
Machines That Create: Contingent Computation and Generative AI

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Abstract

In this article, M. Beatrice Fazi takes up *Media Theory*'s invitation to engage with Alan Díaz Alva's analysis of her philosophical work on contingency in computation. The central argument of Fazi's *Contingent Computation: Abstraction, Experience, and Indeterminacy in Computational Aesthetics* is that computation can be productive of ontological novelty. This piece revisits that argument in the light of the technological developments that have occurred since 2018, when the book was published. Focusing on generative artificial intelligence (generative AI), the article considers how the concepts of generativity, aesthetics and contingency are tackled in the book and in present-day debates about generative AI systems.

Keywords

aesthetics, computation, contingency, creativity, generative artificial intelligence, ontology

Introduction

My book *Contingent Computation: Abstraction, Experience, and Indeterminacy in Computational Aesthetics* was published in 2018. Its main argument was that computation can be productive of ontological novelty. Here, I am accepting the invitation of *Media Theory* to engage with Alan Díaz Alva's article (published by the journal in December 2023) and its analysis of *Contingent Computation* as an opportunity to address that argument again, particularly with regard to the technological developments that have occurred since the book was published.

As I write this, in the summer of 2024, it is impossible not to observe how pervasive statements about the generativity of computers are today. Broadcasters, journalists, legislators, lawyers, marketing consultants, business experts, product developers, advertising executives, health professionals, educators, artists, filmmakers, designers, animators, sociologists, psychologists, media theorists, data scientists, software developers, philosophers and ethicists – these are just some of the many heterogeneous categories of interested parties with an intellectual or practical stake in current discourses on ‘generative artificial intelligence’ (generative AI). This expression denotes computing technologies that can produce high-quality content, such as text, audio, video and images, as well as code and synthetic data, often in response to prompts provided in natural language. Since the early 2020s, generative AI has had a significant impact on public consciousness due to its convincing results and accessibility via user-friendly interfaces.

Although various generative techniques have been successful, the most discussed AI systems employ transformer-based deep neural networks, which build on the previous decade’s accomplishments in machine learning and related collective interest in computer programmes exhibiting a degree of autonomous agency.¹ While with machine learning, the enthusiasm (and, in some cases, hype) concerned prediction as a means of automated selection, classification and recognition, the different associated enthusiasms (and disappointments) attending generative AI derive from its affordance of a new kind of automated autonomy. These generative technologies still learn structures from their training data, yet prediction is geared towards producing new data. In other words, these AI systems do not look for patterns just to make a decision, as machine learning based on discriminative models does (e.g. answering a yes/no question, such as ‘Is this a cat?’). Rather, they output novel data, which resemble the characteristics of the training examples the patterns were originally extracted from (e.g. responding to the prompt of drawing a cat after having seen many examples of what a cat looks like). Generative AI has now become mainstream in ways that other AI techniques had not.² Although researchers have been experimenting with generative computing programmes since the 1960s, in the present technocultural context the very idea of ‘machines that create’ is taken to signal an inflection point, as heralding a new,

contemporary technological paradigm and representing a disruptive phase in the history of computing, altering the way in which society and economy operate.

Readers of *Contingent Computation* have commented that my 2018 book seems prescient of today's climate, in which the generative potential of computation has become the object of much attention. Generative AI systems produce outputs as a form of creation and offer something technically distinctive with respect to other types of computational systems. Computation, moreover, has begun to be addressed more speculatively in debates attempting to grasp the conceptual implications of such generativity. Indeed, *Contingent Computation* wanted to unsettle orthodox conceptualisations of computational technologies, so I welcome the opportunities that present and future AI research opens up for a speculative philosophy of computation.³ At the same time, however, I would stress that there are significant dissimilarities between my philosophical understanding of the creative potential of computational procedures and the modes in which such generativity is considered in popular discourses about generative AI programmes like ChatGPT, Dall-E and Sora. Here, I expand on the three most fundamental of these differences.

Generativity

First, it is important to consider the perceived extents and purposes of machines that create. What is generative of what, how and why? *Contingent Computation* aimed to demonstrate that all computation is generative. This is an ontological argument. I proposed that a computational procedure should be understood as a process of self-actualisation, as a way of determining indeterminacy that begins and ends with its own self-production. Computational processing, I argued, should be understood not as a reductive matrix of total determinism but rather in terms of discrete and dynamic processes of determination. In this sense, all computation can be said to be generative of novelty because it has an internal potential to actualise itself. Novelty in computation is then expressed not by computers doing something strange but by a computational process that does nothing else than what it was supposed to do – that is, it brings itself into being.

The qualifier in the phrase 'generative AI' is, contrarily, more limited; 'generative' is not meant to advance an ontological characterisation of computation but to highlight,

descriptively, the generative models from probability and statistics that these programmes rely on. Because of the type of content that generative AI is primarily used to produce (i.e. media content) and its relatively easy access these days, it has extended into the domains of the creative industries and the arts and humanities. Such media content creation is seen to raise questions about ‘computational creativity’, which themselves have a long history in the interdisciplinary field of research so named.⁴ The fact that generative AI is successfully applied to creative fields and supports the work of creative professionals has prompted renewed examinations of what creativity is – with questions, for instance, about whether creativity is a mental disposition, a faculty or an ability that can ever be explicated, formalised, learned and replicated artificially.⁵ Famously formulated by Turing (1950), the question ‘Can machines think?’ may well be emblematic of AI research. ‘Can machines create?’ is, however, a strictly related query, also via another question, ‘Can machines understand?’, which is particularly relevant to generative AI and its ostensible linguistic competence (traditionally believed to involve some proficiency in meaning making).

Aesthetics

Another fundamental difference concerns the sense of aesthetics mobilised in *Contingent Computation* and that adopted in debates about generative AI. Were we to sketch the categories of reception of generative AI and related points of controversy, we might start by identifying the voice of the tech enthusiast who is curious about the future and thinks it cannot be stopped but who is oblivious to the political economy that sustains the fatalism of such a techno-embrace. We could then outline another position that holds that the human must be defended, that something is lost through and by computational automation and that nothing will ever replace the authenticity of an intentional soul. Finally come mentions of meaning and mediation; according to this view, creative work derived from the automated manipulation of datasets may be possible, and ghosts in the shell may produce surprising outputs, but value is something given through social practice and expertise so does not belong to what is understood as just a perfunctory tool.

These positions exemplify long-standing topics in aesthetics as a philosophical discipline, such as the role of artistic production, the difference between good art and

bad art and the responsibilities of an artist as a creator. Since generative AI produces artefacts that can be addressed via such traditional aesthetic values – for instance, one could ask what genre a machine-generated essay belongs to or whether a synthetic image is beautiful, and the outputs of generative AI are, in fact, often likened to artworks – this well-established sense of aesthetics and aesthetic proprieties is what primarily finds expression and becomes discussed in current debates about these technologies.

Contingent Computation approached aesthetics differently. In my philosophical system, creativity pertains to aesthetic investigations not so much because of artistic motivation, artistic production or art at large. I take aesthetics to be concerned with creativity because I understand aesthetics metaphysically, as a study of the generative potential of the real. I draw from a lineage within continental philosophy that approaches aesthetics in ontological terms. This points to a pre-Hegelian reworking of aesthetic inquiries.⁶ My aesthetic proposition, however, is also post-Kantian for it advances an investigation meant to address the production of reality in terms of the conditions of possibility of the real. The pursuit of this ontological aesthetics (or aesthetic ontology) is key to the development of the concept of contingency in computation that I proposed, and vice versa. My guiding question for *Contingent Computation* was the following: if we want to address computation according to this ontological understanding of aesthetics, what should we be doing? In this sense, I hope it is also evident why I had to situate the investigation of contingency in computation within an aesthetic domain. It was because 1) I understand contingency as indeterminacy; 2) indeterminacy as potentiality is what brings about the new; and 3) aesthetics is the investigation of such ontological production and the inherent potentiality of reality. It follows that an aesthetic study of computation has the objective of uncovering computation's potential to generate novelty, which is to be found in computation's own characteristic form of indeterminacy.

Contingency

Finally, but relatedly, the third key difference between some of the core arguments presented in *Contingent Computation* and the claims advanced in current debates about generative AI pertains to the concept of contingency. In his *Media Theory* article, Díaz

Alva (2023) correctly distinguished claims about an external type of contingency (what he calls ‘the externality thesis’) from those about an internal kind of contingency (i.e. ‘the internality thesis’). I explicitly differentiated between an internal and external type of contingency in the book, so I agree with Díaz Alva’s highlighting of this distinction. The contingency that *Contingent Computation* theorised is not randomness, unpredictability, unknowability, chaos, irrationality or chance; nor is it the result of an accident, error or glitch. Rather, my proposed conceptualisation focused on a formal type of contingency, one that is internal to computation because it is intrinsic to computational processing. By engaging with logico-mathematical notions of incompleteness and incomputability – respectively, those proposed in the 1930s foundational work of Kurt Gödel (1986) and Alan Turing (1936) – the book reworked, philosophically, what indeterminacy within computation is. My philosophical reading of Gödel’s and Turing’s results argued that incompleteness and incomputability show how there is an indeterminacy that pertains to the formal dimension of computing. Computation is defined by the indeterminacy that makes it contingent, and this indeterminacy is the pure potential of computation, central to computing’s operations and prior to any application of them to life, art, society or culture (in other words, prior to anything else that could be a source or model of external indeterminacy).

While the book advocated strongly for the internality thesis, external forms of contingency were also addressed via a critique of inductive computing, which, I argued, computationally simulates the mutability of empirical phenomena. I dubbed inductive computing’s efforts ‘computational empiricism’ and saw this as epitomised by techniques known as ‘unconventional’, ‘natural’ and ‘non-classical’ computing. These computing technologies, often taking inspiration from empirical phenomena, want to endow computational formalisms with the dynamism that pertains to the biological and physical realms, naturalising computation in order to privilege the inductions of the empirical sciences over the deductions of logic. In the book, I criticised computational empiricism because of its implied assumption that the contingent is an ontological status pertaining uniquely to the plane of sense-data reception. This is a naïve and weak form of empiricism, I claimed, which reduces experience to sense experience and elaborates change uniquely in terms of accidental variability.

Recent computational developments

Moving from unconventional, natural and non-classical computing to recent developments in machine learning, we could say that these, too, focus on external contingencies and stand as a form of inductive computing.⁷ Machine learning systems are said to ‘learn’ because they can improve the accuracy of their results by being exposed to large amounts of data and only require limited human intervention (e.g. they do not need explicit instructions). Rules and outputs are calculated from the vast quantity of data via inductive inferences, so the learning strategies of machine learning are set up to imitate those of humans, who learn from experience and teach themselves accordingly. A young child, for instance, may discover quickly what a dog is after being presented with only few canine instances. A machine learning system operates according to the same learning principle (i.e. being shown examples of dogs and learning to abstract what a dog is),⁸ although it needs a considerably larger amount of training data to reach acceptable outcomes, which however remain much less generalisable.

Despite some substantial limitations, machine learning is remarkably powerful. This power exemplifies an important move in the way indeterminacy and change are addressed computationally. Both are understood in terms of that which is statistically probable. Since these systems are designed to learn from experience, they are not only modelled upon empirical variation but also intended to produce predictions regarding this; in this sense, their goal is to bring computation as close as possible to the many indeterminacies of empirical existence, external to computing’s pre-programming, while endorsing the probability of certain outcomes based on patterns of behaviour from a sample of past occurrences. Empiricism, in and for machine learning, is thus a design choice, an ‘empiricism without magic’ (Buckner, 2018) or a ‘moderate empiricism’ (Buckner, 2023), as it has been called, which can adapt to the open-endedness of both nature and nurture and that is largely propelled by Bayesian methodologies for inductive inference. The neural turn, moreover, can be seen as further evidence of this widespread inductivism. With artificial neural networks, computers solve problems not by following the rules of logic but by attempting to mimic brain processes, their architecture being intended to simulate the connections of biological neurons. The fact that machine learning is successful as an engineering

feat that is not yet matched by an adequate set of theoretical models able to fully explain its operations can be added as another instance of this empiricism by design (see Fazi, 2021a).

The externality thesis, Díaz Alva (2023) added, postulates a prosthetic relation between the human and the technological. I would agree that, yes, this kind of externality implies exteriorisation and a view of technics as prosthesis or organ projection, together with a pharmacological understanding of technicity that casts these as always ‘originary’ (Bradley, 2011) and in equal measure constitutive of the human but also a product of it. The externality thesis, furthermore, confines the contingent to the status of the probable or the unpredictable also in virtue of such a prosthetic interdependency that it assumes and sustains. The externality thesis equates contingency in computation with the indeterminacies that originate from life. For the externality thesis, in other words, contingency pertains to technology only insofar as technics partakes in the planes of culture, society, economy, art, economy and suchlike – a plethora of the lived experiences in which the technological is situated, giving rise to what I have elsewhere called an ‘associated milieu’ (Fazi, 2019a).⁹ I used this expression as a Simondonian term; the phrase captures Simondon’s (1989) argument for how technology is transduced across non-technological environments and mediated across domains. In *Contingent Computation*, I was critical of Deleuze-inspired tendencies that, partly drawing from Simondon and largely under the banner of the affective turn in media studies, mistakenly discard the logico-mathematical, quantitative specificity of computing and its formalisms to favour instead the qualitative intensities and affective forces of what technology attaches to, these being (incorrectly) understood as the only possible source of generative contingency.

I am sceptical of positions that heavily rely on such associated milieu as the only means to find and engage with the indeterminacy of computational technologies. For this reason, too, I insist on a non-prosthetic approach to technics. Computational processes are not mere instrumental add-ons to pre-existing human cognitive capacities, and philosophy should move beyond such conceptions of technological agency. Looking for a contingency that is internal to computation and searching for computing’s internal indeterminacy, as *Contingent Computation* did, is, then, an attempt to offer such surpassing. The internality thesis is thus to be developed alongside my

broader philosophical aim to theorise the onto-epistemological specificity of computational procedures. Speculations about the internal contingency of computation are a key moment in such theorisation. Of course, computing machines can augment us. I do not deny that technology has a distinctive projectionist dimension. I believe, however, that we should also be addressing the possibility of *not* reaching any onto-epistemic conciliation between the human and the technological precisely because of the specific onto-epistemic configurations these computational systems give rise to, expressing a form of technological alterity for which there is no shared existential ground.

As a technology meant to deal with noise (e.g. diffusion models for image generation), generative AI can also be seen as aligned with the externality thesis. In this respect, it is interesting to note that developing an argument for a contingency that is internal to the computational procedure – or, conversely, one that focuses on a contingency that is external to it – has an impact on the different uses of the concepts of aesthetics and generativity discussed (above). Moreover, these divergent approaches to contingency and computation can orient discourses on creativity in different ways. Just as with products, producers and processes of production, creativity remains a difficult notion to define. As a human ability or disposition, creativity is much cherished and celebrated today; as a concept, however, it is also rather tired and tiresome, captured as it is by neoliberal imperatives for permanent innovation. In another 2019 article, I advanced a critique of the tendency in the field of computational creativity to classify as creative the behaviours and actions of machines that would be called so were humans performing them (Fazi, 2019b). In that publication, I was arguing against what I called the ‘simulative paradigm’ in AI research. I proposed to shift our theoretical focus towards computing processes that could be generative of novelty in ways that are profoundly unrecognisable to humans precisely because they are inherently computational. The same critique can now be extended to many of the conversations about the creativity of generative AI. These debates also emphasise machine outcomes as ‘surprising’, ‘interesting’ or, indeed, ‘creative’ precisely because they are deemed to be strikingly human-like, evoking human faculties such as insight and intuition.

Asking whether we can ascribe to machines the same type of creativity that is exhibited by human artists or people in general is a legitimate question but one that should be

secondary to investigating the creative outputs of these artificial systems in their own right. I approach this issue in the same way in which I approach the multiple agendas of AI research. It is reasonable to ask (philosophically or otherwise) whether a machine could ever think like a human. In my view, however, the most speculatively significant line of inquiry to be pursued is not this. Rather than asking ‘Does this machine think like a human?’ I believe current developments in AI research compel philosophers to ask, most urgently, what thought is (see Fazi, 2021b). Similarly, in the context of debates about generative AI, a speculative philosophy of computation should pursue a sort of refocusing, away from queries such as ‘Can a computer programme create like a human does?’ to interrogations of what creation and creativity are to begin with. It is this ontological shift that *Contingent Computation* anticipated and defends.

References

- Bergadano, F. (1991) ‘The Problem of Induction and Machine Learning’, in *IJCAI’91: Proceedings of the 12th International Joint Conference on Artificial intelligence. Volume 2*. San Francisco: Morgan Kaufmann, pp.1073-1078.
- Bradley, A. (2011) *Originary Technicity: The Theory of Technology from Marx to Derrida*. Basingstoke: Palgrave Macmillan.
- Buckner, C. (2018) ‘Empiricism Without Magic: Transformational Abstraction in Deep Convolutional Neural Networks’, *Synthese* 195: 5339-5372.
- Buckner, C. (2023) *From Deep Learning to Rational Machines. What the History of Philosophy Can Teach Us about the Future of Artificial Intelligence*. Oxford: Oxford University Press.
- Clark, A. (2008) *Supersizing the Mind: Embodiment, Action, and Cognitive Extension*. Oxford: Oxford University Press.
- Díaz Alva, A. (2023) ‘Technics and Contingency: Ontological Productivity in Computation’, *Media Theory* 7(2): 37-76.
- Fazi, M. B. (2018) *Contingent Computation: Abstraction, Experience, and Indeterminacy in Computational Aesthetics*. London: Rowman & Littlefield International.
- Fazi, M. B. (2019a) ‘Digital Aesthetics: The Discrete and the Continuous’, *Theory, Culture & Society* 36(1): 3-26.
- Fazi, M. B. (2019b) ‘Can a Machine Think (Anything New)? Automation Beyond Simulation’, *AI & Society: Knowledge, Culture and Communication* 34(4): 813-824.

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- Fazi, M. B. (2021a) 'Beyond Human: Deep Learning, Explainability and Representation', *Theory, Culture & Society* 38(7-8): 55-77.
- Fazi, M. B. (2021b) 'Introduction: Algorithmic Thought', *Theory, Culture & Society* 38(7-8): 5-11.
- Gödel, K. (1986) 'On Undecidable Propositions of Formal Mathematical Systems', in S. Feferman, J. W. Dawson Jr., S. C. Kleene, G. H. Moore, R. M. Solovay & J. van Heijenoort (eds.) *Collected Works. Volume I: Publications 1929-1936*. Oxford: Oxford University Press, pp.346–372.
- Hegel, G. W. F. (1975) *Aesthetics: Lectures on Fine Art*, trans. T. M. Knox. Oxford: Clarendon.
- Heidegger, M. (1977) 'The Question Concerning Technology', in *The Question Concerning Technology and Other Essays*, trans. W. Lovitt. New York: Garland Publishing, pp.3-35.
- Kapp, E. (2018) *Elements of a Philosophy of Technology: On the Evolutionary History of Culture*, trans. L. K. Wolfe. Minneapolis: University of Minnesota Press.
- McLuhan, M. (1964) *Understanding Media: The Extensions of Man*. London: Routledge and Kegan Paul.
- Nielson, B. & D. C. Elton (2021) 'Induction, Popper, and Machine Learning' [Preprint]. Available at: <https://arxiv.org/abs/2110.00840> (Accessed 20 August 2024).
- Ruyer, R. (2016) *Neofinalism*, trans. A. Edlebi. Minneapolis: University of Minnesota Press.
- Simondon, G. (1989) *Du Mode D'Existence Des Objets Techniques*, Paris: Aubier.
- Stiegler, B. (1998) *Technics and Time, 1: The Fault of Epimetheus*, trans. R. Beardsworth & G. Collins. Stanford: Stanford University Press.
- Turing, A. M. (1936) 'On Computable Numbers, with an Application to the Entscheidungsproblem', *Proceedings of the London Mathematical Society* 42: 230-265.
- Turing, A. M. (1950) 'Computing Machinery and Intelligence', *Mind* 59(236): 433-460.
- Vaswani, A. et al. (2017) 'Attention Is All You Need', in U. von Luxburg et al. (eds.) *NIPS'17: Proceedings of the 31st International Conference on Neural Information Processing Systems*. Red Hook: Curran Associates, pp.6000-6010.
- Veale, T. & F. A. Cardoso (eds.) (2019) *Computational Creativity: The Philosophy and Engineering of Autonomously Creative Systems*. Cham: Springer.

Notes

- ¹ The transformer architecture was presented by Google researchers in 2017 (see Vaswani et al., 2017), an introduction regarded as a watershed moment for AI technologies. This architecture has since become a cornerstone for generative AI, especially for large language models. The latter are a type of generative AI that can recognise and output general-purpose human-like language.
- ² Released by OpenAI in November 2022, the most popular conversational agent system, ChatGPT, is powered by the large language model GPT-3.5.
- ³ I am interested in the speculative avenues that these systems open up for philosophy although also aware of the commercial propaganda that surrounds them. I believe it is possible to be curious about the philosophical implications of these systems while also remaining critical of some of the narratives and uses that accompany them, specifically in relation to how technological apparatuses comply with and also further the corporate aims and profit-oriented goals of post-industrial, informational society.
- ⁴ For an overview of the philosophy and engineering of computational creativity, see Veale and Cardoso (2019).
- ⁵ Generative AI is successfully applied to areas and tasks beyond the creative industries. In biochemistry, for instance, it is used for molecular design, while in healthcare, it is used for medical diagnosis. These applications have equally important implications for the philosophical study of notions of creativity and novelty in computation. The latter should thus encompass questions about scientific discovery and investigations of the knowledge space of science.
- ⁶ Hegel's lectures on fine art could be taken as the moment in the history of philosophy when aesthetics became a theory of art and consequently tied to principles and concepts central to art theory (see Hegel, 1975).
- ⁷ Machine learning grew out of Statistical Learning techniques such as Linear and Logistic Regression. Statistics is often considered an "inductive" process. Because of this shared history, machine learning is also usually framed in terms of induction' (Nielson and Elton, 2021). Bergadano (1991: 1074) also notes that 'induction, in Machine Learning, is not only taken as the inference from observations to given general rules. It includes the search for these rules in a large set of possibilities.'
- ⁸ This is an admittedly partial account of the human capacity to learn, given just to exemplify popular rationales and ideologies behind some machine learning discourses and the shift in programming paradigms machine learning advocates argue for.
- ⁹ The work of Ernst Kapp (2018), Marshall McLuhan (1964), Raymond Ruyer (2016) and Bernard Stiegler (1998) exemplifies traditional prosthetic approaches to technology and media. Debates in posthuman theory have also often offered comparable arguments about the interdependency of the human and the technological via the notion of the 'assemblage' – a conceptual vehicle that conveys the focus of posthuman theory on the technologically-mediated transversal bonds that construct both being and knowing. The assemblage-like role of technology is equally stressed in philosophical lineages drawing from Martin Heidegger (1997) or arguments about extended, embedded and embodied cognition (see, for instance, Clark, 2008).

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