NUMBERS | NEUROSCIENCE

Why Is the Human Brain So Efficient?

How massive parallelism lifts the brain's performance above that of AI.

BY LIQUN LUO
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The brain is complex; in humans it consists of about 100 billion neurons, making on the order of 100 trillion connections. It is often compared with another complex system that has enormous problem-solving power: the digital computer. Both the brain and the computer contain a large number of elementary units—neurons and transistors, respectively—that are wired into complex circuits to process information conveyed by electrical signals. At a global level, the architectures of the brain and the computer resemble each other, consisting of largely separate circuits for input, output, central processing, and memory.[1]

Which has more problem-solving power—the brain or the computer? Given the rapid advances in computer technology in the past decades, you might think that the computer has the edge. Indeed, computers have been built and programmed to defeat human masters in complex games, such as chess in the 1990s and recently Go, as well as encyclopedic knowledge contests, such as the TV show *Jeopardy!* As of this writing, however, humans triumph over computers in numerous real-world tasks—ranging from identifying a bicycle or a particular pedestrian on a crowded city street to reaching for a cup of tea and moving it smoothly to one's lips—let alone conceptualization and creativity.

So why is the computer good at certain tasks whereas the brain is better at others? Comparing the computer and the brain has been instructive to both computer engineers and neuroscientists. This comparison started at the dawn of the modern computer era, in a small but profound book entitled *The Computer and the Brain*, by John von Neumann, a polymath who in the 1940s pioneered the design of a computer architecture that is still the basis of most modern computers today.[2] Let's look at some of these comparisons in numbers (Table 1).

Table 1

Properties	Computer	Human Brain
Number of Basic Units	Up to 10 billion transistors	~100 billion neurons; ~100 trillion synapses
Speed of Basic Operation	10 billion/sec.	< 1,000/sec.
Precision	1 in ~4.2 billion (for a 32-bit processor)	~1 in 100
Power Consumption	~100 watts	~10 watts
Information Processing Mode	Mostly serial	Serial and massively parallel
Input/Output for Each Unit	1–3	~1,000
Signaling Mode	Digital	Digital and analog

a) Based on personal computers in 2008.

b) The number of transistors per integrative circuit has doubled every 18–24 months in the past few decades; in recent years the performance gains from this transistor growth have slowed, limited by energy consumption and heat dissipation.
References: John von Neumann, The Computer and the Brain (New Haven: Yale University Press, 2012); D. A. Patterson and J. L. Hennessy, Computer Organization and Design (Amsterdam: Elsevier, 2012).

The computer has huge advantages over the brain in the speed of basic operations.[3] Personal computers nowadays can perform elementary arithmetic operations, such as addition, at a speed of 10 billion operations per second. We can estimate the speed of elementary operations in the brain by the elementary processes through which neurons transmit information and communicate with each other. For example, neurons “fire” action potentials—spikes of electrical signals initiated near the neuronal cell bodies and transmitted down their long extensions called axons, which link with their downstream partner neurons. Information is encoded in the frequency and timing of these spikes. The highest frequency of neuronal firing is about 1,000 spikes per second. As another example, neurons transmit information to their partner neurons mostly by releasing chemical neurotransmitters at specialized structures at axon terminals called synapses, and their partner neurons convert the binding of neurotransmitters back to electrical signals in a process called synaptic transmission. The fastest synaptic transmission takes about 1 millisecond. Thus both in terms of spikes and synaptic transmission, the brain can perform at most about a thousand basic operations per second, or 10 million times slower than the computer.[4]

The computer also has huge advantages over the brain in the precision of basic operations. The computer can represent quantities (numbers) with any desired precision according to the bits (binary digits, or 0s and 1s) assigned to each number. For instance, a 32-bit number has a precision of 1 in 232 or 4.2 billion. Empirical evidence suggests that most quantities in the nervous system (for instance, the firing frequency of neurons, which is often used to represent the intensity of stimuli) have variability of a few percent due to biological noise, or a precision of 1 in 100 at best, which is millionsfold worse than a computer.[5]

A pro tennis player can follow the trajectory of a ball served at a speed up to 160 mph.

The calculations performed by the brain, however, are neither slow nor imprecise. For example, a professional tennis player can follow the trajectory of a tennis ball after it is served at a speed as high as 160 miles per hour, move to the optimal spot on the court, position his or her arm, and swing the racket to return the ball in the opponent's court, all within a few hundred milliseconds. Moreover, the brain can accomplish all these tasks (with the help of the body it controls) with power consumption about tenfold less than a personal computer. How does the brain achieve that? An important difference between the computer and the brain is the mode by which information is processed within each system. Computer tasks are performed largely in serial steps. This can be seen by the way engineers program computers by creating a sequential flow of instructions. For this sequential cascade of operations, high precision is necessary at each step, as errors accumulate and amplify in successive steps. The brain also uses serial steps for information processing. In the tennis return example, information flows from the eye to the brain and then to the spinal cord to control muscle contraction in the legs, trunk, arms, and wrist.

But the brain also employs massively parallel processing, taking advantage of the large number of neurons and large number of connections each neuron makes. For instance, the moving tennis ball activates many cells in the retina called photoreceptors, whose job is to convert light into electrical signals. These signals are then transmitted to many different kinds of neurons in the retina in parallel. By the time signals originating in the photoreceptor cells have passed through two to three synaptic connections in the retina, information regarding the location, direction, and speed of the ball has been extracted by parallel neuronal circuits and is transmitted in parallel to the brain. Likewise, the motor cortex (part of the cerebral cortex that is responsible for volitional motor control) sends commands in parallel to control muscle contraction in the legs, the trunk, the arms, and the wrist, such that the body and the arms are simultaneously well positioned to receiving the incoming ball.

This massively parallel strategy is possible because each neuron collects inputs from and sends output to many other neurons—on the order of 1,000 on average for both input and output for a mammalian neuron. (By contrast, each transistor has only three nodes for input and output all together.) Information from a single neuron can be delivered to many parallel downstream pathways. At the same time, many neurons that process the same information can pool their inputs to the same downstream neuron. This latter property is particularly useful for enhancing the precision of information processing. For example, information represented by an individual neuron may be noisy (say, with a precision of 1 in 100). By taking the average of input from 100 neurons carrying the same information, the common downstream partner neuron can represent the information with much higher precision (about 1 in 1,000 in this case).[6]

The computer and the brain also have similarities and differences in the signaling mode of their elementary units. The transistor employs digital signaling, which uses discrete values (0s and 1s) to represent information. The spike in neuronal axons is also a digital signal since the neuron either fires or does not fire a spike at any given time, and when it fires, all spikes are approximately the same size and shape; this property contributes to reliable long-distance spike propagation. However, neurons also utilize analog signaling, which uses continuous values to represent information. Some neurons (like most neurons in our retina) are nonspiking, and their output is transmitted by graded electrical signals (which, unlike spikes, can vary continuously in size) that can transmit more information than can spikes. The receiving end of neurons (reception typically occurs in the dendrites) also uses analog signaling to integrate up to thousands of inputs, enabling the dendrites to perform complex computations.[7]

Your brain is 10 million times slower than a computer.

Another salient property of the brain, which is clearly at play in the return of service example from tennis, is that the connection strengths between neurons can be modified in response to activity and experience—a process that is widely believed by neuroscientists to be the basis for learning and memory. Repetitive training enables the neuronal circuits to become better configured for the tasks being performed, resulting in greatly improved speed and precision.

Over the past decades, engineers have taken inspiration from the brain to improve computer design. The principles of parallel processing and use-dependent modification of connection strength have both been incorporated into modern computers. For example, increased parallelism, such as the use of multiple processors (cores) in a single computer, is a current trend in computer design. As another example, "deep learning" in the discipline of machine learning and artificial intelligence, which has enjoyed great success in recent years and accounts for rapid advances in object and speech recognition in computers and mobile devices, was inspired by findings of the mammalian visual system.[8] As in the mammalian visual system, deep learning employs multiple layers to represent increasingly abstract features (e.g., of visual object or speech), and the weights of connections between different layers are adjusted through learning rather than designed by engineers. These recent advances have expanded the repertoire of tasks the computer is capable of performing. Still, the brain has superior flexibility, generalizability, and learning capability than the state-of-the-art computer. As neuroscientists uncover more secrets about the brain (increasingly aided by the use of computers), engineers can take more inspiration from the working of the brain to further improve the architecture and performance of computers. Whichever emerges as the winner for particular tasks, these interdisciplinary cross-fertilizations will undoubtedly advance both neuroscience and computer engineering.

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Footnotes

1. This essay was adapted from a section in the introductory chapter of Luo, L. *Principles of Neurobiology* (Garland Science, New York, NY, 2015), with permission.

2. von Neumann, J. *The Computer and the Brain* (Yale University Press, New Haven, CT, 2012), 3rd ed.

3. Patterson, D.A. & Hennessy, J.L. *Computer Organization and Design* (Elsevier, Amsterdam, 2012), 4th ed.

4. The assumption here is that arithmetic operations must convert inputs into outputs, so the speed is limited by basic operations of neuronal communication such as action potentials and synaptic transmission. There are exceptions to these limitations. For example, nonspiking neurons with electrical synapses (connections between neurons without the use of chemical neurotransmitters) can in principle transmit information faster than the approximately one millisecond limit; so can events occurring locally in dendrites.

5. Noise can reflect the fact that many neurobiological processes, such as neurotransmitter release, are probabilistic. For example, the same neuron may not produce identical spike patterns in response to identical stimuli in repeated trials.

6. Suppose that the standard deviation of mean (σmean) for each input approximates noise (it reflects how wide the distribution is, in the same unit as the mean). For the average of n independent inputs, the expected standard deviation of means is $\sigma\text{mean} = \sigma / \sqrt{n}$. In our example, $\sigma = 0.01$, and $n = 100$; thus $\sigma\text{mean} = 0.001$.

7. For example, dendrites can act as coincidence detectors to sum near synchronous excitatory input from many different upstream neurons. They can also subtract inhibitory input from excitatory input. The presence of voltage-gated ion channels in certain dendrites enables them to exhibit “nonlinear” properties, such as amplification of electrical signals beyond simple addition.

8. LeCun, Y. Bengio, Y., & Hinton, G. Deep learning. *Nature* **521**, 436–444 (2015).

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Name

James v Stone • 3 years ago

That is a fundamental question, and a good summary answer.

More detail on the biological aspects of neural efficiency can be found in a recent book by Sterling and Laughlin (Principles of Neural Design). This seminal book provides wide-ranging evidence for a set of organizing principles which explain not just how, but also why the the brain is so extraordinarily efficient; see goo.gl/ye8ir7.

I hope you do not mind if I mention another relevant book (by me) on the computational aspects of neural efficiency (Principles of Neural Information Theory, publication in June 2018); chapter 1 can be downloaded from here: https://goo.gl/xKz27r.

As you have already hinted, modern AI will probably have many more lessons to learn from neuroscience in order to progress.

3 • Reply • Share ›

Satyajit Dhawale → James v Stone • 3 years ago

Soon Sir Soon, we will be reaching singularity within 20-25 yrs. :)

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nonlin.org • 3 years ago

AI is a creation of the human brain which we don't understand. The comparison is superficial.
Congratulations on refraining from "evolutionary" pseudo-explanations.

1 • Reply • Share ›

Eugene Lubarsky • 3 months ago

Perhaps we're being unfair to the brain by considering its elementary units to be neurons & synapses - when they may actually be the receptors, ion channels and individual molecules..

Also, a microchip is only "doing something useful" at the tick of its clock, and even if there are 100 billion ticks per second, in the time between the ticks, which is still "most of the time", the microchip is doing nothing. On the other hand, the biochemical machinery of brain is always actively doing stuff, at the maximum speed, without pauses. So from this point of view, perhaps it's the microchip that's vastly slower than the brain?

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Scott Lee Cupp • 2 years ago • edited

A computer may be many times faster in some respects but the brain is much MUCH more complex. After all, computers were invented by thoughts and ideas formed in the brain.

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Altafa • 2 years ago • edited

Excellent article!
Thank you to the author for it! In it the exciting and useful information it is possible to often re-read it! It will be beneficial at the writing of the article.
Have a look at our site:

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Satyajit Dhawale → Guest • 3 years ago

Can you tell me what problems that Machine Learning or standard statistics struggle with?

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Tom Aaron • 3 years ago • edited

Yes and no. The human brain is very inefficient at a 1000 tasks. A dog can proceess smells 'x' numbers of times more subtle...a bat an hear...an eagle can see.... there are many things the human brain is very inefficient at...it can't calculate pi to the 100th decimal ...not even the 50th.

The human brain is efficient at doing what humans need to survive in a mote in a dot in the Universe confined to extremely limited

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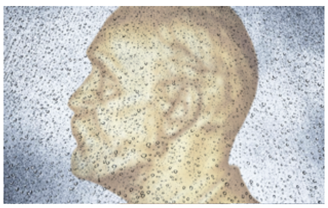

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