Neural networks mad

Ophir Tanz, Cambron Carter
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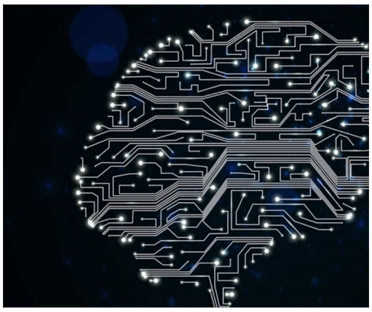

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Cambron Carter leads the image technology team at Gu
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If you've dug into any articles on artificial intelligenc
into the term "neural network." Modeled loosely on

networks enable computers to learn from being fec

The efficacy of this powerful branch of machine lea has been responsible for ushering in a new era of a long-lived "AI Winter." Simply put, the neural netwo fundamentally disruptive technologies in existence

This guide to neural networks aims to give you a co understanding of deep learning. To this end, we'll a instead rely as much as possible on analogies and

Thinking by brute force

One of the early schools of AI taught that if you loa possible into a powerful computer and give it as ma understand that data, it ought to be able to "think." computers like IBM's famous Deep Blue: By exhau possible chess move into a computer, as well as kr it sufficient power, IBM programmers created a ma calculate every possible move and outcome into th of subsequent moves to outplay its opponent. This masters learned in 1997.*

With this sort of computing, the machine relies on f painstakingly pre-programmed by engineers — if th if this happens, do this — and so it isn't human-sty at all. It's powerful supercomputing, for sure, but no

Teaching machines to learn

Over the past decade, scientists have resurrected on a massive encyclopedic memory bank, but inste way of analyzing input data that's loosely modeled

Machines — they're just like u

An artificial (as opposed to human) neural network construct that enables machines to learn everythin playlist curation to music composition and image re consists of thousands of interconnected artificial ne sequentially in rows that are known as layers, form many cases, layers are only interconnected with th after them via inputs and outputs. (This is quite diff brain, which are interconnected every which way.)

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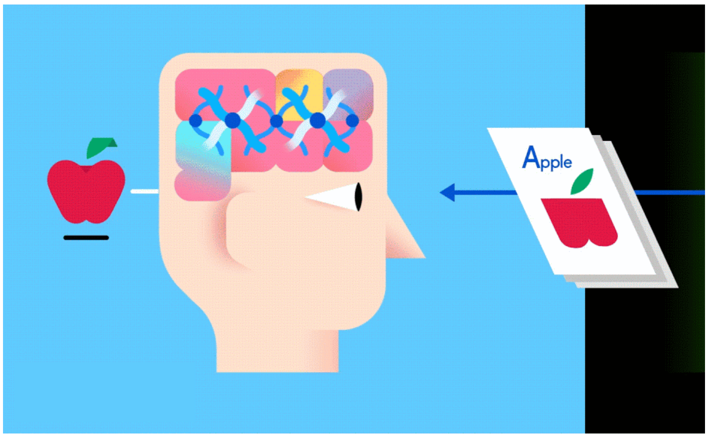


Source: GumGum

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

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

Take, for example, image recognition, which relies network known as the convolutional neural networ uses a mathematical process known as convolutio non-literal ways, such as identifying a partially obs

All aboard the network traini

So how do neural networks learn? Let's look at a v
procedure called supervised learning. Here, we fee
amounts of training data, labeled by humans so tha
essentially fact-check itself as it's learning.

Let's say this labeled data consists of pictures of a
The pictures are the data; "apple" and "orange" are
picture. As pictures are fed in, the network breaks t
components, i.e. edges, textures and shapes. As th
the network, these basic components are combine
concepts, i.e. curves and different colors which, wh
look like a stem, an entire orange, or both green ar

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

The adjustments are carried out through a process
increase the likelihood of predicting "apple" for that
around. This happens over and over until the predi
and don't seem to be improving. Just as when pare
apples and oranges in real life, for computers too, p
head, you just thought "hey, that sounds like learnin
in AI.

So many layers…

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

- Convolution
- Activation

In the initial convolution layer or layers, thousands
filters, scouring every part and pixel in the image, l

more images are processed, each neuron graduall
features, which improves accuracy.

In the case of apples, one filter might be focused o
another might be looking for rounded edges and ye
thin, stick-like stems. If you've ever had to clean ou
prepare for a garage sale or a big move — or work
— then you know what it is to go through everythin
themed piles (books, toys, electronics, objets d'art,
convolutional layer does with an image by breaking

> **One advantage of neural netw
> are capable of learning in a no**

What's particularly powerful — and one of the neur
— is that unlike earlier AI methods (Deep Blue and
designed; they learn and refine themselves purely

The convolution layer essentially creates maps —
of the picture, each dedicated to a different filtered
neurons see an instance (however partial) of the c
various other elements of, in this case, an apple. B
is fairly liberal in its identifying of features, it needs
sure nothing of value is missed as a picture moves

Activation

One advantage of neural networks is that they are
nonlinear way, which, in mathless terms, means th
images that aren't quite as obvious — pictures of a
under direct sunlight and others in the shade, or pil
counter. This is all thanks to the activation layer, wh
highlight the valuable stuff — both the straightforwa

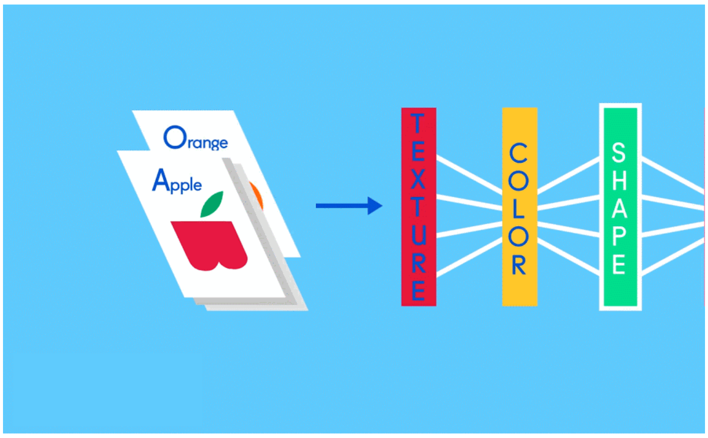
respective category piles for another consideration

Pooling

All this “convolving” across an entire image genera
can quickly become a computational nightmare. Er
shrinks it all into a more general and digestible forr
about this, but one of the most popular is “max poc
feature map into a *Reader’s Digest* version of itself
of redness, stem-ness or curviness are featured.

In the garage spring cleaning example, if we were
consultant Marie Kondo’s principles, our pack rat w
things that “spark joy” from the smaller assortment
pile, and sell or toss everything else. So now we st
by type of item, but only consisting of the items we
everything else gets sold. (And this, by the way, en
help describe the filtering and downsizing that goes

At this point, a neural network designer can stack s
configurations of this sort — convolution, activatior
down images to get higher-level information. In the
pictures, the images get filtered down over and ove
barely discernable parts of an edge, a blip of red or
subsequent, more filtered layers will show entire ap
to start getting results, the fully connected layer co



“pooled,” feature map is “fully connected” to output
the items the neural network is learning to identify.

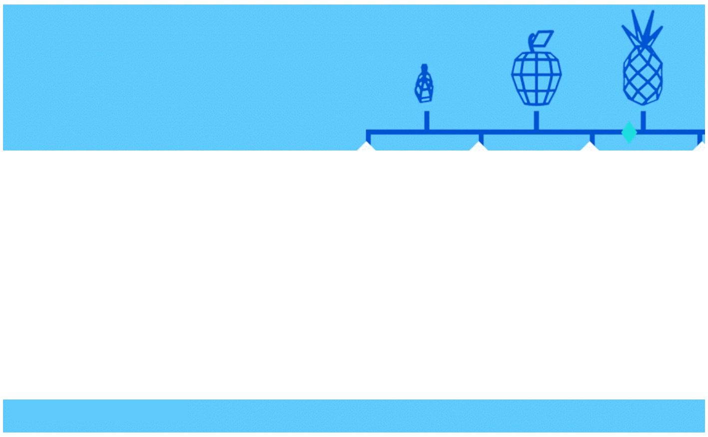
learning how to spot cats, dogs, guinea pigs and g
nodes. In the case of the neural network we've bee
output nodes: one for "apples" and one for "orange

If the picture that has been fed through the networ
has already undergone some training and is getting
it's likely that a good chunk of the feature maps co
features. This is where these final output nodes sta
reverse election of sorts.

> **Tweaks and adjustments are r
> neuron better identify the dat**

The job (which they've learned "on the job") of both
essentially to "vote" for the feature maps that conta
more the "apple" node thinks a particular feature m
more votes it sends to that feature map. Both node
feature map, regardless of what it contains. So in t
send many votes to any of the feature maps, becau
"orange" features. In the end, the node that has se
example, the "apple" node — can be considered th
not quite that simple.

Because the same network is looking for two differe
— the final output of the network is expressed as p
assuming that the network is already a bit down the
predictions here might be, say, 75 percent "apple" a
it's earlier in the training, it might be more inaccura
percent "apple" and 80 percent "orange." Oops.



Source: GumGum

If at first you don't succeed, t

So, in its early stages, the neural network spits out
form of percentages. The 20 percent "apple" and 8
clearly wrong, but since this is supervised learning
network is able to figure out where and how that er
checks and balances known as backpropagation.

Now, this is a mathless explanation, so suffice it to
feedback to the previous layer's nodes about just h
That layer then sends the feedback to the previous
game of telephone until it's back at convolution. Tw
to help each neuron better identify the data at ever
go through the network.

This process is repeated over and over until the ne
and oranges in images with increasing accuracy, e
percent correct predictions — though many engine
acceptable. And when that happens, the neural ne
can start identifying apples in pictures professional

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

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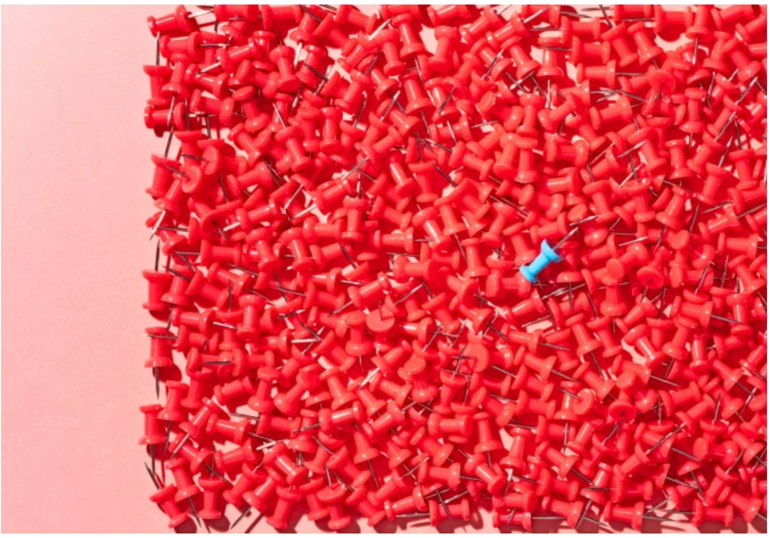

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