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Aesthetics after the Ontological Turn: An Ecological Approach to Artificial Creativity

Miguel Carvalhais

Diniz C. Ribeiro

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Miguel Carvalhais
i2ADS & Faculty of Fine Arts, University of Porto

Diniz Cayolla Ribeiro
i2ADS & Faculty of Fine Arts, University of Porto

Abstract

The development of chatbots and other generative systems powered by AI, particularly the latest version of ChatGPT, rekindled many discussions on topics such as intelligence and creativity, even leading some to suggest that we may be undergoing a "fourth narcissistic wound". Starting from Margaret Boden's approach to creativity, we will argue that if computational systems have always excelled at combinatorial creativity, current AI systems stand out at exploratory creativity but are perceived as still falling flat regarding transformational creativity. This paper explores some of the reasons for this, including how, despite the immensity of the conceptual space that results from training of large language models and other machine learning systems, these systems do not, for the most part, share models of the world with us, thus becoming cognitively inaccessible. This paper argues that rather than trying to bring AI systems to imitate us, our umwelt and psychology, to understand their full creative potential, we need to understand them from an ecological and non-anthropocentric perspective that implies an ontological turn both in science and technology studies and in art studies.

Miguel Carvalhais is Professor of Design at the Faculty of Fine Arts of the University of Porto. His research explores computational art, design and aesthetics, topics to which he dedicated two books: "Art and Computation" (2022) and "Artificial Aesthetics" (2016). His artistic practice spans computer music, sound art, live performance, and sound installations.

Diniz Cayolla Ribeiro is an Assistant Professor at the Faculty of Fine Arts of the University of Porto, where he teaches Anthropology, Art Psychology, and Research Methodology, among other subjects. His background is in Social Sciences, focusing on Anthropology. He later pursued a Ph.D. in Art Sciences, with a thesis on Primitivism in Art. He authored two books, co-edited a book on Cultural Analysis, and has numerous texts published in national and international academic journals in his research areas.

1. Introduction

In a recent interview,[1] philosophers André Barata and Paulo Pires do Vale reflect on the latest developments in the field of artificial intelligence (AI), namely its creative potential, and compare their impact to a fourth narcissistic wound for mankind. This comparison directly references the three narcissistic wounds identified by Freud in 1917 when he described how humans were progressively displaced from the center of the universe: the Copernican revolution, Darwin's Theory of Evolution, and lastly, the introduction of the unconscious, which questions the autonomy of our will and "to prove to the ego that it is not even master in its own house".[2]

If we look at the latest developments in AI, particularly the newer systems based on large language models (LLM) from Margaret Boden's framework for studying creativity,[3] we can realize that AI systems are extraordinary in two of the three types of creativity identified by Boden, but that they are also misunderstood when it comes to the third type, transformational creativity. In this paper, we will try to understand this misunderstanding and argue that the central issue is in our anthropocentric approach to this question. As such, we propose that if we want to understand the creative potential of AI systems, we must take an ontological turn, both in science and technology studies and in art studies, giving a central place to an ecological perspective that balances our anthropomorphic bias. This conceptual reconfiguration, even if not on the magnitude of Freud's narcissistic wounds, will undoubtedly be a severe test of anthropological narcissism that places intelligence and creativity as the strongholds of humanity and the apex of evolution.

1.1. Creativity

Two alternative and competing views have historically framed definitions of creativity. On the one hand, we have a primarily historical, and consensually seen as outdated, view of creativity as something that is, at best, channeled through humans but originates outside of them, as in the muses or a deity. This is the view that humans were created but are not creators, as that is the purview of god(s). A second view on creativity originates from the demise of this first one, namely, from the development of the idea that humans can, themselves, create. Although more recent than the first view, this also has a long story, dating at least back to the Renaissance and the start of print culture, that profoundly transformed the notions of originality and creativity.[4] This second view, in turn, led to centering the very definition of creativity in humans, not so much defining creativity as bounding it to a single source. Therefore, creativity continued to be "a slippery and nebulous concept",[5] at best seen as a power to create *ex*

[1] Alexandra Prado Coelho, "Se os computadores sonharem, o que resta aos humanos?" *Público*, April 2, 2023, https://www.publico.pt/2023/04/02/ciencia/noticia/computadores-sonharem-resta-humanos-2044202

[2] Sigmund Freud, *Introductory Lectures on Psychoanalysis* (New York: W. W. Norton & Company, Inc., 1966), 353.

[3] Margaret A. Boden, *The Creative Mind: Myths and Mechanisms*, 2nd ed. (London: Routledge, 2004).

[4] Walter J. Ong, *Orality and Literacy* (London: Routledge, 1982), 131.

[5] Oli Mould, *Against Creativity* (London: Verso, 2018), 4.

nihilo that works almost miraculously[6] and is only accessible to a few, special, people. Creativity is often seen as a defining human trait that may not be transferred to other, non-human, systems, or machines.[7]

Up to this day, we find an abundance of arguments defending that not only creativity may not be measured, as it cannot even be defined, that it is "a word devoid of identifiable content [...] a word that promises some benefit that cannot be controlled or measured and that can be attained as the unpredictable by-product of some identifiable concrete activity"[8] and that, as such, may not be, ultimately, neither understood nor taught.

Even if it is not easy to define,[9] many have attempted to, sometimes arriving at divergent definitions, as discussed by, e.g., Glăveanu and Kaufman[10] or Runco and Jaeger.[11] Perhaps one of the best-known definitions is the one proposed by Margaret Boden in her study of creativity,[12] a work focused on human cognition but also on computer models and the mechanics of creative processes where she defines creativity as an "ability to come up with ideas or artifacts that are *new*, *surprising* and *valuable*."[13]

Boden's work helps to narrow down what the outputs of creativity can be — ideas and artifacts —, establishes a finite list of criteria for creativity — novelty, surprise, value — and defines creativity as something altogether different from its outputs — as "a process, not the result of a process".[14] This opens the way for new, non-anthropocentric views of creativity and for the development of forms of computational creativity or, if we prefer, artificial creativity (AC).

AC can be seen as a subset of artificial intelligence, in a rationale that connects human creativity to intelligence and thus assumes that the latter is necessary for the former and that AC will inevitably be dependent on AI. More nuanced versions of this view may see creativity (as well as consciousness and other features of the human mind) emerging from intelligence, explicitly linking both. And if this can be true in some conceptions of so-called "strong AI"[15] — a type of AI that would be "human-like"[16] in most or all aspects — and therefore also in what we may call

[6] Vilém Flusser, *Into the Universe of Technical Images*, trans. Nancy Ann Roth (Minneapolis, MN: University of Minnesota Press, 1985).

[7] Ada Lovelace famously articulated this argument in her 1842 notes to Luigi Federico Menabrea's *Sketch of the Analytical Engine Invented by Charles Babbage, Esq.*, an argument that is often cited, notably by Alan Turing in his paper *Intelligent Machinery*.

[8] Gian-Carlo Rota, "The Phenomenology of Mathematical Beauty," in *The Visual Mind II,* ed. Michele Emmer (Cambridge, MA: The MIT Press, 2005), 8-9.

[9] Michael Wooldridge, *The Road to Conscious Machines: The Story of AI* (London: Pelican Books, 2020).

[10] Vlad P. Glăveanu e James C. Kaufman, "Creativity: A Historical Perspective," in *Cambridge Handbook of Creativity*, ed. James C. Kaufman e Robert J. Sternberg (New York, NY: Cambridge University Press, 2019), 11-26.

[11] Mark A. Runco e Garrett J. Jaeger, "The Standard Definition of Creativity," *Creativity Research Journal* 24, no. 1 (2012): 92-96, https://doi.org/10.1080/10400419.2012.650092.

[12] Boden, *Creative Mind*.

[13] Ibid., 1.

[14] David Cope, *Computer Models of Musical Creativity* (Cambridge, MA: The MIT Press, 2005), 44.

[15] Sue Curry Jansen, *What Was Artificial Intelligence?* (mediastudies.press, 2022), https://doi.org/10.32376/3f8575cb.783f45c5

[16] Arlindo Oliveira, *The Digital Mind: How Science Is Redefining Humanity* (Cambridge, MA: The MIT Press, 2017).

strong AC, it is also a perspective that makes sense whenever one broadens the definition of AI so much that it arrives at something that may bear no resemblance whatsoever with human intelligence (or creativity).

In this paper we argue that AC, particularly the type of computational AC we find in current AI, may benefit from intelligence but does not require it. Creativity emerges from complexity and computation and can be developed in ways that do not necessarily fit the definitions (or criteria) for AI.

1.2. Types of Creativity

Boden defines three types of creativity that vaguely correspond to three types of surprise it causes. She terms them *combinatorial* creativity, *exploratory* creativity, and *transformational* creativity. Combinatorial creativity entails the capacity to create new articulations or "unfamiliar combinations" from "familiar ideas" or artifacts. She notes that this is the more common type of creativity in humans and that it can be developed "either deliberately or, often, unconsciously".[17] Exploratory and transformational creativity are more complex because they require a "conceptual space" in one's mind. This concept of conceptual space is not clearly defined. It is alternatively described as a space that is relevant to the tasks at hand and "rich enough to yield indefinitely many surprises".[18] In exploratory creativity, creative processes develop a search in this conceptual space, trying to discover ideas or artifacts that can be new, surprising, and valuable. In transformational creativity the conceptual space is modified, becoming a *new, surprising,* and *valuable* space rife with ideas to discover.

The three types of creativity may have different mechanics, but their boundaries aren't clear-cut. First, often, even simpler processes of combinatorial creativity need to be fed by exploratory processes; otherwise, if all the starting ideas are overly familiar, one can hardly generate much surprise and even less value. Transformational creativity, on the other hand, can be seen as an extreme — or a well-succeeded — type of exploratory creativity. Boden comments on this when she says that it should ideally extend and "perhaps even break out of" the conceptual space it inhabits "and construct another one."[19] A successful transformation must give room to a new conceptual space that itself satisfies the criteria for creativity, which are qualitative rather than quantitative, meaning that these transformations do not need to expand or augment the space but reshape it, even if that entails its decrease.

The three types of creativity can be developed in artificial computational systems, albeit with different degrees of difficulty. Combinatorial creativity is the easiest to implement, and examples of it abound. It is not only easier to model by "picking out two ideas (two data structures) and putting them alongside each other"[20] as it is easy to iterate in open-ended processes. Exploratory and transformation creativity may be more complex to develop, particularly because this development largely depends on how one defines Boden's conceptual space in a computational context. In the next section, we will argue that, although these definitions may vary widely,

[17] Boden, *Creative Mind*, 4.

[18] Ibid., 163.

[19] Ibid., 164.

[20] Ibid., 7.

they do not necessarily require high complexity in models or even software.

For that, we will ground this paper on three assumptions related to AC, namely: Assumption 1) Computational systems have always been good at combinatorial creativity; Assumption 2) Current computational systems are also very good at exploratory creativity; Assumption 3) Computational systems are seen as not being good at, or even unable to, develop transformational creativity.

2. Argument

We will argue that computational systems are capable of being creative,[21] fed by emergent processes and by the very nature of computation and are capable of developing all types of creativity. Ultimately, it can be more difficult for a computational system *not to be creative*, even if residually, than to be creative. However, we will also argue that their creativity may be difficult for humans to recognize, especially when considering these systems and evaluating their creative acts from an anthropocentric perspective. When we use ourselves as the single model and benchmark for intelligence and creativity, we become almost inevitably unable to perceive forms of intelligence and creative processes outside the anthropocentric framework. As we will see, this often happens with creative processes developed by AI systems that are not easily understandable and, thus, seem of limited advantage to humans.

Non-human intelligences and non-human creativity can unquestionably benefit us, and we have been putting them to use in many specialized tasks, resorting to AI systems to, for example, fold proteins, develop medications, analyze data, develop solutions for industrial and engineering processes, and many other applications. More recently, these systems crossed over to the eye of the general public through so-called generative AI systems fed by large language models (LLM). These systems, the better-known of which at the time of writing is ChatGPT, can interpret, manipulate, and generate several types of signs across several modalities and can communicate with humans using text, images, sound, or any other means. This crossover to much wider user bases and broader sets of tasks started to make clear that these systems have limited usefulness, particularly when it comes to the aesthetic relationships we can develop with them. They seem to understand a lot about the world (or about the information we create and let loose in the world), but at the same time, they often fall into roadblocks that painfully reveal how much they do not understand the world. Or how they do not understand it in a way that is similar to ours.

[21] This position is shared by many authors, and although it is not this paper's central goal to defend it, we should point to the view that "Creativity does not depend exclusively on human inspiration, but can originate from other sources, such as machine programs." as David Cope puts it in *Computer Models of Musical Creativity*, is one that is generally accepted in the literature, although not without some reservations, mostly tied to details in defining creativity. For an example of this, we can see how Melanie Mitchell, in *Artificial Intelligence: A Guide for Thinking Humans*, defends that "There are many ways in which a computer program can generate things that its programmer never thought of. (…) I believe that it is possible, in principle, for a computer to be creative." whilst noting that "being creative entails being able to understand and judge what one has created" and that therefore "no existing computer can be said to be creative." We will return to this later.

We argue that the usefulness of these systems, and perhaps of most future AI systems, particularly when targeted at creative and aesthetic applications, lingers in this issue of incomprehension and unreachability. We cannot easily solve this, or at least we cannot solve it on our own. We need to work together with artificial intelligences, not only requiring them to model and imitate us to communicate with us and cater to our needs, but we also need to understand the AIs' worldviews, umwelts[22] and models to be able to understand and unleash their full creative potential.

This requires an ontological turn in science and technology studies, but also in the humanities, where art, design, social sciences, and other fields are primary users and interested parties in these systems. We must resist a tendency to fully anthropomorphize AIs, think about them solely from our human point of view, and be open to at least trying to perceive them in ways that may seem alien to us. It is unclear to which degree we can do this or even if we can. Perhaps more than anthropomorphizing, we are anthropocentric and unable to not anthropomorphize. The fact is that this -morphizing is a two-way street, an aesthetic and ecological process in which, as we receive something, we are also forced to give.[23]

3. Development

We already commented on how the first of Boden's types of creativity, combinatorial, is not only the most common as well as the easiest to model computationally. But what about the other two types, exploratory and transformational? When discussing the first of these, Boden describes it as a generative system, defining it as a set of data and action rules that will, in principle, have the potential to visit or generate every location within a given conceptual space, a number of locations that may be "very large, even infinite."[24] Once again, what a conceptual space is or can be is vaguely described. In a computational context, we may conceive of this in several different ways, from structured problem descriptions in the form of models, algorithms, simulations, etc., but we can also, in simpler but perhaps more encompassing terms, think about the phase space of any computation as equivalent to Boden's conceptual space.[25] A computation's phase space, its field of possibilities, is the aggregate of all possible states it may generate throughout its running. This includes all known states and all yet unknown states, which for the majority of programs are perhaps themselves also in the majority. By systematically exploring this phase space, a computation can eventually arrive at the production of novelty. What is necessary for this to happen is, on the one hand, for those states to already exist, in a latent form, in the computation's phase space, and for it to be discovered, first by the computation arriving at it, and then for the computation, or some other agent, to select it, by recognizing novelty, potential usefulness, and value.

If we consider the phase space of a computation to be its conceptual space, the field

[22] Rosemary Lee, "The Limits of Algorithmic Perception: Technological Umwelt," in *Politics of the Machines: Art and After*, Copenhagen 2018.

[23] Timothy Morton, *Humankind: Solidarity with Nonhuman People* (London: Verso, 2017), 129.

[24] Boden, *Creative Mind*, 90.

[25] Miguel Carvalhais, *Art and Computation* (Rotterdam: V2_Publishing, 2022).

of possibilities explored in creative processes, then what does its transformation amount to? Boden hints at an answer by mentioning how "AI-programs can even transform their conceptual space, by altering their own rules".[26] A change in the rules of a program will often result in a transformation of its phase space. Therefore, what some AI systems do, but also what evolutionary approaches to programming do, may well give rise to instances of transformational creativity. But we should not forget that computations are more than programs. A computation is not the code that is executed but rather what happens during the execution. As such, a computation depends on (and is transformed by) code, the data fed to it, and how other systems may interact. The shape of the phase space and the locations that may be visited in it are also dependent on the irreducible aspects of computation, of what happens when a program is running and how exactly it runs, something that programmers try to control in minute detail but that, ultimately, may never do.[27] Naturally, besides this, a computation's outputs will still need to satisfy Boden's criteria for creativity.

3.1. Boden's criteria for creativity

The first of Boden's criteria, novelty, can generally be assessed through relatively simple processes of comparison, for example, with a system's data sources or with the history of its states. If in a relatively recent past, we could perhaps think of this as an absolute criterium, the sheer dimension of the corpora of data that feed current LLMs makes it very difficult to ascertain whether a given output from one of these systems is, or is not, novel (or to which degree can we say that it is novel, in a scale of derivativeness that is also difficult to define).

The other two criteria, surprise, and value are observer- and context-dependent. Boden discusses this when she argues for the existence of two types of creativity — and results of creative processes — that she terms psychological (or relative) and historical (or absolute) creativity (and novelty). The first of these produces surprise and value locally to the creative system, the latter produces novelty that is absolute, that "has arisen for the first time in human history".[28] One assumes that all the acts of absolute creativity must also be acts of relative creativity, but such an observation also entails that the creative system itself develops the assessment of surprise and value.

A detailed discussion of how and if we can understand surprise in a computational system — and of whether it requires mental states — falls outside of the scope of this paper. The same can be said about value. Many authors defend that although creativity may be, in principle, possible to develop computationally, it most likely requires the capacity to understand and judge what is created.[29] This is what Cope terms as the "consciousness argument", the fact "that creativity requires consciousness"[30] and that Boden also discusses in her "Lovelace-questions", particularly in the third one, about how being creative "requires a capacity for critical

[26] Boden, *Creative Mind*, 9.

[27] Stephen Wolfram, *A New Kind of Science* (Champaign, IL: Wolfram Media, 2002).

[28] Boden, *Creative Mind*, 2.

[29] Melanie Mitchell, *Artificial Intelligence: A Guide for Thinking Humans* (London: Pelican Books, 2019), 359.

[30] Boden, *Creative Mind*, 9.

evaluation".[31] Our proposal is to follow the questions raised by Cope when he questions "is it important that creators know they are creating?" and "is it important that creators appreciate their own creations?"[32] and propose a negative answer to both. A creative system may be involved in a larger system comprising other systems that can be aware of creative outputs and capable of recognizing value and being surprised. Even if we narrow our discussion of creativity to humans, we can find examples of creators who may be unaware of the surprise or value in their outputs.

3.2. The problem of imitation

Imitation has been a central paradigm in the history of digital computation and, subsequently, in AI. When in 1936, Turing postulated the foundational concepts of digital computation,[33] he outlined the workings of what he called an Automatic Computing Engine (ACE), a machine able to compute any computable numbers or sequences, but not *all* computable numbers or sequences.[34] In the same paper, he also proposed a different machine, the Universal Computing Engine (UCE), that could imitate all ACEs, potentially becoming different computational machines. A UCE reads the description of an ACE, interprets it and starts operating like that ACE, producing the same computational process and, thus, the very same outputs. It is important to note that this description focuses on the computational level of the machine, i.e., the information processing and information-generating steps of the machine, and not its physical or mechanical parts. That physical substrate of a computational machine is necessary to the computational process, but Turing proved that a computational process can be abstracted from its physical substrate and replicated across a variety of different physical machines. Computation is substrate-independent; computation is not particles but rather a pattern in the arrangement of particles, and whatever physical systems may allow that pattern to exist are therefore able to support the same computation.[35]

In this sense, computation is not a simulation of an exogenous phenomenon, but an actual entity produced by computing machines when they *become* other computational machines and that can be produced inside other computations when they themselves are universal and can become the substrate for new computations. We can, of course, describe these processes as imitations, but they are far more than that.[36] These are processes of *becoming*.

The imitation paradigm has been ubiquitous throughout the history of computation, shaping the development of computational machines, operating systems, applications, computational media, and many other fields with which computation intersects. Among those is, of course, AI. We can

[31] Ibid., 18.

[32] Ibid., 9.

[33] Alan Mathison Turing, "On Computable Numbers, with an Application to the Entscheidungsproblem," Proceed*ings of the London Mathematical Society* 2, no. 42 (1936), 230-65.

[34] The machine was composed of a physical layer but also of a ruleal layer. The physical layer was standard and unchangeable, and it would, paired to a ruleset, compute a particular number or sequence, but not a different number or sequence. Modifying the rules means modifying the machine, so two different machines would produce two different numbers or sequences.

[35] Carvalhais, *Art and Computation*.

[36] For a more in-depth discussion of this question, see Carvalhais, *Art and Computation*.

place the roots of current approaches to AI also with Turing and his papers *Intelligent Machinery*,[37] where he discusses whether machines can exhibit intelligent behavior, and *Computing Machines and Intelligence*,[38] where he starts from the question "Can machines think?" The work developed in these papers shaped perspectives on AI until our days and established conceptual bases that are still very strong. Chief among these is the idea that machines can imitate parts of the human and that they can "grow", "learn", and be "educated". Another very strong idea in these papers is an anthropocentric definition of intelligence and intelligent behavior as that of imitating human behavior. The *Imitation Game* that Turing proposed in 1950 as a test for intelligence is predicated on a computer being able to imitate the behaviors of a human, on a computer being able to pass as a human in a very particular, strictly informational context.[39]

The idea that human intelligence can be recreated in computational contexts is pervasive in contemporary AI and its public perception. Furthermore, there is a widespread belief that AI will lead to a form of artificial general intelligence (AGI) that is domain-general and at least comparable to the human level of intelligence (when not far surpassing it). This is an idea that Turing already hinted at when he suggested that the development of intelligent machines could lead to a progressive and iterative process where intelligence would increase beyond human levels.[40] It is also an idea central to much of the work developed during the early years of research on AI, a period now referred to as the era of *Expert Systems* or *Good Old Fashioned AI* (GOFAI). Imitation was fundamental to GOFAI, either of aspects of the human body or of physical or mental processes translated to computational systems that would subsequently be able to operate as them. But even more recent approaches to AI, following connectionist or subsymbolic paradigms, are still in the shadow of imitation: of human intelligence, human language, human media, human neurons, or other cognitive processes, with processes of validation that are also largely centered on humans.

This ubiquity of imitation is one of the reasons why some terminology used by computer sciences and many fields that intersect it is often ambiguous. An example of such terms is found with "model", which Boden uses in her definition of AC. If we understand "model" in the sense of a representation of something, of a simplified description of something, or even as something that is used as a template to follow or imitate, we won't fall far outside a common interpretation of the word in computational contexts. A process exists in the world or the programmer's mind; such process is abstracted and coded into an algorithm that is then enacted by the computing machine, giving rise to a

[37] Alan Mathison Turing, "Intelligent Machinery," in *Mechanical Intelligence*, ed. D.C. Ince (Amsterdam: Elsevier Science Publishers B. V., 1948; repr., 1992), 107-27.

[38] Alan Mathison Turing, "Computing Machinery and Intelligence," *Mind* 59 (1950), 433-60.

[39] The imitation that the *Turing Test*, as it is more commonly known as today, was purely informational. The test consisted of a conversation between human judges and a computer that was realized through text only, so as to not require the computer to imitate all physiological and behavioral aspects of a human but only its intelligence (itself limited to language and to the capability to generate a discourse and maintain a conversation).

[40] Alan Mathison Turing, "Intelligent Machinery, a Heretical Theory," *Philosophia Mathematica* 4 (1996), 256-60. Originally written in 1951.

computation that imitates or even simulates the original process.

But "model" can describe something different from an abstraction of a process, an algorithm, or a program. It can describe the computation itself, not what is in the program but rather what happens when such a program is enacted. Not the machine (of which the program is part of) but the machine in operation, the process. Code and algorithms, as frameworks for computation, are always in the past.[41] They capture processes by looking back and trying to automate the past. When code is put into action, on the other hand, computation emerges along with futurality.[42] Computation is a process of continuous self-construction, from where future radiates, along with surprise. Computation is "an entity that is also its own creation, and whose main activity is to create itself".[43] And perhaps except for the simplest of computations, this also entails self-transformation and the capacity to reinvent itself. This apparently contradicts one of the main axioms of digital computation, its determinism, but most computations are simultaneously determinist and irreducible,[44] taking us to states and outputs that we are not able to predict or anticipate. This is apparently paradoxical, but computation is full of paradoxes.

3.3. Failing to recognize creativity

Why do we tend to accept that, as in assumption number three above, computational systems are not good at, or even unable to, develop transformational creativity?

When discussing the very possibility of AI in 1948 and 1905, Turing already listed a number of objections to its acceptance, talking about human exceptionality and religious belief, or about how different computers are from all the machines humans had historically dealt with, or even the limits of computation.[45] He also listed an objection related to Lovelace's comments on how a machine is not able to do anything it hasn't been explicitly told how to do and, henceforth, how any intelligence or creativity it may demonstrate can be nothing but transferred from the human that programmed it. Furthermore, he also lists objections related to what he calls the "heads in the sand" argument — in which the fear of the consequences of machine intelligence leads us to hope and even believe that it is not possible[46] — along with objections related to consciousness, continuity in the human nervous system, and others. To all this, Turing answers, defending the case for AI and, by extension, for AC.

Several of the objections listed by Turing and many other arguments against AI that have been presented over the years, such as the famous "Chinese Room Argument" by John Searle,[47] are predicated on the paradigm of imitation, assuming that the model for intelligence and creativity is the human and that the ultimate goal for AI or

[41] Morton, *Humankind*.

[42] Timothy Morton, *Hyperobjects: Philosophy and Ecology after the End of the World* (Minneapolis, MN: University of Minnesota Press, 2013).

[43] Carvalhais, *Art and Computation*, 98.

[44] Wolfram, *A New Kind of Science*.

[45] Turing, *Intelligent Machinery*.

[46] Turing, *Computing Machinery and Intelligence*.

[47] John R. Searle, "Minds, Brains, and Programs," in *The Mind's I: Fantasies and Reflections on Self and Soul*, ed. Douglas R. Hofstadter e Daniel C. Dennett (New York, NY: Basic Books, 1981; repr., 2000), 353-73.

AC is human-like.[48] An obvious problem with this stance is how, because we expect the behavior of systems to be human-like and because we have a tendency to anthropomorphize everything,[49] we react to systems that may display external behaviors that match our expectations and project intelligence, creativity, and other traits, even in cases where none of these may be present. This leads us to the detection of false positives, a phenomenon first encountered by Joseph Weizenbaum in the relationships that people developed with his early experiment in natural language processing, a program called ELIZA. Weizenbaum alerted for this in his book *Computer Power and Human Reason*,[50] and the effect has subsequently been broadly discussed. The Eliza effect, as it became known, describes this "susceptibility of people to read far more understanding than is warranted into strings of symbols — especially words — strung together by computers",[51] a phenomenon that is derived from our difficulties in recognizing how wired we are to anthropomorphize.[52]

We validate systems that are not necessarily intelligent or creative, and as we do this, we also fail to recognize, engage with, and benefit from forms of intelligence and creativity that are not human-like. By failing to detect human-like traits in the behavior of systems, we assume they are not intelligent or creative.[53] All approaches to AI have been marred to some extent by complexity and opacity, but the newer and pervasive, subsymbolic approaches are particularly prone to develop processes whose processes are impenetrable to humans and that become causal black boxes. There is early evidence pointing to recent AI systems, such as LLMs being able to develop representations and a "nonlinear internal representation" that can be seen as a model of the world.[54] We may not, however, expect that from the limited information that is used to train these systems, they may be able to develop something that can even approximate human understanding.[55] If we add how contrasting the cognition, perception, and even physiology of these systems are, we can conclude that although LLMs and other AI and computational systems can interpret information — both at a lower level when they interpret code and at a higher level when natural language is processed — the models they develop are not, for the most part, comparable with human models. This doesn't mean that, despite differences, they may not be compatible or translatable.

Intelligence is an emergent phenomenon, and concepts such as *thinking* or *mind* can

[48] Or even god-like, in some more utopian discourses on AI, AGI and artificial super intelligence.
[49] Bruce Hood, *The Domesticated Brain* (London: Pelican Books, 2014).
[50] Joseph Weizenbaum, *Computer Power and Human Reason: From Judgment to Calculation* (San Francisco, CA: W. H. Freeman and Company, 1976).
[51] Douglas R. Hofstadter, *Fluid Concepts and Creative Analogies: Computer Models of the Fundamental Mechanisms of Thought* (London: Allen Lane, 1995).
[52] Michael S. Gazzaniga, *Who's in Charge?: Free Will and the Science of the Brain* (New York, NY: Ecco, 2011).
[53] Anil Seth, *Being You: A New Science of Consciousness* (London: Faber & Faber, 2021).
[54] Kenneth Li, Aspen K. Hopkins, David Bau, Fernanda Viégas, Hanspeter Pfister, and Martin Wattenberg. "Emergent World Representations: Exploring a Sequence Model Trained on a Synthetic Task." (2022). arXiv:2210.13382. Accessed October 07, 2023. https://doi.org/10.48550/arXiv.2210.13382.
[55] Jacob Browning and Yann LeCun, "AI and the Limits of Language," *Noēma*, 2022, https://www.noemamag.com/ai-and-the-limits-of-language/.

be defined ecologically and in non-anthropocentric terms, recognizing not only how other living beings cognize, think, and create but also how non-living and artificial beings can, in some cases, do the same. If we define *thinking* as a process of "changing inputs into outputs"[56] or processing information, as Ogas and Gaddam propose, and *mind* as something that "is not defined by the identity of the physical stuff inside an organism", i.e., neurons, molecules and chemical processes, or chips, memory registers and code but is rather "defined by how its thinking elements *interact*",[57] then we will be better equipped to recognize minds as processes and resist anthropomorphism. We may then find it easier to recognize and nurture para-human intelligences rather than searching (or fearing) super-human dystopias.

3.4. Recognizing creativity

Board games have a long history of being used to compare humans and machines.[58] The skills of AI systems in chess have since long surpassed human skills, and current chess engines far outperform any human in the capacity to iterate positions and moves but also in creative terms. The creativity of AI chess engines can be attested by how the Stockfish engine can rediscover peak-creative moves from the history of chess, such as Frank Marshall's 1912 move 23 of the "Gold Coins" game.[59] Stockfish finds this in fractions of a second, trivializing what is still seen as a genius move. A similar example can be found in move 47, played by Alexey Shirov against Veselin Topalov in Linares in 1998. This move denotes a deep knowledge of endgames with bishops of opposite colors and an intuition only attainable by chess Grand Masters after thousands of hours of practice. In human terms, such a move is made possible due to a type of understanding that is far outside of calculation speed, and that relies on pattern recognition and practice-based strategic skills.[60] Chess engines are now able to come up with this move in mere seconds, but as recently as 2020, this move still eluded them.

An even more surprising example from chess is Nigel Short's 1991 move against Jan Timman in Tilburg. This counter-intuitive strategy exposes the king by using it to assist the queen in checkmating the opponent. Once more, Stockfish only requires seconds to come up with a winning strategy, being even able to propose moves that accelerate the win for White. We can understand the ontologic gap in chess in Anatoly Karpov's move 24 from his 1974 Nice game against Wolfgang Unzicker, a highly regarded move for its strategic understanding of chess and ability to anticipate the opponent's moves. It is also a move that computers never come up with, as engines propose lists of moves that, from their perspective, are far more effective. But Karpov moved in a completely different way that is equally advantageous, and that clearly shows different ways of thinking.

[56] Ogi Ogas and Sai Gaddam, *Journey of the Mind: How Thinking Emerged from Chaos* (New York, NY: W. W. Norton & Company, 2022), 11.
[57] Ibid., 22.
[58] Turing also introduces that idea and the possibility to use games such as checkers or chess as testing grounds for AI.
[59] Edward Winter, "Marshall's 'Gold Coins' Game," *Chess History*, December 18, 2022, https://www.chesshistory.com/winter/extra/marshall1.html.
[60] William G. Chase and Herbert A. Simon, "Perception in Chess," *Cognitive Psychology* 4, no. 1 (January 1973), 55-81, https://doi.org/10.1016/0010-0285(73)90004-2.

Where chess engines are still falling behind is in what chess slang terms *fortresses* and in very odd material-imbalanced positions.[61] There are examples where a severely imbalanced position may require the involuntary collaboration of the opponent to secure a win.[62] John D. Barrow exemplifies a position in which a human is able to quickly understand the repetition of moves leading to a stalemate and draw, but chess engines repeatedly fail to assess the position correctly. Engines wrongly choose to capture the tower and get in a position that leads to a defeat. What makes this example particularly interesting is how it is still current at the time of writing. Although newer systems avoid the error of capturing the tower, they still assess the position as advantageous to the side with material superiority and propose an endless array of alternative moves that are seemingly oblivious to the inevitable tie. This shows how, despite technical advances, human skills still have a place in chess.

Another important game in this context is go, a context that is more complex than chess by several orders of magnitude.[63] AI has equally surpassed humans in go since Google DeepMind's Alpha Go defeated Lee Sedol in 2016, a match in which AlphaGo played moves lauded by experts as totally original.[64] If AlphaGo was defeated by Sedol in one of the five games they played, more recent systems, such as AlphaGo Zero,[65] are not only super-human in their performance[66] as they come up with novel moves and strategies that bring new insights to the millennia-old tradition of go.[67]

In board games such as chess and go, AIs outpaced humans not only because of their capacity to secure categorical wins but, above all, because they can come up with plays that humans understand as very creative. We can argue that this superiority is only possible because these are closed games, with no hidden information and no elements of chance. Even if the total number of possible states may be vast, it is still limited and within the capability of current computers. As perfect information games, the phase-spaces of chess and go contain every state of a game that just needs to be discovered. Therefore, we can argue that AIs are exceptional in these fields because they develop a type of exploratory creativity in a closed conceptual space and that their performance may be severely penalized in more open and information-incomplete contexts.

This argument is, however, challenged by the performance of AIs in games such as poker. Poker is an imperfect information game in which not all variables are always

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[61] As, for example, the so-called Penrose positions.

[62] An example of such a position can be found in John D. Barrow, *Impossibility: The Limits of Science and the Science of Limits* (Oxford: Oxford University Press, 1998), 87.

[63] Michael W. Eysenck and Christine Eysenck, *AI Vs Humans* (Routledge, 2021), 24.

[64] Steven Borowiec and Tracey Lien, "AlphaGo Beats Human Go Champ in Milestone for Artificial Intelligence," *Los Angeles Times*, 2016, https://www.latimes.com/world/asia/la-fg-korea-alphago-20160312-story.html

[65] AlphaGo Zero is not taught with historical game databases or by playing against human opponents, as AlphaGo was, but rather through iteratively playing against itself.

[66] With just a few hours of training, AlphaGo Zero can be pitted against AlphaGo and defeat it in virtually every game played.

[67] David Silver et al., "Mastering the Game of Go without Human Knowledge," *Nature* 550, no. 7676 (October 1, 2017), 358, https://doi.org/10.1038/nature24270

known or accessible. It is also a game that includes emotional and strategic elements, such as *bluff*, that go beyond a mere capacity to number-crunch probabilities and assess the states of the board. Poker-playing systems, such as Libratus,[68] are currently able to systematically defeat professional players whilst developing global and specific strategies and meta-identify vulnerabilities.[69] Another system, Pluribus, plays against six other players and develops effective strategies in open and unpredictable scenarios, showing "that despite the lack of known strong theoretical guarantees on performance in multiplayer games, there are large-scale, complex multiplayer imperfect-information settings in which a carefully constructed self-play-with-search algorithm can produce superhuman strategies".[70]

In StarCraft II, a real-time strategy game that involves action, resource management, and both collective and individual control of units in the field, research on AI has also been making strides. This game is challenging for its vast array of cyclic and non-transitive strategies and counter-strategies, making the identification of new tactics untenable through rudimentary methods. Furthermore, the action space in StarCraft II is combinatorial, with a horizon of action and planning that includes thousands of decisions made in real-time and imperfect information. By using general-purpose machine learning strategies, such as multi-agent reinforcement learning with human feedback, systems such as AlphaStar have been rated very highly in games of StarCraft II, achieving the status of Grand Master and defeating 99.8% of players in the official ranking,[71] an accolade that would not be possible without a strong capacity for creativity.

3.5. Computation and creativity

It can be argued that computation is a medium where creativity is natural, almost inevitable. Most computations tend to be sufficiently complex to become, as Wolfram puts it, irreducible.[72] This means that, despite being strictly deterministic, they are also highly unpredictable, and their outputs cannot be anticipated in any way. The only way we have to find out what a computation produces in the long term, how it gets there,[73] and even if it stops at some point,[74] is to wait and observe it. This "Principle of Computational Irreducibility" has far-reaching consequences in our relationships with computation. For once, in our increasingly computational media, that because of computation become discorrelated[75] and divergent. Computational media can create new signs and

[68] Noam Brown and Tuomas Sandholm, "Superhuman AI for Heads-up No-Limit Poker: Libratus Beats Top Professionals," *Science* 359, no. 6374 (2017), 418–24, https://doi.org/10.1126/science.aao1733.

[69] I.e., to understand how opponents may identify vulnerabilities in its own strategy, thus iterating it.

[70] Noam Brown and Tuomas Sandholm, "Superhuman AI for Multiplayer Poker," *Science* 365, no. 6456 (2019), 885–90, https://doi.org/10.1126/science.aay2400.

[71] Oriol Vinyals et al., "Grandmaster Level in StarCraft II Using Multi-Agent Reinforcement Learning," *Nature* 575, no. 7782 (2019), 350–54, https://doi.org/10.1038/s41586-019-1724-z

[72] Wolfram, *A New Kind of Science*.

[73] As Wolfram also discusses a more recent work, in complex phase-spaces, even when computations predictably arrive at the same states, they may do so through a diversity of causal pathways, i.e., following different paths in that phase-space. See Stephen Wolfram, *A Project to Find the Fundamental Theory of Physics*. (Champaign, IL: Wolfram Media, 2020).

[74] As Turing initially researched in his paper on computable numbers.

[75] Shane Denson, *Discorrelated Images*. (Durham, NC: Duke University Press, 2020).

information on their own, endowed as they are with agency and autonomy in ways that no media in history previously had.[76] The stability we always sought for in media is something that computational media promise us, and even if they try to deliver on this promise, they are ultimately bound to fail it.

Computations are always improvisational as, though bound by their rules, each action and choice they perform are inevitably contingent and decided at the moment. The main task of computation is ontological; it is to create itself, being for itself.[77] And the surface, sensorial level of a computation is always produced by a deep, hidden, and mostly inscrutable subface[78] level. The computational is non-perceptual and spectral, found in the processes within and beyond physical objects. It is not at the surface but only manifested through it.[79] Through the rift created by the surface-subface duality, the computational radiates towards humans and other systems, muddling the borders of what and where the computation is, and to which extent humans or other systems it may interact with are independent of the computation, or indeed, a part of it.

This affects all computational systems, from simple task-oriented devices to complex software, computational media, and AI systems. They are all computational and share ontological traits. They are imagination machines that force us to enter indirect relationships mediated by their sensorial effusions and interfaces. As we interact with them and progressively discover the processes at their core, we develop a relationship that allows us to look ahead in their behaviors, to understand what is present and what is absent, and to attune to their conceptual spaces.[80] We do this by developing processes of computational reading that are supported by an algorithmic gaze directed at the subface through the surface.[81] Through this, we find that computational systems do not merely encode some form of human creativity but manifest creative agency in their open-ended future. As they compute, they radiate future and output new states that are also their new beings and that are irreducible, with a high potential for novelty, surprise, and value.

But this creative potential and the intelligences that support it, are not, for the most part, imitating human minds and intelligences. Even when this is the explicit goal, the end results are deeply non-human and oftentimes not even close enough to be human-like to drive us into feelings of uncanniness. Whether or not, at some point, it becomes possible to fully recreate human minds, intelligences, and creativity in computational contexts is something we can only speculate on at this point, but recent

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[76] Pierre Lévy, *Collective Intelligence: Mankind's Emerging World in Cyberspace*, trans. Robert Bononno (Cambridge, MA: Perseus Books, 1997).

[77] Carvalhais, *Art and Computation*, 52.

[78] As Frieder Nake calls it when he discusses the dual nature of the algorithmic sign. Frieder Nake, "The Disappearing Masterpiece." In *xCoAx 2016*, 11-26. Bergamo, 2016.

[79] Miguel Carvalhais and Rosemary Lee. "Spectral and Procedural Creativity: A Perspective from Computational Art." *Transformations*, no. 36 (2022), 71-81. http://www.transformationsjournal.org/wp-content/uploads/2022/02/Trans36_05_carvalhais_lee.pdf

[80] Ibid., 99.

[81] Miguel Carvalhais, "Breaking the Black Box: Procedural Reading, Creation of Meaning and Closure in Computational Artworks," in *Artificial Intelligence and the Arts: Computational Creativity, Artistic Behavior, and Tools for Creatives*, ed. Penousal Machado, Juan Romero, and Gary Greenfield (Berlin: Springer, 2021), 347-362.

work in the field curtails optimism,[82] at least in the near future.

Intelligent and creative machines are not a pipe dream, even if human-like intelligent and creative machines may be. They are very different from us and will most likely continue to be so. They are alien forms of intelligence with which we can develop productive relationships and partnerships but that we will not be able to fully understand and relate to as being analogous to humans. More than McLuhanian extensions of humans, computational AIs are, therefore, autonomous and independent systems that we can try to understand, empathize with, even become a part of.[83] But we should not relate to them by following models familiar to other tools or media, but perhaps by learning from how we have been relating to other non-human intelligences. The contrast between human intelligence and AIs is perhaps not, as Weizenbaum defended in 1976, one between judgment and calculation[84] but one between two types of thinking and of minds that are ontologically very different.

4. An ontological turn

To understand how these relationships can be developed, we can look to anthropology and to a movement within this discipline that defends an *ontological turn*, a repositioning towards the fundamental questions of being, existence and reality at the core of anthropological analyses. This change of perspective was spearheaded by authors such as Eduardo Viveiros de Castro, Martin Holbraad, and Morten Pedersen[85] who tried to answer approaches that used the concept of "culture" to explain human phenomena. The ontological turn rejects separating the symbolic from the material and emphasizes the latter. Furthermore, it proposes that anthropologists start their work from the ideas found in their research, as strange and surprising as these are, instead of trying to fit these ideas in pre-existing categories.[86]

Adopting this ontological focus is not a trivial matter, as it forces researchers to confront Eurocentric assumptions and biases. Instead of observing other cultures and realtors through a Western lens, the ontological turn pushes anthropologists to consider multiple ontologies as equally valid in an epistemological exercise that

[82] Iris van Rooij, Olivia Guest, Federico Adolfi, Ronald de Haan, Antonina Kolokolova, and Patricia Rich, "Reclaiming AI as a Theoretical Tool for Cognitive Science," *PsyArXiv,* (2023), accessed September 7, 2023, https://doi.org/10.31234/osf.io/4cbuv

[83] If a running computation interacts with a different system, thus exchanging information and hybridizing processes, we can consider that a new system is created, one that aggregates both computations. Likewise, if a human interacts with a computation, we can see them as temporarily stepping into the computation and becoming part of a new system with it.

[84] Weizenbaum, *Computer Power and Human Reason*.

[85] Martin Holbraad and Morten Axel Pedersen, "Planet M: The intense abstraction of Marilyn Strathern," *Anthropological Theory* 9 (2009), 371-394; Martin Holbraad and Morten Axel Pedersen, *The Ontological Turn: An Anthropological Exposition* (Cambridge: Cambridge University Press, 2017). Martin Holbraad, Morten Axel Pedersen and Eduardo Viveiros de Castro, "The Politics of Ontology: Anthropological Positions. Theorizing the Contemporary." *Fieldsights*, January 13, 2014. https://culanth.org/fieldsights/the-politics-of-ontology-anthropological-positions.

[86] Paolo Heywood, "Chapter 14: The Ontological Turn School or Style?" in *Schools and Styles of Anthropological Theory*, edited by Matei Candea (New York, NY: Routledge, 2018), 224-35.

aims to not only promote tolerance but also to underline a recognition of diversity, including other cosmogonies.

In this context, we are interested in how the ontological turn can be understood and enacted, in fields beyond anthropology. In science and technology studies, for example, such a change in perspective could help rethink certain dualistic models that artificially separate science from society, technology from culture, and so forth.[87] In the humanities, artistic studies, and creative practices that use AI or intersect with it in any way, an ontological turn can open new perspectives. AI systems have emerging behaviors that cannot be explained or interpreted solely from a human-centered matrix. As such, developing methods that work as heuristic tools that catalyze richer and more creative partnerships between humans and AIs becomes crucial. Refusing to anthropomorphize AI systems may lead us to a deeper understanding of their capabilities, limitations, and affordances.

In conclusion, if we want to maximize the broad creative possibilities of human-machine symbiosis, we cannot afford to adopt non-anthropocentric approaches. The ontological turn, emphasizing plurality and complexity in the ways of being in the world, world views, world models, and umwelts, offers useful methodological and epistemological frameworks for exploring the emerging frontiers of innovation and collaboration.

[87] In this respect, the work developed by Bruno Latour on Actor-Network Theory is particularly relevant. ANT is a methodological approach that challenges the traditional divisions between subjects and objects, nature and culture, human and non-human. Latour argues that in any system, be it scientific, social, or technological, all elements are intrinsically connected in a complex mesh of relationships. In this sense, ANT can be seen as a complement, or even a precursor of the ideas promoted by the ontological turn, as it also insists in the need to rethink fundamental categories and the way how they interact in a complex system. See Matei Candea, "No Actor, No Network, No Theory: Bruno Latour's Anthropology of the Moderns," in *Schools and Styles of Anthropological Theory*, ed. Matei Candea (New York: Routledge, 2018), 208-23. More recently, the ideas put forward by Object-Oriented Ontology take this even further, giving equal attention to all objects, regardless of these being "human, non-human, natural, cultural, real or fictional." See Graham Harman, *Object-Oriented Ontology: A New Theory of Everything* (London: Pelican Books, 2018).

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