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Generalized Neuromorphism and Artificial Intelligence: Dynamics in Memory Space

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Abstract: This paper introduces a multidisciplinary conceptual perspective encompassing artificial intelligence (AI), artificial general intelligence (AGI), and cybernetics, framed within what we call the formalism of generalized neuromorphism. Drawing from recent advancements in computing, such as neuromorphic computing and spiking neural networks, as well as principles from the theory of open dynamical systems and stochastic classical and quantum dynamics, this formalism is tailored to model generic networks comprising abstract processing events. A pivotal aspect of our approach is the incorporation of the memory space and the intrinsic non-Markovian nature of the abstract generalized neuromorphic system. We envision future computations taking place within an expanded space (memory space) and leveraging memory states. Positioned at a high abstract level, generalized neuromorphism facilitates multidisciplinary applications across various approaches within the AI community.

Keywords: stochastic dynamics; artificial intelligence; events; neuromorphism; neuromorphic computing

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1. Introduction

A fundamental principle deeply ingrained in the framework of traditional artificial intelligence (AI) research, traceable back to Turing's seminal article in 1950 [1], can be distilled as follows: intelligence fundamentally resides within the highly constricted domain of "mere computation" [2]. Although the very notion of computation itself may undergo transformations to account for our limited capacity to model human or natural forms of intelligence, the definition of computational intelligence expands dynamically and unrestrictedly, encompassing a wide range of domains and implementations. However, operating within the boundaries of this progressive framework, the proposition "intelligence is just computation" begins to assume a tautological nature, given that the concept of computing is allowed to adapt and mutate to meet prevailing requirements and limitations [3]. At this fundamental level, no significant objections can be raised. Nevertheless, we seek to contribute to the ongoing research exploring the existence (or absence) of boundaries demarcating natural and artificial intelligence by scrutinizing the subtle relationship connecting intelligence, computation, and nature.

Initially, it is important to acknowledge that the field of AI has historically embraced two distinct approaches, described as follows:

1. Artificial computation through designed algorithms.
2. Natural computation through the direct utilization of natural processes.

Despite the existence of these two levels of inquiry, throughout much of its history, AI, particularly within the framework of artificial general intelligence (AGI), has predominantly concentrated on the first approach, often referred to as "computing Nature". Meanwhile, the second option, described as "computing *using* Nature", has received relatively little attention within the practical AI community. Essentially, the latter perspective posits that no fundamental differentiation between natural and artificial intelligence is necessary. Instead, it exploits this lack of ontological demarcation to explore potential avenues for harnessing natural resources that enable direct computation without the intervention of artificially designed algorithms. This alternative approach aims to discover "natural computational rules" capable of replicating intricate natural structures and behaviors, as exemplified by the work of Wolfram [4]. Furthermore, it seeks to leverage inherently computationally rich physical phenomena, such as quantum transformations and information [5]. By tapping into these natural resources, the objective is to circumvent the reliance on algorithmic computation and enable direct computational processes.

In our view, a compelling approach to reevaluating the role of AI, within the context of our current knowledge, involves the exploration of "artificial brains" [6]. The concept revolves around the idea that, if properly designed, these engineered systems, whether they be natural, artificial, or a hybrid of both, should be capable of demonstrating partial or full capabilities akin to natural intelligence. It is important to note that emulating artificial brains does not solely rely on algorithmic methodologies. Instead, it represents an ambitious undertaking that leverages software/hardware co-design strategies [7], with the aim of accomplishing what neuroscience has long aspired to achieve: the reverse engineering of the intricacies of the brain [8,9]. However, achieving scientific supremacy through the development of artificial brains is not limited to being a future frontier confined solely to the realm of neuroscience. Instead, we propose that various fields, including AI, cybernetics, cognitive psychology, and broader technology research, can all reap the benefits of embracing alternative perspectives on intelligence that incorporate elements from both the natural and the artificial. One particularly promising paradigm in this context is "neuromorphism". More specifically, we aim to explore theoretical frameworks that seek to generalize neuromorphism to encompass both AI and artificial brains within a unified abstract framework. By adopting this comprehensive perspective, we encourage interdisciplinary collaborations and harness potential synergies between these domains. This approach paves the way for transformative advancements in our comprehension and replication of intelligence.

The fields of brain science and AI have a longstanding and complex relationship, as demonstrated by their close connection [10]. However, the recent explosive advancements in neuroscience and neural networks within machine learning have not only sparked a revolution in high-tech industries [11] but also significantly reshaped the landscape of AI research and philosophical discourse. With neuroscience now taking a prominent role in the study of brain science [12], it is evident that contemporary AI and machine learning heavily rely on neural networks and deep learning techniques [13,14]. This prevailing trend can be characterized as a kind of de facto neuromorphism, where AI and computing, in general, are seen as expressions of, or potentially realizable through, neural networks [15]. Some authors have even ventured to suggest that the universe itself operates as a fundamental neural network [16]. However, it is crucial to exercise caution and avoid taking extreme positions when considering the boundaries and possibilities of neural computing within the framework of AI. Therefore, in this paper, we use the technical term 'neuromorphism' in a specific and well-defined manner. It refers to a range of ideas, methods, techniques, and concepts that are either inspired by classical neural networks [17] or directly related to the re-emerging field of neuromorphic computing [18].

Figure 1 illustrates the modified bifurcation of the traditional hierarchical model of AI systems. Within this framework, there are three distinct categories. Firstly, we have strong AI, which aims to produce fully autonomous intelligent systems capable of passing the Turing test [1] or delivering the Golem speech [19]. These systems strive for complete autonomy and possess the potential for consciousness-level capabilities. Secondly, there are weak AI systems, exemplified by ANNs (Artificial Neural Networks), which focus on the performance of highly specific intelligent tasks involving learning, reasoning, and representation. These systems do not seek consciousness-level autonomy but excel in specialized domains. Lastly, neuromorphic AI occupies an intermediate position in complexity between fully fledged AI and bottom-up learning systems. It incorporates numerous decision-making functions observed in strong AI but does not pursue complete consciousness or a sentient mind. Instead, its ultimate goal is to emulate a complete brain rather than an emotive mind.

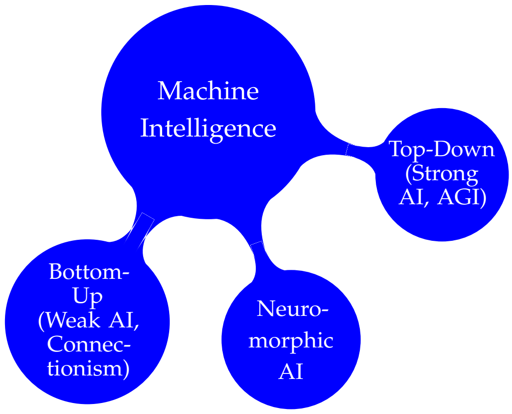

Figure 1. The modified bifurcation of the traditional hierarchical model of AI systems.

Research in neuroscience has revealed the limitations of the simplistic approach taken by McCulloch and Pitts in their simple neuron computational model, which employed discrete time steps for updating calculations [20]. This approach has dominated the field of ANNs and von Neumann computing. However, our current understanding of real-life neurons indicates that they are significantly more complex than the simple computational activation functions, such as sigmoid or limiters, used in traditional models. By considering the chemical and biophysical aspects of neuronal conduction, transmission, and processing, we now recognize that neurons are intricate dynamical systems with rich internal spatiotemporal structures [21]. Furthermore, these processes are inherently random or stochastic, with various noise processes playing a crucial role in the functioning of neural networks. These noise processes contribute to top-down attention mechanisms and decision-making processes [22].

The field of biosemiotics, which explores the semiotic perspective in biology, has provided valuable insights into the nature of intelligence beyond mere information processing of conventional signals [23]. These insights reveal that intelligence is not solely confined to the realm of electrical information processing within the standard connectionist paradigm, as exemplified by the elementary firing neurons of the McCulloch–Pitts model or even more sophisticated mechanisms like the integrate-and-fire model utilized in spiking neural networks (SNNs) [13,18]. Even at smaller scales, such as membranes and molecules, non-electrical forms of information exchange and modification occur among larger molecules, organelles, and cells [24]. This subtle interplay gives rise to a remarkably complex understanding of computational intelligence in living organisms and their evolution [25,26]. Consequently, future advancements in brain processing and AI systems, inspired by the brain, may involve the development of networks comprising significantly more complex processing elements than the simple interconnections of basic neurons.

With the ongoing advancements in biophysical and biochemical theories, as well as empirical data on intra- and inter-cell communications and interactions, there is an anticipation of a shift away from the prevailing preference for the simple neuronal models that have dominated research on ANNs and SNNs. This shift will lead to the emergence of a new paradigm for computing, which we refer to as *generalized neuromorphism*. In this paradigm, the traditional concept of a neuron is replaced by a more versatile and inclusive entity known as a *processing element* or, more specifically, a *processing event*. The use of the term 'event' emphasizes the spatiotemporal nature of neurodynamic information processing, which is already evident in SNNs, where computation is inherently event-driven and asynchronous. In the field of computer science, theoretical and conceptual paradigms such as data-flow graphs, hardware–software co-design, and non-von Neumann computing have long been known but have gained wider attention only recently [27–29]. This can be attributed in part to the emergence of technologies such as TensorFlow-GPU-TPU computing and neuromorphic computing [30–32]. Generalized neuromorphism aligns with this emerging trend of complexification in both space and time, aiming to enhance energy efficiency and information processing capacity [33]. These are two key aspects where biological brains still surpass our artificial computing systems and AI capabilities [8]. Through the adoption of generalized neuromorphism, we strive to bridge the gap between biological intelligence and artificial intelligence, leveraging the complex spatiotemporal dynamics observed in biological systems to enhance the capabilities of our computational systems.

Our theoretical approach involves generalizing neuromorphism through the concept of a *stochastic dynamic system* (SDS). This approach has a rich history and has been applied in various fields, such as physics, mathematical physics, condensed-matter physics, optics, physical chemistry, biochemistry, economics, and information theory [21,34,35]. Dynamical systems have played a crucial role in the revival of ANN research since the early 1980s [13]. Even prior to that, they were recognized for their significance in neurodynamics, influencing both the neuroscience and machine intelligence communities from the 1940s to the 1980s and beyond, particularly in the early development of SNNs [18]. From the perspective of AI and machine learning, dynamical systems were proposed as a general approach to computational intelligence, particularly in connection with fuzzy logic and control [35]. In recent years, SDSs have also been suggested as a foundational framework for understanding how cognition arises in the neuronal circuits of the brain [22]. In this article, motivated by the theory of the SDS, we further highlight its integrative and unifying power in the field of AI. The approach presented here is a development of the conceptual framework proposed in [3]. We note that both classical and quantum systems can be modeled as SDSs [36], offering a comprehensive framework for various AI functions, such as memory, decision-making, and quantum brain dynamics, as well as traditional ANN and SNN systems. This generalized SDS formalism encompasses abstract random or stochastic systems, whether Markovian or non-Markovian in nature [37].

The theoretical program we refer to as generalized neuromorphism serves as a formalism or framework designed to facilitate the development of more specific and concrete models based on tangible physical arrangements in the future. Before delving into the specifics, we offer an overview of this theoretical framework. We propose a synthetic, multidisciplinary perspective that integrates artificial intelligence (AI) and cybernetics through a generalized stochastic dynamic formalism designed to model networks consisting of abstract processing events (see Figure 2). We term this formalism *generalized neuromorphism*, drawing inspiration from spiking neural networks (neurodynamic processing) and the theory of open dynamical systems. Generalized neuromorphism is deliberately constructed at a high level of abstraction to enable its application across diverse approaches within the AI community. In this framework, each processing event can represent a real computing or intelligent agent, such as a spiking neuron processor in a neural circuit, a CMOS gate in a chip, or a consumer in the market. Processing takes place in both space and time, with each event interacting with other events only when their states become available (event-driven computing). In our theory, each event is regarded as a generic stochastic dynamic process with memory, making it a non-Markovian process. The driving force behind an assemblage consisting of such events is the diverse physico-semiotic interactions and information exchange among them. This is achieved through a global displacement network operator, which shifts time signals from one event to another. However, it is important to note that, for each event, time is defined locally. The global displacement operator facilitates the distribution of information, encompassing programming, scheduling, and network connectivity, across the global scale of the event assemblage. This, in turn, gives rise to AI capabilities like learning, prediction, and adaptation. One of the primary applications of this formalism is its capacity to simplify the utilization of information theory, leveraging the well-known properties of the entropy functional in stochastic dynamics. However, from our perspective, the most significant application lies in the ability to directly quantify the event assemblage. This leads to the emergence of a novel concept: quantum neuromorphic computing. The final model bears a resemblance to a stochastic quantum random field that is both spatially and temporally nonlocal. We hypothesize that a nonlocal quantum field could potentially be linked to the fundamental structure of intelligence in both the living and technological domains.

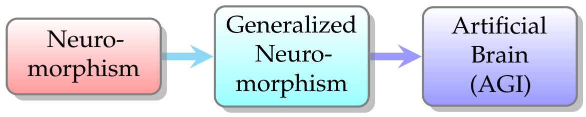

Figure 2. A potential path toward attaining a level of AGI confidence may have to go through a serious attempt to construct artificial brains, effectively using neuroscience and AI to reverse engineer the brain. The traditional theoretical program behind an approach such as this is neuromorphism. In this paper, an AI-oriented generalized neuromorphism (GNM) is seen as a distillation and synthesis of various trains of thought within this framework.

2. Overall Structure and Some Preliminary Considerations

2.1. The Structure of This Article

This paper is structured as follows. Before going into our main presentation, we offer preliminary remarks about the methodology employed in this study (Section 2.2). We then begin by offering an overview of the current landscape of AI, AGI, and neuromorphic computing, emphasizing the conceptual scope of the field and its intrinsic capabilities. While not aiming to comprehensively cover this expansive domain, our intention is to spotlight key aspects crucial for achieving AGI capabilities in the future. Section 3 provides a reexamination of classical AI within its contemporary context. We reexamine AI in Section 3.1 in a conceptually broad yet rigorous manner, setting the stage for a focused analysis of the doctrine of neuromorphism in Section 3.2. This groundwork lays the foundation for our novel contribution in this article: the concept of generalized neuromorphism, introduced conceptually in Section 4. In Section 4.1, we elucidate the core characteristics we envision for generalized neuromorphism, underscoring the unique contribution of neuroscience in providing a brain-inspired approach to intelligence. Conversely, Section 4.2 initiates the exploration of a central theme within our proposed concept of generalized neuromorphism: the pivotal role of memory. This role extends beyond the structure of cognition in intelligence to encompass its significance at both the physical and mathematical levels within the foundational framework of generalized neuromorphism itself.

The principal content of our proposed abstract formalism, termed generalized neuromorphism within this paper, is presented in Section 5. We initiate the discourse by abstractly and broadly defining the various mathematical constituents of a computing generalized neuromorphic system (GNS) using the framework of fiber bundles. Of utmost significance is the introduction of the key concept of the memory state, which represents a novel theoretical feature in our exposition. Here, we endeavor to encapsulate, in straightforward operational terms, the notion of non-Markovianity as an intrinsic memory structure in its own right, constituting an element of a generalized state space, a superspace that we term a memory space. Dynamical concepts are expounded upon in Sections 5.2–5.4, with a focus on both local and global scenarios.

In Section 6, our focus shifts toward exploring potential physical realizations of the framework for AI and AGI, termed generalized neuromorphism. The primary theme we develop there is nonlocality, encompassing both spatial and temporal dimensions. Section 6.1 posits that nonlocality will emerge as a crucial prerequisite in forthcoming physical systems anticipated to embody attributes derived from the abstract framework of generalized neuromorphism described in Section 5. Specifically, we propose a conceivable correlation between memory, manifested physically through nonlocality, and cognitive AGI. Additionally, we explore avenues of physical realization, such as quantum biology, quantum AI, and the potential for conceiving a quantum manifestation of generalized neuromorphism, as outlined in Section 6.2. To provide a more concrete proposal in this direction, Section 6.3 further elaborates on the form, structure, and functionality of a candidate quantum GNS scheme.

Lastly, Section 7 furnishes a concise and targeted overview of how intelligence can be embodied through the operation of generalized neuromorphic systems, such as those envisaged in this article. Initially, in Section 7.1, we specify how machine learning, for instance, can be integrated within a GNS framework. Conversely, Section 7.2 expounds on how certain cognitive functions might be actualized within a framework inspired by stochastic dynamical systems akin to the one proposed here with GNS. In particular, we provide an illustration of decision-making. Finally, we end with conclusions.

2.2. Preliminary Methodological Considerations

Before we begin our main presentation, it is essential to provide a comprehensive introduction to our review, analysis, and synthesis methodologies. Detailing why the proposed topics are relevant, how they were selected, and the rationale behind their classification is crucial. The methodology employed in this article is centered around several key thematic considerations:

1. The priority of AGI: While AGI stands apart from AI, it is worth noting that, historically, AI has been preoccupied with aspects that are now recognized as integral to AGI. Thus, it is essential for a formal framework aspiring to encapsulate the core principles of generalized neuromorphism to prioritize AGI directly, rather than confining itself to the narrower functions within AI, such as those commonly emphasized in contemporary mainstream research, notably machine learning. For a broader critique along these lines, please refer to [38,39].
2. The primacy of brain science in AGI: Neuroscience and AI research represent distinct fields with their respective methodologies. However, this author aligns with a growing minority of researchers who contend that significant advancements in AGI can only occur once a comprehensive understanding of the functioning of the neocortex in real brains is achieved [40]. Although this paper does not go into detailed discussions of neurobiology, our analysis and proposed framework, generalized neuromorphism, draw inspiration from neuroscience, particularly studies focusing on the cerebral neocortex [12,22].
3. The integral role played by memory: A fundamental methodological theme in our investigation is the pivotal role of memory in elucidating the connection between brain structure and AGI agents. Specifically, we observe within the intrinsically open thermodynamic nature of the brain both structural and dynamic characteristics that must be deliberately imbued into both artificial brains and core AGI agents in the future (see Figure 2). Memory, a key aspect of complex open systems, significantly influences both the structure and function of living and intelligent systems alike [41]. This aspect will be underscored throughout our study at various levels, including the review section, the proposed formalism of generalized neuromorphism, and the applications and implementation segment.
4. How AGI should be approached: One of the central inquiries addressed in this study pertains to the most effective approach for achieving AGI. After examining the traditional top-down and bottom-up approaches, we support a novel synthesis that draws inspiration from both and is informed by our current understanding of brain function. This approach aligns with the aspiration of neuroscience to "reverse engineer the brain" [8] and subsequently employs engineering principles to construct an artificial brain [9]. We argue that pursuing the development of artificial brains represents a promising path toward realizing AGI. Generalized neuromorphism emerges as a theoretical framework that offers insights into the feasibility of this endeavor.
5. Avoiding overemphasis on machine learning: While our presentation addresses ML as an essential component of the bottom-up approach to AGI, we aim to avoid overemphasis on it. While acknowledging the significant progress made in ML, particularly within deep learning paradigms, we align with a growing chorus of critical voices that

highlight the fundamental inadequacies of conventional ML, particularly the ANN framework, in solving the problem of general intelligence [38–40,42]. We advocate for considering other directions of research, such as classical and quantum brain theory, non-Markovian dynamical systems, and dissipative structures, to shape the future direction of research outlined in this paper. Hence, in our presentation, training and optimization constitute only a portion of the overarching formalism of generalized neuromorphism.

The present article is intended as neither a survey article nor a comprehensive review of AI and related themes. Instead, it is a conceptual piece aimed at formulating a view on AGI based on a new synthesis of various existing paradigms, which we term generalized neuromorphism. Consequently, some important topics are omitted due to space constraints and being beyond the original scope of the research presented here. Notably, aspects such as the nature, role, and function of consciousness in attaining and maintaining intelligence, whether natural intelligence or AGI, are not addressed. Additionally, we avoid delving into theories of the mind, a detailed examination of cognitive psychology, and discussions on the philosophy of language and mathematical logic. Furthermore, we do not examine the well-known problems of epistemology and logic that typically arise in conjunction with AI, especially strong AI, such as that associated with AGI and artificial brains.

3. Revisiting Classical AI in Light of Neuromorphism

3.1. What Is Artificial Intelligence?

Brain functions are commonly categorized into three main areas: (1) motor control, (2) cognition, and (3) information storage, retrieval, and processing. Throughout the history of AI and AGI, these functions have been of significant interest. Motor control plays a crucial role in applications related to robotics, industrial control, and automation. Cognition was a focal point in early AI systems, including expert systems and electronic assistants. On the other hand, information or data processing has emerged as the dominant topic in contemporary AI and machine learning research, particularly in the context of bottom-up approaches such as connectionism, which emphasize the processing of information at a granular level.

Let us begin by examining the traditional definition of an AI core, which is often considered to be a system that demonstrates most, if not all, of the following four fundamental traits (functional modalities):

1. Knowledge *representation*.
2. *Reasoning* with these representations (information processing and deduction).
3. *Learning* from past and current experiences to adapt ongoing reasoning (and knowledge representations).
4. *Autonomy* via self-organization or the self-sustainability of the entire system, potentially leading to replication and reproduction.

Figure 3 presents a visual representation of this structure. In the diagram, the AI core (core AI system) is depicted at the center of the universe, while various manifestations of this central entity are generated, propagated, and executed like satellites. The diagram highlights the importance of allowing for mutual interactions among the four different modalities, as they are not entirely independent. Uni-directions are not assigned because interactions along both directions are possible for each pair. For instance, reasoning and representations can influence each other reciprocally, leading to the formation or selection of rules, and learning stores the acquired knowledge. Collectively, these interactions express the holistic or globally interconnected nature of the four modalities and their active dynamic relationships.

It should be noted that the definition of AI just provided is extensive and deviates from the typical concise and condensed style of an encyclopedia entry. However, the intention behind this approach is not to present a standard textbook definition of AI, but rather to engage in an analysis of existing ideas. The aim is to explore the potential impact of recent advancements in computing, machine learning, physics, and mathematics and how they might shed new light on the subject matter. By moving deeper into these domains, we hope to uncover novel insights and perspectives that can contribute to the development and understanding of artificial intelligence.

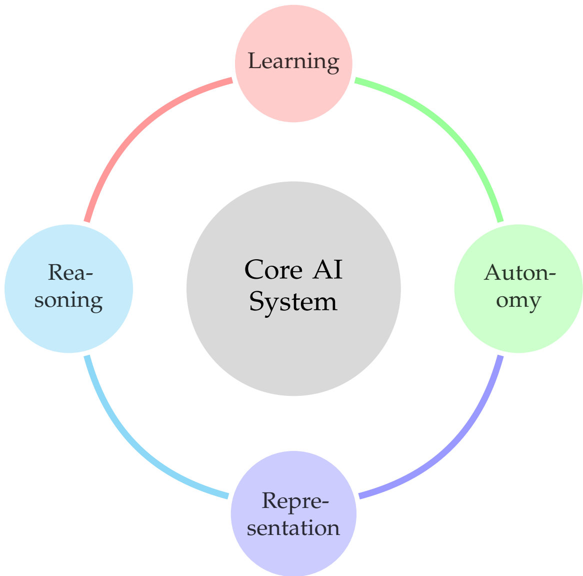

Figure 3. The four fundamental functional modalities of a generic AI core system.

Let us now turn our attention to the fourth modality in the aforementioned list, which is autonomy. The inclusion of autonomy as an essential component of intelligence is a subject of ongoing debate. Many experts in the field of AI do not consider autonomy to be an absolute requirement for a system to be classified as an AI core module. In the early history of computing, autonomy and related abilities, such as self-repair and reproduction, were explored in the context of the origin-of-life problem. Scholars like Freeman Dyson, Erwin Schrödinger, and John von Neumann have contributed significantly to these concepts [43–45]. Reproduction is widely regarded as a fundamental characteristic of living organisms [46]. However, the necessity of replication in the context of AI is a separate matter. Does an AI system need to concern itself with perpetuating its own existence? Strictly speaking, the other three functions—learning, reasoning, and representation—*can* be pursued independently of the requirement for maintaining complete autonomy at the system level. Therefore, an ANN chip, for example, can be considered an AI system even though it may require a supervisor or teacher to operate effectively within its broader environment [13].

Indeed, within the category of autonomy, there are various sub-modes that go beyond self-reproduction. Traits such as self-repair or autoprogramming can enable an agent to be "self-governing" or relatively independent from a supervisor. An AI core equipped with a multitude of sensors, data-gathering probes, and antennas may possess the capability to modify its own internal algorithmic structures through a process known as adaptation, which can be considered a sub-category of learning. It is at this point that the conventional bifurcation of an AI system into two fundamental configurational strategies, namely, the top-down and bottom-up approaches, becomes significant. This is because the same process of adaptation and change is treated differently based on distinct types of information processing and flow (refer to Figures 4 and 5).

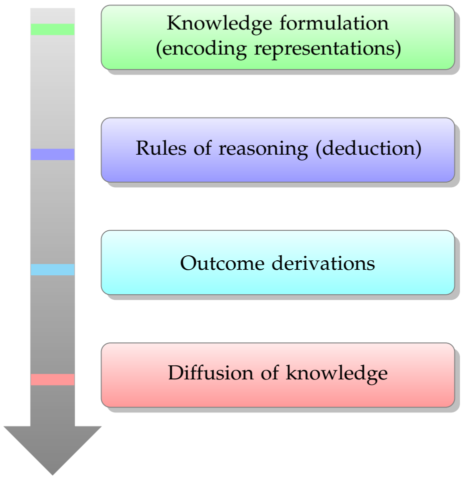

Figure 4. The top-down approach to AI.

Traditional (strong) AI can be represented by the top-down flow diagram shown in Figure 4. The top stratum of the diagram represents a high-level abstract representation of “relevant data”, which aims to extract useful information from the system’s initial “raw data”. In this top-down schema, the “raw data” can be modeled as premises, axioms, hypotheses, or various conceptual states in a deductive chain that is about to unfold. The execution of deductive reasoning, often depicted as a computational process, involves the selection and configuration of a set of rules (meta-axioms, logical deductive schemas, generative rules, etc.). These rules can either be supplied from an external source to the agent (which is the case in most practical systems) or developed internally by the intelligent agent itself (although fully achieving this capability is still not feasible in practice, though research on autoprogramming is being pursued by several researchers). The rules of inference generate outcomes or data that are then passed to the lowest level of the machine, which is responsible for the diffusion, distribution, and communication of these outcomes (including actions) to consumption sinks or other processing nodes in multi-agent networks, such as neuromorphic systems, biological swarms, or economic systems.

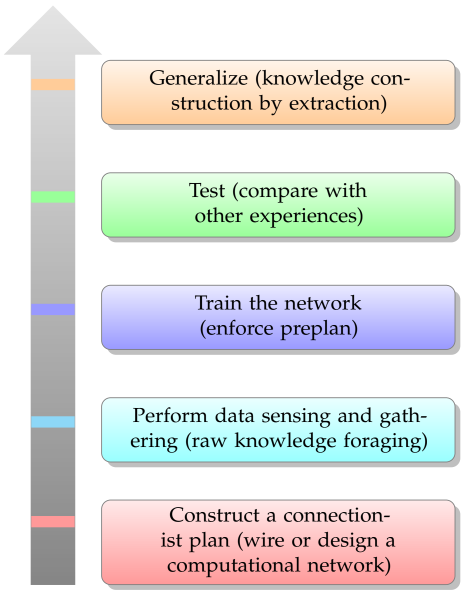

Figure 5. The bottom-up approach to AI.

On the other hand, bottom-up AI, sometimes referred to as “weak” AI, is represented by the flow diagram shown in Figure 5. Incidentally, while the McCulloch–Pitts 1943 neural network model [20] is often considered the first systematic proposal for creating intelligent behavior using simple lower-level neurons [13], it appears that Turing himself developed key ideas shortly after in his 1948 article entitled "Intelligent Machinery" [47]. Nevertheless, the essential objective of bottom-up AI is to move away from the rigid, fixed, homogeneous, and deterministic computing architectures of classical systems. Instead, it aims to adopt a dynamic, network-based, decentralized, adaptive, evolving, self-organizing, and developing approach. This shift toward an open and dynamic system is similar to Turing's Connectionism Paradigm, which is rooted in some of Turing's lesser-known writings [47]. It is also associated with the concept of "intrinsic computing", as described by C. Teuscher [48]. The generalized neuromorphism framework outlined below shares strong similarities with this bottom-up approach to intelligence, emphasizing dynamic and adaptive systems that can self-organize and evolve over time.

Certainly, the category of autonomy can still be utilized in the definition of AI (Figure 3), this time to distinguish between the two major types of AI systems: top-down (strong) AI and bottom-up (weak) AI. Both approaches are necessary, and in a complete solution to constructing a competitive intelligent system, it is expected that the two will be integrated. As illustrated in Figure 6, each form of AI complements the other, forming a dialectical relationship characterized by mutual determination and perpetual circularity. The strong and weak approaches to AI are interdependent and influence each other in a continuous feedback loop. By acknowledging the dialectical relationship between the two approaches, we can appreciate the importance of integrating their strengths and leveraging their respective advantages. This integration can lead to more robust and comprehensive AI systems that benefit from both top-down reasoning and bottom-up learning and adaptation.

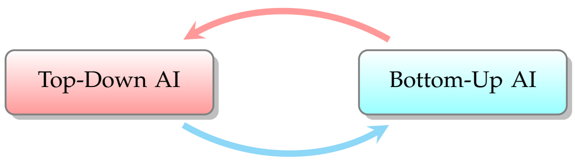

Figure 6. The essentially dialectical relation between strong AI (top-down) and weak AI (bottom-up). While each camp has its own advocates, the final "ultimate" AI system cannot involve only one at the expense of the other.

Being an autonomous agent can indeed serve as a distinguishing marker strongly indicating the presence of top-down control. This notion becomes evident in classic examples such as robots, androids, and cyborgs, which represent futuristic forms of fully autonomous intelligent agents. These systems are often envisioned with a central brain-like command center capable of conducting extensive computations. This computational power enables them to anticipate future actions, plan ahead, and make strategic decisions. (An iconic illustration of this concept is the computer-based chess player that defeated Kasparov, reminiscent of Kubrick and Clarke's sentient AGI agent HAL 9000 in *2001: A Space Odyssey* [49]).

It is evident that the visionary projections of fully autonomous intelligent agents have not materialized as initially envisioned [38,39,42]. One of the primary reasons for this discrepancy is our underestimation of the complexity inherent in the knowledge representation problem. Despite our increasing computational power and ability to perform complex calculations, we have not made significant progress in our understanding of complex cognitive systems in a manner that aligns with those initial visions. The emergence of deep learning, which represents a resurgence of neural networks, can be seen as an acknowledgment of our failure to achieve a complete revolution in AI and move closer to the strong AI approach advocated by the early pioneers of the field. Instead, the focus has shifted toward weak AI, emphasizing the bottom-up strategy. Some researchers now consider weak AI as the primary avenue for progress, although research into knowledge representation from the perspective of symbolic processing and rule extraction has never completely ceased. While deep learning has demonstrated remarkable success in various domains, it is still limited in its ability to provide comprehensive solutions to the broader challenges of intelligence.

3.2. What Is Neuromorphism?

Neuromorphism is a paradigm wherein the generation of both natural and artificial intelligence is believed to arise from intricate computations executed by neural circuits. It constitutes an approach aimed at comprehending and replicating the operational mechanisms of neural systems, encompassing both organic entities and synthetic systems. By harnessing the computational capabilities and parallel processing inherent in neural circuits, neuromorphism strives to engender intelligent systems that emulate the cognitive faculties observed in nature. Through the meticulous study and implementation of neural circuits, researchers aspire to unlock novel prospects for advancing the realms of natural and artificial intelligence. We start with a formal definition of what is generally meant by the bottom-up approach to AI called neuromorphism:

Definition 1. *(Neuromorphism) Neuromorphism is an intellectual framework in which natural and artificial intelligence is believed to emerge through the interconnected computations of neural circuits. It encompasses the concept of a vast rhizome, where the collective interactions of neural circuits give rise to intelligence and cognitive phenomena.*

It is important to note that neuromorphism is considered to be more encompassing than connectionism. Although these terms are often used interchangeably today, it is conceivable that, in the future, the emergence of intelligence in large and complex neural-like computing circuits may not solely be explained by connectionist theories. Non-connectionist theories of intelligence are now emerging in fields such as quantum biology, quantum psychology, and quantum brain dynamics (see Section 6 for further references). In some of these alternative proposals, the existence of a field-like global structure that sustains long-range correlations is postulated to underlie higher-level cognitive functions such as consciousness and long-term memory. In other words, while neuromorphism remains rooted in the significance of neuronal computational circuits as the fundamental material substrate of intelligence, it may also attribute certain AI functions to global or nonlocal physical processes that are yet to be discovered and utilized in the creation of artificial brains and AGI, as well as in elucidating the workings of the human brain.

Due to the factors mentioned above, as well as additional considerations discussed later, we propose an expansion of the original Definition 1 to incorporate novel concepts derived from ongoing and future research in neuroscience and AI.

Definition 2. *(Generalized neuromorphism) Generalized neuromorphism (GNM) is a theoretical framework that posits the emergence of both natural and artificial intelligence through computations executed by parallel assemblages of processing events. These events bear a resemblance to neural networks but exhibit distinct characteristics, such as being inherently open stochastic dynamical systems, leveraging intrinsic memory structures, and relying on spatiotemporal modes of processing.*

It is accurate to acknowledge that certain aspects of generalized neuromorphism, as outlined in Definition 2, may also be found in various forms of neuromorphism. However, our primary aim is to construct a specific formalism that explicitly emphasizes these aspects within the framework of generalized neuromorphism. We recognize that there are commonalities and intersections between the two frameworks, especially in areas such as spatiotemporal processing and intrinsic memory elements. Nonetheless, our central focus is on establishing a formalism that accentuates the specific facets of neuromorphism that we believe will be of utmost significance for future research in advanced AI, artificial brains, and AGI.

4. Generalized Neuromorphism

4.1. Main Features of Neuromorphism

The philosophy behind neuromorphism is that the surest path toward successful and strong AI must go through the following steps:

1. Understanding the structure and functions of the brain.
2. Implementing this understanding via specialized neuromorphic (brain-inspired) hardware.

Hence, this constitutes an exceptionally ambitious program, making bold claims that, in principle, cannot be proven a priori but are certainly worthy of in-depth investigation. Currently, the most promising approach for neuromorphism is the development of advanced AI chips employing technologies like SNNs. It is essential for the convergence between the fields of neuroscience and the semiconductor, computer, and AI communities to strengthen, ultimately paving the way for the gradual emergence of a comprehensive multidisciplinary initiative in machine intelligence in the coming decades. This initiative could give rise to neuromorphic AI or, for brevity, neuromorphism.

When it comes to the organizational ontology of generalized neuromorphism, there are several options to consider, including both vertical (Cartesian) ontologies and flat (Deleuzian) ontologies. In Figure 7, we present a non-hierarchical model depicting the emergence of strong AI and AGI from lower-level, bottom-up AI representations of computational tasks, such as ANNs, SNNs, HMMs, and others. In this model, a generalized neuromorphic system (GNS) serves as a transitional step toward AGI. If we assume a monist position in which the mind and brain are ontologically identical, a GNS may, on its own, exhibit strong AI capabilities if it successfully emulates a real brain. We advocate that generalized neuromorphism should adopt such a flat or horizontal approach to the relations between the various ontological components of the system.

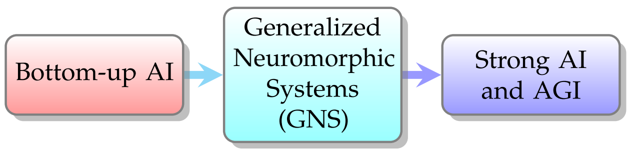

Figure 7. A non-hierarchical model for the emergence of strong AI and AGI.

There are several crucial traits within neuromorphism that warrant emphasis before moving on to the formulation of a comprehensive approach to AI systems founded on SNNs with spatiotemporal processing capabilities:

1. The AI system is an *open* system.
2. The AI system must make use of intrinsic *memory* elements.
3. The AI system processes information in space *and* time.

These characteristics are somewhat distinctive and serve to distinguish SNNs from ANNs, laying the foundation for a potential new paradigm in computational intelligence for the future.

Openness and memory represent two noticeable changes in emphasis in the traditional paradigm of bottom-up AI. Note that both features already exist (somehow) in top-down and bottom-up AI, but in the emerging paradigm of SNN and neuromorphic computing, there is a drift toward a new structural possibility. ANNs are of course capable of exhibiting memory-like performance (for instance, Hopefield networks and recurrent networks), where much of this capability is based on realizing what are essentially memoryless neurons using feedback mechanisms (recurrent networks) or exploiting the deep nonlinear structure of the neuron (Hopefield networks) [13]. On the other hand, top-down AI has been traditionally aware and conscious of the importance of exploiting memory for the successful implementation of various decision strategies; e.g., expert systems make extensive use of context-addressable memory-based decision rules, while the very standard von Neumann architecture, which was developed at the same time as top-down AI was envisioned, requires the use of a fundamental addressable memory space.

The emphasis on openness is less obvious in the older approaches. For example, a circuit implementation of an ANN on a chip, say an ASIC or FPGA, must ensure that the circuitry is isolated from extraneous environmental disturbances (EMC considerations). But, again, reinforcement learning is a striking example where the interaction of the learning system with the external environment is treated as fundamental. Should we consider such systems genuine open systems, then? The answer is no: open systems must involve *intrinsic* generators of randomness that are due to what is essentially an unpredictable coupling with the external reservoir. On the other hand, reinforcement systems work by incorporating a set of highly structured and specific measures dictating how the learning system behaves and interacts with the surrounding milieu, e.g., risk functionals, reward cost, penalty measures, and so on. Those various loss functions are then coupled with special search algorithms in order to fine-tune the system parameters through the learning process (learning by optimization of loss/cost functionals). While the time evolution of reinforcement learning systems does appear random, clearly, this is not an example of an open dynamical system in the conventional sense of the term, as understood in stochastic dynamics; e.g., see [34,36].

In neuromorphism, these three features—openness, memory, and spatiotemporality—serve as driving forces for innovation and complexity. Let us begin by exploring the least obvious trait: openness. A neuromorphic system endeavors to replicate actual brain functions to tackle intriguing computational tasks. Evidently, the ultimate aim in emulating a system like the brain is to approach the most fundamental aspects exhibited by such a highly complex structure: conscious awareness and even emotional intelligence. This is why neuromorphism is inherently associated with the *strong* version of AI, which has traditionally been considered achievable primarily through a top-down strategy [50]. The brain, however, differs from a chip in numerous aspects, with one of the least-discussed differences being that a brain, like all biological systems, is fundamentally an open system. This means that it constantly exchanges energy, momentum, and information with the external world. While the skull provides thermal and mechanical insulation to protect the cerebral cortex from the external environment, the brain continues to engage in continuous interaction with the rest of the body through various systems, including the nervous, circulatory, and endocrine systems. The cortex actually exists in a far-from-equilibrium thermodynamic state. Such systems are fundamentally distinct from those addressed in equilibrium thermodynamics, where the concept of temperature is only applicable in the latter case [51]. Nonequilibrium systems, particularly dissipative systems, have the potential to exhibit significant self-organization and self-ordering behaviors [52]. Of particular significance are strongly nonlinear open systems that demonstrate chaos and operate in the vicinity of strange attractors [53]. While the mathematical theory behind these systems is highly intricate, recent proposals have suggested that self-organization through chaos in complex open dynamical systems could offer a novel way to understand intelligence without relying on strictly computational methods [54]. For instance, the concept of chaos cannot be adequately comprehended using conventional computing theory [55].

4.2. The Function of Memory and Non-Markovianity in Generalized Neuromorphism Viewed as a Stochastic Open System

Open dynamical systems are inherently characterized by random or stochastic dynamics, known as stochastic dynamic systems (SDSs). Consequently, their behavior cannot be entirely determined by a set of deterministic laws, as is the case with ANNs, SNNs, and noise-free neurodynamics. The most straightforward approach to incorporating randomness involves modeling noise. This noise may originate from fluctuations in the external and internal degrees of freedom that interact with the neural or computing system [12] or may result from the finite nature of the dynamical system concerning the external degrees of freedom [12,22,36,37]. In either case, it has been suggested that noise can play a constructive and even essential role in the emergence of intelligence in various computing systems, whether they are biological, such as brain systems [12,22], or physico-chemical systems [52,55–57].

In the most extensively studied cases of stochastic dynamic systems (SDSs) in the literature, the Markovian approximation is commonly employed to model the SDS as a Markovian stochastic process. In a Markovian system, information primarily flows from the system to the environment, where it becomes irreversibly lost, as discussed in detail in the literature [34]. In non-Markovian dynamical systems, information can flow in the reverse direction, specifically from the environment to the finite system, as illustrated in Figure 8. This phenomenon is particularly evident when multiple subsystems are interconnected with the surrounding domain. The subtle interplay between various subunits, all integrated into a larger network of interconnected processes, can result in delicate patterns of complex mutual information exchange between the system and its surrounding informative environment. This could potentially pave the way for innovative opportunities in intelligent computing systems, encompassing the brain, artificial brains, and AGI systems. In such scenarios, significant knowledge about the external world could be directly integrated into the inner workings of the computing core. In simpler terms, a process of "non-Markovian learning" becomes conceivable within such memory-like open quantum systems, given the close relationship between non-Markovianity and memory (nonlocality in time).

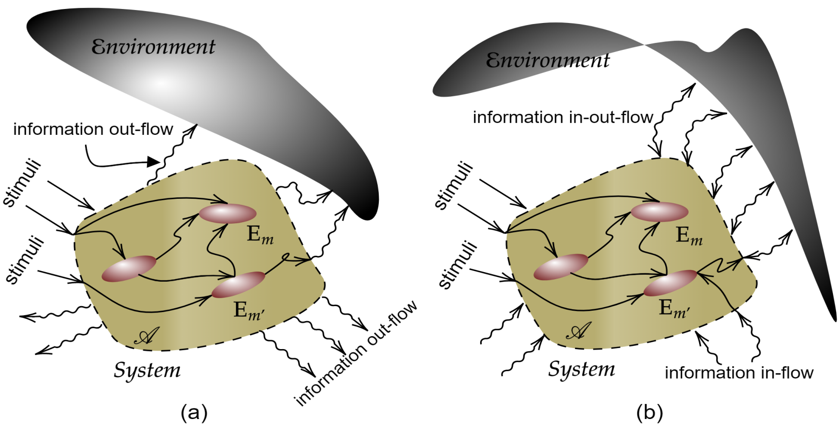

Figure 8. An illustration of the main topological features of information flow in Markovian (memoryless) and non-Markovian (memory-laden) stochastic open systems. The wavy arrows capture the direction of information flow between the system and the environment. (**a**) A Markovian open system. Information always flows away from the system to the environment. (**b**) A non-Markovian open system. Information can be drawn from the environment.

5. The Structure and Dynamics of Memory Space

5.1. Structure of Memory States in Generalized Neuromorphism

Let us start by outlining the fundamental structural elements of the generalized neuromorphic system (GNS), referred to as $\mathscr{A}$. Essentially, $\mathscr{A}$ can be described as a collection of processing events (PEs). The foundational (base) manifold for the assembly of computing events is denoted by $\mathcal{M}$. This manifold serves as the overarching spatiotemporal configuration, forming the basis for the GNS $\mathscr{A}$. It functions akin to an "index space" or "label space", where labels differentiate evolving physical states responsible for generating the event E, with $\mathcal{M}$ serving as its base manifold.

Remark 1. *For instance, $\mathcal{M}$ might adopt the form of a discrete, finite-dimensional space such as $\mathbb{Z}^d$, $d = 1, 2, 3$, representing one-dimensional, two-dimensional, or three-dimensional lattices, respectively, commonly observed in traditional ANNs [13] and SNNs [18]. However, within generalized neuromorphism, we entertain the prospect of a continuous spatial base space underlying the event* E*—a feature crucial for accommodating nonstandard processing events in the future, as envisaged in hypercomputing paradigms and post-Turing Computing machines [48]. In such cases, $\mathcal{M}$ can be* *endowed with a conventional smooth manifold structure [58], enabling computing to progress as an analog process indexed by multidimensional real spaces [59].*

At every point $m \in \mathcal{M}$, we associate a fiber X_m, which functions as a generalized (abstract) *state space* for the mth processing event (PE), denoted by E_m, rooted at or labeled by m. In Figure 9, the event assembly is illustrated as a fibration of the base manifold $\mathcal{M}$, following the conventional approach [60,61]. This approach links a state space X_m to each point $m \in \mathcal{M}$ in the base manifold. Each space X_m operates as a complete, self-contained, and independent state space.

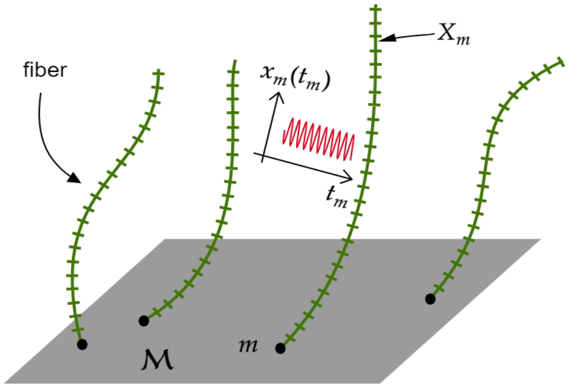

Figure 9. The event assemblage viewed as a fiber space.

Remark 2. *In most applications, X_m is typically assumed to be finite-dimensional. Conventionally, discrete values for each state's dimension* $\dim(X_m)$ *are employed, akin to the classical theory of Markov chains, where $x_m \in A$, and $|A|$ (the cardinality of A) is finite [62]. However, in generalized neuromorphism, we adopt a broader perspective, allowing x_m to encompass continuous, discrete, or a combination of both types, and each fiber space X_m can potentially accommodate a countably infinite number of dimensions. The latter scenario involves X_m being isomorphic to a Hilbert space, which is particularly pivotal for imbuing the GNS with a quantum structure [63].*

Every state $x_m \in X_m$ within the mth event E_m is endowed with a local dynamical evolution relative to the corresponding event's time variable. In Figure 10, the dynamics of a generic non-Markovian event are depicted within its dedicated memory space $\mathfrak{M}$ (refer to Definition 7). The dynamics of each processing event are exclusively defined locally, confined to this specific event only. This distinction is reflected in the utilization of distinct time variables for each processing event. The *local time* pertaining to the mth processing event E_m is represented by $t_m \in \mathbb{R}^+$, where the instantaneous state locally corresponds to $x_m(t_m) \in X_m$ for all $t_m \in \mathbb{R}^+$. It is important to note that, in this paper, all stochastic processes are irreversible, and time is considered to belong to the positive time axis only.

Remark 3. *Viewed from an AI system's standpoint, each fiber space X_m embodies the internal states of a sophisticated intelligent agent, where these states mirror the underlying physics of the material system. AI functionalities, such as memory storage, decision-making, and other cognitive processes, are inherently encoded within the memory space $\mathfrak{M}_m$ correlated with each physical state space X_m, as will be explicated below.*

The laws governing dynamical changes are inherently stochastic, typically expressed through a probability space defined on X_m. As the details from probability theory are widely recognized, we refrain from reiterating them here. Our approach aligns with the standard methodology employed in ergodic and dynamical system theory, as seen in references like [64]. Notably, each state space X_m may be associated with a distinct probability space, particularly relevant for "hybrid" event assemblies accommodating a mixture of discrete random states within the same model. In the classical version of GNS theory, x_m represents a random variable, whereas in quantum GNSs, the state assumes the form of a quantum density operator $\rho_m(t)$.

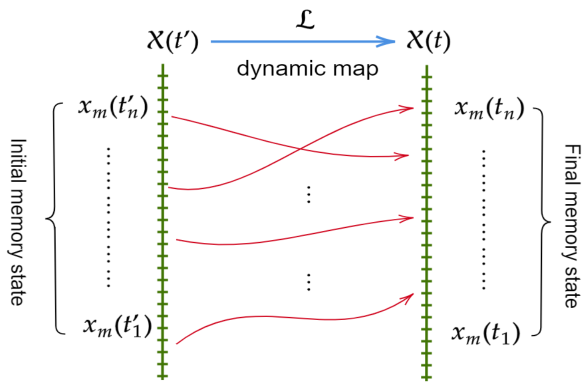

Figure 10. Event dynamics on memory space $\mathfrak{M}$.

Definition 3. *(Markovianity and Non-Markovianity) Let $x(t)$ be a stochastic dynamic process corresponding to a processing event (PE) whose state space is X. We say that the dynamics on X captured by the event's local time flow $x(t)$ is Markovian if the following condition holds:*

$$\Pr\left[x(t) \in B \middle| x(t_1), \ldots, x(t_n)\right] = \Pr\left[x(t) \in B \middle| x(t_n)\right], \tag{1}$$

for every Borel set B and all arrangements of ordered n time samples satisfying

$$t_1 < t_2 < \cdots < t_{n-1} < t_n < t, \tag{2}$$

for all $n \in \mathbb{N}$. If condition (1) is not satisfied, we say that $x(t)$ is non-Markovian.

In essence, a process adheres to Markovian dynamics when its behavior at a given moment relies solely on the most recent state. However, if the evolution of $x(t)$ is influenced by more than just the immediate past state, the system displays dynamics reminiscent of memory, as its time evolution is contingent upon an entire historical sequence.

Remark 4. *In the various literature, Markov processes are defined diversely; however, the fundamental concept is that the current state relies solely on the immediately preceding moment in discrete system models or the infinitesimally immediate state in continuous models. Put differently, predicting the future necessitates only one state. Although most models emphasize the discrete case, it is important to note the discrete–continuous distinction. For further details, refer to [65] for a mathematical perspective and [34,66] for insights from the physics and mathematical physics standpoint.*

It is important to highlight that the definition of non-Markovianity lacks a constructive nature. This complicates the development of a comprehensive theory for non-Markovian processes, as it remains unclear how to effectively construct processes that exhibit non-Markovian behavior. In the subsequent discussion, we present a particular formulation of non-Markovianity that, while less general, encompasses a broad range of applications within generalized neuromorphism. Our approach involves introducing the concept of *memory states* and establishing non-Markovian dynamics directly as a function of these memory states.

We gather all past states contributing to the generation of a specific present state $x_m(t_m) \in X_m$ within a newly defined structure termed the *causal history* of the stochastic process relative to the local time instant t_m, denoted by $\mathcal{X}_m(t_m)$. The aim is to consolidate all microstates that causally determine the system's evolution up to the local time t_m of the processing event E_m. For brevity in notation, we use t instead of t_m when the processing event in context is evident.

Definition 4. *(Memory states) We define the memory state $\mathcal{X}_m(t)$, with a temporal length denoted by T_m, aligning with the mth processing event $x_m(t)$, as follows:*

$$\mathcal{X}_m(t) := \{x_m(t) \in X_m, \text{ s. t. for all sequences like (2) condition (4) holds } \forall n \in \mathbb{N}\}. \quad (3)$$

The fundamental probabilistic causal law is the following:

$$\Pr\left[x_m(t) \in B \middle| \bigcup_{0 \le t' \le t} \{x_m(t')\}\right] = \Pr\left[x_m(t) \in B \middle| \{x_m(t_1), \ldots, x_m(t_n), \forall\, |t_n - t_1| \le T_m\}\right]\Big\}, \quad (4)$$

for every Borel set B. The condition

$$t_m - T_m \ge 0 \quad (5)$$

must be satisfied for all $m \in \mathcal{M}$ and $t_m \in \mathbb{R}^+$. (Recall that t_m is t in expressions like $x_m(t)$, i.e., the local time of the mth event.)

The length of a given memory state, T_m, need not be unique. However, we can define a unique nonnegative number $T_m^* := \sup\{T_m\}$ as the memory depth of the mth PE's non-Markovian process at t. Note that T_m^* is possibly dependent on t.

In general, $T_m^* \neq 0$, representing the more common situation encountered in nature, where strongly coupled complex systems often exhibit memory. However, when $T_m = 0$, it can be readily demonstrated that Markovian behavior is recovered, as illustrated by the following theorem:

Theorem 1. *A processing event whose memory state $\mathcal{X}(t)$ has zero memory ($T_m^* = 0$) depth at every time instant t is Markovian.*

Proof. Subject to constraints (2) and (5), the condition $|t_n - t_1| \le T_m$ in (3) can only be fulfilled under $T_m^* = 0$ when $T_m \to 0$. Consequently, in the conditional joint probability (4), only a single "infinitesimally prior" state contributes, leading to a reduction akin to the Markovian expression (1). □

Non-Markovian systems exhibit a complex state structure where dynamical rules govern memory states rather than the states themselves. As the depth or recall capability of memory states diminishes to zero, the dynamics regress to the standard local-in-time Markovian scenario. In this scenario, the laws of nature and information processing rules directly impact the microstates of the state space. Consequently, within the classical framework of generalized neuromorphism, Markovianity encompasses classical Newtonian dynamics and closed quantum systems.

The collective space encompassing all memory states can be endowed with a Hilbert space structure. To facilitate this, let us introduce a helpful technical concept: the discrete approximation of a continuous memory state.

Definition 5. *(n-approximation) We define the n-approximation of a memory state $\mathcal{X}(t)$ as a set of states $x(t_i)$ evaluated at time instants $t_i, i = 1, \cdots, n$, satisfying condition (2).*

Given the n-approximation, defining linear combinations such as $\alpha_1 \mathcal{X}_m^1(t) + \alpha_2 \mathcal{X}_m^2(t')$, where $\alpha_1, \alpha_2 \in \mathbb{C}$, and any two memory states, $\mathcal{X}_m^1(t)$ and $\mathcal{X}_m^2(t')$ (not necessarily based at the same time instant; i.e., in general, $t \neq t'$), is straightforward using obvious pointwise operations involving $X_m^1(t_i) \in X_m$ and $X_m^2(t_i') \in X_m$. Hence, we conclude the following.

Theorem 2. *The set of memory states can be endowed with a linear (vector) space structure inherited from X_m.*

Next, we show that this linear space can be endowed with an inner product structure, too.

Definition 6. *(Inner product on memory states) Assume that the state space X is a vector space equipped with an inner product form* $\langle\cdot,\cdot\rangle$*. Let* $\mathcal{X}(t)$ *and* $\mathcal{X}(t')$ *be two memory states belonging to the same event but based at two time points, t and* t'*. To streamline the notation, we abstain from using superscripts or subscripts to label generally distinct memory states* $\mathcal{X}_m$*. Instead, we rely on the time index to indicate the potential distinction among memory states. For instance,* $\mathcal{X}(t)$ *and* $\mathcal{X}(t')$ *denote two potentially distinct memory states, which might correspond to* $\mathcal{X}^1(t)$ *and* $\mathcal{X}^2(t')$*. Let the n-approximations corresponding to the above memory states be* $\{t_i\}_{i=1}^n$ *and* $\{t'_i\}_{i=1}^n$*, respectively. The n-approximation inner product* $\langle\mathcal{X}(t),\mathcal{X}(t')\rangle_n$*, or n-form for short, is defined as*

$$\langle\mathcal{X}(t),\mathcal{X}(t')\rangle_n := \sum_{i=1}^{n}\langle x(t_i), x(t'_i)\rangle. \tag{6}$$

It is straightforward to demonstrate that the summation in (6) adheres to the properties of an inner product when each term individually satisfies the criteria for an inner product. Definitions 5 and 6 are most appropriate for depicting discrete or digitized computing systems, where time operates in a discrete manner and the count of computations within each finite temporal interval is limited.

It is evident that the inner product between two memory states, $\mathcal{X}(t)$ and $\mathcal{X}(t')$, as defined previously, relies on the n-approximations of the two memory states considered in computing (6). Extending this definition to the scenario where $n\to\infty$ while maintaining the depth of the memory state allows for a version more apt for continuous time representations.

For example, consider the following two measurable maps: $t_\tau : [0,1]\to[t-T,t]$ and $t'_\tau : [0,1]\to[t'-T',t']$. These maps essentially establish a continuous version of the segmentation (2), replacing the discrete index i with the real variable τ. Here, T and T' represent the depths of the memory states $\mathcal{X}(t)$ and $\mathcal{X}(t')$, respectively. Additionally, we can define the inner product for an infinite number of samples using the following formula:

$$\langle\mathcal{X}(t),\mathcal{X}(t')\rangle_{L_2} := \int_{\tau\in[0,1]}\langle x(t_\tau), x(t'_\tau)\rangle\,\mathrm{d}\tau\,, \tag{7}$$

whenever the Lebesgue integral exists. Again, it is easy to check that the integral above is an inner product, provided that the integrand is an inner product, too.

The size of the memory state $\mathcal{X}_m(t)$ can be defined in terms of the norm induced by the inner product, i.e., $\|\mathcal{X}_m(t)\| = \langle\mathcal{X}_m(t),\mathcal{X}_m(t)\rangle$. (This size should be distinguished from the temporal depth captured by quantities such as T_m and T_m^*.) The distance between two elements of the memory space $\mathfrak{M}$ is given by

$$\mathrm{dist}\big[\mathcal{X}_m(t),\mathcal{X}_m(t')\big] := \big\|\mathcal{X}_m(t)-\mathcal{X}_m(t')\big\|, \tag{8}$$

where we have exploited the fact that each memory space inherits an obvious linear (vector) space structure from the original state space X_m. With a distance, one can introduce metric topology and perform analysis.

Now, equipped with all the necessary tools, we can define a concept of a memory space that is comprehensive enough to accommodate dynamics within it.

Definition 7. *(Memory space) Let* $\mathcal{X}_m(t)$ *be a generic memory state belonging to the mth event* E_m *based at time* $t\in\mathbb{R}^+$*. The set*

$$\mathfrak{M}_m := \bigcup_{t\in\mathbb{R}^+}\{\mathcal{X}_m(t)\}, \tag{9}$$

equipped with an inner product as defined above, is called the memory space associated with the event E_m.

An immediate consequence of this definition is that the memory space is a Hilbert space:

Theorem 3. *If X has a Hilbert space structure, then the memory space $\mathfrak{M}$, whose inner product is defined in Definition 6, is a Hilbert space denoted by $\mathfrak{M}^n$ or $\mathfrak{M}^{L_2}$, depending on the type of the utilized inner product on memory states.*

It is interesting to note that the memory space $\mathfrak{M}_m$ is a larger space than the state space X_m. More precisely, if X_m is a finite Hilbert space of dimension l, then $\mathfrak{M}^n$ has the dimension nl. On the other hand, the memory space $\mathfrak{M}^{L_2}$ as a Hilbert space is infinite-dimensional even with finite l.

There is then a tremendous increase in complexity, which is an inevitable outcome of taking memory effects into account. The dynamics of non-Markovian systems are considerably more complex than memoryless Markovian processes because the usual state space in the latter is no longer adequate for capturing the essential dynamical effects of time change and information flow.

Nonlocality in time, akin to nonlocality in general, is recognized for introducing infinite superspaces, an outcome arising from the inherently more intricate and richer underlying topological structure of such systems [67]. However, from an AI perspective, this may be perceived as an *added advantage*. Despite the computational complexity rising with larger configuration space dimensions, the computing system itself, particularly the event assemblage in our context, gains additional degrees of freedom. Specifically, the memory space structure with its potential infinite dimensions can be harnessed for the development of innovative intelligent search and computing strategies.

5.2. The Dynamical Map

We have witnessed how the inclusion of memory, i.e., non-Markovianity, notably amplifies the complexity of the stochastic process's dynamic behavior. This is evident in the larger dimensionality of the memory space $\mathfrak{M}$ compared to the original state space X associated with the event. Furthermore, another contributing factor to this complexity surge is the intricate involvement of *correlations* between two or more past states within the causal history of the non-Markovian stochastic process under scrutiny.

In a generalized dynamics scenario wherein the dynamic process of a given PE can manifest as either Markovian or non-Markovian, the crux of the theory resides in the *transformations of time histories*, whose formal structure might be encapsulated by the following expression:

$$\mathcal{X}_m(t') \xrightarrow{\text{Dynamical Map } \mathcal{L}} \mathcal{X}_m(t), \tag{10}$$

where t' and t pertain to the local time of the PE indexed by $m \in \mathcal{M}$ (strictly speaking, denoted by t'_m and t_m). Notably, in (10), we intentionally refrain from utilizing the term 'evolution' to characterize the dynamics of time alteration in the states. This is because the concept of dynamics, understood as the evolution from an initial state, strictly pertains to a purely Markovian (local-in-time) attribute, applicable only to systems neglecting memory effects. Conversely, a general non-Markovian dynamical system surpasses the simple tracking of a single state's evolution over time. It must encompass the behavior of two or more (sometimes a continuum of) states, namely, those belonging to the initial memory state $\mathcal{X}_m(t')$ of the mth event. In this case, the physics becomes notably more intricate, as the *correlation* or stochastic dependence *among different* states will influence how each state develops dynamically over time.

We depict this structure of dynamical transformation in Figure 10, representing a "thick slice" of the history within the non-Markovian system as an n-approximation of an initial memory state $\mathcal{X}_m(t')$. Conversely, the "output" of the dynamical transformation of the internal original states in x_m of the event E_m is represented by another memory state, denoted by $\mathcal{X}_m(t)$, now based at the later time instant $t > t'$. This final memory state is itself discretized via an n-approximation. Consequently, we can conceive the total dynamical transformation as a shift of the "entire durational block" of initial states along the direction of an irreversible increase in *local* time from t' to t. However, it is crucial not to interpret this transformation as a result of a "point-by-point" conversion, where each discrete moment of the final memory state, e.g., $x_m(t_i)$, is perceived as having "evolved" from an earlier moment (e.g., $x_m(t'_l)$) belonging to the initial memory state, where, in general, $l \neq n$.

Another complicating factor arises in systems with memory, particularly in the case of dynamical maps, where, contrary to the Markovian scenario, the map $\mathcal{L}$ may depend on the initial states $x_m \in \mathcal{X}_m(t)$. This dependence is observed in quantum stochastic dynamics, where the quantum map, generated by the Kraus operators, transforms a generic density operator into another in open quantum systems and itself relies on the initial quantum state (see, for example, [66], Theorem 3.1.2, p. 23.). While we are dealing with classical systems here, it is essential to note that the general structure of the quantum map with memory is still applicable in the classical case. This is because its origin lies in the existence of memory operations rather than quantum effects per se. Therefore, in general, we should express (10) as $\mathcal{X}'_m = \mathcal{L}(\mathcal{X}_m)[\mathcal{X}_m]$ instead of $\mathcal{X}'_m = \mathcal{L}[\mathcal{X}_m]$ to explicitly indicate the dependence of the dynamic operators on initial states.

In essence, the dynamic map $\mathcal{L}$ cannot always be reduced to a multiple-input–multiple-output (MIMO) system. Non-Markovian systems encompass a new aspect of "holism" that is absent in Markovian systems yet precisely expressed using our mathematical framework: the complete memory state evolves over time as a unified "whole unit". This signifies that the actual transformation induced by the system transpires from one memory state to another. The individual moments within each memory state in a given n-approximation merely serve to model or manifest this inseparable transformation of memory states. Particularly in non-Markovian systems, states in X_m that are temporally close may not be regarded as discrete or separate degrees of freedom due to the substantial correlation effect stemming from the intrinsic memory structure in the system (where memory originates from temporal correlations).

5.3. The Dynamics of Events with Intrinsic Memory: The Local Theory

Next, we derive explicit dynamical transformation equations for the evolution of a generalized neuromorphic system (GNS), potentially equipped with an intrinsic memory structure. Our formulation emphasizes the treatment of each event's dynamical change as a purely *local* theory. This process's dynamics were previously encapsulated in Section 5.2 through the map $\mathcal{L}_m$ in (10) (refer also to Figure 10). Here, we aim to present a more comprehensive overview.

Fix a base manifold $\mathcal{M}$, which can be continuous or discrete (or even both). Consider an event assemblage,

$$\mathscr{A} = \bigcup_{m \in \mathcal{M}} \{\mathrm{E}_m\}, \tag{11}$$

where the mth event is a general stochastic dynamic system (SDS), possibly non-Markovian. Without compromising generality, we approach the problem in terms of the memory space. (For Markovian systems, a memory space with zero depth becomes isomorphic to the state space, as illustrated in Theorem 1). In addition to the initial memory, external inputs $u_m(t)$ enter each processing event E_m, bringing in information from other processing events. The set of all inputs belonging to E_m is denoted by U_m, while the total inputs of the assemblage $\mathscr{A}$ are defined by $\mathscr{U}$, represented as the disjoint sum (performed over evental data) of all inputs. Here, we employ the disjoint sum to signify that local data, such as local time signals and local states (local in the sense of being part of a specific event), cannot be combined. Overall, we define the total state space $\mathscr{X}$ and the total memory space $\mathscr{M}$. These are

$$\mathscr{U} = \bigsqcup_{m \in \mathcal{M}} \{U_m\}, \;\; \mathscr{M} = \bigsqcup_{m \in \mathcal{M}} \{\mathfrak{M}_m\}, \;\; \mathscr{X} = \bigsqcup_{m \in \mathcal{M}} \{X_m\}, \tag{12}$$

where $\bigsqcup$ is the disjoint union operation. Here, the set of inputs U_m is the space of time functions $u_m : \mathbb{R}^+ \to \mathbb{K}$, where $\mathbb{K}$ is either $\mathbb{R}^l$ or $\mathbb{C}^l$, with l possibly infinite. Note that, depending on the application, additional conditions like continuity and smoothness might be necessary, but at present, we do not go into these specifics. Moreover, more abstract target spaces can be introduced if the Hilbert space is deemed insufficient. Indeed, in open quantum systems, there are instances where a transition to a larger space, such as the rigged Hilbert space, becomes necessary to accurately model irreversible phenomena like Markov processes [55].

We obtain all external data arriving at the mth event in the *presynaptic excitation operator* $\mathcal{E}$, which maps all other events' memory states and outputs to a single signal $u(t)$ inserted into the mth event. The general structure of this operator is the operator family

$$\mathcal{E} = \bigcup_{m \in \mathcal{M}} \{\mathcal{E}_m\}, \tag{13}$$

where $\mathcal{E}_m$ is the mth component of the global excitation operator $\mathcal{E}$ representing the process

$$\mathcal{E}_m : \mathscr{X} \times \mathscr{U} \times \mathscr{M} \to U_m \times \mathscr{H}^{\mathrm{U}}_{\mathcal{M}} \times \mathscr{H}^{\mathcal{X}}_{\mathcal{M}} \times \mathscr{H}^{\mathrm{X}}_{\mathcal{M}}. \tag{14}$$

Here, the following spaces represent the *total histories* of $\mathscr{X}$, $\mathscr{M}$, and $\mathscr{U}$, respectively:

$$\begin{aligned}
\mathscr{H}^{\mathrm{X}}_{\mathcal{M}} &:= \bigsqcup_{m \in \mathcal{M}} \bigcup_{\tau \in [0,\infty[} \{x_m(\tau)\}, \\
\mathscr{H}^{\mathcal{X}}_{\mathcal{M}} &:= \bigsqcup_{m \in \mathcal{M}} \bigcup_{\tau \in [0,\infty[} \{\mathcal{X}_m(\tau)\}, \\
\mathscr{H}^{\mathrm{U}}_{\mathcal{M}} &:= \bigsqcup_{m \in \mathcal{M}} \bigcup_{\tau \in [0,\infty[} \{u_m(\tau)\}.
\end{aligned} \tag{15}$$

On the other hand, for $S \subseteq \mathcal{M}$, one may create specialized segments of the total history based on the most recent current data using the following segmentation history operators:

$$\begin{aligned}
\mathscr{H}_S x_m(t) &:= \bigsqcup_{m \in S} \bigcup_{\tau \in [0,t]} \{x_m(\tau)\}, \\
\mathscr{H}_S \mathcal{X}_m(t) &:= \bigsqcup_{m \in S} \bigcup_{\tau \in [0,t]} \{\mathcal{X}_m(\tau)\}, \\
\mathscr{H}_S u_m(t) &:= \bigsqcup_{m \in S} \bigcup_{\tau \in [0,t]} \{u_m(\tau)\}.
\end{aligned} \tag{16}$$

For example, upon operating on the current state $x_m(t)$, the operator $\mathscr{H}_S$ will produce the entire time history of all past states $\{x_m(\tau)\}, \tau \leq t$, belonging to all events whose space indices are in $S \subseteq \mathcal{M}$.

From the detailed structure outlined earlier, it is evident that $\mathcal{E}_m$ functions as a *global* operator, capable of accessing all other states and signals continuously to generate a specific input u_m and other historical data, such as those identified in expressions of the form (16). Conversely, the outputs of this operator are presented locally to the mth event. This distinction characterizes it as a global/local operator.

The overall local structure of an event assemblage simplifies to the configuration illustrated in Figure 11, illustrating specific details relevant to individual events. Interconnections with other events are established solely via the global/local operator $\mathcal{E}_m$. Despite each event being described as operating locally, it retains its status as an *open* system, engaging in continuous interaction with the surrounding environment. Conversely, interaction between events is facilitated through the global operator $\mathcal{E}_m$.

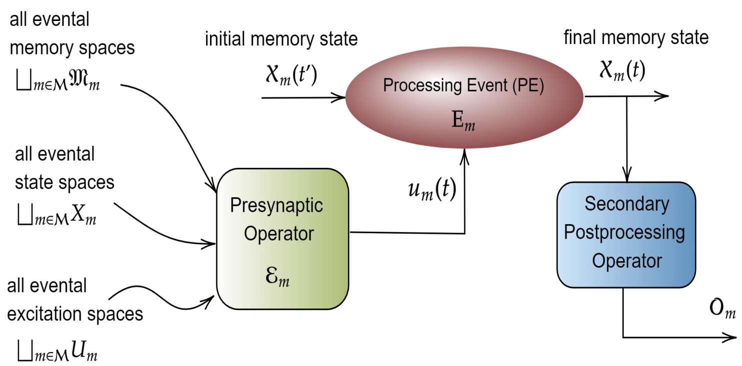

Figure 11. The fundamental components of a processing event, including circuits for processing and outputting information from and into the other events in the GNS.

The dynamical equations of the mth event can be represented in the following form:

$$\frac{\mathrm{d}x_m(t)}{\mathrm{d}t} = \mathcal{F}\{x_m, u_m, t; \mathscr{H}_S x_m(t), \mathscr{H}_S u_m(t), \mathscr{H}_S \mathcal{X}_m(t)\}, \tag{17}$$

The map $\mathcal{F}$ represents the system dynamics map, defining the internal mechanism of the processing event. Here, $S \subseteq \mathcal{M}$ denotes the indices of the events influencing the mth event, whose dynamics are under consideration. The historical segment $\mathscr{H}_S x_m(t)$ encompasses the entirety of unstructured previous states, while $\mathscr{H}_S u_m(t)$ generates the history of past inputs. Conversely, the historical segment $\mathscr{H}_S \mathcal{X}_m(t)$ provides the past history of structured memory states from other events that may impact the dynamics of the current event. In this context, the historical slice $\mathscr{H}_S \mathcal{X}_m(t)$ might be conceived as a "second-order state history" or a "meta-historical dataset", furnishing information about how the internal dynamics of the present event (when $m \in S$) and other events are structured.

The solution of (17) leads to the dynamic operator of the mth processing event E_m, represented by $\mathcal{L}_m$, as given in (10). It is worth noting that, in general, this operator itself may depend on the initial states or the memory state.

5.4. The Dynamics of Events with Intrinsic Memory: The Global Theory

A generalized neuromorphic system (GNS) can be represented as a collection of interconnected processes, each realized by a system described by the form (17). Each subsystem operates within its own locally accessible state space X_m, where m represents a discrete or continuous index corresponding to the mth neuronal process, and $\mathcal{M} \ni m$ denotes the index space. The overarching theory of GNS emerges from the interconnection of all processing elements (PEs). Each PE is governed by an equation akin to (17). The global excitation operator $\mathcal{E}$, introduced earlier, serves as a mechanism for global synchronization, facilitating the coordination of the manifold $\mathcal{M}$ and orchestrating the complex spatiotemporal relationships among the various PEs composing the GNS.

A global time operator τ is defined by the expression

$$(t, \mathcal{T}) = \tau[t_m, \mathcal{X}_m(t_m), m \in \mathcal{M}], \tag{18}$$

where τ operates on the local time array $[t_m]_{m\in M}$ of all PEs' local time variables, ultimately yielding a unified global time t to be applied to the entirety of the temporal dynamics within the global assemblage. Additionally, supplementary data stored within an appropriate mathematical object $\mathcal{T}$ are generated to facilitate the temporal scheduling of information propagation and flow throughout the networked assemblage. This framework finds utility in various contexts, such as event-driven information flow paradigms, data-flow graphs, neurodynamics, spiking neural networks, and neuromorphic computing [13,21,22,27,32,33,68].

The entire "state" of this generalized neuromorphic system is encompassed by the distribution function in the classical scenario or the global density operator in the quantum scenario, collectively referred to as the global state, denoted by $\mathfrak{R}_\tau$. The dynamical law can be expressed as

$$\mathfrak{R}_\tau = \Phi_\tau\{\mathcal{E}_m, \mathcal{X}_m(t_m), m \in \mathcal{M}\}, \tag{19}$$

where Φ_τ represents the collective (global) dynamical evolution operator of the entire assemblage. It is important to note that, due to the necessity to account for nonlocality arising from non-Markovianity, the operator Φ is not required to be a semigroup [66] or analyzable as products of semigroups. The comprehensive dynamics of a networked assemblage of dissipative non-Markovian networks remains less understood compared to the Markovian case.

6. Physical Realization and the Prospect for Quantum Generalized Neuromorphism

6.1. Cognitive AGI and Nonlocality

It is in the highly nontrivial correlations between multiple states operative at the microevolutionary level of time change where one finds what makes non-Markovian flows, or systems with memory in general and neuromorphic systems in particular, highly interesting, both for theory and applications. Since information processing in a GNS (or even a plain SNN with simple firing neurons) depends on the spatiotemporal dynamics of the signal flow, while such a flow, in turn, exhibits strong collective or nonlocal "holistic" behavior due to stochastic correlations between several states in each memory state $\mathcal{X}_m(t)$, it is expected to have great potential in computing (and subsequently computation-based AI) for realizing new intelligent functions.

In generalized neuromorphic systems (GNSs), the primary objective is to achieve artificial intelligence (AI) functions through the deployment of strongly interacting intelligent agents (IIAs) within advanced dense dissipative networks, known as the IIA paradigm. In such intricate systems, the intensity of interactions often leads to nonlocal effects, even at the classical level [69]. Conversely, quantum physics is fundamentally regarded as nonlocal [70]. Consequently, nonlocality emerges as a pivotal concern in GNS-based approaches to AI, as discussed in this article. Therefore, it is imperative to provide additional insights into this crucial topic of nonlocality, as it serves to motivate the exploration for new physical hardware capable of realizing and harnessing non-Markovianity in natural systems, a central theme in our project.

Nonlocality in field theories refers to the phenomenon where the response of a field system at one spacetime point depends on the system's history at other spacetime points [69,71]. This concept has a rich history in physics, tracing back to plasma and crystal physics [72,73], and has regained attention recently due to its fundamental role in nanostructures [74–78]. In the context of this article, the significance of nonlocality in AI systems arises from the nontrivial role played by topology in dynamical interactions within complex systems [55,67]. Memory, as it directly involves mechanisms such as recall and storage [79], can be viewed as nonlocal in time, hence linking it to the physical concept of nonlocality just cited above. Conversely, cognitive operations encompass activities such as concept formation and processing [80].

The theory of concepts in AGI is inherently complex and still subject to controversy. However, simplifying the presentation by focusing on one characteristic aspect of concepts, namely, order, can facilitate understanding. Order relations are crucial in the realm of concepts, whether they are representational or not, particularly in the context of AGI. Concepts typically entail a minimum requirement of order relations between different parts, whether for storing or representing information. Furthermore, cognitive processing, achieved through the manipulation of concepts, is best implemented or modeled as transformations of the order relations inherent in the concepts themselves. If we define *order* as a long-range spatial correlation, then we may equate order with nonlocality in space. Combining these two aspects—memory and order—we recognize that the two essential structural manifestations of cognition jointly require spatiotemporal nonlocality (Figure 12).

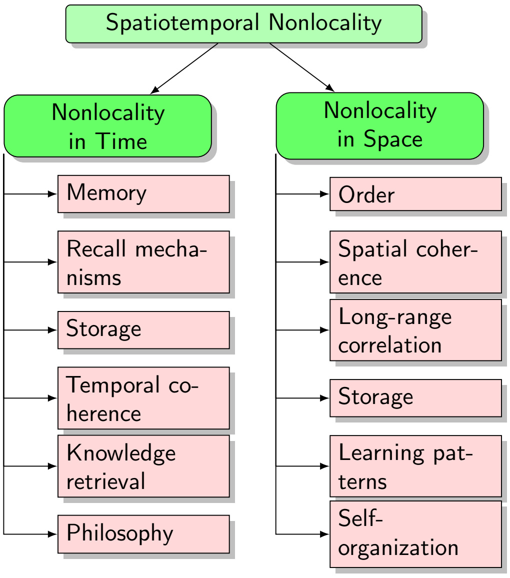

Figure 12. The fundamental role played by nonlocality in space and time in generalized neuromorphism stems from the importance of nonlocal interactions and processes in the theory of complex systems.

In neuroscience, nonlocality is often described using alternate terms, such as *mass action*, where it has a more specific meaning: memory cannot be localized within the confines of a single cortical domain but instead tends to be distributed nonlocally throughout the entire cortex [81]. In essence, memory, which embodies nonlocality in time (see Figure 12), is distributed spatially in a nonlocal manner [82]. Presently, the origin and structure of memory are commonly believed to reside within the neuronal circuitry of the brain, reflecting a reductionist approach [83]. It is reasonable to anticipate that neurodynamic networks, such as SNNs and beyond, should be capable of replicating this collective, fundamentally nonlocal behavior. Previously, there was speculation that memory could only be elucidated by postulating a new field—a "neuron field"—which would then explain the nonlocalizable nature of memory processes. In generalized neuromorphism, this field will represent the total stochastic or random field of the networks, defined as the collection of random states belonging to the various processing events indexed over the GNS's base manifold $\mathcal{M}$.

6.2. Quantum Biology, Quantum AI, the Quantum Brain, and the Prospect for Quantum Neuromorphism

While numerous researchers have explored the potential of explaining consciousness through quantum physical processes [84–87], in neuroscience, there is now a prevailing conviction, held by many (if not all) scientists in this field, that classical mechanics, classical statistical mechanics, and classical field theory alone cannot account for consciousness. This realization is also linked to the decline (or at least the erosion) of the prevailing belief in molecular reductionism—a hallmark inherited from deterministic classical science [88]. A non-reductionist, or nonlocal, perspective—sometimes termed "holistic"—is deemed necessary to elucidate the apparently non-mechanistic emergence of intelligent behavior in organisms governed by complex systems like the brain. In recent years, emerging interdisciplinary fields such as quantum biology, quantum brain dynamics, and quantum models of consciousness have raised serious questions about whether strong AI can ever be realized without resorting to quantum information processing operations executed by biological material systems.

Contrary to the prevailing modern belief, which persists, that all computations are ultimately Turing-effective (achievable using a standard Turing machine), a minority of writers and scientists argue that the laws of physics should not be constrained solely to what is Turing-computable. This perspective is exemplified by Roger Penrose, who contends that (1) quantum mechanics is incomplete [89] and (2) achieving the completion of quantum theory will necessitate the incorporation of fundamentally non-commutable physical processes [90]. While initially grounded in Godel's incompleteness theorem [50,91], our focus lies on its implications for an open dynamical model of the brain. Irrespective of technical intricacies, the unconventional perspective on consciousness and intelligence championed by Hameroff and Penrose necessitates a level of quantum coherence spanning substantial spatiotemporal scales [85]. While mainstream neurobiology typically operates under the assumption, empirically adequate thus far, that cognitive functions, motor functions, internal organ regulation, etc., can be explained solely by neuronal firing and action potential transmission [12], proposals like those put forth by Penrose and others are frequently categorized within the discipline of quantum biology.

We differentiate between quantum brain dynamics (QBD) and quantum neurodynamics (QND). QBD typically involves the systematic application of concepts and methods from quantum field theory (QFT) to explore how the structure of the brain may underpin cognitive functions and memory-like states. Conversely, QND is primarily focused on remodeling some or all neurons using a quantum model instead of the classical activation function commonly utilized in conventional neuroscience. Classical and quantum neurodynamics both investigate the cortical neural network of the brain, albeit through different physical frameworks and methodologies. QBD, being rooted in quantum field theory, offers a broader perspective compared to QND, as it encompasses traditional processes involved in understanding brain function, including neural network structure. Moreover, QBD introduces concepts such as the global coherent memory state, the corticon, and super-radiance, which transcend both classical and quantum neurodynamics [92].

Generalized neuromorphism should indeed take cues from advances in quantum biology, particularly QBD, as certain quantum concepts directly intersect with key features in GNSs, such as memory, nonlocality, and long-range order. Interestingly, some QBD approaches heavily utilize the formalism and methods of open (dissipative) complex nonlinear systems, specifically stochastic dynamics. Therefore, the theory of generalized neuromorphism represents a logical extension and enhancement of ongoing unconventional research on brain dynamics and intelligence, which is now gaining traction in the burgeoning field of quantum biology.

6.3. Quantum GNS Circuits

A significant obstacle to the projected transition from a general theory of non-Markovian neuromorphic circuits to a quantum version lies in the fundamental disparity between the structures of probability in the classical and quantum realms. It is now established that probability relationships valid in classical physics can be contravened in the quantum domain [93,94]. While this issue has garnered considerable attention from theorists, it remains relatively obscure to the broader public. For a comprehensive mathematical and conceptual exploration of probability in physics and related fields, I recommend consulting [95].

For our main objectives here, a significant technical challenge lies in constructing non-Markovianity within the quantum framework. Since joint probability distributions cannot be defined in the quantum realm for all potentially relevant cases (as not all quantum observables or measurement operators can have joint density functions [96]), it follows that the formulation presented in Definition 3 for classical GNM cannot be directly applied to construct quantum GNM. The extension of non-Markovianity from the classical to the quantum domain is currently a vibrant and expanding multidisciplinary research field. Various proposals have been published on quantum non-Markovian stochastic processes, although there is no universal agreement on the best formulation of the problem [34,97–99].

Figure 13 showcases a quantum generalized neuromorphic circuit illustrating a single quantum processing event (PE) with the supporting presynaptic and postprocessing circuits. In contrast to the classical GNS architecture in Figure 11, both the presynaptic and post-event processing must involve quantum measurement operators to reduce the evolved quantum memory state $\tilde{\rho}(t)$ to output signals O_m. At the input (presynaptic) stage, the presynaptic quantum measurement operator $\tilde{\mathcal{E}}_m$ will measure (collapse) previous quantum states belonging to previous PEs and process them in order to prepare the input signal u_m to be fed into the quantum stochastic dynamic (SD) process of the quantum event E_m. The quantum dynamic map Φ_m specifies the dynamical details of the evental's SD.

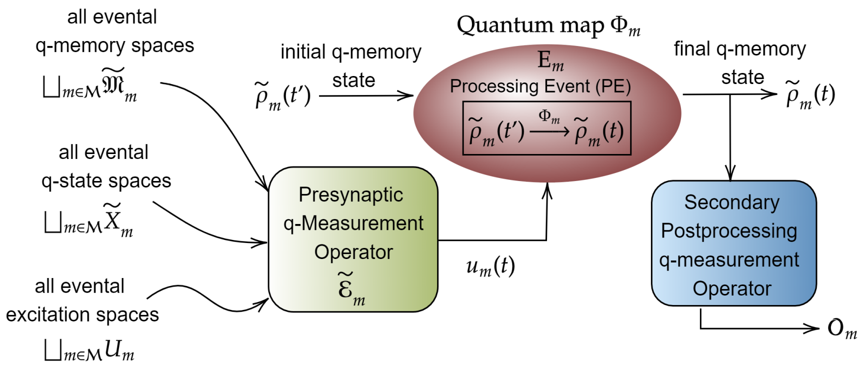

Figure 13. A proposed quantum GNS architecture generalizing the classical system shown in Figure 11.

Let us begin with the description at the single-processing-element (PE) system level without introducing the quantum memory state. Let ρ_t represent a quantum density operator [34,55] characterizing the state of a physical dynamical system defined on a state space X. The system is characterized by an internal state $x_t \in X$ and an input $u_t \in \mathcal{U}$ at time t, where $\mathcal{U}$ represents the space of input classical/quantum excitation fields (a collection of physical inputs carrying information from the environment and possibly other interacting agents represented by other dynamical processes). It is important to distinguish between the internal state x_t and the physical state captured by ρ_t; the latter is a statistical density defined on the state space $X \ni x_t$. While the evolution equations in terms of the density operator ρ_t (in the quantum case) are linear [66], the underlying dynamics, when expressed in terms of the internal states x_t, can be highly nonlinear.

To incorporate memory effects and thus generate nonlocal behavior, we introduce a quantum *history operator* $\mathscr{H}$. This operator transforms a given input V_t into the past temporal history or time slice of past instantiations, denoted by $\mathscr{H}V_t$. Technically, we introduce three distinct quantum history operators, $\mathscr{H}_{\mathrm{phys}}$, $\mathscr{H}_{\mathrm{int}}$, and $\mathscr{H}_{\mathrm{pre}}$, for updating past time slices of the physical state, internal states, and the presynaptic input excitations, respectively. A generic memory operator is nonlocal in time. Through the evolution of various coupled degrees of freedom in complex systems, this temporal nonlocality transforms into nonlocality in spacetime, rendering the resulting dynamical system effectively nonlocal.

Motivated by the standard Markovian dynamical theories prevalent in memoryless systems, as discussed in works such as [34,36,37,66], the general dynamical law governing non-Markovian (memory-inclusive) processes can be expressed as a first-order differential equation involving the density operator/distribution ρ_t. This equation takes the form of a generalized master equation [3]:

$$\frac{\mathrm{d}}{\mathrm{d}t}\rho_t = \mathcal{S}\{\mathscr{H}_{\mathrm{s}}\rho_t, \mathscr{H}_{\mathrm{i}}X_t, \mathscr{H}_{\mathrm{p}}U_t, t\}, \tag{20}$$

where t represents a local time variable, and $\mathcal{S}$ denotes the dynamical evolution superoperator. In the quantum context, where ρ_t represents an operator, the preferred term is *superoperator* [55], which signifies a transformation from operators to operators.

The solution to Equation (20) offers a comprehensive understanding of the evolution of the physical state, captured by the density operator ρ_t. Within this framework, information processing involves either direct access to internal states or the possible utilization of hidden Markovian network estimation techniques [100]. However, the inclusion of three quantum memory operators in the equation introduces intricate nonlocal behaviors, posing a significant challenge for a direct solution without resorting to approximations [97]. Given these complexities, it is common in the literature to simplify matters by focusing on the quantum Markovian case, which is well studied and can be succinctly described using the GKSL master equation process [36,101]. In this regard, we leverage the abstract and powerful formalism of stochastic semigroups in probability theory, serving as a direct link between classical and quantum scenarios in Markovian settings [66,102,103]. However, it is crucial to acknowledge that the detailed exploration of a quantum non-Markovian theory of generalized neuromorphism falls beyond the scope of this article. Navigating this complexity requires balancing accuracy with tractability. While approximations may facilitate solutions, they often impose additional restrictive assumptions, which we aim to avoid in our comprehensive treatment.

Equation (20) maps out a localized application, elucidating the behavior of an individual agent within an interacting dynamical agent framework. While our focus has centered on prescribing the rules governing individual agents for the sake of clarity, it is paramount to recognize the broader context within which these agents operate. In population-based AI methodologies, clusters of agents engage in interactions over time, orchestrated by engineered interaction Hamiltonians. These interactions steer their collective behaviors toward problem-solving objectives, thereby showcasing emergent intelligent behavior [32,104–108]. Furthermore, each subsystem described by (20) may exhibit non-Markovian behavior attributable to the incorporation of nontrivial history operators $\mathcal{L}$ [34,102]. When viewed through the lens of a stochastic dynamic system, it also displays dissipative or irreversible flow characteristics [55,109]. Understanding these dynamics not only enriches our comprehension of the system's behavior but also underscores the complexity inherent in modeling and analyzing such intricate systems.

7. Generalized Neuromorphism and the Dynamic Approach to Intelligent Systems Design

7.1. Incorporating Machine Intelligence into the Dynamic Multi-Agent Assemblage

Introducing intelligence into the system can be accomplished through various methods, inspired by ML and DL but also potentially surpassing them in the future. To attain this, various risk, reward, and policy functionals can be constructed on the assemblage $\mathfrak{R}$ through the application of machine learning [14] and reinforcement learning techniques [110]. To elucidate, consider $\mathcal{V}$ as the environment, $\mathcal{A}$ as a mathematical entity encapsulating learning, reward, and policy parameters, and C_t as the cost function value at global time instant t corresponding to a learning task $\mathcal{K}$. In this context, we express

$$C_t = \mathfrak{Y}_{\mathfrak{R}_\tau}\{\mathcal{V}, \mathcal{A}, \mathcal{K}\}, \tag{21}$$

where $\mathfrak{Y}_{\mathfrak{R}_\tau}$ denotes the global AGI operator of the assemblage $\mathfrak{R}$ assessed utilizing the time operator τ. This operator comprehensively encapsulates internal states, presynaptic excitation fields, temporal scheduling data $\mathcal{T}$, local and global time variables, and other pertinent information. Real-time data flow is contained within the environment object $\mathcal{V}$, which also encompasses access to the local and global time parameters of the assemblage $\mathfrak{R}$. In the domain of AGI systems, both the cost function C and the task $\mathcal{K}$ are anticipated to be complex multidimensional constructs. This complexity is essential to accommodate the diverse array of interaction scenarios possible with the environment $\mathcal{V}$.

In orchestrating the learning process within the assemblage $\mathfrak{R}$, one can tailor its dynamics by adjusting the interconnections among its constituent dynamical processes or agents. These agents collectively form a networked structure, as depicted in (19). While the methods for achieving such adjustments are diverse, our focus here remains on providing a high-level overview. In this model, the modifications primarily revolve around the three history operators $\mathscr{H}_\mathrm{s}$, $\mathscr{H}_\mathrm{i}$, and $\mathscr{H}_\mathrm{p}$, which extend beyond the confines of individual agents or processes outlined in (20). Instead, they establish connections with every other agent, resembling a generalized neuron subsystem characterized by equations akin to (20). This progressive extension ultimately spans the entirety of the assemblage (19). Adjustments to these history operators, driven by the learning algorithm cost in (21), can be likened to the synaptic connections' adaptation observed in contemporary neural networks [13]. This comparison underscores the dynamic nature of the learning process within the assemblage $\mathfrak{R}$, where the fine-tuning of inter-agent interactions mirrors the plasticity inherent in biological neural systems.

7.2. The Dynamic Approach to Cognition

The GNS is not a closed device like a computer or a ship but is more akin to the organism and the brain: an open system that is operating in a far-from-equilibrium thermodynamic mode and is constantly interchanging information with its immediate (and sometimes distant) surrounding environing sphere (Figure 14). The AI capabilities of either GNS ASIC chips or artificial brains alike will crucially depend on the bidirectional nature of energy/information exchange between the event assemblage and the world (Figure 8). Knowledge can be extracted from the AI-directed dynamically evolved memory states of the GNS, e.g., eventually making decisions, directing attention, or releasing short-term memories. These and other various outcomes may be fed back into the computing agents through the world or passed forward to an action-producing module (Figure 14).

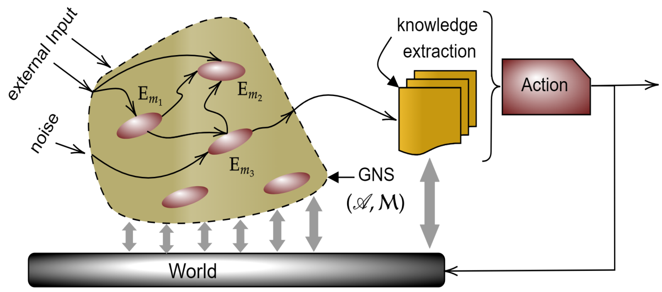

Figure 14. The fundamental functional circuit of the GNS as an AGI agent.

Figure 14 presents the core functional circuitry of the GNS AI domain. Central to this depiction is the event assemblage $\mathscr{A}$, nestled within the physical domain $\mathcal{M}$, where computational processes unfold. This setup characterizes an inherently open stochastic dynamic (SD) system engaged in continuous interactions with its surrounding environment. This environment comprises two primary constituents: (1) the world and (2) the knowledge/action base. Within this framework, information flow between the GNS and the external world occurs bidirectionally, driven by the inherent non-Markovian nature of the system. Actions initiated within the GNS can reverberate back into the system through the encompassing sphere of the world, establishing intrinsic coupling with the assemblage.

Figure 15 illustrates the implementation of decision-making processes, whether cognitive or non-cognitive, within generalized neuromorphism. This is achieved through attractor decision circuits operating within the memory space. Panel (a) depicts the potential energy landscape of a decision GNS featuring two possible decisions: D_1 and D_2. The initial state is denoted by the blue dot, situated within a stable region in the memory space of the system. Depending on stochastic fluctuations, depicted by the dashed arrows representing symmetry breaking, the system may transition to either decision D_1 or D_2. In a quantum GNS, a novel possibility emerges wherein quantum tunneling flow can directly transition the GNS from its initial state to one of the two decisions, such as D_2, even when it resides at a higher energy level. Panel (b) illustrates the bifurcation diagram of the decision GNS process. An initial memory state (depicted as the blue dot) encapsulates micromemories concerning past actions. As the system undergoes dynamic evolution propelled by internal memory-like alterations (represented by complete trajectories in memory space rather than traditional state space) alongside external inputs (such as stimuli, control signals, and environmental information feedback due to non-Markovianity), the GNS might undergo a symmetry-breaking bifurcation (highlighted by the green dot). This bifurcation leads to the selection of one of the two decisions (represented by the red dots), D_1 or D_2.

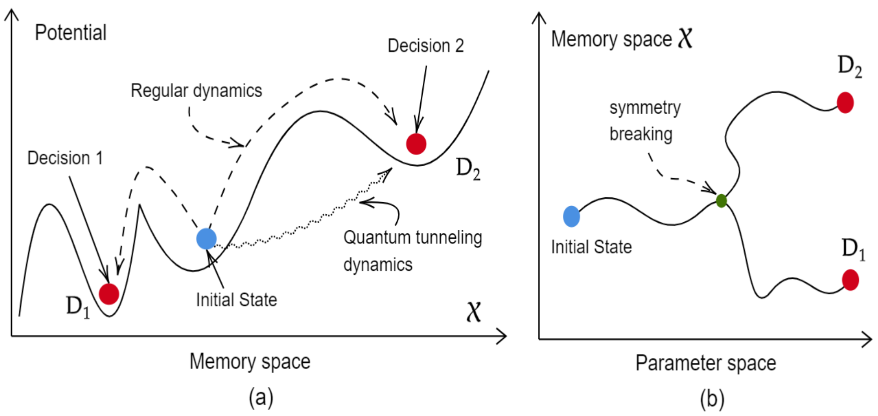

Figure 15. Decision-making using dynamical systems.

8. Conclusions

A synthetic multidisciplinary view of artificial intelligence (AI) and cybernetics is proposed in terms of a generalized stochastic dynamic formalism developed to model generic networks comprising assemblages of abstract processing events. The formalism, dubbed *generalized neuromorphism*, was inspired by spiking neural networks (neurodynamic processing) and the theory of open dynamical systems. Generalized neuromorphism was intentionally constructed at a high abstract level to allow for multidisciplinary applications to different approaches within the AI community. Each processing event represents a real computing or intelligent agent, such as a spiking neuron processor in a neural circuit, a CMOS gate in a chip, or a consumer in the market. Processing is executed in space and time, where each event interacts with other events only when their states are made available (event-driven computing). In our theory, each event is viewed as a generic stochastic dynamic process with memory (non-Markovian process). The prime mover of an assemblage comprising such events is the various possible physico-semiotic interactions and information exchange among them, enacted via a global displacement network operator that shifts time signals from one event to another. On the other hand, for each event, time is defined only locally. The global displacement operator allows information (programming, scheduling, network connectivity) to be distributed on the global scale of the event assemblage, thereby giving rise to AI capabilities such as learning, prediction, and adaptation.

Among the possible future applications of this formalism is the simplification of the use of information theory since the entropy functional in stochastic dynamics is well known. However, the most important application from our perspective is the ability to directly quantize the event assemblage, leading to a possible future concept, quantum neuromorphic computing. The final model appears to resemble a stochastic quantum random field that is spatiotemporally nonlocal. We conjecture at the end that a nonlocal quantum field could then be related to the basic structure of intelligence in both the living and technological worlds.

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Abbreviations

The following abbreviations are used in this manuscript:

AGI	Artificial general intelligence
ANN	Artificial Neural Network
ASIC	Application-Specific IC
GKSL	Gorini–Kossakowski–Sudarshan–Lindblad
SNN	Spiking neural network
TPU	Tensor Processing Unit
IIA	Interacting intelligent agent
PE	Processing element/event
HMM	Hidden Markov Model
ML	Machine learning
SD	Stochastic dynamic/dynamics
ND	Neurodynamic/neurodynamics
GNM	Generalized neuromorphic/neuromorphism
GPU	Graphical Processing Unit
GA	Genetic Algorithm
QBD	Quantum brain dynamics
QND	Quantum neurodynamics
PSO	Particle Swarm Optimization

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