frontiers for Young Minds

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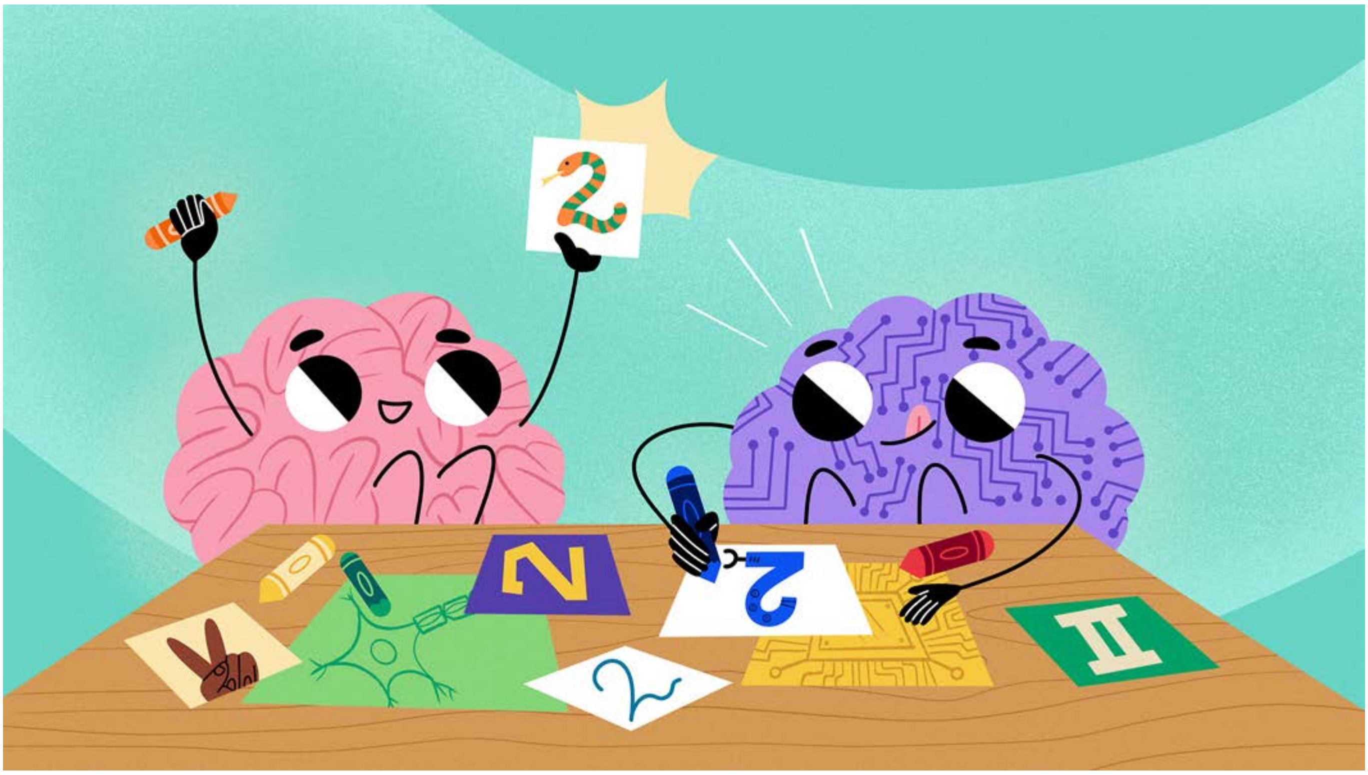

THE POWER OF LEARNING: FROM BRAINPOWER TO ARTIFICIAL INTELLIGENCE

Terrence Sejnowski[1,2*]

[1] *Salk Institute for Biological Studies, La Jolla, CA, United States*

[2] *Department of Neurobiology, University of California, San Diego, San Diego, CA, United States*

YOUNG REVIEWERS:

ASHTON
AGE: 9

ELIZABETH
AGE: 13

SERENA
AGE: 11

SOPHIE
AGE: 11

Computation is not just something computers do—it is happening everywhere, from inside our cells to the circuits of artificial intelligence. It is the foundation of our greatest superpower: learning—and now, it is becoming the superpower of machines too. Did you know that AI systems learn by mimicking how our brains work, and can even create brand-new ideas from past experiences? In this article, we explore how learning unfolds through "recipes" called algorithms—in both brains and machines—and why AI is not here to replace us, but to work with us. As these tools become part of our daily lives, they may also help us "close the loop" and better understand the most powerful computational system of all: the human brain.

Professor Terrence Sejnowski won the Brain Prize in 2024, together with Professors Larry Abbott and Haim Sompolinsky "for their

foundational research in computational and theoretical neuroscience".

The Brain Prize is an international award that recognizes and celebrates highly original and groundbreaking advances in any area of brain research, from basic neuroscience to applied clinical research. Since it was founded in 2011 and up until 2025, The Brain Prize has been awarded to 49 scientists from 11 countries.

COMPUTATION IS EVERYWHERE

What does "compute" mean to you? Counting on your fingers? Solving math problems? Or what computers do when we give them tasks?

To me and my colleagues, computing means all of that—and much more. It is a process happening everywhere around us and inside us, constantly. Your body's cells are working right now to keep you healthy and balanced. This special balance is called **homeostasis**. Keeping this balance requires **computation**: cells sense information by detecting molecules, figure out what it means, then decide what to do—like making hormones or sending chemical signals. It is calculation at the biochemical level, and every plant and animal does this type of computing all the time.

Brain cells, like all body cells, perform complicated computations to maintain homeostasis—keeping the right levels of components such as salt, oxygen, and hemoglobin to function well (Figure 1A). But brain cells do something extra special: they compute with electrical signals.

HOMEOSTASIS

How our bodies keep everything balanced inside—like temperature, water, and energy—so that we can stay healthy.

COMPUTATION

The process of taking in information, figuring out what it means, and deciding what to do next—something both computers and living cells do all the time.

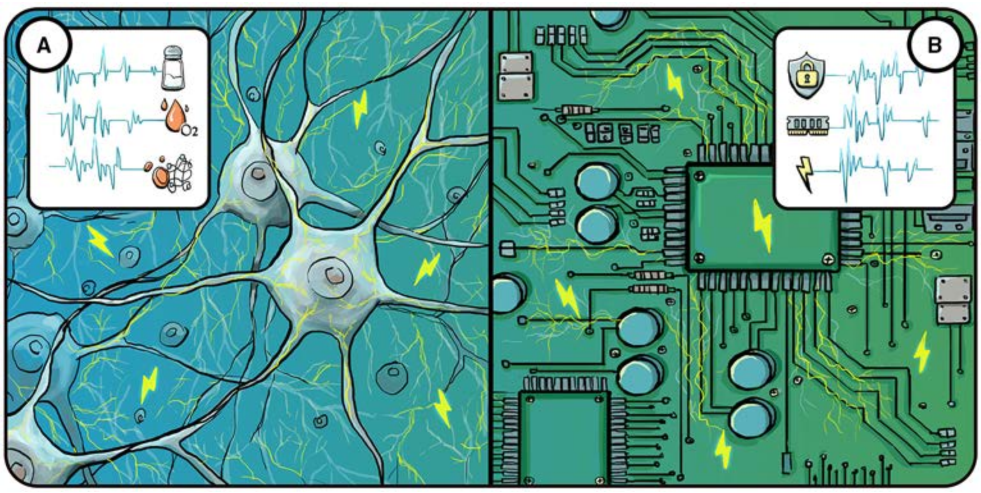

Figure 1

Figure 1

Computations in brain cells and computer chips. **(A)** Brain cells are constantly doing calculations to keep themselves healthy—like making sure there is the right amount of salt, oxygen, and other crucial components. **(B)** Similarly, computer chips do their own kind of calculations to help the computer work properly, including managing memory, electricity, and keeping the system secure.

RETINA

The retina is the thin layer at the back of your eye that catches light and turns it into electrical signals your brain understands, so you can see.

COMPUTATIONAL NEUROSCIENTIST

A brain scientist who uses math and computer models to understand how the brain performs its computations.

ALGORITHM

A set of step-by-step instructions for solving a problem or completing a task.

As an example, let us look at how you see: when light hits your **retina** (the back of your eye), it transforms that light into electrical signals that zoom to your brain. This transformation is computation in action. Then your brain processes these electrical signals through more computations involving other brain cells that generate and transmit electrical signals. All these electrical computations working together eventually let you recognize what you are looking at—say, a purple flower.

In the most general sense, computation works like a function—it takes inputs, changes them, and produces outputs. It is a mathematical transformation from input to output. Your brain runs these transformations using electrical and chemical signals moving through brain cells. Computers do the same thing using electrical signals running on silicon chips (Figure 1B). Though brains and computers compute differently in the details, they follow similar basic *principles*. As a **computational neuroscientist**, I use math and computer models to understand these principles—both to figure out how the brain works and to create powerful computer programs that imitate how the brain computes.

LEARNING BRAINS AND LEARNING MACHINES

One of the most powerful forms of computation is learning. Learning is our brain's superpower. We are so good at it that I can tell you something and you can immediately do it—you have transformed words into actions. That is learning in action! Learning also happens when you meet someone new and remember their name, when you practice a new skill like playing piano or tennis, and when you are exposed to new material in class (if you want to learn *how* to learn tough subject more easily, you can enroll to our free online course "learning how to learn"). No matter what type of learning you experience, the outcome is always the same: changes in the connections between your brain cells. Every time you learn, some connections get stronger while others get weaker. But what determines how these connections change?

The function that determines how learning changes your brain is called an **algorithm**. Think of algorithms like recipes—similar to those for baking bread or making a nice souffle. These learning "recipes" contain instructions that tell brain connections how to change. A simple recipe might have two steps: weaken the connection between cell 1 and cell 3 by 20%, then strengthen the connection between cell 1 and cell 4 by 10% (Figure 2). In your brain, there are incredibly complex learning recipes with countless steps. It is these recipes—or algorithms—that my colleagues and I are trying to understand.

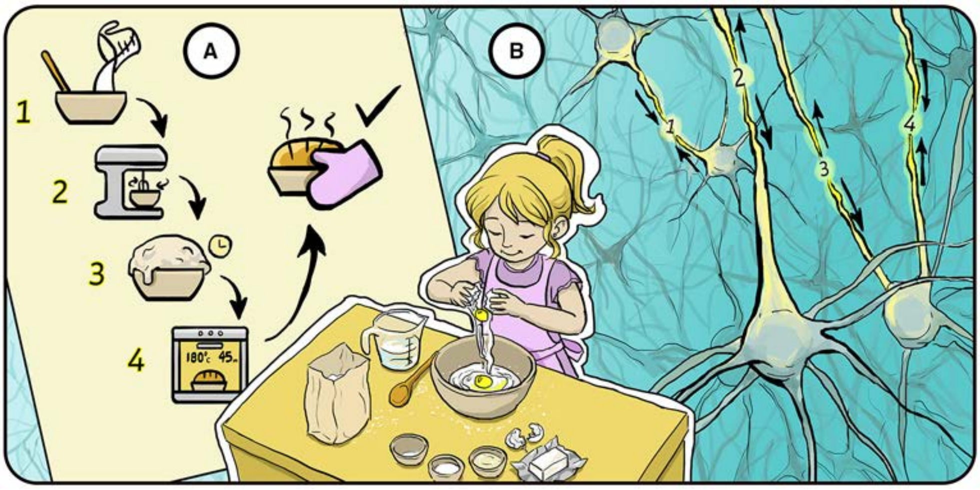

Figure 2

Figure 2

Learning algorithms in the brain are like recipes. **(A)** Algorithms are like recipes—they give step-by-step instructions for what to do, just like a recipe tells you how to make bread. **(B)** In the brain, learning algorithms guide how connections between neurons change, telling them when to get stronger or weaker based on experience.

In the 1980s, my colleagues and I discovered new ways to create learning machines that copy how the brain learns. We built digital versions of brain cells and their connections inside computers, then changed these connections using learning algorithms. The technical name for this type of learning computer program is an **Artificial neural network** (to learn more about artificial neural networks and how they work, read the following article by Turing Prize Awardee Prof. Yann LeCun).

ARTIFICIAL NEURAL NETWORK

A computer program with connected parts, mimicking connected brain cells, that is capable of learning how to perform various tasks like recognizing patterns in images or completing sentences.

Artificial neural networks are the foundation of AI tools you might know, like ChatGPT, Gemini, and Claude. The original idea goes all the way back to the 1940s [1], but in the 1980s, my thesis advisor John Hopfield (who won the 2024 Nobel Prize in Physics) helped shape how we build and use these networks today [2].

John created the "Hopfield network", one of the first artificial neural networks that could do a simple computation pattern completion. If you gave it partial input like "N _ U R _ N" with missing letters, it would complete the word to "NEURON".

Building on this, my colleague Geoffrey Hinton (who shared that Nobel Prize with John Hopfield in 2024) and I developed the **Boltzmann machine** [3, 4]. Think of it as an upgrade of the Hopfield network—it does not just recognize patterns in data, it also creates new data. Simply put, the Boltzmann Machine create new patterns because it learns the rules and probabilities behind the patterns. It then uses a bit of randomness to explore different combinations that still fit those rules, which lets it generate brand-new examples.

BOLTZMANN MACHINE

A type of artificial neural network that learns patterns in data by itself and can use that knowledge to generate new, similar examples that it has never seen before.

To further understand how the Boltzmann machine is more advanced than simpler networks, let us look at a task often given to neural networks: recognizing handwritten digits.

To teach a neural network to recognize the handwritten digit "2", we feed it thousands of examples of "2s" written by different people. The network's job is simple: answer "yes" or "no" to whether the input shows a "2". These examples were previously labeled by humans who said whether the images contained "2" or not. When the network gives the wrong answer, it adjusts the strength of connections—called *weights*—between its artificial neurons using a learning algorithm. This happens over and over until the network gets it right almost every time.

Unlike simpler networks that just say "yes" or "no" when asked if a number is a 2, the Boltzmann machine does something amazing—it learns the style of 2s and can create brand new ones it is never seen before (Figure 3)! After being fed examples, it runs by itself and automatically generates new examples from the same category. Think how incredible this is—automatically creating completely new outputs based on past examples. This creative intelligence became the foundation for the AI tools we know today.

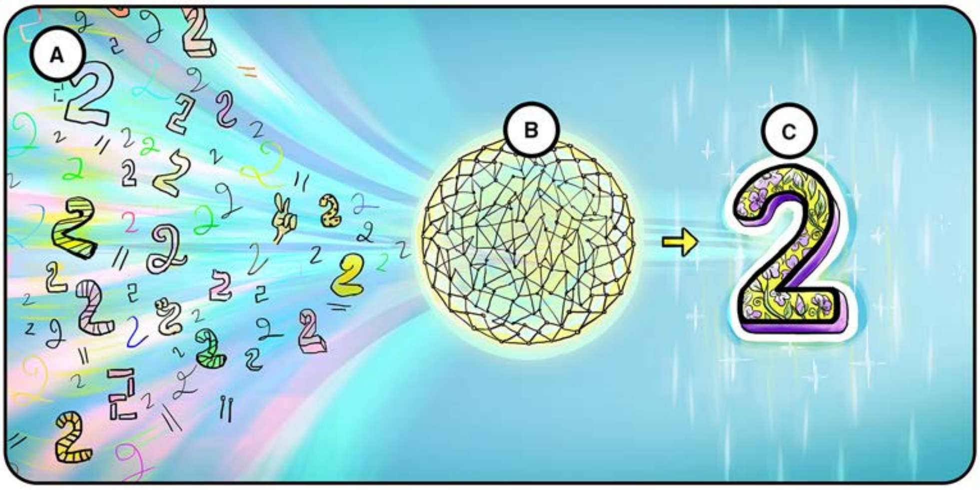

Figure 3

Figure 3

The Boltzmann machine generates new examples from what it has learned. Unlike earlier artificial neural networks, the Boltzmann machine was the first to automatically generate new examples from a category it had learned. For example, after many handwritten "2s" **(A)** are fed into it **(B)**, it can create a brand-new version of a "2" **(C)**—one it has never seen before, but that still belongs to the same group.

OUR NEW INTELLIGENT PARTNERS

AI tools are revolutionizing our world. In just a few years, they have made huge impacts in science, medicine, and language translation. They even assisted in making this article simpler and clearer for you! Predicting our future with AI is very difficult, but I can share some insights based on what is happening now.

First, think of these tools as new partners, not threats. To get the most from this partnership, we need to learn how to work with them by understanding their strengths and weaknesses. It is actually great that AI has different strengths than humans—it helps us do our jobs better.

Medicine shows this very well. As an example, doctors who are examining skin lesions for cancer are 92% accurate in their analysis. AI programs trained for the same task are also 92% accurate. But when doctors use AI together, they reach 98% accuracy [5]! That jump from 92 to 98% might seem small, but it could save countless lives—and it is based on combining the strengths of human doctors and trained AI programs.

Some people do not trust AI because we do not understand exactly how it reaches answers. But here is the thing—do we know how your brains reach their answers? Of course not! How brains work is as mysterious as how AI works. The difference is that AI is completely transparent—we can see all its inputs and artificial neuron activity. This transparency lets mathematicians study how these networks compute and generate answers. Once we understand artificial networks, we will get new ideas about how brains work. Ultimately, AI could be a powerful route to understanding ourselves better.

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FURTHER RESOURCES

- Brain Prize 2024: Computational and theoretical neuroscience
- Learning How to Learn: Powerful mental tools to help you master tough subjects

AI TOOL STATEMENT

The author(s) declared that generative AI was not used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

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CONFLICT OF INTEREST: The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

YOUNG REVIEWERS

ASHTON, AGE: 9
I am Ashton and I collect Pokemon cards. I also play Legends: Z-A on Nintendo Switch.

ELIZABETH, AGE: 13
I am currently in the eighth grade. My favorite school subject is math. I like music and play the trumpet and piano. I also enjoy cooking and baking. I plan to have a career in biomedical science.

SERENA, AGE: 11
I am an 11-year-old who is fascinated by pandas, Pokemon, and poop (the three Ps!). I also play football and solve Rubik's cubes.

SOPHIE, AGE: 11
Hi I am Sophie and I am 11 years old. I love playing with my brothers and making music. I also like taking photos and sharing fun facts.

AUTHORS

TERRENCE SEJNOWSKI
Professor Terry Sejnowski is a leading scientist who explores how brains learn—and how computers can learn too. He helped invent the Boltzmann machine, one of the first computer models that could find patterns and learn from data, much like a brain does. He also created NETtalk, a program that taught itself to read words out loud. Terry's work helped build the foundation for today's artificial intelligence and gave scientists new ways to understand how real brains learn and remember. His goal has always been to connect biology and technology—to make machines smarter, and to understand ourselves better. In 2024, he was awarded the Brain Prize, one of the highest honors in brain science. He works at the Salk Institute for Biological Studies (La Jolla, California, USA) and in the Department of Neurobiology at the University of California, San Diego (USA) where he continues to conduct research, teach, and inspire young scientists. *terry@salk.edu