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The Relationships Between Intelligence and Consciousness in Natural and Artificial Systems

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This paper explores some of the potential connections between natural and artificial intelligence and natural and artificial consciousness. In humans we use batteries of tests to indirectly measure intelligence. This approach breaks down when we try to apply it to radically different animals and to the many varieties of artificial intelligence. To address this issue people are starting to develop algorithms that can measure intelligence in any type of system. Progress is also being made in the scientific study of consciousness: we can neutralize the philosophical problems, we have data about the neural correlates and we have some idea about how we can develop mathematical theories that can map between physical and conscious states. While intelligence is a purely functional property of a system, there are good reasons for thinking that consciousness is linked to particular spatiotemporal patterns in specific physical materials. This paper outlines some of the weak inferences that can be made about the relationships between intelligence and consciousness in natural and artificial systems. To make real scientific progress we need to develop practical universal measures of intelligence and mathematical theories of consciousness that can reliably map between physical and conscious states.

Keywords: Intelligence; Consciousness; Artificial Intelligence; AI; Measure of Intelligence; IQ; *g*-Score; Artificial Consciousness; Prediction.

1. Introduction

Intelligence is a complex multifaceted term and many overlapping definitions have been put forward. These include cognitive ability, rational thinking, problem solving and goal-directed adaptive behavior [Bartholomew, 2004]. Most people believe that intelligence is some kind of general ability to think, understand and solve problems. It has also been claimed that there are multiple types of intelligence [Gardner, 2006] and that intelligence is a high-dimensional space of abilities [Warwick, 2000]. In humans, intelligence is usually regarded as some kind of aptitude or capacity for learning and solving new problems, rather than an ability to remember stored knowledge. This distinction between a capacity for learning and solving new problems and the reproduction of previous knowledge has been formalized as a distinction between

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fluid and crystallized intelligence [Cattell, 1971]. Modern intelligence tests are typically designed to measure fluid intelligence: a person's capacity to solve new problems regardless of their previous education and environment.

Intelligence cannot be directly measured. The first part of Sec. 2 summarizes the large amount of work that has been done on the indirect inference of intelligence using written and aural tests of people's verbal, mathematical and spatial reasoning abilities. The results of these tests are typically converted into intelligence quotient (IQ) or g-score values. It is difficult to use a test-based approach to measure the intelligence of animals and it fails completely when we try to use it to measure intelligence in machines. To address this issue a number of people have developed universal measures of intelligence that can be applied to humans, animals and artificial systems. Regardless of the way that we measure it, intelligence is a functional property of a system. The details of a system's implementation of intelligence have no effect on the amount of intelligence that is attributed to the system.

After the demise of behaviorism there was a renaissance of interest in consciousness. Progress has been made with the philosophical problems and solid scientific research has been carried out on the neural correlates of consciousness. Some empirically oriented theories of consciousness have been developed — for example, global workspace theory [Baars, 1988] and the information integration theory of consciousness [Oizumi *et al.*, 2014]. We are also starting to develop a clearer vision about how we can use mathematical theories of consciousness to map between descriptions of consciousness and descriptions of the physical world [Gamez, 2018]. This type of theory would be developed and tested on humans and then we could use it to make believable predictions about the consciousness of animals and machines. Sec. 3 introduces this work on consciousness and then Sec. 4 discusses why consciousness cannot be solely linked to computations, functions or information patterns in the physical brain. Consciousness must be tied to particular spatiotemporal patterns in specific physical substrates: a system cannot be conscious purely because it is executing a particular function. Artificial consciousness has also made rapid progress in recent years and a substantial amount of theoretical and empirical research has been carried out in this area (see Sec. 5).

Sec. 6 discusses the relationship between intelligence and consciousness in natural systems. It is likely that the functions that implement intelligence overlap with the functions that implement consciousness in biological systems. The spatial and temporal complexities of a system's consciousness are also likely to be weakly connected to its intelligence. With artificial systems, progress in artificial intelligence is likely to lead to AI systems that exhibit more conscious human behaviors, and models of consciousness and models of the correlates of consciousness could be used to build more intelligent machines (see Sec. 7). The relationship between AI and artificial phenomenal consciousness can only be properly studied when we have a practical universal intelligence measure and a mathematical theory of consciousness that can generate believable predictions about the consciousness of machines.

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2. Measures of Intelligence

Intelligence is not a precisely defined property, like mass or charge, and it cannot be directly measured. People recognize intelligent behavior and rank people according to their intelligence, but we cannot point to the intelligence in a brain and we cannot program general intelligence into a machine. To address this issue people often use batteries of behavioral tests to measure intelligence and there have been attempts to formulate universal measures of intelligence.

Over the last 100 years there has been a large amount of work on the indirect measurement of intelligence through tests that measure behavioral characteristics judged to be linked to intelligence. In the early days these tests included significant numbers of questions based on factual knowledge (crystallized intelligence). Modern human intelligence tests are now mostly based on verbal reasoning, spatial manipulation and mathematics. The results from these tests can be treated as raw scores, but they are typically converted into values of IQ or g-score. To calculate IQ you take the test results from a sample of the population and calculate the mean and standard deviation. The mean score is assigned an IQ of 100 and each standard deviation above and below the mean corresponds to 15 IQ points. The resulting IQ score can be used to rank individuals according to how well they perform on a battery of intelligence tests. IQ is a population-derived measure that does not correspond to a property of a particular individual.

Within the scientific community intelligence test results are often analyzed for factors that explain the relationships between the test results. Studies have shown that factors related to specific cognitive abilities — for example, reasoning, memory and processing speed — can explain the results of closely related tests, and these factors are, in turn, linked to a single underlying factor, g, which is thought to correspond to intelligence. Like intelligence, g cannot be directly measured, so the test results are expressed as a g-score. Measures of IQ and g-score are controversial and they have often been misused. However, they have played a valuable role in scientific research on intelligence and they can be an effective way of preprocessing large numbers of applicants for jobs, education or the military.

The measurement of intelligence through batteries of tests has some plausibility with humans, since we generally agree about which behaviors are linked to intelligence. However, it becomes much more problematic when we want to compare the intelligence of different species. Most animals cannot take human intelligence tests, so there has been some work on the development of cognitive test batteries in animals [Shaw and Schmelz, 2017]. It might be possible to come up with a plausible set of tests that could be applied to similar animals, but this approach is likely to neglect the different types of intelligence that animals develop to survive in their ecological niche. A measure of intelligence that is designed for sheep or fish, for example, cannot be easily transferred to birds or bees. For example, suppose we want to develop a test that compares human and pigeon intelligence. We could include mathematical abilities and spatial reasoning in our tests, which might be common to both.

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But pigeons have a greater capacity to map and navigate through their environment, so should this be included in the test as well? As our test battery expands with each species we will end up with a very ad-hoc collection, with each animal scoring well on the tests that are specific to its own set of abilities. It seems highly unlikely that we will be able to design a single set of cognitive tests that would enable us to meaningfully compare intelligence across all species. These problems become even more acute when we attempt to measure intelligence in machines and try to compare the intelligence of natural and artificial systems. A computer that was programmed to outperform humans on IQ tests could be completely incapable of performing any other task that we consider to be intelligent. It is likely to be impossible to use batteries of behavioral tests to compare human and machine intelligence.

One approach to this problem is to give up on the idea of a meaningful set of tests to measure intelligence across all animals and possible machines. Instead, we can take humans as our benchmark and rank animals and machines according to the extent to which they match or exceed human intelligence. This is a form of Turing testing. A different response to this problem is to develop more abstract definitions and tests of intelligence that enable humans to be compared with other species and artificial systems. An influential example of this approach was put forward by Legg and Hutter [2007], who defined intelligence as the ability of an agent to achieve goals in different environments. The total intelligence of the agent is the sum of the rewards that an agent achieves across all possible environments, with some adjustment made for the complexity of different environments. This measure has some intuitive plausibility, but it is not practically calculable because it sums across all possible actions of the agent and across all possible environments. A more practical goal/reward-based measure of intelligence has been proposed by Hernández-Orallo and Dowe [2010].

In my own work I have been developing a measure of intelligence based on a system's ability to make predictions. Many behaviors linked to intelligence, such as spatial, mathematical and verbal reasoning, require prediction, and our ability to succeed in a variety of environments is closely tied to our ability to predict the consequences of our actions in different environments. A predictive approach to intelligence also fits in well with the recent surge of interest in the predictive brain hypothesis [Clark, 2016]. If brains are intelligent and the brain's core function is prediction, then brains that are better predictors will be more intelligent. The recent successes of artificial intelligence have also been largely based on the ability of machine learning algorithms to generate predictions. Predictive ability can be measured through external tests and I am developing an algorithm that will measure a system's predictive intelligence from its internal states.

There has been a substantial amount of research on the neuroscience of intelligence [Haier, 2017]. This might enable us to measure intelligence more directly and accurately in humans — for example, using a brain scanner instead of a battery of tests. However, intelligence is likely to be implemented in different ways in

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cephalopods and birds, which have very different brain architectures, and this approach fails completely when it is applied to artificial systems that use different mechanisms to generate external behavior.

In all of this work on the definition and measurement of intelligence, intelligence is treated as a purely functional property. Biological and artificial systems are, in principle, capable of the same level of intelligence and the specific details of the implementation of intelligence have no consequences for the amount of intelligence that is attributed to a system.

3. Consciousness

I define consciousness as a bubble of experience [Gamez, 2018]. When we are conscious we are immersed in a bubble of space, roughly centered on our bodies, within which objects and non-physical properties, such as color and smell, are distributed. My bubble of experience currently contains green trees and I smell coffee on my desk. When I am at the beach my bubble of experience contains white sand, blue sea and the taste of tequila. In online perception objects and properties in our bubbles of experience co-vary with the physical world. We can also change our conscious experiences offline, independently of the world, in dreams and imagination.

Bubbles of experience have multiple dimensions of variation. The spatial size of bubbles of experience can vary, there is variation in temporal depth [Husserl, 1964] and there can be more or less objects and properties and more or less types of objects and properties. The contents of bubbles of experience can also appear with different levels of intensity. In dreams, imagination and on the edges of sleep contents are vague, washed out and unstable. In online perception contents are vivid and stable with rich colors. A person on hallucinogenic drugs can have experiences with greater intensity than the normal waking state. The contents of a single experience can have a range of intensities. There might be a fleeting impression of a bird at the edge of my field of vision while I am looking at a bright red bus rushing towards me and experiencing intense feelings of fear and panic.

There are challenging philosophical problems with consciousness, such as the hard problem and the relationship between consciousness and the physical world. Elsewhere I have shown how our modern concept of consciousness (and some of its problems) co-evolved with the development of modern scientific theories about the physical world. I have also proposed a minimal set of assumptions that can neutralize the philosophical problems with consciousness and provide a solid foundation for its scientific study [Gamez, 2018].

Over the last 30 years there has been some solid scientific work on the neural correlates of consciousness. This has measured consciousness, measured brain states and looked for correlations between the two [Koch *et al.*, 2016]. Promising data has been gathered, but, as Popper [2002] points out, scientific theories are ultimately not going to be long lists of correlations between consciousness and the physical world. We need to develop a compact mathematical theory that describes the relationship between measurements of conscious states and measurements of physical states. This mathematical theory would convert a description of a conscious state into a description of a physical state and vice versa, and it should be applicable to both biological and artificial systems. One of the challenges with developing such a theory is that we need to find an appropriate way of describing consciousness that is applicable to both humans and machines. There are also issues with the amount of data that would need to be processed to develop and test such a theory. The latter problem could potentially be addressed using machine learning and other AI techniques that have been used in computational scientific discovery [Dzeroski and Todorovski, 2007].

4. Physical, Computational, Functional and Informational Theories of Consciousness

A *physical* theory of consciousness links consciousness to particular spatiotemporal physical patterns. These could be neural patterns or a pattern in a property of firing neurons, such as electromagnetic waves [Pockett, 2000]. Quantum theories also fit into this category [Hameroff and Penrose, 1996]. In this type of theory consciousness is not just linked to a particular spatiotemporal pattern, but to a spatiotemporal pattern *in a particular physical material*. This is similar to other scientific theories: a moving electron produces a magnetic field; a moving neutron does not.

Many people believe that consciousness is linked to computations or functions [Cleeremans, 2005]. They claim that consciousness is present wherever a particular computation or function is executed, independently of how the computation or function is implemented. For example, people have connected consciousness with the implementation of a global workspace [Dehaene, 2014]. Information integration theory connects particular patterns of information to consciousness, independently of the physical implementation of the information [Tononi, 2008].

Physical and computational/functional theories of consciousness have some common ground. It might be the case that global workspace theory, for example, captures a certain kind of pattern, which is linked to consciousness when it is implemented in a particular way in a biological brain. However, computational and functional theories of consciousness lose plausibility when the claim is made that a computation or function is linked to consciousness independently of the material in which the computation or function is realized. One problem with this claim is that a system executing a computer program is just a sequence of physical states. There is nothing special about this sequence of physical states (that is the whole point of separating the computation from the physical implementation). So *any* sequence of physical states can be interpreted as implementing a particular run of a given computation [Putnam, 1988; Bishop, 2009]. This leads to an implausible panpsychism and to the untenable result that every brain is associated with an infinite number of different consciousnesses.

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A second problem with computational/functional theories of consciousness is that they can only be scientifically tested if we have an objective way of measuring the presence or absence of a computation or function in a system. For example, to prove that global workspace theory is correct, we need to be able to determine whether there is an active global workspace in the conscious brain and show that no global workspaces are being executed in the unconscious brain. Unfortunately, we do not have a way of unambiguously measuring the computations or functions that are being executed in a physical system [Gamez, 2014]. Information integration theory has similar problems with the subjectivity of information and with the measurement of information in a system [Gamez, 2016]. The only reasonable conclusion is that computations, functions and information are subjective — not objectively measurable properties of physical systems.

5. Artificial Consciousness

Artificial consciousness has been extensively discussed and working systems have been built to explore different aspects of this topic. We are now seeing the re-launch of an academic journal dedicated to artificial consciousness and the public awareness of this topic has been raised through films, such as *Chappie* and *Ex Machina*, and Netflix series, such as *Altered Carbon* and *Black Mirror* [Gamez, 2020].

Artificial consciousness is a complicated field that can be broken down into at least four overlapping areas [Gamez, 2018]:

- **MC1.** *Machines with the same external behavior as conscious systems.* Humans behave in particular ways when they are conscious. For example, they are alert, they can respond to novel situations, they can inwardly execute sequences of problem-solving steps and they can learn. MC1 machine consciousness is the creation of AI systems that exhibit some or all of these external behaviors. Watson [Ferrucci, 2012] is an example of an MC1 system that mimics the external behavior of conscious humans when they are playing Jeopardy.
- **MC2.** *Models of the correlates of consciousness.* Theories about the neural and functional correlates of consciousness in humans can be modeled in a computer. For example, global workspace implementations have been used to control a naval dispatching system [Franklin, 2003] and a video game avatar [Gamez *et al.*, 2013].
- **MC3.** *Models of consciousness.* Phenomenal experiences have characteristic features that can be modeled in computers and used to control robots. One example of this type of system was developed by Chella *et al.* [2007], who used a virtual environment (analogous to the robot's consciousness) to control a museum guide robot. Marques and Holland [2009] built a system in which a robot used a simulation of itself to solve a motor control problem and executed the solution with its real body.
- **MC4.** *Machines that are phenomenally conscious.* When humans are conscious they are immersed in bubbles of experience that contain colors, smells, sounds, etc. A machine that was immersed in a bubble of experience that contained something

similar to our colors, smells and sounds would be MC4-conscious. MC4 consciousness will only be fully solved when we have discovered a mathematical theory of consciousness that can reliably map between physical and conscious states. We have no idea whether any of our current machines are MC4-conscious.

These categories are not exclusive: systems can implement several of them at the same time. For example, a robot based on the neural correlates of consciousness (MC2) could be phenomenally conscious (MC4) and exhibit conscious external behavior (MC1).

6. Natural Intelligence and Natural Consciousness

Intelligence is purely functional property of a system and its components — the amount of intelligence in a system is independent of the way in which the intelligence is implemented. In Sec. 4, I outlined good reasons for thinking that consciousness must be linked to particular spatiotemporal patterns in specific physical materials. Intelligence and consciousness can overlap in a system when the implementation of the intelligence functions produces spatiotemporal physical patterns (for example, neuron firing patterns) that are correlated with consciousness.

While there has been a substantial amount of work on the neuroscience of intelligence [Haier, 2017] and on the correlates of consciousness [Koch *et al.*, 2016], we do not know enough about either to be able to say whether the brain's implementation of the functions linked to intelligence is the same as the neural correlates of consciousness. The best that we can say is that some of the functions that have been proposed to be linked to consciousness in the brain are also likely to be linked to intelligence. For example, Aleksander and Dunmall [2003] claim that depiction, imagination, attention, planning and emotion are minimally necessary to support consciousness. These functional properties are clearly connected with intelligence — for example, we need imagination to do IQ tasks, such as Ravens' matrices, and planning is related to predictive intelligence and goal achievement. Other people have hypothesized that the brain's implementation of a global workspace is connected with its consciousness [Dehaene, 2014]. Global workspace theory has been shown to be good way to implement AI systems [Franklin, 2003; Gamez *et al.*, 2013], so if global workspace theory is a correct theory of consciousness, then the brain's implementation of a global workspace is likely to be linked to its intelligence. While the exact relationship between prediction and consciousness is an open question, there is clearly a lot of non-conscious prediction going on in the brain, so there is unlikely to be a close match between the brain's predictive abilities and its consciousness. More abstract theories about consciousness, such as higher-order thought [Rosenthal, 1986], recurrent processing [Maia and Cleeremans, 2005] and information integration theory [Tononi, 2008], point to brain mechanisms that might also be involved in intelligence. For example, a brain that can integrate more information (possibly using recurrent connections) and which contains meta-information about

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its internal states is likely to be more intelligent. Intelligence can be implemented in many different ways, so there is unlikely to be a strong relationship between the spatiotemporal patterns linked to consciousness and the intelligence functionality of the brain.

Weak inferences can also be made from phenomenological observations about consciousness to the potential intelligence of a system. This connection is weak because most of the data and functions that produce intelligence are not consciously experienced. For example, when an insight spontaneously appears to me, I typically lack insight into the exact mechanisms by which it was arrived at, presumably because it was the result of unconscious processing. However, some of our reasoning is carried out consciously using imagination. With this type of reasoning, a consciousness with more contents could potentially solve more problems, achieve more goals and generate more predictions. So we might have weak grounds for believing that a system with more conscious contents has greater potential for intelligence. This is only a weak inference because there could be systems with rich states of consciousness that are not capable of intelligent behavior, and an impoverished binary consciousness, which could only contain a 1 or 0, could potentially write every single document that has ever been created by humans. While the intensity of conscious contents plays a role in tagging states as online or offline, this does not appear to be strongly linked to intelligence.

7. Artificial Intelligence and Artificial Consciousness

The relationship between artificial intelligence and artificial consciousness varies with the type of artificial consciousness that is under discussion.

MC1 machine consciousness focuses on machines that behave in a similar way to conscious humans. Many external behaviors linked to consciousness are also linked to intelligence and most of the behaviors that we judge to be intelligent in humans can only be carried out consciously. So there is likely to be a close relationship between progress in MC1 machine consciousness and progress in artificial intelligence. As machines mimic more human behaviors, they will appear to be more conscious and more intelligent. However, there is also a potential dissociation between MC1 machine consciousness and AI. Machines could implement forms of intelligence that achieve low g-scores on human test batteries, but score highly on universal measures of intelligence. These highly intelligent machines might not exhibit any conscious human behaviors.

MC2 and MC3 machine consciousness research uses models of the correlates of consciousness and models of consciousness to produce more intelligent machines. This has already led to the development of systems that exhibit human-like intelligence [Gamez *et al.*, 2013] and general intelligence [Chella *et al.*, 2007] and MC2 and MC3 research is likely to contribute to the increase in both forms of artificial intelligence in the future. However, AI is a very diverse field and MC2 and MC3 are only two ways of building intelligent machines. A large number of other AI approaches,

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such as deep neural networks, can be used to develop intelligent systems, and these have few connections to research on consciousness.

We know almost nothing about the MC4 consciousness of artificial systems. It is possible that some of our current AI systems have conscious states that are as rich and vivid as our own. It is also possible that consciousness is only linked to systems that implement certain functions in something approximating to biological hardware. Since consciousness is not a purely functional property and a given piece of intelligent behavior can be implemented in an infinite number of different ways [Putnam, 1988], there is not a necessary connection or nomological law linking intelligence and MC4 consciousness. The amount of overlap between MC4 machine consciousness and AI is an empirical question that can only be answered when we have a reliable mathematical theory of consciousness and a practical universal measure of intelligence that does not depend on batteries of anthropocentric tests.

8. Conclusions

Progress has been made with the measurement of intelligence in natural systems and many scientists believe that g-score reliably measures intelligence in humans and some animals. However, the test battery approach that is used to measure g-score is unlikely to be generalizable to the wide variety of behaviors and intelligences in artificial systems. One solution to this problem is to design tests that only measure human-like intelligence — in the AI context this is a version of Turing testing. Another approach is to design universal intelligence measures that can be applied to any system at all, such as Legg and Hutter's [2007] goal/reward-based test or the prediction-based measure that I am developing.

While there is still considerable philosophical controversy about consciousness, many of the philosophical problems can be neutralized with assumptions that provide a reasonable starting point for the scientific study of consciousness [Gamez, 2018]. Scientific research on the correlates of consciousness has made considerable progress and several theories about the functional and informational correlates of consciousness have been put forward, such as global workspace theory and information integration. These theories might be good ways of specifying the neural patterns that are linked to consciousness. However, computations, functions and information are not objective properties of the physical world, so they cannot be linked to consciousness independently of the way in which they are implemented in a particular physical material.

Intelligence is a purely functional property; consciousness is not, so there cannot be a strong connection between consciousness and the many different ways in which intelligence can be implemented in artificial and natural systems. In natural systems, the spatiotemporal physical patterns linked to consciousness might be closely linked to the brain's implementation of intelligence. Weak inferences can also be made from the richness and structure of natural consciousness to the potential intelligence of a system. In artificial systems there is a reasonably close connection between the development of machines that exhibit human-like intelligent behavior and the development of MC1 machines. MC2 and MC3 research is likely to contribute to the development of more intelligent machines.

At the present time we do not have the theories or the data that are required to make stronger conclusions about the relationship between intelligence and consciousness. We will be able to systematically study this relationship when we have a practical universal measure of intelligence that can be applied to natural and artificial systems and a reliable mathematical theory of consciousness that can map between descriptions of physical and conscious states.

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References

Aleksander, I. and Dunmall, B. [2003] Axioms and tests for the presence of minimal consciousness in agents, *J. Conscious. Stud.* **10**(4–5), 7–18.

Baars, B. J. [1988] *A Cognitive Theory of Consciousness* (Cambridge University Press, Cambridge, UK; New York, NY).

Bartholomew, D. J. [2004] *Measuring Intelligence: Facts and Fallacies* (Cambridge University Press, Cambridge).

Bishop, J. M. [2009] A cognitive computation fallacy? Cognition, computations and panpsychism, *Cogn. Comput.* **1**, 221–233.

Cattell, R. B. [1971] *Abilities: Their Structure, Growth, and Action* (Houghton Mifflin, Boston).

Chella, A., Liotta, M. and Macaluso, I. [2007] CiceRobot: A cognitive robot for interactive museum tours, *Ind. Robot, Int. J.* **34**(6), 503–511.

Clark, A. [2016] *Surfing Uncertainty: Prediction, Action, and the Embodied Mind* (Oxford University Press, Oxford).

Cleeremans, A. [2005] Computational correlates of consciousness, *Prog. Brain Res.* **150**, 81–98.

Dehaene, S. [2014] *Consciousness and the Brain: Deciphering How the Brain Codes Our Thoughts* (Penguin, New York).

Dzeroski, S. and Todorovski, L. (eds.) [2007]. *Computational Discovery of Scientific Knowledge: Introduction, Techniques, and Applications in Environmental and Life Sciences* (Springer, Berlin).

Ferrucci, D. A. [2012] Introduction to "This is Watson", *IBM J. Res. Dev.* **56**(3–4), 1:1–1:15.

Franklin, S. [2003] IDA, a conscious artifact? *J. Conscious. Stud.* **10**(4–5), 47–66.

Gamez, D., Fountas, Z. and Fidjeland, A. K. [2013] A neurally-controlled computer game avatar with human-like behaviour, *IEEE Trans. Comput. Intell. AI Games* **5**(1), 1–14.

Gamez, D. [2014] Can we prove that there are computational correlates of consciousness in the brain?, *J. Cogn. Sci.* **15**(2), 149–186.

Gamez, D. [2016] Are information or data patterns correlated with consciousness? *Topoi* **35**(1), 225–239.

Gamez, D. [2018] *Human and Machine Consciousness* (Open Book Publishers, Cambridge).

Gamez, D. [2020] Consciousness technology in black mirror: Do cookies feel pain? in D. K. Johnson (ed.), *Black Mirror and Philosophy* (Wiley-Blackwell, Hoboken), pp. 273–281.

Gardner, H. [2006] *Multiple Intelligences: New Horizons* (Basic Books, New York).

Haier, R. J. [2017] *The Neuroscience of Intelligence* (Cambridge University Press, Cambridge).

Hameroff, S. and Penrose, R. [1996] Orchestrated reduction of quantum coherence in brain microtubules: A model for consciousness? *Math. Comput. Simul.* **40**, 453–480.

Hernández-Orallo, J. and Dowe, D. L. [2010] Measuring universal intelligence: Towards an anytime intelligence test, *Artif. Intell.* **174**, 1508–1539.

Husserl, E. [1964] *The Phenomenology of Internal Time-Consciousness*, Transl. J. S. Churchill (Martinus Nijhoff, The Hague).

Koch, C., Massimini, M., Boly, M. and Tononi, G. [2016] Neural correlates of consciousness: progress and problems, *Nat. Rev. Neurosci.* **17**(5), 307–321.

Legg, S. and Hutter, M. [2007] Universal intelligence: A definition of machine intelligence, *Minds Mach.* **17**, 391–444.

Maia, T. V. and Cleeremans, A. [2005] Consciousness: Converging insights from connectionist modeling and neuroscience, *Trends Cogn. Sci.* **9**(8), 397–404.

Marques, G. H. and Holland, O. [2009] Architectures for functional imagination, *Neurocomputing* **72**(4–6), 743–759.

Oizumi, M., Albantakis, L. and Tononi, G. [2014] From the phenomenology to the mechanisms of consciousness: Integrated Information Theory 3.0, *PLoS Comput. Biol.* **10**(5), e1003588.

Pockett, S. [2000] *The Nature of Consciousness: A Hypothesis* (Writers Club Press, San Jose, CA).

Popper, K. R. [2002] *The Logic of Scientific Discovery* (Routledge, London).

Putnam, H. [1988] *Representation and Reality* (The MIT Press, Cambridge, MA; London, UK).

Rosenthal, D. M. [1986] Two concepts of consciousness, *Philos. Stud.* **49**(3), 329–359.

Shaw, R. C. and Schmelz, M. [2017] Cognitive test batteries in animal cognition research: Evaluating the past, present and future of comparative psychometrics, *Anim. Cogn.* **20**, 1003–1018.

Tononi, G. [2008] Consciousness as integrated information: A provisional manifesto, *Biol. Bull.* **215**(3), 216–242.

Warwick, K. [2000] *Qi: The Quest for Intelligence* (Piatkus, London).

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