by a selection process and it is a stretch to claim the bots had evolved agency.

OpenAI game designers may be preventing their own progress by relying as they do upon the impoverished metaphor of evolutionary adaptation put forward by Dawkins and Krebs (1979) that focuses on the “arms race” between and among species. Despite recent claims (Liu et al., 2019) that qualitatively different cooperative teamwork has *emerged* in reinforcement-learning (RL) game play, we note that team members are merely availing themselves of fellow team members as

tools. In a truly cooperative ecosystem, species and individuals benefit off each other's by-products, wastes and excesses, a situation which is more interdependent than competitive (See Alexander, 2021). Species often depend upon the survival of their own predators to ensure the overall health of their ecosystem and themselves. When an OpenAI game reinvents itself such that the goals of winners and losers become so coupled that the game never ends, and they spend some time in useless “fun” play, that might be considered truly emergent behavior.

Predator and prey, symbiont and parasite mutually create the constraints by which ecosystems self-regulate the conversion of energy into work enabling them to self-repair, self-maintain and self-produce populations towards ever greater levels of complexity. Such evolution of complex and seemingly useless energetic constraints is purposefully excluded from AI game worlds. The Turing machine's power to simulate the independent state manipulations of any other Turing equivalent machine is only made possible by employing symbols that do not resonate with environmental conditions and are insulated from such thermodynamic processes—such as we explored in the example of resonating chemical oscillators in Saigusa et al.'s (2008) description of slime mold learning—which are at the core of living processes. Programmers trying to preserve this insulated nature of symbols used in machine computation also prevent a “broken” code that achieves the end in a surprising way from being passed on to the next game design.

## 4. General intelligence

### 4.1. From artificial intelligence to Turing's Turn

Despite popular appeals, there is no credible theory that neurons or other biological cells are behaving strictly like digital Turing machines. The Church-Turing thesis outlines a special case of calculation by manipulating symbols such that any solvable function can be taken as input and its solution automatically output. However, the creative act that came up with numbers and Turing machines is a behavior that is a superset of recursive calculation, viz. computation. Based on our analysis we may define creativity, in its most basic form, using semiotics: creativity can be understood as a response to a trigger as if it were a sign of something else in the environment when, in fact, that something else is nonexistent; nevertheless, that response leads to an effect that is self-reinforcing and the agent adopts that response as a new way of negotiating with its world. An organism uses generalization, association and encryption to learn to pursue new goals, and these are qualitative not quantitative processes because they build upon qualities that are not easily quantified, such as similarity and contiguity. Because of this, humans can do a great deal more than any of the machines we have so far created.

This gets at why there is an abyssal difference between the symbolic processing of living systems and that of computers. The computer symbols are given, whereas the biological symbols are evolved, and this implies a process of exploration of qualities that leads to absolute novelties that can be passed on to future generations. If we understand the emergence of novelty in this way, we can avoid the dualism of a secular “god of the gaps,” where everything that is not accounted for by the nature and activities of the encoded nodes themselves is supposed to be accounted for by the selection of outcomes from random state changes.

We have described some ways in which biological learning might be mimicked by machine learning, e.g., generalizing as statistical approximation (when a bot consults its “look up table,” finds a distribution of similar opponents and responds accordingly), making associations (Turing systems modeled as entangled cybernetic circuits), and, by “breaking the game,” repurposing a code in a way not anticipated by the designers. Nevertheless, game design still depends on a Creator controlling the code, while organisms can evolve and learn entirely without the imposition of an external design.

<sup>6</sup> We thank Benjamin Brihoum and Benjamin Chambolle, students at ITMO University, for bringing this example of surprising bot behavior to our attention.



The physicality of signs is what is missing from machine processing. Often it is the chemical reactivity, due to physical shape and bonding affinity or repulsion, of a signal molecule that determines its relationship to a signal network in an organism. A signal molecule might coincidentally interact with different signal networks in distinct ways resulting in distinct, yet often interrelated, work pathways. This allows for an immediate generalization that could be a more useful response to an unfamiliar situation than a random response. Chemical networks are not all-or-nothing; there are strong and weak reactions due to many superposed physical attributes. In digital computing, on the other hand, these numerous simultaneous attributes are excluded by design. There is no cross-talk in a functioning computer. Consequently, missed or near-associations may not occur spontaneously in computer game play.

In the 1950s, Turing began to more aggressively pursue the idea that biological learning was more complicated than the statistical selection (reward-punishment) of machine learning he had previously envisioned. He discovered that another layer of constraint affected individual events in a non-linear fashion. While trying to understand how homogeneous egg cells could suddenly differentiate, he found that statistically *insignificant* local fluctuations could spontaneously initiate reactions that created a feedback scenario that switched back and forth between two different reactions, resulting in differential wave fronts, that is, spatial patterning at the global level. The reactants can function as self-activators and self-inhibitors.

In one of his last papers before his death “The chemical basis of morphogenesis,” (1952) Turing explores the reaction-diffusion equations that might explain the spatial patterning in animal patterns. He manually solved differential equations describing the chemical feedback loops introduced to create patterns similar to those on, for example, fish (See [Hiscock and Megason, 2015](#); [Kondo, 2017](#)). Turing's idea was that the self-organizing chemical patterns that differentiated neighboring cells would differentially trigger genes. Turing systems have also been found ([Raspopovic et al., 2014](#)) to be responsible for the patterning of digit formation, marking the areas to be carved out of the limb buds to create fingers and toes; a Turing system is also believed ([Nijhout, 1990, 2010](#)) to be responsible for laying down the topography of butterfly wing patterns ([Fig. 5](#)). Pattern formation in these examples occurs in an essentially homogeneous field of cells. After the initial pattern develops, the interactions of any further propagating waves become very complex, like the multiple interfering waves propagating from raindrops on a water surface. The equations used to describe such processes soon become intractable. Consequently, actual biological Turing systems are not easily identified or modeled except when they first occur in otherwise undifferentiated fields.

Digital computation works exactly because the symbolically encoded states of individual nodes are perfectly determined by the encoded states that they have received from other connected nodes, whereas biological reaction-diffusion processes—as proposed by Turing in his morphogenesis paper—are physically interactive with each other, with conditions in the intervening spaces as well as with the shape of their container. Additionally, the distance between connected cells affects their outcomes. In the next section, we explore how machine computation might be designed to better imitate biological information processing. We keep in mind that true internally produced codepoiesis may require hardware that grows through a process of artificial embryonic development, or perhaps, AI might make use of slime mold in unconventional forms of computing as [Adamatzky \(2007, 2010\)](#) has explored.

#### 4.2. Modeling resonant response and the emergence of novel global information

In this section, expanding upon Turing's discoveries in morphogenesis, we hypothesize how artificial computing might better approach bi-

ological-type processing by moving beyond the Turing machine as well as the Turing system. While it is possible that regulatory networks, as [Shirakawa and Sato \(2013\)](#) describe for slime molds (see [Fig. 3](#)), might be mimicked by computer designers, biological systems have networks of signal molecules that interact physically and have physical side effects. As noted above, discrete and independent symbols in digital machines do not interrelate with their physical conditions. They can *simulate* interrelations; they are not themselves physical interrelations ([Bacigalupi, 2013](#)). This distinction becomes particularly salient when we ask ourselves how a brain, for example, can create virtual networks due to the similarities and contiguities of nodes in the network ([Kelso et al., 1991](#); [Uhlhaas et al., 2009](#); and [De Assis, 2015](#)). Global patterns, simultaneously affecting and affected by local nodal behavior, act as a “virtual” network able to leverage similar and contiguous physical phenomena towards *non-random* adaptation. We argue that life's capacity to accrue these relatively ephemeral emergent patterns of information are the basis of memory, adaptive habits and learning. Current AI lacks this capacity.

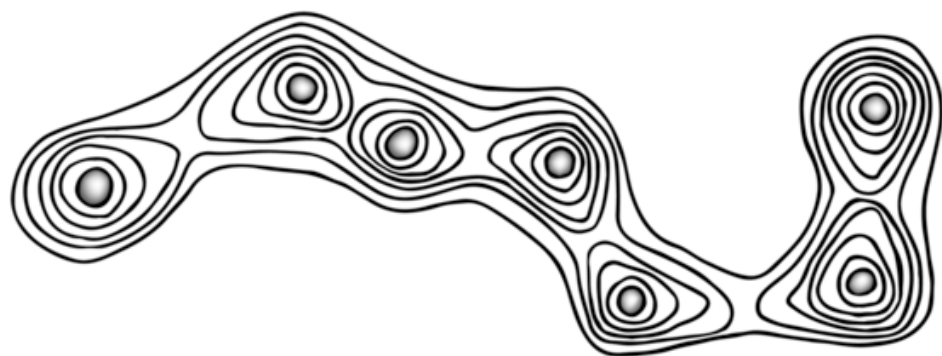
The Artificial Life (AL) research that grew out of Turing's chemical reaction-diffusion model was a step in the right direction but was hindered by a number of factors. As [Emmeche \(1991\)](#) notes, AL is “strong” AI insofar as it pursues a bottom-up rather than a top-down strategy, but AL researchers falsely assume that the essence of life can be adequately captured in its form and functions, *not its material qualities*. To the extent that AL uses discrete symbols representing chemical states, some analog information is lost about how chemicals themselves, with differing rates of reaction and diffusion, may resonate with one another locally, forming global patterns based on contiguity of similar frequencies. Paul [Weiss \(1967\)](#) is useful in helping us to imagine how the physical terrain *in between* the nodes and cells is causal. We see in individual points the figure as a single shape, a “big dipper” that is incrementally more salient in our perception than surrounding stars (See [Fig. 4](#)); perhaps similar to this Gestalt effect, proximal cells' chemical and/or electromagnetic behavior both mold and are molded by their shared interstitial surroundings, simultaneously.

We may also compare this to butterfly wing patterns, which are formed by Turing systems (See [Fig. 5](#)).

A number of neuroscientific studies have characterized not only the local field potentials (LFP) among the cells that collectively generate them (See [Hales and Pockett, 2014](#)), but also how these distributed potential terrains, in turn, modify the behaviors of adjacent cells ([Anastassiou et al., 2011](#)), independent of synaptic signaling, with functional outcomes ([Weiss and Faber, 2010](#)). [Alexander and Grimes \(2017\)](#) suggest that because neurons are able to respond to signals that are merely similar to the “correct” one according to their habits, signal diffusion is less likely to be impeded, and “mistakes” do not prevent the overall global pattern from emerging, in fact, mistakes may allow it to do so.

In light of this and similar research, [Bacigalupi \(2013\)](#) argues that in order to develop machine intelligence that approaches that of biological intelligence, each node must be able to respond differently than its diversely tuned neighbors to energetic patterns in their shared environment, which is a shared milieu that both affects and is affected by each diverse nodal response, simultaneously. This may be compared to the example described in [Weiss \(1967\)](#) as shown in [Fig. 4](#). To illustrate, we can imagine a population of diversely tuned nodes—the black spots, or *primary nodes*, under each frequency designation in [Fig. 6](#)—such that each primary node is sensitive to a distinct range of frequencies, similar to a loosely tuned tuning forks. In [Fig. 6](#), it is supposed that the C Major chord has occurred in the system's surroundings; the stimulated primary nodes are those that are sensitive to frequencies at or close to the musical notes C, E and G. Importantly, there is no one-to-one mapping; the C Major chord, composed of its constitutive notes, stimulate an arbitrary number of nodes whose distributions of sensitivity can overlap with sensitivities of other primary nodes. This stimulation, which re-

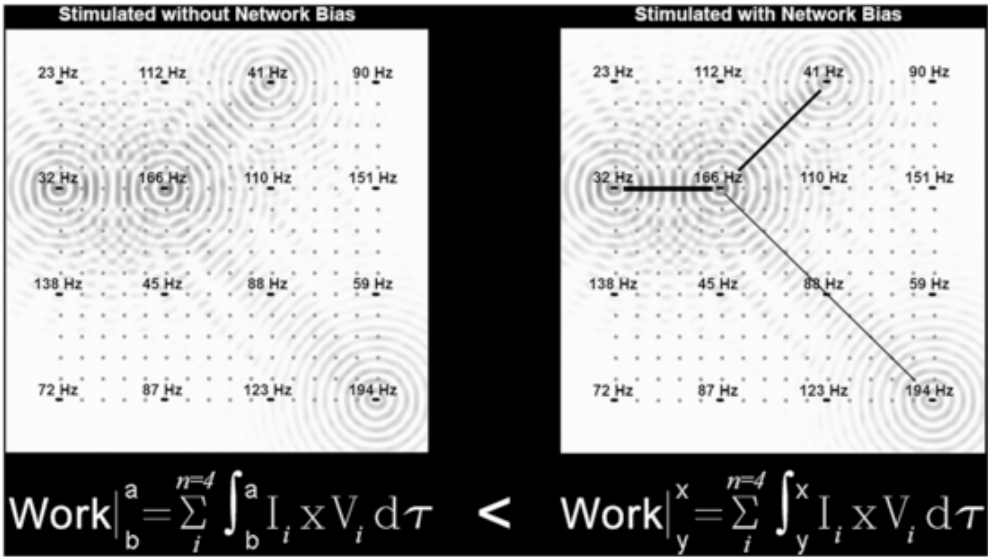




**Fig. 4.** Figure based on Paul Weiss 1 + 1 = 2 (1967) Droplets of silver salt on a chromate solution-soaked gelatin plate form periodic rings of insoluble silver chromate. The rhythmic character stems from a threshold phenomenon. The interaction between the droplets that are near enough to affect each other forms a virtual group that has a specific shape, similar to the Big Dipper. Such relationships may constrain the likelihood of recognizing shapes as such.



**Fig. 5.** The diffusion of a chemical that differentially activates pigmentation in butterfly wing patterns is affected by neighboring conditions, including the wing edge and the distance between the source points of the diffusing reactant. A normal *Bicyclus anynana* is shown on the left, a mutant form, called Spotty, is on the right. From Beldade et al. (2009). Creative Commons.



**Fig. 6.** At left, select primary nodes respond to an environmental energy pattern—C Major chord in this model—by vibrating to create an interference pattern in their shared physical milieu. At right, biasing connections formed as secondary nodes sense the constructive interference within the emergent interference pattern. Work equations demonstrate how work capacity of nodes increases as connections synchronize phases of voltage and current response within connected nodes.

sults in ripples emanating from stimulated primary nodes, creates an interference pattern in the interstitial physical milieu amongst the diversely tuned nodes, which can be electromagnetic, chemical, acoustic or even of water; no matter the contiguous transductive medium, it can embody arbitrary levels of superposed patterns. For example, a C Major chord can co-occur with an E minor chord to create a unique interference pattern for C Major 7th. The music theory is not the point, per se; it merely illustrates how arbitrary levels of complexity—distinct events and their levels of myriad interrelations—can be embodied in a finite medium.

This emergent and ephemeral complexity is not an abstraction. Its ephemeral nature may render it “virtual” with respect to more static systems. Nevertheless, it is a physical terrain with distinct physical properties that can be sensed by a secondary sensory system—the gray *secondary nodes* between the primary nodes in Fig. 6. These secondary nodes are sensitive to amplitude such that the emergent order—the constructive interference in the illustrated interference pattern—can be harnessed. This harnessing is analogous to growing synaptic connections that, once formed, bias the network structure. And this novel bias alters the electrical response such that the adapted system will elicit a greater response to future occurrences of C Major, or similar acoustic phenomena, in its surroundings. This is due to the fact that the system is now more sensitive to more complex patterns in its environment because the novel circuit biases can synchronize the phasic relationship between current and voltage among the connected primary nodes. The work equations in Fig. 6 reflect this synchronization because, as the phases between alternating voltage and current align due to these accrued biases, more real power ( $I_i \times V_i$  for each  $i$ th node) is available to do physical work, which in this case would be an amplified system response to C Major, or similar patterns.

Such resonating nodes in an artificial system would allow for ways to cohere, but also simultaneously ways to adaptively decohere, as in Saigusa's slime mold model, as in productive errors or potentially adaptive miss-associations. There would be no artificially added randomness in this scenario, but emergent outcomes would be possible that can allow the nodal state to escape the previously structured state, or local minimum, a huge problem for current AI.

Because a digital node is specifically designed to *not* leverage these overlapping possibilities, the resources needed to simulate interrelations will increase rapidly and exponentially, whereas a node sensitive to analog signals could spontaneously form part of a coherence pattern through its situatedness with other nodes without requiring additional resources. As Bacigalupi (2013) argues in this hypothetical model, both environmental physical phenomena and their relationships are physically re-created via a novel physical milieu, which creates a global interference pattern, not unlike Turing's (1952) reaction-diffusion patterns. Given this structured “noise,” *i.e.*, initially non-internalized stimulation, from its environment, these patterns can be harnessed by the system via biased connections discussed above; this emergent and internalized network biasing is arguably an *interpretation* of complex signals from the environment.

This hypothesis leverages the ubiquity of chemical and/or electromagnetic interference patterns as means for unsupervised learning, an area of AI that is underdeveloped compared to supervised learning strategies. This approach embraces the *actual* nonlinear physical systems *artificially* modeled by Turing's work on morphogenesis. Digital computers are not well suited to these complex systems. The combinatorial explosion endemic to computational models of nonlinear systems is not a burden to living neural systems. On the contrary, neural systems have had billions of years to take advantage of the ambient and structured “noise,” our modern technologies and symbolic systems have endeavored for hundreds of years to eliminate. The goal of truly intelligent machines would not be to *model* the complex dynamics, such as those described above, but to leverage their behaviors towards adap-

tive outcomes, by physically *being* similar to and contiguous with those dynamics.

The models proposed by Bacigalupi (2013) and Saigusa et al. (2008) are both linear summations that exhibit non-linear complex behavior through internally emergent physical structures and dynamics. These internal physical mediums are “molded” through physical exposure to specific energy and mechanical patterns in their environment and can emerge whenever relevant patterns in their indeterminate environment occur in the future. These moldable mediums are the voltage and phase biased nodes in Bacigalupi and phase biased oscillators in Saigusa, along with their respective interstitial milieus. In both cases, there exists a population of diversely “tuned” structures that are physically sensitive to signals in their internal and external environments. In addition, each of these mediums exhibit *both* reactivity at the local oscillator *and* more distributed global responses via their shared milieus: the interstitial chemical milieu, in the case of Saigusa, and an arbitrary interstitial transductive physical medium, in the case of Bacigalupi. This population of diverse structures, in addition to their shared milieu, creates a physical medium, which can be biased, not just by single patterns (generalizable similarities), but patterns of associated patterns (contiguities). These internalized complex biases are active learning. And subsequent passive capacity to respond to these complex patterns of patterns is the basis for adaptation and codepoesis. From out of these emergent processes based upon analog qualities of similarity and contiguity, a threshold response is generated that can be represented digitally, but it is important to note that such state changes emerge from the system itself and are not arbitrarily selected by an external programmer.

## 5. Conclusions

Despite the fact that we have a number of impressive examples of AI networks mimicking human activities, playing games, or painting portraits, we are still a long way from truly intelligent AI. The main obstacle may be the hardware of digital computing itself as well as the discrete nature of digital symbols. Intelligent adaptability and contextualization seem to require analog dynamics as they involve, at the local level, the interrelations of physical qualities of the signs themselves, their physical forms and how near they happen to be in space and time to other signs, reinforcing effects, and structural biases. At a shared global level, which emerges from these local interactions, biological intelligence also seems to involve spatial/temporal wave patterns and/or oscillators that both constrain local sign action and may function as further, much more dynamic and complex signs.

More generally we have offered an analysis of the similarities and differences between biological information processing and machine computation to make the points that 1.) Sign use is not limited to organisms with mental capacities; sign use, via similarities, contiguities, and arbitrary encryption, appears in the most primitive of life forms 2.) Semiosis is not a spiritual or miraculous process inexplicable in material and relational terms. Indeed, semiosis is the interrelations of material qualities. 3.) Creating true (albeit primitive) AI is probably not impossible but will likely require systems with pre-symbolic dynamics, namely similar and contiguous, in that order. We exhort researchers to note the essential differences that currently exist between biological and artificial information processing. Impoverished machine-like models of biological processes may impede biological research, especially medical research. Conversely, the inappropriate characterization of current machine learning as “intelligent” may mislead researchers to inappropriately apply AI in human affairs.

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## Declaration of competing interest

We have no conflicts of interest.

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