Neural networks made e

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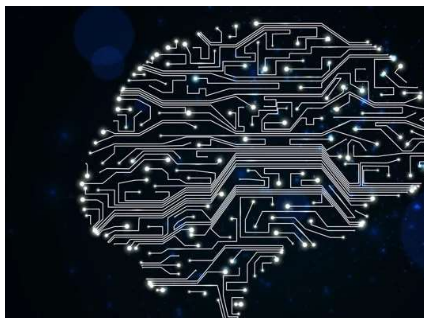

If you've dug into any articles on artificial intelligence, you've almost certainly run into the term "neural network." Modeled loosely on the human brain, artificial neural networks enable computers to learn from being fed data.

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.

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and currently lives in Los Angeles.

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Cambron Carter
Contributor

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 subse opponent. This actually works, as chess masters learne

With this sort of computing, the machine relies on fixed painstakingly pre-programmed by engineers — if this ha this happens, do this — and so it isn't human-style flexil all. It's powerful supercomputing, for sure, but not "think

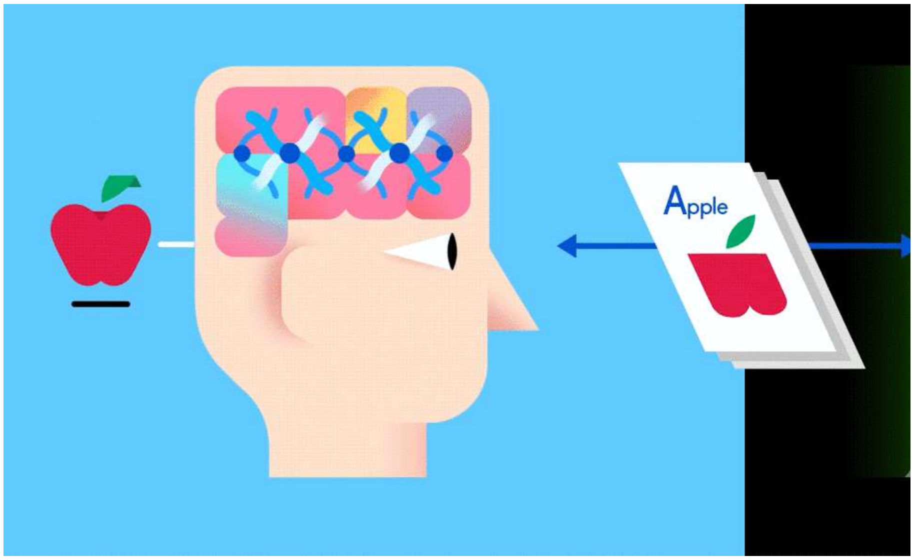
Teaching machines to learn

Over the past decade, scientists have resurrected an ol massive encyclopedic memory bank, but instead on a s analyzing input data that's loosely modeled after humar learning, or neural networks, this technology has been a because of today's exponential proliferation of data — ir browsing habits and more — along with supercharged and affordable processors, it is at last able to begin to fulfill its true potential.

Machines — they're just like us!

An artificial (as opposed to human) neural network (ANN) is an algorithmic construct that enables machines to learn everything from voice commands and playlist curation to music composition and image recognition.The typical ANN consists of thousands of

interconnected artificial neurons, which are stacked seq
known as layers, forming millions of connections. In ma
interconnected with the layer of neurons before and afte
(This is quite different from neurons in a human brain, w
which way.)



Source: GumGum

This layered ANN is one of the main ways to go about n
feeding it vast amounts of labeled data enables it to lea
like (and sometimes better than) a human.

> **Just as when parents teach their
> apples and oranges in real life, fo
> practice makes perfect.**

Take, for example, image recognition, which relies on a
network known as the convolutional neural network (CNN) — so called because it uses a mathematical process known as convolution to be able to analyze images in non-literal ways, such as identifying a partially obscured object or one that is viewable only from certain angles. (There are other types of neural networks, including recurrent neural networks and feed-forward neural networks, but these are less useful for identifying things like images, which is the example we're going to use below.)

All aboard the network training

So how do neural networks learn? Let's look at a very s
called supervised learning. Here, we feed the neural ne
data, labeled by humans so that a neural network can e
it's learning.

Let's say this labeled data consists of pictures of apples
The pictures are the data; "apple" and "orange" are the
picture. As pictures are fed in, the network breaks them
components, i.e. edges, textures and shapes. As the pic
network, these basic components are combined to form
curves and different colors which, when combined furth
entire orange, or both green and red apples.

At the end of this process, the network attempts to mak
the picture. At first, these predictions will appear as ranc
learning has taken place yet. If the input image is an ap
the network's inner layers will need to be adjusted.

The adjustments are carried out through a process calle
the likelihood of predicting "apple" for that same image t
happens over and over until the predictions are more or
to be improving. Just as when parents teach their kids t
in real life, for computers too, practice makes perfect. If,
"hey, that sounds like learning," then you may have a ca

So many layers…

Typically, a convolutional neural network has four essen
the input and output layers:

- Convolution
- Activation
- Pooling
- Fully connected

Convolution

In the initial convolution layer or layers, thousands of ne
filters, scouring every part and pixel in the image, lookin
more images are processed, each neuron gradually lea
which improves accuracy.

In the case of apples, one filter might be focused on finc
another might be looking for rounded edges and yet anc
stick-like stems. If you've ever had to clean out a clutter
garage sale or a big move — or worked with a professic
know what it is to go through everything and sort it into
toys, electronics, objets d'art, clothes). That's sort of wh
with an image by breaking it down into different features

> **One advantage of neural networl capable of learning in a nonlinear**

What's particularly powerful — and one of the neural ne
is that unlike earlier AI methods (Deep Blue and its ilk),
designed; they learn and refine themselves purely by lo

The convolution layer essentially creates maps — differ
the picture, each dedicated to a different filtered feature
neurons see an instance (however partial) of the color r
various other elements of, in this case, an apple. But be
fairly liberal in its identifying of features, it needs an extr
nothing of value is missed as a picture moves through t

Activation

One advantage of neural networks is that they are capable of learning in a nonlinear way, which, in mathless terms, means they are able to spot features in images that aren't quite as obvious — pictures of apples on trees, some of them under direct sunlight and others in the shade, or piled into a bowl on a kitchen counter. This is all thanks to the activation layer, which serves to more or less highlight the valuable stuff — both the straightforward and harder-to-spot varieties.

In the world of our garage-sale organizer or clutter consultant, imagine that from each of those separated piles of things we've cherry-picked a few items — a handful of rare

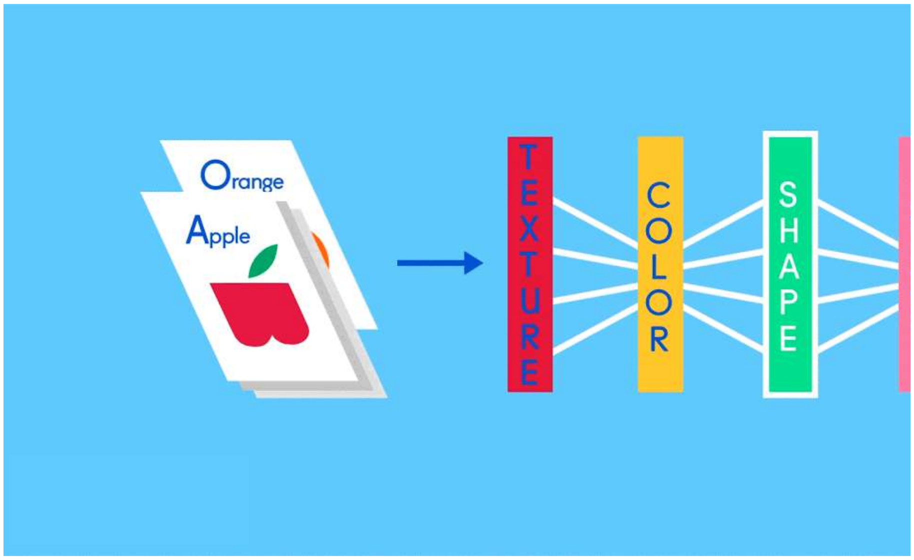
books, some classic t-shirts from our college days to we
want to keep. We stick these “maybe” items on top of th
for another consideration later.

Pooling

All this “convolving” across an entire image generates a
quickly become a computational nightmare. Enter the p
into a more general and digestible form. There are man
one of the most popular is “max pooling,” which edits dc
Reader’s Digest version of itself, so that only the best e:
or curviness are featured.

In the garage spring cleaning example, if we were usinç
consultant Marie Kondo’s principles, our pack rat would
that “spark joy” from the smaller assortment of favorites
or toss everything else. So now we still have all our pile
but only consisting of the items we actually want to keep
(And this, by the way, ends our de-cluttering analogy to
downsizing that goes on inside a neural network.)

At this point, a neural network designer can stack subse
of this sort — convolution, activation, pooling — and co
get higher-level information. In the case of identifying ar
get filtered down over and over, with initial layers showi
of an edge, a blip of red or just the tip of a stem, while s
will show entire apples. Either way, when it’s time to sta
connected layer comes into play.



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Source: GumGum

Fully connected

Now it's time to start getting answers. In the fully conne
"pooled," feature map is "fully connected" to output node
items the neural network is learning to identify. If the net
how to spot cats, dogs, guinea pigs and gerbils, then it'l
case of the neural network we've been describing, it'll ju
for "apples" and one for "oranges."

If the picture that has been fed through the network is o
has already undergone some training and is getting bet
likely that a good chunk of the feature maps contain qua
features. This is where these final output nodes start to
reverse election of sorts.

> **Tweaks and adjustments are mac neuron better identify the data at every level.**

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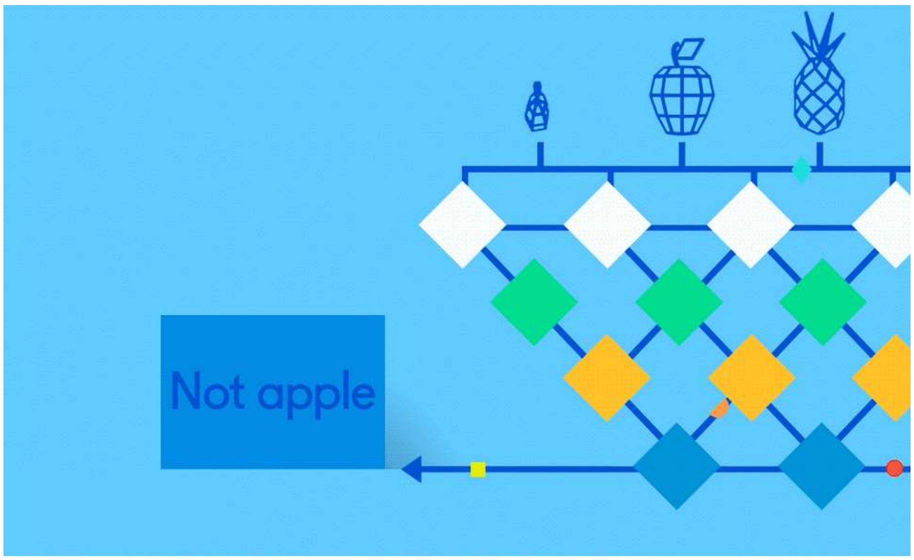
The job (which they've learned "on the job") of both the apple and orange nodes is essentially to "vote" for the feature maps that contain their respective fruits. So, the more the "apple" node thinks a particular feature map contains "apple" features, the more votes it sends to that feature map. Both nodes have to vote on every single feature map, regardless of what it contains. So in this case, the "orange" node won't send many votes to any of the feature maps, because they don't really contain any "orange" features. In the end, the node that has sent the most votes out — in this

example, the “apple” node — can be considered the ne
not quite that simple.

Because the same network is looking for two different tl
the final output of the network is expressed as percenta
assuming that the network is already a bit down the roa
predictions here might be, say, 75 percent “apple” and 2
earlier in the training, it might be more inaccurate and d
“apple” and 80 percent “orange.” Oops.



Source: GumGum

If at first you don't succeed, try,

So, in its early stages, the neural network spits out a bu
form of percentages. The 20 percent “apple” and 80 per
clearly wrong, but since this is supervised learning with
network is able to figure out where and how that error o
checks and balances known as backpropagation.

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

This process is repeated over and over until the neural r
and oranges in images with increasing accuracy, eventu
correct predictions — though many engineers consider
And when that happens, the neural network is ready for
identifying apples in pictures professionally.

**This is different than Google's AlphaGo which used a s
evaluate board positions and ultimately beat a human a
used a hard-coded function written by a human.*

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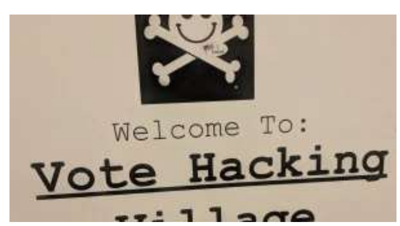

Blind loyalty

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