

# 1 Brains as computers: metaphor, analogy, theory or fact?

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## 6 Abstract

7 Whether electronic, analog or quantum, a computer is a programmable machine. Wilder Penfield held  
8 that the brain is literally a computer, because he was a dualist: the mind programs the brain. If this  
9 type of dualism is rejected, then identifying the brain to a computer requires defining what a brain  
10 “program” might mean and who gets to “program” the brain. If the brain “programs” itself when it  
11 learns, then this is a metaphor. If evolution “programs” the brain, then this is a metaphor. Indeed, in  
12 the neuroscience literature, the brain-computer is typically not used as an analogy, i.e., as an explicit  
13 comparison, but metaphorically, by importing terms from the field of computers into neuroscientific  
14 discourse: we assert that brains compute the location of sounds, we wonder how perceptual  
15 algorithms are implemented in the brain. Considerable difficulties arise when attempting to give a  
16 precise biological description of these terms, which is the sign that we are indeed dealing with a  
17 metaphor. Metaphors can be both useful and misleading. The appeal of the brain-computer metaphor  
18 is that it promises to bridge physiological and mental domains. But it is misleading because the basis  
19 of this promise is that computer terms are themselves imported from the mental domain (calculation,  
20 memory, information). In other words, the brain-computer metaphor offers a reductionist view of  
21 cognition (all cognition is calculation) rather than a naturalistic theory of cognition, hidden behind a  
22 metaphoric blanket.

23

24 *Keywords: brain-computer metaphor; algorithms; programs; philosophy; metaphors.*

25

## 26 What is a computer?

27 It is common to assert that the brain is a sort of computer. It goes without saying that no one believes  
28 that people have a hard drive and USB ports. More broadly, a computer is a machine that can be  
29 programmed. Computers can be programmed in many different ways: procedural programming (a  
30 series of elementary steps, as in a recipe or the C language), logic programming (using logical  
31 propositions as in the language Prolog), and so on. There can be such things as “non-conventional”  
32 computers, parallel computers, analog computers, quantum computers, and so on, which execute  
33 programs in different ways.

34 “Programmable machine” is both the common usage and the technical usage of “computer”. Computer  
35 science offers no formal definition of computer: it is the concept of program that unifies much of  
36 theoretical computer science. In computability theory, a function  $f$  is said to be computable if there  
37 exists a program that can output  $f(x)$  given  $x$  as an input. In computability theory, an undecidable  
38 problem is a decision problem for which no program gives a correct answer, such as the halting  
39 problem. Complexity theory examines the number of steps that a program takes before it stops, and  
40 classifies problems with respect to how this number scales with input size. Kolmogorov complexity is  
41 the size of the shortest program that produces a given object.

42 Richards and Lillicrap (2022) rightfully recommend to clarify the exact definition of computer we use,  
43 and they offer “some physical machinery that can in theory compute any computable function”.  
44 Unfortunately, this definition hides the notion of a programmable machine behind the vagueness of  
45 the phrase “can in theory”. What does it mean that an object *can* do certain things?

46 Consider a large (say, infinite) pile of electronic components. For any computable function, one “can in  
47 theory” assemble the elements into a circuit that computes that function. But this does not make the  
48 pile of components a computer. To make it a computer, one would need to add some machinery to  
49 build a particular circuit from instructions given by the user. Certainly, the electronic elements “can in  
50 theory” compute any computable function, but in the context of computers, what is meant by “can” is  
51 that the computer *will* compute the function *if* it is given the adequate instructions, in other words it is  
52 a programmable machine.

53 In the same way, the fact that any logical function can be decomposed into the operations of binary  
54 neuron models (McCulloch and Pitts, 1943) does not make the brain a computer, because the brain is  
55 not a machine to assemble neurons according to some instructions, as if neurons were construction  
56 blocks. Thus, it is fallacious to assert that the brain is literally a computer on the mere basis that formal  
57 neural networks can approximate any function (Richards and Lillicrap, 2022), for this would attribute  
58 computerness to a disorganized pile of electronic components or to any large enough group of atoms,  
59 and this is neither the common usage nor the technical usage in computer science.

60

### 61 **A dualistic entity**

62 As pointed out by Anthony Bell (Bell, 1999), the computer is a fundamentally dualistic entity, where  
63 some machinery (“hardware”) executes instructions (“software”) defined by an external agent. It is  
64 exactly in this sense that Wilder Penfield, who discovered the cortical homunculi (sensory and motor  
65 “maps” of the body on the cortex), claimed that the brain is literally a computer (Penfield, 1975).  
66 Penfield was a dualist: he considered that the brain is literally a computer, which gets programmed by  
67 the mind.

68 Although modern neuroscience is deeply influenced by Cartesian dualism, most neuroscientists do not  
69 embrace this type of dualism (Brette, 2019; Cisek, 1999; Mudrik and Maoz, 2015). Therefore, it is  
70 generally not believed that the brain gets *literally* programmed by some other entity. Perhaps the  
71 brain-computer is “programmed by evolution” or “self-programmed”, but these are rather vague  
72 metaphorical uses. To give some substance to the statement “the brain is a computer”, one needs to  
73 identify programs in the brain, and a way in which these programs can be changed arbitrarily.

74 For example, classical connectionism might propose that the program is the set of synaptic weights,  
75 and that some process may change these weights. This view, as any attempt to identify a program in  
76 the brain, assumes that the brain can be separated into a set of modifiable elements (software) and a  
77 fixed set of processes (hardware) that act on those elements, for otherwise the “program” would not  
78 unambiguously specify what it does, i.e., would not be a program at all. But synaptic weights are  
79 certainly not the only modifiable elements in the brain. This hardware/software distinction is  
80 precisely what Bell (1999) opposed because everything in the brain, or in a biological organism, is  
81 “soft”: *“a computer is an intrinsically dualistic entity, with its physical set-up designed not to interfere  
82 with its logical set-up, which executes the computation. In empirical investigation, we find that the brain  
83 is not a dualistic entity”*. A living organism does not simply adjust molecular knobs: it continuously  
84 produces its own structure, synapses and everything else (Kauffman, 1986; Montévil and Mossio,  
85 2015; Rosen, 2005; Varela et al., 1974).

86 Furthermore, to make the case that the brain is a computer, one must demonstrate that there is a way  
87 in which the brain’s programs can be changed arbitrarily. The problem with this claim is that it implies  
88 some form of agency. If not a distinct mind, then who decides to change the program? One might say  
89 that the brain is programmed by evolution to achieve some goals, but unless we believe in intelligent  
90 design, we know that evolution is not literally a case of programming but rather the natural selection  
91 of random structural changes. One might say that the brain “programs itself”, but it is not  
92 straightforward to give substance to this claim either, beyond the trivial fact that the structure of the  
93 brain is plastic. If this plasticity follows some particular rules, then the “programs” that the brain  
94 produces are in fact not arbitrary. And indeed, it is not the case that a cat can “self-program” itself into  
95 playing chess. Perhaps it might “in theory” be able to play chess, that is, if we allow some fictional  
96 observer to rewire the cat’s brain in certain ways, but this is not a case self-programming. In the idea  
97 that the cat’s brain is a computer, there appears to be a confusion of Umwelts (Gomez-Marin, 2019):  
98 an observer might be able to “program” a cat’s brain in some sense, but the cat itself cannot.

99

### 100 **Theory, analogy or metaphor?**

101 Therefore, it is not a fact that brains are computers. It might be a certain type of dualist theory, or a  
102 fundamentalist connectionist theory, but those theories are at odds with what we know about the  
103 biology of brains. However, in most cases, the statement is not taken literally in the neuroscience  
104 literature. Is it an analogy or a metaphor? The distinction is that an analogy is explicit while a metaphor  
105 is implicit. It might be occasionally stated that the brain is *like* a computer, but a much more common

106 case in the neuroscience literature is that one speaks of sensory *computation*, *algorithms* of decision-  
107 making, *hardware* and *software*, *reading* and *writing* the brain (for measuring and stimulating),  
108 biological *implementation*, *neural codes*, and so on. These are clear cases of metaphorical writing,  
109 borrowing from the lexical field of computers without explicitly comparing the brain to a computer.

110 Metaphors can be powerful intellectual tools because they transport familiar concepts to an unfamiliar  
111 setting, and they have shaped the history of neuroscience (Cobb, 2020). The linguists Lakoff and  
112 Johnson (1980) have shown that metaphors pervade our language and shape the concepts with which  
113 we think, even though we usually do not notice it (“to shape” in this sentence and “to transport” in the  
114 previous one, both applied to concepts). As the authors emphasized: “*What metaphor does is limit what*  
115 *we notice, highlight what we do see, and provide part of the inferential structure that we reason with*”. It  
116 is this inferential structure that deserves closer attention. The brain-computer metaphor might be a  
117 “semantic debate” (Richards and Lillicrap, 2022), but meaning is actually important. What do we mean  
118 when we say that the brain implements algorithms, and is it true?

119

## 120 **A double metaphor**

121 Before we discuss algorithms in the brain, it is useful to reflect on why the brain-computer metaphor  
122 is appealing. The brain-computer metaphor seems to offer a natural way to bridge mental and  
123 physiological domains. But it is important to realize that it does so precisely because computer words  
124 are themselves mental metaphors. In the 17th century, a “computer” was a person who did  
125 calculations. Later on, by analogy, devices built to perform calculations were called computers. We say  
126 for example that computers have “memory”, but memory is a cognitive ability possessed by persons:  
127 it is people who remember, and then we metaphorically say that a computer “memorizes” some  
128 information; but when you open some text file, the computer does not literally remember what you  
129 wrote. This is why Wittgensteinian philosophers point out that “*taking the brain to be a computer [...]*  
130 *is doubly mistaken*” (Smit and Hacker, 2014).

131 No wonder computers offer a natural way to describe how the brain “implements” cognition:  
132 computers were designed with human cognition in mind in the first place. For this reason, there is a  
133 sense in which certain persons (but not brains, cats or young children) might literally and trivially be  
134 computers: an educated person can execute a series of instructions, for example the integer  
135 multiplication algorithm. This trivial sense exists precisely because the computer is modeled on a  
136 subset of human cognitive abilities, namely doing calculations. But of course, the relevant scientific  
137 question is whether all cognitive activity is of this kind, that is, is a sort of unconscious calculation. In  
138 other words, the brain-computer metaphor is a reductionist view of cognition, which claims that all  
139 cognitive activity in all animal kingdom (perception, decision, motor control, etc.) is actually composed  
140 of elementary cognitive steps, these steps being those displayed by educated humans when they  
141 calculate.

142 At the very least, this claim is not trivially true.

143

## 144 **Algorithms of the brain**

145 What do we mean when we say that the brain implements algorithms? The textbook definition of  
146 algorithm in computer science is: “*a sequence of computational steps that transform the input into the*  
147 *output*” (Cormen et al., 2009). There are different ways to define those steps, but it must be a procedure  
148 that is reducible to a finite set of elementary operations applied in a certain order.

149 What is *not* algorithmic is, for example, the solar system. The motion of planets follows some laws, but  
150 it cannot be decomposed into a finite set of operations. These laws constitute a *model* of planet motion,  
151 not an algorithm. In the same way, a feedback control system is not in general an algorithm (see e.g.  
152 van Gelder’s example of Watt’s centrifugal governor (van Gelder, 1995)). Of course, some algorithms  
153 can be feedback control systems, but the converse is not true.

154 In the same way, a model of brain function is not necessarily an algorithm. Of course, some are. For  
155 example, networks of formal binary neurons (McCulloch and Pitts, 1943) are algorithmic. Each  
156 “neuron” is defined as a binary function and a feedforward network transforms an input into an output  
157 by a composition of such functions. The same applies to deep learning models. Backpropagation is an

158 algorithm too. But the Hodgkin-Huxley model (Hodgkin and Huxley, 1952) is not an algorithm. It is, as  
159 the name implies, a model: laws that a number of physical variables obey.

160 Of course, the Hodgkin-Huxley model can be *simulated* by an algorithm. But the membrane potential  
161 is not in reality changed by a sequence of Runge-Kutta steps. More generally, the fact that a relationship  
162 between two measurable variables is computable does not imply that the physical system actually  
163 implements an algorithm to map one variable to the other. It only means that *someone* can implement  
164 the mapping with an algorithm.

165 Biophysical models of the brain are typically dynamical systems. But dynamical systems are not  
166 generically algorithms, and therefore asserting that the brain runs algorithms is a particular  
167 commitment that deserves proper justification. To justify it, one needs to identify elementary  
168 operations in the brain. For example, the computational view of mind holds that cognition is the  
169 manipulation of symbols, that is, the elementary operations are symbolic operations. This leaves the  
170 issue of identifying symbols in the brain, which is generally done through the concept of “neural codes”,  
171 but this concept is problematic both theoretically and empirically (Brette, 2019). Among other  
172 examples, Minsky (1988) attempted to describe cognition in terms of elementary cognitive operations,  
173 and Marr (1982) tried to describe vision as a sequence of well-identified signal processing operations,  
174 with limited success (Warren, 2012). More generally, it is not so obvious that behavior can be entirely  
175 captured by algorithms (Roli et al., 2022).

176 The word “algorithm” is sometimes used in a broader sense, to mean some kind of detailed quantitative  
177 description of brain function. But this metaphorical use is confusing: not everything lawful in the world  
178 is algorithmic. A quantitative description is a model, not an algorithm, and there are many kinds of  
179 model.

180

### 181 **Computation in the brain**

182 Perhaps a less misleading term is “computation”. The brain might not be a computer, because it is not  
183 literally programmable, and it might not literally run algorithms, but it certainly computes: for  
184 example, it can transform sound waves captured at the ears into the spatial position of a sound source.  
185 But what do we mean by that exactly?

186 If what we mean is that we are able to locate sounds, look at their expected position and generally  
187 behave as a function of source position, then should we not just say that we can perceive the position  
188 of sound sources? The word “computation” certainly suggests something more than that. But if so, then  
189 this is not a trivial statement and it requires proper justification. Perhaps what is meant is that  
190 perception is the result of a series of small operations, that is, by an algorithm, but this is far from  
191 obvious.

192 Perhaps we mean something broader: the brain transforms the acoustic signals into some neural  
193 activity that can be identified to source position, and that then leads to appropriate behavior and  
194 percepts. But this assumes some form of separability between an encoding and a decoding brain, which  
195 can be questioned (Brette, 2019). Or perhaps “computation” is simply meant to designate a  
196 transformation from sensory signals to some mental entity that represents source position. The  
197 difference between a computation and a mere transformation is then the fact that the output is a  
198 representation, not just a value. But then we need to explain what “representation” means in this  
199 context, for example that a representation has a truth value (it is correct or not), and how  
200 representations relate to brain activity.

201 Thus, it is not at all obvious in what sense the brain “computes”, if it does, and the metaphorical use of  
202 the word tends to bury the important questions.

203

### 204 **Conclusion**

205 Computers are programmable machines. Let us leave aside the concept of a “machine”, which would  
206 deserve specific treatment (see e.g. (Bongard and Levin, 2021; Nicholson, 2019)), and allow for an even  
207 broader definition: a computer is a programmable thing. Brains are not programmable things - at least  
208 not literally.

209 Except in rare Cartesian views where the mind is seen to program the brain (Penfield, 1975), the brain-  
210 computer metaphor is indeed a metaphor. Explicit formal comparisons with computers are rare, but  
211 brain processes are often described using words borrowed from the lexical field of computers  
212 (algorithms, computation, hardware, software, and so on). It is in fact a double metaphor, because  
213 computers are themselves metaphorically described with mental terms (e.g. they memorize  
214 information). This circular metaphorical relationship explains why the metaphor is (misleadingly)  
215 appealing.

216 The brain-computer metaphor is a source of much confusion in the literature. “Computer” might be  
217 used metaphorically to mean something complicated and useful. But computers run programs: what  
218 programs are we referring to? Evolution? The connectome? Neither is actually a program, and it is  
219 misleading to suggest they are. “Algorithm” might be used metaphorically to mean “laws” or “model”.  
220 But this is misleading: “algorithm” suggests elementary operations and codes, which are not found in  
221 all models, and certainly not obviously found in brains (Brette, 2019). “Computation” is used  
222 metaphorically, but what is meant exactly is generally undisclosed: is it a claim about the algorithmic  
223 nature of cognition? about representations? or simply about the fact that behavior is adequate?

224 Once the meanings of these computer terms are properly disclosed, the scientific debate might begin.  
225

## 226 Acknowledgments

227 This work was supported by Agence Nationale de la Recherche (ANR-20-CE30-0025-01 and ANR-21-  
228 CE16-0013-02), Programme Investissements d’Avenir IHU FOrReSIGHT (Grant ANR-18-IAHU-01), and  
229 Fondation Pour l’Audition (Grant FPA RD-2017-2).

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