

Les neurones et le cerveau

Let's start by taking a look at how the brain works and how that relates to neural networks. The human brain, or maybe more generally, the biological brain demonstrates a higher level or more capable level of intelligence and anything else would be on the bill so far. So neural networks has started with the motivation of trying to build software to mimic the brain. Work in neural networks had started back in the 1950s, and then it fell out of favor for a while.

Neural networks

Origins: Algorithms that try to mimic the brain.



Then in the 1980s and early 1990s, they gained in popularity again and showed tremendous traction in some applications like handwritten digit recognition, which were used even backed then to read postal codes for writing mail and for reading dollar figures in handwritten checks. But then it fell out of favor again in the late 1990s. It was from about 2005 that it enjoyed a resurgence and also became re-branded little bit with deep learning.

Neural networks

Origins: Algorithms that try to mimic the brain.



Used in the 1980's and early 1990's.
Fell out of favor in the late 1990's.

Resurgence from around 2005.

One of the things that surprised me back then was deep learning and neural networks meant very similar things. But maybe under-appreciated at the time that the term deep learning, just sounds much better because it's deep and this learning. So that turned out to be the brand that took off in the last decade or decade and a half. Since then, neural networks have revolutionized application area after application area.

I think the first application area that modern neural networks or deep learning, had a huge impact on was probably speech recognition, where we started to see much better speech recognition systems due to modern deep learning and authors such as [inaudible] and Geoff Hinton were instrumental to this, and then it started to make inroads into computer vision. Sometimes people still speak of the ImageNet moments in 2012, and that was maybe a bigger splash where then [inaudible] draw their imagination and had a big impact on computer vision.

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speech → images

Sometimes people still speak of the ImageNet moments in 2012, and that was maybe a bigger splash where then [inaudible] draw their imagination and had a big impact on computer vision. Then the next few years, it made us inroads into texts or into natural language processing, and so on and so forth. Now, neural networks are used in everything from climate change to medical imaging to online advertising to product recommendations and really lots of application areas of machine learning now use neural networks.

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speech → images → text (NLP) → ...

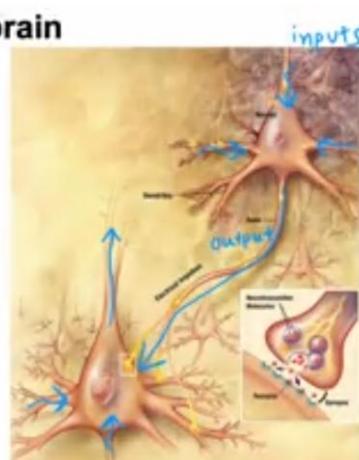
Even though today's neural networks have almost nothing to do with how the brain learns, there was the early motivation of trying to build software to mimic the brain. So how does the brain work? Here's a diagram illustrating what neurons in a brain look like.

Neurons in the brain



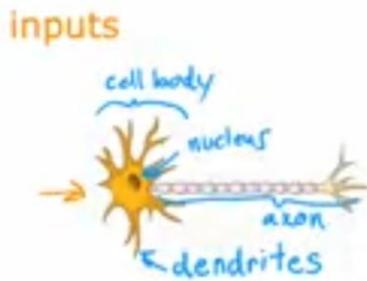
All of human thought is from neurons like this in your brain and mine, sending electrical impulses and sometimes forming new connections of other neurons. Given a neuron like this one, it has a number of inputs where it receives electrical impulses from other neurons, and then this neuron that I've circled carries out some computations and will then send this outputs to other neurons by this electrical impulses, and this upper neuron's output in turn becomes the input to this neuron down below, which again aggregates inputs from multiple other neurons to then maybe send its own output, to yet other neurons, and this is the stuff of which human thought is made.

Neurons in the brain



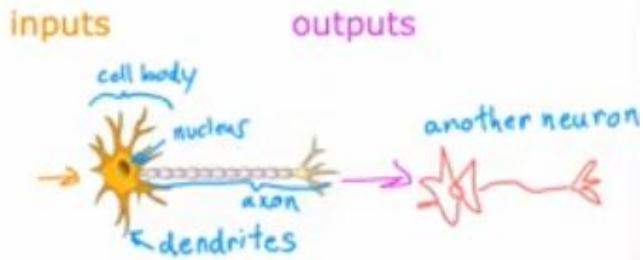
Here's a simplified diagram of a biological neuron. A neuron comprises a cell body shown here on the left, and if you have taken a class in biology, you may recognize this to be the nucleus of the neuron. As we saw on the previous slide, the neuron has different inputs. In a biological neuron, the input wires are called the dendrites, and it then occasionally sends electrical impulses to other neurons via the output wire, which is called the axon. Don't worry about these biological terms.

Biological neuron



If you saw them in a biology class, you may remember them, but you don't really need to memorize any of these terms for the purpose of building artificial neural networks. But this biological neuron may then send electrical impulses that become the input to another neuron. So the artificial neural network uses a very simplified Mathematical model of what a biological neuron does. I'm going to draw a little circle here to denote a single neuron.

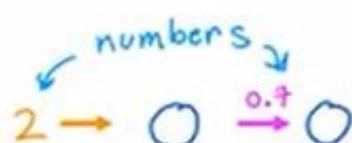
Biological neuron



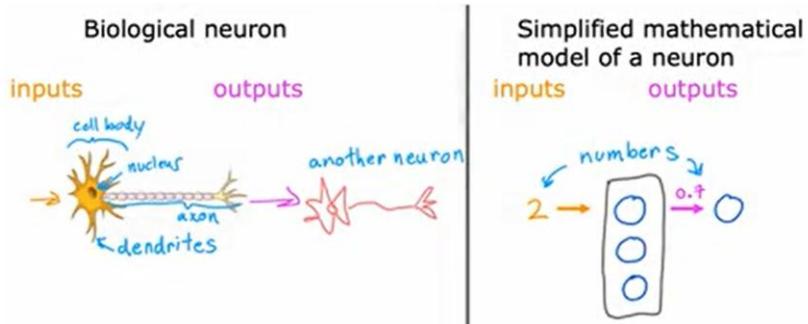
What a neuron does is it takes some inputs, one or more inputs, which are just numbers. It does some computation and it outputs some other number, which then could be an input to a second neuron, shown here on the right. When you're building an artificial neural network or deep learning algorithm, rather than building one neuron at a time, you often want to simulate many such neurons at the same time.

Simplified mathematical model of a neuron

inputs outputs



In this diagram, I'm drawing three neurons. What these neurons do collectively is input a few numbers, carry out some computation, and output some other numbers. Now, at this point, I'd like to give one big caveat, which is that even though I made a loose analogy between biological neurons and artificial neurons, I think that today we have almost no idea how the human brain works.



In fact, every few years, neuroscientists make some fundamental breakthrough about how the brain works. I think we'll continue to do so for the foreseeable future. That to me is a sign that there are many breakthroughs that are yet to be discovered about how the brain actually works, and thus attempts to blindly mimic what we know of the human brain today, which is frankly very little, probably won't get us that far toward building raw intelligence. Certainly not with our current level of knowledge in neuroscience.

Having said that, even with these extremely simplified models of a neuron, which we'll talk about, we'll be able to build really powerful deep learning algorithms. So as you go deeper into neural networks and into deep learning, even though the origins were biologically motivated, don't take the biological motivation too seriously. In fact, those of us that do research in deep learning have shifted away from looking to biological motivation that much.

But instead, they're just using engineering principles to figure out how to build algorithms that are more effective. But I think it might still be fun to speculate and think about how biological neurons work every now and then. The ideas of neural networks have been around for many decades. A few people have asked me, "Hey Andrew, why now?"

Why is it that only in the last handful of years that neural networks have really taken off?" This is a picture I draw for them when I'm asked that question and that maybe you could draw for others as well if they ask you that question. Let me plot on the horizontal axis the amount of data you have for a problem, and on the vertical axis, the performance or the accuracy of a learning algorithm applied to that problem.

Over the last couple of decades, with the rise of the Internet, the rise of mobile phones, the digitalization of our society, the amount of data we have for a lot of applications has steadily marched to the right. Lot of records that use P on paper, such as if you order something rather than it being on a piece of paper, there's much more likely to be a digital record. Your health record, if you see a doctor, is much more likely to be digital now compared to on pieces of paper. So in many application areas, the amount of digital data has exploded.

What we saw was with traditional machine-learning algorithms, such as logistic regression and linear regression, even as you fed those algorithms more data, it was very difficult to get the performance to keep on going up. So it was as if the traditional learning algorithms like linear regression and

logistic regression, they just weren't able to scale with the amount of data we could now feed it and they weren't able to take effective advantage of all this data we had for different applications.

What AI researchers started to observe was that if you were to train a small neural network on this dataset, then the performance maybe looks like this. If you were to train a medium-sized neural network, meaning one with more neurons in it, its performance may look like that. If you were to train a very large neural network, meaning one with a lot of these artificial neurons, then for some applications the performance will just keep on going up.



So this meant two things, it meant that for a certain class of applications where you do have a lot of data, sometimes you hear the term big data toss around, if you're able to train a very large neural network to take advantage of that huge amount of data you have, then you could attain performance on anything ranging from speech recognition, to image recognition, to natural language processing applications and many more, they just were not possible with earlier generations of learning algorithms. This caused deep learning algorithms to take off, and this too is why faster computer processors, including the rise of GPUs or graphics processor units.