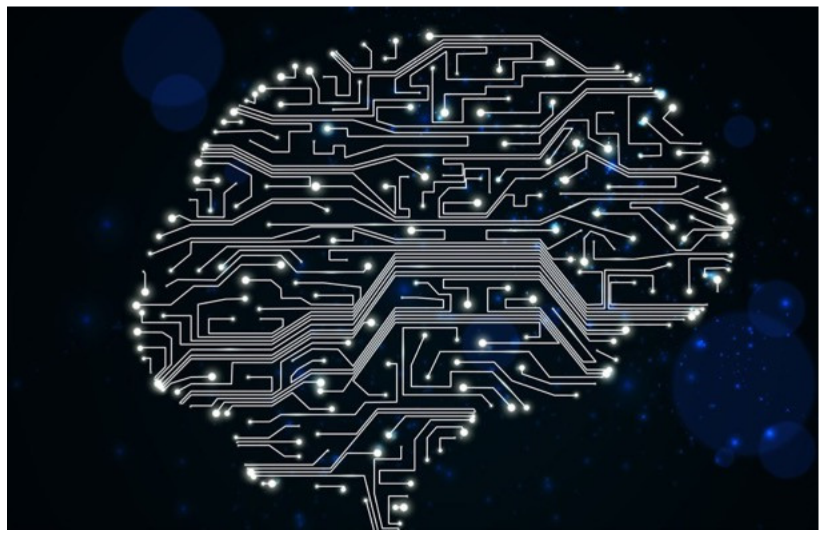
Neural networks made easy

Ophir Tanz, Cambron Carter / 2:00 pm PDT • 3, 2017



If you've dug into any articles on artificial intelligence, you've almost certainly run into the term "neural network." Modeled loosely on the human brain, artificial neural networks enable computers to learn from being fed data.

The efficacy of this powerful branch of machine learning, more than anything else, has been responsible for ushering in a new era of artificial intelligence, ending a long-lived "AI Winter." Simply put, the neural network may well be one of the most fundamentally disruptive technologies in existence today.

This guide to neural networks aims to give you a conversational level of understanding of deep learning. To this end, we'll avoid delving into the math and instead rely as much as possible on analogies and animations.

Thinking by brute force

One of the early schools of AI taught that if you load up as much information as possible into a powerful computer and give it as many directions as possible to understand that data, it ought to be able to “think.” This was the idea behind chess computers like IBM’s famous Deep Blue: By exhaustively programming every possible chess move into a computer, as well as known strategies, and then giving it sufficient power, IBM programmers created a machine that, in theory, could calculate every possible move and outcome into the future and pick the sequence of subsequent moves to outplay its opponent. This actually works, as chess masters learned in 1997.*

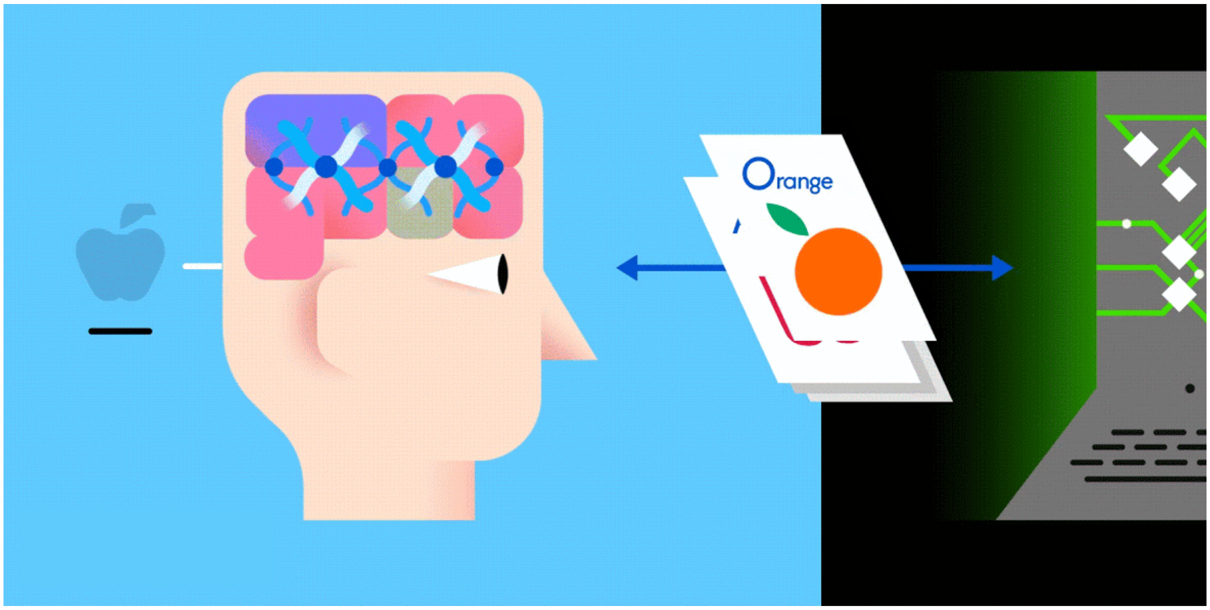
With this sort of computing, the machine relies on fixed rules that have been painstakingly pre-programmed by engineers — if this happens, then that happens; if this happens, do this — and so it isn’t human-style flexible learning as we know it at all. It’s powerful supercomputing, for sure, but not “thinking” per se.

Teaching machines to learn

Over the past decade, scientists have resurrected an old concept that doesn’t rely on a massive encyclopedic memory bank, but instead on a simp way of analyzing input data that’s loosely modeled after human thinking. Kno learning, or neural networks, this technology has been around since the 1940 today’s exponential proliferation of data — images, videos, voice searches, b more — along with supercharged and affordable processors, it is at last able true potential.

Machines — they’re just like us!

An artificial (as opposed to human) neural network (ANN) is an algorithmic co enables machines to learn everything from voice commands and playlist cura composition and image recognition.The typical ANN consists of thousands o artificial neurons, which are stacked sequentially in rows that are known as la millions of connections. In many cases, layers are only interconnected with tl before and after them via inputs and outputs. (This is quite different from neu brain, which are interconnected every which way.)



Source: GumGum

This layered ANN is one of the main ways to go about machine learning toda vast amounts of labeled data enables it to learn how to interpret that data like better than) a human.

Just as when parents teach their kids to identify apples and oranges in real life, for computers too, practice makes perfect.

Take, for example, image recognition, particular type of neural network know convolutional neural network (CNN) — it uses a mathematical process known be able to analyze images in non-litera identifying a partially obscured object viewable only from certain angles. (Th of neural networks, including recurrent neural networks and feed-forward neu these are less useful for identifying things like images, which is the example v below.)

All aboard the network training

So how do neural networks learn? Let's look at a very simple, yet effective, p

supervised learning. Here, we feed the neural network vast amounts of trainir
humans so that a neural network can essentially fact-check itself as it's learn

Let's say this labeled data consists of pictures of apples and oranges, respec
are the data; "apple" and "orange" are the labels, depending on the picture. A
in, the network breaks them down into their most basic components, i.e. edg
shapes. As the picture propagates through the network, these basic compon
to form more abstract concepts, i.e. curves and different colors which, when
start to look like a stem, an entire orange, or both green and red apples.

At the end of this process, the network attempts to make a prediction as to w
At first, these predictions will appear as random guesses, as no real learning
yet. If the input image is an apple, but "orange" is predicted, the network's in
to be adjusted.

The adjustments are carried out through a process called backpropagation to
likelihood of predicting "apple" for that same image the next time around. Thi
and over until the predictions are more or less accurate and don't seem to be
when parents teach their kids to identify apples and oranges in real life, for co
practice makes perfect. If, in your head, you just thought "hey, that sounds lik
you may have a career in AI.

So many layers…

Typically, a convolutional neural network has four essential layers of neurons
and output layers:

- Convolution
- Activation
- Pooling
- Fully connected

Convolution

In the initial convolution layer or layers, thousands of neurons act as the first
scouring every part and pixel in the image, looking for patterns. As more and
processed, each neuron gradually learns to filter for specific features, which i

In the case of apples, one filter might be focused on finding the color red, wh be looking for rounded edges and yet another might be identifying thin, stick- you've ever had to clean out a cluttered basement to prepare for a garage sa or worked with a professional organizer — then you know what it is to go thro and sort it into different-themed piles (books, toys, electronics, objets d'art, c of what a convolutional layer does with an image by breaking it down into dif

What's particularly powerful — and one of the neural network's main claims to fame — is that unlike earlier AI methods (Deep Blue and its ilk), these filters aren't hand designed; they learn and refine themselves purely by looking at data.

One advant networks is capable of l nonlinear w

The convolution layer essentially creates maps — different, broken-down versions of the picture, each dedicated to a different f that indicate where its neurons see an instance (however partial) of the color and the various other elements of, in this case, an apple. But because the co fairly liberal in its identifying of features, it needs an extra set of eyes to make value is missed as a picture moves through the network.

Activation

One advantage of neural networks is that they are capable of learning in a no in mathless terms, means they are able to spot features in images that aren't pictures of apples on trees, some of them under direct sunlight and others in into a bowl on a kitchen counter. This is all thanks to the activation layer, whic or less highlight the valuable stuff — both the straightforward and harder-to-s

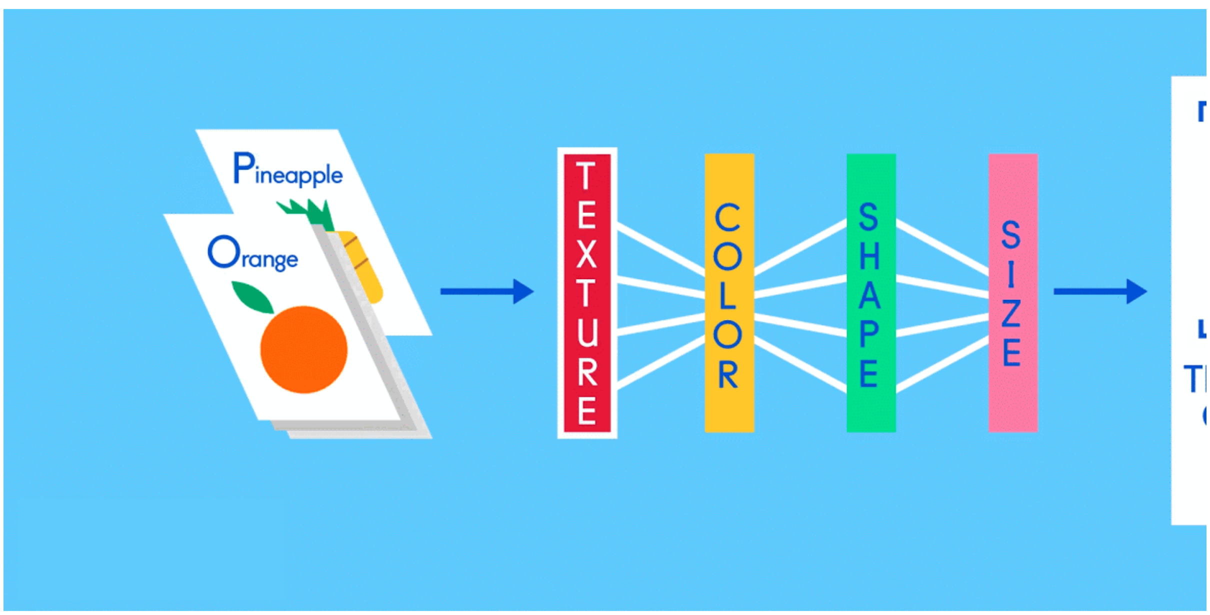
In the world of our garage-sale organizer or clutter consultant, imagine that fr separated piles of things we've cherry-picked a few items — a handful of rare classic t-shirts from our college days to wear ironically — that we might want these "maybe" items on top of their respective category piles for another co

Pooling

All this "convolving" across an entire image generates a lot of information, an become a computational nightmare. Enter the pooling layer, which shrinks it a general and digestible form. There are many ways to go about this, but one c is "max pooling," which edits down each feature map into a *Reader's Digest* that only the best examples of redness, stem-ness or curviness are featured.

In the garage spring cleaning example, if we were using famed Japanese clut
Marie Kondo's principles, our pack rat would have to choose only the things
from the smaller assortment of favorites in each category pile, and sell or tos
So now we still have all our piles categorized by type of item, but only consis
actually want to keep; everything else gets sold. (And this, by the way, ends
analogy to help describe the filtering and downsizing that goes on inside a ne

At this point, a neural network designer can stack subsequent layered config
— convolution, activation, pooling — and continue to filter down images to g
information. In the case of identifying an apple in pictures, the images get filt
over, with initial layers showing just barely discernable parts of an edge, a bli
tip of a stem, while subsequent, more filtered layers will show entire apples. E
time to start getting results, the fully connected layer comes into play.



Source: GumGum

Fully connected

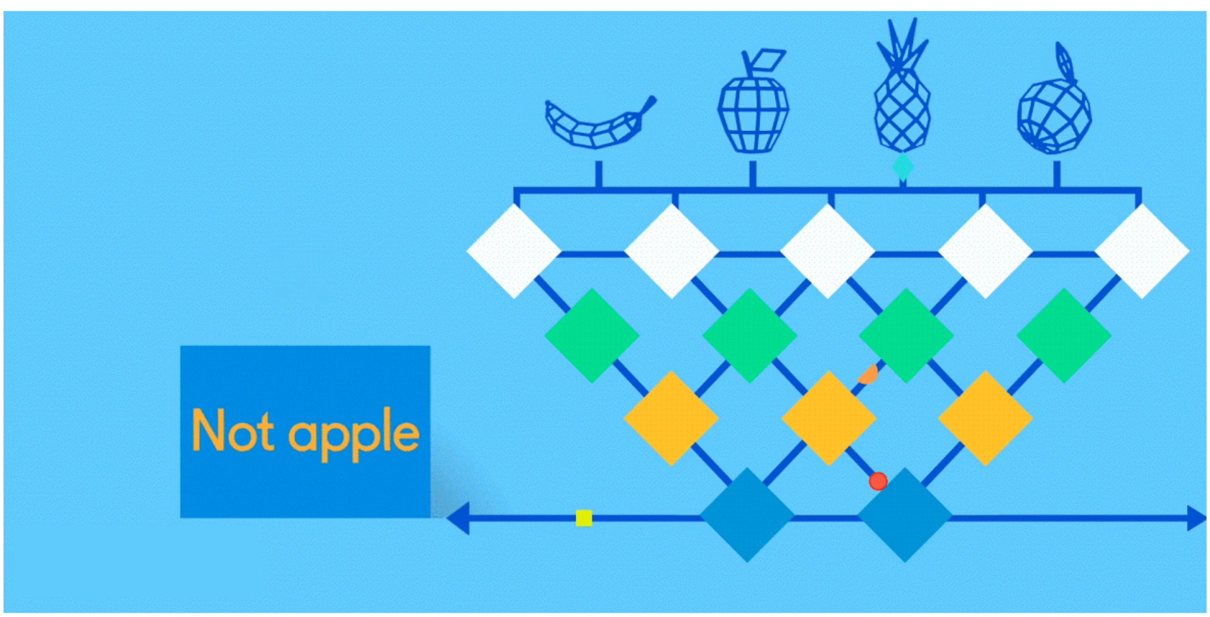
Now it's time to start getting answers. In the fully connected layer, each redu
feature map is "fully connected" to output nodes (neurons) that represent the
network is learning to identify. If the network is tasked with learning how to s
guinea pigs and gerbils, then it'll have four output nodes. In the case of the n
we've been describing, it'll just have two output nodes: one for "apples" and

If the picture that has been fed through the network is of an apple, and the ne undergone some training and is getting better with its predictions, then it's lik chunk of the feature maps contain quality instances of apple features. This is output nodes start to fulfill their destiny, with a reverse election of sorts.

Tweaks and adjustments are made to help each neuron better identify the data at every level.

The job (which they've learned "on the apple and orange nodes is essentially feature maps that contain their respec more the "apple" node thinks a particu contains "apple" features, the more vo feature map. Both nodes have to vote feature map, regardless of what it contains. So in this case, the "orange" nod votes to any of the feature maps, because they don't really contain any "oran end, the node that has sent the most votes out — in this example, the "apple considered the network's "answer," though it's not quite that simple.

Because the same network is looking for two different things — apples and c output of the network is expressed as percentages. In this case, we're assum network is already a bit down the road in its training, so the predictions here ı percent "apple" and 25 percent "orange." Or, if it's earlier in the training, it mi inaccurate and determine that it's 20 percent "apple" and 80 percent "orange



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If at first you don't succeed, try, try, try again

So, in its early stages, the neural network spits out a bunch of wrong answers percentages. The 20 percent "apple" and 80 percent "orange" prediction is c since this is supervised learning with labeled training data, the network is abl where and how that error occurred through a system of checks and balances backpropagation.

Now, this is a mathless explanation, so suffice it to say that backpropagation the previous layer's nodes about just how far off the answers were. That layer feedback to the previous layer, and on and on like a game of telephone until i convolution. Tweaks and adjustments are made to help each neuron better ic every level when subsequent images go through the network.

This process is repeated over and over until the neural network is identifying in images with increasing accuracy, eventually ending up at 100 percent corr though many engineers consider 85 percent to be acceptable. And when tha neural network is ready for prime time and can start identifying apples in pict

**This is different than Google's AlphaGo which used a self-learned neural net positions and ultimately beat a human at Go, versus Deep Blue, which used a function written by a human.*

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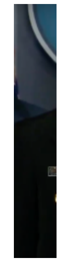

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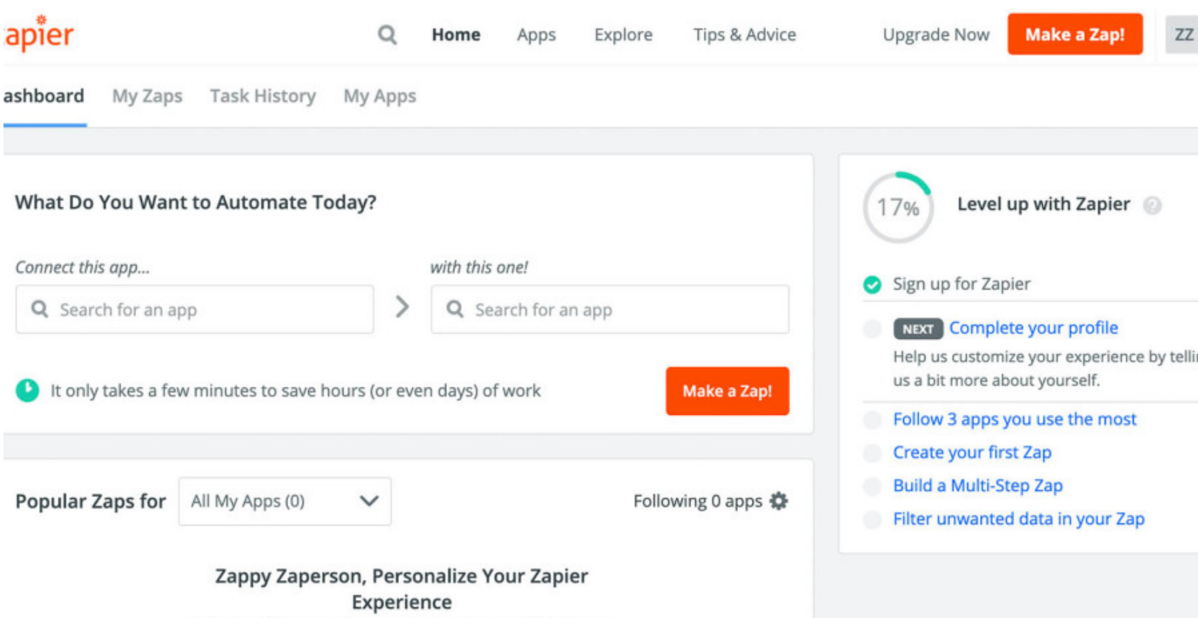

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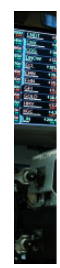

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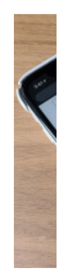
Wait, you all haven't been wiping down your smartphones this whole time?



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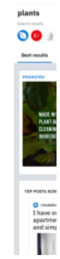

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