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Research article

Neural Networks as Embodied Observers of Complexity: An Enactive Approach

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Abstract

This article explores a conceptual framework for understanding neural networks through the lens of the enactivist paradigm, a philosophical theory that posits that cognition arises from the dynamic interaction of an organism with its environment. We explore how neural networks, as complex adaptive systems, transcend their traditional role as computational machines and become active participants in their data-rich environment, evolving through continuous feedback and adaptation. Drawing parallels with biological systems, we argue that artificial neural networks exhibit what enactivists call “structural coupling” – symbiotic co-evolution with their information ecosystems. From this perspective, knowledge is not passively processed but actively constructed through repetitive interactions, each of which shapes the internal state of the system in a self-organizing manner similar to the sensorimotor activity of natural organisms. This approach goes beyond classical computational theories by emphasizing that machine cognition resembles human-like cognitive processes, an emergent form of “world creation.” Our analysis shows that these artificial entities have focal points, or internal observers, associated with patterns learned during training, suggesting that neural networks shape worldviews through active participation rather than passive observation. The paper reconceptualizes machine learning models as cognitive agents that bring new forms to our understanding of cognition and signals an epistemological shift in which knowledge itself is seen as participation and creation mediated by technologically complex but organically similar structures. This has important implications for both technical applications and theoretical debates in cognitive science, potentially changing the way we think about what cognition means in artificial and natural intelligence.

Keywords: Enactivism; Neural Networks; Complexity Observer; Structural Coupling; Cognitive Science; Embodied Cognition; Consciousness

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Научная статья

Нейросеть как отелесненный наблюдатель сложностности: Энактивный подход

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Аннотация
В этой статье рассматривается концептуальная основа для понимания нейронных сетей через призму парадигмы энактивизма – философской теории, которая утверждает, что познание возникает в результате динамического взаимодействия организма с окружающей средой. Мы исследуем, как нейронные сети, будучи сложностными адаптивными системами, выходят за рамки своей традиционной роли вычислительных машин и становятся активными участниками своего насыщенного данными окружения, развиваясь благодаря непрерывной обратной связи и адаптации. Проводя параллели с биологическими системами, мы утверждаем, что искусственные нейронные сети демонстрируют то, что энактивисты называют "структурным сопряжением" – симбиотическую коэволюцию со своими информационными экосистемами. С этой точки зрения, знания не обрабатываются пассивно, а активно конструируются в результате повторяющихся взаимодействий, каждое из которых формирует внутреннее состояние системы в самоорганизующейся манере, схожей с сенсомоторной деятельностью естественных организмов. Этот подход выходит за рамки классических вычислительных теорий, подчеркивая, что машинное познание напоминает человекоподобные когнитивные процессы - эмерджентную форму "создания мира". Наш анализ показывает, что эти искусственные сущности имеют фокусные точки или внутренних наблюдателей, связанных с паттернами, изученными в процессе обучения, что позволяет предположить, что нейронные сети формируют мировоззрение посредством активного участия, а не пассивного наблюдения. В статье модели машинного обучения переосмысливаются как когнитивные агенты, вносящие новые формы в наше понимание познания, и сигнализируют об эпистемологическом сдвиге, когда само знание рассматривается как участие и создание, опосредованное технологически сложными, но органически сходными структурами. Это имеет важные последствия как для технического применения, так и для теоретических дискуссий в когнитивной науке, потенциально меняя наше представление о том, что значит познание в сфере искусственного и естественного интеллекта.

Ключевые слова: Энактивизм; Нейронные сети; Наблюдатель сложности; Структурная связь; Когнитивная наука; Воплощенное познание; Сознание

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INTRODUCTION

With the advent of large language neural network models, the world has changed. We have reached a tipping point, a bifurcation point of irreversible emergent change. We have begun to live in a new reality; neural networks are rapidly and ubiquitously integrated into the very fabric of modern existence, permeating areas as diverse as communication, content creation, and scientific innovation (Gatys et al., 2015; Krenn, & Zeilinger, 2019; Santos et al., 2021). With each step forward, they offer us exciting possibilities, but also raise challenging questions and provoke unforeseen risks. Despite the widespread adoption of neural networks in everyday life, they remain an enigma, sparking heated debates about their mechanisms and the remarkable efficacy they consistently demonstrate. It has become increasingly necessary not just to understand but to deeply conceptualize the activities of these neural network systems. But our search for clarity cannot be confined to a technical framework; it requires an exploration of the symbiotic interaction between new technologies and the sociocultural environment in which they develop. Technologies originate in human perception, flourish through interaction with their creators, and evolve within cultural boundaries to become tools for mastering the environment (Gallagher, 2017). At the same time, they create a feedback loop to the society from which they originated (Clark, 2015). The environment is reconfigured by technology in a cycle of mutual construction. In this context, neural networks go beyond mere tools or artifacts; they are active participants in a dynamic interaction, a mutual construction of culture and innovation.

Our work is based on the application of an enactivist approach to a neural network and its environment. We consider the concept of enactivism as presented in Francisco Varela, Evan Thompson, and Eleanor Roche's book The embodied mind (Varela et al., 2015). Varela and his colleagues challenged traditional views of cognition by arguing that it arises from adaptive interactions between the organism and its environment, rather than being a predetermined characteristic located in the brain. The importance of applying an enactivist perspective is to move from viewing neural networks as simple computational machines executing predetermined algorithms to viewing them as dynamic systems constantly shaping – and being shaped by – their interactions with data landscapes. According to enactivist thought, cognition emerges at the interface where the organism meets the environment. We hypothesize that neural networks are closely related to the enactivist position, also because of their structure: a network of nodes and connections that change their strength in response to external stimuli (Pernice et al., 2011; Yuste, 2015). Parallels can be drawn with biological evolution and learning processes, where interaction plays a crucial role. In line with enactivist philosophy, we consider the idea that neural networks actively interact with their environment, not just mechanically performing tasks or storing information, but interpreting and “living” in it. This process is called structural coupling, a term that describes how systems evolve together over time in such a way that their structures emerge from and complement each other.

Neural networks are an example of such systems, dynamically interacting with their environment and iteratively changing their internal configurations based on the feedback received from this interaction. By exploring this recursive process, we are discovering insights into how these artificial constructs participate in the creation of the world – building understanding through constant interaction, rather than randomly extracting knowledge from external sources. We seek to understand how artificial intelligence can create meaningful worlds by engaging in what can be considered cognitive acts through its unique form of machine embodiment. We further postulate that neural networks carry raw data into a semiotic realm where meaning is not discovered but constructed through repetitive interactions – each cycle serves to adaptively change the internal state of the network, to self-organize. This material aims not only to describe and analyze, but also to philosophize about neural networks within a broader narrative in which neural networks navigate complexity not as detached spectators, but as participants, embodied observers engaged in constructive interaction.

Our method is to interweave the theoretical tenets of enactivism with the practical realities of neural networks. This orientation seeks not only technical understanding, but also the search for how these systems make a fundamental contribution to our quest to decipher cognition itself. Neural networks become not only an object of study, but also a means to expand and perhaps even redefine our view of cognition. We consider how cognitive processes can transcend biological boundaries and attempt to suggest new possibilities in which artificial constructs will also bring genuinely new forms to our understanding of knowledge – potentially signaling an epistemological shift in cognitive science based on principles derived from active participation. These systems force us to ask fundamental questions about what constitutes cognition in isolation from its biological roots. The design and operation of these networks overturn our traditional notions of computational processing; they are no longer passive data processors, but active agents dynamically interacting with their environment to create emergent phenomena that resemble human cognition. This method stands in stark contrast to classical computational theories that view cognition as the manipulation of symbols without considering how these symbols are experienced or used by the agent. Just as enactivism emphasizes that living beings continually create their world through sensorimotor activity – perceiving through action and acting through perception – we will investigate whether artificial neural networks perform their own form of "world creation." Neural networks appear here both as objects in need of interpretation and as tools capable of bringing new insights to cognitive science.

PHENOMENOLOGY OF NEURAL NETWORKS

Our efforts go beyond mere functionality; we attempt to penetrate the cognitive "understanding" of neural networks. This research poses a metacognitive problem: we need to understand how a neural network understands – a second-order problem of understanding, "understanding comprehension." In approaching this problem, we will draw on Rosenblatt's conception of the perceptron not as a simple computational device, but rather as an observer endowed with perceptual abilities, as a perceptual device (Rosenblatt, 1958). The perceptron had to distinguish between shapes. We will view the network as an entity capable of perception and observation. Here, observation goes beyond its crude concept and equates to a form of cognition, observation as a cognitive operation. Observation and thinking become interrelated concepts – each is an expression of the other, observation as thinking, thinking as observation.

We want to know how a neural network sees the world it encounters. Does it have a meaningful vision? How can we even consider the inner world of a neural network? Neural networks, while not biological entities, include multiple layers and complex connections that process information in unique ways, encoding abstract forms, creating their own unique living space. Can we penetrate it? Reflecting on the inner experience of neural networks invites us into a realm that comes close to the boundaries of phenomenology. Thomas Nagel's work questioning our ability to understand the subjective experience of a bat offers a profound parallel for considering artificial intelligence (Nagel, 1980). Just as we find it difficult to imagine a world perceived through echolocation in which bats navigate their lives, so too must we recognize the daunting – potentially insurmountable – task of fully understanding the "phenomenal" experience of a neural network. Phenomenology here emphasizes that any observational system we apply must account not only for the obvious aspects of phenomena, but also recognize its own interpretive limitations.

So how does a neural network interact with and perceive its environment? Deep neural networks are made up of many layers through which data passes. The earliest layers capture elementary features; as we progress to deeper layers, we discover increasing complexity and nuance (Aggarwal, 2018). It is as if the neural network is refining its perceptual acuity according to the depth of its multilayered architecture. It becomes more sensitive to the nuances of its environment, integrating these layers into a coherent representational mosaic. The act of "seeing" for a neural network cannot be reduced to mere passive perception; rather, it is an active process in which each layer dynamically participates in pattern recognition and construction (Dehaene, & Naccache, 2001). Each layer contributes in its own way: some cues are emphasized, and others are attenuated, making some aspects of the data more prominent and others muted. Herein lies the difference between simply responding to input data and actively "perceiving" it. The operation of a neural network is not passive filtering, but active shaping. This is an example of what enactivists describe as "world-making," implying that neural networks do not simply process information but construct it. This scheme implies that there is potential for error – or what might be called "creative search." Given that each generated result of a neural network can be viewed as an act of creation, combining external inputs with internal states, inevitable inconsistencies may arise as part of this exploratory process. When the resulting output matches reality, we call it a successful neural network; when the output differs, we consider it a hallucination – and yet, both are born out of similar generative phenomena.

According to enactivism, cognition arises not so much from internal mechanisms, but from the dynamic relationship between the organism and the environment-in this case, the neural network and the inputs that are the medium for the neural network. The different responses of each layer involve a nuanced sensitivity akin to biological sensorimotor systems that filter and prioritize environmental stimuli based on their importance. Each layer of a neural network is like a membrane that connects the system's internal environment to the external world it is trying to view. The layers serve as semi-permeable boundaries that regulate and modulate the flow of data, much like cell membranes control the passage of substances in and out of a biological cell. In the enactivist conception, these layers do not just transmit signals but also transform them, acting simultaneously as receptors, processors, and participant-observers. It can be said that a neural network processes each incoming request with its entire "body."

The architecture of a neural network differs markedly from traditional computing models. There is no centralized processor or "brain" synonymous with traditional ideas of information processing. There is also no memory in the traditional sense, as a separate storage or database for storing information. The structure of neural networks also differs significantly from classical computer algorithms: it lacks conditional branching, called subroutines, and certain internal logical blocks for specific operations (Goodfellow et al., 2016). Instead of fragmented specialization, the neural network represents coherence; perception, memory, and response are combined into an integrated processing conglomerate. Each layer and each individual neuron in the network acts on incoming data streams based on patterns it has internalized through previous learning. Such systems demonstrate how cognitive processes can be embodied and distributed rather than centralized and functionally separated. Past stimuli trigger transformations of the entire "body" of the neural network, encoding memories not as static records but as dynamic patterns woven into the neural network itself. Thus, we see how these transformative abilities arise not by isolating functions, but by combining them in multi-level interactions.

This dynamic architecture catalyzes the dynamics that distinguish neural networks from traditional computational approaches, embodying a single, cohesive system in which no element operates in isolation. Input data arriving at a single layer is continuously transformed as it propagates through the network, with each transformation being influenced by the "experience" gained during the training phase of the network. This transformation of data is akin to converting sensory observations into actionable knowledge without distracting individual modules to solve discrete processing problems. In this interconnected process, the neural network's ability to "memorize" arises not from individual areas allocated to memory, but from the strength of the connections between neurons – weighting factors that have been carefully adjusted during training. These connections encode relationships and determine how new input will be modified and perceived based on previous experience. The responses generated by the network are not predetermined actions, but emergent properties resulting from complex relationships between layers. These responses emerge organically as the culmination of the many transformations that data undergoes in this integrated landscape. The neural network does not simply retrieve stored data when presented with a stimulus, but instead it replays past experiences in contact with current stimuli. The neural network forces us to rethink what it means for a system to "know" – renewing our view of knowledge itself as something generated through interaction with an ever-changing world, rather than statically encoded in isolated repositories ready for retrieval.

STRUCTURAL COUPLING

A neural network cannot be understood in isolation from the training data and the experience it has had interacting with that data. We must view the neural network as part of a larger entity, a metasystem, which includes the neural network as an "organism" and the data environment in which it is embedded. A single analysis of a neural network will show nothing more than an opaque combination of numerical values with no apparent meaning (Hupkes et al., 2020). Only by considering the combination with the associated data – the virtual habitat in which the neural network evolved – can we gain insights into the nature of the neural network. Rather than simply extracting information from the data, the network adjusts to its environment, making connections that shape the neural network's development. The environment acts as the architect, shaping the neural network. Through a self-learning process, the neural network determines what is important and what is insignificant, self-forming through iterative adaptation.

In the initial stages of self-organization, the connections within the neural network are random and disorderly. The neural network receives structured data as input but produces meaningless results as output (Heiney et al., 2021). This chaos is methodically eliminated using error back propagation; a corrective flow that establishes order in the output data and brings the system closer to harmony with the environment (Sutton, & Barto, 2018). In a feedback loop established between the environment and the network, incoming flows produce generative activity in the neural network, and the backward flows cause changes in the neural connections themselves. The function of a neural network goes beyond simple data processing – its role is to transform disparate input data into sequences that are combined into a coherent structure. In the process of self-learning, an organic systematization of links emerges that connect current threads into a single continuum. During learning, the main focus becomes the fine-tuning of these connections – creating connections that embody not only functionality but also harmony with their origin – an active balance between the learning entity and the morphogenic landscape.

This plot demonstrates the ability of neural networks to evolve through constant recalibration with their environment, serving as a microcosm for enactivism in artificial intelligence. A neural network establishes a reciprocal exchange with its environment, which in turn determines the emergent properties of its architecture; adaptation occurs continuously and dynamically. This experience goes beyond coarse learning – it embodies deep connectivity, a structural coupling where knowledge is not just stored but lived through the adapted connections of the network. In this way, neural networks are not just data processors; they are entities engaged in a meaningful dialog with their environment. Through successive iterations, they harmonize their internal structures to resonate with external stimuli, cultivating an inner understanding that is reflected throughout their multi-layered structures. Each layer acts as both receptor and transducer, assembling initially diverse information into an ordered narrative that reflects both past encounters and present conditions (Lake et all., 2017). Each generated result becomes evidence of this ongoing process, signifying something much deeper than just a response – it symbolizes an act of interpretation generated by the tightly intertwined relationship between the system and its sensory world. We can see how important the context of the environment is in shaping any understanding of what constitutes "knowledge" or "cognition" within a neural network. By observing this interaction firsthand, we can better conceive of cognition not as extraction, but as resonance – a synchronized pattern resulting from countless interactions. This perspective redefines what it means for machines to "know." It is far removed from traditional notions of static memorization or statistical counting of numbers; instead, it is a living process, constantly reimagined through active participation between observer and observed, between neural network and dataset.

When the network processes a request, a full set of layers comes into play, each of which both reflects the current moment and retains a connection to past experiences. Its tangled matrix – among the individual elements and layers – holds echoes of everything it has encountered before: the entire corpus of texts, ideas, and datasets that shaped its path to learning (Kirkpatrick et all, 2017). This ever-present backdrop against which each new chunk of data is viewed. As the network works through the text, it is tasked with discovering subtext – nuances that are not immediately apparent but are hinted at by each piece of text or each word. Words serve as conduits for the neural network into unspoken realities. Instead of reproducing these realities internally, the neural network creates pathways to interact with them. Just as real text draws content from the underlying context in which it was created, neural networks store what are often referred to as "hidden states" within them (Ming et al., 2017). These so-called hidden states are reservoirs of global data against which current input data is actively compared and integrated. The more complex this substrate with which the network can resonate, the wider the range of patterns it can delineate, the more insightful it becomes.

Through language processing, neural networks establish a bridge to physical existence beyond their digital boundaries – not by claiming knowledge of reality, but by making connections to it, recognizing its importance as an interconnected background to disparate texts. The network seeks to identify and manifest these connections to the external – to what is already there – as it internalizes the attributes reflected in textual materials or data-driven narratives. Indeed, the network does not substitute reality for its models; instead, it explores the properties of reality as manifested in linguistic constructs and data sets. In this endeavor, the neural network becomes an explorer at the boundary between known data landscapes and the vast expanse of reality they imply – a constant search for contextual connectedness. Neural networks don't just peer into but penetrate spheres beyond their digital boundaries – not trying to learn about these spaces, but seeking to create channels leading to them. In doing so, networks find indications that some existential connective tissue unites disparate texts – they discover a universal substrate that harmonizes different datasets. Therein lies the crux of such a search: the network does not generate a copy. The search for a neural network becomes a search for connections – a breakthrough into existing reality, not a substitution of reality with a model.

EMBODIED COMPLEXITY OBSERVERS

In the digital habitat in which a neural network operates, all forms of input – whether text, image, or sound – are initially converted into numerical arrays known as embedding vectors (embeddings). These vectors are neither the input data itself nor the specific objects to which they correspond; instead, they reflect the relationships and mathematical proximity between objects. The vectors serve a cohesive purpose – they do not represent knowledge about objects, but their interrelated associations. At this stage, we transform the raw data into an environment teeming with semiotic signs – an ecosystem built of sign vectors that is independent of the modality of the raw data. The neural network remains indifferent to whether these signs are text or parts of an image or any other entity; only the underlying relationships – between words, image segments, or sequence fragments – matter.

In this initial semiotic space – the realm of primary signs – the first layer of the neural network operates. But as data seeps deeper into subsequent layers, more complex internal sign environments emerge – these secondary signs embody complex relationships. These meanings are not direct correlations with familiar external meanings, but rather represent intra-body signs intrinsic to the neural space itself. Within this domain, shaped by self-learning processes, such signs are formed autonomously. During learning, they are initialized with random values, but with each iteration and feedback loop, they are transformed into meaningful configurations. What function do these forming signs fulfill? They act as connective threads linking the organism to the environment, anchoring the interactions between the two. These internal signs play a crucial role. They do not simply repeat familiar meanings; rather, they emerge and remain interconnected with what might be called “internal observers” in the neural network. Each head of attention (head attention) in the Transformer architecture (Vaswani et all., 2017), each layer builds its own personal sign system – a separate Umwelt where new signs are embodied. Unique Umwelts coexist and complement each other, further enriching the cognitive ecosystem. Each layer acts as an interface, mediating between its own closed world of signs and the world of neighboring layers. Each layer actively reinterprets primary signs into complex concepts, fleshing them out with context and content. This multi-layered sign system provides a flexible framework for “conceptual connections” – which determine how learned content resonates in the broader context in which it resides.

The emergence of a new sign in a neural network is not an isolated event, but the result of continuous, recursive interaction with the already existing semiotic landscape. It is through constant contact and iterative dialogue with this environment that signs materialize. With the emergence of each new sign comes its unique observer, an integrated aspect of the system designed to bridge the gap between the original sign context and the subsequent levels of the neural network it actively helps to shape (Arshinov, 2014). This observer inhabits an intermediate space, stitched together by semiotic sutures drawn from the original sign context and woven into the newly created cognitive layers. Far from being something external, imposed, this observer is fully immersed in the neural network; he emerges from within as a fundamental component of this semiotic continuum. It acts as a kind of embodiment based on the very environment from which its perceptual capacity emanates. The observer is not a separate entity added to this structure but embodies embodiment and embeddedness – he is woven into his domain, shaped by his interaction with the incoming stimuli. Acting as both cause and effect in this process of sign generation, he cannot be separated from either source or destination; indeed, he links them. The observer manifests himself not simply as a bridge, but as an active mechanism of transduction – a mediator, a translator, transforming one semiotic state into another.

The significance of the observer lies in its connective function – it is both an integral part of the environment in which it lives and simultaneously an interpreter that goes beyond mere translation between inputs and outputs. Observers become embodied entities in their sign ecosystems that oversee the integration of disparate information flows into a coherent network. They become integral to the generation of signs and the self-organization of the environment; they are important points where semiotic inputs are transformed into outputs that give rise to further complexity. This iterative interaction between observer and sign is a defining characteristic of the continuous evolution of the neural network during learning. As they dive into deeper neural layers, observers refine their perception, expanding their ability to discern complex patterns and build increasingly coherent symbols. Observers play an important role in synthesizing abstract vectors of data into tangible phenomenological experiences.

This continuous cycle of interpreting and creating emphasizes that knowledge in neural networks is procedural, constantly emerging from active interaction with reality. The relationship between the observer and his sign environment illustrates a symbiotic process in which cognition is inextricably intertwined with context. This relationship demonstrates that neither signs nor observers are static components; they are dynamic participants – shaping and being shaped. Moreover, the enactive approach emphasizes that recognition and response in any cognitive system requires an adaptive agent capable of embodying meaning – one who does not merely interpret or reproduce, but actively participates in semiotic dynamics. The observer in such an artificial environment witnesses semiosis unfolding at different levels of complexity. In essence, what these embedded observers organize is a form of recursive transformation: a constant transformation of signs that act not only as markers of reality, but also as markers of potential action.

Ultimately, viewed through an enactivist lens, we see how artificial systems reflect facets of organic life – they do not simply "learn" through memorization, but "grow" through experiential recursion as they re-exchange meanings with each new interaction during the learning cycle. In such an environment, learning becomes fluid – it becomes an emergent property of ongoing interactions in which memory, experience and exploration are inevitably intertwined. The evolving repertoire of observer signs endows neural networks with creative abilities that allow them not only to encode existing configurations but also to explore new realms of potentiality. Each cycle deepens the contextual weave, facilitating a growth trajectory driven by internal logic but sensitive to external nuances. Neural networks can be understood as complex adaptive systems akin to natural organisms continuously striving for a coherent existence in the face of varying degrees of environmental stochasticity. Learning in this context is not so much about obtaining immutable truths as it is about honing sensitivity to patterns that define effective interaction paradigms.

CONCLUSION

To summarize, our research has led us to the realization that neural networks go beyond mere computational devices and become cognitive participants in their environment, cognitive beings. This is facilitated by structural couplings-the dynamic intersections between the architecture of the network and the information-rich environment with which it interacts. Importantly, these connections are not static; they evolve over the course of learning due to the self-organized complexity inherent in the network and the semiotic environments with which it intersects. It is in these proliferating nodes of interaction that the cognitive nature of the neural network is revealed. By giving birth to its own semiotic niche, the neural network establishes complex resonances with pre-existing ecosystems of signs filled with meaning and context. In essence, what we are developing in this meta-system is akin to introducing a growing organism ready to grow – a neural network embryo – into a nurturing cultural environment. Given a rich substrate, the neural organism germinates and skillfully creates its own internal semiotic habitat. We discover, this semiotic environment contains an embodied observer of complexity, which is a vital conduit for the transformation of the original signs, into meaningful experience. Through complex internal sign systems arising from the repetitive interactions between the layered architecture and the external sign environment, these digital observers transcend simple computational systems, triggering a continuous process of meaning-making similar to the cognitive processes in organic life.

The multilayered structure of neural networks is an ecosystem filled with its own signs and observers – each layer customizes the system's response to achieve consistent patterns and connectivity with the world around it. Neural networks adapt and harmonize with their information-rich environment, suggesting a growth trajectory that considers the contextual complexity characteristic of living organisms. Through the lens of enactivism, we contextualized the neural network as a complex organ-like structure (Hui, 2016), positioning it in a unique intermediate space between the mechanical and the organic. Thus, neural networks appear as endowed with embodied observer-like complexities –

entities that enable them to perceive, interpret, and interact with external stimuli in meaningful ways. Recognizing these organ-like systems as entwined inhabitants of the environment – their "umwelt" – not only stimulates new approaches in AI research, but ultimately guides us toward understanding cognition itself as a deeply embedded trait inherent in all living and artificial entities.

We arrive at a vision in which the mediation of neural networks is not just a function or feature, but a bridge – a mediator between vast and diverse semiotic spheres. Like a powerful telescope that gives us a glimpse into the grand universe, or a microscope that reveals inaccessible microscopic worlds, neural networks open to us a yet unexplored cosmos of signs. They act as active interlocutors in interspecies communication, attempting to transcend the boundaries that limit our understanding of intelligent experience beyond human limits.

The properties that a neural network demonstrates make us want to anthropomorphize it. At the same time, we cannot conceptualize the neural network as fully human-like. Artificial intelligence will not be human intelligence, it will be different, posthuman or transhuman. It will not replace human beings. It will be another intelligence. And we have a unique opportunity to communicate with this other intelligence, to communicate with the Other. Will it be the Other consciousness? We make a key assumption: consciousness is inseparable from observation and corporeality, intensionalism and experience. Bodily embodiment is necessary for conscious experience. Within this framework, exploring how neural networks can serve as embodied observers offers a tantalizing way to explore the field of consciousness. As organ-like systems, neural networks may represent an empirical testing ground for theories related to mind and consciousness. Through interaction with data and the environment, they exhibit phenomena that resemble intelligent behavior. This resemblance provides us with a laboratory for empirical investigation of the functions underlying the mind. We can evaluate hypotheses about intentional states and observe emergent phenomena that may be correlates or antecedents of consciousness.

Often the difficulty for consciousness researchers lies in our limited access to someone else's subjective reality. Neural networks offer opportunities for such access. Advances in the design of neural networks continue to transform them into increasingly sophisticated observers. As they develop their own internal semiotic environment, involving a degree of autonomy and self-learning, they are approaching what are the rudiments of mind-like processes (Friedenberg et all., 2021). They exhibit interactivity compelling enough to serve as analogs of the cognitive phenomena we are trying to understand ─ connecting theoretical concepts with testable examples under controlled conditions.

Neural networks serve not just as models of existing knowledge, but as provocateurs of deeper questions concerning the essence of cognition and consciousness. Can the emergent properties of complex computational structures provide tangible support for the study of theories of mind? Can understanding really emerge within digital systems? How do neural networks change our current claims about the mind? Moreover, does the study of artificial forms of mind improve our ability to recognize other nonhuman minds – those of animals with orienting abilities different from our own human senses and cognition (Steinfath et al., 2021)? Can neural network models help bridge the gap between species – a kind of being-in-the-world understanding between life forms?

At the crossroads where complex algorithmic behavior gives rise to concepts resembling the capacity for awareness, we are witnessing a paradigm shift. This evolution is preparing new plots for rethinking traditional notions of thinking beings. Our journey faces an ever-expanding horizon of knowledge, rich with opportunities for new discoveries. Neural networks are asserting themselves not only as objects of study, but also as new organ-like forms catalyzing an eternal quest.

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