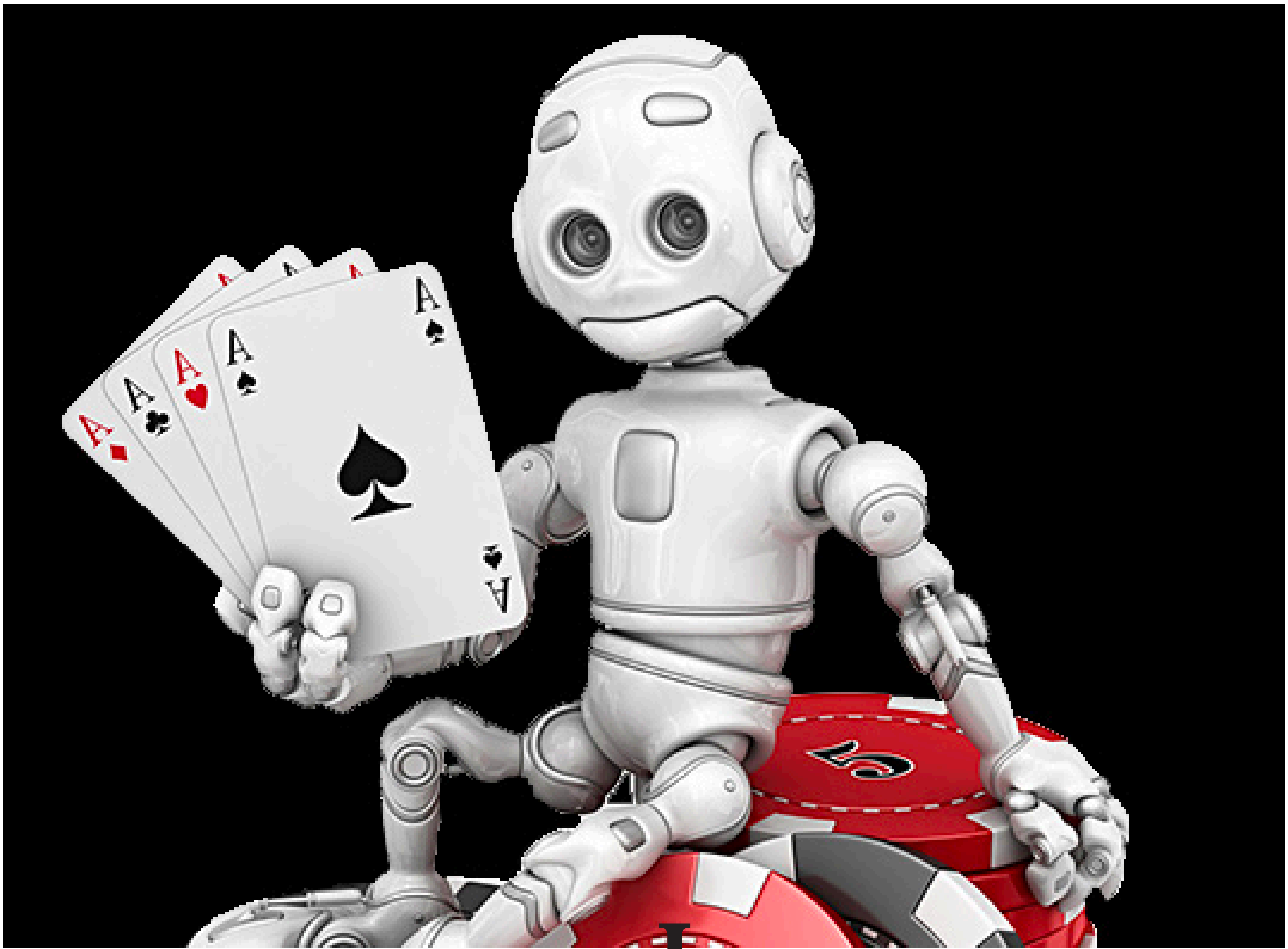

AI & V

Reinforcement Learning....

By experimenting, computers are figuring out how to do things that no programmer could teach them. Are we losing the game???

Inside a simple computer simulation, a group of self-driving cars are performing a crazy-looking maneuver on a four-lane virtual highway. Half are trying to move from the right-hand lanes just as the other half try to merge from the left. It seems like just the sort of tricky thing that might flummox a robot vehicle, but they manage it with precision.

I'm watching the driving simulation at the biggest artificial-intelligence conference of the year, held in Barcelona this past December. What's most amazing is that the software governing the cars' behavior wasn't programmed in the conventional sense at all. It learned how to merge, slickly and safely, simply by practicing. During training, the control software performed the maneuver over and over, altering its instructions a little with each attempt. Most of the time the merging happened way too slowly and cars interfered with each other. But whenever the merge went smoothly, the system would learn to favor the behavior that

This approach, known as reinforcement learning, is largely how AlphaGo, a computer developed by a subsidiary of Alphabet called DeepMind, mastered the impossibly complex board game Go and beat one of the best human players in the world in a high-profile match last year. Now reinforcement learning may soon inject greater intelligence into much more than games. In addition to improving self-driving cars, the technology can get a robot to grasp objects it has never seen before, and it can figure out the optimal configuration for the equipment in a data center.

Reinforcement learning copies a very simple principle from nature. The psychologist Edward Thorndike documented it more than 100 years ago. Thorndike placed cats inside boxes from which they could escape only by pressing a lever. After a considerable amount of pacing around and meowing, the animals would eventually step on the lever by chance. After they learned to associate this behavior with the desired outcome, they eventually escaped with increasing speed.

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Jostling for position

Silver, a mild-mannered Brit who became fascinated with artificial intelligence as an undergraduate at the University of Cambridge, explains why reinforcement learning has recently become so formidable. He says that the key is combining it with deep learning, a technique that involves using a very large simulated neural network to recognize patterns in data

Reinforcement learning works because researchers figured out how to get a computer to calculate the value that should be assigned to, say, each right or wrong turn that a rat might make on its way out of its maze. Each value is stored in a large table, and the computer updates all these values as it learns. For large and complicated tasks, this becomes computationally impractical. In recent years, however, deep learning has proved an extremely efficient way to recognize patterns in data, whether the data refers to the turns in a maze, the positions on a Go board, or the pixels shown on screen during a computer game.

In fact, it was in games that DeepMind made its name. In 2013 it published details of a program capable of learning to play various Atari video games at a superhuman level, leading Google to acquire the company for more than $500 million in 2014. These and other feats have in turn inspired other researchers and companies to turn to reinforcement learning. A number of industrial-robot makers are testing the approach as a way to train their machines to perform new tasks without manual programming. And researchers at Google, also an Alphabet subsidiary, worked with DeepMind to use deep reinforcement learning to make its data centers more energy efficient. It is difficult to figure out how all the elements in a data center will affect energy usage, but a reinforcement-learning algorithm can learn from collated data and experiment in simulation to suggest, say, how and when to operate the cooling systems.

But the setting where you will probably most notice this software's remarkably humanlike behavior is in self-driving cars. Today's driverless vehicles often falter in complex situations that involve interacting with human drivers, such as traffic circles or four-way stops. If we don't want them to take unnecessary risks, or to clog the roads by being overly hesitant, they will need to acquire more nuanced driving skills, like jostling for position in a crowd of other cars.

The highway merging software was demoed in Barcelona by Mobileye, an Israeli automotive company that makes vehicle safety systems used by dozens of carmakers, including Tesla Motors. After screening the merging clip, Shai Shalev-Shwartz, Mobileye's vice president for technology, shows some of the challenges self-driving cars will face: a bustling roundabout in Jerusalem; a frenetic intersection in Paris; and a hellishly chaotic scene from a road in India. "If a self-driving car follows the law precisely, then during rush hour I might wait in a merge situation for an hour," AAA

Deep Learning

With massive amounts of computational power, machines can now recognize objects and translate speech in real time. Artificial intelligence is finally getting smart.

When Ray Kurzweil met with Google CEO Larry Page last July, he wasn't looking for a job. A respected inventor who's become a machine-intelligence futurist, Kurzweil wanted to discuss his upcoming book How to Create a Mind. He told Page, who had read an early draft, that he wanted to start a company to develop his ideas about how to build a truly intelligent computer: one that could understand language and then make inferences and decisions on its own.

It quickly became obvious that such an effort would require nothing less than Google-scale data and computing power. "I could try to give you some access to it," Page told Kurzweil. "But it's going to be very difficult to do that for an independent company." So Page suggested that Kurzweil, who had never held a job anywhere but his own companies, join Google instead. It didn't take Kurzweil long to make up his mind: in January he started working for Google as a director of engineering. "This is the culmination of literally 50 years of my focus on artificial intelligence," he says.

Kurzweil was attracted not just by Google's computing resources but also by the startling progress the company has made in a branch of AI called deep learning. Deep-learning software attempts to mimic the activity in layers of neurons in the neocortex, the wrinkly 80 percent of the brain where thinking occurs. The software learns, in a very real sense, to recognize patterns in digital representations of sounds, images, and other data.

The basic idea—that software can simulate the neocortex's large array of neurons in an artificial "neural network"—is decades old, and it has led to as many disappointments as breakthroughs. But because of improvements in mathematical formulas and increasingly powerful computers, computer scientists can now model many more layers of virtual neurons than ever before.
With this greater depth, they are producing remarkable advances in speech and image recognition.

> ***" Last June, a Google deep-learning system that had been shown 10 million images from YouTube videos.Some of today's artificial neural networks can train themselves to recognize complex patterns.Google also used the technology to cut the error rate on speech recognition in its latest Android mobile software."***

In October, Microsoft chief research officer Rick Rashid wowed attendees at a lecture in China with a demonstration of speech software that transcribed his spoken words into English text with an error rate of 7 percent, translated them into Chinese-language text, and then simulated his own voice uttering them in Mandarin. That same month, a team of three graduate students and two professors won a contest held by Merck to identify molecules that could lead to new drugs. The group used deep learning to zero in on the molecules most likely to bind to their targets.

Google in particular has become a magnet for deep learning and related AI talent. In March the company bought a startup cofounded by Geoffrey Hinton, a University of Toronto computer science professor who was part of the team that won the Merck contest. Hinton, who will split his time between the university and Google, says he plans to "take ideas out of this field and apply them to real problems" such as image recognition, search, and natural-language understanding, he says.

All this has normally cautious AI researchers hopeful that intelligent machines may finally escape the pages of science fiction. Indeed, machine intelligence is starting to transform everything from communications and computing to medicine, manufacturing, and transportation.

Building a Brain

There have been many competing approaches to those challenges. One has been to feed computers with information and rules about the world, which required programmers to laboriously write software that is familiar with the attributes of, say, an edge or a sound. That took lots of time and still left the systems unable to deal with ambiguous data; they were limited to narrow, controlled applications such as phone menu systems that ask you to make queries by saying specific words.

Neural networks, developed in the 1950s not long after the dawn of AI research, looked promising because they attempted to simulate the way the brain worked, though in greatly simplified form. A program maps out a set of virtual neurons and then assigns random numerical values, or "weights," to connections between them. These weights determine how each simulated neuron responds—with a mathematical output between 0 and 1—to a digitized feature such as an edge or a shade of blue in an image, or a particular energy level at

Programmers would train a neural network to detect an object or phoneme by blitzing the network with digitized versions of images containing those objects or sound waves containing those phonemes. If the network didn't accurately recognize a particular pattern, an algorithm would adjust the weights. The eventual goal of this training was to get the network to consistently recognize the patterns in speech or sets of images that we humans know as, say, the phoneme "d" or the image of a dog. This is much the same way a child learns what a dog is by noticing the details of head shape, behavior, and the like in furry, barking animals that other people call dogs.

But early neural networks could simulate only a very limited number of neurons at once, so they could not recognize patterns of great complexity. They languished through the 1970s.

In the mid-1980s, Hinton and others helped spark a revival of interest in neural networks with so-called "deep" models that made better use of many layers of software neurons. But the technique still required heavy human involvement: programmers had to label data before feeding it to the network.

Big Data

Training the many layers of virtual neurons in the experiment took 16,000 computer processors—the kind of computing infrastructure that Google has developed for its search engine and other services. At least 80 percent of the recent advances in AI can be attributed to the availability of more computer power, reckons Dileep George, cofounder of the machine-learning startup Vicarious.

There's more to it than the sheer size of Google's data centers, though. Deep learning has also benefited from the company's method of splitting computing tasks among many machines so they can be done much more quickly. That's a technology Dean helped develop earlier in his 14-year career at Google. It vastly speeds up the training of deep-learning neural networks as well, enabling Google to run larger networks and feed a lot more data to them.

Already, deep learning has improved voice search on smartphones. Until last year, Google's Android software used a method that misunderstood many words. But in preparation for a new release of Android last July, Dean and his team helped replace part of the speech system with one based on deep learning.

Because the multiple layers of neurons allow for more precise training on the many variants of a sound, the system can recognize scraps of sound more reliably, especially in noisy environments such as subway platforms. Since it's likelier to understand what was actually uttered, the result it returns is likelier to be accurate as well. Almost overnight, the number of errors fell by up to 25 percent—results so good that many reviewers now deem Android's voice search smarter than Apple's more famous Siri voice assistant.

For all the advances, not everyone thinks deep learning can move artificial intelligence toward something rivaling human intelligence. Some critics say deep learning and AI in general ignore too much of the brain's biology in favor of brute-force computing.