Journal of
Risk and Financial Management

MDPI

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Multiple Neighborhood Cellular Automata as a Mechanism for Creating an AGI on a Blockchain

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Abstract: Most Artificial Intelligence (AI) implementations so far are based on the exploration of how the human brain is designed. Nevertheless, while significant progress is shown on specialized tasks, creating an Artificial General Intelligence (AGI) remains elusive. This manuscript proposes that instead of asking how the brain is constructed, the main question should be how it was evolved. Since neurons can be understood as intelligent agents, intelligence can be thought of as a construct of multiple agents working and evolving together as a society, within a long-term memory and evolution context. More concretely, we suggest placing Multiple Neighborhood Cellular Automata (MNCA) on a blockchain with an interaction protocol and incentives to create an AGI. Given that such a model could become a "strong" AI, we present the conjecture that this infrastructure is possible to simulate the properties of cognition as an emergent phenomenon.

Keywords: AGI; machine learning; consciousness; identity; blockchain; small world phenomenon; mandala networks; multiple neighborhood cellular automata

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Citation: Sgantzos, Konstantinos, Ian Grigg, and Mohamed Al Hemairy. 2022. Multiple Neighborhood Cellular Automata as a Mechanism for Creating an AGI on a Blockchain. *Journal of Risk and Financial Management* 15: 360. https://doi.org/10.3390/jrfm15080360

Academic Editor: Shigeyuki Hamori

Received: 7 June 2022
Accepted: 8 August 2022
Published: 12 August 2022

1. Introduction

In "Gödel, Escher, Bach" (Hofstadter 1979), Hofstadter presents a set of enticing ideas: one of these is that the formal system that underlies all mental activity transcends the system which supports it. If life can grow out of the formal chemical substrate of the cell, if consciousness can emerge out of a formal system of firing neurons, then so too, computers will attain human-like intelligence. In the same book, he applied the Incompleteness Theorem of Gödel (Gödel 1931) to the computability theory of Alan Turing. Originated in the work of recursion theory (Davis 2004), the Incompleteness Theorem postulates as follows: Provided there is a formal theoretical system of rules that can be expressed in computational form, so that a problem formulated within the rules of that system can be proven by an algorithm as false or correct, then it is also possible to formulate, within that theoretical system, a problem that cannot be proven either false or correct. Such a problem is called "undecidable" (Clote 1999).

As with every scientific field, recursion theory is not immune to Gödel's famous theorem. In the same notion, the construction of an AGI seems to be, as a problem, fundamentally undecidable. Nevertheless, our approach focuses on the conjecture that, even if the mathematical proof within the recursion theory system can be elusive, the construction of an AGI can be approximated with an adequate Gödel Expansion (Sgantzos and Grigg 2019) that will be sufficient to expand the system so that the problem can be solved, even partially. Such an expansion is graph theory. Other expansions such as computational biology, anthropology, and psychology may be required in the process as well.

A current working hypothesis is that, if we can construct an AGI of the general sophistication and network topology of the human brain, then properties such as consciousness, identity, and self-hood may consequently emerge from that construction. Crowder, et al. postulate that we can even endow an AGI with metacognition—an introspective ability of the AI to report their internal mental states. Such an ability is broadly considered to be one of the main functions of consciousness (Crowder and Fries 2011).

This hypothesis is questionable, since consciousness is only loosely understood, and whatever perception exists among scientists diverges on key points. However, an investigation of the origins of these perceptions provides new directions in AGI construction, including further emergent properties.

In this paper, we postulate that a secure, persistent, and self-referencing environment such as a blockchain can be used as a medium to construct an AGI, by using the synergy of a set of generalist agents, or automata, who collaborate and work together as a culture. These are named MNCA. Furthermore, we present the conjecture that this infrastructure is possible to simulate the properties of cognition as an emergent phenomenon.

The major contributions of this article are summarized as follows:

- In Section 2.1 we approach the definitions of identity and consciousness in humans and how these properties emerge. We also present a summary of the research in current literature on nerves, signal propagation in the brain, and neuromorphic computing (Section 2.2);
- In Section 2.3 we explore a single-cell organism as computational unit, and we present its analogy with a Random Forest Decision graph. We then investigate the assessment of the brain and the role of the Mandala Network as the most prominent topology for fast signal propagation between nodes (Section 2.4);
- In Section 3 we present a novel definition of agents and AI as Analysis of Information (Section 3.1). We also present the probabilistic and deterministic nature of computation in the brain and how it perceives reality (Section 3.2);
- In Section 3.3 we explore the usage of Turing Complete Cellular Automata as agents and how they function in collaboration towards constructing an AGI within a blockchain network topology;
- In Section 4 we discuss the idea of blockchain as a medium of storage for an AGI and real-world Big Data. We also explore the merits it provides versus isolated (i.e., non-shared) systems. We present as a proof of concept the creation of a perceptron in sCrypt language (Section 4.1). We also address the problem of scalability and current technological advancements (Section 4.2);
- In Section 5 we discuss the limitations, concerns, and ethics involved in the role of such a computational entity towards the advancement of humanity and the incentives for creating one.
- In Section 6 we present the conclusions of our research.

The related research, which is based on existing literature, is presented in Sections 2.2–2.4; while Sections 3.1–3.3, 4.1 and 4.2 are based on our own ideas and research of the past. Finally, the code by Xiaohui Liu which is included in Appendix A was created solely by him based on discussions on the above subjects as a proof of concept.

2. Materials and Methods for AI, a Review of Current Approaches

2.1. Approaching Intelligence and Consciousness

In searching for the definition of consciousness, one must seek into the Ancient Greek thesaurus for the word suneidésis, “Συνείδησις” (< συν − (σύν) + εἴδησις < οἶδα), the essence of which means “together <we> + know”. The Latin equivalent was translated as “conscientia” which was used in modern times by René Descartes and later John Locke for creating the word “consciousness” (Lewis and Short 1999). Descartes coined the famous aphorism, “Cogito, ergo sum”, or “I think, therefore I am”. This casts consciousness as the emergent property of our mind, called thinking, and its relations to existence, personality, intelligence, and perception of self. “I am” is the primary rule; and my thoughts are my elegant proof of my individuality, my identity.

There is an evident contradiction here: "I" may think of myself as axiomatic, but "we" may have forgotten that knowledge comes from togetherness. This divergence is found not only in the ancient definitions of consciousness but is also apparent in non-western traditions. From modern African philosophy, "I am because we are, and since we are, therefore I am" (Mbiti [1975] 1990). According to Ubuntu principles, a newborn baby is born without "ena" and therefore is not a person (Gyekye 2011). On the other hand, a 20-year-old adult undeniably demonstrates personhood, identity, consciousness. A valid question here is where those properties emerge from.

As Zelazo et al. propose, consciousness develops through a series of levels, each of which has distinct consequences for the quality of subjective experience, the potential for episodic recollection, the complexity of children's explicit knowledge structures, and the possibility of the conscious control of thought, emotion, and action (Zelazo et al. 2007). A baby is born with a prefabricated network of neurons capable of providing consciousness, but it only provides little mental functionality beyond some survival instincts. As humans grow up, the neural network of the brain expands and increases its connectivity. Bruchhage et al. showed that the number of functional networks recruited increases with skill complexity, with an exceeding involvement of higher-order networks enabling daily maintenance and coordination of cognitive functions (Bruchhage et al. 2020). As humans grow, they learn, socialize, work, invent, lead, teach, create, and share new knowledge, and eventually start families, have new babies, and start the cycle of life again; often, all these activities happen in parallel. This process is governed by complexity in society, seemingly not so distant from chaos itself. In that regard not only do we see that consciousness can never be solely deterministic, and thus echoes the "incompleteness theorem", but the larger part of this mystery happens before the child becomes self-conscious, and certainly well before adulthood.

Humans, in the form of a society, can solve far more problems than a single person. Perhaps the same principle applies to AI. Following Gödel, a fundamental barrier exists that limits any isolated unit of intelligence whether it is artificial or human. In any case, such a limit should not be perceived as an internal construction challenge to overcome, but as an invitation to bring diverse bits of intelligence of others to work together rather than try to compete with them.

As young adults, humans may well understand their existence because they can think, but they do so because their family, mentors, friends, and community taught them how to think and draw meaningful conclusions. This training task is so dominant in the child's emerging consciousness that what the child perceives as reality is strongly bound to a collective of "trusted others" in the community certifying it; in other words, it is the observers who confirm that the personal "reality" is actually "real" (Grigg 2021).

Several great thinkers have theorized on the possibilities of constructing an AGI. The evolution of computers in the 1930s was engraved by two giants of computer science. Claude Shannon and Alan Turing. Notwithstanding, Shannon's famous work *A Symbolic Analysis of Switching and Relay Circuits*, which is now considered one of the most important works in history of computer science, is based on the great contribution of George Boole's work *The laws of thought*, which in turn, was inspired by the famous *Organon* of Aristotle. Logic is likely the most important element to both humans and machines.

Turing believed that a brain can be simulated via a multi-machine construction. Gödel argued that the effective computability of the mind far exceeds any computation-capable construction, as the brain is a constantly evolving system (Gödel 1972). Penrose, supporting Gödel's ideas, believes that creating a sentient machine is impossible because consciousness is not a mathematical problem, and thus cannot be solved. He contends that while an AGI may be able to be constructed, the ability to determine its soundness or correctness of function of this machine, may be beyond the power of human understanding (Penrose 1991, 1994).

As Wright further describes the Church–Turing thesis argument: "While Turing would see that each mental procedure could be deemed equivalent to a mechanical procedure, Gödel would argue that the system is fundamentally different in that a human mathematician can calculate an un-computable sequence by virtue of the creation of new symbols and hence new methods. Whilst it is, in theory, possible for an evolutionary computational system to involve new symbols and methodologies, even evolutionary computation does not at present work in this manner. Hence the nature of how mathematicians compute and develop new systems is a problem for the mechanistic view of computation that could be solved if an evolutionary computer were to develop such capabilities" (Wright 2021).

This limit of the base case hypothesis of AI suggests that to construct an intelligence which can simulate our capabilities and consciousness, we must consider how humans got there ourselves. It is quite probable that an AGI will not be able to reach our level of cognition without traveling our path, or at least learn from us. Without the intervention of a community of peers, who "together" they "know", it may be impossible to grow advanced cognitive abilities.

This alternate approach suggests a generalist AI agent as a growing individual in a society of other agents who together are oriented to that task.

2.2. The Neuron as the "Computational Element" of the Brain

In search of consciousness, it benefits to review some of the basic elements and constructs that suggest or contribute to intelligence. A single neuron acts as the basic computational unit of the brain, and it is likely that any attempt to simulate the brain will first need to simulate the neuron and its innate characteristics. These would include, but not limited to: (1) a common way to propagate signals, like the chemical substances do when a neuron is electrochemically propagating information through a synapse; (2) information is submitted with adequate security, e.g., similarly to the brain's nerves which are protected so that the chemical signals cannot be intercepted or manipulated, constructing a secure network (Figure 1); (3) being able to switch to a state of ON or OFF (DeWeese et al. 2003) and being able to switch that state based on inputs; (4) a form of "neurogenesis" which is the biological process of creating new neurons each time we create new memories, skills or knowledge (Eriksson et al. 1998); and (5) "neuroplasticity" being the biological process of the brain to assign tasks to other neurons via new connections when an existing neuron functioning is impaired in some way (Voss et al. 2017).

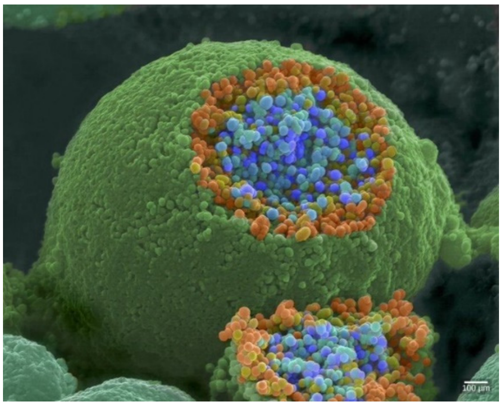

Figure 1. A scanning electron microscope picture of a nerve ending, with the protective outer part, the presynaptic membrane acting as shield, broken open to reveal vesicles (orange and blue) containing the chemicals used to pass messages in the nervous system. (Image by: Carvalho, T.; 2015. "Nerve Ending" Flickr/CC BY-NC-ND 2.0) (Carvalho 2015).

A device that can switch between ON and OFF is known as a Deterministic Finite State Automaton (DFSA). Neurons as a unit of computation is not a new idea. Benayoun et al. simulate neurons as coupled, continuous-time, two-state Markov (stochastic) chains (Benayoun et al. 2010). Each can exist in either the active state, representing a neuron firing an action potential and its accompanying refractory period, or a quiescent state, representing a neuron at rest (Nunomura et al. 2001).

Neuromorphic computing seeks to find an economic way to construct a new platform for AI. Modern computers, based on the Von Neumann architecture, are constrained in many ways. The bottleneck between the CPU and memory seriously inhibits asynchronous or parallel processing, characteristic of the mind's thinking. Neuromorphic chips' architecture represents a tight set of biological neurons with high performance (Vishwa et al. 2020), yet they are constrained with permanent interconnections, inhibiting the stimulation of neurogenesis and neuroplasticity. This is the reason we propose that software agents like MNCA can solve these problems.

2.3. The Intelligence of a Single-Cell Organism

Nakagaki et al. showed that the single-celled slime mold plasmodium Physarum polycephalum (Figure 2) can solve simple tasks such as navigating a simple maze to reach a food source (Nakagaki et al. 2000). Zhu et al. showed that it can solve the Traveling Salesman Problem and even "remembering" substances (Zhu et al. 2018).

Figure 2. A Physarum plasmodium, presents a neuron expansion topology similar to a Random Forest Decision Tree. (Image by: Carolina Biological Supply Company/Flickr/CC BY-NC-ND 2.0) (Starr 2021).

The growth and spatial expansion of the organism suggests what is known in data science as Random Forest Decisions Trees (Figure 3) (Venkata 2020), and its topological complexity also strongly resembles the biological structure of the dendrites and synaptic bonds of a human neuron. Random forests follow a technique known as bagging (also known as Bootstrap aggregation). This is an ensemble technique where a number of decision trees are built based on subsets of data and an aggregation of the predictions is used as the final prediction.

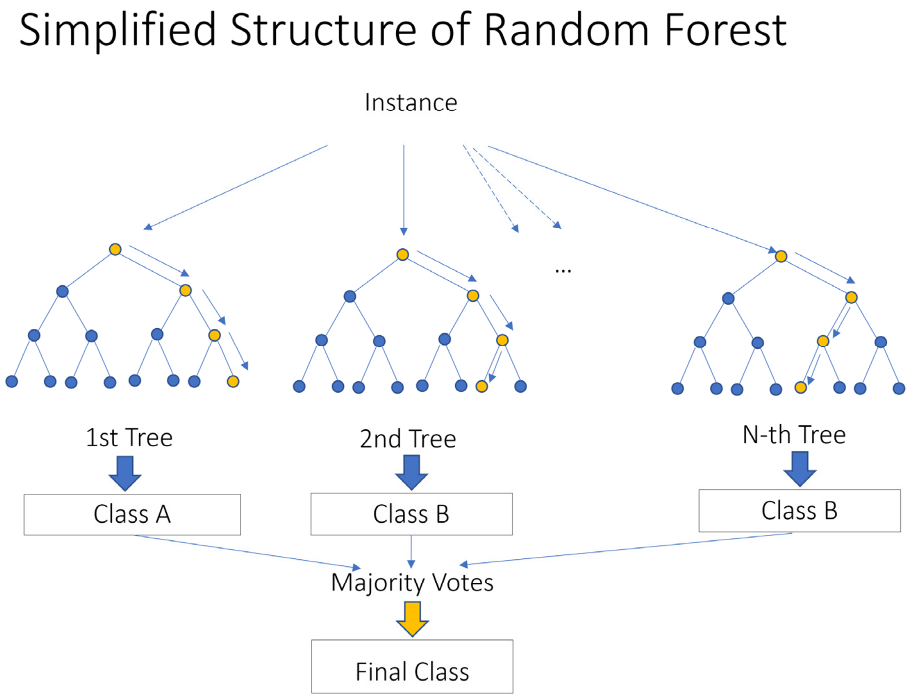

Figure 3. A random decision forest graph. The above illustration shows three decision trees and a classification obtained from each of them. The final prediction is based on majority voting and will be "Class B" in the above case (Image reproduced based on the work from Venkata, J. 2020. "Random Forest Template for TIBCO Spotfire". CC BY-SA 4.0) (Venkata 2020).

Echoing Turing, Nakagaki et al. and Zhu et al. argue that a neuromorphic organism like Physarum, can exhibit cognitive abilities without a brain, but these capabilities appear limited to only very narrow tasks. For emergent phenomena such as consciousness, it is evident that a network with more complex structures needs to be built.

2.4. The Network of the Mind

Significant progress has been made using techniques such as diffusion imaging and MRI into mapping the human connectome. Connectome is considered the brain's neural system and how it is interconnected (Figure 4).

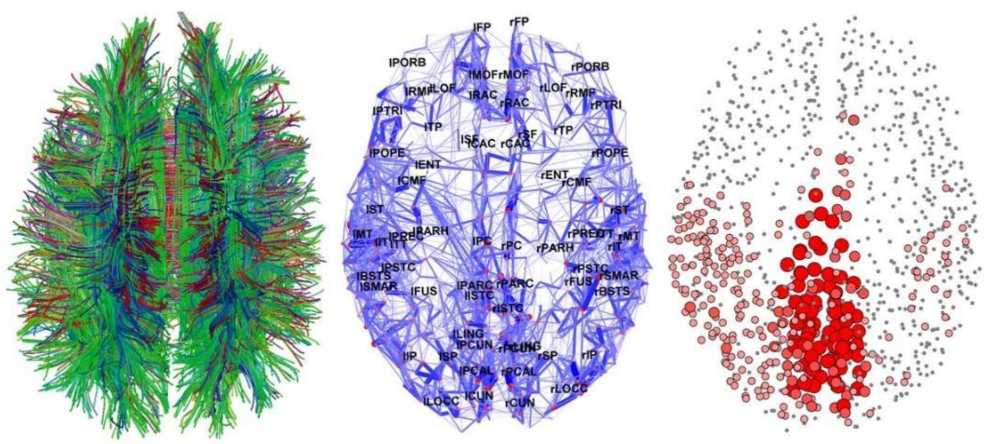

Figure 4. Representation of the human connectome. Images show the fiber architecture of the human brain as revealed by diffusion imaging (**left**), a reconstructed structural brain network (**middle**), and the location of the brain's core, its most highly and densely interconnected hub (**right**). The image on the left is courtesy of Patric Hagmann, University of Lausanne; the middle and right panels are from Hagmann et al. (Hagmann et al. 2008), (Sporns 2010).

While the complexity of mapping the human brain of approximately 86 billion neurons is challenging for the foreseeable future, a mapping of the neurons of the brain of Macaque monkey which contains only 1.38 billion neurons is informative, showing strong clustering of neurons into "regions" (Figure 5). Experimental mapping has also shown that the regions of neurons strongly correlate to single tasks. These regions can be considered "neighborhoods" of functional agents (Collins et al. 2010).

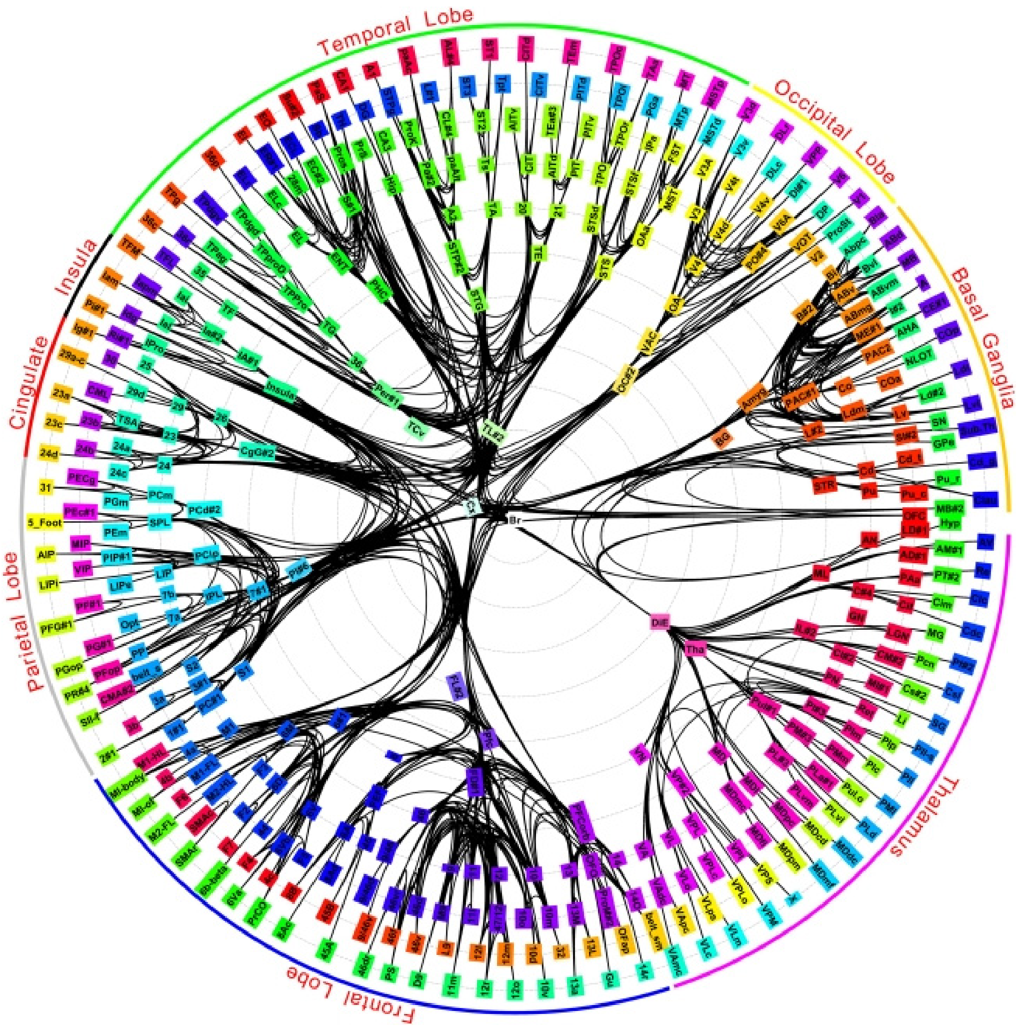

Figure 5. "The Mandala of the Mind": The long-distance network of the Macaque monkey brain, spanning the cortex, thalamus, and basal ganglia, showing 6602 long-distance connections between 383 brain regions. (Image by: Bernard Goldbach. "Network architecture of the long-distance pathways in the macaque brain")". (CC BY 2.0) (Modha and Singh 2010).

The Macaque's brain also bears a strong resemblance to a Mandala Network, which can be considered as an ultra-small-world and highly sparse graph, optimal for efficiently connecting both nodes and regions of nodes (Figure 6) (Sampaio et al. 2015).

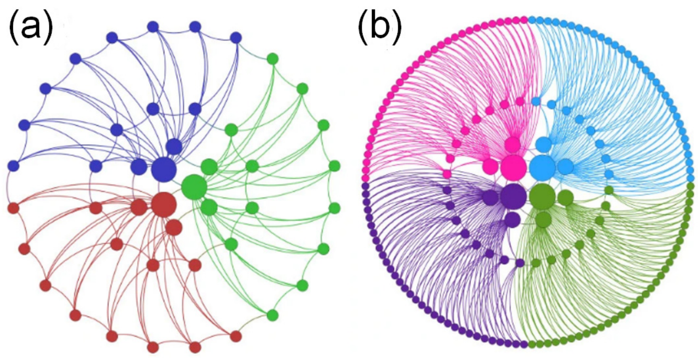

Figure 6. Representations of Mandala Type networks and their node connections (**a**) type A, generated with parameters $b = 2$, $n_1 = 3$ and $\lambda = 2$. (**b**) type B, generated with parameters $b = 4$, $n_1 = 4$ and $\lambda = 2$. (Image by: Sampaio, F.; Moreira, C.; Andrade, A.; et al.; 2015. "Mandala Networks: ultra-small-world and highly sparse graphs") (Sampaio et al. 2015).

The prominent organization of regions highlights the benefits of the neurons' characteristics, being a common signaling method through Ranvier nodes and dendrites, a common computational capability, and both neurogenesis and neuroplasticity to form and reform new networks as automata, or multiple agents who, in synergy, can perform a task. In a classical network such as the Internet and the design of many AI models, the communication protocol and the computational units are separate.

The Small World network phenomenon is apparent in many social, biological, and physical complex networks, and is ideal because it represents an optimal balance between global and local processing, preserving tightly interconnected clusters. For example, lattice networks that are theorized to support segregated and specialized processing with a short path length (a key feature of the random network, facilitating integration between different clusters) (Smith Basset and Bullmore 2006).

One approach is to imitate the network topology of the brain, by defining functional agents implemented in our AI model to mimic the tasks that the brain's regions exhibit, and connecting them as a Mandala network, much like a microservices architecture. Those can be a set of generalist agents, or "automata", referring to a wide range of technical ideas which we will examine below.

We theorize that the absence of agency, which is composed of sets of independent units with computational, communication, and self-organizing capabilities is one possible reason we do not see emergent human-like properties such as probabilistic computation or simulation of cognitive abilities within the current implementations of AI and machine learning networks.

3. Novel Approaches for Constructing an Artificial Brain

3.1. A New Definition of Artificial Intelligence and Agents

AI is probably one the most overused terms of recent years and many data scientists would propose that the term should probably be replaced by "Analysis [of] Information" since in that way we would be able to overcome the problem to define "Intelligence" in the sense of how humans understand it. In the same way, there needs to be a novel definition of what an Agent is. As Anna Harutunian describes it: "Anything that perceives an environment with sensors and acts upon the environment with effectors is an agent". (Harutyunyan 2020) Historically, Ada Lovelace ruled out automated intelligence, saying that "The Analytical Engine has no pretensions to originate anything. It can do whatever we know how to order it to perform" (Perl 1979). Alan Turing's approach differed from her deterministic approach and focused not on the ability of the Agents to think, but on the behavior that they would demonstrate if they did (Turing 1950). In other words, if an agent could persuade us to believe it is "intelligent", would it really matter how we define it?

3.2. Deterministic and Probabilistic Computation

Computationally wise, the human brain is both a deterministic and probabilistic machine. Giddon, et al. showed in a recent study that compartments in the dendritic arms of cortical neurons can each perform complicated mathematical operations, but the computational abilities go down to the individual dendritic sections. It seems that they, as units, can also perform a particular computation; an "exclusive OR" that mathematical theorists had previously categorized as unsolvable by single-neuron systems (Giddon et al. 2020). That part seems to be complementary to the probabilistic part of the brain which constantly works on a single task: To predict what comes next.

The human brain works on a ceaseless "guessing and matching" feedback principle. As the cognitive scientist Anil Seth (and others), paraphrased Descartes: "I predict (myself) therefore I am" (Corlett 2017). The Brain operates based on previous knowledge, to predict and associate new data to stored patterns, or previously stored memories. As an example, let us imagine that our eyes see for the first time a new unfamiliar shape. When that image moves into the cognitive area of the cerebral cortex from the visual system, the brain tries to associate it with something already recognized and stored in our memory.

The act of association is clearly a probabilistic process and often leads to misunderstandings and misconceptions; therefore, different people perceive the same thing differently from others. A representative example is the case of anthropomorphism, a phenomenon widely examined and discussed in recent years in Psychology. The misconception of anthropomorphism, or anthropomorphic bias, is the innate characteristic of the human brain to personify non-human things or concepts, like countries, machines, or weather phenomena (Gomez-Marin 2019).

As Joscha Bach postulates, "we live in a world which our mind creates". Every single moment our mind fabricates a perception of our reality as a continuous process that only stops when we are unconscious (Collins 2018; Resnick 2020). We reach towards more confident predictions by combining our probabilistic perceptions. Within the confines of the brain, there is no reality, only a sequence of ever better predictions; within a society of individuals, we also find the reality is a shared consensus—entirely dependent on the ability of humans we trust to verify what they agree as real with others and ourselves.

Then, while a deterministic part of the brain would be computationally easy to construct, it cannot on its own match the full processing power of the brain. There also needs to be a construction of a probabilistic part of the brain if we want to get close to emergent properties. After all, as biological machines, humans have both a deterministic part, our DNA, also as our probabilistic part, the epigenome; and of course, the biochemistry of the brain, or our "wetware". To construct something as complex as consciousness, both probabilistic and deterministic parts need to be present.

3.3. The Game of Life—Turing Complete Cellular Automata

The simplest form of a Turing Complete Cellular Automaton is Rule 110 which was discovered by Stephen Wolfram in 1983 (Figure 7).

Its Universality has been proven by Stephen Wolfram in 2002 and Matthew Cook in 2004 (Wolfram 2002). Evolution of life is defined as the constant replication, mutation, and differentiation of a species' characteristics so that the next generations gain advantages through Darwinian natural selection. The first computer representation of life within a computer environment was implemented with a cellular automaton called "Game of Life", or simply "Life" by John Horton Conway (Izhikevich et al. 2015). It is considered a Universal Constructor (Poundstone 1985), which means it can simulate any other Turing Machine (Figure 8).

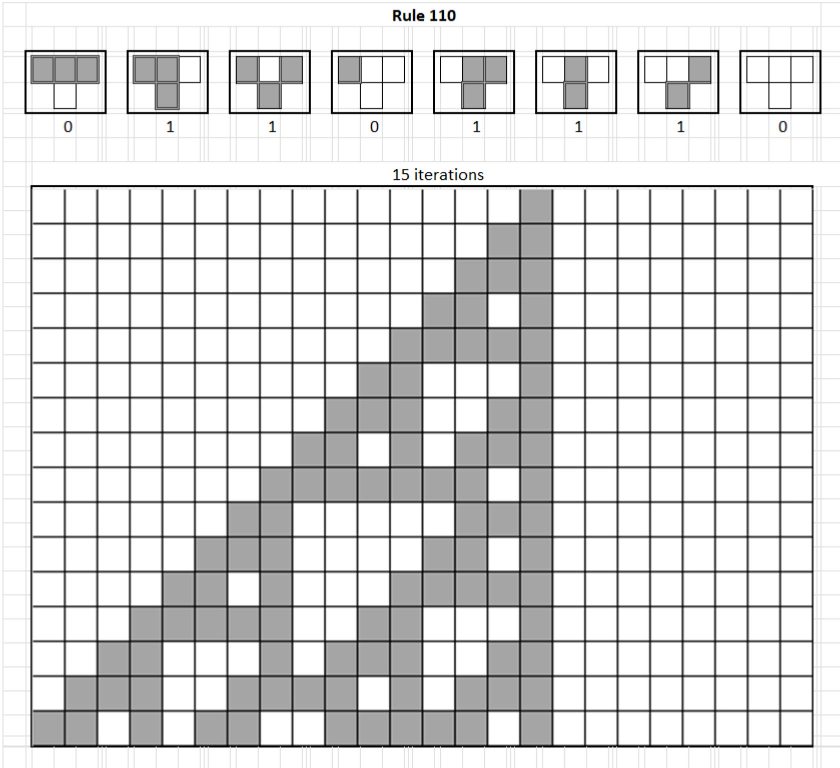

Figure 7. Diagram of Rule 110 Elementary cellular automaton and its consequent evolution. The rule specifies the next color in a cell, depending on its color and its immediate neighbors. The rule is illustrated above together with the evolution of a single black cell it produces after 15 steps. (Image reproduced in Microsoft® Excel® based on Rule 110 by S. Wolfram's *A New Kind of Science*) (Wolfram 2002).

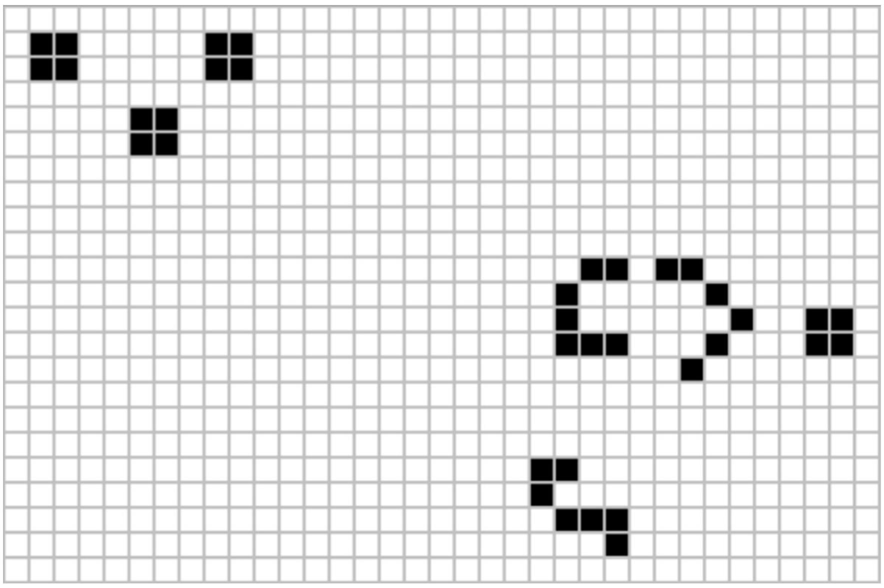

Figure 8. Game Of Life, showing the Simkin glider gun; found by Michael Simkin in 2015. It consists of a Herschel running in a loop made of two B60 conduits, producing infinite copies of the first natural glider. (Image by: Liambdonegan01; 2020. "Game of life Simkin glider gun". Wikipedia, Licence: CC 0).

Even though the Game of Life seems paradoxical to be used as a prime element to model brain dynamics, it presents several similarities with other well-known models. For instance, the stochastic rate model proposed by Benayoun et al. (2010) we referred to in Section 2.2.

Fraile et al., in their work "Cellular Automata and Artificial Brain Dynamics" show that the advantage of using the Game of Life lies in the fact that its simplicity makes it computationally cheap; a million neurons can be modeled in a single inexpensive computer, and simulations containing several millions of neurons are feasible without the use of supercomputers. Their implementation is preferable, as the more rules a system has, the more "constrained" it is. More specifically, it is computationally more economic to construct complex systems via simple rules (Fraile et al. 2018).

It seems emergent phenomena, like consciousness, tend to be born by simple initial structures and rules, which can turn into enormous complexity. In his tutorial Alan Zucconi, using the Simkin glider gun among others, has managed to construct simulations from simple digital clocks up to even a Z80, 8-bit CPU only by using Game of Life (Zucconi 2021). However, the most intriguing part about being Turing complete is not to simulate a computer in Life, but to simulate "Life" from "Life" itself (Bradbury 2021). As Clune postulates, using AI to make AI could be an important step on the road that one day leads to artificial general intelligence (AGI) (Clune 2020).

In search of what could be the secret ingredient for creating something so complex as a multicellular organism, there is evidence that the Game of Life "cells" can behave the same way as the biological cells do when they exist in "neighborhood communities" and they follow a certain topology. In several cases as noted in Section 2, multiple people when they form societies who trust each other they can overperform the single individuals who form the society. This seems to be the norm in Nature and in the world of Computer Science (i.e., parallel versus linear computation).

Apart from the design of the agent and the set they form as MNCA, the Machine Learning part is also important. The notion of a generalist agent called "Gato" presented recently by Reed et al. that was trained on different datasets, can perform as good as a specialized agent but in every trained field (Reed et al. 2022). We theorize that Multiple Agents not only will be able to present a generalist approach but if they coexist in the same Neighborhood, they will form a generalist society no different than what humans were able to create thousands of years ago.

Ben Kraakman (Kraakman 2021) found that single generalist agents, or automata, in proximity create what he called, "Multiple Neighborhood Cellular Automata" (MNCA). Those produce complex and robust emergent structures not commonly seen in simpler models (Figure 9).

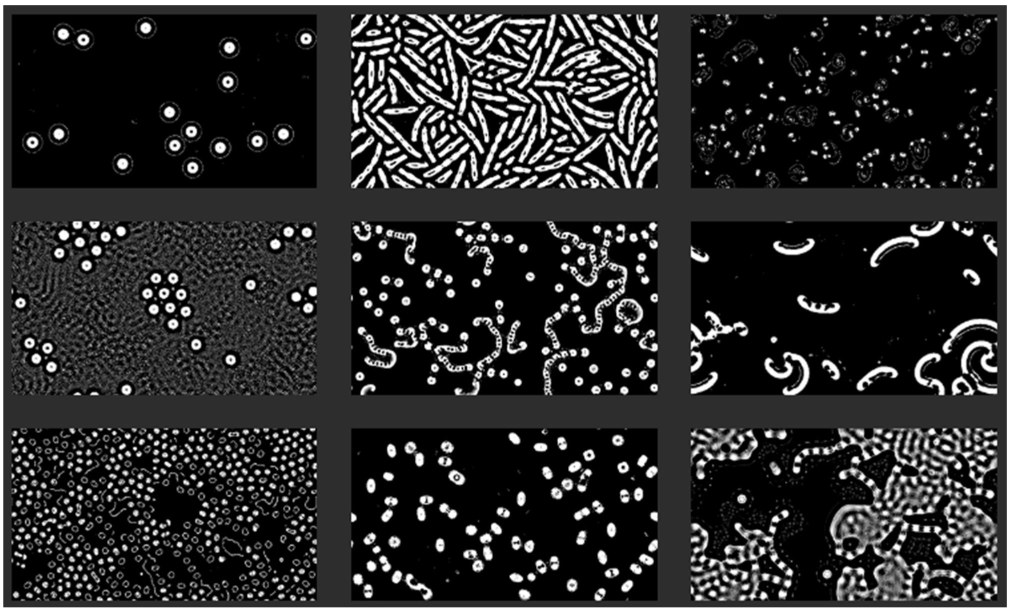

Figure 9. Emergent structures of Multiple Neighborhood Cellular Automata (Image by: Kraakman, B. 2021. "Understanding Multiple Neighborhood Cellular Automata") (Kraakman 2021).

From the biological perspective, a direct comparison shows that there is an obvious correlation of the above representations with electron microscopy pictures of biological colonies of Escherichia Coli (Figure 10) or similar bacteria (Moyer 2008).

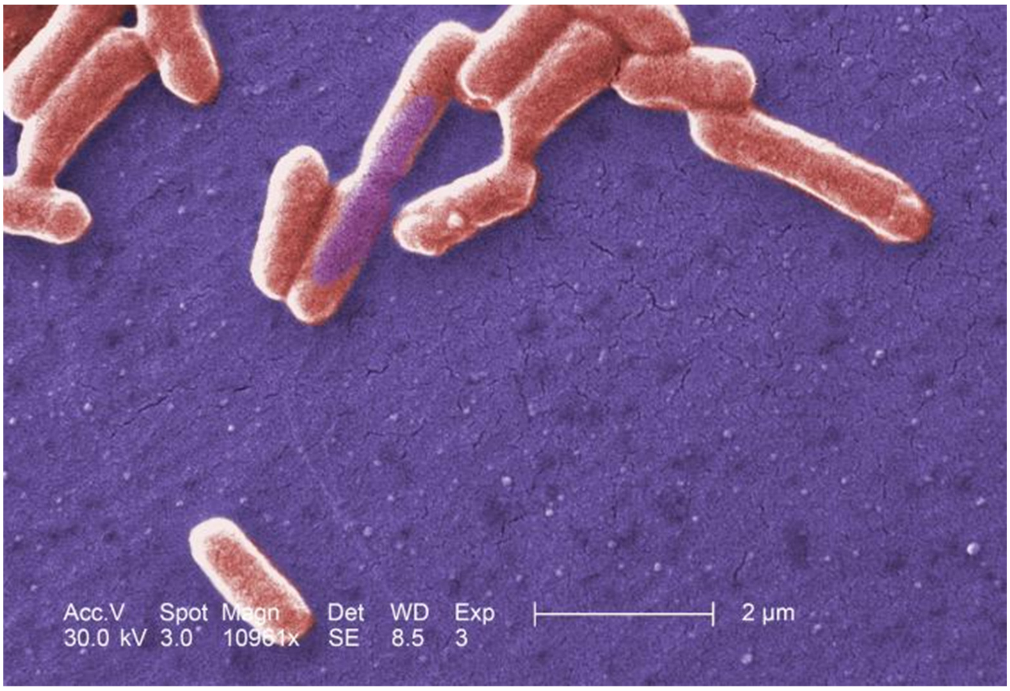

Figure 10. Scanning electron micrograph of an E. coli colony (Image by: Moyer, P. 2008. "E. coli colony". Photo courtesy CDC/Janice Haney Carr) (Moyer 2008).

The direct analogy of this representation seems no different to our prime hypothesis of this manuscript, that both digitally, also biologically, cellular formations "together, they know" each other. As with every scientific postulation though, solid experimental evidence needs to be present, and more research is needed.

4. Results

4.1. AGI on the Blockchain

In our previous work, we analyzed the advantages that blockchain suggests for AI (Sgantzos and Grigg 2019). AGI mechanics are based on a simulated digital "brain". Such a venture is both weighty and an attractive target, and we face dire implications for humanity if one successful AGI is controlled by one company or one country. There is also a need to face the threat of possible hacking and misuse. We explored the prospects that Artificial Intelligent Agents (AIAs), collaborating in the relatively secure environment of distributed ledger technology, could form a democratized AGI that can be utilized by everyone.

Data within transactions on the blockchain are automatically labeled and collated onto a perpetual record, creating reliable facts about economic events and when those have happened. In a scenario where every transaction results in a movement of tokens, even a non-financial event has an economic impact, adding the gravity of micropayments to such events. Stakeholders (governments, central banks, beneficiaries) gain as the process is publicly auditable. Another positive fact is that this technology presents a way to mitigate illicit actions such as money laundering and financial crime.

Blockchain as a permanent record keeper is built on top of a network of nodes. The resemblance of the human brain wiring with the current topology of the Bitcoin Network graph (Figure 11) is remarkable. Its topology matches the Mandala Network infrastructure we explored in Section 2 (The Bitcoin SV Test Network 2021; The Bitcoin SV Wiki 2021).

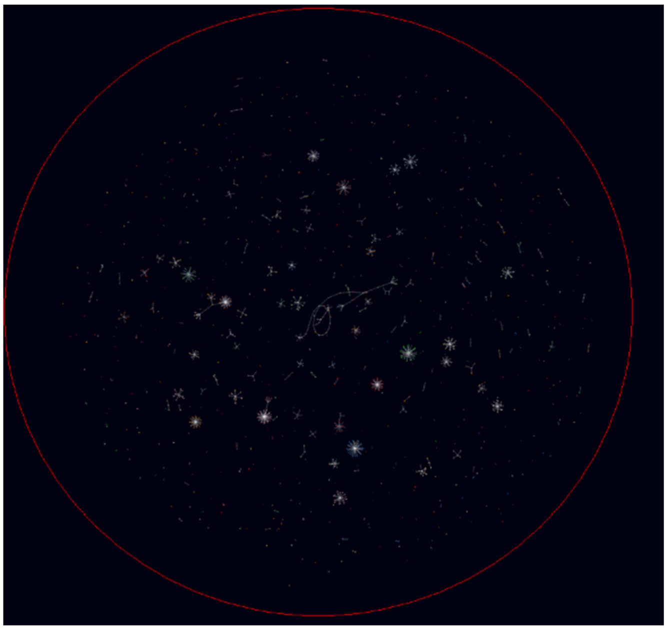

Figure 11. The Node Map of the Bitcoin Network resembles the topology of a Small World Network. The picture is a 2D representation of a 3D map (Image by: viz, cash 2021. "Bitcoin SV Network") (The Bitcoin SV 2021).

Significant progress has been made to build the elements of an AGI on the blockchain. For instance, a neuron could be computationally represented by a perceptron. Liu (2021a) recently demonstrated the construction of a perceptron as a stateful contract coded in his own implemented language called sCrypt which is a high-level interpreter of the FORTH variant Bitcoin script is using (Figure 12).

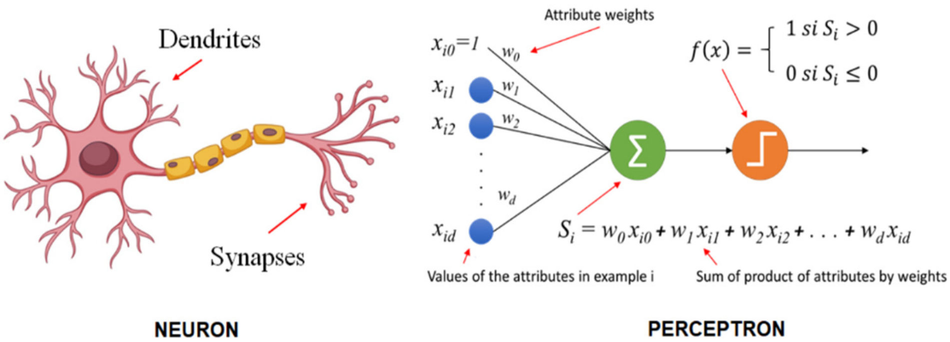

Figure 12. A physical Neuron (**left**) and its computational analogy; a Perceptron (**right**) (Image by: Liu, X.; 2021. "How to Train AI using Bitcoin") (Liu 2021b).

Liu also developed a smart contract to delegate the Machine Learning process (training) in the form of a public bounty that can be collected by anyone offering the right "weights" which will make the predictions that match outputs for all training dataset inputs. The computationally intensive training is done off-chain and the smart contract only verifies the training is valid, thus making training an AI agent on Bitcoin significantly more cost-efficient (Liu 2021b). Another implementation, necessary for Machine Learning is Matrix calculations (Liu 2021d) and, among others, "Game of Life" (Liu 2021e) which we explored in Section 3.3. Finally, the most significant part is the ability of one Agent to call another Agent for exchanging information in the form of stateful contracts (Liu 2021c). A set of those communicating agents can be considered as MNCA. For code implementation and further information of the language sCrypt please see Appendix A.

Moving from the features of a blockchain to running the project on a blockchain will eventually meet the platform's scaling limits. Yet, this is no longer a technical issue, as indicated by recent innovations: A refactored microservices Bitcoin node that can process at O(50 k) transactions per second and sustained block sizes of more than 1000 Mb (Shadders 2021; The Bitcoin SV Test Network 2021). As the technology evolves, this number will probably be raised accordingly in the next few years.

4.2. Scaling Possibilities on the Blockchain

The importance of new directions in AI training has been exemplified by OpenAI's GPT-3. This complex neural network consists of 175 billion parameters (neurons) and it is estimated that a single "run" to train GPT-3 costs about 12 Million USD (Wiggers 2020; Shaabana 2021). Evidently, large budgets mean large teams and big corporations, which exclude independent researchers who have limited funds to experiment with. From another point of view, increasing the number of parameters and training data shows clear limits. The technology is getting marginally better at specialized AI tasks, but not closer to the elusive AGI.

We enumerated and analyzed, so far, several technical components which are necessary to build an AGI on the blockchain. Yet, even if we manage to assemble as many neurons, or agents, as the human brain has, there is no certainty that the model will be able to form the equivalent of a human brain, as the construction of a neural network is only half of the journey, the gestation of the mind. Machine Learning, or training, might take years or even decades before the model can achieve a level of adulthood, of "general" intelligence.

Nevertheless, we must not underestimate the biggest advantage that blockchain produces for Machine Learning, being the automatic labeling of data recorded. For example, in a scenario where a token issued is used as a digital currency (i.e., a digital Euro) then every transaction will represent a detailed record of purchase with information of the item barcode, price, date of production, to name a few. The data can be pseudonymous (i.e., the client will not likely be revealed) and the attempt to fake the data will be expensive. This will solve the most expensive process to date for producing high-quality datasets, the process of "labeling". Governments and Central Banks can benefit from this process since the suitability of a public ledger is the best way to mitigate illicit actions such as money laundering and other financial crimes. Moreover, the generic data stored on the blockchain will be able to produce a generic form of AI since the agents (classifiers) will have the ability of using multiple sources for training. In our opinion, the transparency, auditability, and fact-based provenance of the blockchain presents the only option for ensuring the independence and oversight needed to take AI projects forward, perhaps to an AGI that society can accept.

5. Discussion

5.1. Concerns and Limitations of Machine Learning

There are many concerns in the AI research community regarding the AGI supremacy of "intelligent" capabilities compared to human ones. A valid antilogy here is that this hypothesis may never become reality, for two primary causes. Firstly, because up until now we have lacked a common medium to avoid the data siloing problem. Every company has its own personal datasets, which are only partially what is needed. Second, Machine Learning is based mainly on pattern recognition through big datasets. Algorithms use regression models, convolutional filters, funneling, and similar techniques on data gathered and audited carefully by humans (supervised learning).

These datasets are representations of knowledge we already possess, and no algorithm so far has offered anything new to the existing scientific knowledge. In other words, the learning curve and cross-validation scores in existing models can never go over 100% (Figure 13) (Scikit 2021).

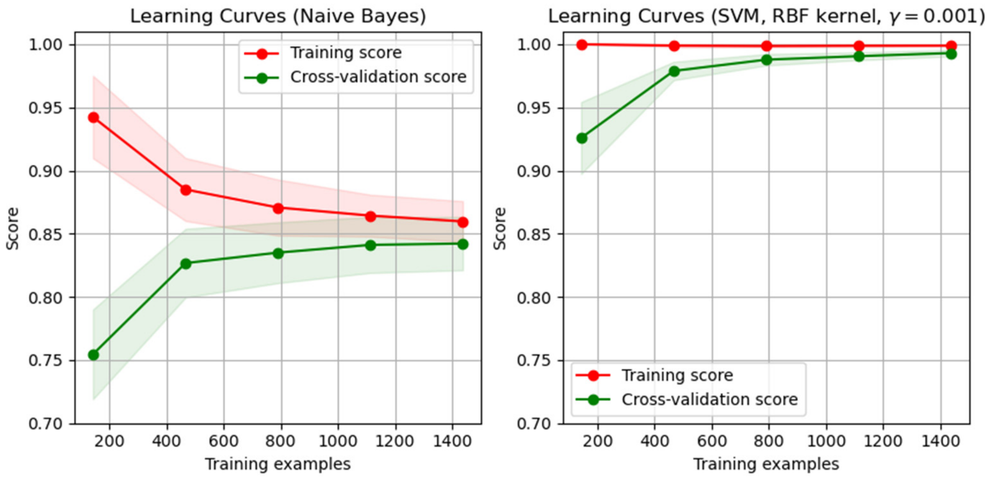

Figure 13. Learning curves (naïve Bayes) and cross-validation scores in existing models can never go over 100% (Image created with scikit 0.24.2. 2021. "Plotting Learning Curves") (Scikit 2021).

In unsupervised learning, the AI algorithms are not producing anything significantly different, except for the fact that they may be able to discover hidden patterns that humans cannot, in the respective supervised datasets. To express this in simple terms, there is no machine learning model to date able to create "new" knowledge. Yet, an AGI can never exceed the total lot of generalized knowledge existing in humans as a collective lot, even if this is shared with the system as a total. Therefore, there are no indications that a Superhuman Intelligence may occur under the current technical limitations. Nevertheless, it will be considered by the majority such as powerful because the asymptotic curve of machine learning accumulation will go hand in hand with the human's willingness to participate in such a model; and since we are talking about an AGI, which actively "learns" from data of a global payment system, that probably means everybody on this planet.

5.2. Consequences, Ethics, Accountability, and Equal Rights to Use

Recently, the European Commission announced that the EU would ban certain uses of "high-risk" artificial intelligence systems altogether, and limit others from entering the bloc if they do not meet its standards. The rules are the first of their kind to regulate artificial intelligence, and the EU is keen to highlight its unique approach. The bloc says it wants a "human-centric" approach that both boosts the technology, but also keeps it from threatening its strict privacy laws (Heikkila 2021). A non-used parameter so far to certify that there is a control over the usage of AI, would be Blockchain as storage with minimal fees for usage (i.e., micropayments).

Blockchain, as a WORM (Write Once, Read Many) tape, was created as an electronic cash system and a permanent record keeper (Wright 2008). A goal in mind was to make auditing procedures easier and more efficient. Each transaction has a distinctive timestamp that certifies its uniqueness and ownership. Not only that, but it is also publicly available for all parties to watch, as well as every other observer, provided they know which public key to track. The ideas we laid out in our previous work (Sgantzos and Grigg 2019), included the storage and verification of separate AI agents on the blockchain because the platform presents unique characteristics of security and accountability of usage and ownership. Similar technologies have found their way to the field of data analytics in capital markets in the form of a time-series database (TSDB). Such a database stores, catalogs, and retrieves data records that are part of a time series, or a set of data points associated with timestamps. The timestamps provide a critical context for each of the data points in how it relates to others (Cassin 2021).

Each transaction would indicate a certain point in time that the specific agent functioned, an AI without such an agent's transactional signature can be considered rogue.

Even if there is a synergy of agents to achieve a certain result, every single one will be orchestrated to function via a timestamp on the blockchain.

The immutability of the blockchain as a system is a prominent way to hold back the participants from malicious actions. The justification behind this notion is based on Plato's "Ring of Gyges" parable (Woods 2010), in which he roughly concludes that "All men are bound to do malice when they think they can get away with it". As Cicero retells the story, "a wise or good individual bases decisions on a fear of moral degradation as opposed to more direct punishment or negative consequences" (Froschouer 1560).

This would suggest that responsible operators of AIs record their key actions on a publicly auditable distributed ledger such as a blockchain. If sufficient key events of access, usage, and/or design exist on the blockchain, every citizen may audit the outcomes, enrolling the public in a democratic distribution of power over such algorithms.

5.3. Incentives

There is a fundamental difference between humans and AGI. Humans create knowledge by incentives. We had to use our imagination and creativity to evolve our techniques for hunting, collecting and harvesting our food because it was important for our survival. We similarly had to evolve our engineering and machinery to create bigger-scale constructions that led to the civilization we have today. The finiteness of time we have as mortal beings expanded the incentives from just us, to our progeny, leading to a notion of wisdom being the knowledge to ensure that next generations can survive.

Such incentives will be a challenging task for a machine to self-program. One potential path is to ensure that a human is always responsible for the machine, which also means that the human is responsible for the outcomes. Thus, the incentives can flow easily from the human, even if the hard work might be done by the machine. Designation of a responsible person behind every machine may counteract the current tendency to hide behind the opacity of outcomes, for example the commonly used excuse, "we don't know why the AI did that". On the other hand, this brings up the possibility of ending up with the same problem of Machine Learning Bias (Dietterich and Kong 1995; Birhane 2021), which is a problem widely discussed lately in the AI community. The designation of incentives to a human is a double-edged sword. Potentially, blockchain-issued digital currencies can address the problem of Machine Learning Bias in the same way as capitalism; every transaction will be a costly signal, with every AI getting a reward based on the usage, leading to obsoletion of those AIs that do not earn their place.

Humans also gain intelligence by analogy, which is a capability extent in the adult human mind. It is trained into the child-learning phase, by encouragement from the adults in various ways, for example by playing games, storytelling, interactions, safe play boundaries. Then curiosity emerges from the child's innate activities. Curiosity leads to fantasy, and creativity as in an imaginary theatrical play with dolls, or plastic soldiers and role-playing, desire for story and interactions. Then, all these things speak to intelligence evolving as the outcome of an interactive process with many agents providing independent and random inputs, whereas current AI processes are stuck with one learning Neural Network model and one dataset for the training phase.

On a more philosophical note, in the film Blade Runner (1982), when Deckard meets Rachel, he first stares at the owl. "Do you like our owl"? she asks him. "Is it artificial?" he asks her back. The owl represents the wisdom of the machine. Our existence is no different from any other in this world. For the sake of argument, let us hypothesize that Rachel is an AGI that can beguile everybody that is a human; even herself. What would make her indistinguishable from an ordinary human? The answer is, possibly, death; or maybe, the birth of a child; which was considered impossible for the replicants.

Finally, it must be noted here that self-assigned incentives form an undecidable problem for the machines; similarly, to consciousness and identity, we need to seek solutions by approximation.

6. Conclusions

In this paper we proposed a novel hypothesis of using a synergy of automata like a set of MNCA to build an AGI on a secure medium such as a blockchain; we showed that such an AGI, if constructed, is unlikely to develop superhuman intelligence, under the current limitations of ML. We also approached the ability of an AGI gaining cognitive abilities as an emergent phenomenon on computational, biological, and philosophical levels. Even though the mechanics are here, a lot more research is needed, since it is hard to predict if the functionality of our theoretical construction will be close, even if inferior, to the cognitive abilities of an actual human brain. Mainly this is due to our lack of knowledge of how those cognitive abilities emerge in humans (Chalmers 1995).

In any case, it is evident that constructing the agents and the neural network seems to be the easy part. Finding the data to train the model seems to be the hardest and most costly process. A technological solution seems to be the outsourcing of the machine learning procedure to diverse and competitive independent agents. In this task, blockchain can be of great help, both as it enforces all signals as costly, and as potentially rewarded. Moreover, on a scalable enough blockchain infrastructure, the data can be stored on-chain and if a sufficiently reliable monetary system, such as a Central Bank Digital Currency, is built on it, then this data can aspire to be a factual representation of our daily habits as a society.

Such an AGI as an assistant, connected with Internet of Things (IoT) devices would be able to predict with high accuracy the logistics, from a household and smart cities up to a whole country, or even the entire planet; to predict the weather, to drive a car or an autonomous drone from point to point without the possibility of a collision, to create personalized medicines via protein design, based on a person's DNA, securely and privately (Madani et al. 2021); and many more.

Finally, we explored the importance of synergy. We form societies based on the collaboration of individuals. Our somatic and nerve cells follow the same synergetic pattern depending on the task they were assigned by our DNA information. We suggest that it will not be different for artificial agents, or cells, like Multiple Neighborhood Cellular Automata. Maybe what was absent all this time, was a common protocol for all the agents to communicate with each other and work together. A secure, robust, impenetrable-from-hackers medium that secures our potentially biggest invention. An artificial representation of ourselves (Porras and Sánchez-Escribano 2022). We postulate that the breakthrough we were looking for is a community of many, generalist automata (MNCA) living, communicating and evolving on the Blockchain.

Author Contributions: K.S. conceived the ideas and authored the paper except for Section 2.1. K.S. and I.G. equally contributed to Section 2.1. I.G. conceived the idea of Identity and K.S. reformed and extended it to express the idea of consciousness. M.A.H. added some ideas on AGI, reviewed and corrected the manuscript. All three authors helped in reforming some ideas and all three contributed to minor corrections. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Acknowledgments: The authors would like to thank Bernhard Müller Hug, Georgios N. Papageorgiou, Joseph Harvey Perling and Costas Cavathas, for their helpful discussions and proofreading on early drafts of this work. Finally, Xiaohui Liu for his valuable contribution with his code as a proof of concept.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

sCrypt (pronounced "ess crypt") is a high-level smart contract language for Bitcoin SV. Bitcoin supports smart contracts with its FORTH-like stack based Script language. However, writing smart contracts in native Script is cumbersome and error prone. It quickly becomes intractable when the contract size and complexity grow. sCrypt is designed to facilitate writing smart contracts running on-chain. Syntactically, sCrypt is like Javascript and Solidity, making it easier to be adopted by existing web and smart contract developers. It is statically typed. Type checking can help detect many errors at compile time.

Desktop IDE

A desktop version is available as a Visual Studio Code Extension. It can easily be found by searching "sCrypt" in the Extensions Marketplace. This IDE comes with advanced language features and is intended for professional development. A boilerplate project is a good base to kickstart your own sCrypt project.

Web IDE

A browser-based IDE can be found at https://scrypt.studio. It is useful for testing sCrypt right away without any installation and is suitable only for small-length smart contracts.

Notable code examples in sCrypt language mentioned in the manuscript:

Perceptron as a stateful contract on sCrypt. Published under license from the author (Liu 2021a).

```
// Perceptron's internal state includes 2 inputs: height & weight
struct State {
    int heightWeight;
    // 1st weight means weight in KGs
    int weightWeight;
    int bias;
}

struct Input {
    // in inches
    int height;
    // in KGs
    int weight;
}

// correct classification of gender: 0 means female, 1 male
type Output = int;

/*
* A simple perceptron classifying gender based on height & weight
*/
contract Perceptron {
    // sample size
    static const int N = 10;
    // learning rate
    static const int LR = 1;

    // training data set
    // inputs
    Input[N] inputs;
    // outputs
    Output[N] outputs;

    // train the perceptron
```

```
    function train(State s): State {
        loop (N): i {
         int prediction = this.predict(s, i);
         int delta = this.outputs[i] - prediction;
         s = this.adjust(s, delta);
        }
        return s;
    }

    // prediction for the i-th input
    function predict(State s, int i): int {
        int sum = s.bias;
        sum += this.inputs[i].height * s.heightWeight + this.inputs[i].weight * s.weightWeight;
        return stepActivate(sum);
    }

    // learn internal state
    function adjust(State s, int delta): State {
        int scaledDelta = delta * LR;
        loop (N): i {
         s.heightWeight += this.inputs[i].height * scaledDelta;
         s.weightWeight += this.inputs[i].weight * scaledDelta;
        }
        s.bias += scaledDelta;
        return s;
    }

    // binary step function
    static function stepActivate(int sum): int {
        return (sum >= 0 ? 1: 0);
    }
```

Smart contract for outsourcing the AI training of a perceptron in sCrypt. Published under license from the author (Liu 2021b).

```
contract Perceptron {
    // sample size
    static const int N = 100,000;

    // training dataset
    // inputs
    Input[N] inputs;
    // outputs
    Output[N] outputs;

    // prediction for the i-th input
    function predict(int heightWeight, int weightWeight, int bias, int i): int {
        int sum = bias;
        sum += this.inputs[i].height * heightWeight + this.inputs[i].weight * weightWeight;
        return stepActivate(sum);
    }

    // whoever can find the correct weights and bias for the training dataset can take the bounty
    public function main(int heightWeight, int weightWeight, int bias) {
```

```
        // every dataset must match
        loop (N): i {
         int prediction = this.predict(heightWeight, weightWeight, bias, i);
         // prediction must match actual
         require(this.outputs[i] == prediction);
        }

       require(true);
       }

    // binary step function
    static function stepActivate(int sum): int {
       return (sum >= 0 ? 1: 0);
    }
}
```

Conway's Game of Life smart contract implementation in sCrypt whose evolution is determined by its initial state. Each generation is a pure function of the preceding one. Published under license from the author (Liu 2021e).

```
import "util.scrypt";

// Conway Game Of Life on a board of N * N
contract GameOfLife {
        static const int N = 5;
        // effctively we play on a grid of (N + 2) * (N + 2) without handling boundary cells
        static int BOARD_SIZE = GameOfLife.N + 2;
        static bytes LIVE = b'01';
        static bytes DEAD = b'00';
        static const int LOOP_NEIGHBORS = 3;

        public function play(int amount, SigHashPreimage txPreimage) {
        require(Tx.checkPreimage(txPreimage));

        bytes scriptCode = Util.scriptCode(txPreimage);
        int scriptLen = len(scriptCode);

        int BOARDLEN = GameOfLife.BOARD_SIZE * GameOfLife.BOARD_SIZE;
        int boardStart = scriptLen - BOARDLEN;
        bytes oldBoard = scriptCode[boardStart: ];

        // make the move
        bytes newBoard = this.evolve(oldBoard);

        // update state: next turn & next board
        bytes scriptCode_ = scriptCode[: scriptLen - BOARDLEN] + newBoard;
        bytes output = Util.buildOutput(scriptCode_, amount);
        bytes outputs = output;

        require(hash256(outputs) == Util.hashOutputs(txPreimage));
        }

        function evolve(bytes oldBoard): bytes {
        bytes newBoard = oldBoard;
```

```
        int i = 1;
        loop (GameOfLife.N) {
        int j = 1;
        loop (GameOfLife.N) {
                bytes nextState = this.next(oldBoard, i, j);
                newBoard = Util.setElemAt(newBoard, this.index(i, j), nextState);

                j++;
        }

        i++;
        }

        return newBoard;
        }

        function next(bytes oldBoard, int row, int col): bytes {
        // number of neighbors alive
        int alive = 0;

        int i = - 1;
        loop (LOOP_NEIGHBORS) {
        int j = - 1;

        loop (LOOP_NEIGHBORS) {
                if (!(i == 0 && j == 0)) {
                if (Util.getElemAt(oldBoard, this.index(row + i, col + j))) {
                alive++;
                }
                }
                j++;
        }

        i++;
        }

        bytes oldState = Util.getElemAt(oldBoard, this.index(row, col));
        /* rule
        1. Any live cell with two or three live neighbours survives.
        2. Any dead cell with three live neighbours becomes a live cell.
        3. All other live cells die in the next generation. Similarly, all other dead cells stay dead.
        */
        return(alive == 3 || alive == 2 && oldState == LIVE) ? LIVE: DEAD;
        }

        function index(int i, int j): int {
        return i * GameOfLife.BOARD_SIZE + j;
        }
}
```

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