

Letters

■ Editor:

In their report on the Second International Workshop on Human and Machine Cognition (*AI Magazine* 13(3): 17–20), Eric Dietrich and Stephen Downes repeat a “quick but convincing” yet fallacious argument for the computational equivalence of neural networks and Turing Machines. Although they then cite a “slow, rigorous proof” by K. Hornik et al. that implies the superiority of neural systems to digital ones, the contrast needs to be reemphasized.

In practice, since neural nets and Turing-equivalent systems are simulated on systems constructed from digital integrated circuits, they are of course equivalent. However, in theory, the fundamental computations of neural networks depend on the arithmetic of real numbers rather than integers. The ideal neural unit computes in a noise-free, infinite precision fashion. These computations can be simulated arbitrarily closely by a Turing machine, yet as the Greek philosopher Zeno observed 2200 years ago, the continuous computation can attain values in a fixed time that the digital approximation with uniform timestep will take infinite time to reach. Thus, theoretical neural networks have superior computational power to all but infinitely fast theoretical digital computers. They achieve their superiority by their ability to compute “between the cracks” that separate one bit from another.

The details of what this superiority entails remain unclear. Traditional connection-oriented networks perform operations that are mathematically dense and continuous only in their values, retaining the discrete timesteps and spatial extent of their digital predecessors. Considering neural systems like the human brain, with tens of billions of asynchronously active units and a long-distance (axonal) communication system based on a continuous range of variation in the temporal frequency (i.e., the temporal density) of constant-amplitude and constant-duration action-potential pulses, it seems clear that the best generalization of their properties will be in the form of mathematical expressions concerning objects that are dense, if not continuous, in space and time as well as value. Steps towards understanding neural networks in these terms have been taken by Bruce McLennan, Hornik, and others, but a long distance remains to be covered. McLennan’s work has largely been concerned with linear function spaces such as Hilbert and Banach spaces, yet neural systems are highly nonlinear. Hornik’s universal approximation proof concerns static feedforward nets rather than the recurrent spatio-temporal architectures found in even the simplest of living nervous systems.

In addition, it should be emphasized that proving the equivalence of some class of neural nets to some class of Turing Machines is not sufficient grounds to argue adequacy as a substrate for intelligence. The importance of Turing’s 1936 paper comes from the description of a particular class of TM, the Universal Turing Machine, which is programmable with emulation modes for all other TMs. A corresponding kind of universality for neural nets would consist of the ability to accept a representation of a neural

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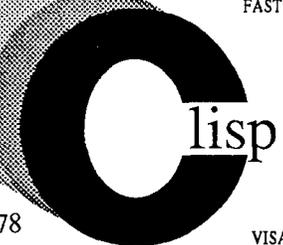
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network architecture as input and then to operate on an internal elaboration of that representation, producing the same output as would the represented network in its own operation.

This kind of neural universality is dependent on several interesting subsidiary abilities, including spatial and temporal memory; one-trial learning using rehearsal; recursive pattern rescaling and transformation; and serialization—the ability to transform a spatial pattern into a temporal one and vice versa. Understanding how to embed these properties in physical devices that are subject

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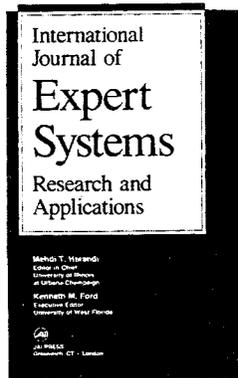
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to constraints (possibly weak ones) on connectivity and interpenetration of connections will give important insights into the evolution of brains in living organisms, and the capabilities of the minds that reside in them.

George McKee
Houston, Texas

■ Editor:

We wish to reply to George McKee's letter. He has bought into the myth that artificial neural nets are "stronger" than universal Turing machines because the former but not the latter "compute" continuous functions. This is false: nothing computes continuous functions; computers approximate continuous functions. McKee makes several other errors: (1) Hornik et al.'s (Hornik, K.; Stinchcombe, M.; and White, H. 1989. Multilayer Feedforward Networks Are Universal Approximators. *Neural Networks* 2:359-366) result in no way implies "the superiority of neural systems to digital ones"; (2) it is not true that "in theory, the fundamental

computations of neural networks depend on the arithmetic of real numbers"; (3) networks do not compute values "that are mathematically dense and continuous"; and (4) artificial neural networks in no way "compute between the cracks that separate one bit from another."

For the record: (a) the mathematical theory of computation presupposes sets that are at most countable, (b) the fundamental working assumption of current cognitive science is that the brain computes, therefore (c) the brain can be described completely using at most the rational numbers. As far as we know, the assumptions regarding continuity in neural network research are heuristics. Making such assumptions, e.g., that time is continuous, is enormously useful, maybe even pragmatically or epistemologically necessary. But this is no way means that neural networks can "compute" continuous functions.

Finally, there is not one shred of evidence that the brain is "stronger" than a universal Turing machine.

Desires for such evidence are due to unexorcised dualism. On the other hand, there is a substantial amount of evidence that the brain does compute. Indeed there is substantial evidence that the brain is a collection of modular computers. No one, however, thinks that the brain resembles modern digital computers (of course, there is a heated debate about whether cognitive science and AI need to operate at the level of brains and neurons).

Neural network research is one of the most important endeavors in cognitive science. But the importance of this research has nothing to do with continuity and continuous valued functions; rather it has to do with computation over distributed information—a notion we are just beginning to understand.

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