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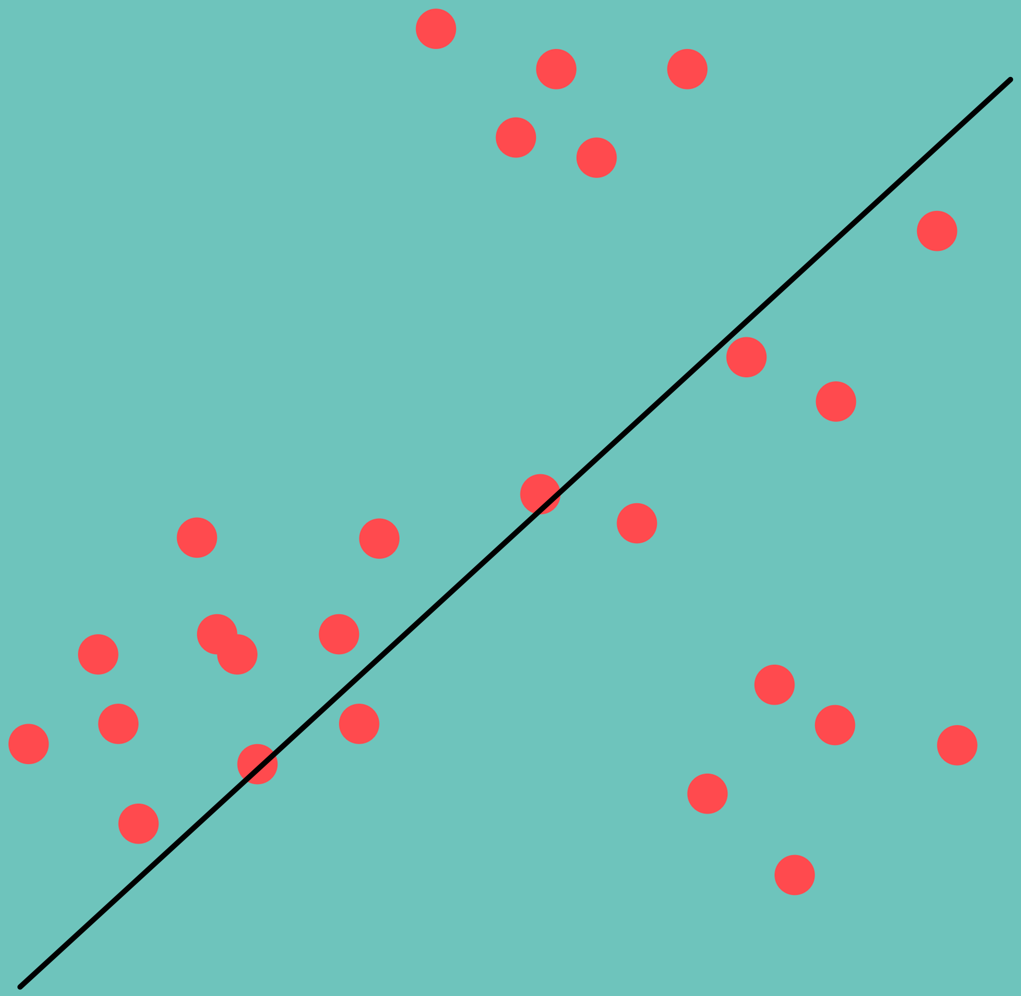

Francis Hunger

Unhype Artificial 'Intelligence'! A proposal to replace the deceiving terminology of AI.

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Unhype Artificial 'Intelligence'! A proposal to replace the deceiving terminology of AI.

> "… those of us who work in science and technology – as builders, policy-makers, commentators, researchers, investors – must reckon with our own complicity in the use of hype." Gemma Milne (2021, 119)

> "But reminding ourselves that all of that work is on our side, the human side, is of critical importance because it allows us a clearer view of the present …" (Bender 2022)

Abstract

Artificial Intelligence as a field of research and also its criticism is dominated by notions such as 'intelligence', 'learning' or 'neuronal'. This paper discusses how the use of anthropomorphising language is fueling AI hype. AI hype involves many promises, such as that 'AI can be creative', or 'AI can solve world hunger'. This hype is problematic since it covers up the negative consequences of AI use. Instead, the author proposes to use alternative terminology such as: 'Automated Pattern Recognition', 'Machine Conditioning', or 'Weighted Network'.

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1 Introduction

We can currently observe a hype around Artificial 'Intelligence' (AI) involving many promises, such as that Artificial Intelligence can be creative, Artificial Intelligence can solve world hunger or Artificial Intelligence will help to automate medical cancer care.[1] This hype features AI as a seemingly autonomous agent, which supposedly resembles human thinking and agency. This text investigates how the use of language such as 'intelligence', 'learning' or 'neuronal' is fuelling AI hype, both in AI research and AI critique.

The cultural theorist Ramon Amaro argues that AI hype comes with a certain audacity: framing AI as new, when indeed AI has a genealogy with regard to data, statistics and the quantifiable that has already existed for a long time, extending back to the eighteenth century at least (Amaro 2020, at 16:49 min). While the framing as new makes AI exciting, we can all agree that 'statistics', for instance, sounds less exciting – even if it permeates our lives to a great extent today. Hype, says Amaro, allows us to distance ourselves from the social, from

[1] This text is based on a lecture held at Gaîté Lyrique in Paris on 21 January 2021 on invitation of Marie Lechner. The author would like to thank Yiannis Colakides and Eryk Salvaggio for reviewing the text and providing valuable comments and Boris Kremer for copy editing.

human-to-human processes. Hype is a deception, using technology as 'the other'. At the same time, hype also builds on the complicity of the audiences who agree to be misled. So, discussions around Artificial 'Intelligence', be they affirmative or critical, sometimes sound as if the participants were attending a magician show – they want to believe in the magic abilities. This principle of the willing involvement of the public in a deception is what Slavoj Žižek has described in his early publications as the special function of ideology (Žižek 1997, 7–14). Thus, ideology is interestingly in this case not something produced by the state or the government, but instead by a plethora of public figures who are invested in AI: scientists, business owners, (venture) capitalists, journalists and even the critical public, including myself.[2]

How can we recognise AI hype? First, according to Amaro, hype does not question whether a certain task is actually necessary. Nor does hype question whether a 'problem' needs to be solved by AI at all, which leads to a lot of 'AI for nonsense' or 'AI snake oil' (Arvind Narayanan). Second, we can identify misleading claims, such as 'AI will end poverty'. Ending poverty is a wicked problem. AI can help solve a proxy; it can help deliver statistics or detect certain patterns that correlate with poverty. However, correlation is not causation (Chun 2021, 55–59). Neither can AI actively 'end poverty', nor can it express the causes of an issue. Computational linguistics professor Emily M. Bender calls out tech-journalists in a detailed text dissecting a New York Times article on Open AI's GPT-3 for "Puff pieces that fawn over what Silicon Valley techbros have done" (Bender 2022) and exemplarily dissects the myths on which AI hype builds. She emphasizes that "it matters that the public at large have a clear understanding of what 'AI' can actually do, which purported applications are so much snake oil, and what questions to ask to discover the possible harms from these systems […]" (ibid.). Tech policy analyst Frederike Kaltheuner points out the different uses of the word 'AI' among the public and in research: "Yet, while […] computer scientists are quick to offer a precise definition and remind us that much of what we call AI today is in fact machine learning, in the public imagination, the term AI has taken on a meaning of its own" (Kaltheuner 2021, 12). While I mostly agree with Kaltheuner, it seems to me that the problematic use of 'intelligence', 'learning' or 'neuronal' goes beyond just the hype. The problematic terminology is, as this article will show, deeply interwoven with the research field itself. Artificial 'Intelligence' in the public discourse is framed in a specific way to appear necessary, unavoidable, and overwhelming. To explore this framing, I will discuss below the language we use for AI and try to provide alternatives.

Before doing so, it makes sense to describe the urgency and context of my approach. Media scholar Luke Stark, building on the work of scholars like Simone Browne, Wendy Hui Kyong Chun, Lisa Nakamura, Sianne Ngai, and Safiya Umoja Noble has argued that "Facial recognition is the plutonium of AI" (Stark 2019). According to Stark, the use of automated pattern

[2] Adrian Daub has dissected how ideologies have grown in engineering and venture capitalism, looking at the cultures of disruption, failure and genius in his book *What Tech Calls Thinking* (Daub 2020).

recognition is often employed for problems, which already have been solved otherwise, and using the analogy to plutonium Stark calls for a ban of unnecessary technology.
In a recent paper scholars Birhane et. al. present evidence that current AI research is far from value-neutral. Instead, this research field favors the needs of academic and commercial researchers over societal demands, neglecting and outright ignoring the socially marginalized, who get subjected to AI technologies. How do these tendencies manifest? Birhane et. al. critically point out how "the choice of projects, the lack of consideration of potential negative impacts, and the prioritization and operationalization of values such as performance, generalization, efficiency, and novelty" (Birhane et al. 2022, 15) shapes the research field of 'Artificial Intelligence'.
Yarden Katz suggest that 'Artificial Intelligence' is a re-branding of systems which have been associated with surveillance to enable further capitalist exploitation of social relations. "But unlike previous iterations, the rebranded AI became part of ostensibly progressive discourses, which surround a slew of corporate academic initiatives" (Katz 2020, 65). He hints, for instance, at the limits of 'AI ethics' in mitigating the dispossession and capture of data. This analysis is corroborated, for instance, by the firing of Timnit Gebru from Google's Ethical Artificial Intelligence Team after co-authoring the now famous paper *On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?* (Bender et al. 2021). The paper discussed the environmental footprint and the proneness to bias of large language models. Central to the paper is the realization of large language models being 'stochastic parrots' leading to real-world risks of harm, where "[…] the risks associated with synthetic but seemingly coherent text are deeply connected to the fact that such synthetic text can enter into conversations without any person or entity being accountable for it" (Bender et al. 2021, 618).

Based on these critical voices a problematization of the terminology used in the field of 'Artificial Intelligence' becomes even more urgent. After shortly discussing the use of active verbs, we will look into how to replace the often-misleading terminology of AI hype.

2 Active verbs

When reviewing both critical and evangelistic texts about AI, the use of active verbs leaps out at one. Art historian Andreas Broeckmann recently commented: "the technical system 'sees', it 'learns', it 'deals with'". I would extend this list with verbs like "creates", or "produces". Broeckmann also reminds us that these verbs are often connected with concepts like 'meaning', 'image' and 'machine', and I would add concepts like 'art' or 'creativity' and so on (Broeckmann 2020).
A question such as "Can AI create art?" can be simply answered with no, but the hype produces countless news articles claiming that it can. It is important to acknowledge that the use of active verbs like "AI does this and that" perpetuates a reading of AI not as a techno-social system, but instead as a consciously acting entity (which it is not). The use of subjects, such as 'art', 'creativity', 'medicine' or 'poorness', which Artificial 'Intelligence' supposedly actively acts upon, conflates separate knowledge domains. Before Artificial 'Intelligence' assemblages could be applied to these knowledge domains, they had been formalised for algorithmic processing through human labour. No magic here, just labour (cf. D'Ignazio and Klein 2020,

173–201; Hunger 2022). Consider, for example, a statement like "The most impressive cases are where AI is pushing us up as humans into the new" (Haynes 2019). This highly problematic statement is taken from an article about an allegedly "creative" AI robot entitled *This Robot Artist Just Became the First to Stage a Solo Exhibition. What Does That Say About Creativity?* The article presents a humanoid, feminised robot called AI-DA, posing as a painter, with paint palette and brush in front of an abstract painting.[3] It was developed by Aidan Meller and Lucy Seal and their collaborators and was presented, among other projects, at Ars Electronica 2019.

Rereading this statement by Haynes, a journalist, it becomes obvious that it is not AI that is pushing us into the new, but it is instead humans who set an algorithmic AI assemblage in motion. This could be easily reformulated to "The most impressive cases are those in which humans are pushing us into the new, using automated pattern recognition or statistics". This is how a de-hyped language might sound.[4]

3 Terminology

Language is flexible. Language reflects thought and thinking, as the discussion on language use and gender shows. We can learn how language shapes perception from this discussion of the performativity of language. Imagine the headline "Can statistics be creative?". We would immediately shake our heads. Statistics? How could one even ask whether statistics can be creative? That is hugely different from the same question in hype lingo: 'Can Artificial Intelligence be creative?'.

Compared to the 1950s, when the metaphor of the computer as a brain was prominent – for instance, in Norbert Wiener's book *Cybernetics: Or Control and Communication in the Animal and the Machine* (1948) – we now know for a fact that the human brain is not a computer (cf. Peters 2018). Our understanding has shifted, and so can our language.

Starting from this realisation, I considered how to change metaphors to speak in a less hyped way.[5] I am not claiming that this is a comprehensive, practical, or fully developed proposal. In a tweet on 9 July 2021, I suggested these new translations:

1. Artificial Intelligence	=>	Automated Pattern Recognition
2. Machine Learning	=>	Machine Conditioning
3. Neural Network	=>	Weighted Network
4. Deep Learning	=>	Deep Conditioning
5. Neuron	=>	Weight (Hunger 2021)

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[3] Also see https://www.ai-darobot.com/. The robot's creators are a bit more moderate with their claims than the article, but they nevertheless decided to frame the robot in a certain way: humanised, female and dressed as a stereotypical artist. In contrast, the project https://betterimagesofai.org/ critically discusses depictions of AI.

[4] An excellent guide on agency and Artificial 'Intelligence' was developed at https://www.aimyths.org/ai-has-agency by Daniel Leufer, Alexa Steinbrück, Zuzana Liptakova, Kathryn Mueller, and Rachel Jang.

[5] Adrian MacKenzie's 2017 book *Machine Learners* using de-anthropomorphized language like 'nodes' and 'weights' instead of 'neurons', made me aware of the problem and potential alternatives (c.f. Mackenzie 2017, 209).

This proposal comes with its own problems, but it is the best I could come up with for the moment. I will discuss it in detail below.

3.1 Intelligence?

The word ‘intelligence’ takes on different meanings in different languages. In French (*intelligence artificielle*) and German (*Künstliche Intelligenz*), ‘intelligence’ means understanding, prudence, conception, comprehension, while in English it refers to prudence, conception, comprehension, but also to reconnaissance and intelligence information, or news, like the Central Intelligence Agency (CIA) would collect. The English meaning thus more pronouncedly references the reconnaissance aspect and is mistranslated into French or German. Generally, we can see how using the word ‘intelligence’ poses a problem.

We will now investigate historical developments to see how anthropomorphising[6] metaphors emerged and travelled through several fields of Artificial ‘Intelligence’. Historian Pamela McCorduck traces the notion of ‘Artificial Intelligence’ back to Dartmouth Summer Research Project on Artificial Intelligence in 1956 (McCorduck 2004, 111–136). According to her research, John McCarthy, the conference’s organizer, preferred the more flashy ‘Artificial Intelligence’ over the then prevalent and more dry notion of ‘Automata Studies’. Part of the genealogy of AI thus is how exactly this notion succeeded over others, being successful in generating funding.
When around the same time and independently of the Dartmouth conference psychologist Frank Rosenblatt, worked on the premise of the computer as an “electronic brain”, he developed a parametric machine, called perceptron, that could detect simple visual features (Rosenblatt 1957).[7] His cybernetic understanding of the brain as networks composed of neurons can be considered ‘connectionist’. It refers to the connections between the nodes in weighted networks (then called neural networks). The term ‘Artificial Intelligence’ was not widely used then.
However, in the 1970s, in critiques of the connectionist neural network approach and its overly optimistic promises, the term ‘Artificial Intelligence’ came to be used more widely. Researchers like John McCarthy, Marvin Minsky, Herbert A. Simon, and Allen Newell now looked into creating symbolic and logical relations in computerised knowledge production – a different approach to that of the connectionists. Again, generous promises were made and not kept, now for “Symbolic Artificial Intelligence”, which led to the first ‘AI winter’ in the late 1970s. Funding and research were reduced. The tide turned again when, building on earlier research, the backpropagation algorithm for connectionist weighted networks appeared

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[6] Anthropomorphisation is the attribution of human qualities to non-human entities.
[7] The brain analogy can also be found in a series of publications, for instance in *Speculations Concerning the First Ultraintelligent Machine* (Good 1966) or *What the Frog’s Eye Tells the Frog’s Brain* (Lettvin et al. 1959). Another more recent, discursive thread in AI research unfolds from experimental psychology, which perceives intelligence as measurable and quantifiable through IQ tests, as discussed, for example, in *Universal Intelligence: A Definition of Machine Intelligence* (Legg and Hutter 2007). Phil Agre critically frames early AI approaches as post-war views, according to which the whole world was perceived as “one large technical system” (Agre 1997, 134).

in 1986 under the title *Learning Representations by Back-Propagating Errors* (Rumelhart, Hinton, and Williams 1986) and allowed the fine-tuning of ‘neural’ networks in a new way. The ‘Artificial Intelligence’ metaphor now transitioned from the symbolic approach to AI towards the connectionist approach. After 1989, complicated networks called ‘convolutional neural networks’ emerged (LeCun et al. 1989). These algorithmic developments and increasing computing power after the 2000s paved the way for today’s connectionist AI. The term ‘Artificial Intelligence’, which could originally be seen as in opposition to the cybernetic, connectionist approach and should have been disposed of, has remained as today’s basic metaphor and as hype.

Apart from these historical considerations, hype is at present evident in the concepts of both “singularity“, a point at which the processing power of artificial intelligence exceeds that of humans (Kurzweil 2005), or “super intelligence”, which suggests a human-level machine intelligence (Bostrom 2014). These ideas recently fuelled a new wave of human-versus-machine phantasms. From a psychoanalytical perspective, these concepts play into the subconscious human wish to be dominated and controlled in exchange for abdicating responsibility – an unspeakable wish that, I would argue, makes even more sense against the backdrop of the impending climate catastrophe. Critical voices, like for instance, Phil Agre’s 1997 *Toward a Critical Technical Practice Lessons Learned in Trying to Reform AI* were widely ignored (Agre 1997).
Today, this is not just a critique developed from the perspective of the humanities. Practitioners of the field mention the problem themselves, like François Chollet, the creator and maintainer of the machine learning library Keras in this tweet acknowledges: “When it comes to similarities between the brain and deep learning, what's really striking is that everything that was actually bio inspired (e.g. sigmoid/tanh activations, spiking NNs, hebbian learning, etc.) had been dropped, while everything that has durably outperformed (backprop, relu, dropout, MultiheadAttention, MixUp, separable convs, BatchNorm, LayerNorm and many others) makes no sense biologically and has basically been developed by trying a bunch of things and keeping what worked empirically” (François Chollet [@fchollet] 2023).
The problematic use of the term ‘intelligence’, seen through the focus of languages such as German or French, unfolds along a problematic metaphor that alludes to intent, alludes to the capacity for dealing with complexity and abstraction, and alludes to being able to identify problems and come up with solutions. When human intelligence gets equated with machine information processing it feeds into AI hype.

One way to resolve this tension would be to refer not to ‘intelligence’ or cognition, but rather to recognition, this meaning in particular pattern recognition.[8] Cognition would thus be an

[8] Indeed, the field of Artificial ‚Intelligence‘ comprises a plethora of techniques, many of them pattern recognition and some not. What is common to most of these techniques is that they have a built-in ability to self-modulate, that is to optimize their own calculations and inner state, given they are provided with a set of test data, against which they can verify their own function. A historical perspective on pattern recognition is available in Aaron Mendon-Plasek’s text *Mechanized Significance and Machine Learning* (Mendon-Plasek 2021, 42–45).

active thing, an active understanding, while the 're-' in recognition already has a certain passivity built in. What I am aiming for is to uncover these mystifications and make clear that we are dealing with machines, and that it is humans who set these machines in motion, even when we form human-machine assemblages. We should de-anthropomorphise the term by introducing a hierarchy, a human-machine hierarchy, according to which it was clearly the human being who set the process of knowledge-building in motion. That is how we arrive at:

Artificial Intelligence => Automated Pattern Recognition

3.2 Learning?

The 1957 perceptron paper by Frank Rosenblatt is one of many of that time to insist that machines can indeed learn. Rosenblatt proposes that "[…] it should be feasible to construct an electronic or electromechanical system which will learn to recognise similarities or identities between patterns of optical, electrical, or tonal information, in a manner which may be closely analogous to the perceptual processes of a biological brain" (Rosenblatt 1957, 2).
Rosenblatt's and others' usage of 'learning' resulted in today's term 'machine learning'. Looking closer however, it becomes obvious that machines do not learn anything, and humans do not teach them. 'Learning' would imply an intellectual, bodily, or social endeavour, a relatively orderly process of change. This change of behaviour, thinking or feeling builds on experience and self-reflection, both of which require a 'self' to begin with. Now, a neural network with data inputs is hardly a 'self', nor even a nucleus of a 'self'. Learning requires consciousness, the ability to think about an issue or object in the absence of its perception: learning presupposes the ability of representation – through language (Bickerton 1996, 95–105) and diagrams (Krämer 2010).
Today, there are, however, moments of change and modulation in weighted networks, mostly through the process of backpropagation as described by Rumelhart et al., that is the algorithmic optimisation of weights in a weighted network.[9] They are part of a machine 'learning' practice, in which the learning methods could be described as finding the best model within a space of statistical hypotheses, automatically generated by the algorithm (Cardon, Cointet, and Mazières 2018, 16). Configuring an artificial network by a human consists of letting an algorithm modify the weights of each node. The human-devised algorithm influences the nodes to decide whether they should allow a signal to pass to the next layer, and to which nodes in that next layer the signal shall be passed. This process of feeding back information to the weights is called backpropagation and is often wrongly characterised as 'learning'. We might instead more precisely describe it as a semi-automated, iterative testing and adjustment of parameters, largely a mathematical optimisation.

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[9] Note how 'learning' is also used in the title of Rumelhart et al.'s paper *Learning Representations by Back-Propagating Errors*, when it also could have been titled 'Feedback of Representations by Back-Propagating Errors'. In the conclusion, the authors mention that, "The learning procedure, in its current form, is not a plausible model of learning in brains" (Rumelhart, Hinton, and Williams 1986, 536). Still, they continue to use "learning" to suggest that their mathematical discovery might pave the way for a brain-like cognition process.

The problematic use of 'learning' is further emphasised when looking at the more recent research on the functioning of the human brain: from a neuroscientific perspective, the molecular biologist Francis Crick, for example, commented on the emergence of backpropagation in weighted networks such: "[…] as far as the learning process is concerned, it is unlikely that the brain actually uses back propagation" (Crick 1989).
In short, automation and iterative reconfiguration are not 'learning'. Instead, the fuzzy usage of 'learning' anthropomorphises a mathematical optimisation process, an experimental tweaking and tinkering with parameters or weights. Language needs to be updated here. Simply because the concept of 'learning' in its narrow sense involves acts of comprehension and causation, and this is not what these parametric machinic assemblages do. As much as the field of machine 'learning' and artificial 'intelligence' is a natural science approach, it is also a craft. All the tweaking of parameters, such as error loss or convolutions, and all the experimental setups suggest that 'experimentation', 'tinkering', 'muddling' or 'moulding' might also be associated with it.

Instead of using 'learning', in the original tweet, I proposed the notion of 'conditioning', as in the Pavlovian reflex, in which a potent stimulus is paired with a previously neutral stimulus. I was suggesting that the process of backpropagation, which adjusts the weights in weighted networks through the iterative change, has its similarities with the conditioning or training of a Pavlovian dog. After a few discussions, it appears as if the concept of conditioning is not precise enough.[10] Alternatives to 'conditioning', like 'forming', would result in terms like 'machine forming', which simply does not work. A word like 'refiguration' again does not fully reflect the ability of weighted networks to adapt (within a given range) in an iterative process. Maybe 'auto-refiguration' is more precise, and we could talk about 'auto-refigurative parametric machines.' However, maybe we are already in language hell, if such a thing exists. There might not be a direct replacement for 'learning'. So, instead of providing a replacement, this section is a reminder of what we discussed above: the need to avoid active verbs. Instead of a statement like 'A neural network learns the meaning of images and then describes other images', a sentence like 'A weighted network is iteratively refigured to repeat image-label relations on uncharted images' might be less anthropomorphising. And maybe 'machine learning' becomes 'machine auto-refiguration' or 'machine conditioning'.

3.3 Neuron?

If we agree that brains do not resemble a computer, we might want to change the language that is still being used. I argue here from a perspective that takes the embodiment of human

[10] In an email exchange, Yiannis Colakides argues: "A dog that is trained/conditioned to find drugs, for example, 'knows' that it will receive a treat when it finds them. It might not know or understand the legalities of its job, but it understands 'why' a treat was given to it. […] In some sense conditioning is a process that forces us to go against our character, nature, or nurture. If this thought is in any way correct, the 'conditioning' of a machine may not be possible as it has no 'nature'" (Colakides 2022).

cognition into account: the promise of the now historical term ‘computer brain’ is that thinking machines functioning like a brain would eventually exist. This includes the suggestion that the brain is the only part in humans that thinks. However, human thinking is shaped not only by abstractions, but also by embodiment. For example, it is influenced by high blood pressure or speaking anxieties, by domain awareness and by reaction to contexts, meaning that a thought on a street can be different from the same thought in a prison isolation cell. The context of thinking also includes friendship, relationships, and the utterances of others: with whom do I exchange ideas? These ‘external’ stimuli also affect our thinking. Finally, desire: a fight with our lover, for instance, shapes thought. Embodiment also includes the fact that we have to move our human body through the world, experience it – we do not have a neutral, orthogonal, or superficial view, as many AI approaches suppose. All these factors influence thinking. Without these embodiments and contexts, I would not call a process thinking or cognition (for a media theory of the evolution of the human body and thought see Leroi-Gourhan 1964, 25–60 and 187–218; a complex discussion of embodiment from a cybernetic perspective is to found in Hayles 1999, especially pp. 1–14).
If we take the metaphor of learning seriously, we could also speculate about the role of engineers: are they educators and teachers? Are they psychotherapists, speech or occupational therapists? How have they been trained to assume these educational roles? The closest role that comes to mind is that of parents, since, as a parent, you do not need a formal education, but instead only the ability to procreate. Even as parents, I wonder if engineers are willing to provide care for the ‘intelligences’ they are ‘teaching’, at least until legal age.

I thus suggest that a ‘neuron’, in the sense of ‘neural network’, becomes a ‘node’. A node is a unit that connects relations within a network (König 1936, 1–34), and it is as a notion much more neutral towards anthropomorphising than the biological metaphor of the ‘neuron’. Since these nodes are connected using weights in a mathematical sense, which lean to one or the other side and open or close the route for a signal to the next nodes, we might also simply call them ‘weights.’ A ‘convolutional neural network’ would become a ‘convolutional weighted network’.
Initially I thought this would be a new, genuine idea. After reading quite a few machine conditioning papers, I discovered that the use of ‘weights’ is indeed an established idea. One of the founding papers of today’s connectionist weighted networks, LeCun et al.’s *Backpropagation Applied to Handwritten Zip Code Recognition (1989)* for instance, uses the notion of ‘weights’ throughout. Using ‘weights’ instead of ‘neurons’ would just be more honest because nothing similar to biological neurons is involved.

Neural Network	=>	Weighted Network
Neuron	=>	Node or Weight

4 Outlook

In its origins, and in present reincarnations, the field of Artificial ‘Intelligence’ alludes to human brain functions for strategical reasons. The anthropomorphising of automated statistics as ‘intelligence’, ‘learning’ or ‘neurons’ keeps funding flowing and craves (successfully) for public attention. The downside is evident as overexaggeration, solutionism, AI snake-oil and even public deception. This includes not only AI proponents, but to some extent also its critics, who thoughtlessly perpetuate simplistic biological metaphors.

The good news is that, as humans, we can always trust in the incompleteness of software figurations. We need to understand automated pattern recognition as embedded into other software applications. While complex pattern recognition software may appear to be semi-autonomous, it is important to stress that they are human-made and human-initiated. This opens space for human social and political intervention. How this political intervention might look like is alluded to by researcher J. Khadijah Abdurahman, when she proposes: “We can forge solidarities among workers, tenants, and technologists to help them organize for different futures” (Abdurahman 2021).

Let us reread technology as social relations. Let us question the social relations that encourage a specific extractivist, racist, gendered, and capitalist framing of pattern recognition. Let us acknowledge the hype around automated pattern recognition. The hype will surge at some point, but the discussions will not go away, so it is also a question of institutionalising a critical discussion on Artificial ‘Intelligence’ and having an impact in the real world beyond demonstrative hacks. We need to unhype pattern recognition.

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