

WHAT'S NEXT IN AI?

Artificial Intelligence Trends

2019

Table of Contents

CONTENTS

NExTT framework	3
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NECESSARY

Open-source frameworks	6
Edge AI	9
Facial recognition	12
Medical imaging & diagnostics	16
Predictive maintenance	18
E-commerce search	20

EXPERIMENTAL

Capsule Networks	23
Next-gen prosthetics	26
Clinical trial enrollment	28
Generative Adversarial Networks (GANs)	31
Federated learning	37
Advanced healthcare biometrics	40
Auto claims processing	43
Anti-counterfeiting	45
Checkout-free retail	50
Back office automation	53
Language translation	55
Synthetic training data	58

THREATENING

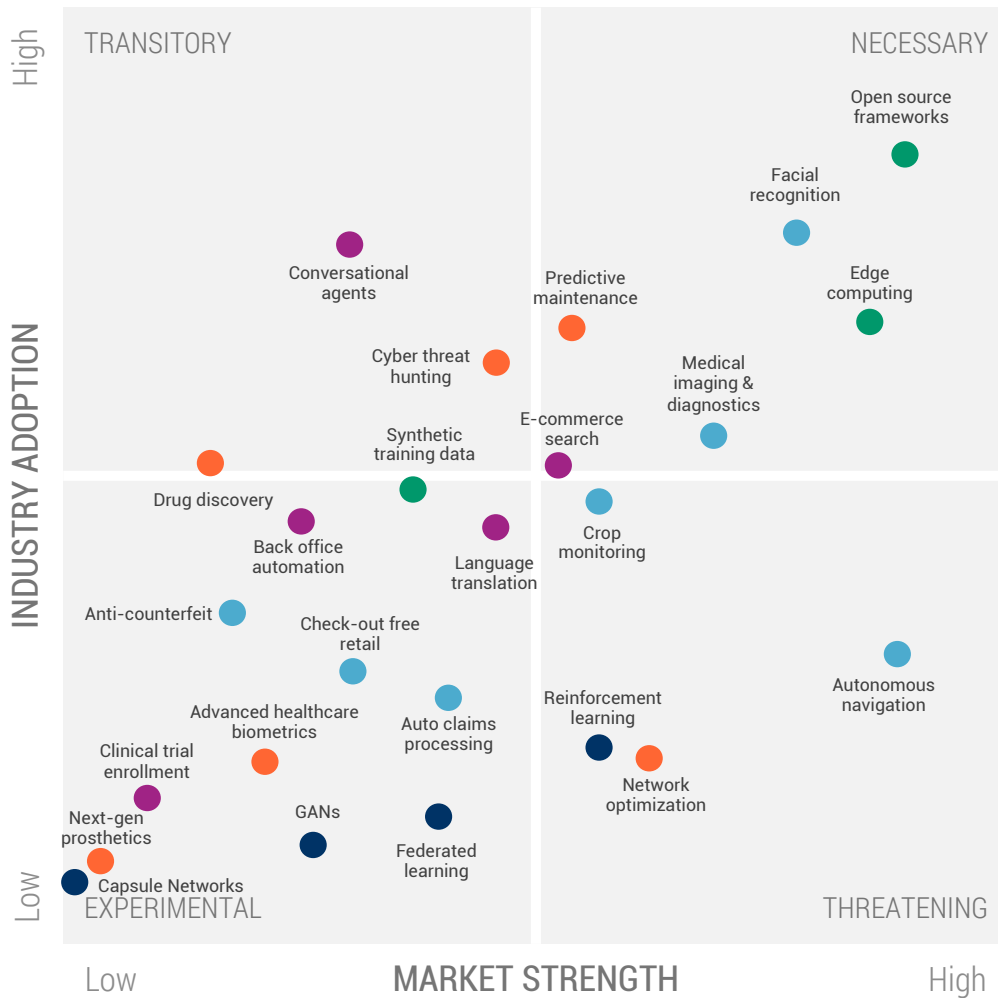
Reinforcement learning	62
Network optimization	66
Autonomous vehicles	70
Crop monitoring	73

TRANSITORY

Cyber threat hunting	75
Conversational AI	78
Drug discovery	81

NExTT FRAMEWORK

Artificial Intelligence Trends in 2019



- Application: Computer vision
- Application: Natural language processing/synthesis
- Application: Predictive intelligence
- Architecture
- Infrastructure

NExTT Trends



We evaluate each of these trends using the CB Insights NExTT framework.

The NExTT framework educates businesses about emerging trends and guides their decisions in accordance with their comfort with risk.

NExTT uses data-driven signals to evaluate technology, product, and business model trends from conception to maturity to broad adoption.

The NExTT framework’s 2 dimensions:

INDUSTRY ADOPTION (y-axis): Signals include momentum of startups in the space, media attention, customer adoption (partnerships, customer, licensing deals).

MARKET STRENGTH (x-axis): Signals include market sizing forecasts, quality and number of investors and capital, investments in R&D, earnings transcript commentary, competitive intensity, incumbent deal making (M&A, strategic investments).

NExTT framework's 2 dimensions

Industry Adoption (y axis)

Signals include:



momentum of startups
in the space



media attention



customer adoption
(partnerships, customer,
licensing deals)

Market Strength (x axis)

Signals include:



market sizing forecasts



earnings transcript
commentary



quality and number of
investors and capital



competitive intensity



investments in R&D



incumbent deal making
(M&A, strategic investments)



Necessary

OPEN-SOURCE FRAMEWORKS

The barrier to entry in AI is lower than ever before, thanks to open-source software.

Google open-sourced its TensorFlow machine learning library in 2015.

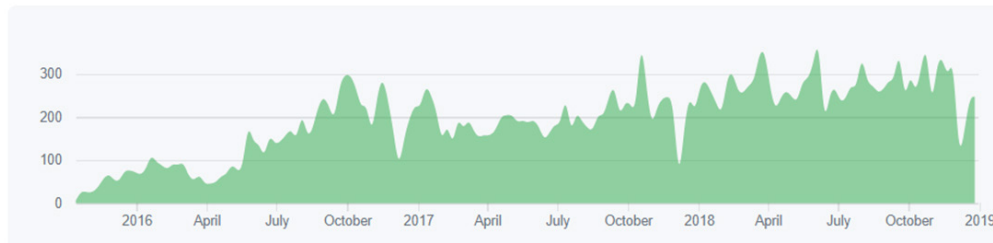
Open-source frameworks for AI are a two-way street: It makes AI accessible to everyone, and companies like Google, in turn, benefit from a community of contributors helping accelerate its AI research.

Nov 1, 2015 – Jan 18, 2019

 tensorflow / tensorflow

Contributions: Commits ▾

Contributions to master, excluding merge commits



Source: GitHub

Hundreds of users contribute to TensorFlow every month on GitHub (a software development platform where users can collaborate).

Below are a few companies using TensorFlow, from Coca-Cola to eBay to Airbnb.



Source: TensorFlow

Facebook released Caffe2 in 2017, after working with researchers from Nvidia, Qualcomm, Intel, Microsoft, and others to create a “a lightweight and modular deep learning framework” that can extend beyond the cloud to mobile applications.

Facebook also operated PyTorch at the time, an open-source machine learning platform for Python. In May’18, Facebook merged the two under one umbrella to “combine the beneficial traits of Caffe2 and PyTorch into a single package and enable a smooth transition from fast prototyping to fast execution.”

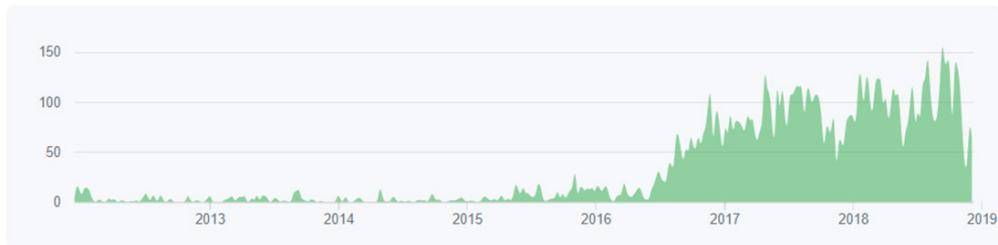
The number of GitHub contributors to PyTorch have increased in recent months.

Jan 22, 2012 – Jan 18, 2019

pytorch / pytorch

Contributions: Commits ▾

Contributions to master, excluding merge commits



Source: GitHub

Theano is another open-source library from the Montreal Institute for Learning Algorithms (MILA). In Sep'17, leading AI researcher Yoshua Bengio announced an end to development on Theano from MILA as these tools have become so much more widespread.

“The software ecosystem supporting deep learning research has been evolving quickly, and has now reached a healthy state: open-source software is the norm; a variety of frameworks are available, satisfying needs spanning from exploring novel ideas to deploying them into production; and strong industrial players are backing different software stacks in a stimulating competition.”

- YOSHUA BENGIO, IN A MILA ANNOUNCEMENT

A number of open-source tools are available today for developers to choose from, including Keras, Microsoft Cognitive Toolkit, and Apache MXNet.



EDGE AI

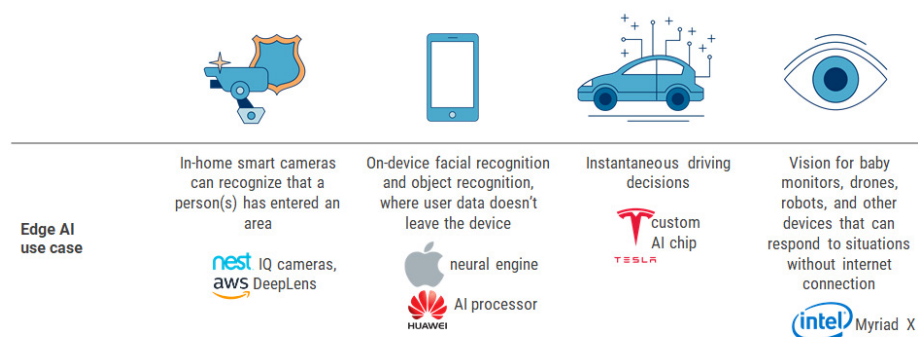
The need for real-time decision making is pushing AI closer to the edge.

Running AI [algorithms on edge devices](#) – like a smartphone or a car or even a wearable device – instead of communicating with a central cloud or server gives devices the ability to process information locally and respond more quickly to situations.

Nvidia, Qualcomm, and Apple, along with a number of emerging startups, are focused on building chips exclusively for AI workloads at the “edge.”

From consumer electronics to telecommunications to medical imaging, edge AI has implications for every major industry.

For example, an autonomous vehicle has to respond in real-time to what’s happening on the road, and function in areas with no internet connectivity. Decisions are time-sensitive and latency could prove fatal.





Big tech companies made huge leaps in edge AI between 2017-2018.

Apple released its A11 chip with a “neural engine” for iPhone 8, iPhone 8 Plus, and X in 2017, claiming it could perform machine learning tasks at up to 600 billion operations per second. It powers new iPhone features like Face ID, running facial recognition on the device itself to unlock the phone.

Qualcomm launched a \$100M AI fund in Q4’18 to invest in startups “that share the vision of on-device AI becoming more powerful and widespread,” a move that it says goes hand-in-hand with its 5G vision.

As the dominant processor in many data centers, Intel has had to play catch-up with massive acquisitions. Intel released an on-device vision processing chip called Myriad X (initially developed by Movidius, which Intel acquired in 2016).

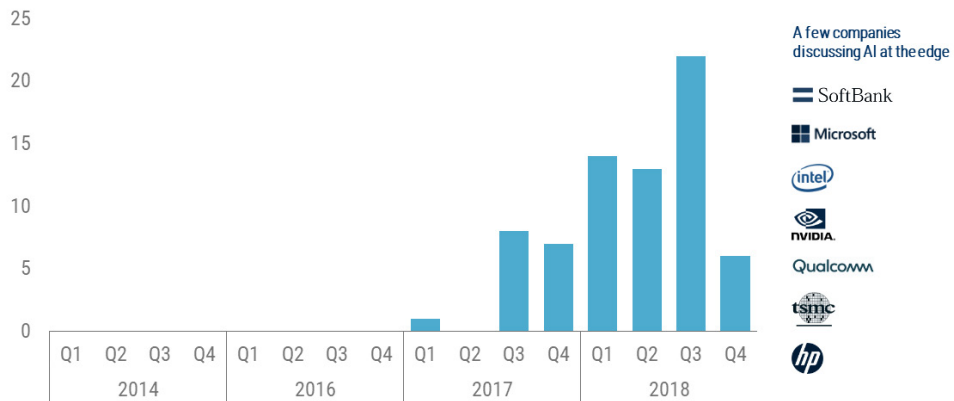
In Q4’18 Intel introduced the Intel NCS2 (Neural Compute Stick 2), which is powered by the Myriad X vision processing chip to run computer vision applications on edge devices, such as smart home devices and industrial robots.

The CB Insights earnings transcript analysis tool shows mentions of edge AI trending up for part of 2018.



Edge AI peaked on Q3'18 earnings calls

Number of mentions of AI at the edge



Source: [CB Insights earnings transcript search engine](#)

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Microsoft said it introduced 100 new Azure capabilities in Q3'18 alone, "focused on both existing workloads like security and new workloads like IoT and edge AI."

Nvidia recently released the Jetson AGX Xavier computing chip for edge computing applications across robotics and industrial IoT.

While AI on the edge reduces latency, it also has limitations. Unlike the cloud, edge has storage and processing constraints. More hybrid models will emerge that allow intelligent edge devices to communicate with each other and a central server.



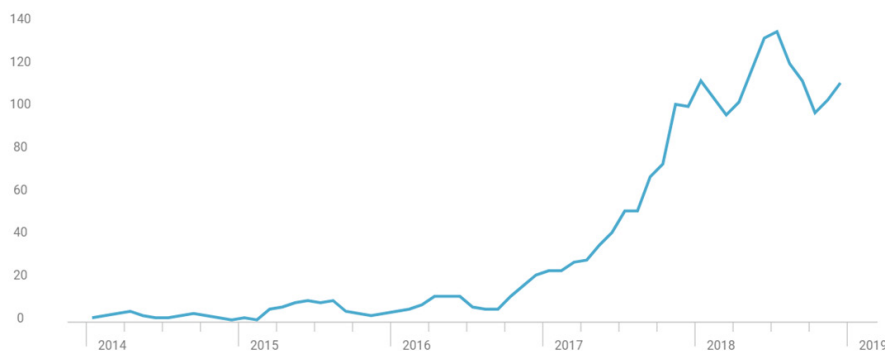
FACIAL RECOGNITION

From unlocking phones to boarding flights, face recognition is going mainstream.

When it comes to facial recognition, China's unapologetic push towards surveillance coupled with its AI ambitions have hogged the media limelight.

China's facial recognition trends up in news mentions

Number of news mentions of "China" and "facial recognition"



Source: CB Insights

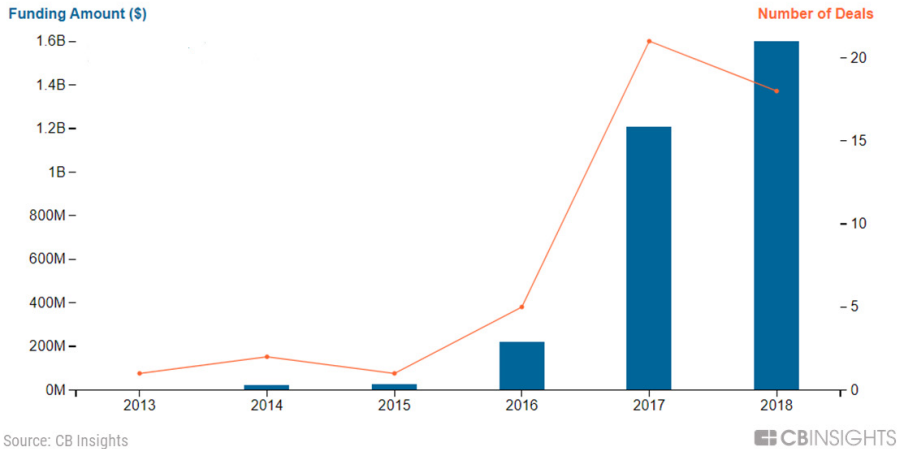
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As the government adds a layer of artificial intelligence to its surveillance, startups are playing a key role in providing the government with the underlying technology. A quick search on the CB Insights platform for face recognition startup deals in China reflect the demand for the technology.



Demand for facial recognition tech rises in China

Equity and non-equity deals, 2013 – 2018

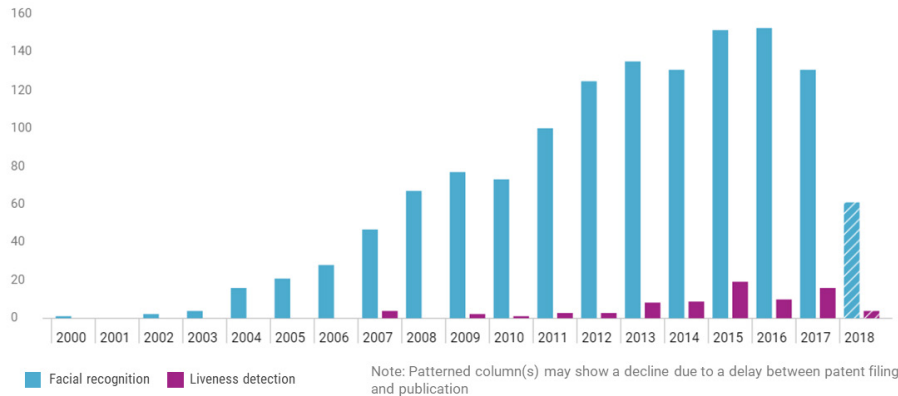


Unicorns like SenseTime, Face++, and more recently, CloudWalk, have emerged from the country. (Here's our [detailed report](#) on China's surveillance efforts.)

But even in the United States, interest in the tech is surging, according to the CB Insights patent analysis tool.

US patent applications for facial recognition

Number of patents by date of filing, based on keyword searches in title and abstract





Apple popularized the tech for everyday consumers with the introduction of facial recognition-based login in iOS 10.

Amazon is selling its tech to law enforcement agencies.

Academic institutions like Carnegie Mellon University are also working on technology to help enhance video surveillance.

The university was granted a patent around “hallucinating facial features” – a method to help law enforcement agencies identify masked suspects by reconstructing a full face when only the periocular region of the face is captured. Facial recognition may then be used to compare the “hallucinated face” to images of actual faces to find ones with a strong correlation.



Source: USPTO

But the tech is not without glitches. Amazon was in the news for reportedly misidentifying some Congressmen as criminals.

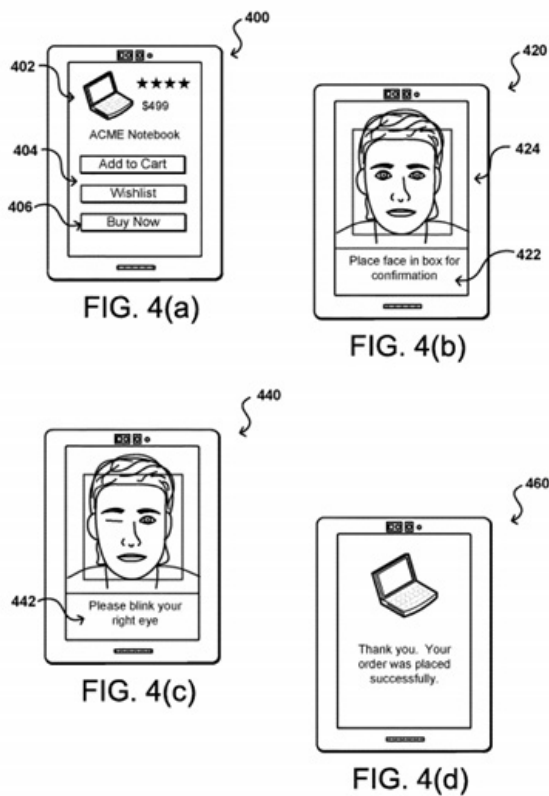
Smart cameras outside a Seattle school were easily tricked by a WSJ reporter who used a picture of the headmaster to enter the premises, when the “smile to unlock feature” was temporarily disabled.

“Smile to unlock” and other such “liveness detection” methods offer an added layer of authentication.



For instance, Amazon was [granted](#) a patent that explores additional layers of security, including asking users to perform certain actions like “smile, blink, or tilt his or her head.”

These actions can then be combined with “infrared image information, thermal imaging data, or other such information” for more robust authentication.



Source: USPTO

Early commercial applications are taking off in security, retail, and consumer electronics, and facial recognition is fast becoming a dominant form of biometric authentication.



MEDICAL IMAGING & DIAGNOSTICS

The FDA is greenlighting AI-as-a-medical-device.

In April 2018, the FDA approved AI software that screens patients for diabetic retinopathy without the need for a second opinion from an expert.

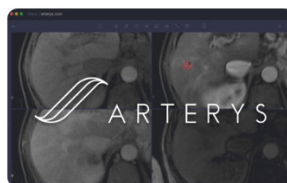
It was given a “breakthrough device designation” to expedite the process of bringing the product to market.

The software, IDx-DR, correctly identified patients with “more than mild diabetic retinopathy” 87.4% of the time, and identified those who did not have it 89.5% of the time.

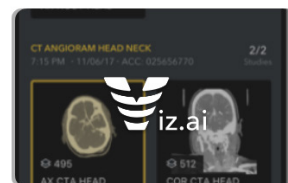
IDx is one of the many AI software products approved by the FDA for clinical commercial applications in recent months.



Diabetic retinopathy



Liver and lung AI lesion



CT-scan analysis for strokes

The FDA cleared Viz LVO, a product from startup Viz.ai, to analyze CT scans and notify healthcare providers of potential strokes in patients. Post FDA clearance, Viz.ai closed a \$21M Series A round from Google Ventures and Kleiner Perkins Caufield & Byers.

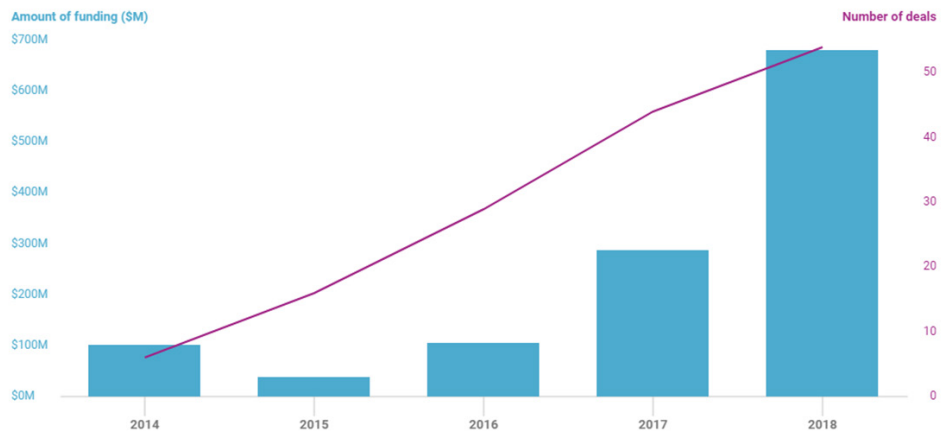
The FDA also cleared GE Ventures-backed startup Arterys for its Oncology AI suite initially focused on spotting lung and liver lesions.

Fast-track regulatory approval opens up new commercial pathways for over 80 AI imaging & diagnostics companies that have raised equity financing since 2014, accounting for a total of 149 deals.



Diagnostics is a major driver of health AI deals

Equity deals, 2014 – 2018



Source: CB Insights

 CBINSIGHTS

On the consumer side, smartphone penetration and advances in image recognition are turning phones into powerful at-home diagnostic tools.

Startup Healthy.io's first product, Dip.io, uses the traditional urinalysis dipstick to monitor a range of urinary infections. Users take a picture of the stick with their smartphones, and computer vision algorithms calibrate the results to account for different lighting conditions and camera quality. The test detects infections and pregnancy-related complications.

Dip.io, which is already commercially available in Europe and Israel, was cleared by the FDA.

Apart from this, a number of ML-as-a-service platforms are integrating with FDA-approved home monitoring devices, alerting physicians when there is an abnormality.



PREDICTIVE MAINTENANCE

From manufacturers to equipment insurers, AI-IloT can save incumbents millions of dollars in unexpected failures.

Field and factory equipment generate a wealth of data, yet unanticipated equipment failure is one of the leading causes of downtime in manufacturing.

A recent GE [survey](#) of 450 field service and IT decision makers found that 70% of companies are not aware of when equipment is due for an upgrade or maintenance, and that unplanned downtime can cost companies \$250K/hour.

Predicting when equipment or individual components will fail benefits asset insurers, as well as manufacturers.

In predictive maintenance, sensors and smart cameras gather a continuous stream of data from machines, like temperature and pressure. The quantity and varied formats of real-time data generated make machine learning an inseparable component of IloT. Over time, the algorithms can predict a failure before it occurs.

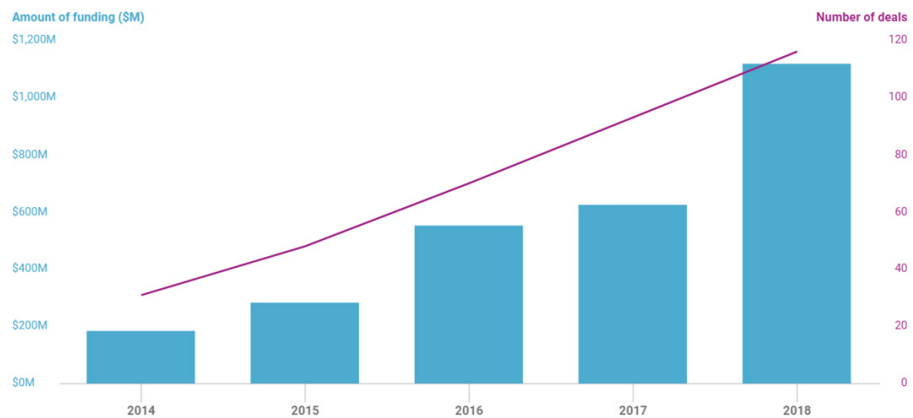
Dropping costs of industrial sensors, advances in machine learning algorithms, and a push towards edge computing have made predictive maintenance more widely available.

A leading indicator of interest in the space is the sheer number of big tech companies and startups here.



Deals to AI startups focused on industrials & energy

Equity deals, 2014 – 2018



Source: CB Insights

CBINSIGHTS

Deals to AI companies focused on industrials and energy, which includes ML-as-a-service platforms for IIoT, are rising. Newer startups are competing with unicorns like C3 IoT and Uptake Technologies.

GE Ventures was an active investor here in 2016, backing companies including Foghorn Systems, Sight Machine, Maana, and Bit Stew Systems (which it later acquired). GE is a major player in IIoT, with its Predix analytics platform.

Competitors include Siemens and SAP, which have rolled out their own products (Mindsphere and Hana) for IIoT.

India's Tata Consultancy announced that it's launching predictive maintenance and AI-based solutions for energy utility companies. Tata claimed that an early version of its "digital twin" technology – replicating on-ground operations or physical assets in a digital format for monitoring them – helped a power plant save ~\$1.5M per gigawatt per year.

Even big tech companies like Microsoft are extending their cloud and edge analytics solutions to include predictive maintenance.



E-COMMERCE SEARCH

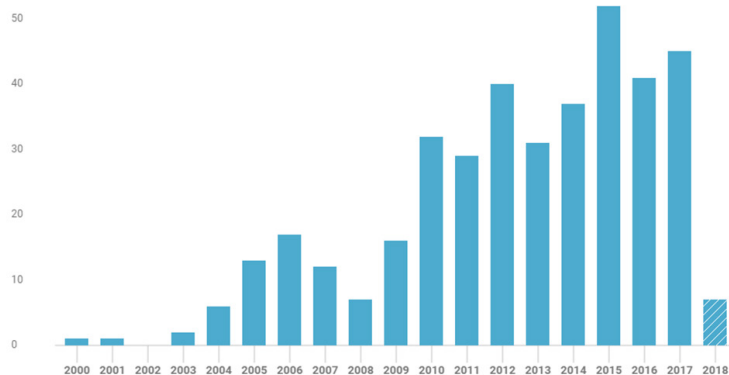
Contextual understanding of search terms is moving out of the “experimental phase,” but widespread adoption is still a long ways off.

Amazon has applied for over [35 US patents](#) related to “search results” since 2002.

It has an exclusive subsidiary, A9, focused on product and visual search for Amazon. A9 has [nearly 400 patent applications](#) in the United States (not all of them related to search optimization).

Amazon’s search arm A9 has a robust R&D pipeline

Number of patents filed by A9.com, by date of filing



Note: Patterned column(s) may show a decline due to a delay between patent filing and publication

Source: [CB Insights patent analytics](#)

 CBINSIGHTS

Some of the search-related patents include using convolutional neural networks to “determine a set of items whose images demonstrate visual similarity to the query image...” and using machine learning to analyze visual characteristics of an image and build a search query based on those.



Amazon is hiring for over 150 roles exclusively in its search division – for natural language understanding, chaos engineering, and machine learning, among other roles.

But Amazon’s scale of operations and R&D in e-commerce search is the exception among retailers.

Few retailers have discussed AI-related strategies on earnings calls, and many haven’t scaled or optimized their e-commerce operations.

But one of the earliest brands to do so was eBay.

The company first mentioned “machine learning” in its Q3’15 earnings calls. At the time, eBay had just begun to make it compulsory for sellers to write product descriptions, and was using machine learning to process that data to find similar products in the catalog.

Using proper metadata to describe products on a site is a starting point when using e-commerce search to surface relevant search results.

But describing and indexing alone is not enough. Many users search for products in natural language (like “a magenta shirt without buttons”) or may not know how to describe what they’re looking for.

This makes natural language for e-commerce search a challenge.

Early-stage SaaS startups are emerging, selling search technologies to third-party retailers.

Image search startup ViSenze works with clients like Uniqlo, Myntra, and Japanese e-commerce giant Rakuten. ViSenze allows in-store customers to take a picture of something they like at a store, then upload the picture to find the exact product online.



It has offices in California and Singapore, and raised a \$10.5M Series B in 2016 from investors including the venture arm of Rakuten. It entered the Unilever Foundry in 2017, which allows startups in Southeast Asia to test pilot projects with its brands.

Another startup developing AI for online search recommendations is Israel-based Twiggle.

The Alibaba-backed company is developing a semantic API that sits on top of existing e-commerce search engines, responding to very specific searches by the buyer. Twiggle raised \$15M in 2017 in a Series B round and entered the Plug and Play Accelerator last year.



Experimental

CAPSULE NETWORKS

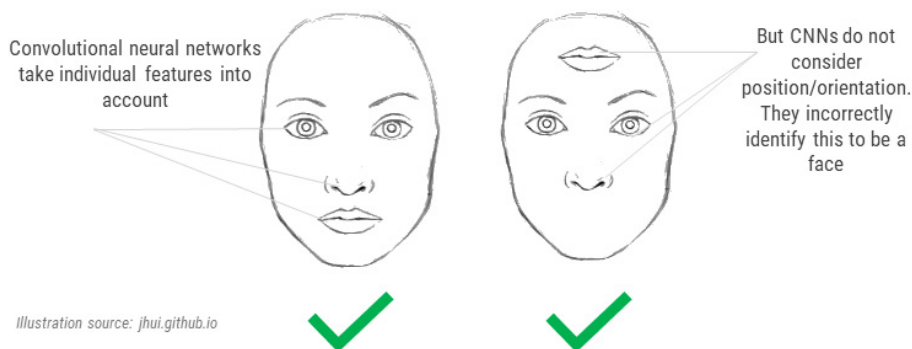
Deep learning has fueled the majority of the AI applications today. It may now get a makeover thanks to capsule networks.

Google’s Geoffrey Hinton, a pioneering researcher in deep learning, introduced a new concept called “capsules” in a [paper](#) way back in 2011, arguing that “current methods for recognizing objects in images perform poorly and use methods that are intellectually unsatisfying.”

Those “current methods” Hinton referred to include one of the most popular neural network architectures in deep learning today, known as convolutional neural networks (CNN). CNN has particularly taken off in image recognition applications. But CNNs, despite their success, have shortcomings (more on that below).

Hinton published 2 papers during 2017-2018 on an alternative concept called “capsule networks,” also known as CapsNet – a new architecture that promises to outperform CNNs on multiple fronts.

Without getting into the weeds, CNNs fail when it comes to precise spatial relationships. Consider the face below. Although the relative position of the mouth is off with respect to other facial features, a CNN would still identify this as a human face.





Although there are methods to mitigate the above problem, another major issue with CNNs is the failure to understand new viewpoints.

“Now that convolutional neural networks have become the dominant approach to object recognition, it makes sense to ask whether there are any exponential inefficiencies that may lead to their demise. A good candidate is the difficulty that convolutional nets have in generalizing to novel viewpoints.”

– PAPER ON [DYNAMIC ROUTING BETWEEN CAPSULES](#)

For instance, a CapsNet does a much better job of identifying the images of toys in the first and second rows as belonging to the same object, only taken from a different angle or viewpoint. CNNs would require a much larger training dataset to identify each orientation.

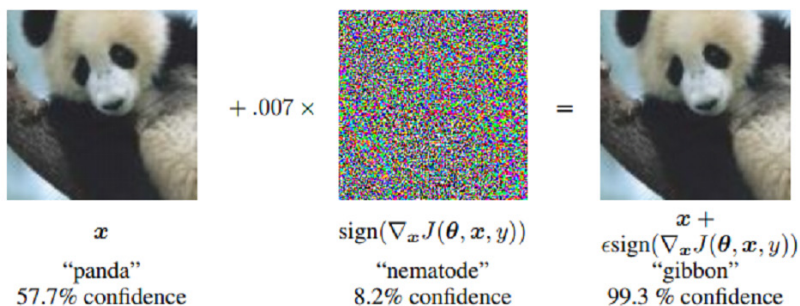


(The images above are from a database called *smallNORB* which contains grey-scale images of 50 toys belonging to 1 of 5 categories: four-legged animals, human figures, airplanes, trucks, and cars. Hinton's paper found that CapsNets reduced the [error rate by 45%](#) when tested on this dataset compared to other algorithmic approaches.)

Hinton claims that capsule networks were tested against some sophisticated adversarial attacks (tampering with images to confuse the algorithms) and were found to outperform convolutional neural networks.

Hackers can introduce small variations to fool a CNN. Researchers at Google and OpenAI have demonstrated this with several examples.

One of the more popular examples CapsNet was tested against is from a 2015 [paper](#) by Google's Ian Goodfellow and others. As can be seen below, a small change that is not readily noticeable to the human eye means the image results in a neural network identifying a panda as a gibbon, a type of ape, with high confidence.



Research into capsule networks is in its infancy, but could challenge current state-of-the-art approaches to image recognition.



NEXT-GEN PROSTHETICS

Very early-stage research is emerging, combining biology, physics, and machine learning to tackle one of the hardest problems in prosthetics: dexterity.

DARPA has spent millions of dollars on its advanced prosthetics program, which it started in 2006 with John Hopkins University to help wounded veterans. But the problem is a complex one to tackle.

For instance, giving amputees the ability to move individual fingers in a prosthetic arm, decoding brain and muscle signals behind voluntary movements, and translating that into robotic control all require a multi-disciplinary approach.

As Megan Molteni explained in an article for Wired last year, take a simple example of playing the piano. After repeated practice, playing a chord becomes “muscle memory,” but that’s not how prosthetic limbs work.

More recently, researchers have started using machine learning to decode signals from sensors on the body and translate them into commands that move the prosthetic device.

John Hopkins’ Applied Physics Labs has an ongoing project on neural interfaces for prosthetics using “neural decoding algorithms” to do just that.

In June last year, researchers from Germany and Imperial College London used machine learning to decode signals from the stump of the amputee and power a computer to control the robotic arm. The research on the “brain-machine interface” was published in [Science Robotics](#).

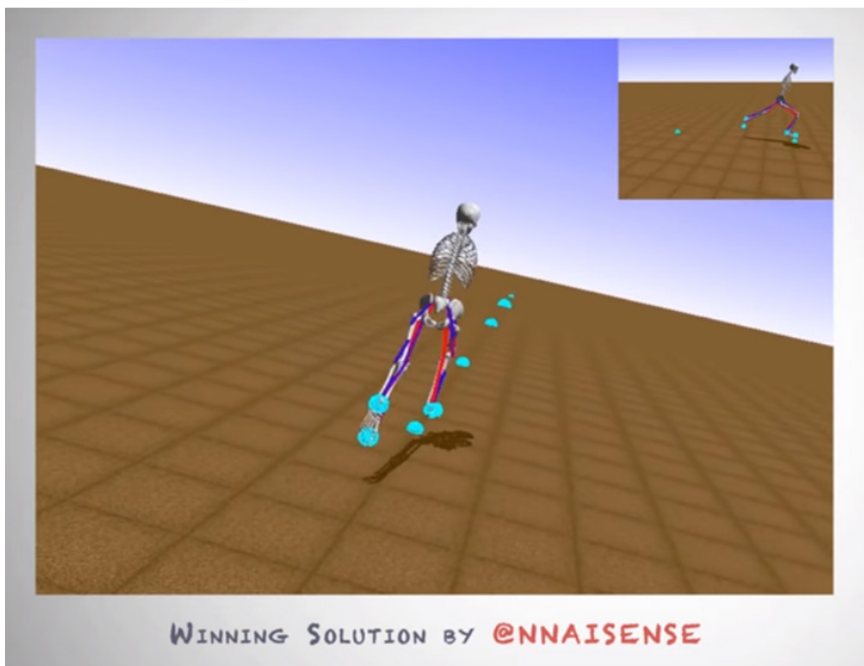


Other [papers](#) explore intermediary solutions like using myoelectric signals (electric activity of muscles near the stump) to activate a camera, and running computer vision algorithms to estimate the grasp type and size of the object before them.

Further highlighting the AI community's interest in the space, the "AI for Prosthetics Challenge" was one of the competition tracks in NeurIPS'18 (a leading, annual machine learning conference).

The 2018 challenge was to predict the performance of a prosthetic leg using reinforcement learning (more on reinforcement learning in the following sections of this report). Researchers use an open-source software called OpenSim which simulates human movement.

The previous year's focus was "Learning to Run," which saw [442 participants](#) attempting to teach AI how to run, with sponsors including AWS, Nvidia, and Toyota.



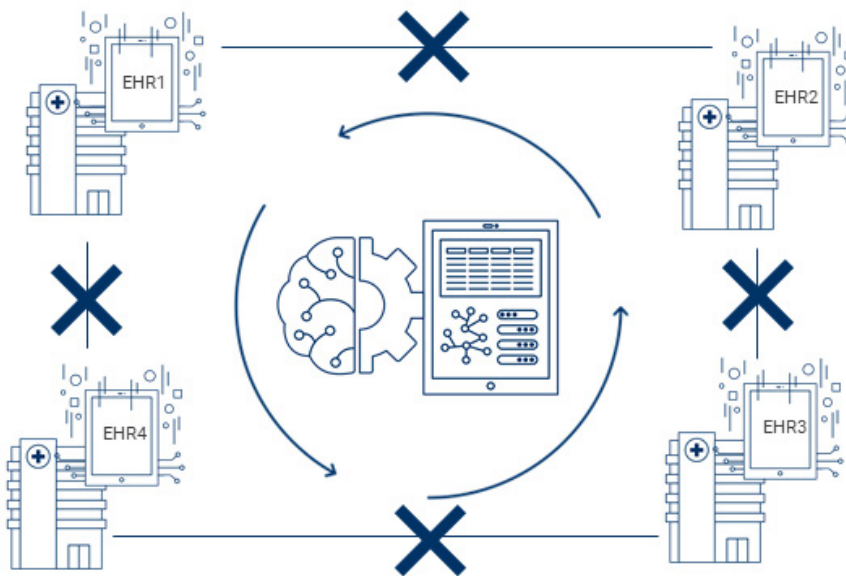
source: <http://osim-rl.stanford.edu/>



CLINICAL TRIAL ENROLLMENT

One of the biggest bottlenecks in clinical trials is enrolling the right pool of patients. Apple might be able to solve this issue.

Interoperability – the ability to share information easily across institutions and software systems – is a one of the biggest issues in healthcare, despite efforts to digitize health records.



This is particularly problematic in [clinical trials](#), where matching the right trial with the right patient is a time-consuming and challenging process for both the clinical study team and the patient.

For context, there are over 18,000 clinical studies that are currently recruiting patients in the US alone.

Patients may occasionally get trial recommendations from their doctors if a physician is aware of an ongoing trial.



Otherwise, the onus of scouring through ClinicalTrials.Gov – a comprehensive federal database of past and ongoing clinical trials – falls on the patient.

An ideal AI solution would be artificial intelligence software that extracts relevant information from a patient’s medical records, compares it with ongoing trials, and suggests matching studies.

Few startups are working with clients directly in the clinical trials space. The biggest barriers to entry for smaller startups streamlining clinical trials are that the technologies are relatively new and the industry is slow to adapt.

Tech giants like Apple, however, have seen success in bringing on partners for their healthcare-focused initiatives.

Apple is changing how data flows in healthcare and is opening up new possibilities for AI, specifically around how clinical study researchers recruit and monitor patients.

Since 2015, Apple has launched two open-source frameworks – ResearchKit and CareKit – to help clinical trials recruit patients and monitor their health remotely.

The frameworks allow researchers and developers to create medical apps to monitor people’s daily lives, removing geographic barriers to enrollment.

For example, nearly 10,000 people use the mPower app, which provides exercises like finger tapping and gait analysis to study patients with Parkinson’s disease who have consented to share their data with the broader research community.

Researchers at Duke University developed an Autism & Beyond app that uses the iPhone’s front camera and facial recognition algorithms to screen children for autism.



Apple is also working with popular EHR vendors like Cerner and Epic to solve interoperability problems.

In January 2018, Apple announced that iPhone users would have access to all their electronic health records from participating institutions on their iPhone's Health app.

Called "Health Records," the feature is an extension of what AI healthcare startup Gliimpse was working on before it was acquired by Apple in 2016.

In an easy-to-use interface, users can find all the information they need on allergies, conditions, immunizations, lab results, medications, procedures, and vitals.

In June 2018, Apple rolled out a Health Records API for developers.

Users can now choose to share their data with third-party applications and medical researchers, opening up new opportunities for disease management and lifestyle monitoring.

The possibilities are seemingly endless when it comes to using AI and machine learning for early diagnosis, enrolling the right pool of patients, and even driving decisions in drug design.



GENERATIVE ADVERSARIAL NETWORKS

Two neural networks trying to outsmart each other are getting very good at creating realistic images.

Can you identify which of these images are fake?



<https://arxiv.org/abs/1809.11096>

The answer is all of the above. Each of these highly realistic images were created by generative adversarial networks, or GANs.

(Note: the bottom right image represents a “class leakage” — where the algorithm possibly confused properties of a dog with a ball — and created a “dogball”)

GAN, a concept introduced by Google researcher Ian Goodfellow in 2014, taps into the idea of “AI versus AI.” There are two neural networks: the generator, which comes up with a fake image (say a dog for instance), and a discriminator, which compares the result to real-world images and gives feedback to the generator on how close it is to replicating a realistic image.



This forms a constant feedback loop between two neural networks trying to outsmart each other.

The images above are from a Sept'18 paper by Andrew Brock, an intern at Google DeepMind, published along with other DeepMind researchers. They trained GANs on a very large scale dataset to create "BigGANs."

One of the challenges Brock and team encountered with BigGANs: A spider, for example, has "lots of legs." But how many is "lots"?



Andrew Brock
@ajmooch

Follow



-Global coherence is the primary challenge at high resolution--a model may understand that a spider has "a number" of legs, and that number is between "many" and "lots" but nothing in the networks' inductive biases really forces it to learn "eight"



6:38 PM - 30 Sep 2018



The primary challenge to scaling large-scale projects like GANs, however, is computational power. Here's an excerpt from [FastCompany](#), with a rough estimation of the amount of computing power that went into this research:

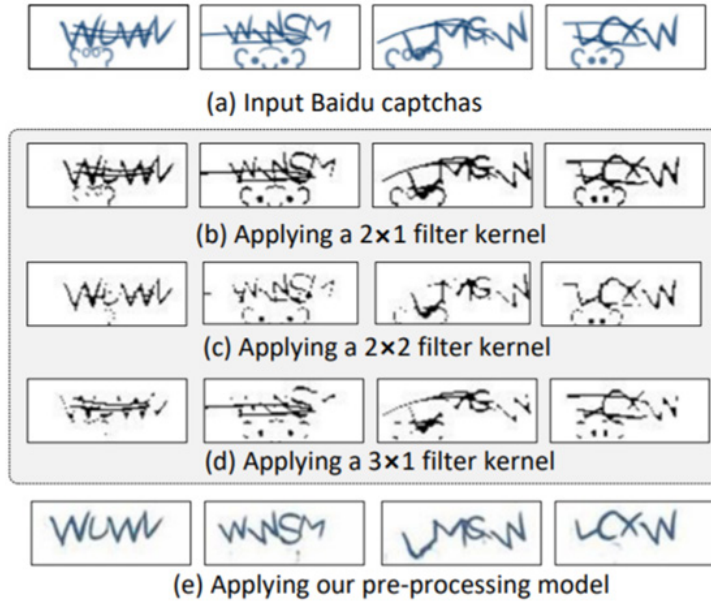
These experiments have environmental implications as well. Brock used 512 of Google's Tensor Processing Units (or TPU) to generate his 512 pixel images, and he says his experiments generally run for between 24 and 48 hours. If each TPU uses about 200 watts in an hour of computation, then a single one of Brock's 512 pixel experiments could be using between 2,450 and 4,915 kilowatt hours. That's the equivalent of the electricity that the average American household uses in just under six months.

For GANs to scale, hardware for AI has to scale in parallel.

Brock's is not the only GAN-related paper published in recent months.

Using GANs, researchers from Lancaster University in the UK, Northwest University in the China, and Peking University in China developed a captcha solver.

The paper demonstrated that GANs can crack text-based captchas in just 0.05 seconds using a desktop GPU, with a relatively higher success rate compared to previous methods.



Source: lancaster.ac.uk/staff/wangz3/publications/ccs18.pdf

Researchers at CMU used GANs for “face-to-face” translation in this iteration of “deepfake” videos. In the deepfake example below, John Oliver turns into Stephen Colbert:



Source: <http://www.cs.cmu.edu/~ajaythb/Recycle-GAN/>



Researchers at the Warsaw University of Technology developed a **ComixGAN** framework to turn videos into comics using GANs.

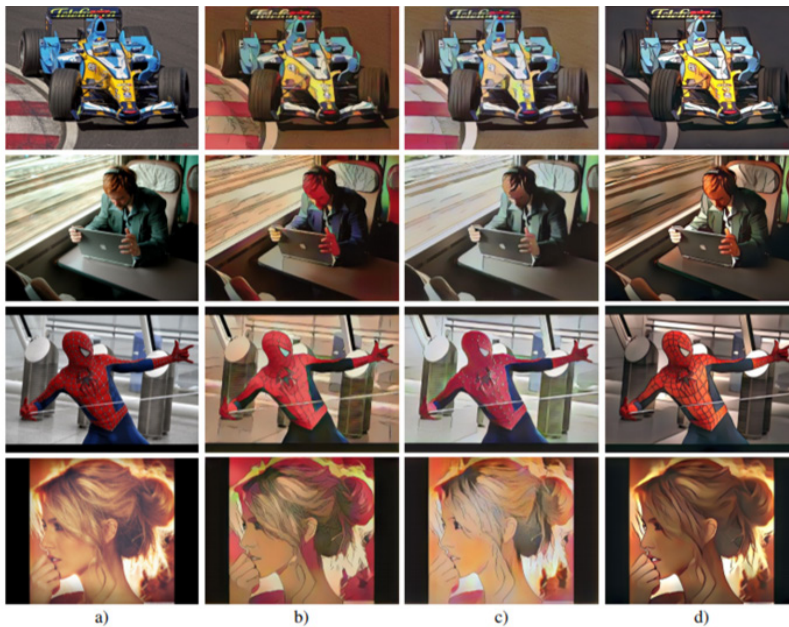


Figure 8: Results for different comixification approaches. Columns: a) content images, b) original CartoonGAN model (Hayao), c) original CartoonGAN model (Hosoda), d) ComixGAN.

Source: <https://arxiv.org/pdf/1812.03473.pdf>

Art auction house Christie's sold its first ever GAN-generated painting for a whopping \$432,500.



Portrait of Edmond Belamy, 2018, created by GAN (Generative Adversarial Network). Sold for \$432,500 on 25 October at Christie's in New York. Image © Ovious



And in a more recent [paper](#) on GANs, Nvidia researchers used a “style-based generator” to create hyper-realistic images.



Source: <https://arxiv.org/pdf/1812.04948.pdf>

GANs aren't just for fun experiments. The approach also has serious implications, including fake political videos and morphed pornography. The Wall Street Journal is already training its researchers to spot deepfake videos.

As the research scales, it will change the future of news, media, art, and even cybersecurity. GANs are already changing how we train AI algorithms (more on this in the following section on “synthetic training data.”)



FEDERATED LEARNING

The new approach aims to protect privacy while training AI with sensitive user data.

Our daily interaction with smartphones and tablets – from the choice of words we use in messaging to the way we react to photos – generates a wealth of data.

Training AI algorithms using our unique local datasets can vastly improve their performance, such as more accurately predicting the next word you’re going to type into your keyboard.

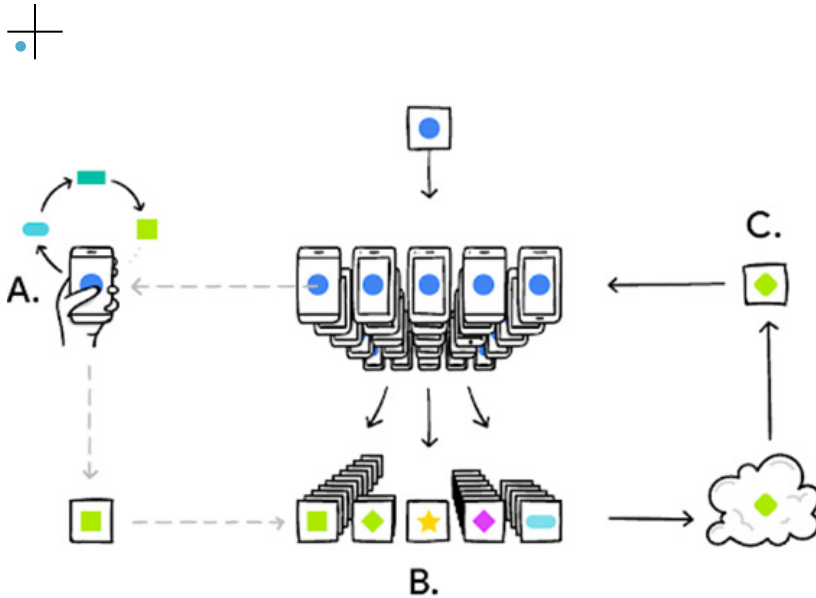
As researchers from Google explain in a 2017 [paper](#), “the use of language in chat and text messages is generally much different than standard language corpora, e.g., Wikipedia and other web documents; the photos people take on their phone are likely quite different than typical Flickr photos.”

But this user data is also personal and privacy sensitive.

Google’s federated learning approach aims to use this rich dataset, but at the same time protect sensitive data.

In a nutshell, your data stays on your phone. It is not sent to or stored in a central cloud server. A cloud server sends the most updated version of an algorithm – called the “global state” of the algorithm – to a random selection of user devices.

Your phone makes improvements and updates to the model based on your localized data. Only this update (and updates from other users) are sent back to the cloud to improve the “global state” and the process repeats itself.



Source: Google AI blog

Google is testing federated learning in its Android keyboard called Gboard.

Note that the mechanism of aggregating individual updates from each node is not the novelty here. There are algorithms that do that already.

But unlike other distributed algorithms, the federated learning approach takes into account two important characteristics of the dataset:

- **Non-IID:** Data generated on each phone (or other device) is unique based on each person's usage of the device. And so these datasets are not "Independent and identically distributed (IID)" – a common assumption made by other distributed algorithms for the sake of statistical inference, but not reflective of practical real-world scenarios.
- **Unbalanced:** Some users are more actively engaged with an app than others, naturally generating more data. As a result, each phone, for instance, will have varying amounts of training data.



Firefox tested out federated learning to rank suggestions that appear when a user starts typing into the URL bar, calling it “one of the very first implementations [of federated learning] in a major software project.”

In another application of federated learning, Google Ventures-backed AI startup OWKIN, which is focused on drug discovery, is using the approach to protect sensitive patient data. The model allows different cancer treatment centers to collaborate without patients’ data ever leaving the premises, according to investor Otium Venture.



ADVANCED HEALTHCARE BIOMETRICS

Using neural networks, researchers are starting to study and measure atypical risk factors that were previously difficult to quantify.

Analysis of retinal images and voice patterns using neural networks could potentially help identify risk of heart disease.

Researchers at Google used a neural network trained on retinal images to find cardiovascular risk factors, according to a [paper](#) published in Nature this year.

The research found that not only was it possible to identify risk factors such as age, gender, and smoking patterns through retinal images, it was also “quantifiable to a degree of precision not reported before.”

Similarly, the Mayo Clinic partnered with Beyond Verbal, an Israeli startup that analyzes acoustic features in voice, to find distinct voice features in patients with coronary artery disease (CAD). The [study](#) found 2 voice features that were strongly associated with CAD when subjects were describing an emotional experience.

Recent [research](#) from startup Cardiogram suggests “heart rate variability changes driven by diabetes can be detected via consumer, off-the-self wearable heart rate sensors” using deep learning. One algorithmic approach showed 85% accuracy in detecting diabetes from heart rate.

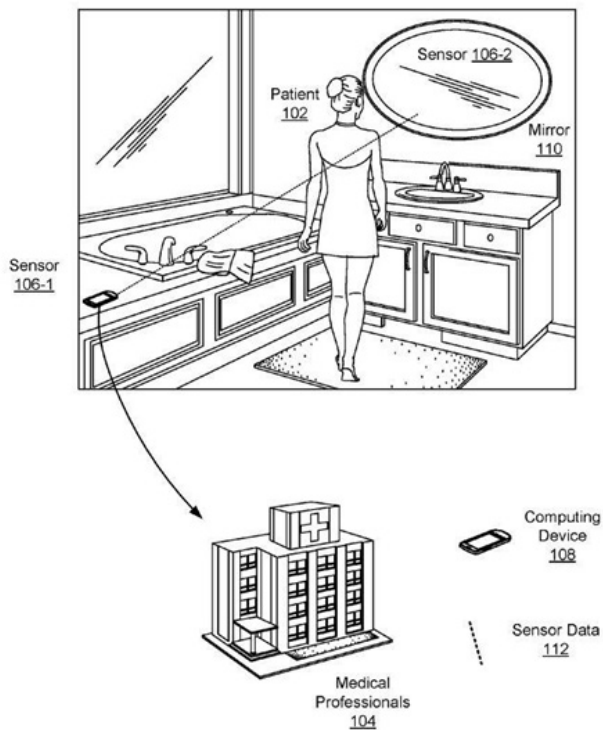
A more futuristic use case is passive monitoring of healthcare biometrics.

In January 2018, a Google [patent](#) was published with an ambitious vision



for analyzing cardiovascular function from a person's skin color or skin displacement.

The sensors might even be positioned (per the patent's illustrations) in a "sensing milieu" in a patient's bathroom.



Source: USPTO

By recognizing skin color changes at the wrist and cheek, for example, and "comparing the times [of measurement] and distance between these regions," the system could calculate a "pulse-wave velocity (PWV)." The velocity information could then be used to determine cardio-health metrics such as arterial stiffness or blood pressure.

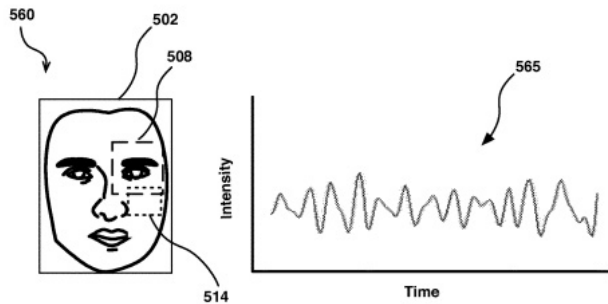
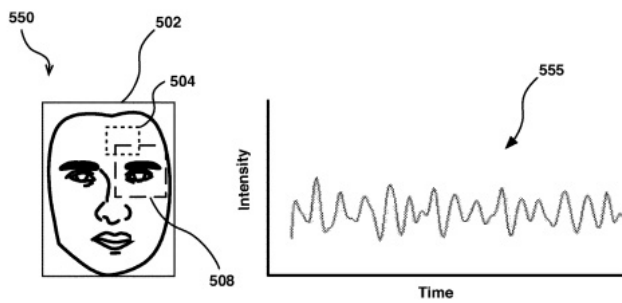
"Machine learning could be applied to create a patient specific model for estimating blood pressure from PWV," according to the patent.

Amazon applied for a similar [patent](#) for passive monitoring in 2014,



which was later granted in 2017. It combines recognition of facial features (using neural nets or other algorithmic approaches) with heart rate analysis.

For example, algorithms can track color changes in two areas of the face, like regions near the eyes and cheek, using that data to calculate heart rate detection.



Source: USPTO

AI's ability to find patterns will continue to pave the way for new diagnostic methods and identification of previously unknown risk factors.



AUTO CLAIMS PROCESSING

Insurers and startups are beginning to use AI to compute a car owner's "risk score," analyze images of accident scenes, and monitor driver behavior.

China's Ant Financial, an Alibaba affiliate, uses deep-learning algorithms for image processing in its "accident processing system."

Currently, car owners or drivers take their vehicles to an "adjuster," a person who inspects the damage to the vehicle and logs the details, which are then sent to the auto insurance company.

Advances in image processing are now allowing people to take a picture of the vehicle and upload it to Ant Financial. Neural networks then analyze the image and automate the damage assessment.

Another approach Ant is taking is to create a risk profile of the driver to influence the actual pricing model of auto insurance.

"The development of technologies such as Big Data and artificial intelligence enables insurance companies to further leverage the consumer data and analyze the probable risk exposure of vehicle owners. Therefore, risk factors for auto insurance can shift from a "car-oriented" approach to a "car/owner combination."

— ALIBABA CLOUD BLOG



Alibaba introduced something called “Auto Insurance Points,” using machine learning to calculate a car owner’s risk score based on factors such as credit history, spending habits, and driving habits, among other things.

Smaller startups are also getting into insurance and claims processing but adopting a different approach.

[Nexar](#), for instance, incentivizes drivers to use their smartphones as a dashcam and upload the footage to the Nexar app. In return, owners get a discount on their insurance premiums.

The app uses computer vision algorithms to monitor road conditions, driver behavior, and accidents. It also offers a “crash recreation” feature to reconstruct and analyze the circumstances in which accidents take place, and works with insurance clients to process claims.

UK-based Tractable allows insurers to upload an image of the damage and an estimate into its claims management platform. The “AI Review” feature compares this with thousands of images to adjust the price accordingly.

Interestingly, Tractable is targeting other players in the ecosystem as well, such as car repairers, appraisers, vendors, and car hire companies.



ANTI-COUNTERFEITING

Fakes are getting harder to spot, and online shopping makes it easier than ever to buy fake goods. To fight back, brands and pawnbrokers are beginning to experiment with AI.

From drugs to handbags to smartphones, counterfeiting is a problem that affects all types of retail.

Some product imitations look so authentic that they are classified as “super fakes.”

China’s rapidly growing e-commerce platform Pinduoduo [mentioned](#) “counterfeit” 11 times in its Q3’18 earnings call, describing “a very hard fight against counterfeit goods and ... problematic merchants.”

“In 2017, we...proactively removed a total of 10.7 million problematic products and blocked 40 million links that...raised infringement issues...We have also partnered with over 400 brands to work together on combating counterfeit.”

– COLIN HUANG, FOUNDER AND CEO OF PINDUODUO



Brands are fighting the war against fakes on two fronts:

- In the online world, identifying and removing online listings that infringe on brand trademarks like brand name, logo, and slogans
- In the physical world, identifying fake goods like luxury handbags that are rip offs

Online counterfeiting is vast and complex in scope and scale.

E-commerce giant Alibaba, which has been under some fire for not doing enough to counter fake goods on its sites, reported that it's using deep learning to continuously scan its platform for IP infringements. It uses image recognition to identify characters in images, coupled with semantic recognition, possibly to monitor brand names or slogans in images of products listed on its sites.

Counterfeiters use keywords and images very similar to the original brand listing to sell fake goods on fake websites, fake goods on legitimate marketplaces, and promote fake goods on social media sites like Instagram.

When one listing is taken down, counterfeiters may repost the same fake product with a different string of keywords.

Barcelona-based startup Red Points is using machine learning to scan websites for potential infringements and find patterns in the choice of keywords counterfeiters use. It boasts clients in the cosmetics, luxury watch, home goods, and apparel industries, including MVMT, DOPE, and Paul Hewitt.



Spotting fakes is trickier and more manual in the physical world.

When a seller posts a second-hand luxury handbag for sale, or goes to a pawnbroker to trade it, the verification process usually involves an authentication expert physically examining the bag, including the make, material, and stitching pattern.

Here's how much eBay and others charge to authenticate one luxury handbag using identification experts.

Markup for authenticating a \$1,500 handbag



Source: eBay Authenticate pricing comparison

20%

eBay  POSHMARK

30-45%

TheRealReal

But with the rise of “super fakes” or “triple-A fakes,” it’s becoming nearly impossible to tell the difference with the naked eye.

Building a database of fake and authentic goods, extracting their features, and training an AI algorithm to tell the difference is a cumbersome process.

Startup Entrupy worked with authentication experts to build a database of fake vs. real goods for training its algorithms for 2 years. The process is harder for rare vintage luxury goods.



Entrupy developed a portable microscope that attaches to a smartphone. When users take and upload a picture of the product (handbag, watch, etc), AI algorithms analyze microscopic signatures that are unique to each product, and verify it against a database of known and authentic products.

The database is growing, but there isn't a complete set products out in the market. A paper published by Entrupy highlights some other operating assumptions and limitations.

The key idea is that objects manufactured using standard or prescribed methods will have visually similar characteristics, compared to the manufacturing process a counterfeiter would use (non-standardized, inexpensive mass production). Secondly, the tech may not work for things like electronic chips that are nano-fabricated (variations at a scale that Entrupy's microscope cannot detect).

Cypheme is taking a different approach. Its ink-based technology can be used as a sticker on the product, or directly printed onto labels and packaging.



Random ink prints
verifiable by neural nets



Online verification with
machine learning



Handheld microscopic
device

Nikkei Asian Review detailed the tech in an interview with the CEO: A random pattern is generated from a drop of ink, the pattern is surrounded by another circle of orange ink that Cypheme claims is proprietary to the company and impossible to replicate, then each unique pattern is associated with a specific product on a database.



It uses a smartphone camera and neural networks for pattern recognition to verify the ink pattern for the specific product against its database.

This means Cypheme has to work directly with brand manufacturers to make sure products are shipped with the tracing ink. It recently entered into a partnership with AR Packaging, a leading packaging company in Europe working with food brands like Unilever and Nestle.

While printing ink on packaging is efficient for tracking an item from the manufacturing plant and along the distribution chain, the tech doesn't work for secondhand purchase authentication. For instance, a buyer may remove Cypheme's sticker from the packaging of a luxury watch, and decide to resell it at a broker shop or online. In this case, verifying authenticity is not possible unless the printing is part of the product itself.

The solution for luxury brands and other high-stake retailers, moving forward, may be to identify or add unique fingerprints to physical goods at the site of manufacturing and track it through the supply chain.



CHECKOUT-FREE RETAIL

Entering a store, picking what you want, and walking out almost “feels” like shoplifting. AI could make actual theft a thing of the past and check-out free retail much more common.



Amazon Go did away with the entire checkout process, allowing shoppers to grab items and walk out.

Amazon has no public plans to sell its tech-as-a-service to other retailers yet, and has been tight-lipped about the operations, success, and pain points — only revealing that it uses sensors, cameras,

computer vision, and deep learning algorithms. It has denied using facial recognition algorithms.

Startups like Standard Cognition and AiFi have seized the opportunity, stepping in to democratize Amazon Go for other retailers.

A challenge for grab-and-go stores is charging the right amount to the right shopper.

Loss of inventory due to shoplifting and paperwork error, among other things, cost US retailers around \$47B in 2017, according to the National Retail Federation.

“Stealing is buying,” Steve Gu, co-founder and CEO of startup AiFi, said in an interview with The AI Podcast, discussing the technology behind grab-and-go stores.



So far, Amazon Go is the only successful commercial deployment, but the the parameters of success are tightly controlled.

The chance of someone shoplifting is minimized when you control who enters the store, and automatically charge them.

Amazon already has an established base of Prime members. All the Go stores so far have been restricted to members, with other retail operations like the Kindle store, which is open to the general public, still relying on a manual checkout process.

Smaller bodegas, convenience stores, and even several established supermarkets have to build that membership base from scratch.

Steve Gu hinted in the same podcast that there could be a “grab-and-go” section for people willing to download the app, and a separate checkout line for those who don’t want to.

It’s not clear how a store’s infrastructure would support both.

That still leaves the issue of point-of-sale inventory shrinkage such as incorrectly billed items or POS theft. China’s Yitu Technology and Toshiba, with its intelligent camera for checkout, are some of the companies separately working on the shrinkage problem.

The complexity of preventing theft depends on the size and scale of operations, and type of products on the shelves.

Amazon Go stores are only about 1,800 to 3,000 sq. ft, and use hundreds of cameras covering nearly every inch of ceiling space. In comparison, traditional supermarkets can be 40,000 sq. ft. or more.

Go, which uses weight sensors on shelves in addition to cameras for visual recognition, currently only offers a limited selection of items, like prepared and packaged meal kits.

Some things to consider are how floor space will be utilized, especially in densely packed supermarkets, to ensure cameras are optimally placed to track people and items. Loose vegetables and other produce that



are billed per pound would presumably rely on sensor tech, but multiple shoppers picking items simultaneously from the same carton would not work with sensors alone. Even pre-packaged or diced vegetables have slight variations in price from one package to another.

Apparel too is particularly hard for computer vision systems to track. Identifying the size (S/M/L) and tracking clothes that are easily folded and tucked away are some of the pain points.



Standard Cognition has partnered with Japan's CPG wholesaler Paltac Corporation



AiFi reportedly has around 20 retail clients in the pipeline

While startup AiFi promises to utilize existing store infrastructure and a combination of sensors and cameras, Standard Cognition claims to completely do away with sensors, relying solely on machine vision.

Standard Cognition announced a partnership with Paltac Corporation, Japan's largest CPG wholesaler, to outfit 3,000 Japanese stores ahead of the Tokyo Olympics in 2020. AiFi reportedly has around 20 retail clients in the pipeline, including a contract with a major retailer in New York.

In the near term, it comes down to what the cost of deployment and cost of inventory loss due to potential tech glitches would be, and whether a retailer can take on these costs and risks.



BACK OFFICE AUTOMATION

AI is automating administrative work, but the varied nature and formats of data make it a challenging task.

Challenges for automating “back office tasks” can be unique, depending on the industry and the application.

Take clinical trials for instance. Many trials still rely on paper diaries for entering patient data. These diaries are stored digitally, often in difficult-to-search formats, while handwritten clinical notes pose unique challenges for natural language processing algorithms to extract information (accounting for spelling errors, jargon, abbreviations, and missing entries).

Automating auto claims processing, on the other hand, brings a different set of challenges, in this case assessing the damage and drilling down into the root cause.

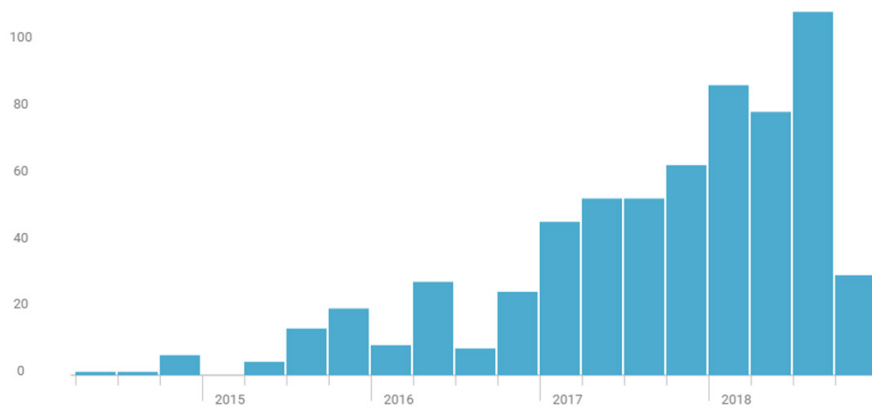
But different sectors are beginning to adopt ML-based workflow solutions to varying degrees.

Robotic Process Automation (RPA), a loose term for any back office drudge work that is repetitive and can be automated by a bot, has been the subject of much buzz. But, like AI, it’s an umbrella term that encompass a wide range of tasks from data entry to compliance to transaction processing to customer onboarding, and more.



Mentions of RPA peaked in earnings calls in Q3'18

Number of mentions of "RPA" or "robotic process automation," by quarter of call



Source: [CB Insights earnings transcript search engine](#)

 CBINSIGHTS

While not all RPAs are ML-based, many are beginning to integrate image recognition and language processing into their solutions.

[WorkFusion](#), for example, automates back-end operations like Know Your Customer (KYC) and Anti-Money Laundering (AML) processes.

Unicorn UiPath's services have been used by over 700 enterprise clients globally, including DHL, NASA, and HP, across industries ranging from finance to manufacturing to retail.

[Automation Anywhere](#) is another unicorn in the RPA space. One of the company's case studies highlights a partnership with a global bank to use machine learning to automate human resource management. An "IQ Bot" extracts information from forms that come in from several countries and in many languages, cleans the data, and then automatically enters it into a human resource management system.

Despite the concept of RPA being around for years, many industries are just beginning to overcome inertia and experiment with newer technologies. In other areas, there's a need for digitization before there can be a layer of predictive analytics.



LANGUAGE TRANSLATION

NLP for language translation is both a challenge and an untapped market opportunity. Big tech companies are pushing the boundaries here.

Machine-based language translation is a huge untapped opportunity with applications in back office automation for multinational corporations, customer support, news & media, and other things.

Baidu recently announced that it's launching new translator earbuds, similar to Google Pixel Buds, which can reportedly translate between 40 different languages in real-time.

Some startups like Unbabel are using human-in-the-loop machine translation systems, with the goal that the feedback loop will train the algorithms to get better over time.

NLP for translation has several challenges. For instance, Chinese natural language processing alone is complex, with 130 spoken dialects and 30 written languages.

A year after Yoshua Bengio, a pioneering researcher in deep learning, published a [paper](#) proposing a new architecture for machine translation – a novel way of using neural networks instead of traditional statistical approaches – Google upgraded its own algorithms for the Google Translate Tool.

“This breakthrough will help us provide even more accurate translations for people around the world,” CEO Sundar Pichai said in an earnings call in 2016.



Google wanted to move away from its old algorithmic approach of Phrase-Based Machine Translation (PBMT) and proposed a new Google Neural Machine Translation (GNMT) system.

Although different papers had been published on neural machine translation, there were limitations, like the time and computational resources that went into training these models, and failure in translating rare words.

Google suggested improvements to address these issues, and tested its algorithms on English to Chinese, Chinese to English, Spanish to English, among other examples.

Language pair	<i>Input sentence:</i>	<i>Translation (PBMT):</i>	<i>Translation (GNMT):</i>	<i>Translation (human):</i>
Chinese->English	2015年到2016年，亚太地区的信用卡交易总额将增加1.7万亿美元，增幅最大，其次是北美地区，增幅将达到1870亿美元。	2015 to 2016 , the total amount of credit card transactions in Asia Pacific will increase by \$ 1.7 trillion , the largest increase , followed by North America , growth will reach \$ 187 billion .	Total credit card transactions in the Asia-Pacific region will increase by \$ 1.7 trillion in 2015-2016, the largest increase, followed by North America with \$ 187 billion.	Total credit card transactions in the Asia-Pacific region will increase by \$ 1.7 trillion in 2015-2016, the largest increase followed by North America with \$ 187 billion.
Chinese->English	100年前，预测引力波的爱因斯坦或许都无法想象人类可以直接观测到引力波。	100 years ago, the prediction of Einstein's gravitational waves probably can not imagine humans can directly observe gravitational waves.	100 years ago, Einstein predicted gravitational waves may not be able to imagine humans can directly observe the gravitational waves.	100 years ago, Einstein who predicted gravitational waves may not be able to imagine that humans can directly observe the gravitational waves.

Source: Google AI Blog

Several research papers have been published on the topic. But the most recent breakthrough comes from Facebook.

According to the [paper](#), “Most research in multilingual NLP focuses on high-resource languages like Chinese, Arabic or major European languages, and is usually limited to a few (most often only two) languages. In contrast, we learn joint sentence representations for 93 different languages, including under-resourced and minority languages.”



ISO3	ISO2	Details			Training corpus size	Tatoeba Error [%]		Tatoeba test set size
		Name	Family	Script		en → xx	xx → en	
hye	hy	Armenian	Armenian	Armenian	6k	59.97	67.79	742
bel	be	Belarusian	Slavic	Cyrillic	5k	31.20	36.50	1000
mya	my	Burmese	Sino-Tibetan	Burmese	2k	n/a	n/a	–
ntp		Central/Kadazan Dusun	Malayo-Polynesian	Latin	1k	92.10	93.50	1000
khm	km	Central Khmer	Khmer	Khmer	625	77.01	81.72	722
cbk		Chavacano	Creole, Romance	Latin	1k	24.20	21.70	1000
kzj		Coastal Kadazan	Malayo-Polynesian	Latin	560	91.60	94.10	1000
cor	kw	Cornish	Celtic	Latin	2k	91.90	93.20	1000
mhr		Eastern Mari	Uralic	Cyrillic	1k	87.70	91.50	1000
ido	io	Ido	constructed	Latin	3k	17.40	15.20	1000
ina	ia	Interlingua	constructed	Latin	9k	5.40	4.10	1000
ile	ie	Interlingue	constructed	Latin	3k	14.70	12.80	1000
gle	ga	Irish	Irish	Latin	732	93.80	95.80	1000
kaz	kk	Kazakh	Turkic	Cyrillic	4k	80.17	82.61	575
lfn		Lingua Franca Nova	constructed	Latin	2k	35.90	35.10	1000
oci	oc	Occitan (post 1500)	Romance	Latin	3k	39.20	38.40	1000
wuu		Wu Chinese	Chinese	Chinese	2k	25.80	25.20	1000
yue		Yue Chinese	Chinese	Chinese	4k	37.00	38.90	1000

Table 2: List of the 18 very low-resource languages included during training of the proposed model, along with their language family, writing system, the resulting similarity error rate on the Tatoeba test set, and the number of sentences in it. Dashes denote language pairs excluded for containing less than 100 test sentences.

Source: <https://arxiv.org/pdf/1812.10464.pdf>

As big tech companies continue devoting resources to improving translation frameworks, efficiency and language capabilities will improve and adoption will increase across industries.



SYNTHETIC TRAINING DATA

Access to large, labeled datasets is necessary for training AI algorithms. Realistic fake data may solve the bottleneck.

AI algorithms are only as good as the data they are fed, and accessing and labeling this data for different applications is time and capital intensive.

Access to this type of real-world data may not even be feasible.

Consider an autonomous vehicle for instance. Training AVs on dangerous, less frequent situations, such as blinding sun or a pedestrian jumping out from behind parked cars, using real data is hard.

That's where synthetic datasets come in.

In March 2018, Nvidia launched a cloud-based photorealistic simulation for autonomous vehicles called DRIVE Constellation. AVs can drive in virtual reality simulation for billions of miles before hitting the roads – a venture aimed at creating “a safer, more scalable method for bringing self-driving cars to the roads.”

Imagine AVs driving through a thunderstorm. Nvidia's solution simulates what data sensors in the car, (like a camera or LiDAR) would generate under these conditions. The synthetic sensor data is fed to a computer which makes decisions as if it were driving on an actual road, sending commands back to the virtual vehicle.

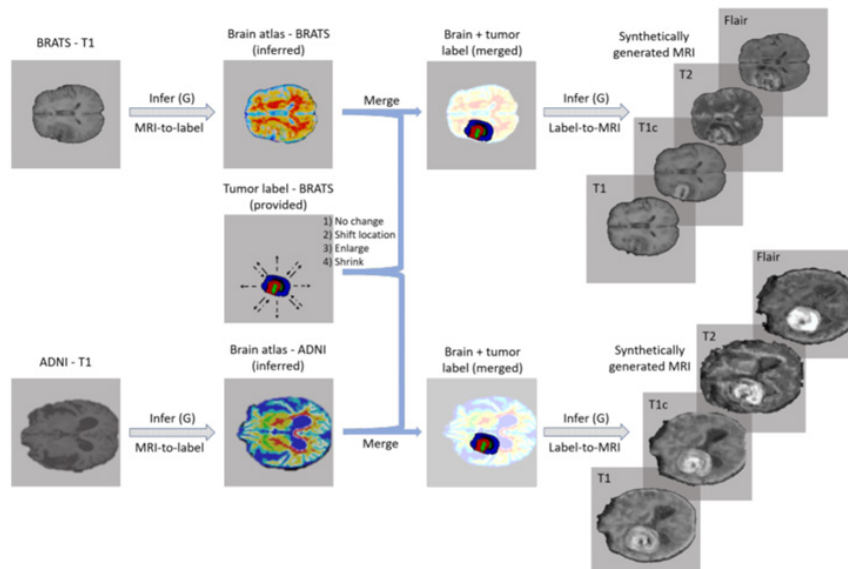


An interesting emerging trend is using AI itself to help generate more “realistic” synthetic images to train AI.

Nvidia, for instance, used generative adversarial networks (GANs) to create fake MRI images with brain tumors.

“Together, these results offer a potential solution to two of the largest challenges facing machine learning in medical imaging, namely the small incidence of pathological findings, and the restrictions around sharing of patient data.”

— NVIDIA RESEARCH PAPER



Source: <https://arxiv.org/pdf/1807.10225.pdf>



GANs are being used to “augment” real world data, meaning AI can be trained with a mix of real world and simulated data to have a larger, more diverse dataset.

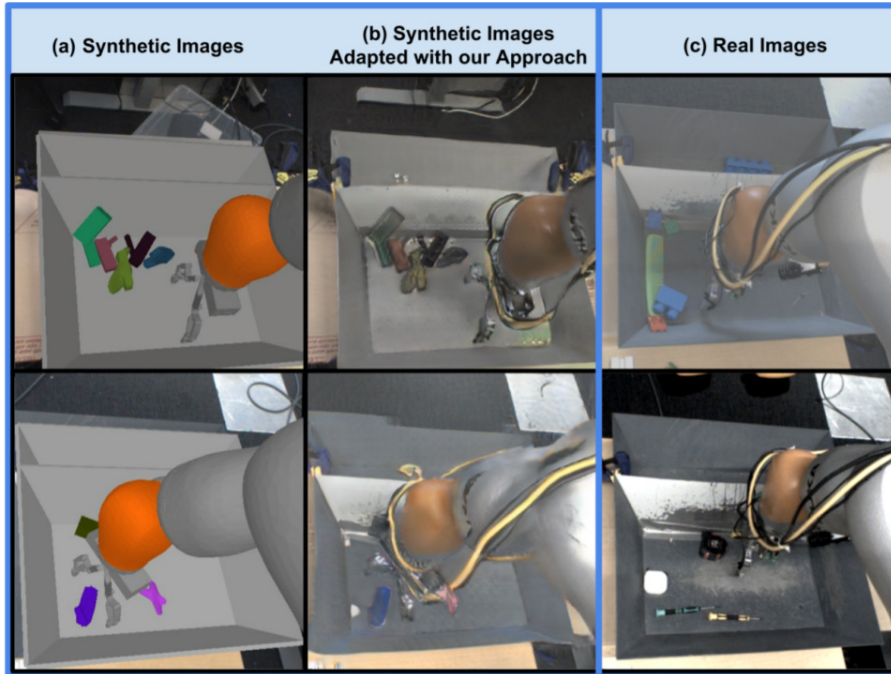
Robotics is another field that can greatly benefit from high-fidelity synthetic data.

Consider a simple task of teaching a robot to grasp something. In 2016, Google [researchers](#) used 14 robotic arms tasked with learning how to grasp different objects. Data from the failed and successful attempts from all 14 robots were used to train a neural network to help the robots “share their experiences” and predict the outcome of a grasp.

In all, it took 800,000 grasp attempts, “equivalent to about 3000 robot-hours of practice” to “see the beginnings of intelligent reactive behaviors,” according to the research team.

But simulations – having hundreds of virtual robots practice in a virtual environment – can vastly simplify this process.

One of the challenges is creating realistic objects (like making the simulation of an apple or pencil look as close to a real-life objects as possible). In 2017, Google researchers [used](#) generative adversarial networks (GANs) to do just that, drastically reducing the amount of real-world data needed to train the robot.



Source: <https://arxiv.org/pdf/1709.07857.pdf>

Early-stage startups like AI.Reverie are developing simulation platforms to generate datasets for a variety of industries and scenarios.

As the tech scales and synthetic data mimics real-world scenarios more accurately, it will act as a catalyst for smaller companies that don't have access to large datasets.



Threatening

REINFORCEMENT LEARNING

From training algorithms to beat world champions in board games to teaching AI acrobatics, researchers are pushing the boundaries with reinforcement learning. But the need for massive datasets currently limits practical applications.

Reinforcement learning gained media attention when Google DeepMind's AlphaGo defeated a world champion in the complex and strategic Chinese game of Go.

In a nutshell, the point of reinforcement learning is this: What action do you need to take to reach your goal and maximize rewards?

Because of this approach, reinforcement learning has particularly taken off in gaming and robotic simulation.

DeepMind's AlphaGo was initially trained using supervised learning (using data from other human players to train the algorithm) and reinforcement learning (AI playing against itself).

DeepMind later released AlphaGo Zero, which it claimed achieved super-human performance. It was trained purely based on reinforcement learning (playing against itself given just a set of rules).



Recently, researchers at UC Berkeley used computer vision and reinforcement learning to teach algorithms acrobatic skills from YouTube videos. Computer-simulated characters were able to replicate the moves in the videos without the need for manually annotating poses.



Source: <https://bair.berkeley.edu/blog/2018/10/09/sfv/>

With reinforcement learning, the simulated characters can apply their skills to new environments. For example, if a man in a YouTube video did a backflip on flat ground, the simulated character can adapt the skill to do a backflip on uneven terrain.

Despite these rapid advances, reinforcement learning adoption hasn't yet taken off because of how much data it requires compared to supervised learning, which is the most prevalent AI paradigm today.



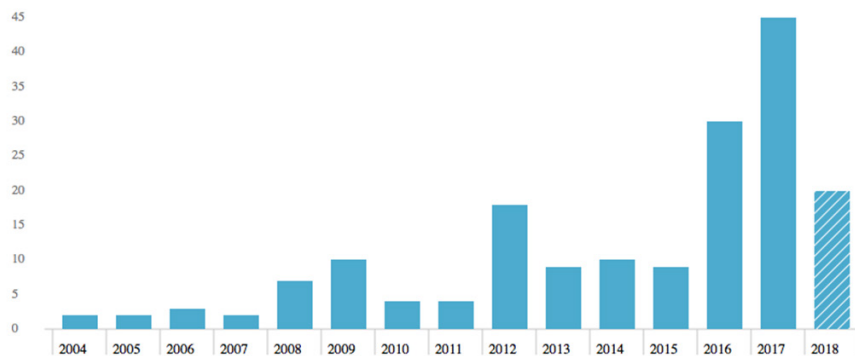
“There’s a rapid fall off as you go down this list [of different approaches to learning] as you think of the economic value created today ... Reinforcement Learning is one class of technology where the PR excitement is vastly disproportionate relative to the actual deployments today.”

— ANDREW NG, [EMTECH 2017 PRESENTATION](#)

But research into RL applications is increasing. A keyword search in title and abstract of US patent applications shows an uptick in activity in the last 2 years.

US patent applications for reinforcement learning

Number of patents by date of filing, based on keyword searches in title and abstract



Note: Patterned column(s) may show a decline due to a delay between patent filing and publication

Source: [CB Insights patent analytics](#)

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Top applicants include Google, IBM, Alphaics (an AI startup), Mobileye



(acquired by Intel), Microsoft, Adobe, and FANUC.

In earnings calls, Baidu actively discussed reinforcement learning, mentioning it 7 times in its Q1'18 call.

“One highlight in Q1 is that for the first time, we deployed a powerful reinforcement learning based infrastructure that can significantly improve our ability to better match ads to our users and increase clickthrough rates and conversions”

– BAIDU ON A Q1'18 EARNINGS CALL



NETWORK OPTIMIZATION

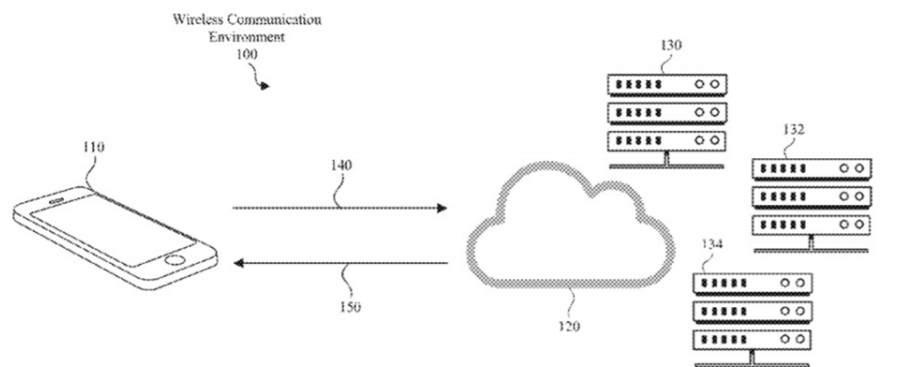
From facilitating spectrum sharing to monitoring assets and coming up with optimal designs for antenna, AI is beginning to change telecommunication.

Telecommunication network optimization is a set of techniques to improve latency, bandwidth, and design or architecture – anything that augments the flow of data in a favorable way.

For communication service providers, optimization directly translates into better customer experience.

One of the biggest challenges in telecommunications, apart from bandwidth constraints, is network latency. Applications like AR/VR on mobile phones will only optimally function with extremely low lag times.

Apple was granted a [patent](#) recently to use machine learning to form “anticipatory networks,” which anticipate what action wireless-enabled devices like smartphones may likely perform in the future and download data packets in advance to reduce latency.



Source: USPTO



Another emerging application of machine learning is in spectrum sharing.

The government licenses certain frequencies of the electromagnetic spectrum to companies like Verizon in an auction.

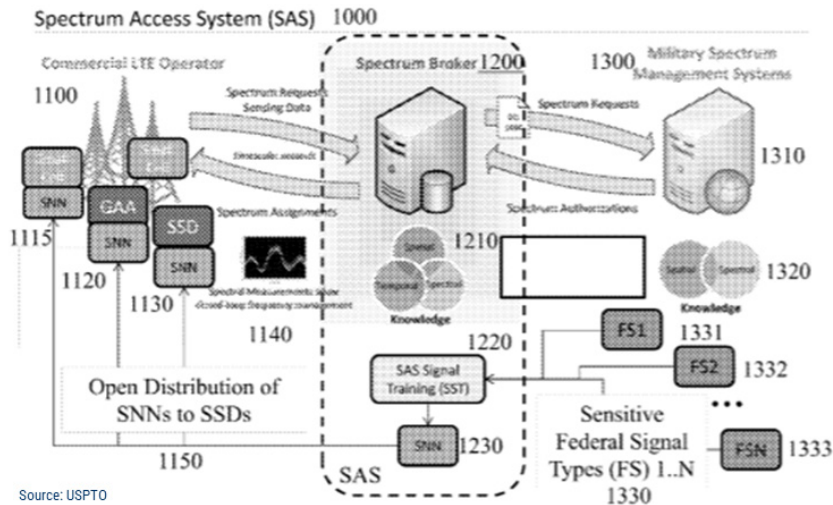
The Federal Communications Commission (FCC) ruled that the 3.5 to 3.7GHz spectrum will be shared between different users.

This means carriers can dynamically access shared frequencies based on availability. This will allow them to scale bandwidth up and down based on network demand. It will also provide spectrum access to smaller commercial users that don't license a dedicated spectrum of their own.

Parts of the 3.5GHz band is used by the US Navy and other federal agencies. They are given the first tier of access, and if the spectrum is not being used by them, then it goes to tier 2 and tier 3 users.

Companies like Federated Wireless provide Secure Spectrum Access (SAS) to dynamically assign spectrum between different tiers of users and ensure there's no interference with federal signals – and it leverages machine learning to do that.

In 2018, Federated Wireless was granted a [patent](#) to use ML to classify radio signals into different categories, such as federal signals, noise signals, and unknown signals. It does this while obscuring features of federal signals (so that hackers never gain access to specific features or weaknesses in military/defense signals).



DARPA wants to eventually move away from SAS players that facilitate spectrum sharing to an automated ML-based system. To this end, it launched the Spectrum Collaboration Challenge in 2016. Participants in the competition have to use ML to come up with unique ways for radio networks to “autonomously collaborate to dynamically determine how the radio frequency (RF) spectrum should be used moment to moment.”

DARPA also launched a Radio Frequency Machine Learning Systems (RFMLS) program in 2017. Similar to the Federated Wireless patent above, DARPA wants to use ML to differentiate between different types of signal, especially spotting malicious signals that intend to hack into end devices (such as IoT devices).

Telecom players are also preparing to integrate AI-based solutions in the next generation of wireless technology, known as [5G](#).

Samsung acquired AI-based network and service analytics startup Zhilabs in preparation for the 5G era.



Samsung said in a press release that AI software will be used to “analyze user traffic, classify applications being used, and improve overall service quality.”

Qualcomm sees AI edge computing as a crucial component of its 5G plans (edge computing reduces bandwidth constraints and frequent communications with the cloud – a main focus area for 5G).

Early research papers are also emerging exploring the use of neural nets to come up with the most optimal design for antenna in telecommunication networks.



AUTONOMOUS VEHICLES

Despite a substantial market opportunity for autonomous vehicles, the timeline for full autonomy is still unclear.

A number of big tech companies and startups are competing intensely in the autonomous vehicles space.

Google has made a name for itself in the auto space. Its self-driving project Waymo is the first autonomous vehicle developer to deploy a commercial fleet of AVs.

Investors remain confident in companies developing the full autonomous driving stack, pouring hundreds of millions of dollars into GM's [Cruise Automation](#) (\$750M from Honda in October 2018 and \$900M from SoftBank in May prior) and [Zoox](#) (\$500M in July 2018). Other startups here include Drive.ai, Pony.ai, and Nuro.

China, in particular, has ramped up its AV efforts. The Chinese science ministry announced last year that the nation's first wave of open AI platforms will rely heavily on Baidu for autonomous driving.

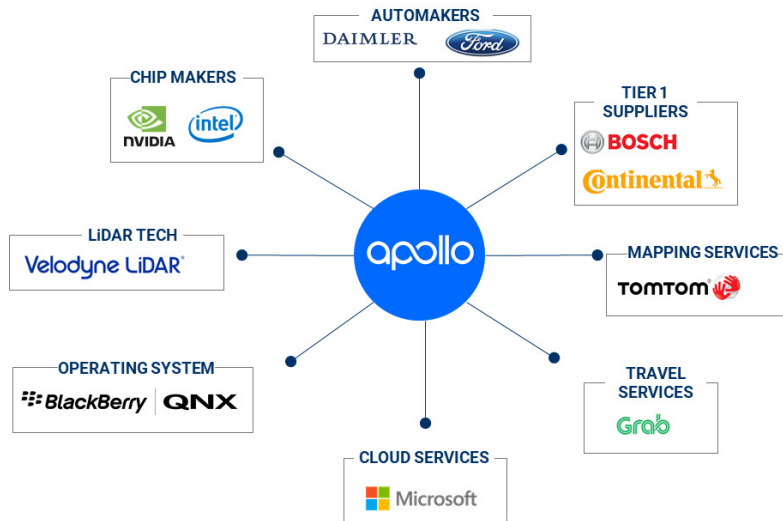
In April 2017, Baidu announced a one-of-a-kind open platform — Apollo — for autonomous driving solutions, roping in partners from across the globe.

As with other open-source platforms, the idea is to accelerate AI and autonomous driving research by opening it up to contributions from other players in the ecosystem. Making the source code available to everyone allows companies to build off of existing research instead of starting from scratch.



Baidu builds global autonomous driving ecosystem

Select international partners of Baidu's Apollo project



Partnerships source: Apollo.auto

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Alibaba also recently conducted test drives of its autonomous vehicle. But interestingly, just over a year ago, Alibaba was skeptical about the long-term commercial opportunity of autonomous vehicles, mentioning in an earnings call that “nobody has figured out the long-term economic model for this, but people are doing it because there is some very interesting artificial intelligence-related technology” involved in building autonomous vehicles.

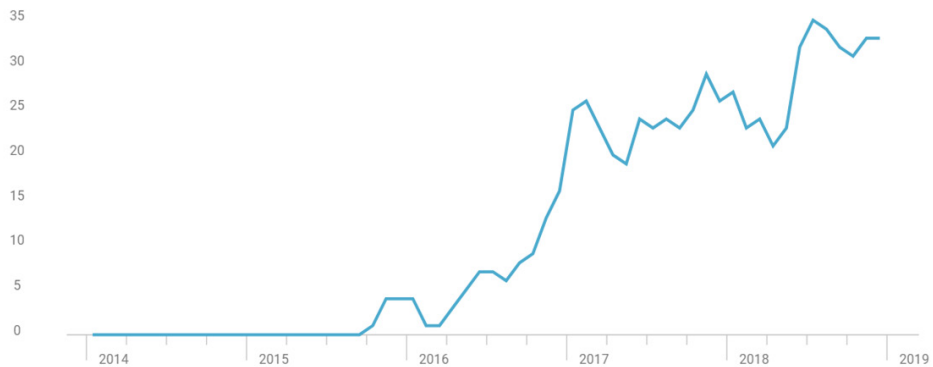
Even with hesitation surrounding the future of the technology, automakers are still working full steam ahead. The market is projected to reach roughly \$80B by 2025.

Some applications could see earlier adoption of fully self-driving vehicles, such as logistics and fulfillment.



Autonomous last-mile delivery is making news

Number of news mentions for “autonomous” and “last mile”



Source: CB Insights News Trends tool

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Autonomous logistics — specifically autonomous last-mile delivery — is top-of-mind for retailers and fulfillment companies, and may be the first area where we see full autonomy. Self-driving vehicles could help tackle the costly and arduous challenge of delivering goods at the last mile, which can add up to nearly a third of an item’s total delivery cost.

States like Arizona which have liberal laws for autonomous vehicle deployment are emerging as test beds. In June 2018, robotics startup Nuro partnered with Kroger, one of the largest brick-and-mortar grocers in the US, to deliver groceries. Nuro is designed to drive on neighborhood roads, not just sidewalks like other delivery robot and vehicle prototypes that have been developed.

In the restaurant space, pizza companies like Domino’s and Pizza Hut have been at the forefront of testing out autonomous vehicles. Ford is piloting autonomous delivery in Miami with pizza, groceries, and other goods. The OEM partnered with over 70 businesses, including Domino’s, in early 2018.



CROP MONITORING

*Three types of crop monitoring are taking off in agriculture:
On-ground, aerial, and geospatial.*

The precision agriculture drone [market](#) is expected to reach \$2.9B in 2021.

Drones can map the field for farmers, monitor moisture content using thermal imaging, and identify pest infested crops and spray pesticides.

Startups are focusing on adding a layer of analytics to data captured by 3rd party drones.

[Taranis](#), for example, uses 3rd party Cessna airplanes to do this. Taranis also acquired agtech-AI startup Mavrx Imaging last year, which was developing ultra high resolution imaging tech to scout and monitor fields.

The screenshot shows the profile for Taranis on the CB Insights platform. It includes navigation tabs for Overview, Transactions, Signals, Tech/IP, and Network. A table lists a transaction from 5/17/2018 where Taranis acquired Mavrx Imaging for \$12.4M in Series A. Below this, a 'Funding' section shows 6 fundings totaling \$29.5M, with a 'DOWNLOAD CSV' button and a note to 'Please select items to export'. The funding table lists rounds from 2015 to 2018, including Series B, Series A-II, Series A, Seed VC, and Incubator/Accelerator rounds.

Date	Company	Valuation ¹	Total Funding	Investment Stage	Note	Sources
5/17/2018	Mavrx Imaging		\$12.4M	Series A	Acquired	4

Date	Round	Amount	Investors	Valuation ¹	Sources
11/6/2018	Series B	\$20M	Cavallo Ventures, Eyal Gura, and 7 more		4
10/17/2017	Series A - II		BNP Paribas, and CM-CIC Investissement		1
5/4/2017	Series A	\$7.5M	Eshbol Ventures, Eyal Gura, and 4 more	\$31.81M	6
3/30/2016	Seed VC	\$2M	Eshbol Ventures, iAngels, and 3 more		3
3/20/2015	Incubator/Accelerator - II		Microsoft ScaleUp		1
1/1/2015	Incubator/Accelerator		8200 EISP		1

Source: CB Insights

CBINSIGHTS



Taranis uses AI to stitch together images of the field and also to identify potential issues with crops. John Deere, a farming equipment manufacturer, tapped the startup along with a few others, to collaborate on potential solutions for John Deere.

Deere has been reinventing itself with AI. It bought [Blue River Technology](#) – an agricultural equipment company leveraging computer vision – for \$300M+. Among other things, Blue River was working on “smart weeding” and “see-and-spray” solutions.

This type of individual crop monitoring can become a major disruptor for the agricultural pesticide industry. If on-the-ground farming equipment gets smarter with computer vision and sprays only individual crops as needed, it will reduce the demand for non-selective weed killers that kill everything in the vicinity. Precision spraying would also mean a reduction in the amount of herbicide and pesticide used.

Beyond the field, using computer vision to analyze satellite images provides a macro-level understanding of agricultural practices.

Geo-spatial data can provide information on crop distribution patterns across the globe and the impact of weather changes on agriculture.

Cargill invested in [Descartes Labs](#), which uses satellite data to develop a forecasting model for crops like soybean and corn. This application of computer vision has also piqued the interest of commodities traders and government agencies. DARPA is working with Descartes to forecast food security.



Transitory

CYBER THREAT HUNTING

Reacting to cyber attacks is no longer enough. Proactively “hunting” for threats using machine learning is gaining momentum in cybersecurity.

Advancements in computing power and algorithms are turning previously theoretical hacks into real security problems.

According to the Breach Level Index, a global database of public data breaches, 4.5B data records were compromised worldwide in H1’18 (for reference, the figure was 2.6B for all of 2017).

Rank	Organization Breached	Records Breached	Date of Breach	Type of Breach	Source of Breach	Location	Industry	Risk Score
1	Facebook	2,200,000,000	04/04/18	Identity Theft	Malicious Outsider	United States	Social Media	10.0
2	Exactis	340,000,000	06/01/18	Identity Theft	Accidental Loss	United States	Other	9.1
3	Under Armour	150,000,000	02/01/18	Account Access	Malicious Outsider	United States	Retail	9.1
4	Twitter	336,000,000	05/03/18	Financial Access	Accidental Loss	United States	Social Media	9.0
5	Firebase (Google)	100,000,000	06/20/18	Identity Theft	Accidental Loss	United States	Technology	8.6

Source: Breach Level Index top H1’18 breaches

Unlike other industrial applications of AI, cyber-defense is a cat-and-mouse game between hackers and security personnel, both leveraging advances in machine learning to up their game and keep ahead of the other.

Threat hunting, as the name suggests, is the practice of proactively seeking out malicious activity instead of merely reacting to alerts or a breach after it has occurred.



Hunting begins with a hypothesis on potential weaknesses in the network, and manual and automated tools to test out the hypothesis in a continuous, iterative process. The sheer volume of data in cybersecurity makes machine learning an inseparable part of the process.

A quick search on [LinkedIn](#) for “threat hunters” shows 70+ job listings in the United States from organizations such as Microsoft, Raytheon, Verizon, Booz Allen Hamilton, and Dow Jones.

While this reflects an emerging demand for threat hunters across diverse business types, it also indicates that the title itself is still niche.

“Results from the SANS 2018 Threat Hunting Survey show that, for many organizations, hunting is still new and poorly defined from a process and organizational standpoint ... The survey of 600 respondents reveals that most organizations that are hunting tend to be larger enterprises or those that have been heavily targeted in the past.”

- SANS 2018 SURVEY SPONSORED BY IBM



As the SANS 2018 survey suggests, the stakes are higher for larger enterprises whose differentiating factor is their access to a treasure trove of data.

Amazon, for instance, faces mounting pressure from AWS customers to secure the cloud. Wrongfully configured AWS servers have resulted in data breaches at customers like Verizon, WWE, Dow Jones, and Accenture.

Amazon acquired threat hunting startup [Sqrrl](#) to develop a new product for hunting hackers on AWS clients' accounts.

[Cylance](#), another AI startup with a focus on threat hunting, was acquired by Blackberry last year.

The more spread out a network becomes the more vulnerable it becomes.

Threat hunting is likely to gain further traction, however it does come with its own set of challenges, such as dealing with an ever-changing, dynamic environment and reducing false positives.



CONVERSATIONAL AI

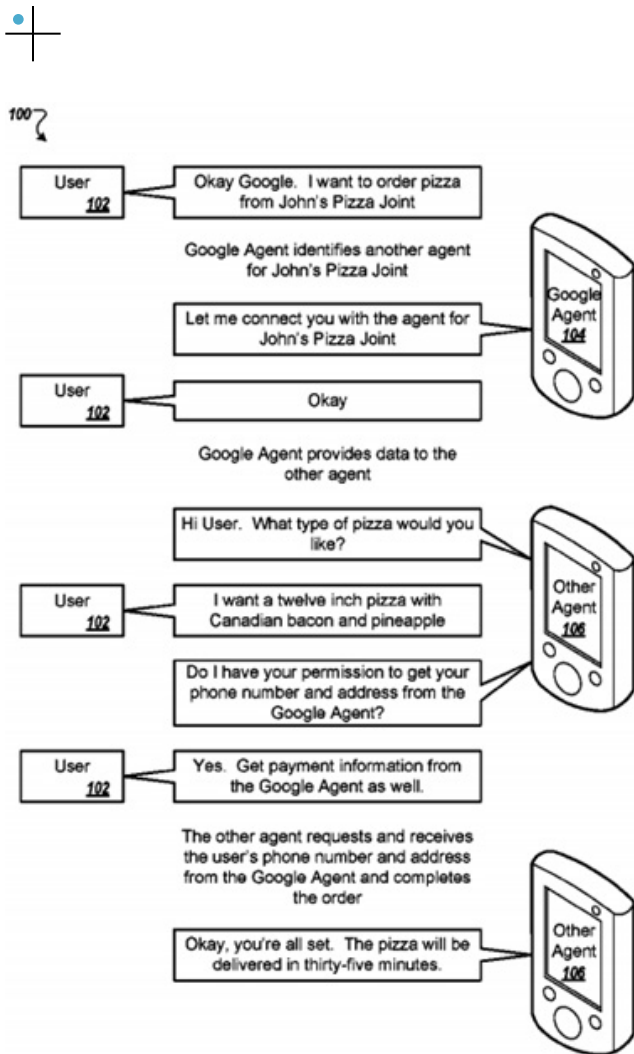
For many enterprises, chatbots became synonymous with AI – but the promise isn't keeping up with the reality.

Recently, Google was in hot water over its conversational AI feature, Duplex.

Duplex can make phone calls and reservations on behalf of the user, but communicates like a real human (complete with “umms” and pauses). It sparked ethical concerns over whether or not Duplex needs to identify itself as a conversational agent when speaking to real people.

Google added Duplex to its new phone, Pixel 3. It has turned the Pixel 3 into an AI powerhouse, including a “screen call” option that allows the Google Assistant to screen for spam callers.

Google has been applying to patent the interactions between two conversational agents since 2014. The most recent application, [“Conversational Agent Response Determined Using A Sentiment,”](#) was filed in April 2018.



Source: USPTO

Despite FAMGA and China's big tech companies (Baidu, Alibaba, and Tencent) focusing heavily on this space, conversational agents — both voice- and text-based — are more feasible in some applications than others.

One of the most widespread applications of chatbots is in customer service. Bots form the first layer of interaction with the user (note: not all bots use natural language processing) and hand off queries to a human based on the level of complexity.



This is still challenging for applications like health and insurance, where triaging (gauging the urgency of a situation) is complex.

Similarly, shopping through voice-based conversations alone, without a visual cue, is challenging.

Although analysts and CPG brands, from Sephora and Nestle to Capgemini, have talked up voice shopping as the next big thing in retail, it hasn't taken off. With the exception of reordering specific items, it fails to provide key customer experiences that drive online commerce.

Mental healthcare is another area where chatbots seem like a potentially disruptive force.

High costs of mental health therapy and the appeal of round-the-clock availability is giving rise to a new era of AI-based mental health bots. Early-stage startups are focused on using cognitive behavioral therapy – changing negative thoughts and behaviors – as a conversational extension of the many mood tracking and digital diary wellness apps in the market.

But mental health is a spectrum. There is variability in symptoms, subjectivity in analysis, and it requires a high level of emotional cognition and human-to-human interaction.

This makes areas like mental healthcare – despite the upside of cost and accessibility – a particularly hard task for algorithms.



DRUG DISCOVERY

With AI biotech startups emerging, traditional pharma companies are looking to AI SaaS startups for innovative solutions to the long drug discovery cycle.

In May 2018, Pfizer entered into a strategic partnership with XtalPi – an AI startup backed by tech giants like Tencent and Google – to predict pharmaceutical properties of small molecules and develop “computation-based rational drug design.”

But Pfizer is not alone.

Top pharmaceutical companies like Novartis, Sanofi, GlaxoSmithKline, Amgen, and Merck have all announced partnerships in recent months with AI startups to discover new drug candidates for a range of diseases from oncology and cardiology.

“The biggest opportunity where we are still in the early stage is to use deep learning and artificial intelligence to identify completely new indications, completely new medicines.”

– BRUNO STRIGINI, FORMER CEO OF NOVARTIS ONCOLOGY

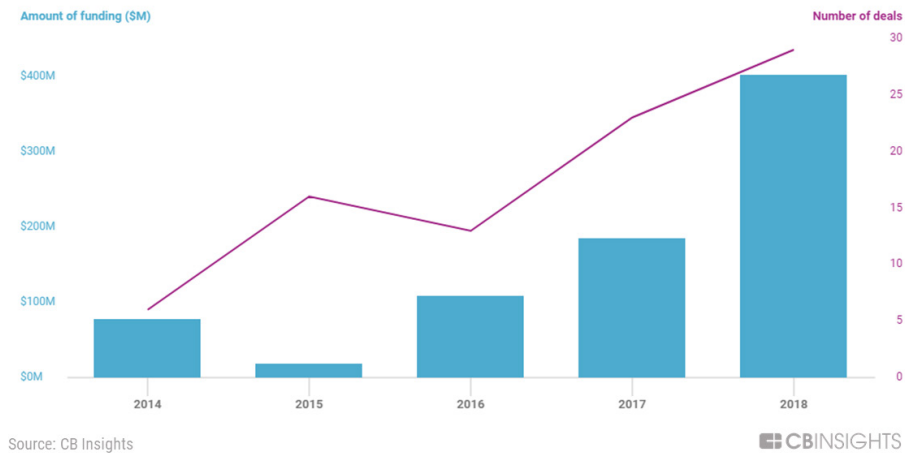
Interest in the space is driving the number of equity deals to AI drug



discovery startups: 20 as of Q2'18, equal to all of 2017.

Big pharma's interest boosts AI drug discovery deals

Equity deals, 2014 – 2018



While biotech AI companies like Recursion Pharmaceuticals are investing in both AI and drug R&D, traditional pharma companies are partnering with AI SaaS startups.

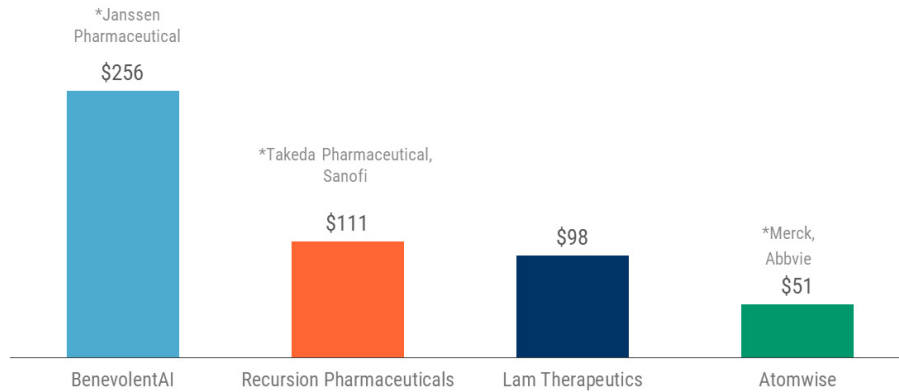
Although many of these startups are still in the early stages of funding,



they already boast a roster of pharma clients.

Top biotech and SaaS startups using AI in drug R&D

Most well-funded by total equity (\$M), as of Aug 28, 2018 *(*select disclosed partnerships)*



Source: cbinsights.com

 CBINSIGHTS

There are few measurable metrics of success in the drug formulation phase, but pharma companies are betting millions of dollars on AI algorithms to discover novel therapeutic candidates and transform the drawn-out drug discovery process.

WHERE IS ALL THIS DATA FROM?

**The CB Insights platform
has the underlying data
included in this report**

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