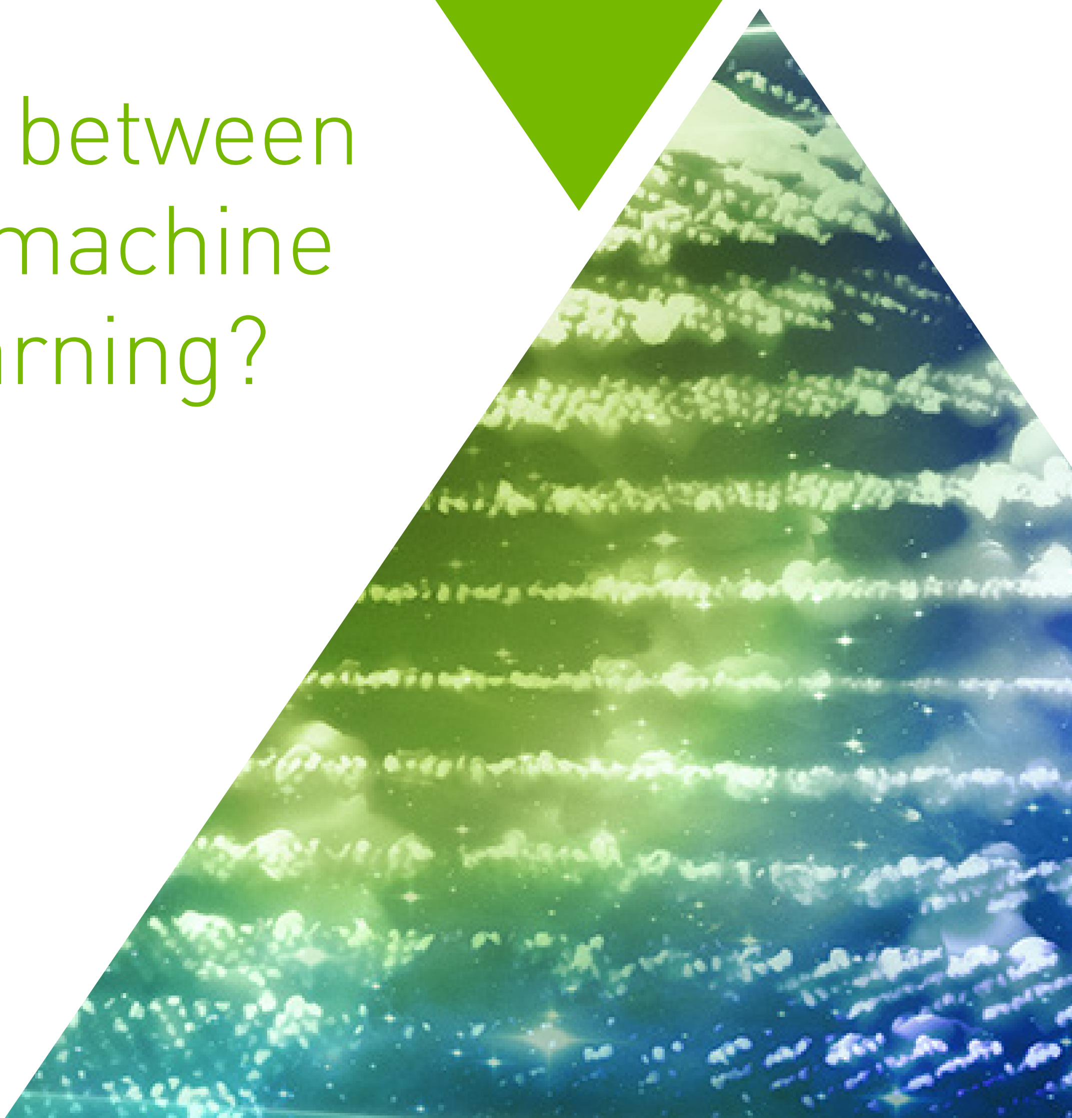
DEEP LEARNING EXPLAINED

WHAT IT IS, AND HOW IT CAN DELIVER BUSINESS VALUE TO YOUR ORGANIZATION

CHAPTER 1 | ARTIFICIAL INTELLIGENCE

What is the difference between artificial intelligence, machine learning, and deep learning?



ARTIFICIAL INTELLIGENCE IS...

THE FUTURE

SCIENCE FICTION

PART OF OUR EVERYDAY LIVES

Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – the first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

When Google DeepMind's AlphaGo program defeated South Korean Master Lee Se-dol in the board game 'Go' this year, the terms AI, machine learning, and deep learning were used in the media to describe how DeepMind won. And all three are part of the reason why AlphaGo trounced Lee Se-Dol. But they are not the same things.

The easiest way to think of their relationship is to visualize them as concentric circles with AI -- the idea that came first – the largest, then machine learning – which blossomed later, and finally deep learning – which is driving today's AI explosion – fitting inside both.

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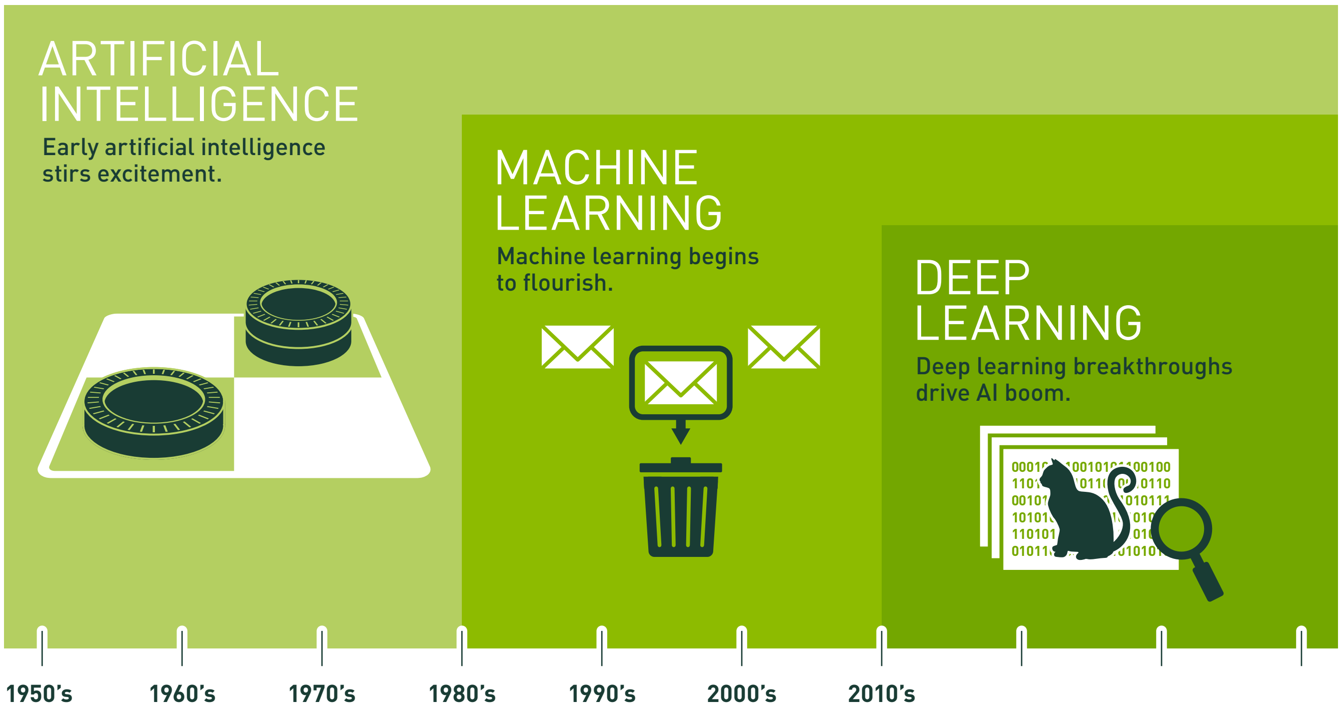


AI HAS BEEN PART OF OUR IMAGINATIONS AND SIMMERING IN RESEARCH LABS ...

since a handful of computer scientists rallied around the term at the Dartmouth Conferences in 1956 and birthed the field of AI.

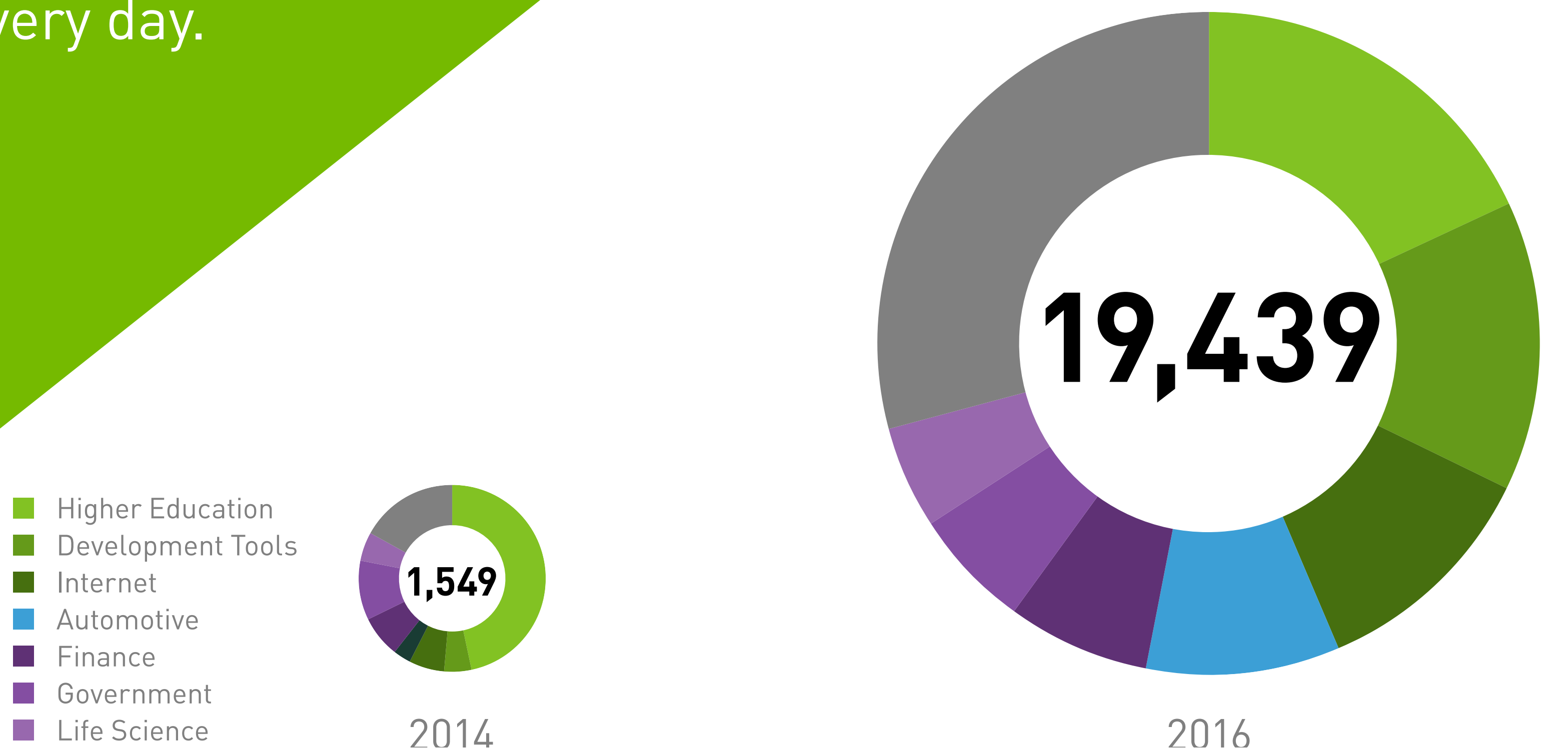
In the decades since, AI has alternatively been heralded as the key to our civilization's brightest future, and tossed on technology's trash heap as a harebrained notion of over-reaching propeller-heads.

Frankly, until 2012, it was a bit of both.

Over the past few years artificial intelligence (AI) has exploded, and especially since 2015. Much of that has to do with the wide availability of GPUs that make parallel processing ever faster, cheaper, and more powerful.

It also has to do with the simultaneous one-two punch of practically infinite storage and a flood of data of every stripe (that whole Big Data movement) – images, text, transactions, mapping data, you name it.

Computer scientists have moved from something of a bust – until 2012 – to a boom that has unleased applications used by hundreds of millions of people every day.



ORGANIZATIONS ENGAGED WITH NVIDIA ON DEEP LEARNING

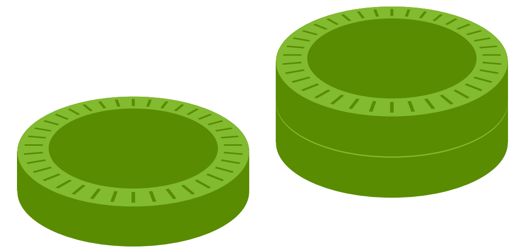
READ Ovum's Report on how AI solutions can be applied to today's business use cases

Back in that summer of '56 conference the dream of those AI pioneers was to construct complex – enabled by emerging computers – that possessed the same characteristics of human intelligence.

This is the concept that we of as "General AI" – fabulous machines that have all of our senses (maybe even more), all our reason, and think just like we do.

You've seen these machines endlessly in movies as friends – C3PO – and foe – The Terminator.

General AI machines have remained in the movies and science fiction novels for good reason; we can't pull it off, at least not yet.



Computer programs that played checkers were among the earliest examples of Artificial Intelligence, stirring an early wave of excitement in the 1950s.

What we can do falls into the concept of "Narrow AI." Technologies that are able to perform specific tasks as well as, or better than, we humans can. Examples of narrow AI are things such as image classification on a service like Pinterest and face recognition on Facebook.

Those are examples of Narrow AI in practice. These technologies exhibit some facets of human intelligence. But how? Where does that intelligence. But how? Where does that intelligence come from? That gets us to the next circle, Machine Learning.

Machine Learning at its most basic is the practice of using algorithms to parse data, learn from it, and then make a determination or prediction about something in the world.

So rather than hand-coding software routines with a specific set of instructions to accomplish a particular task, the machine is "trained" using large amounts of data and algorithms that give it the ability to learn how to perform the task.

Machine learning came directly from minds of the early AI crowd, and the algorithmic approaches over the years included decision tree learning, inductive logic programming, clustering, reinforcement learning, and Bayesian networks among others.

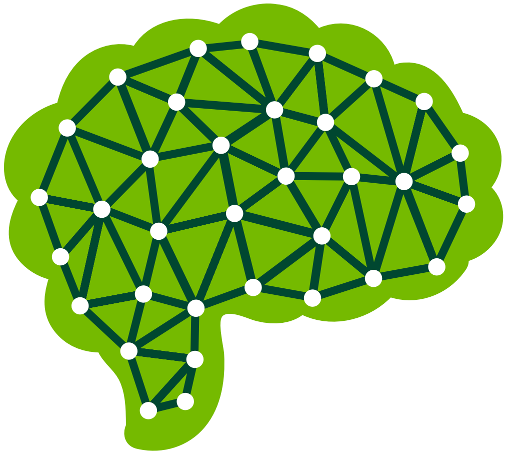
ONE OF THE VERY BEST APPLICATIONS AREAS FOR MACHINE LEARNING FOR MANY YEARS WAS COMPUTER VISION

though it still required a great deal of hand-coding to get the job done. People would go in and write hand-coded classifiers like edge detection filters so the program could identify where an object started and stopped; shape detection to determine if it had eight sides; a classifier to recognize the letters "S-T-O-P."

From all these hand-coded classifiers they would develop algorithms to make sense of the image and "learn" to determine whether it was a stop sign. Good, but not mind-bendingly great. Especially on a foggy day when the sign isn't perfectly visible, or a tree obscures part of it. There's a reason computer vision and image detection didn't come close to rivaling humans until very recently, it was too brittle and too prone to error.

Time, and the right learning algorithms made all the difference.

Deep Learning – A Technique for Implementing Machine Learning



Another algorithmic approach from the early machine – learning crowd, Artificial Neural Networks, came and mostly went over the decades. Neural networks are inspired by our understanding of the biology of our brains – all those interconnections between the neurons. But, unlike a brain where any neuron can connect to any other neuron within a certain physical distance, these artificial neural networks have discrete layers, connections, and directions of data propagation.

You might, for example, take an image, chop it up into a bunch of tiles that are inputted into the first layer of the neural network. In the first layer individual neurons, then passes the data to a second layer. The second layer of neurons does its tasks, and so on, until, the final layer and the final output is produced.

Each neuron assigns a weighting to its input – how correct or incorrect it is relative to the task of being performed. The final output is then determined by the total of those weightings. So think of our stop sign example. Attributes of a stop sign are chopped up and "examined" by the neurons – its octagonal shape, its fire-engine red color, its distinctive letters, its traffic sign size, and its motion or lack thereof.

The neural network's task is to conclude whether this is a stop sign or not. It come up with a "probability vector," really a highly educated guess, based on the weightings. In our example the system might be 86% confident the image is a stop sign, 7% it's a speed limit sign, and 5% it's a kite stuck in a tree, and so on – and the network architecture then tells the neural network whether its right or not.

Even this example is getting ahead of itself, because until recently neural networks were all but shunned by the AI research community. They had been around since the earliest days of AI, and had produced very little in the way of "intelligence." The problem was even the most basic neural networks were very computationally intensive, it just wasn't a practical approach. Still, a small heretical research group led by Geoffrey Hinton at the University of Toronto kept at it, finally parallelizing the algorithms for supercomputers to run and proving the concept, but it wasn't until GPUs were deployed in the effort that the promise was realized.

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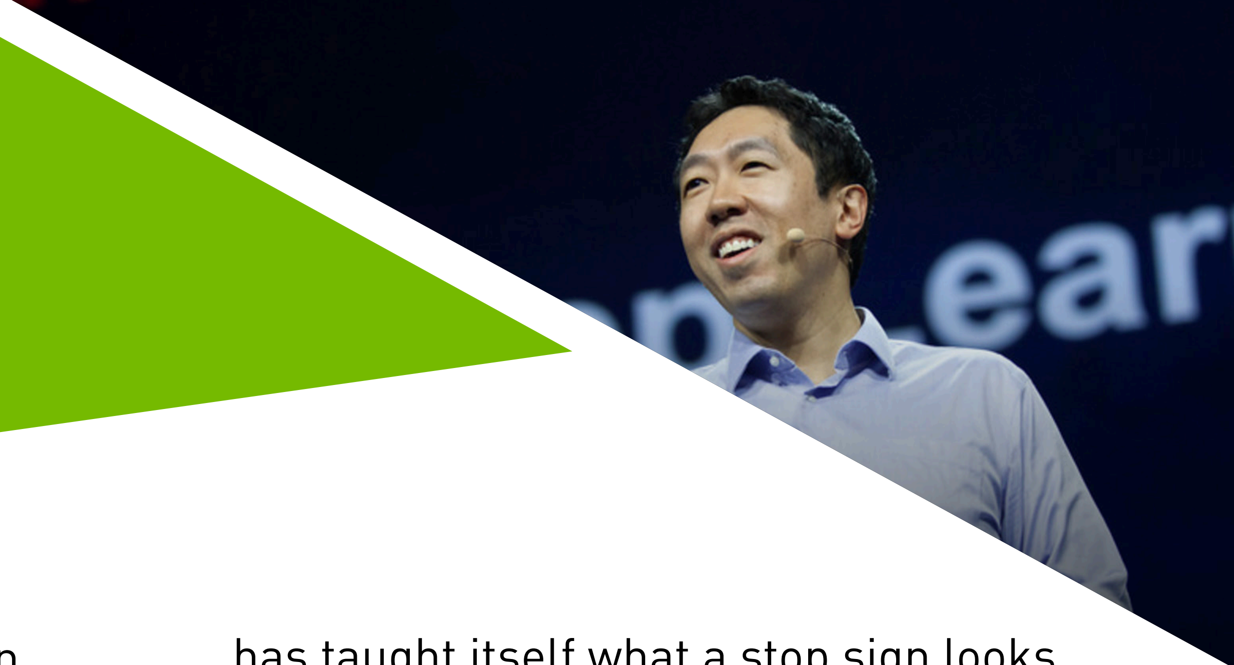


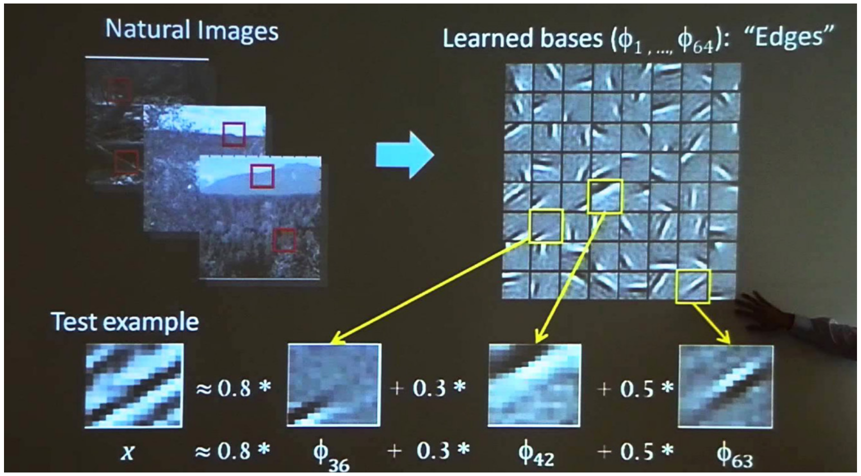
If we go back again to our stop sign example, chances are very good that as the network is getting tuned or “trained” it’s coming up with wrong answers – a lot. What it needs is training.

It needs to see hundreds of thousands, even millions of images, until the weightings of the neuron inputs are tuned so precisely that it gets the answer right practically every time – for or no fog, sun or rain.
It’s at that point that the neural network has taught itself what a stop sign looks like; or your mother’s face in the case of Facebook; or a cat, which is what Andrew Ng did in 2012 at Google.

Ng’s breakthrough was to take these neural networks, and essentially make them huge, increase the layers and the neurons, and then run massive amounts of data through the system to train it.

In Ng's case it was images from 10 million YouTube videos. Ng put the "deep" in deep learning, which describes all the layers in these neural networks.

Today, image recognition by machines trained via deep learning in some scenarios is better than humans, and ranges from cats to identifying indicators for cancer in blood and tumors in MRI scans. Google's AlphaGo learned the game, and trained for its 'Go' match – it tuned its neural network – by playing against itself over and over.



Andrew Y. Ng's lecture on deep learning, self-taught learning, and unsupervised feature learning.

AI IS THE PRESENT AND THE FUTURE.

With Deep Learning's help, AI may even get
to that science fiction state we've so long imagined.

MICHAEL V. COPELAND
AUTHOR

A long-time journalist based in Silicon Valley, Michael has been in the thick of technological change since the web took hold. Writing and editing for such outlets as WIRED, Fortune, and Business 2.0, Michael has been a part of identifying and explaining some of the most monumental (and monumentally stupid) trends in technology from the time Netscape was a thing. He helped lead editorial efforts as a partner at venture capital firm, Andreessen Horowitz and is now a partner at Story Made Good.