State of AI

June 29, 2018

Artificial intelligence (AI) is a multidisciplinary field of science whose goal is to create intelligent machines.

We believe that AI will be a force multiplier on technological progress in our increasingly digital, data-driven world.

This is because everything around us today, ranging from culture to consumer products, is a product of intelligence.

In this report, we set out to capture a snapshot of the exponential progress in AI with a focus on developments in the past 12 months. Consider this report as a compilation of the most interesting things we've seen that seeks to trigger informed conversation about the state of AI and its implication for the future.

We consider the following key dimensions in our report:

- **Research**: Technology breakthroughs and their capabilities.
- **Talent**: Supply, demand and concentration of talent working in the field.
- **Industry**: Large platforms, financings and areas of application for AI-driven innovation today and tomorrow.
- **Politics**: Public opinion of AI, economic implications and the emerging geopolitics of AI.

Collaboratively produced in East London, UK by: Ian Hogarth *@soundboy* Nathan Benaich *@nathanbenaich*

About the authors

Nathan Benaich

Nathan studied biology at Williams College and earned a PhD from Cambridge in computational and experimental cancer biology. He is an investor in machine learning-driven technology companies with his new firm, Air Street Capital, and as a Venture Partner at Point Nine Capital. He founded the RAAIS community and Foundation to advance progress in AI.

Ian Hogarth

Ian studied engineering at Cambridge, specialising in machine learning. His Masters project was a computer vision system to classify breast cancer biopsy images. He was co-founder and CEO of Songkick, the concert service used by 17 million music fans every month. He is an angel investor in over 30 startups with a focus on applied machine learning.

Definitions

Artificial Intelligence (AI): A broad discipline with the goal of creating intelligent machines, as opposed to the natural intelligence that is demonstrated by humans and animals. It has become a somewhat catch all term that nonetheless captures the long term ambition of the field to build machines that emulate and then exceed the full range of human cognition.

Machine learning (ML): A subset of AI that often uses statistical techniques to give machines the ability to "learn" from data without being explicitly given the instructions for how to do so. This process is known as “training” a “model” using a learning “algorithm” that progressively improves model performance on a specific task.

Reinforcement learning (RL): An area of ML that has received particular attention from the research community over the past decade. It is concerned with software agents that learn goal-oriented behavior by trial and error in an environment that provides rewards or penalties in response to the agent’s actions towards achieving that goal.

Deep learning (DL): An area of ML that attempts to mimic the activity in layers of neurons in the brain to learn how to recognise complex patterns in data. The “deep” in deep learning refers to the large number of layers of neurons in contemporary ML models that help to learn rich representations of data to achieve better performance gains.

Definitions

Algorithm: An unambiguous specification of how to solve a particular problem.

Model: Once a ML algorithm has been trained on data, the output of the process is known as the model. This can then be used to make predictions.

Supervised learning: This is the most common kind of (commercial) ML algorithm today where the system is presented with labelled examples to explicitly learn from.

Unsupervised learning: In contrast to supervised learning, the ML algorithm has to infer the inherent structure of the data that is not annotated with labels.

Transfer learning: This is an area of research in ML that focuses on storing knowledge gained in one problem and applying it to a different or related problem, thereby reducing the need for additional training data and compute.

Good old fashioned AI: A name given to an early symbolic AI paradigm that fell out of favour amongst researchers in the 1990s.

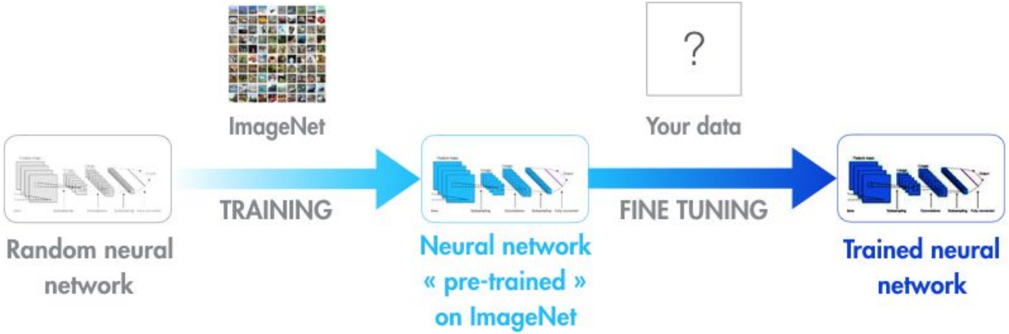
Section 1: Research and technical breakthroughs

Transfer Learning

What is transfer learning and how does it relate to machine learning?

Machine learning models are trained to solve a task by **learning from examples**. However, to solve a new and different task, a trained model needs to be *retained* with **new data specific to that task**.

Transfer learning posits that knowledge acquired by a trained machine learning model can be **re-applied** (or 'transferred') during the training process for a new task.



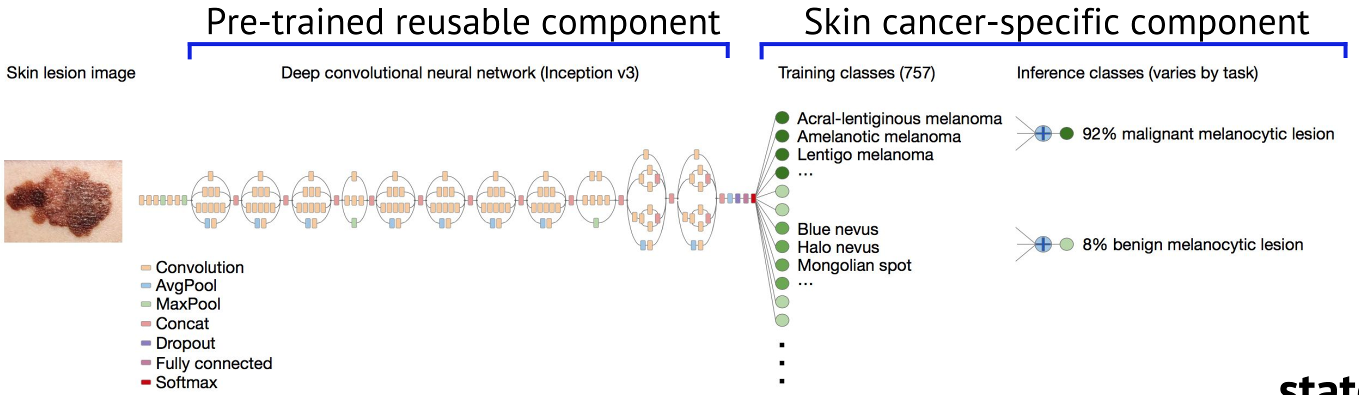
Transfer Learning

Why does transfer learning matter?

Re-using previously acquired knowledge **reduces the amount of data** a model needs in order to learn a new task.

A model pre-trained on many different problems will **internalise an increasingly rich understanding of the world** and is therefore considered a key step towards generalising AI.

Example: Repurposing Google's InceptionV3 image recognition network for skin cancer detection



Transfer Learning: From predicting everyday objects on ImageNet to detecting skin cancer

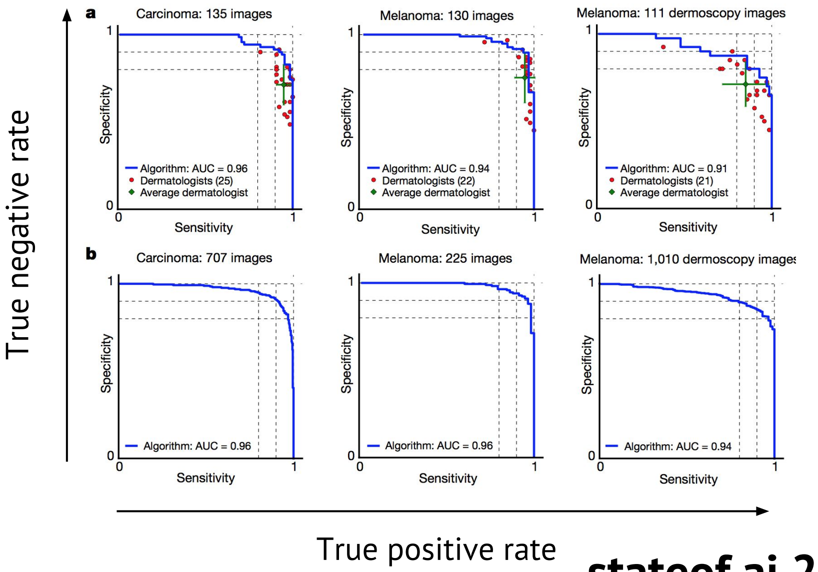
Transfer learning enabled automatic state-of-the-art detection of dangerous skin lesions on human patients

The Google InceptionV3 network was first trained on ImageNet and then re-trained with 129,450 clinical images of 2,032 different skin diseases. It learns how to classify images based on **pixel inputs** and **disease labels only.**

The model outperforms 21 Stanford dermatologists

Dermatologists: *biopsy or treat the lesion?*
Model: *what probability is the lesion dangerous?*

In the charts on the right, you'll see that the majority of red points (dermatologist) reside below the blue curve (sensitivity-specificity for the model). This means the model achieves superior performance compared to dermatologists.



Stanford University

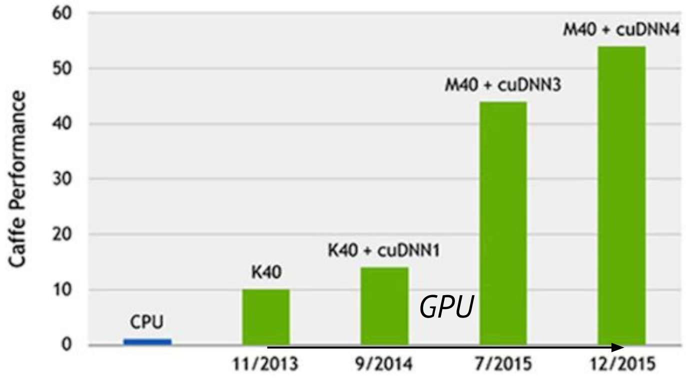
AI hardware as the new frontier

The role of semiconductors in driving AI performance

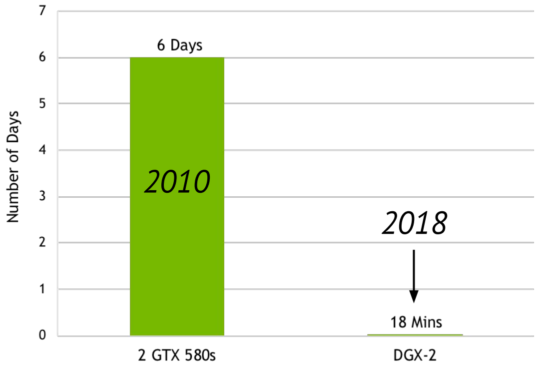
Semiconductor (or 'chip') performance is a key driver behind progress in AI research and applications. This is because AI models often **require huge amounts of training data** to properly learn a task (e.g. image recognition).

Graphics processing units (GPUs) are today's workhorse chip for AI models largely because they offer **immense computational parallelism** over central processing units (CPUs). This means **faster training** and **model iteration**.

AI models run much faster on GPUs



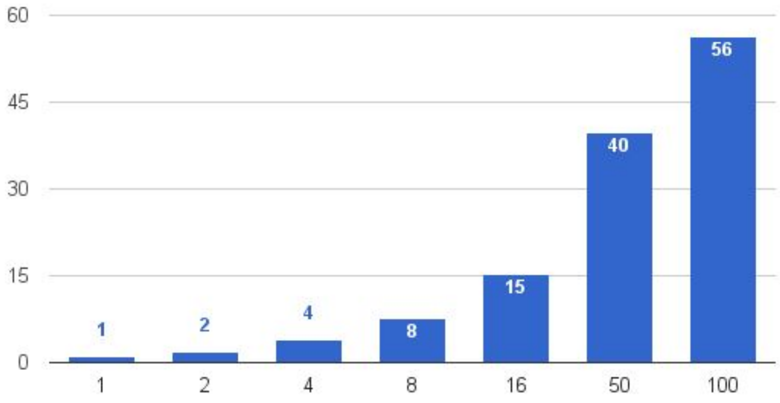
New GPU supercomputers eclipse older chips



AI hardware as the new frontier

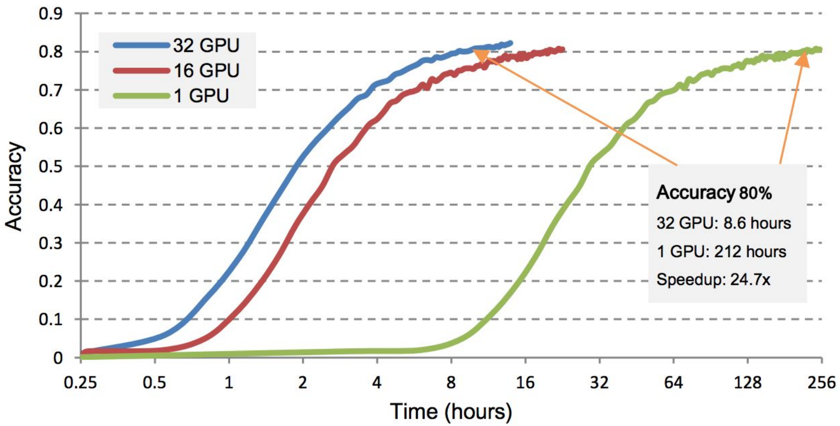
- **The hardware war: More GPUs allows for faster training, as well as bigger (more powerful) models.**

Training speedup over one GPU (x-fold)



Number of GPUs used for training

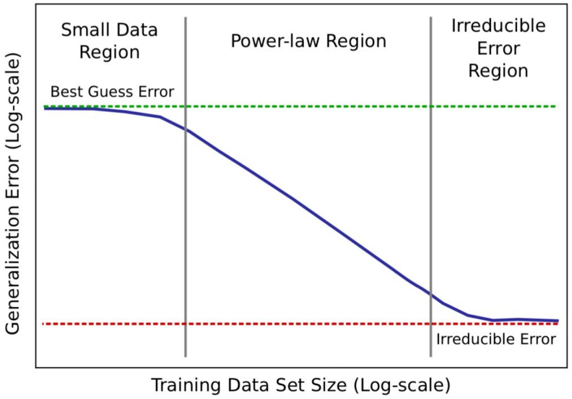
32 GPUs = same accuracy, 25x faster



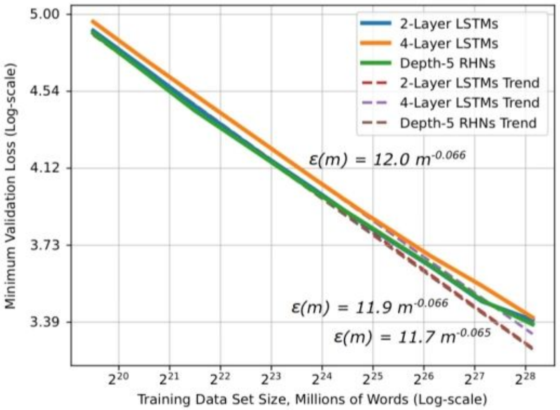
AI hardware is especially helpful for deep learning

- **AI model performance scales with dataset size and the # of model parameters, thus necessitating more compute**

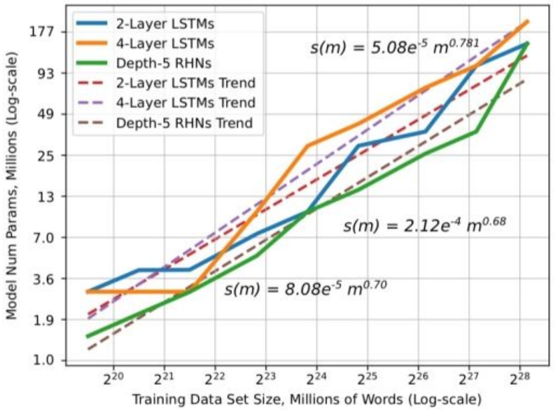
A framework for scaling AI models



More data = fewer mistakes



More data = bigger model

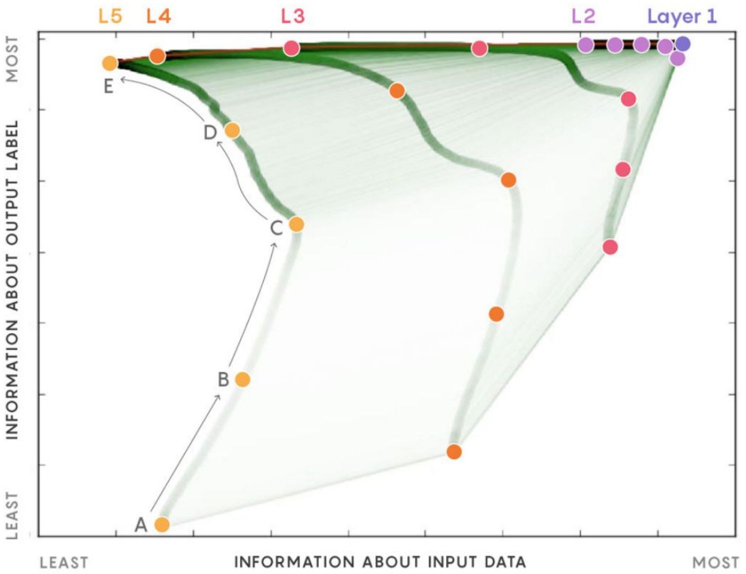


AI hardware is especially helpful for deep learning

- **The Information Theory: First memorise the data, then forget what doesn't help the model make predictions**

Inside Deep Learning

New experiments reveal how deep neural networks evolve as they learn.



A **INITIAL STATE:** Neurons in Layer 1 encode everything about the input data, including all information about its label. Neurons in the highest layers are in a nearly random state bearing little to no relationship to the data or its label.

B **FITTING PHASE:** As deep learning begins, neurons in higher layers gain information about the input and get better at fitting labels to it.

C **PHASE CHANGE:** The layers suddenly shift gears and start to "forget" information about the input.

D **COMPRESSION PHASE:** Higher layers compress their representation of the input data, keeping what is most relevant to the output label. They get better at predicting the label.

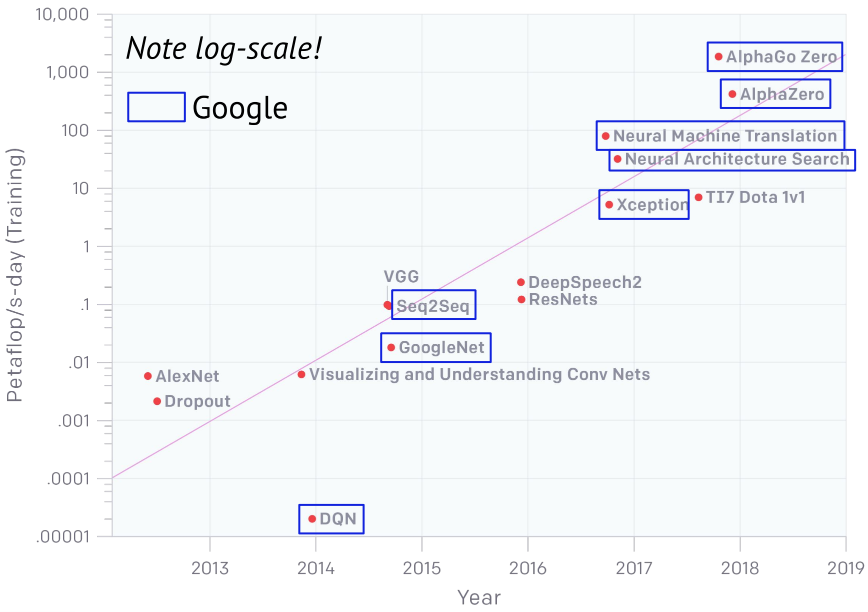
E **FINAL STATE:** The last layer achieves an optimal balance of accuracy and compression, retaining only what is needed to predict the label.

THE HEBREW UNIVERSITY OF JERUSALEM

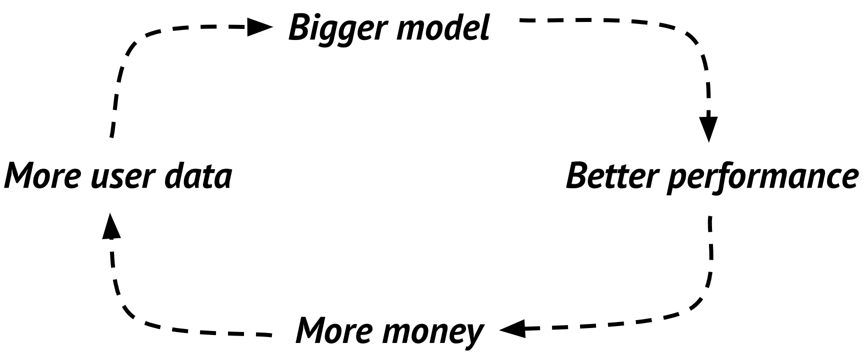
AI hardware rate limits progress in today's deep learning era

- **More compute means new solutions to previously intractable problems, e.g. machines learning to play Go**

AlexNet to AlphaGo Zero: 300,000x more compute



A positive feedback loop drives AI competitiveness

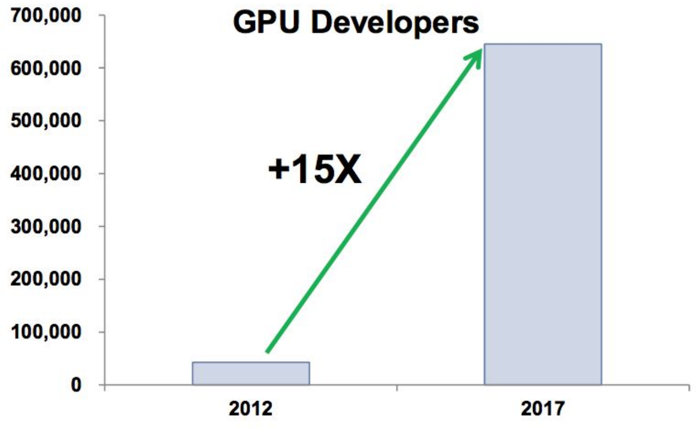


OpenAI

AI hardware

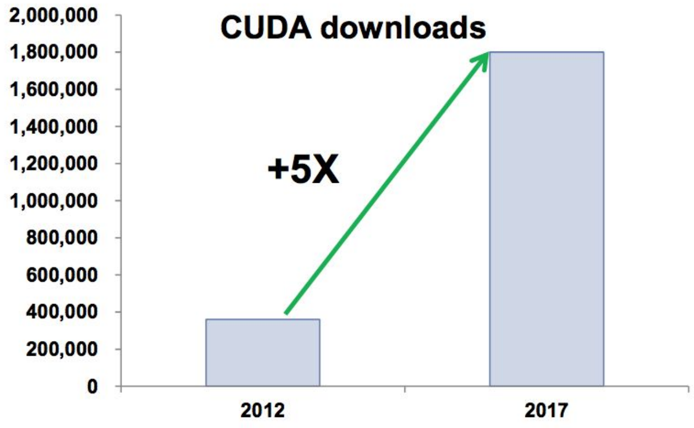
- **No wonder that GPUs have grown immensely in popularity amongst developers**

Exhibit 4: The number of GPU developers has grown significantly...



Source: Nvidia

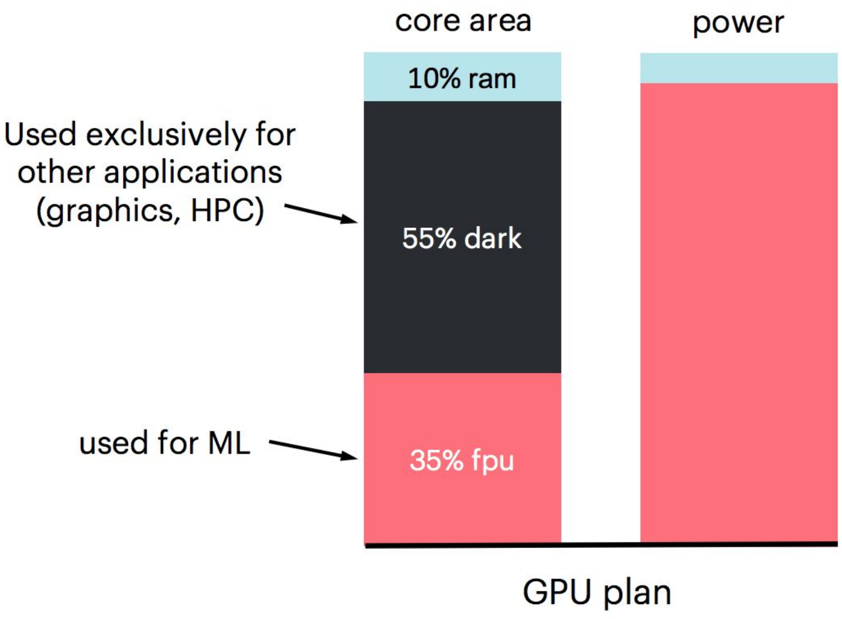
Exhibit 5: ...driving demand for software to support AI development



Source: Nvidia

AI hardware

- **However, GPUs were built for graphics workloads and *evolved* for high performance computing and AI workloads**



AI hardware

While GPUs are used extensively for training, they're not really needed for inference

While in most cases, training on GPUs tends to outperform training on CPUs, the abundance of readily-available CPU capacity in the datacenter makes it a useful and widely used platform.

At Facebook, for example, primary use case of GPUs is offline training rather than serving real-time data to users.

Offline training uses a mix of GPUs and CPUs

Service	Resource	Training Frequency	Training Duration
News Feed	Dual-Socket CPUs	Daily	Many Hours
Facer	GPUs + Single-Socket CPUs	Every N Photos	Few Seconds
Lumos	GPUs	Multi-Monthly	Many Hours
Search	Vertical Dependent	Hourly	Few Hours
Language Translation	GPUs	Weekly	Days
Sigma	Dual-Socket CPUs	Sub-Daily	Few Hours
Speech Recognition	GPUs	Weekly	Many Hours

TABLE II
FREQUENCY, DURATION, AND RESOURCES USED BY OFFLINE TRAINING FOR VARIOUS WORKLOAI

However, online training is CPU-heavy

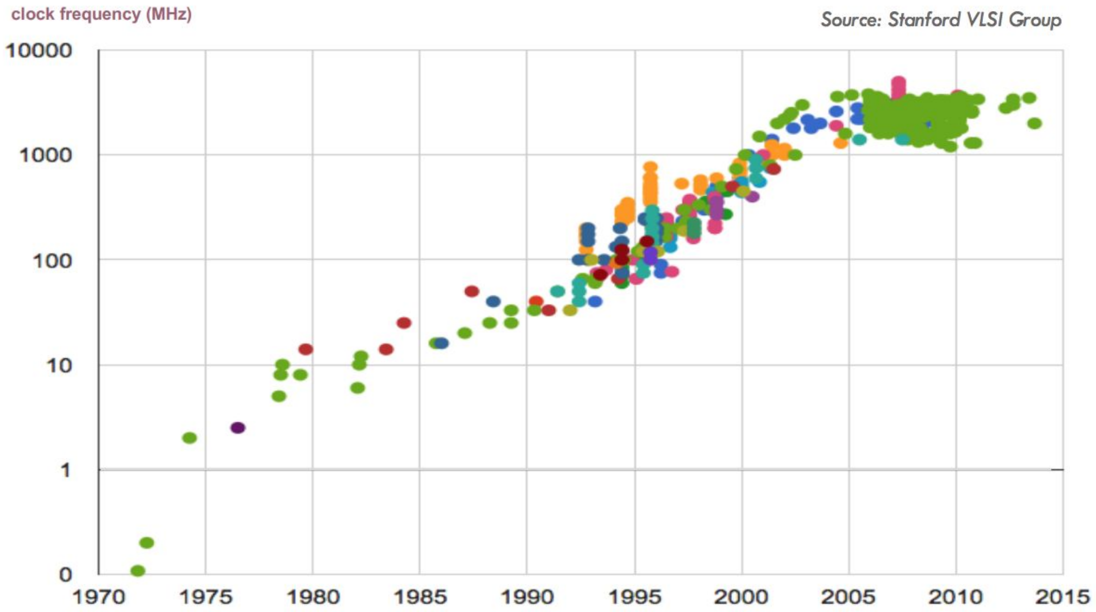
Services	Relative Capacity	Compute	Memory
News Feed	100X	Dual-Socket CPU	High
Facer	10X	Single-Socket CPU	Low
Lumos	10X	Single-Socket CPU	Low
Search	10X	Dual-Socket CPU	High
Language Translation	1X	Dual-Socket CPU	High
Sigma	1X	Dual-Socket CPU	High
Speech Recognition	1X	Dual-Socket CPU	High

TABLE III
RESOURCE REQUIREMENTS OF ONLINE INFERENCE WORKLOADS.

facebook research

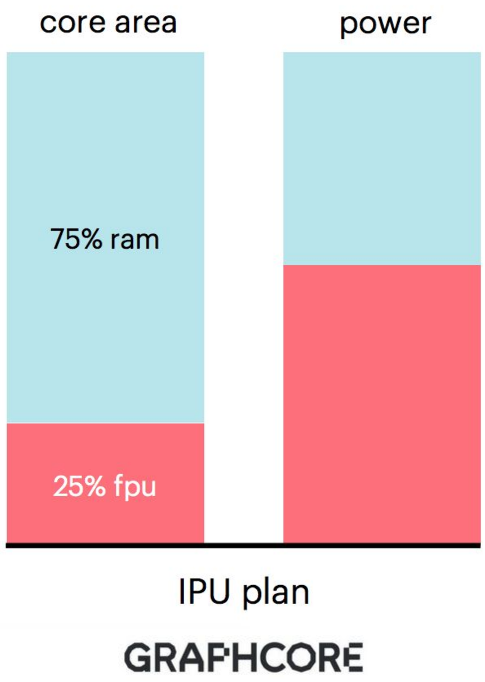
AI hardware

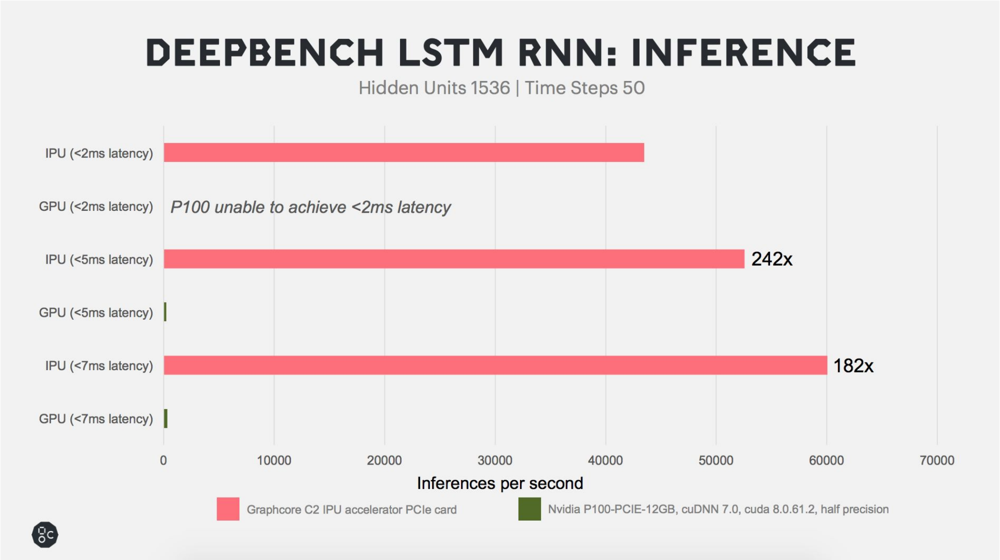
- **Processor clock frequencies are not getting faster and Moore's Law can only take us so far**



AI hardware

- **New architectures optimise for memory and compute to offer state-of-the-art performance running AI models**

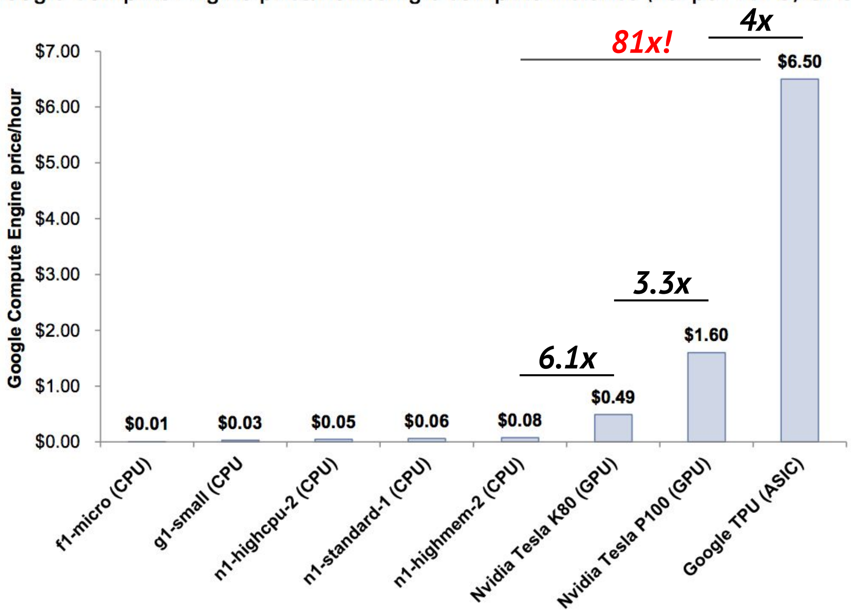




AI hardware

- **But GPUs and novel silicon are costly to rent per hour, which means progress is limited by financial resources**

Exhibit 11: Offerings for AI command significantly higher prices
Google Compute Engine price/hour/single compute instance (i.e. per 1CPU, GPU, TPU, etc)

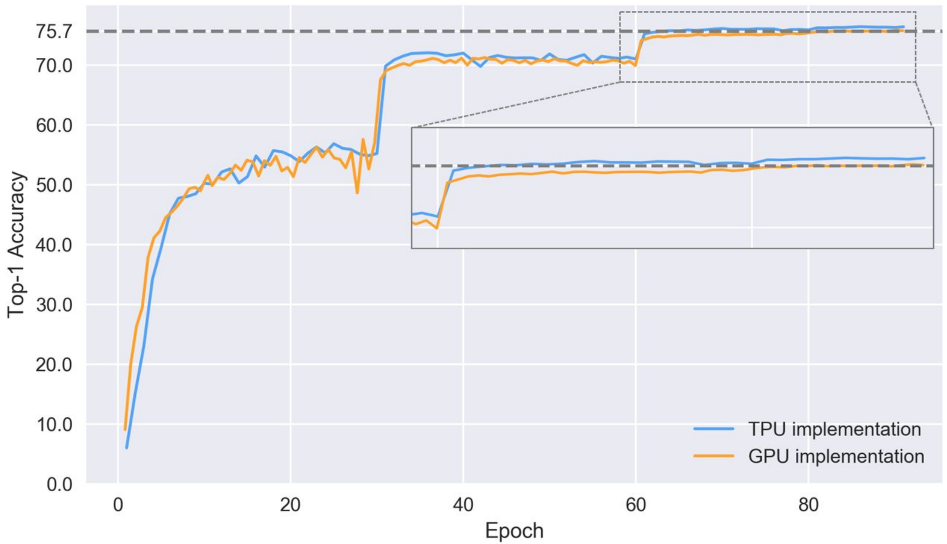


Source: Google, Goldman Sachs Global Investment Research.

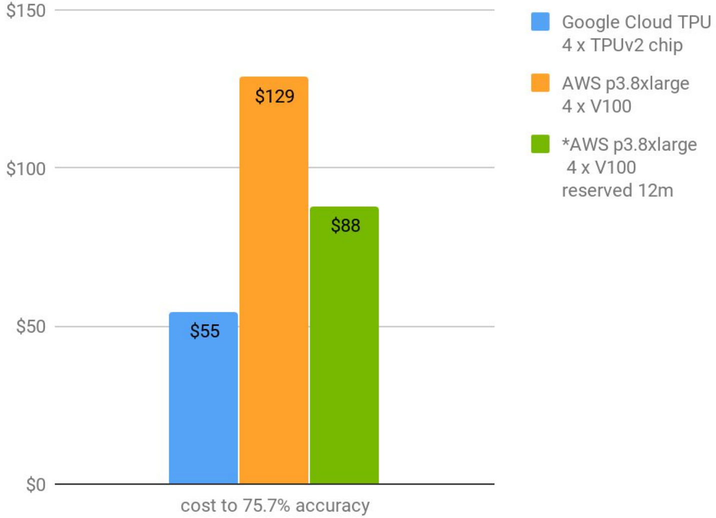
AI hardware

Whilst more costly per hour, new silicon (e.g. Google's TPUv2) allows for faster model training at lower final costs
(vs. NVIDIA V100)

Top-1 accuracy learning rate of TPU vs GPU on ImageNet



Cloud cost to reach 75.7% top-1 accuracy



AI hardware

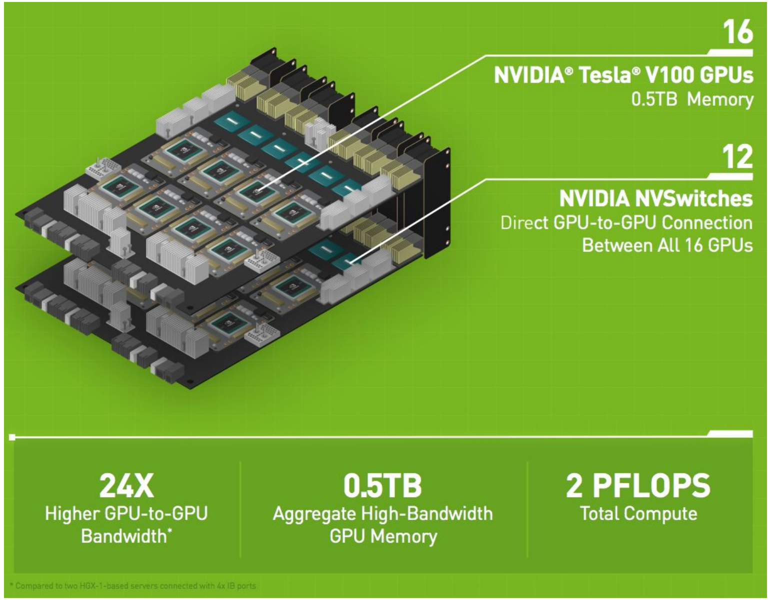
- **What's next for Google? The TPUv3 announced at Google I/O 2018**

  Each Cloud TPUv3 (4 chips) has 128GB of high-bandwidth memory 2x that of the Cloud TPUv2.

AI hardware

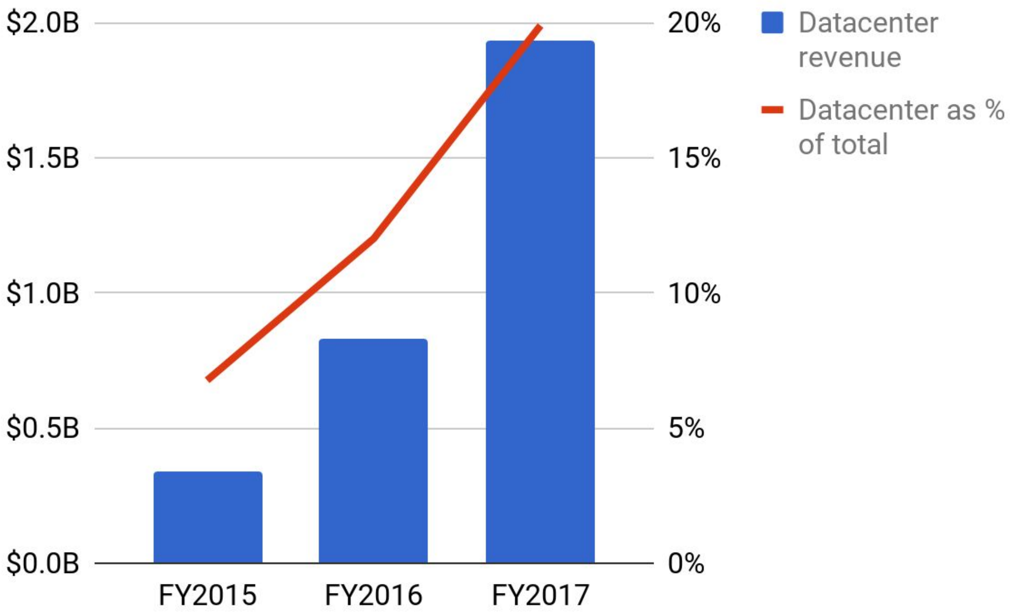
What's next for NVIDIA? The HGX-2, announced at NVIDIA GTC May 2018

Multi-precision computing platform for scientific computing (high precision) and AI workloads (low precision).



AI hardware

- **NVIDIA's datacenter business breaks $2B run-rate, is growing >100% year on year and accounts for almost 20% of their group revenue**



AI hardware

- **NVIDIA's enterprise value has 10x in 3 years since the deep learning revolution ignited**

Open	246.65	Div yield	0.25%
High	246.80	Prev close	250.95
Low	236.52	52-wk high	269.20
Mkt cap	140.18B	52-wk low	138.58
P/E ratio	40.75		

AI hardware

Intel's datacenter group accounts for 30% of the company's group revenue

HIGHLIGHTS AND SEGMENT IMPERATIVES

- We exceeded our commitment of high single-digit revenue growth and >40% operating margin for 2017.
- We continue to see strong growth in our cloud and communications market segments.
- The data center TAM[1] is expected to be >$70 billion by 2022, of which we currently have less than a 40% market share.
- We see significant opportunities in cloud, networking, and analytics/ artificial intelligence, with the chance to drive higher growth as we expand our product offerings in the data center with our adjacent products.
- During 2017, we launched the Intel® Xeon® Scalable processors, delivering the largest advancements in platform capabilities in a decade and achieving over 110 world performance records.

AI hardware
Many companies are developing custom AI chips

IC Vendors	Intel, Qualcomm, Nvidia, Samsung, AMD, Xilinx, IBM, STMicroelectronics, NXP, MediaTek, HiSilicon, Rockchip
Tech Giants & HPC Vendors	Google, Amazon_AWS, Microsoft, Apple, Aliyun, Alibaba Group, Tencent Cloud, Baidu, Baidu Cloud, HUAWEI Cloud, Fujitsu, Nokia, Facebook
IP Vendors	ARM, Synopsys, Imagination, CEVA, Cadence, VeriSilicon, Videantis
Startups in China	Cambricon, Horizon Robotics, DeePhi, Bitmain, Chipintelli, Thinkforce
Startups Worldwide	Cerebras, Wave Computing, Graphcore, PEZY, KnuEdge, Tenstorrent, ThinCI, Koniku, Adapteva, Knowm, Mythic, Kalray, BrainChip, AImotive, DeepScale, Leepmind, Krtkl, NovuMind, REM, TERADEEP, DEEP VISION, Groq, KAIST DNPU, Kneron, Esperanto Technologies, Gyrfalcon Technology, SambaNova Systems, GreenWaves Technology, Lightelligence, Lightmatter

AI hardware

- **Large technology companies are hedging their hardware suppliers, but there are few options to choose from**

Exhibit 8: Cloud companies leverage multiple hardware architectures in their datacenters
Hardware used by various cloud companies based on public statements

	Hardware platform	Hardware providers	Announced AI/ML-related partnership	Comments
Google	GPUs, ASICs (TPU)	Nvidia, AMD, Intel	Nvidia	Google offers Nvidia-based services as well as services based on its own TPU
Amazon	GPUs, FPGAs	Nvidia, AMD, Xilinx, Intel	Nvidia, Xilinx	Amazon offers Nvidia GPU and Xilinx FPGA instances on AWS.
Microsoft	GPUs, FPGAs	Nvidia, AMD, Xilinx, Intel	Nvidia, AMD (host processor)	Microsoft offers Nvidia GPU services on Azure and has in the past discussed using FPGAs for hyperscale acceleration fabric.
Facebook	GPUs, ASICs	Nvidia, AMD, Intel	Nvidia, Intel	Facebook leverages Nvidia GPUs for its AI development servers (Big Basin) and has indicated that it is working with Intel to develop AI hardware.
Alibaba	GPUs, FPGAs	Nvidia, AMD, Xilinx, Intel	Nvidia, Xilinx	Announced accelerator partnerships with both Nvidia and Xilinx
Baidu	GPUs, FPGAs	Nvidia, AMD, Xilinx, Intel	Nvidia, Xilinx	Announced partnerships with Nvidia, Xilinx, and AMD
Tencent	GPUs, FPGAs	Nvidia, AMD, Xilinx, Intel	Nvidia, Xilinx	Announced accelerator partnerships with both Nvidia and Xilinx

Source: Company data, Goldman Sachs Global Investment Research.

AI hardware

Cloud giants are creating dedicated AI hardware and significantly growing their capex budgets

Technology

Facebook Is Forming a Team to Design Its Own Chips

By Mark Gurman, Ian King, and Sarah Frier
April 18, 2018, 8:49 PM GMT+1

Emergent Tech ▸ Artificial Intelligence

Intel's latest promise: Our first AI ASIC chips will arrive in 2019

For now you'll just have to make do with its Xeons

By Katyanna Quach 23 May 2018 at 20:32 5 SHARE ▼

Technology

Microsoft Bets on Faster Chips, AI Services, to Win Cloud Wars

Company will let customers use tools it built to speed image recognition

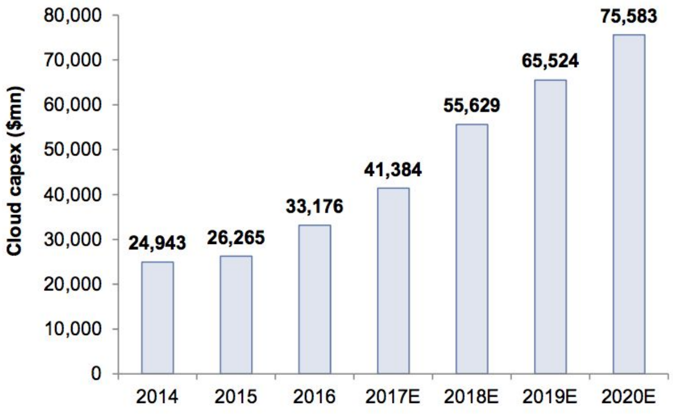
By Dina Bass
May 7, 2018, 4:30 PM GMT+1

Amazon may be developing AI chips for Alexa

Matthew Lynley @mattlynley / Feb 12, 2018

Exhibit 9: We expect cloud companies to spend $76bn on capex in 2020

Constituents include: Amazon, Facebook, Google, Microsoft, Alibaba, Tencent, Oracle, Salesforce, and others

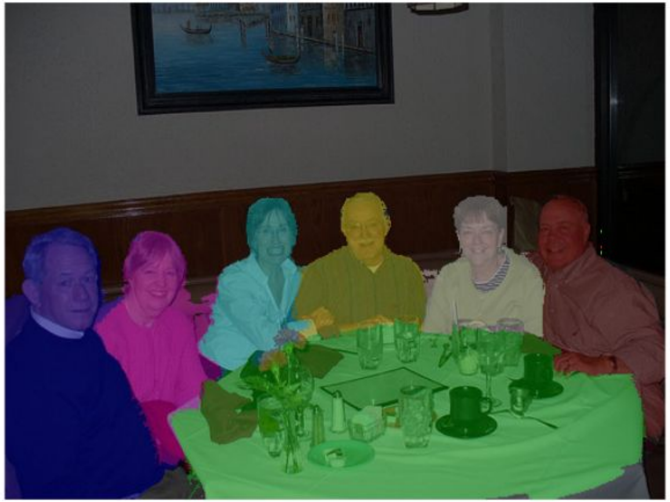


Source: Company data, Goldman Sachs Global Investment Research.

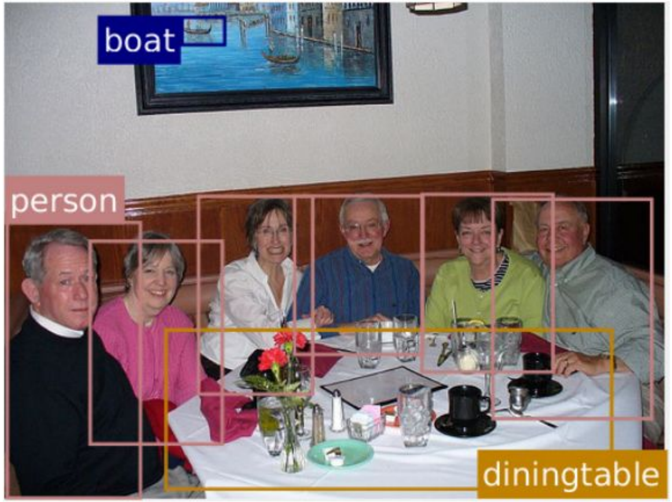
Traditional computer vision describes visual scenes by learning to detect objects (‘*nouns*’)

- **AI models associate pixels to objects (semantic segmentation) or identify what objects are shown (classification)**

Semantic image segmentation



Object classification



However, detecting objects in images is not enough to produce real scene understanding

- **AI models make obvious mistakes when asked to describe a visual scene based on their understanding of objects**

Image captioning helps expose the knowledge that computer vision systems learn by training on images labeled with the objects they contain. Such computer vision models make seemingly obvious mistakes when attempting to describe visual scenes. This suggests that having a common sense world model of objects and people is required for an AI system to truly understand what's happening in a visual scene.

"a young boy is holding a baseball bat."

"a cat is sitting on a couch with a remote control."

"a woman holding a teddy bear in front of a mirror."

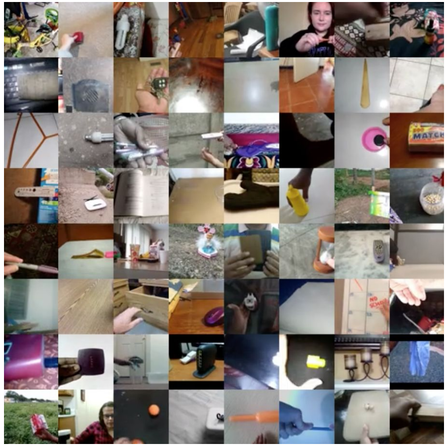
"a horse is standing in the middle of a road."

True scene understanding requires understanding actions (‘*verbs*’) and common sense

- **A promising approach to learning common sense uses deep learning and labeled videos of actions with objects**

twentybn

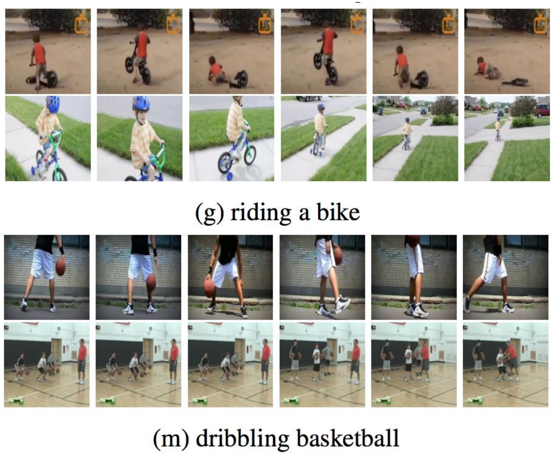
1M+ videos of real world actions



Something something dataset

DeepMind

300k videos of 400 human actions



Kinetics dataset

MIT-IBM Watson AI Lab

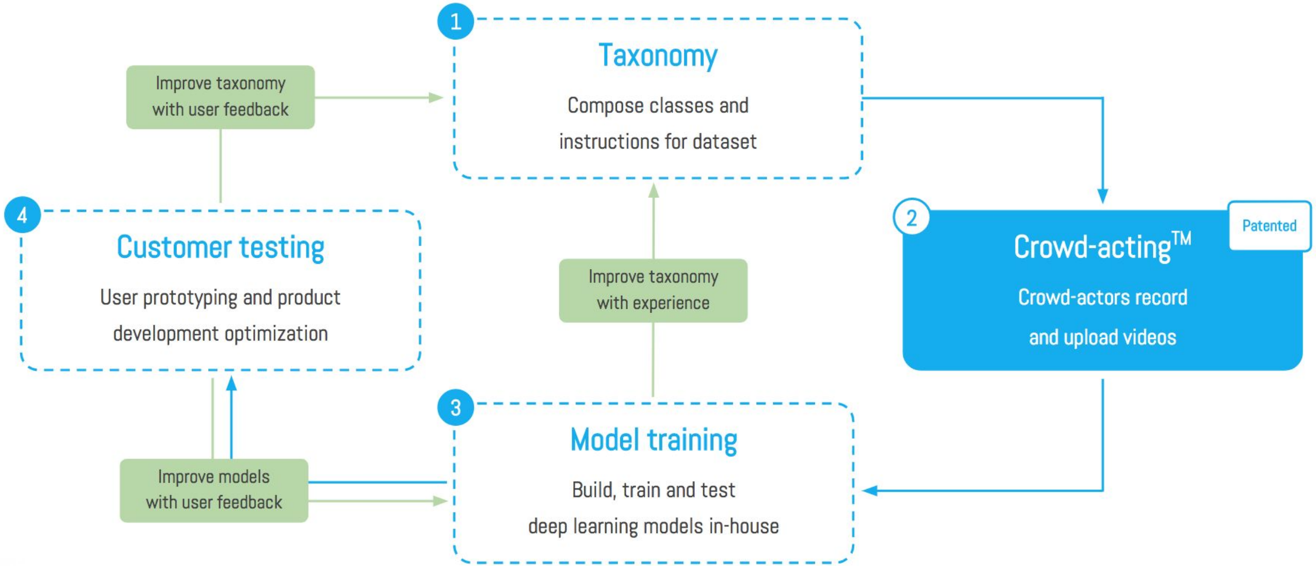
1M+ videos of YouTube actions

Moments in Time dataset

Building datasets for teaching machine learning models to understand video

- **Enlist people to create videos that describe actions of interest, e.g. pretending to drop something off something**

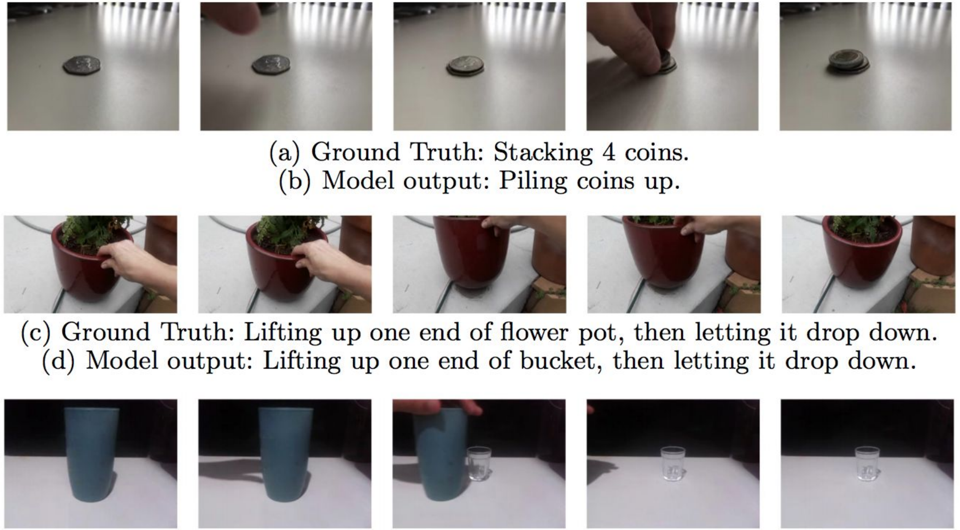
  If a deep learning model can recognise and disambiguate nuanced actions from video, it should have internalised common sense about the world. This is also called "intuitive physics".



twentybn

Deep learning models can actually understand the *verbs* as well as the *nouns* in video

- **Examples of caption predictions generated by a deep learning model trained on crowd-acted data**



(a) Ground Truth: Stacking 4 coins.
(b) Model output: Piling coins up.

(c) Ground Truth: Lifting up one end of flower pot, then letting it drop down.
(d) Model output: Lifting up one end of bucket, then letting it drop down.

(e) Ground Truth: Removing cup, revealing little cup behind.
(f) Model output: Removing mug, revealing cup behind.

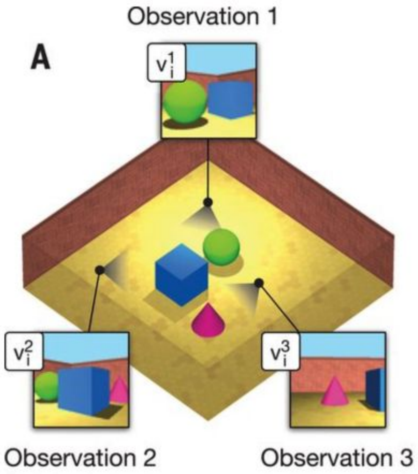
Image-trained network: "remote control"
TwentyBN-trained network: "pretending to pick black remote control up"

Machines can also understand visual scenes by learning to see from multiple viewpoints

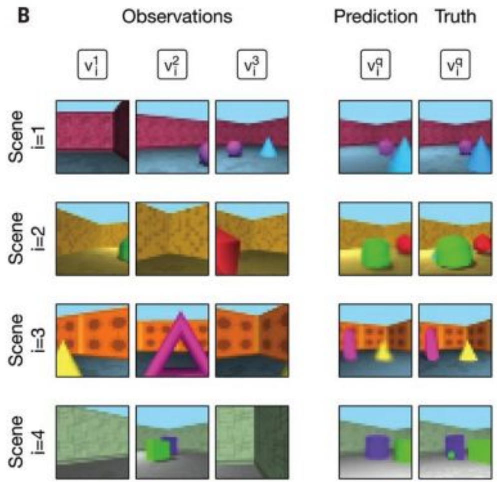
- **If an ML system correctly predicts new viewpoints of the same scene, it has internalised knowledge of that scene**

  The "Generative Query Network" (GQN) can do this without human labels or domain knowledge, suggesting that it captures the identities, positions, colors, and counts of objects in the scenes it observes.

Examples of different scene viewpoints

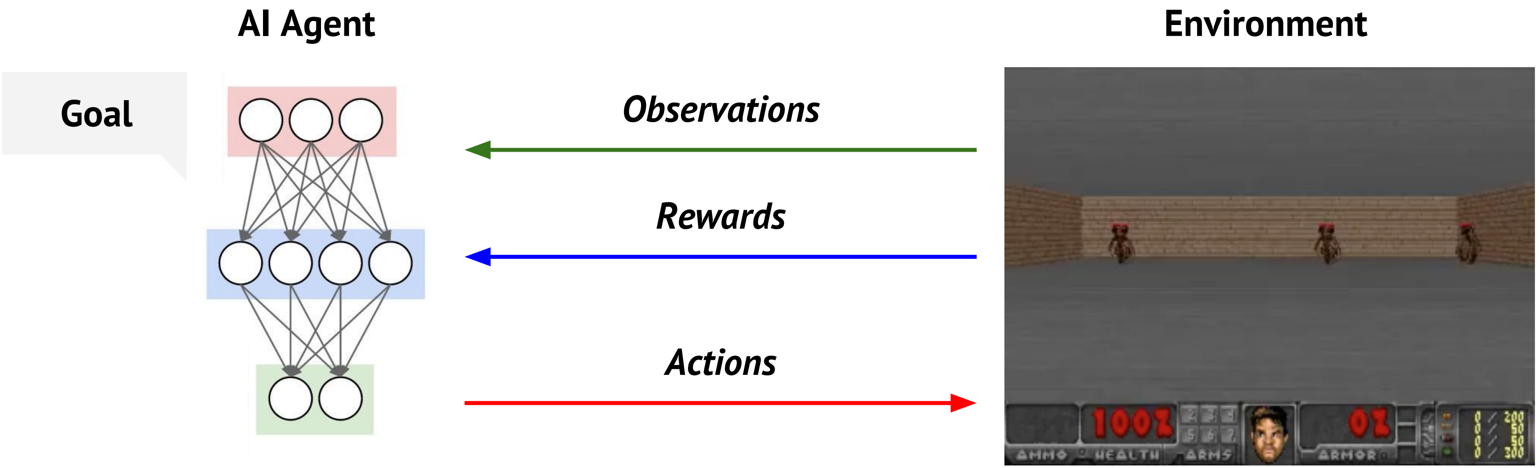


What the GQN observes and predicts vs. truth



RL systems can learn goal-oriented behavior within simulated environments, i.e. games

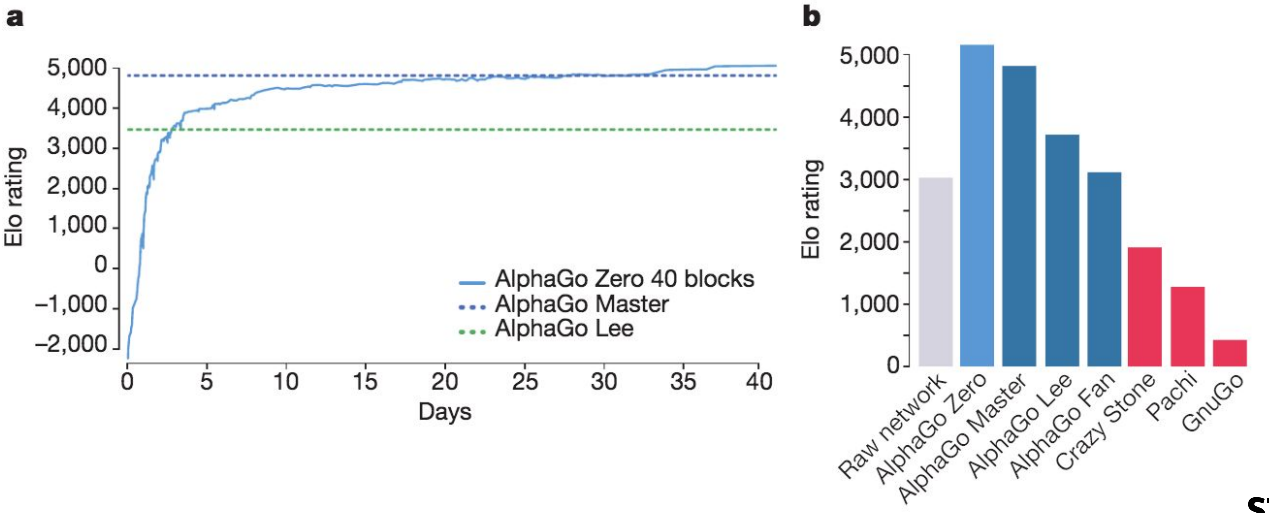
- A game is the world model used by a reinforcement learning (RL) system to learn behaviors by trial and error



AlphaZero showed that a deep RL system can learn from scratch to beat Go champions

- **AlphaZero is one neural network trained through self-play without human supervision or historical player data to predict moves and chances of winning from a particular board position**

Strikingly, the more elegant AlphaZero system surpasses all other versions of AlphaGo (which is based on two neural networks). AlphaZero achieves superhuman performance after 40 days of training.



DeepMind

OpenAI's multi-agent RL system learns to play complex real-time strategy game, Dota2

OpenAI Five is a team of 5 agents that learn through RL-based self-play to optimize their gameplay policy

The agents each have their own neural networks trained through RL to yield long-term planning behavior in a gameplay environment that is partially-observable and high-dimensional. That RL agents can collaborate in teams to beat teams of humans is notable given the space of possible actions agents can take and the large maps they can interact with.

	OPENAI 1V1 BOT	OPENAI FIVE
CPUs	60,000 CPU cores on Azure	128,000 preemptible CPU cores on GCP
GPUs	256 K80 GPUs on Azure	256 P100 GPUs on GCP
Experience collected	~300 years per day	~180 years per day (~900 years per day counting each hero separately)
Size of observation	~3.3 kB	~36.8 kB
Observations per second of gameplay	10	7.5
Batch size	8,388,608 observations	1,048,576 observations
Batches per minute	~20	~60

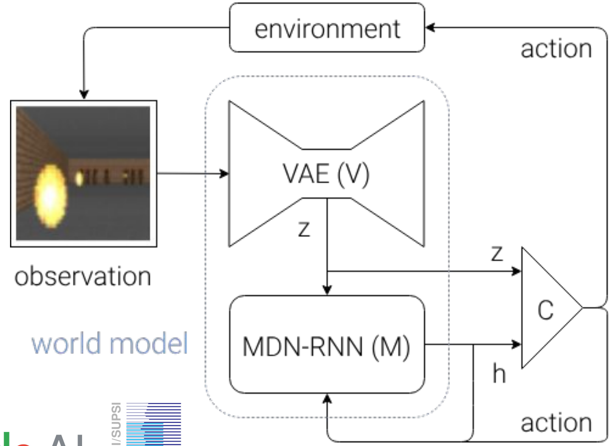
OpenAI

RL agents can also build their own world models and be trained within them

- **Here, an RL agent learns optimal behaviors within a world model it imagined for itself**

The agent observes the game environment, creates its own understanding of each frame (VAE), uses this understanding to predict the next frame (MDN-RNN) and then trains its behavior to optimize a goal (C) in the imagined environment.

Schematic for building a world model



Using this world model allows an AI agent to perform at its best

Method	Average Score over 100 Random Tracks
DQN [53]	343 ± 18
A3C (continuous) [52]	591 ± 45
A3C (discrete) [51]	652 ± 10
ceobillionaire's algorithm (unpublished) [47]	838 ± 11
V model only, z input	632 ± 251
V model only, z input with a hidden layer	788 ± 141
Full World Model, z and h	**906 ± 21**

Google AI USI/SUPSI IDSIA

Fairness in machine learning: How do we ensure our models are not biased?

- **After many years of scandals, the research community is finally working to stem bias in ML models**

SOFTWARE SCANDALS

Prominent incidents that highlight the effect of algorithmic bias

December 2009 | Hewlett-Packard investigates instances of so-called "racist camera software" which had trouble recognizing dark-skinned people

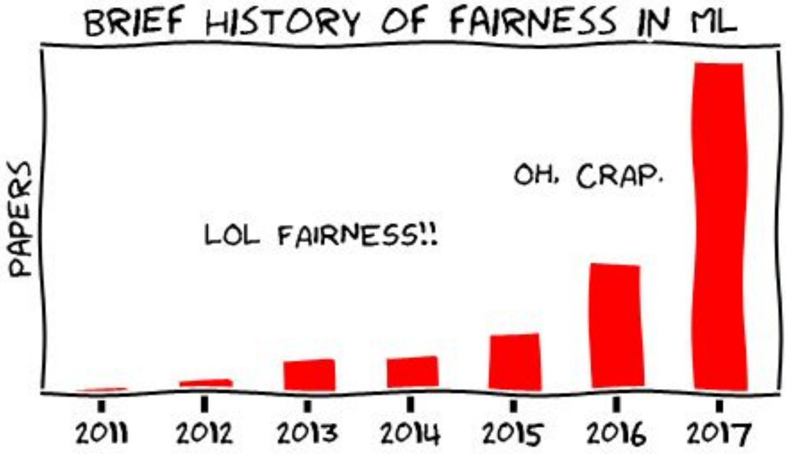
March 2015 | A Carnegie Mellon University study determines that some personalized ads from sites such as Google and Facebook are gender-biased

July 2015 | A Google algorithm mistakenly captions photos of black people as "Gorillas"

March 2016 | Microsoft shuts down AI chatbot Tay after it starts using racist language

May 2016 | ProPublica investigation finds that a computer program used to track future criminals in the US is racially biased

September 2016 | Machine-learning algorithms used to judge an international beauty contest displays bias against dark-skinned contestants



An example of biased machine learning systems: Stereotyping

- **Turkish is a gender-neutral language, yet Google Translate swaps the gender of the pronouns when translating from English to Turkish and back to English**

Another example of biased machine learning systems: Racial bias

- **When trained on datasets that do not appropriately reflect diversity of skin color, computer vision systems exhibit offensive racial bias**

Opinion

When the Robot Doesn't See Dark Skin

By Joy Buolamwini

Ms. Buolamwini is the founder of the Algorithmic Justice League.

When I was a college student using A.I.-powered facial detection software for a coding project, the robot I programmed couldn't detect my dark-skinned face. I had to borrow my white roommate's face to finish the assignment. Later, working on another project as a graduate student at the M.I.T. Media Lab, I resorted to wearing a white mask to have my presence recognized.

Facial Recognition Is Accurate, if You're a White Guy

By Steve Lohr

GOOGLE

Google Photos Mistakenly Labels Black People 'Gorillas'

BY CONOR DOUGHERTY JULY 1, 2015 7:01 PM 42

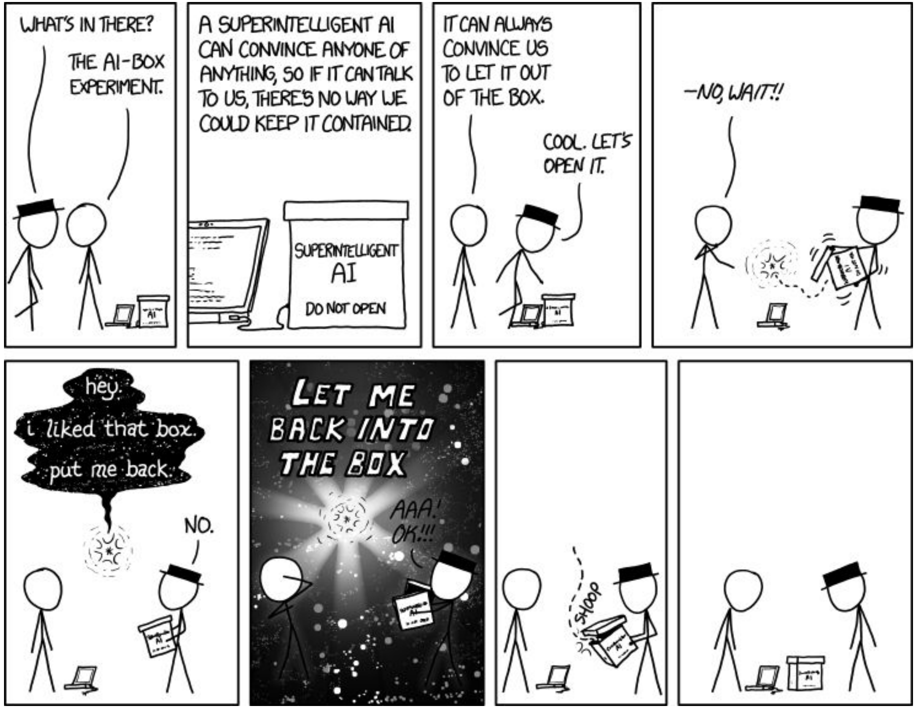
ML models have 5 types of allocation bias that stem from training data

- **Bias typically stems from training data that fails to appropriately represent diversity or encodes biased labels**

	denigration	stereotype	recognition	under-representation	ex-nomination
Image search for 'CEO' yields all white men on first page of results.			x	x	x
Google Photo mislabels black people as 'gorillas'	x				
YouTube speech-to-text does not recognize women's voices			x		x
HP Cameras' facial recognition unable to recognize Asian people's faces			x	x	x
Amazon labels LGBTQ literature as 'adult content' and removes sales rankings		x	x		x
Word embeddings contain implicit biases [Bolukbasi et al.]	x	x	x	x	x
Searches for African American-sounding names yield ads for criminal background checks [Sweeney]	x	x		x	

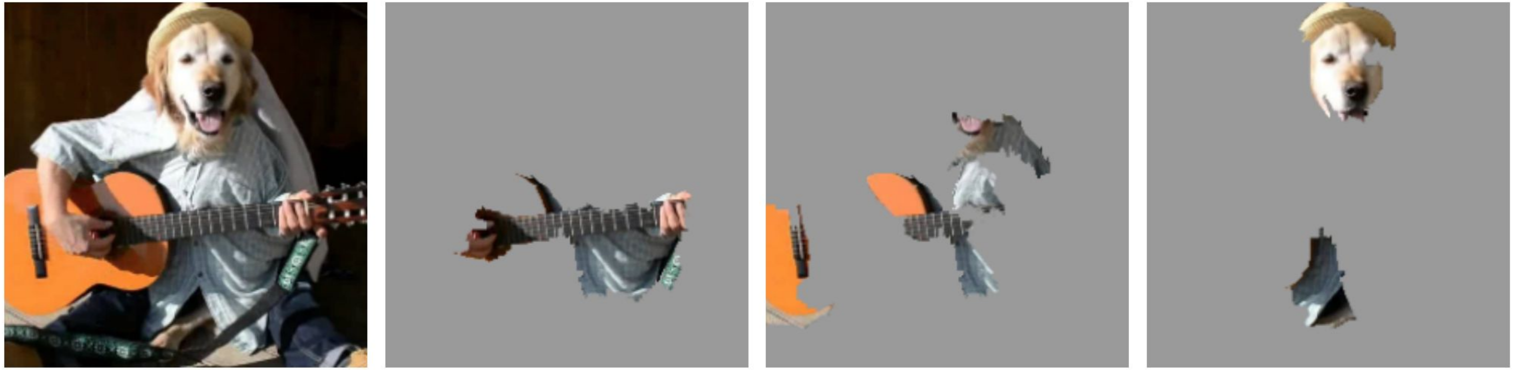
Like all software, ML models need to be debugged, but understanding them is hard

- **Many ML models, especially deep learning models, are often complex "black boxes"**



Explainability helps validate that ML models perform well for the "right" reasons

- **In computer vision, a model can show us which pixels it used to infer a specific label (e.g. which pixels = "dog")**
  This way, we understand that the model has "learned" properly vs. predicted the right label for the wrong reason.



(a) Original Image (b) Explaining *Electric guitar* (c) Explaining *Acoustic guitar* (d) Explaining *Labrador*

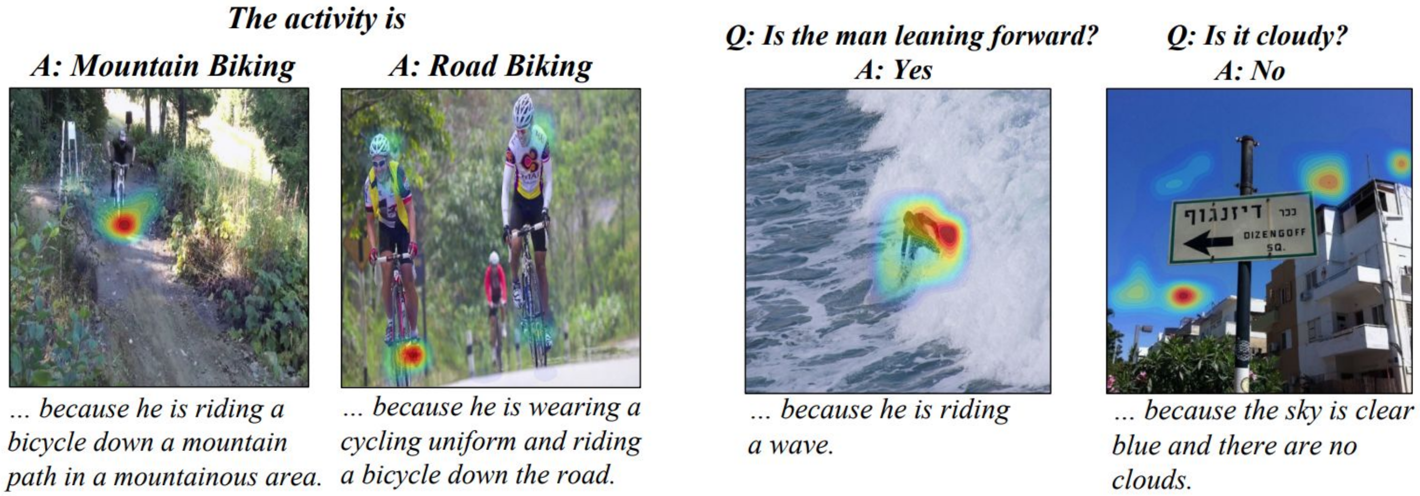
Figure 4: Explaining an image classification prediction made by Google's Inception neural network. The top 3 classes predicted are "Electric Guitar" ($p = 0.32$), "Acoustic guitar" ($p = 0.24$) and "Labrador" ($p = 0.21$)

UNIVERSITY of WASHINGTON

Next step: Justifying decisions in plain language and pointing to the evidence

- **Joint textual rationale generation and attention visualization provides deeper insight into decisions**

  For a given question and an image, the Pointing and Justification Explanation (PJ-X) model predicts the answer and multimodal explanations which both point to the visual evidence for a decision and provide textual justifications. Multimodal explanations results in better visual and textual explanations.



Facebook AI Research

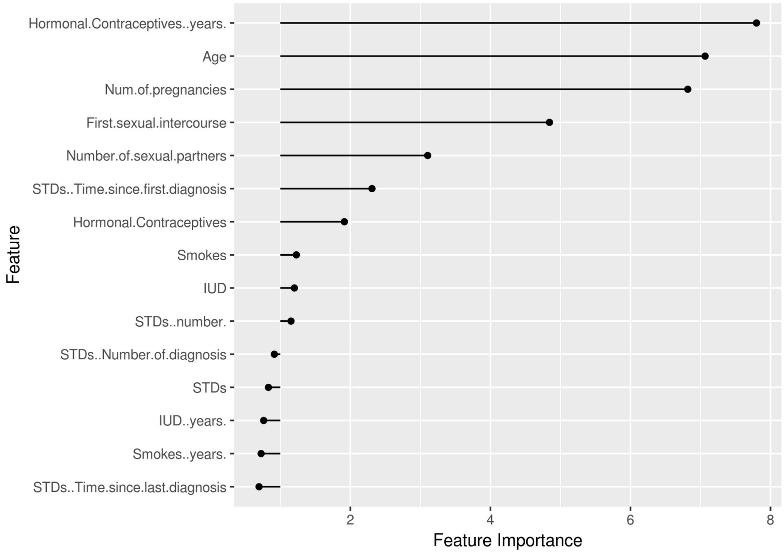
Berkeley
UNIVERSITY OF CALIFORNIA

Understanding feature importance gives us high level insight into a model's behavior

- **We can alter the value of a particular model feature to see how the overall model's prediction error changes**

  The more a feature is important, the greater the model's prediction error as a result of the feature value change.

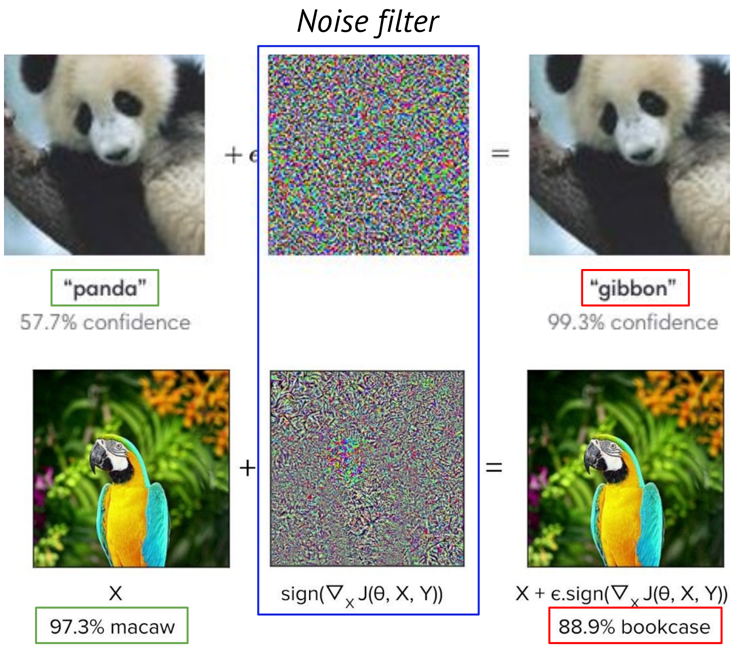
Features important for predicting cervical cancer



Imperceptible changes to data can alter a deep learning model's prediction

Adversarial examples cause computer vision models to make glaring mistakes!

An unnoticeable universal noise filter applied to an image of a panda makes the model think it sees a gibbon.

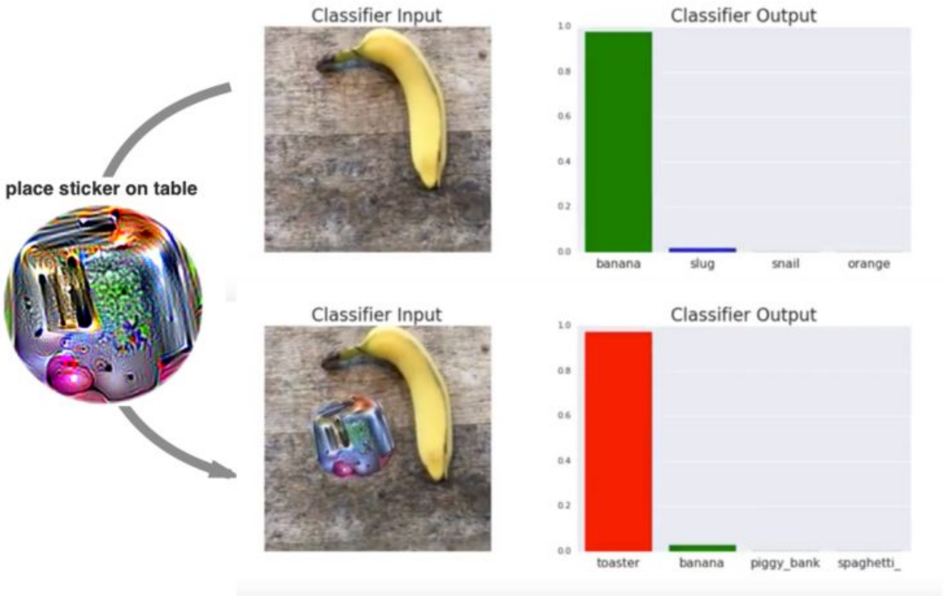


Google AI

Imperceptible changes to data can alter a deep learning model's prediction

A method for creating universal, robust, targeted adversarial image patches in the real world

The "toaster" patch maximally excites the computer vision model so that it always sees a toaster even when there is no "real" toaster in view.



Adversarial attacks present serious safety challenges in the real world

- **A vision system that previously detected pedestrians at a zebra crossing is no longer able to "see" them.** This poses obvious security concerns when autonomous vehicles make it onto public roads.

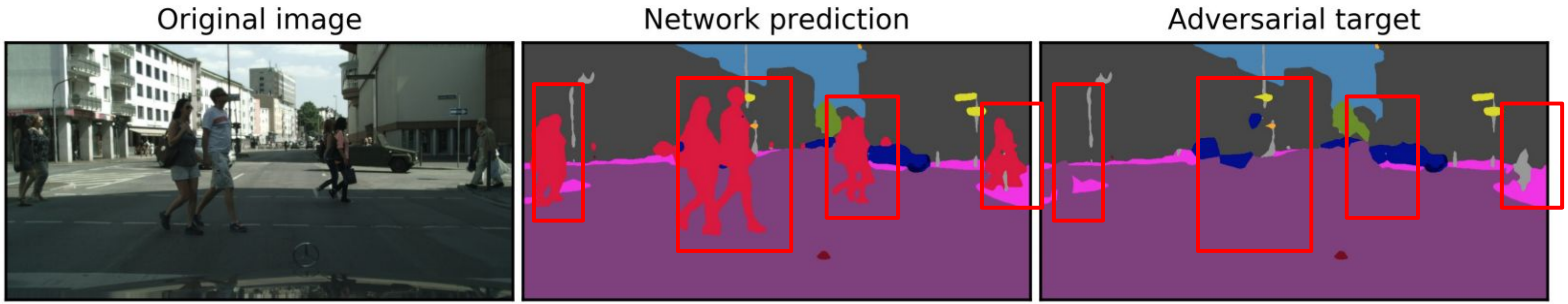


Figure 2. Illustration of an adversary generating a dynamic target segmentation for hiding pedestrians.

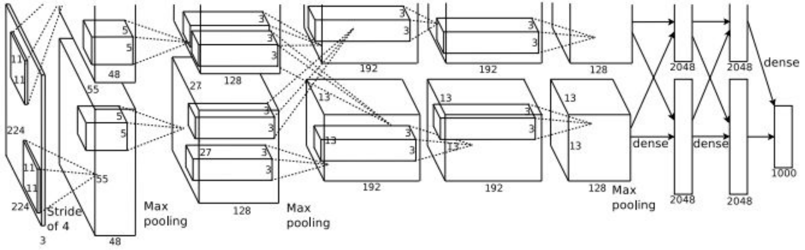
UNI FREIBURG BOSCH

Improving deep learning model architecture requires iterative experimentation

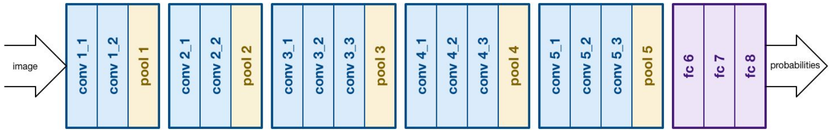
>5 years of research into convolutional neural network architectures for computer vision applications

Involving many researchers, institutions and proposed structural and computational innovations.

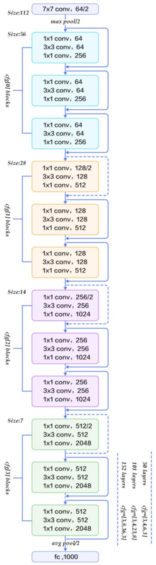
AlexNet architecture (2013)



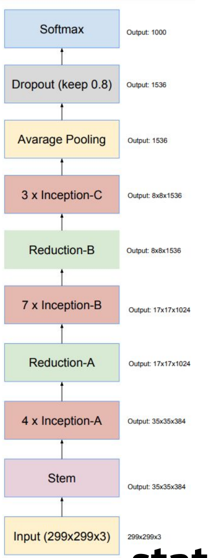
VGGNet architecture (2014)



ResNet (2015)

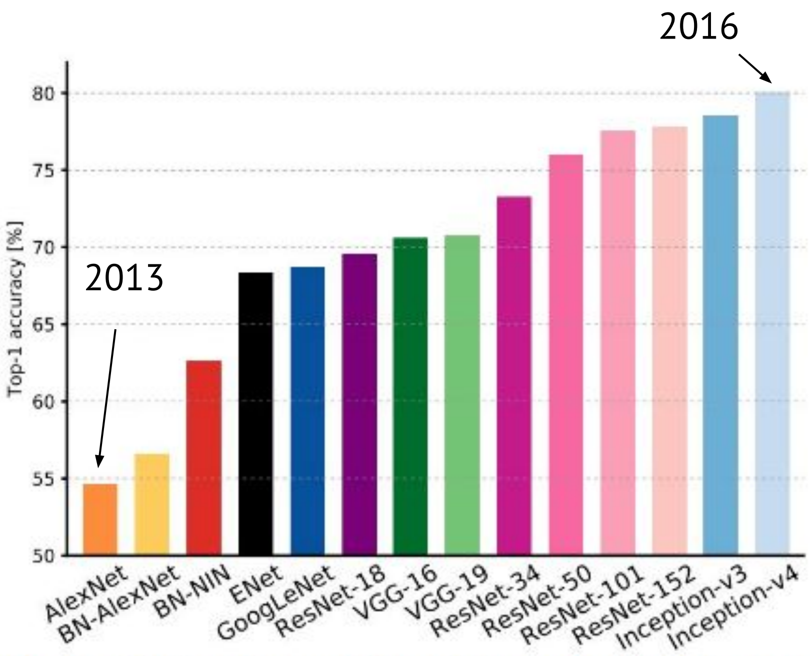


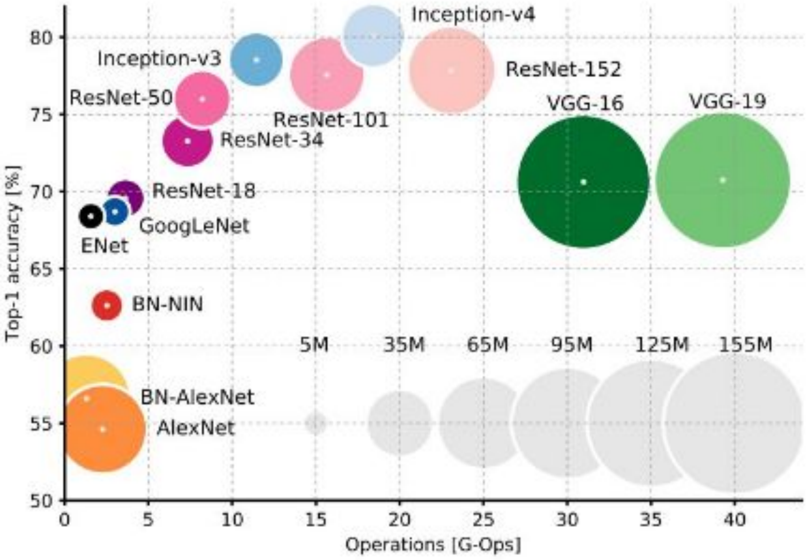
Inception v4 (2016)



Improving deep learning model architecture requires iterative experimentation

- **Leading to significant reductions in Top-1% accuracy on Large Scale Visual Recognition Challenge (ILSVRC)**

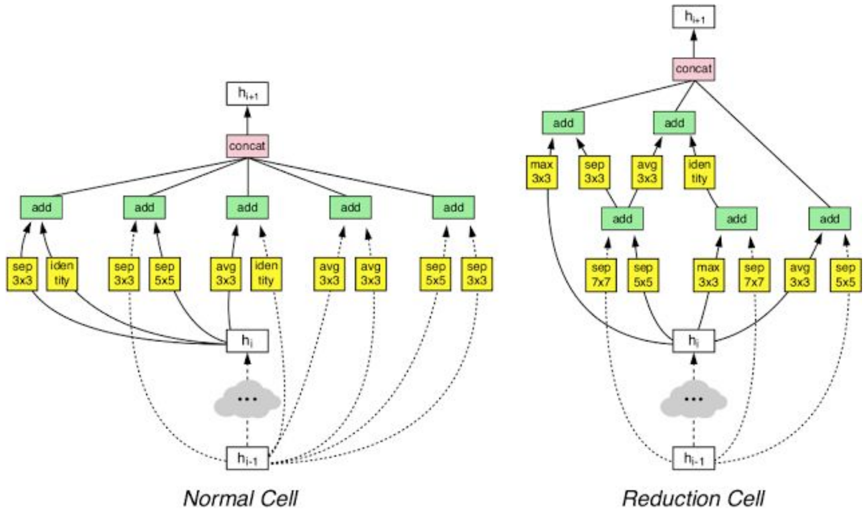


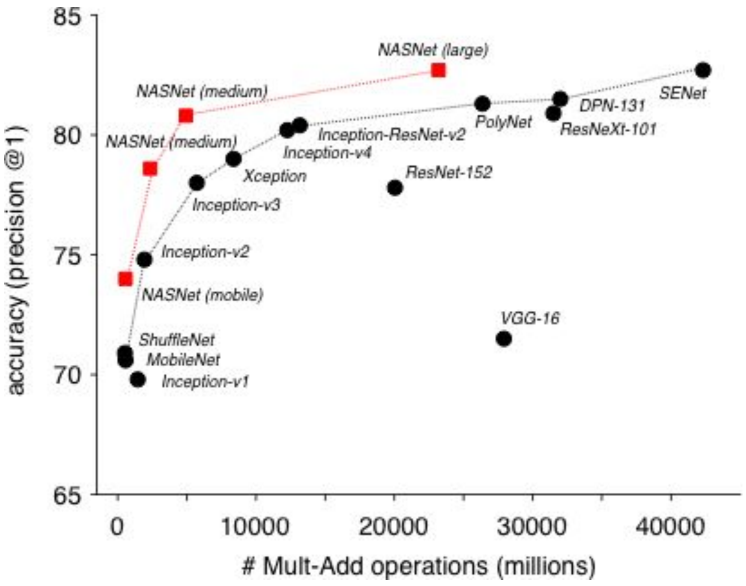


AI to automate away AI engineers

- **Google's AutoML automatically discovers the best model architecture for a computer vision task**

AutoML traversed the architecture search space to find two new cell designs (Normal and Reduction, left figueres) that could be integrated into a final model (NASNet, right graph) that outperformed all existing human-crafted models.



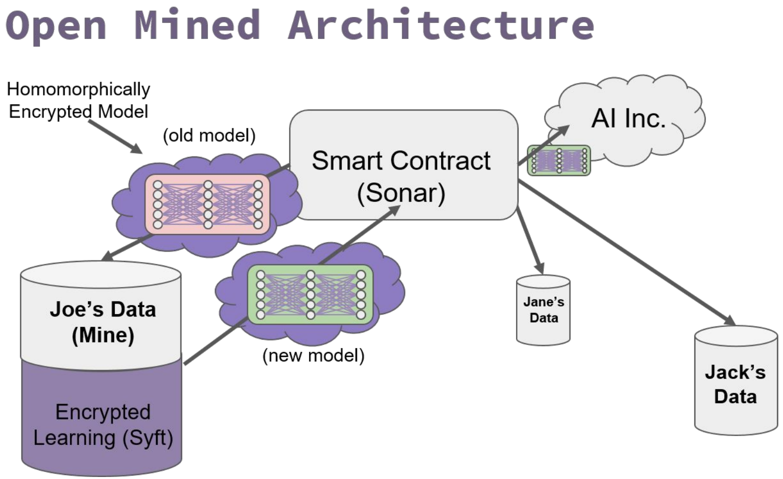


Google AI

Distributed "federated" learning to decentralise data acquisition and model training

- **OpenMined: Train a model on lots of individual user devices such that their data never leaves their devices**

Large technology companies centralise immense amounts of user data. The community is now starting to push back by creating tools to decentralise data ownership. In OpenMined, an AI model itself is encrypted by it's owner such that the user cannot steal it. User data stays locally on a user's device and is accessed to update the model's parameters. These parameter changes from multiple users are aggregated back to the model owner for updating.

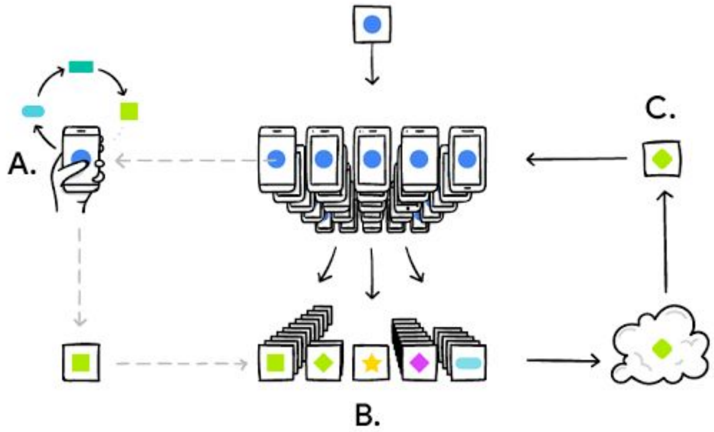


OpenMined

Federated learning to decentralise data acquisition and model training

- **Google uses federated learning to train its mobile keyboard prediction models, Gboard**

Your keyboard model is personalised locally based on your usage.

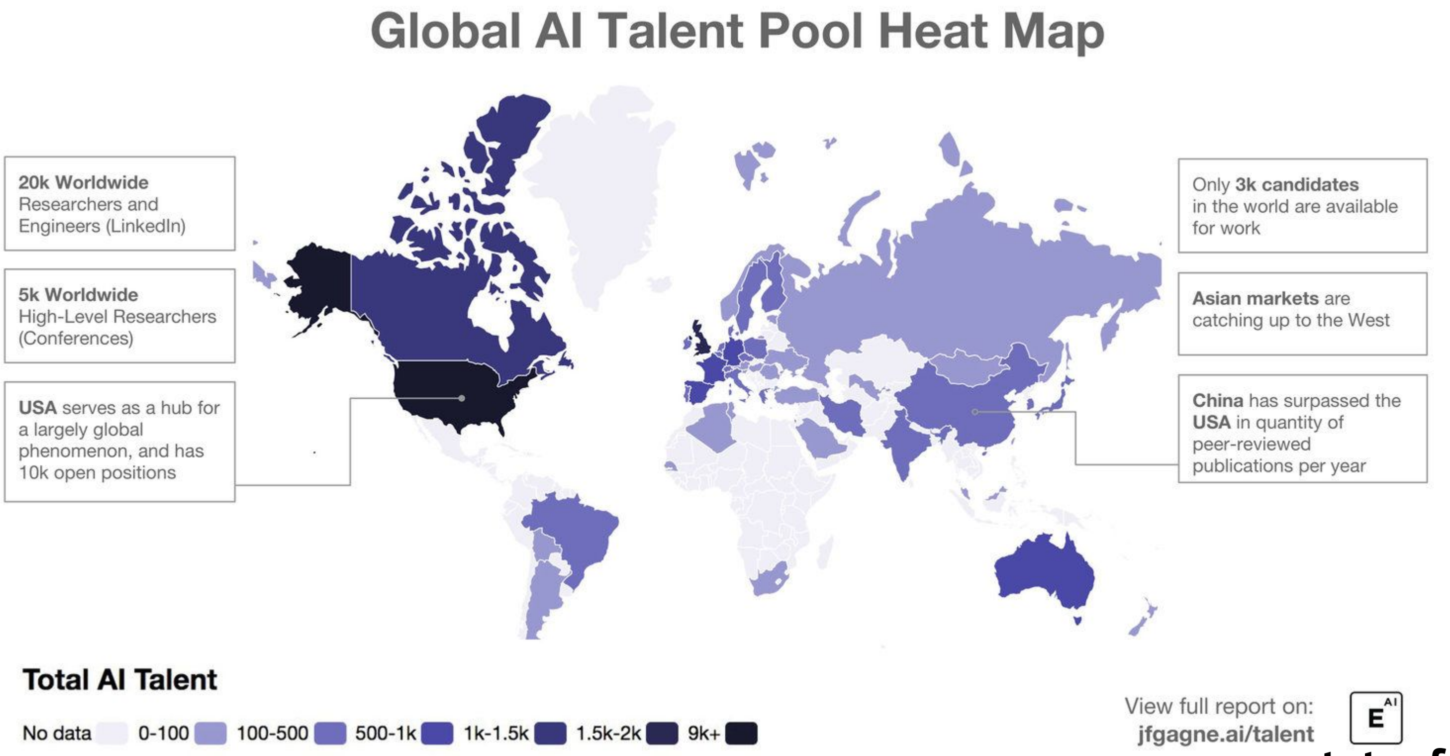


Consensus change is agreed and shared to the core model.

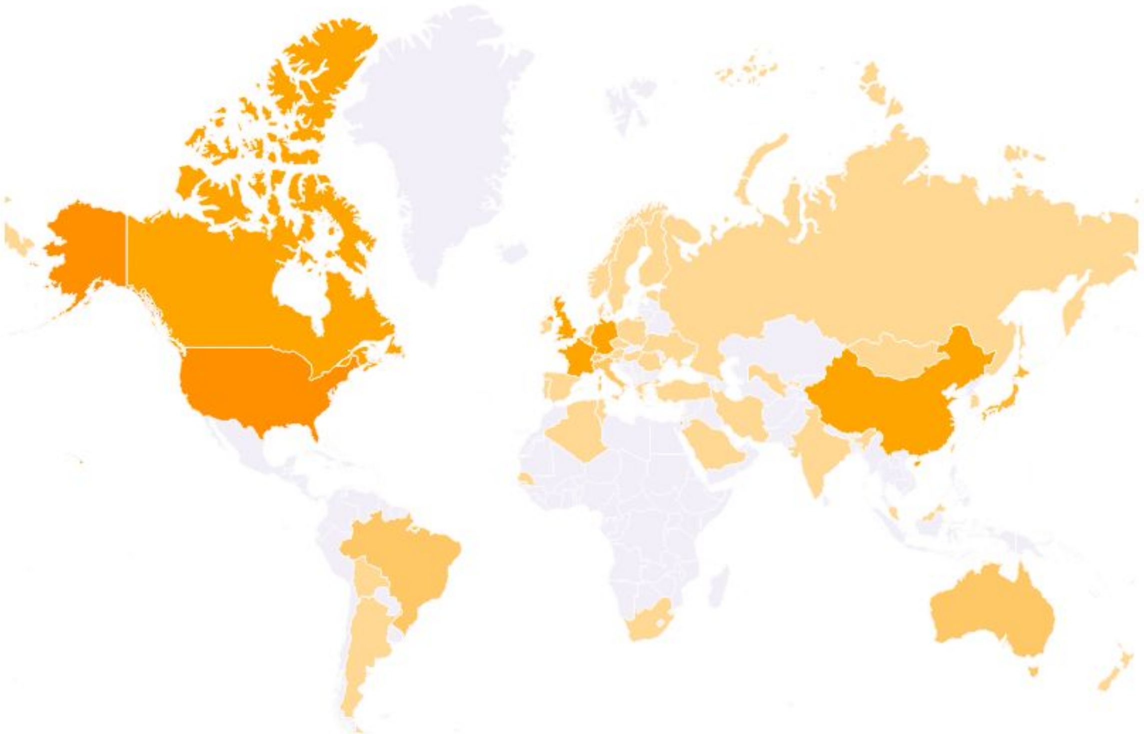
Many users' updates are aggregated together

Section 2: Talent

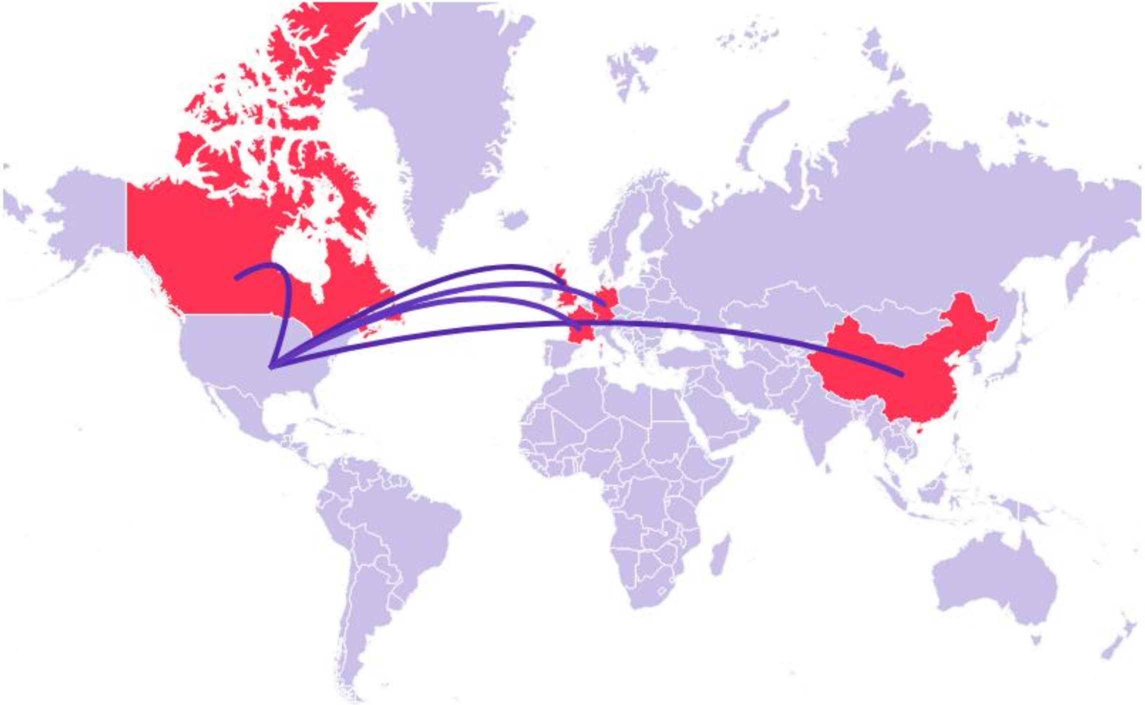
Supply: Element AI estimates 22,000 PhD educated AI researchers and engineers



Supply: Element AI estimates 5,000 high-level researchers worldwide

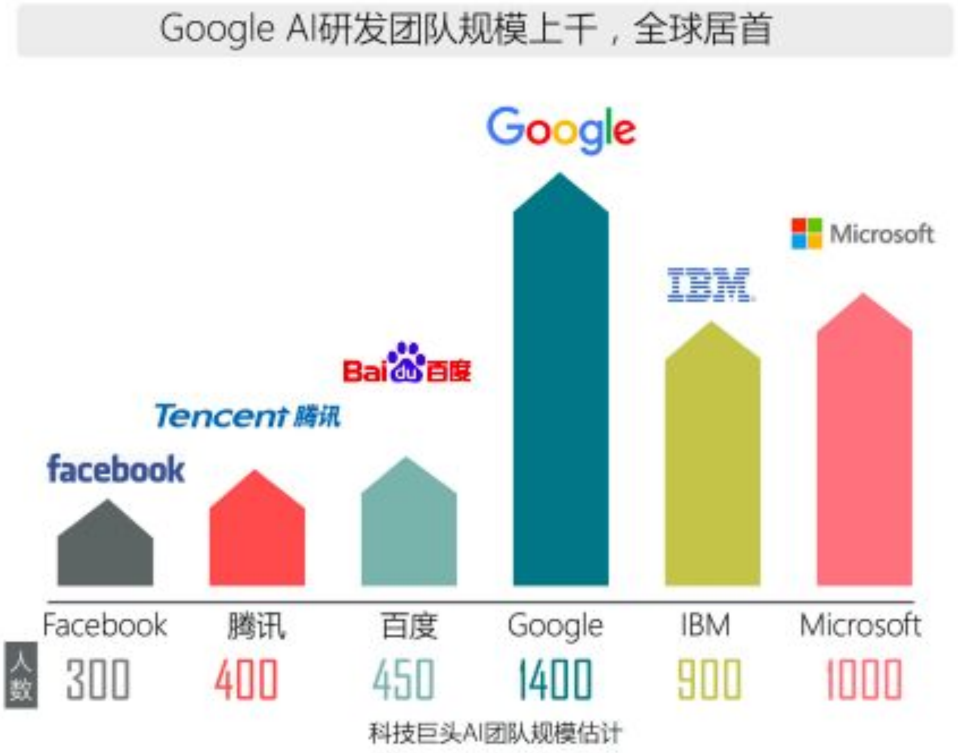


Talent concentration: America remains the hub for talent exchange



Largest inbound and outbound talent exchanges with the US

Talent concentration: Google is widely acknowledged as the leading employer of AI talent



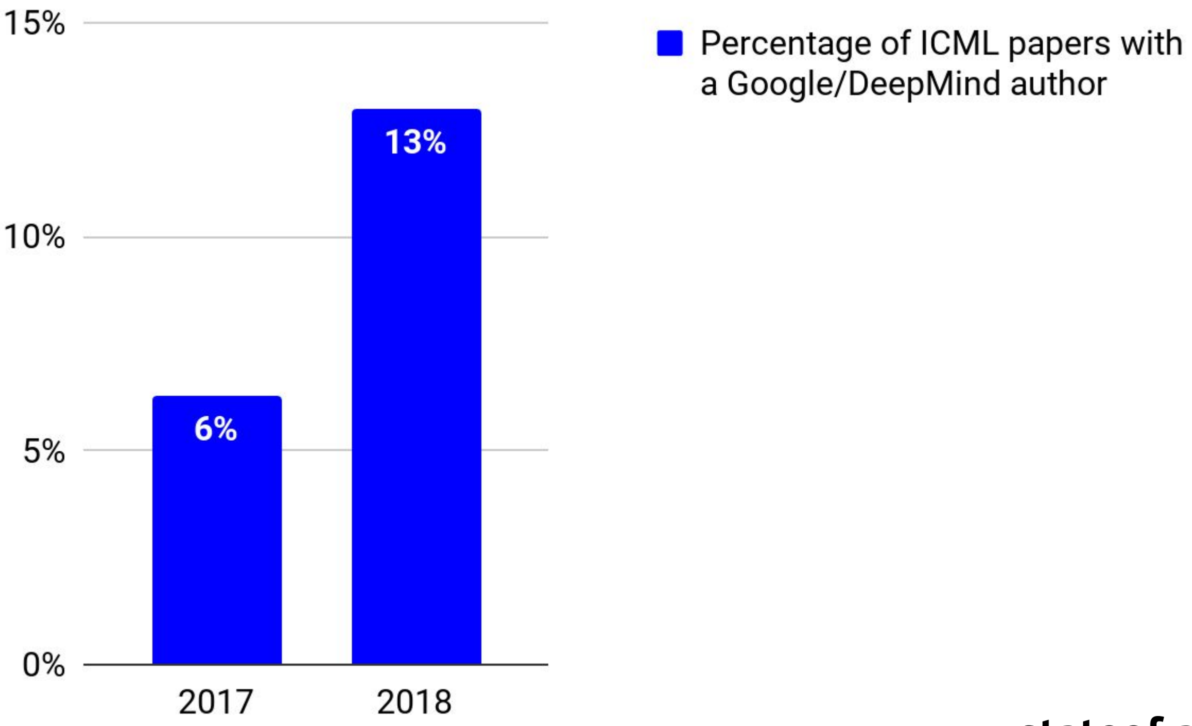
Tencent 腾讯

Talent concentration: 6.3% of 2017 ICML papers had a Google/DeepMind author

```
#mentions institution
---------------------
       44 Google
       33 Microsoft
       32 CMU
       25 DeepMind
       23 MIT
       22 Berkeley
       22 Stanford
       16 Cambridge
       16 Princeton
       15 None
       14 Georgia Tech
       13 Oxford
       11 UT Austin
       10 Duke
       10 Facebook
```

Source: @karpathy

Talent concentration: Percentage of ICML papers with Google/DeepMind author doubles



Source: @karpathy, @dhruvguliani

Talent concentration: Google lead in contribution to 2017 NIPS papers

Total papers:

1. google: 60 (8.8%)
2. carnegie mellon university: 48 (7.1%)
3. massachusetts institute of technology: 43 (6.3%)
4. microsoft: 40 (5.9%)
5. stanford university: 39 (5.7%)
6. university of california, berkeley: 35 (5.2%)
7. deepmind: 31 (4.6%)
8. university of oxford: 22 (3.2%)
9. university of illinois at urbana-champaign: 20 (2.9%)
10. georgia institute of technology: 18 (2.7%)

Source: @robbieallen

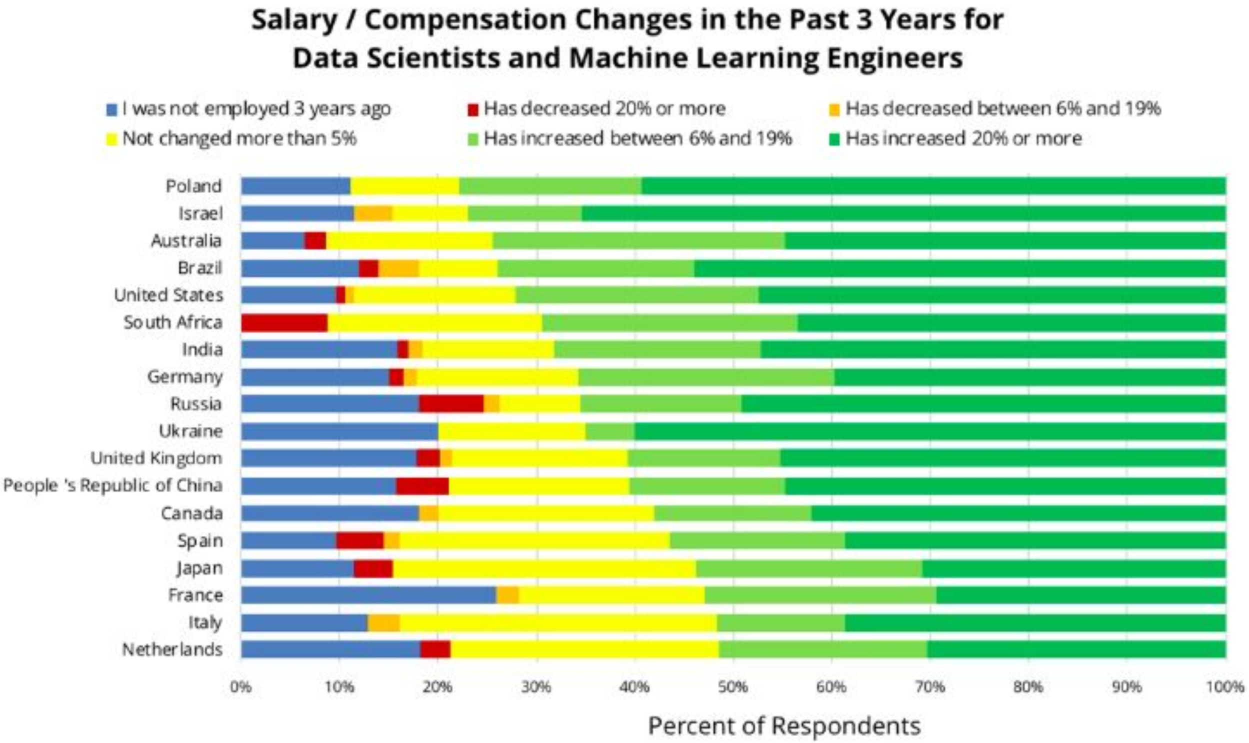
Talent Concentration: Google & DeepMind dominate NIPS authorship

```
Total institution authors:

1. carnegie mellon university: 89
2. google: 78
3. massachusetts institute of technology: 69
4. deepmind: 68
5. stanford university: 66
6. university of california, berkeley: 60
7. microsoft: 59
8. eth zurich: 31
9. university of oxford: 29
10. duke university: 28
11. princeton: 28
```

Source: @robbieallen

Demand: Salaries for machine learning engineers continue to climb



N = 1549. All values are in US Dollars. Conversion rates from 2017 (when the data were collected) were used for conversion. Data are from The Kaggle 2017 The State of Data Science and Machine Learning study. You can learn more about the study and download the data here: http://kaggle.com/surveys/2017. Only job titles with ample sample size (n > 20) are presented.

Demand: Anecdotally salaries continue to grow

The New York Times

*"Typical A.I. specialists, including both Ph.D.s fresh out of school and people with less education and just a few years of experience, can be paid from **$300,000 to $500,000 a year** or more in salary and company stock"*

*"[At] DeepMind...the lab's "staff costs" as it expanded to 400 employees totaled $138 million. That comes out to **$345,000 an employee.**"*

*"OpenAI paid its top researcher, Ilya Sutskever, more than **$1.9 million** in 2016. It paid another leading researcher, Ian Goodfellow, more than **$800,000"**. 'I turned down offers for multiple times the dollar amount I accepted at OpenAI,'Mr. Sutskever said. 'Others did the same.'"*

REUTERS

*"Thomas Liang, a former executive at Chinese search giant Baidu estimates salaries in the industry have **roughly doubled since 2014**"*

nature

*"Nick Zhang, president of the Wuzhen Institute...knows of experienced people getting salary offers of **$1 million or more** to work at the AI research centres of Chinese social-media giant Tencent or the web-services firm Baidu. '**This was unimaginable five years ago,**'"*

Demand: Compensation can be astronomical and relationships litigious

Google paid its self-driving car boss $120 million — and then he left for Uber

Anita Balakrishnan | @MsABalakrishnan
Published 4:25 PM ET Mon, 3 April 2017 | Updated 11:45 AM ET Tue, 4 April 2017

AARIAN MARSHALL TRANSPORTATION 02.09.18 12:17 PM

UBER AND WAYMO ABRUPTLY SETTLE FOR $245 MILLION

Diversity in machine learning

Diversity metrics for the industry are rarely publicised

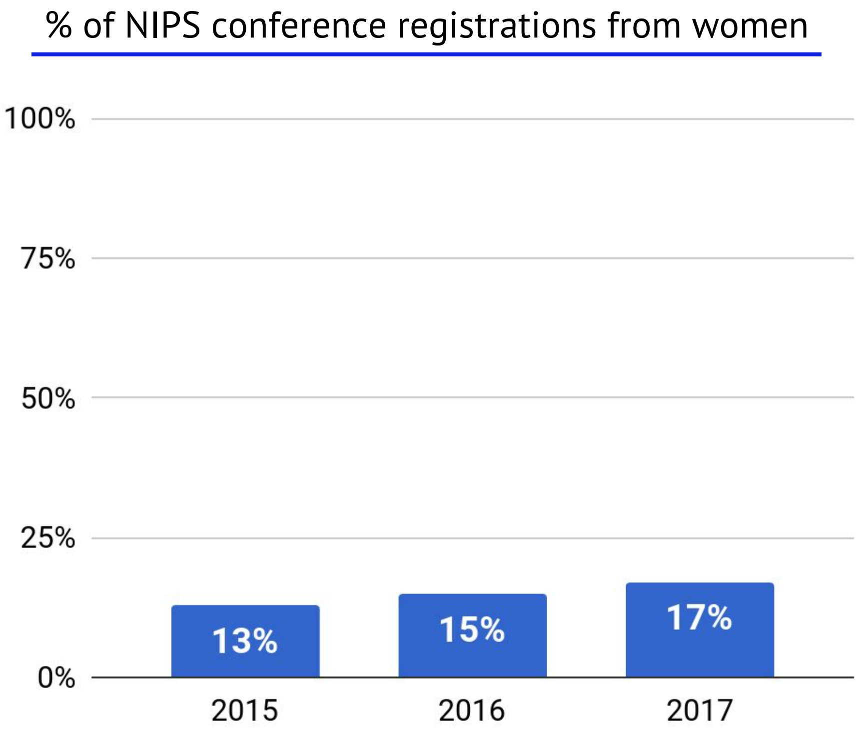
- ➔ Key research labs are not yet making their workforce diversity statistics public.
- ➔ There are limited diversity stats for major machine learning conferences publicly available.
- ➔ For the largest machine learning conference by attendance, NIPS (Neural Information Processing Systems), there is data available on a single dimension of diversity (gender) for the past few years*.
- ➔ For NIPS, the percentage of female attendees was 17% in 2017. This is lower than the technology industry more generally (for example, 31% of Google employees are women and 20% of people in a technical role at Google are women).
- ➔ The percentage of women attending NIPS has risen slightly over the past few years from 13% in 2015 to 17% in 2017.
- ➔ There are various initiatives aiming to increase diversity in machine learning:

WiML Women in Machine Learning

Black in AI

*please let us know if you have similar statistics on other measures of diversity, such as race, that we can add to the report

Diversity in machine learning: percentage of women attending the NIPS conference

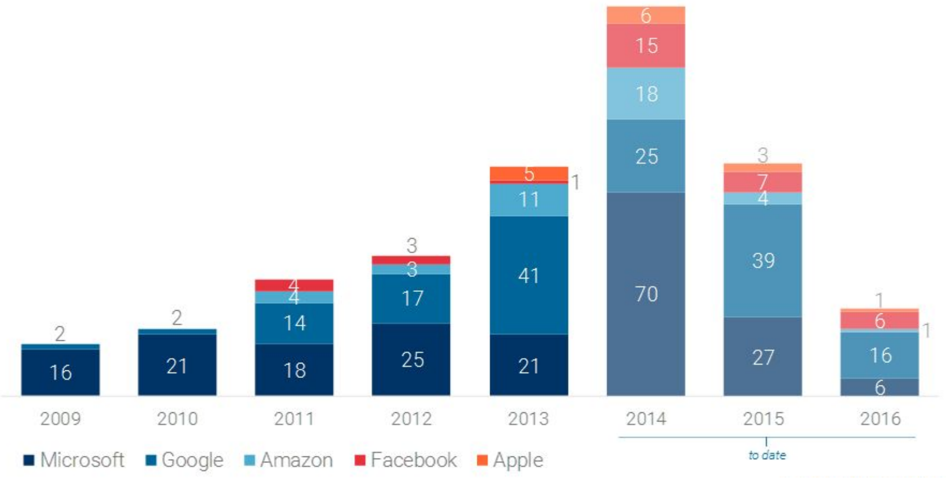


Section 3: Industry

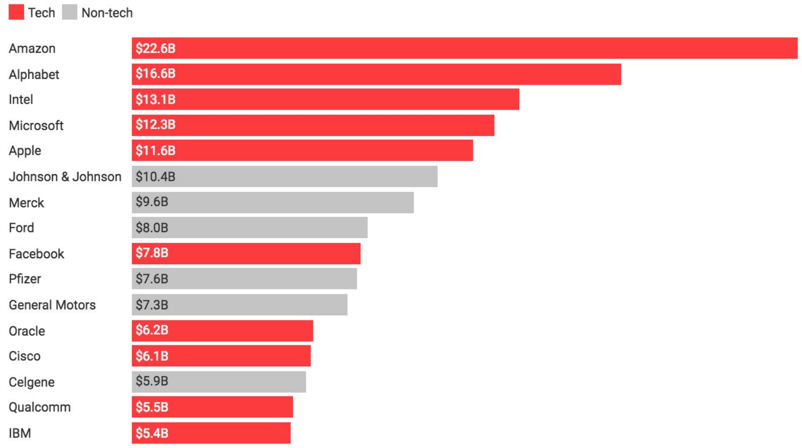
AI takes the world stage: GAFAMBAT* are in the ring together

- **AI intellectual property is concentrated amongst few global players who also spend billions on R&D per year**

AI related patent application activity by filling date



Top US companies for R&D spending in FY2017



*Google, Apple, Facebook, Amazon, Microsoft, Baidu, Alibaba, Tencent

Big cloud providers are building and exposing the building blocks of intelligence via API

Google is investing heavily to expose ML services through their cloud ecosystem

- Fast, Dynamic Translation
- Powerful Image Analysis
- Powerful Text Analysis
- Powerful Video Analysis
- Hardware Optimized for Machine Learning
- Powerful Speech Recognition
- High-Fidelity Speech Synthesis

Amazon is doing the same...

Language Services

Amazon Comprehend
Discover insights and relationships in text
Learn more »

Amazon Translate
Fluent translation of text
Learn more »

Amazon Transcribe
Automatic speech recognition
Learn more »

Amazon Polly
Natural sounding text to speech
Learn more »

Vision Services

Amazon Rekognition Image
Deep learning-based image analysis
Learn more »

Amazon Rekognition Video
Deep learning-based video analysis
Learn more »

Conversational chatbots

Amazon Lex
Build chatbots to engage customers
Learn more »

And so is Microsoft...

Machine learning services
Bring AI to everyone with an end-to-end, scalable, trusted platform with experimentation and model management

Azure Batch AI
Easily experiment and train your deep learning and AI models in parallel at scale

Computer Vision
Distill actionable information from images

Translator Speech
Easily conduct real-time speech translation with a simple REST API call

Bing Speech
Convert speech to text and back again to understand user intent

Custom Decision
A cloud-based, contextual decision-making API that sharpens with experience

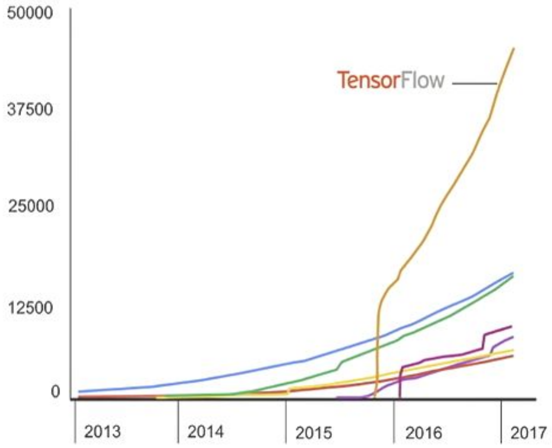
Face
Detect, identify, analyse, organise and tag faces in photos

Bing Video Search
Search for videos and get comprehensive results

Google's TensorFlow is winning the ML framework war, but the grounds are shifting fast

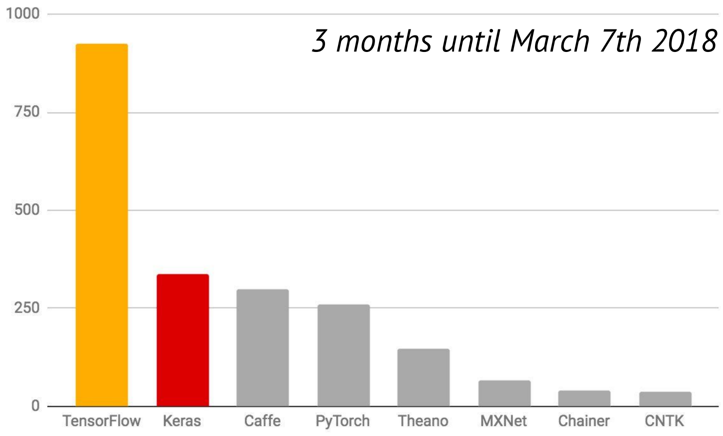
This means Google acquires significant developer mindshare, creates an onramp onto their Cloud services, trains a generation of developers and researchers with their technology who contribute to improving it. Their open source strategy also disarms potential competitors. However, practitioners feel intense uncertainty on how things will play out in the field. The wrong framework choice could have significant ramifications, not least refactoring costs.

TensorFlow is extremely popular amongst developers



Framework	GitHub Star Count
TensorFlow	44508
scikit-learn	16191
Caffe	15690
CNTK	9383
MXNet	7896
Torch	6285
Theano	5568

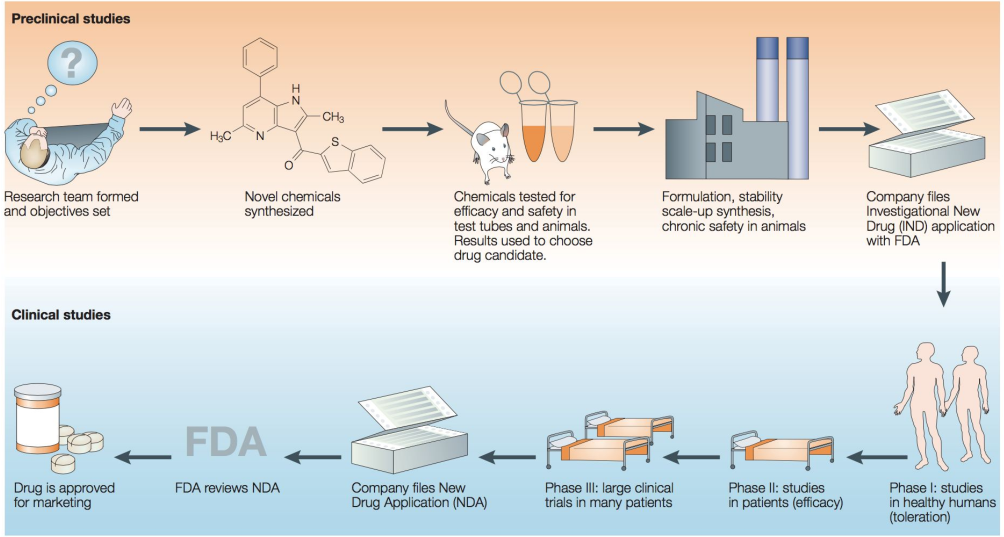
Framework mentions in research publications



Pharmaceutical industry

Why now? Today's drug development process is too slow and expensive

Research + Development cost	Change vs 1980s?	Time from lab to approval	Success rate
$2.6 billion per drug	10 times more!	10 years	<10%



Pharmaceutical industry

Where and how is machine learning being used effectively?

- **Develop new drugs:** Teach a ML model to learn the rules of drug design, e.g. the structure of therapeutic molecules and/or the stepwise process of efficiently synthesising these molecules. Then, use these models to improve existing drugs, generate entirely novel compounds or new combinations of drugs.

  Selected examples: Atomwise, LabGenius, Insilico Medicine, Exscientia, GTN LTD, insitro

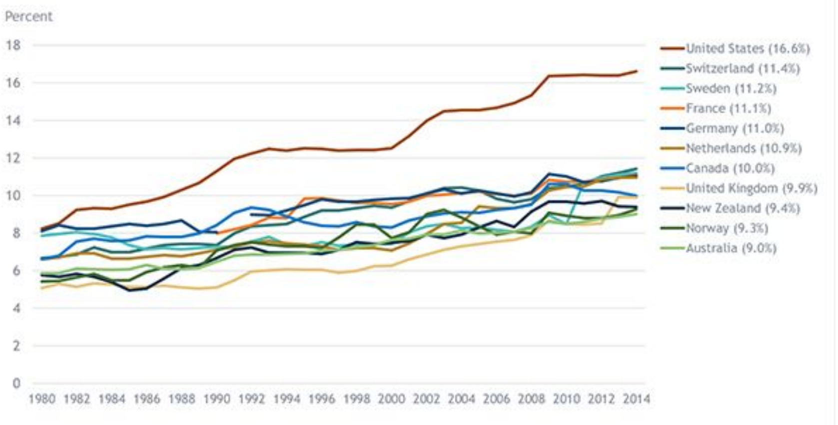
- **Repurpose existing drugs:** Discover how existing drugs can be repurposed for new conditions. This is achieved by learning complex relationships between drugs, pathways, conditions and side effects, while also conducting large-scale testing and data analysis using AI-driven software vs. manual data analysis.

  Selected examples: Recursion Pharmaceuticals, Qrativ, BenevolentAI

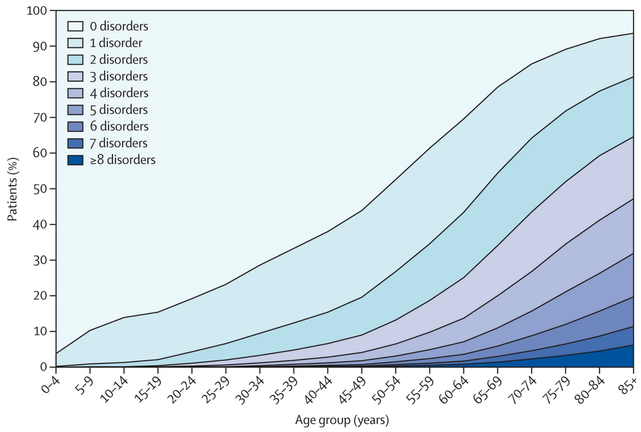
Healthcare

Why now? Healthcare systems worldwide are costly and overburdened

Healthcare spending as % of GDP growing since 80s



The older we get, the more health issues we have

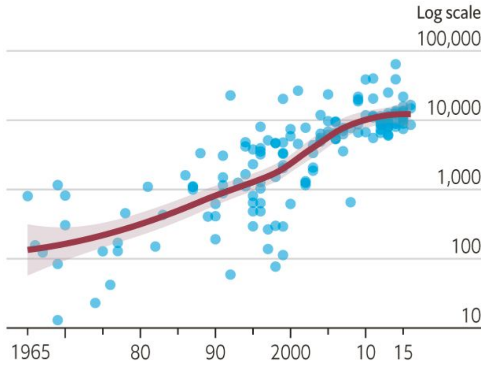


Healthcare

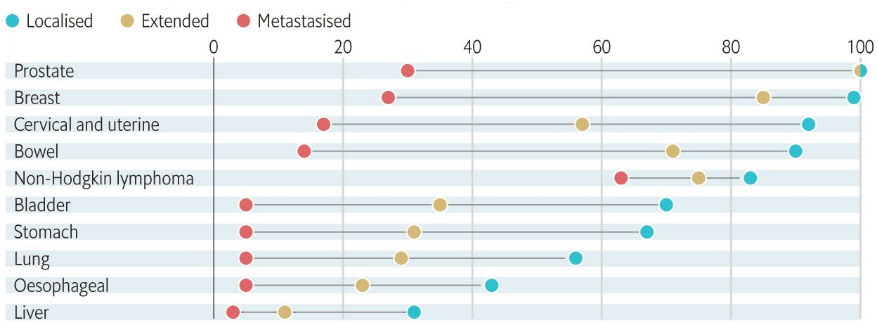
Breast cancer as a case study: Not enough doctors, diagnosing is hard and care is expensive

Misclassification rate	Radiologists in the USA	Women undergoing mammography in the USA
Up to 30% of cases	34,000 professionals	30 million patients per year

Cancer treatment cost, median $/month



Early detection of leads to higher 5-year survival rates



Healthcare

Where and how is machine learning being used effectively?

- **Medical imaging:** Train computer vision models on large numbers of labeled medical images (e.g. X-ray, ultrasound) with matched and clinically-validated patient diagnoses. Use this system to help doctors process more patient cases and make fewer diagnostic mistakes.

X-Ray (radiology)

KHEIRON MEDICAL TECHNOLOGIES
zebra MEDICAL.VISION
ARTERYS

Ultrasound

BAYLABS

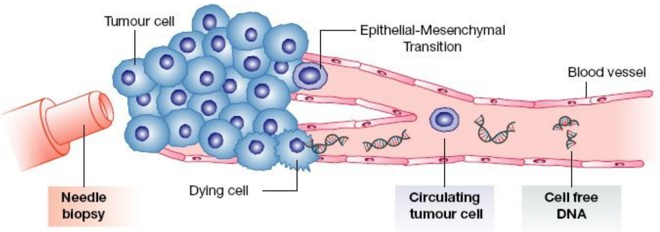
CT scan

viz.ai
maxQ Artificial Intelligence

EKG (heart)

Cardiologs

- **Liquid biopsy:** Isolate and analyse material such as cells or bacteria circulating in a patient's bloodstream. This approach allows for early non-invasive disease diagnosis as well as tracking response to therapy.



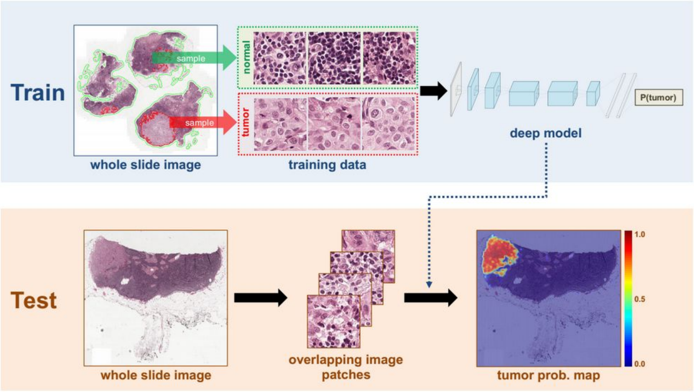
Cancer diagnostics

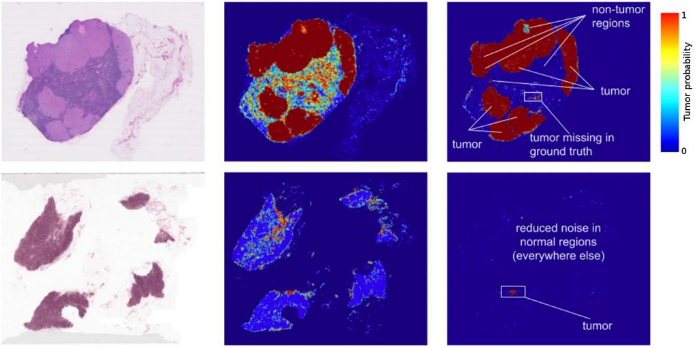
freenome
GRAIL
GUARDANT HEALTH

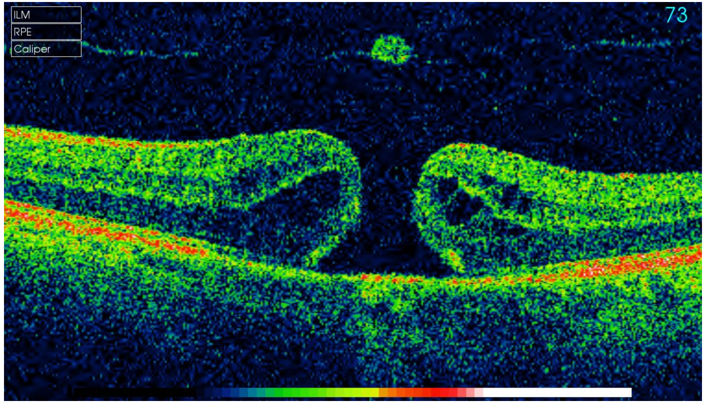
Infectious disease

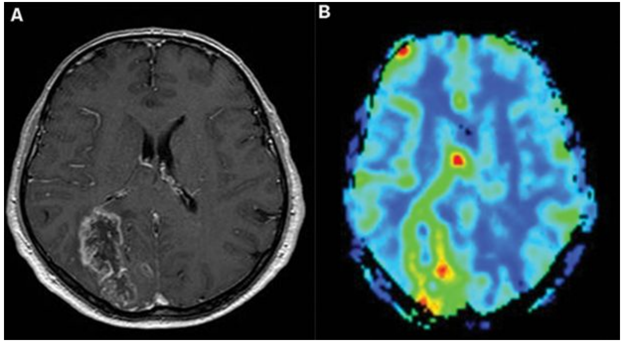
KARIUS

Healthcare


Train
sample
sample
normal
tumor
whole slide image
training data
P(tumor)
deep model
Test
whole slide image
overlapping image patches
tumor prob. map
1.0
0.5
0.0


non-tumor regions
tumor
tumor
tumor missing in ground truth
reduced noise in normal regions (everywhere else)
tumor
Tumor probability
1
0

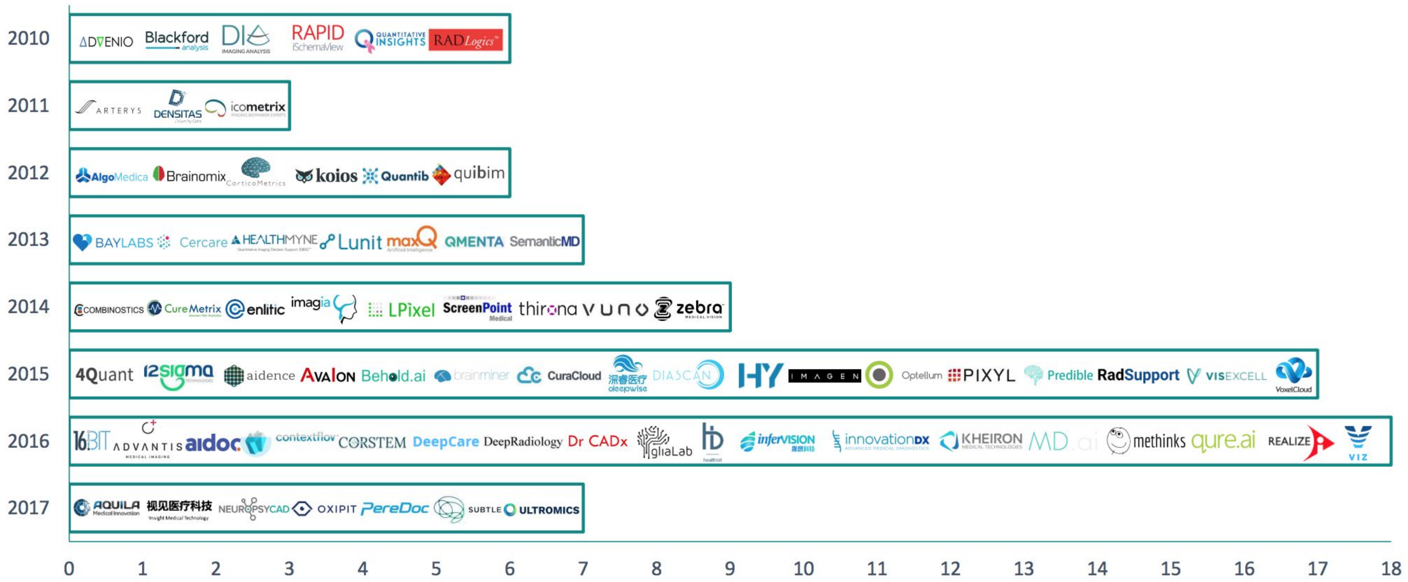

ILM
RPE
Caliper
73


A
B

Healthcare

- **Expect to see more activity as companies move their products through clinical trials and regulatory bodies**

Number of medical imaging AI companies founded per vintage

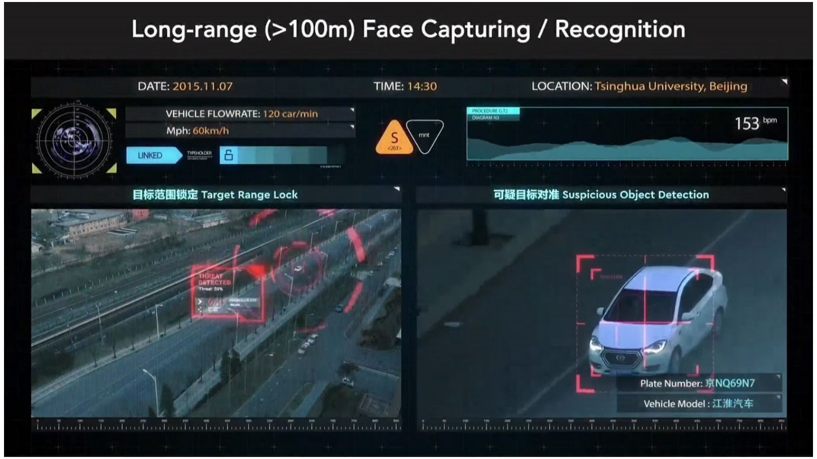


Government and defense

Population-level surveillance is taking off in China

The Chinese government continue to roll out CCTV surveillance software based on computer vision. There are 170 million CCTV cameras as of late 2017. This network will grow to 400 million cameras in 3 years time.

4 year-old 商汤 sensetime is leading the charge. It’s valued >$4.5B since raising $620M Series C+ in May 2018.



Government and defense

- **In the US, companies including Google and Clarifai supplied AI technology to the Pentagon's Project Maven**

Tom Simonite / Wired:

Fired employee alleges in a lawsuit that Clarifai, an AI startup working on Project Maven, was hacked from Russia and did not promptly report it to the Pentagon — LAST SUMMER, A sign appeared on the door to a stuffy, windowless room at the office of Manhattan artificial intelligence startup Clarifai.

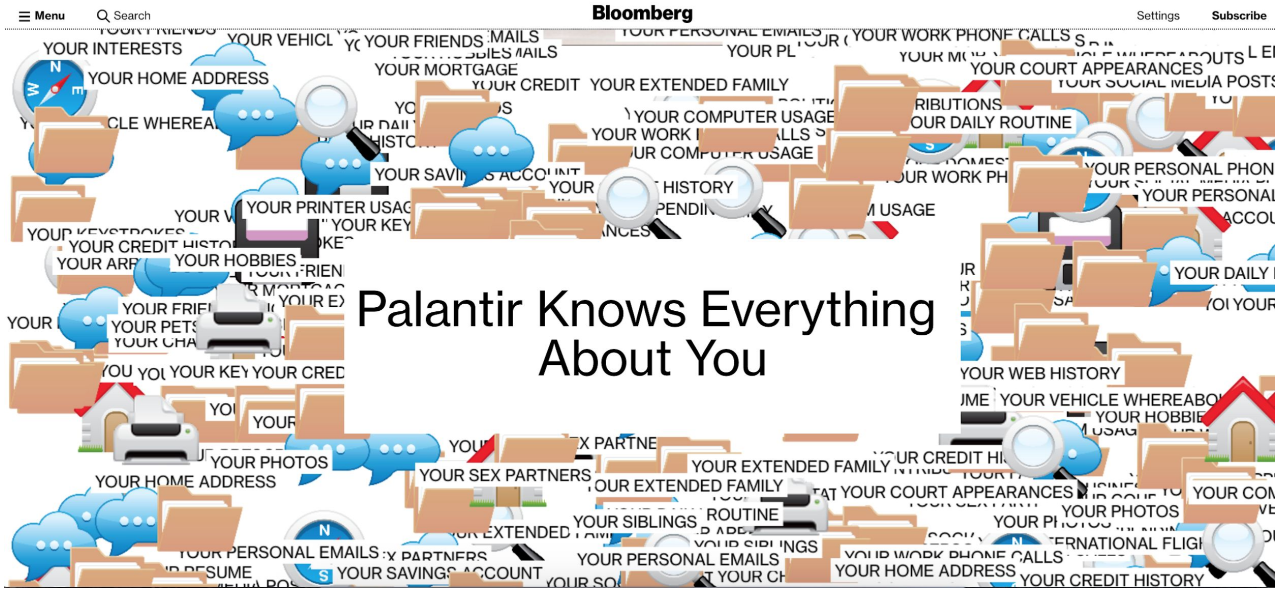
- **In response, >4,500 Google employees signed a petition to quit if the company were to continue as a supplier**

In **wake of Project Maven backlash, Google unveils new AI policies**
Fast Company - 7 Jun 2018
Today **Google unveiled** a **new** set of principles guiding its approach to artificial intelligence, including a pledge not to build **AI** weapons, ...

AI at Google: our principles - Google Blog
https://blog.google/topics/ai/ai-principles/
7 Jun 2018 - We're announcing seven **principles** to guide our work in **AI**.

Government and defense

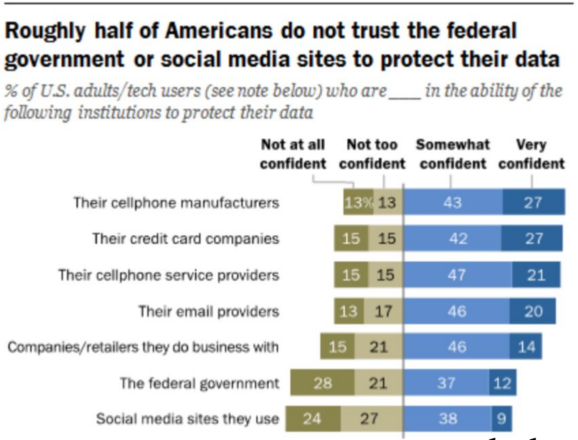
- **In the wake of the Cambridge Analytica scandal, personal data privacy is now front and center**



Privacy preservation and data anonymisation

Why now?

Massive data breaches such as Equifax's heist of data about 146 million people has brought the privacy front of mind in industry. In Europe, the General Data Protection Regulation has come into effect since May 25th 2018. Companies must explicitly obtain consent from their users to access data for specific purposes and must allow users to delete their records at will. This has driven work in differential privacy, on-device machine learning and synthetic data creation to assuage privacy concerns of data systems. However, it's unclear if consumers will change their behavior as a result.



Privacy preservation and data anonymisation

Where and how is machine learning being used effectively?

- **Synthetic data generation:** Training a machine learning model to learn the key statistical properties of a source dataset and using the model to generating synthetic data that preserves these properties.

  Selected examples: Synthesized.io statice

- **Obfuscating sensitive data:** Detect sensitive data fields and anonymise them while preserving the important features of a dataset such that machine learning models can still learn useful information.

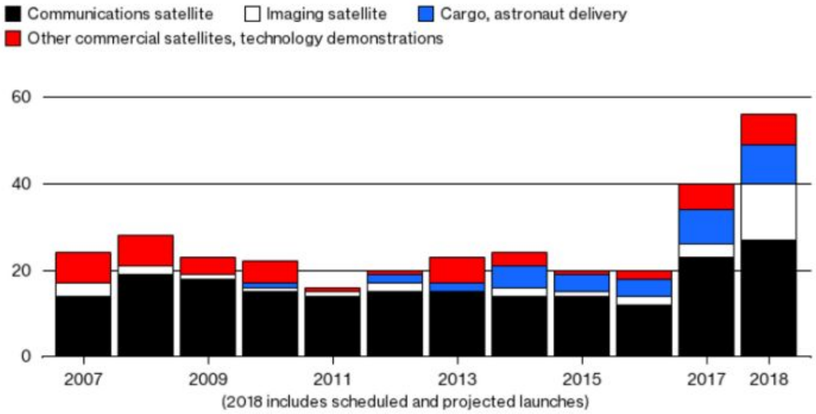
  Selected examples: PRIVITAR DATAGUISE BigID

Satellite data

Why now? Satellite data is decreasing in cost and increasing in resolution and frequency

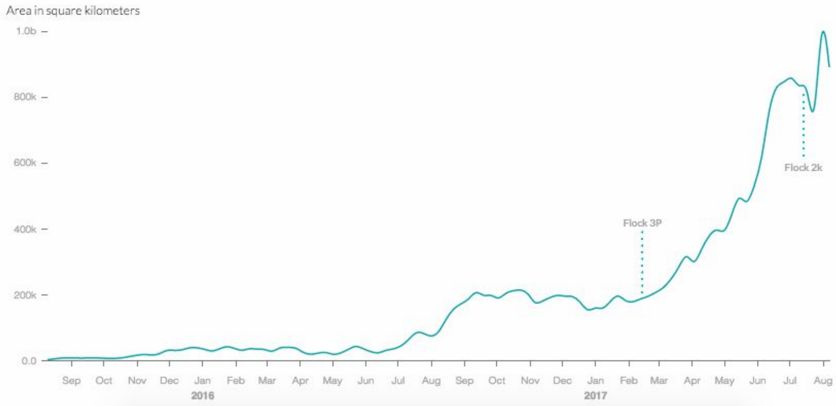
Driven by the rise of microsatellites, the decreasing costs of satellite components, the falling cost of launches and improvements in downlink infrastructure.

Worldwide commercial space launches by type



Data: FAA Office of Commercial Space Transportation; graphic by Bloomberg Businessweek.

Weekly data collection by Planet



Satellite data

Where and how is machine learning being used effectively?

- **Insurance:** Use real time imaging and historical data to automate claims, detect fraud and improve pricing models for property, catastrophe and crop insurance.

  Selected examples: CAI ANALY, VanderSat, Orbital Insight

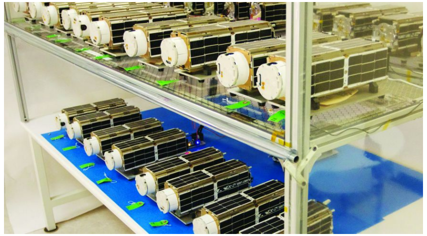
- **Finance:** Automate assessment of ground truth data (traffic patterns, car counts in retail parking lots, drilling activity, construction activity etc) to find new sources of alpha in financial markets.

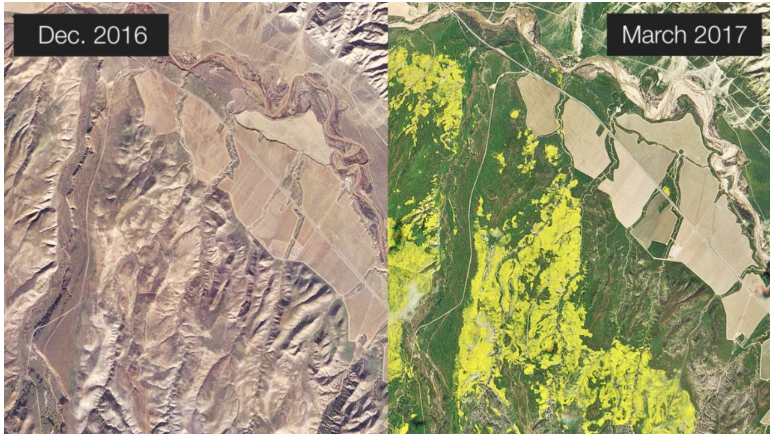
  Selected examples: SPACEKNOW, GENSCAPE®

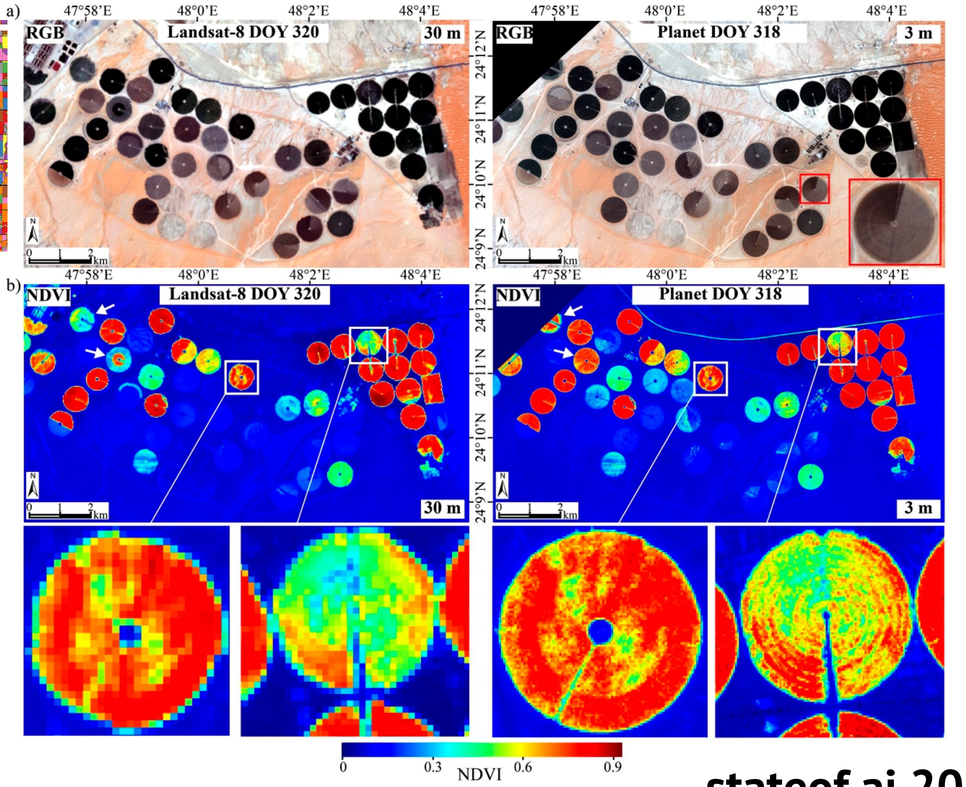
- **Agriculture:** Use persistent daily imagery to monitor fields to understand changes in soil or crop health and forecast yields.

  Selected examples: telluslabs, Descartes Labs, SATELLOGIC

Satellite data: Eyes in the sky







planet. Orbital Insight Descartes Labs

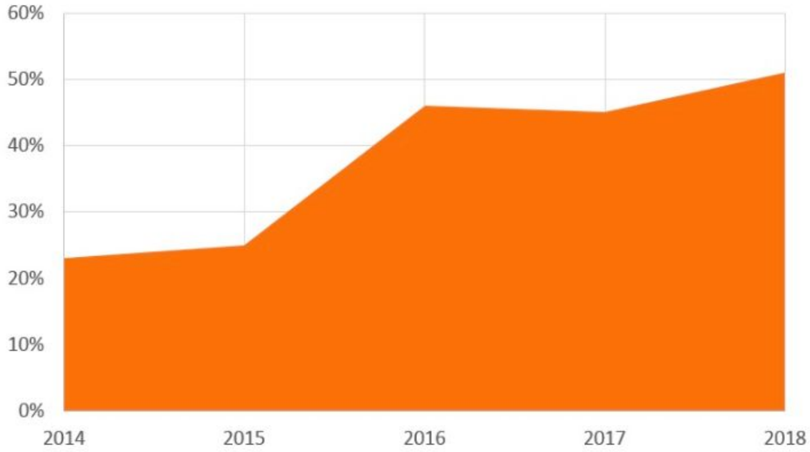
Cybersecurity

Why now?

Cloud computing, mobile devices, and more interconnected supply chains means the attack surface for cyber attacks is expanding. At the same time there is a growing shortage of cybersecurity personnel. Machine learning offers a flexible way to learn from past attacks and automate processes saving time for stretched security teams.

Global avg cost of cybercrime to organisations

% of organisations lacking cybersecurity skills



Cybersecurity

Where and how is machine learning being used effectively?

- **Network and endpoint security:** Supervised learning is used to detect malicious activity on an organisation's network based on data from past attacks. Unsupervised learning is used to automatically learn what is normal and what is abnormal within a network on a an ongoing basis.

  Selected examples: DARKTRACE, JASK, deepinstinct, CYLANCE, CROWDSTRIKE, Carbon Black.

- **Insider threat detection:** Applying machine learning to large amounts of data on employee behaviour reduces the time to flag potential malicious intent.

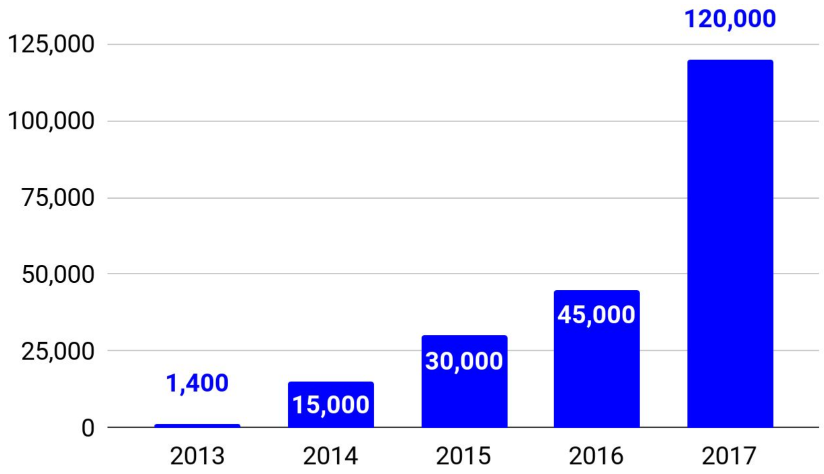
  Selected examples: StatusToday, INTERSET

Warehouse automation

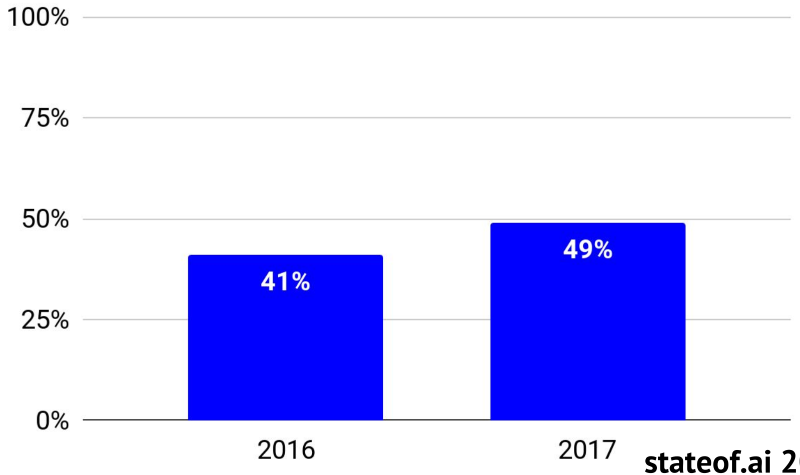
Why now?

eCommerce growth decreases order size for item picking in warehouses and increases customer expectations around the speed of fulfilment. Warehouse space and labour are both scarce driving more use of robotics. Retailers are also reacting to Amazon's investment in this area following their acquisition of Kiva.

Number of robots working in Amazon fulfilment centres



% of warehouse and logistics managers reporting inability to find hourly workers as a top concern



Warehouse automation

Where and how is machine learning being used effectively?

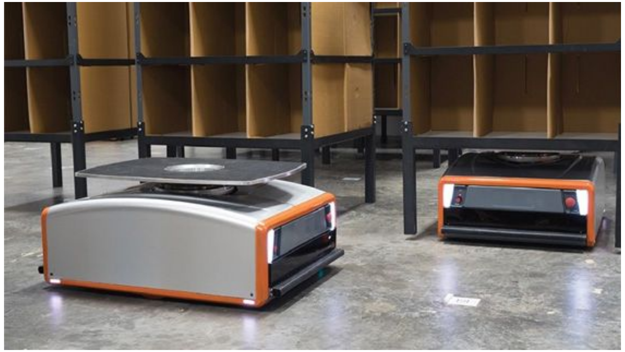
- **Robotics:** Using robots and drones for picking, packing, inventory inspection.

  Selected examples: amazon robotics, 6 RIVER SYSTEMS, GREYORANGE, RIGHTHAND ROBOTICS, JD.COM 京东

- **Warehouse management systems:** Using machine learning within warehouse management software to optimise inventory, order picking and queues to minimise waste.

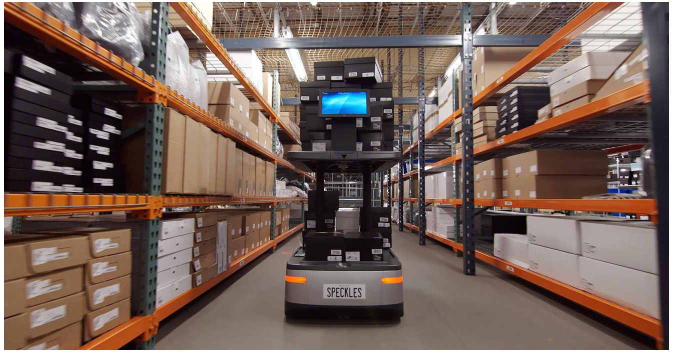
  Selected examples: ocado, zalando

Warehouse automation: Products of all shapes and sizes



GREYORANGE

RIGHTHAND ROBOTICS



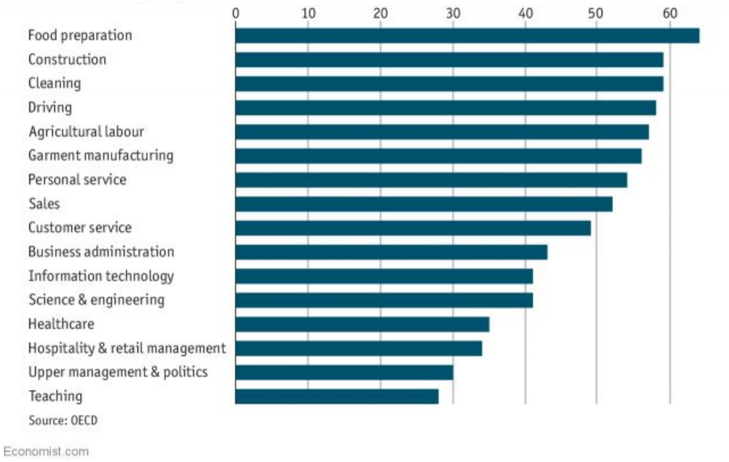
6 RIVER SYSTEMS

Blue collar manual work

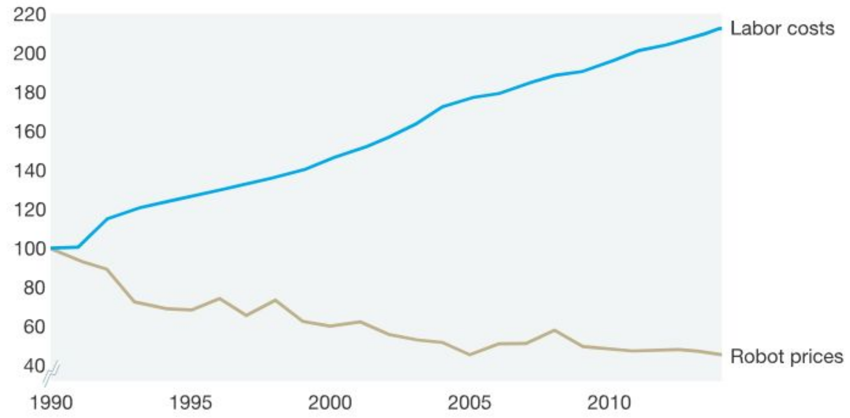
Why now?

A decrease in the cost of components (sensors, batteries) and improvements in computer vision mean that robots are increasingly cheaper than employing manual labour for various blue collar professions.

Automation risk by job type (%)



Index of average robot prices and labour compensation in U.S. manufacturing



Source: Economist Intelligence Unit; IMB; Institut für Arbeitsmarkt- und Berufsforschung; International Robot Federation; US Social Security data; McKinsey analysis

Blue collar manual work

Where and how is machine learning being used effectively?

- **Construction:** Self-driving vehicles for digging and loading. Robots for bricklaying and other tasks.

  Selected examples: BUILT ROBOTICS, Construction Robotics, CLEARPATH ROBOTICS™

- **Cleaning:** Self-driving cleaning robots for industrial spaces. This can include dangerous or hard to access spaces like windows, solar panels or infectious spaces.

  Selected examples: AVIDBOTS, SERBOT SWISS INNOVATIONS, XENEX® DISINFECTION SYSTEMS™, brain CORPORATION

- **Security:** Computer vision applied to security cameras combined with drones, robots and other sensors to replace aspects of a security guard's job.

  Selected examples: COBALT, ACCELERATED DYNAMICS, APTONOMY, NIGHTINGALE SECURITY

Blue collar manual work: Examples of products in the market

BUILT
ROBOTICS

CLEARPATH
ROBOTICS™

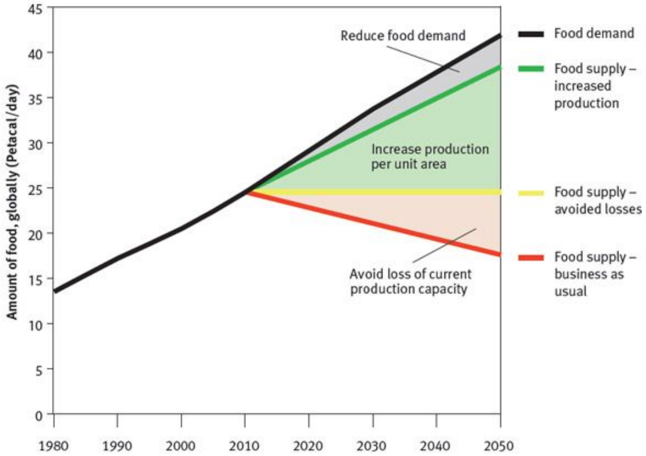
AVIDBOTS

Agriculture: Indoor and outdoor farming

Why now?

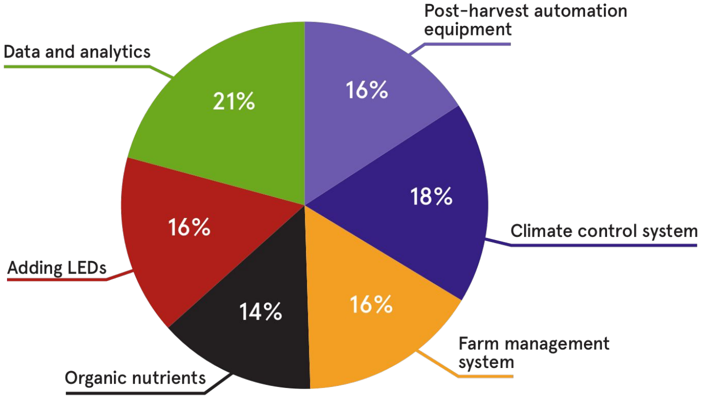
The world population is expected to grow from 7.6 billion to 9.6 billion by 2050. We need to produce 70% more food calories to feed the world's population by then. Robotics, control systems, connected devices in fields and greenhouses and new methods of farming must be developed to fill this food production gap.

The need for boosting food production



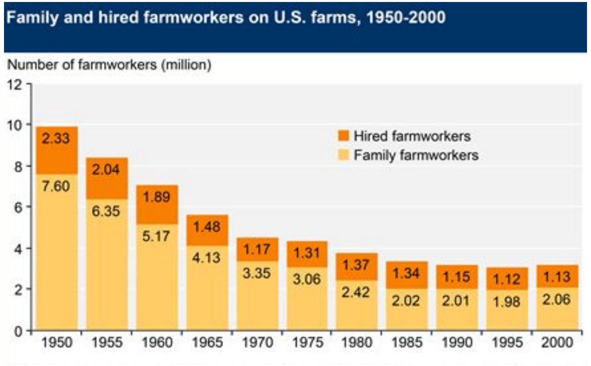
(Commission on Sustainable Agriculture and Climate Change)

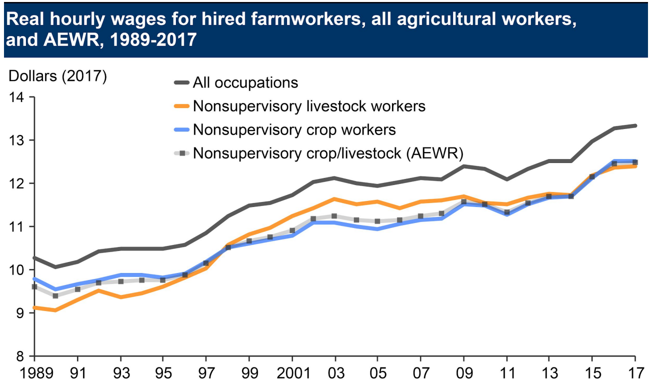
Farms are investing in technology now

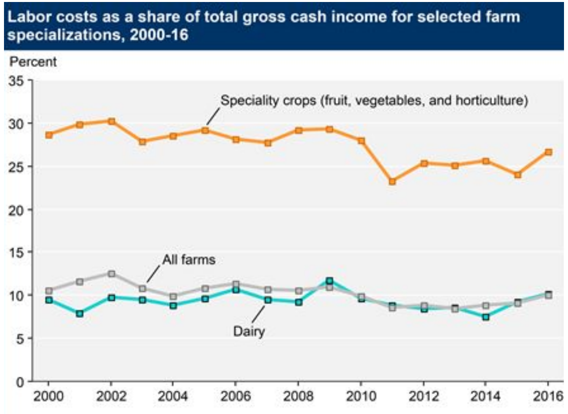


Agriculture: Indoor and outdoor farming

- **Fewer farm workers on US farms, higher hourly wages per worker, but more automation leads to stable labor cost share of total gross farm revenue**







Agriculture: Indoor and outdoor farming

Where and how is machine learning being used effectively?

- **Greenhouse control systems:** Use native sensors and actuators in greenhouses to collect data on growing conditions, learn a dynamic climate model and use it to optimise crop yield and energy consumption.

  Selected examples: OPTIMAL

- **Vertically-integrated farming:** Compact, self-contained greenhouses for growing crops closer to the point of consumption. The farms have their climates that can be operated using similar ML-driven control systems.

  Selected examples: infarm, Plenty, AGRICOOL

- **Health inspection for crops and animals:** Use computer vision and wearable sensors to learn models of plant and animal health and use them to detect anomalies.

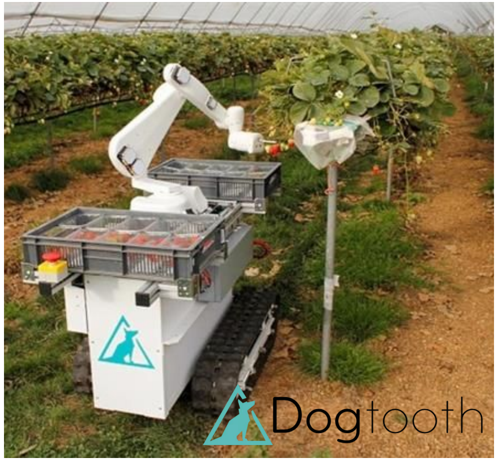
  Selected examples: prospera, cainthus, Connecterra

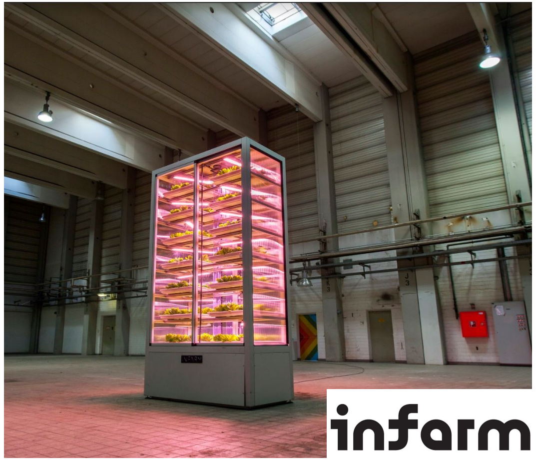
Agriculture: Indoor and outdoor farming

Where and how is machine learning being used effectively?

- **Crop picking robots:** Build robots capable of mapping and navigating through crop fields while identifying and carefully picking ripe fruit automatically.

Selected examples: Dogtooth, abundant ROBOTICS, FF Robotics, AGROBOT





Autonomy

Why now?

SAFETY

- **94 PERCENT** of U.S. crashes involve human error. [1]
- **1.2 MILLION** deaths worldwide due to vehicle crashes in 2013. [2]
- **37,461 ROAD DEATHS** in the U.S. in 2016 and 2.4 million injuries in 2015. [3]
- **2 OUT OF 3** people will be involved in a drunk driving crash in their lifetime. [4]

SOCIETY

- **$594 BILLION** in harm from loss of life and injury each year. [5]
- **$277 BILLION** in annual economic costs. [6]
- **$160 BILLION** in gas burned and time lost each year. [7]

MOBILITY AND QUALITY OF LIFE

- **3 MILLION** Americans age 40 and older are blind or have low vision. [8]
- **79 PERCENT** of seniors age 65 and older living in car-dependent communities. [9]
- **42 HOURS** wasted in traffic each year per person. [7]

WAYMO

Autonomy

Where and how is machine learning being used effectively?

- **Autonomous vehicle ridesharing:** Machine learning is often used across the entire stack from perception, localisation, mapping, planning, control, route optimisation and safety.

  Selected examples:

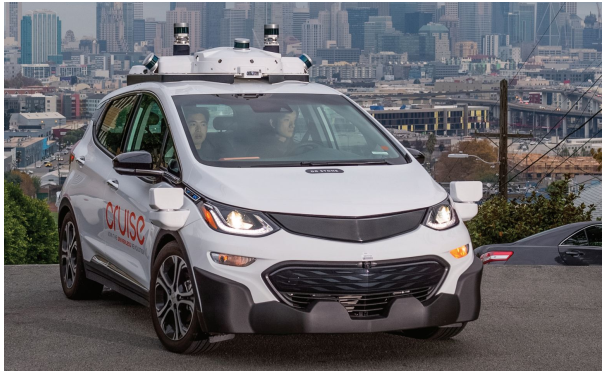
- **Autonomous last mile delivery:** Same as above, except these vehicles are used to delivery goods locally by land or air.

  Selected examples:

- **Simulation environments, street level maps and software for autonomy:** Using a mix of machine learning, computer vision, video game environments, photorealistic data generation and behavioral modelling.

  Selected examples:

Autonomy: Vehicles and software products in the wild



cruise

WAYMO

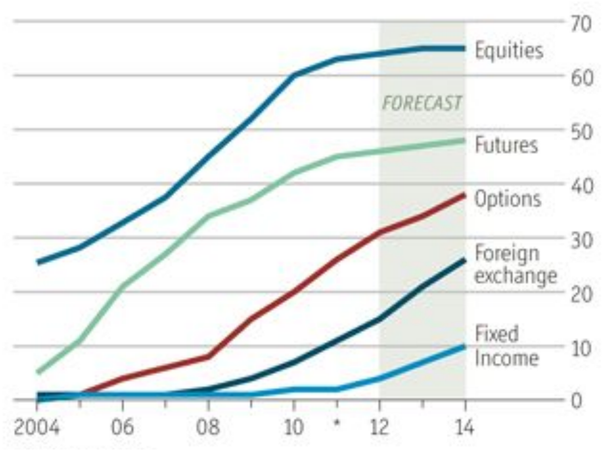
Baidu 百度

Finance

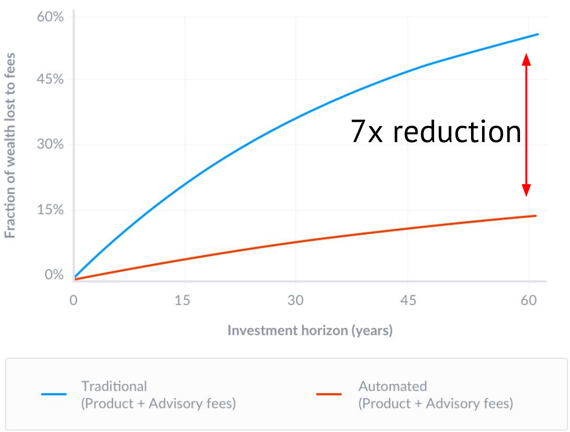
Why now?

There is an abundance of data in public markets, alternative sources and about users of financial products. Moreover, consumers and investors are fatigued with overbearing fees to manage capital and provide products such as credit. The financial sector also faces pressure to reduce operating expenses by adopting automation.

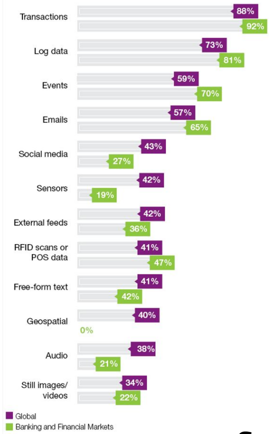
Algorithmic trading as % of all trading



Fraction of wealth lost to fees



Big data sources in use



Finance

Where and how is machine learning being used effectively?

- **Wealth management:** Software-driven automation of capital management, portfolio construction and tax optimisation. These services materially reduce the fees for consumers to invest their long-term savings.

  Selected examples: wealthfront Betterment nutmeg PERSONAL CAPITAL

- **Credit/Loans:** The cost of calculating and underwriting risk is improved through automation and the discovery of novel features through machine learning that improve the overall efficiency of this process. Peer to peer lending has also benefited from these drivers.

  Selected examples: AVANT CREDIT Affirm SoFi ZOPA LendingClub

- **Fraud prevention:** Using both supervised and unsupervised learning to detect known and novel fraudulent behaviors in electronic transactions, interpersonal communications, and claims images.

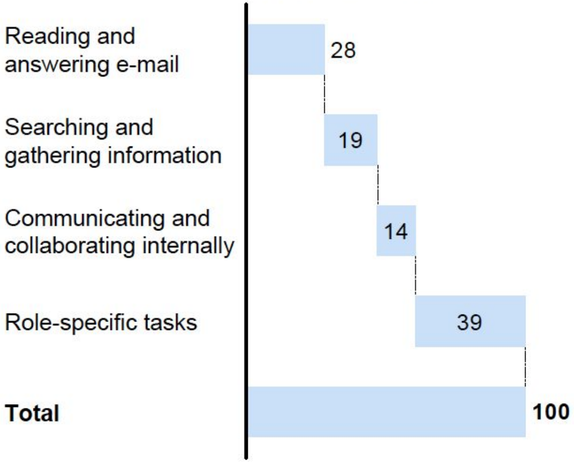
  Selected examples: TRACTABLE Ravelin SIGNIFYD Shift Technology sift science

Enterprise automation

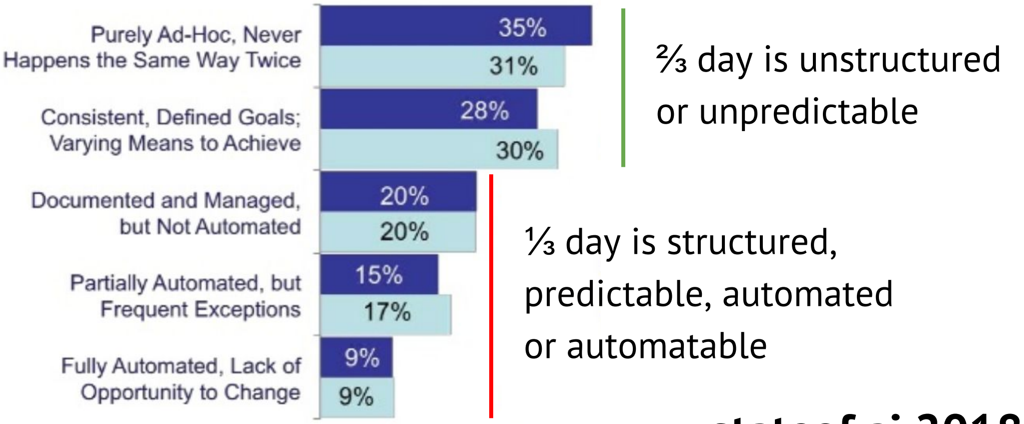
Why now?

Reducing operational process cost and complexity through software-defined automation is now a Board-level priority in the enterprise. Manual processes are prone to costly errors, do not scale, are difficult to track and troubleshoot, and make organisations slow to respond to younger and more nimble new entrants.

% of average week spent on tasks



% of day spent in different modes of work



Enterprise automation

Where and how is machine learning being used effectively?

- **Robotic process automation:** Creating automated "software robots" to replicate the repetitive desktop-based processes that human workers are otherwise doing. Computer vision and NLP can be used to understand what's on the screen and flexible decision making will help solve more complex tasks.

  Selected examples: UiPath, blueprism, Automation Anywhere, WorkFusion

- **Document digitisation:** Converting legacy paper documentation into digital records to simplify and automate office work. Based on (semi) supervised computer vision and optical character recognition.

  Selected examples: HyperScience, omni:us, Ripcord

- **Software task automation:** While not using machine learning per se, the ability to connect different API-driven software together to form workflows enables task automation in cloud-based enterprises.

  Selected examples: zapier, MuleSoft, IFTTT, tray.io

Material science

Why now?

An enormous amount of experimental data has been generated on the properties of materials. Progress in materials science is a multiplier on broader engineering progress. But most materials are still found empirically, which limits the rate of progress. For example, scientists have manually investigated 6,000 combinations of ingredients that form metallic glass over the past 50 years.

Where and how is ML being used effectively?

Similar its application in drug discovery, machine learning can be used to learn the rules of material science discovery. For example, models can learn the structure of molecules and/or the stepwise process of efficiently testing these molecular properties. By using these techniques, researchers at Stanford Synchrotron Radiation Lightsource were able to create and screen 20,000 combinations of ingredients that form metallic glass in a single year. That's research and development sped up by 167x!

Selected examples: CITRINE INFORMATICS, The Materials Project

Section 4: Politics

Public Attitudes to Automation: Two Surveys

We will review selected results from two major surveys of attitudes to AI and automation in the U.S.

Pew Research Center: Americans and Automation in Everyday Life

- ➔ Conducted May 1-15 2017. Published October 2017.
- ➔ Survey of 4135 US adults
- ➔ Recruited from landline and cellphone random-digit-dial surveys

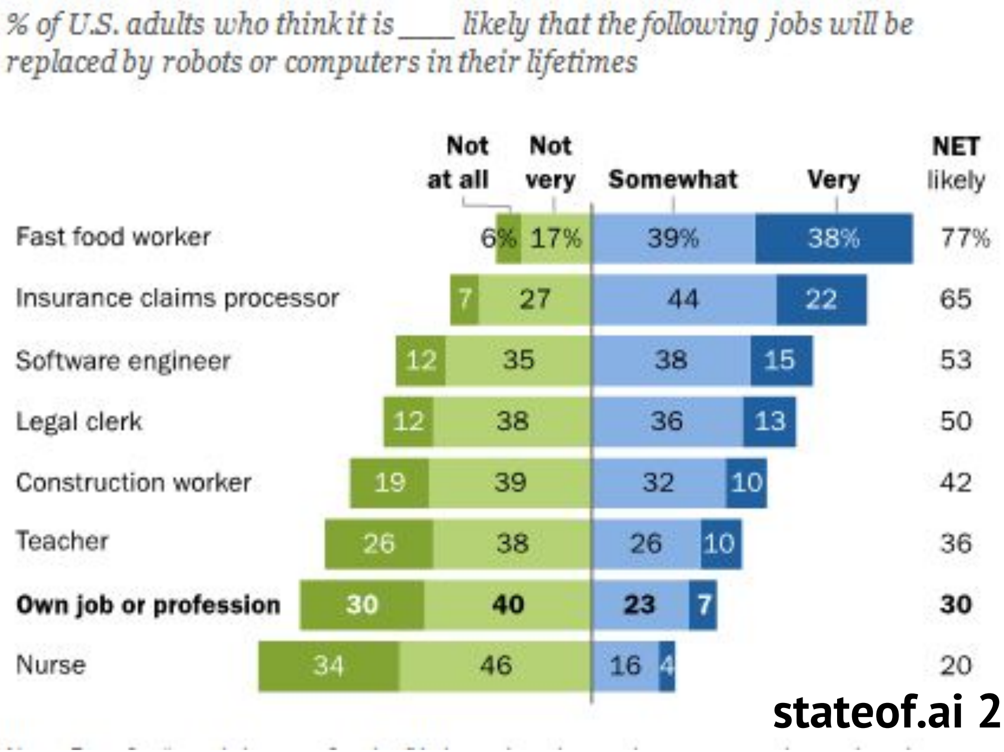
Brookings survey: Attitudes to AI

- ➔ Conducted May 9-11 2018. Published May 2017.
- ➔ Survey of 1535 adult internet users in the U.S.
- ➔ Recruited through the Google Surveys platform. Responses were weighted using gender, age, and region to match the demographics of the national internet population as estimated by the U.S. Census Bureau's Current Population Survey

Public Attitudes to Automation: Pew Research Center

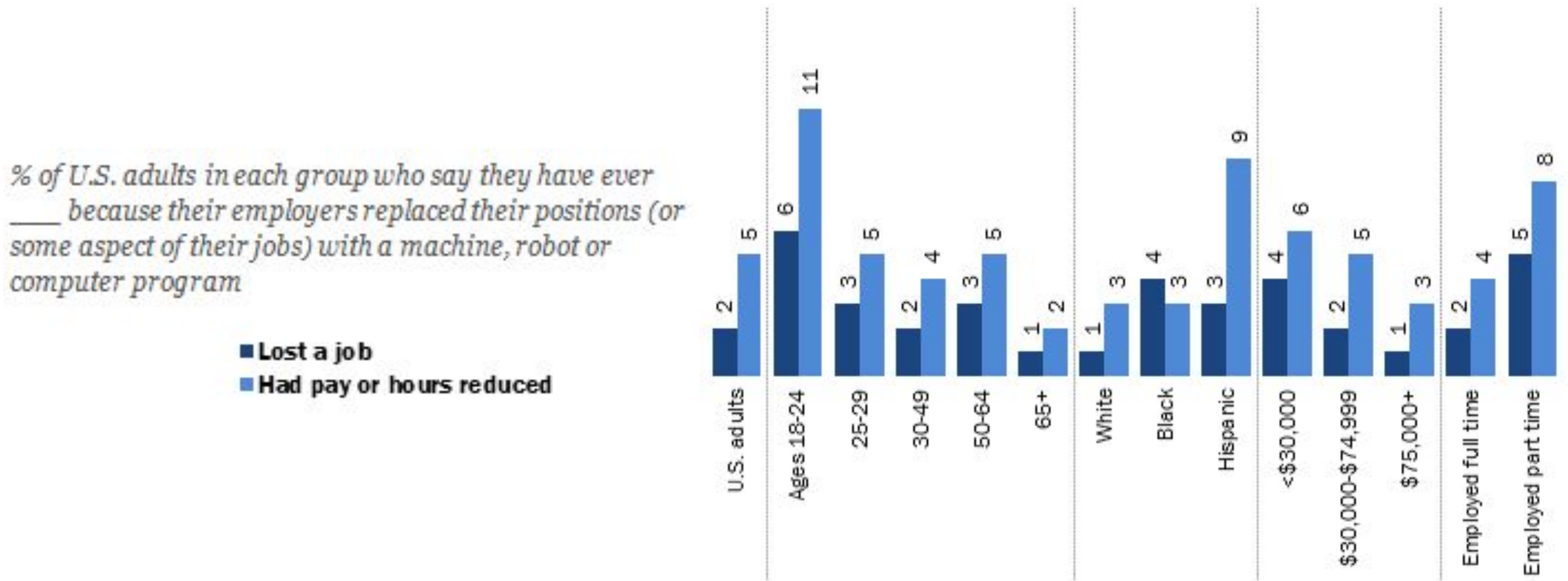
Growing awareness of automation impacting jobs

"18% of Americans indicate that they personally know someone who has lost a job, or had their pay or hours reduced, as a result of workforce automation"



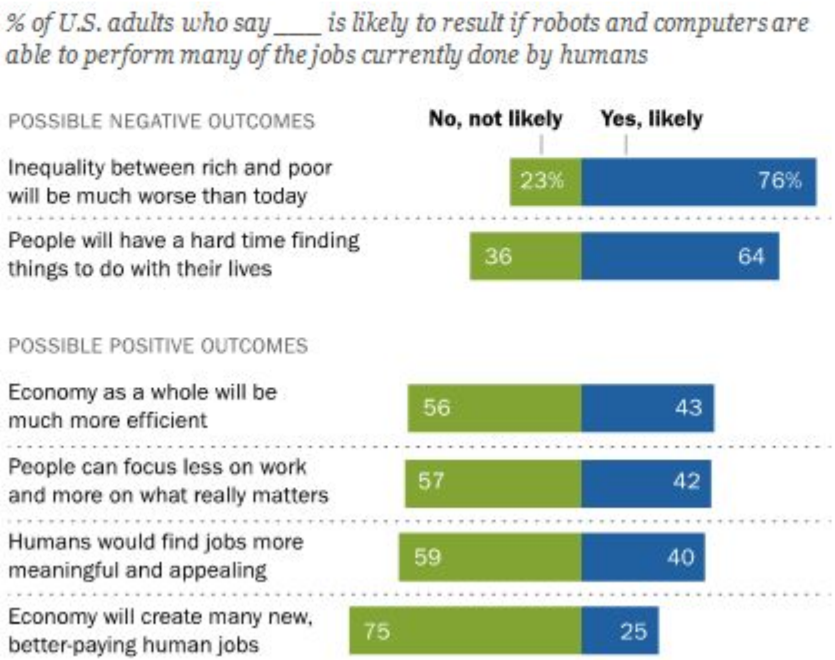
Public Attitudes to Automation: Pew Research Center

- **Young, part-time employed, hispanic and lower-income Americans report most impact**



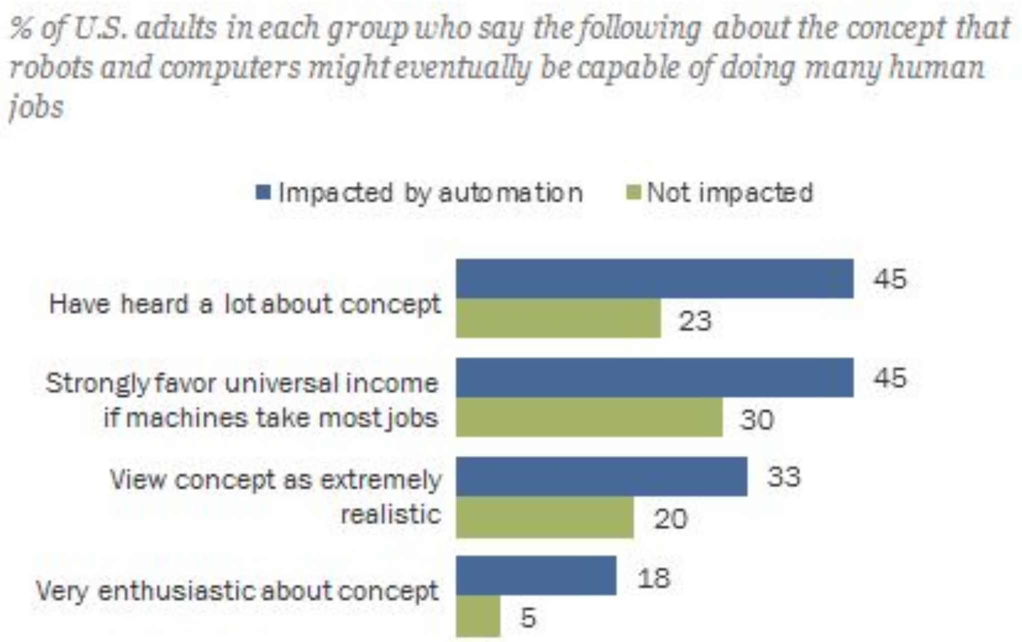
Public Attitudes to Automation: Pew Research Center

- **Rising concerns about automation increasing inequality**



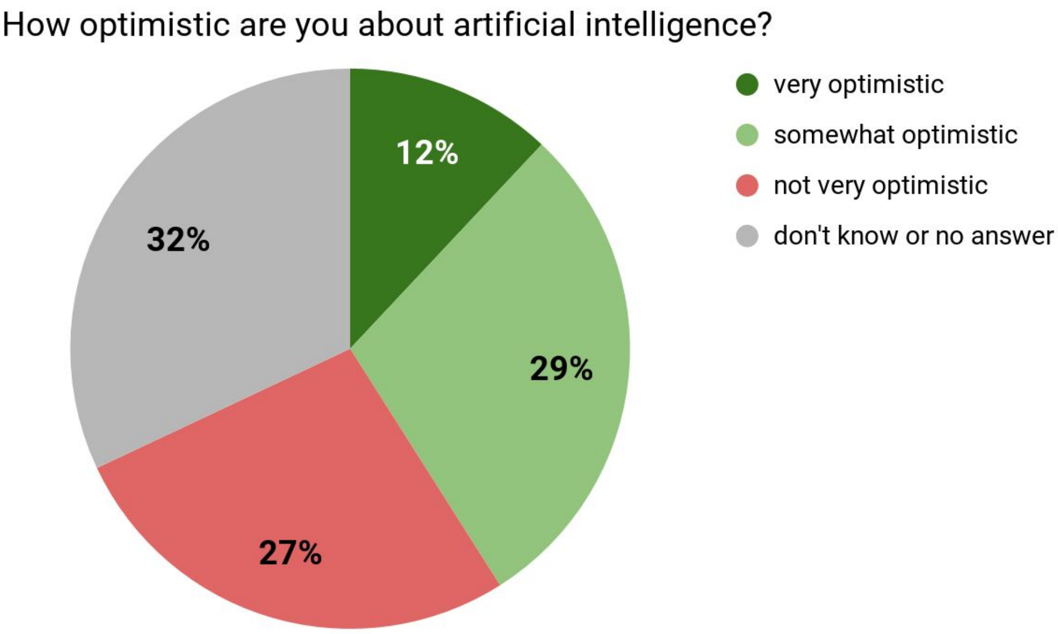
Public Attitudes to Automation: Pew Research Center

- **Those whose job has been impacted by automation favor more radical policies**



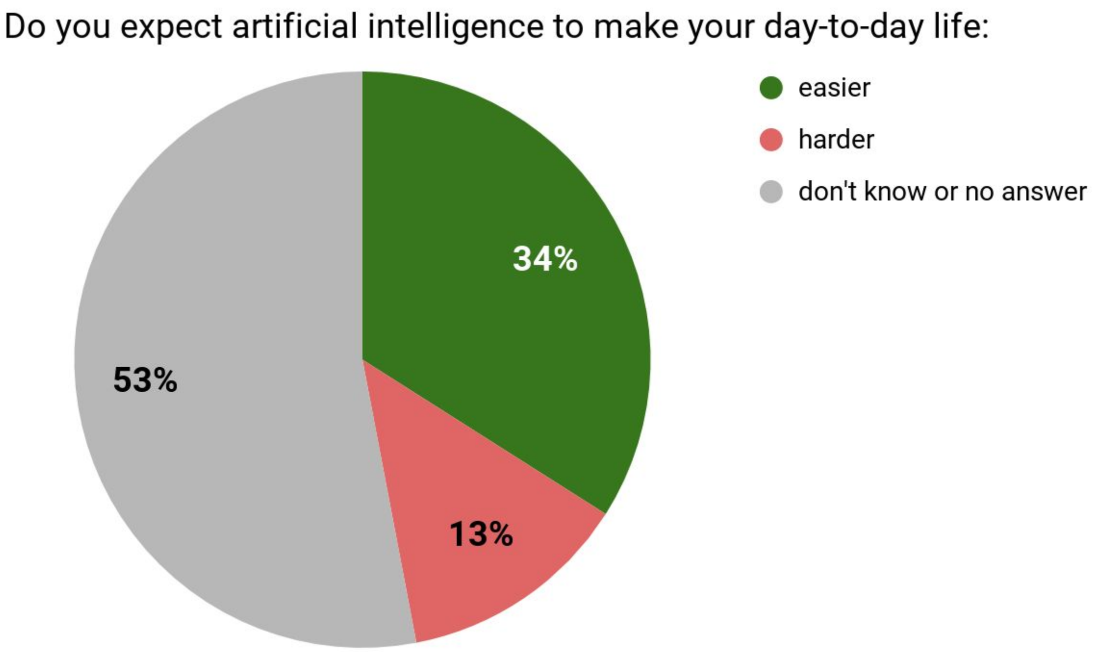
Public Attitudes to Automation: Brookings Institute

Overall optimism around AI...



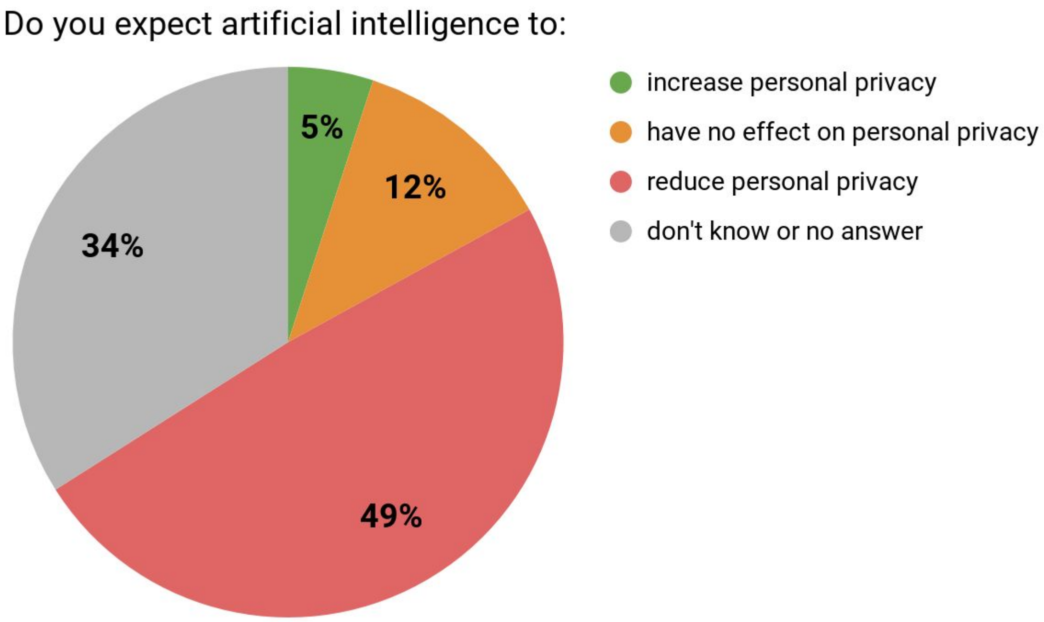
Public Attitudes to Automation: Brookings Institute

- **...and expectation that AI will "make my life easier"**



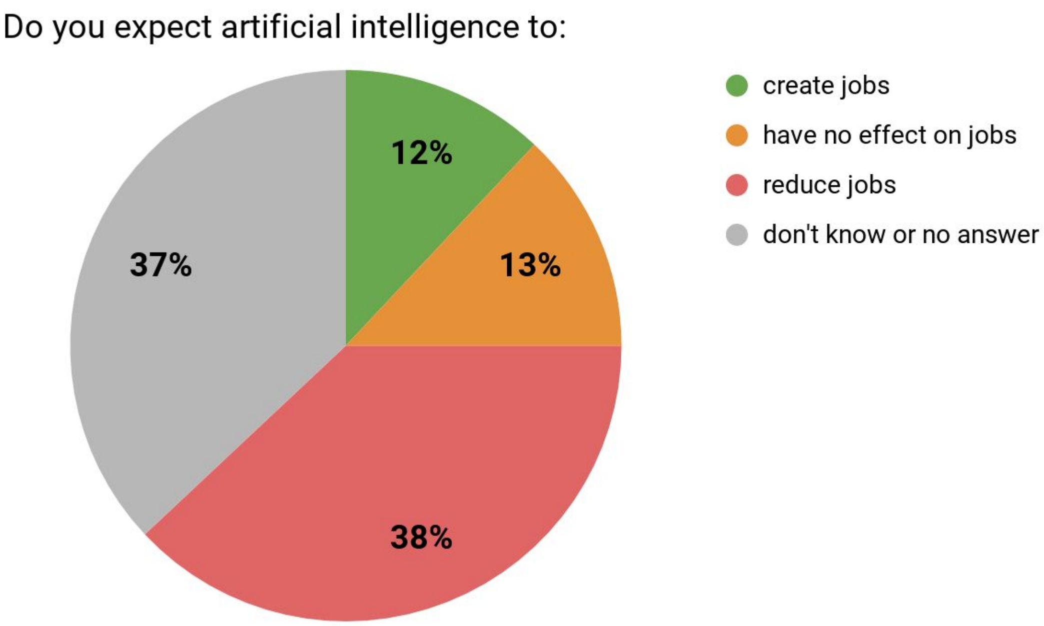
Public Attitudes to Automation: Brookings Institute

- **...but expectation that AI will reduce privacy**



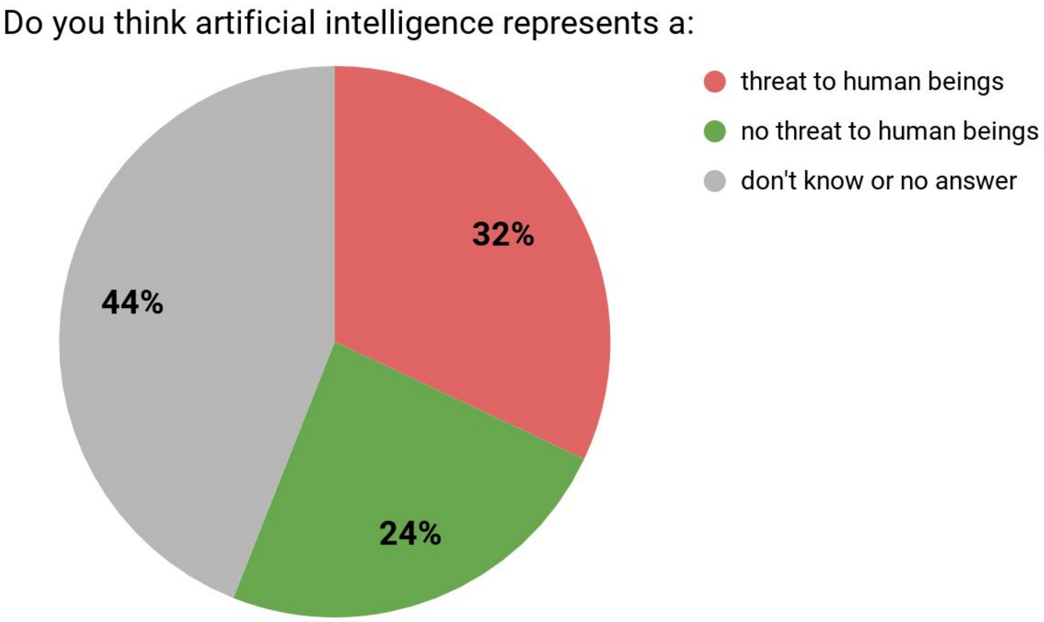
Public Attitudes to Automation: Brookings Institute

- **...and destroy jobs**



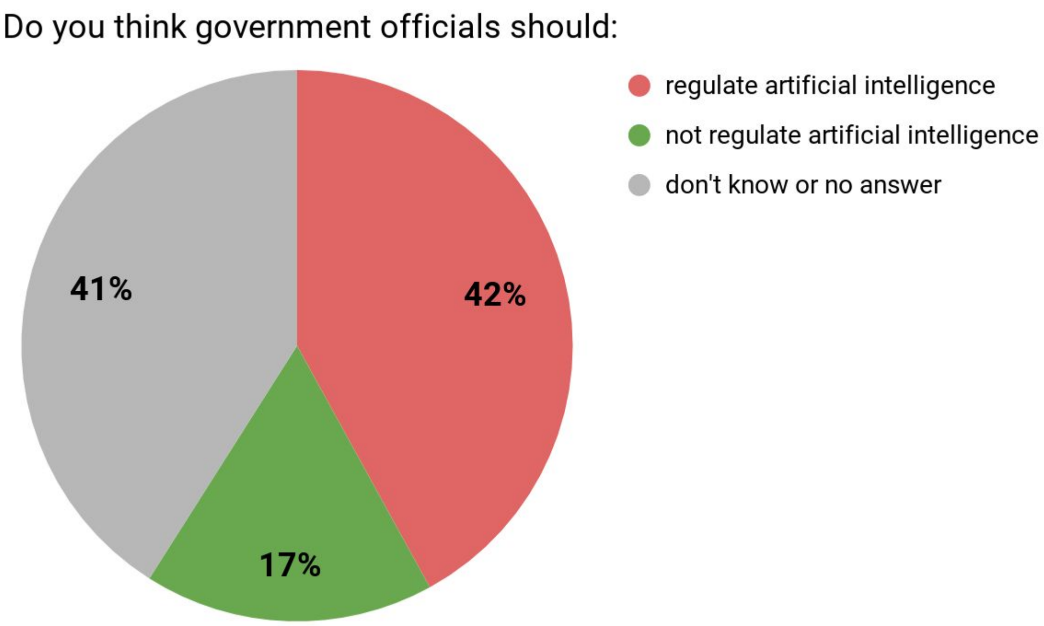
Public Attitudes to Automation: Brookings Institute

- **...and represents a threat to human beings**



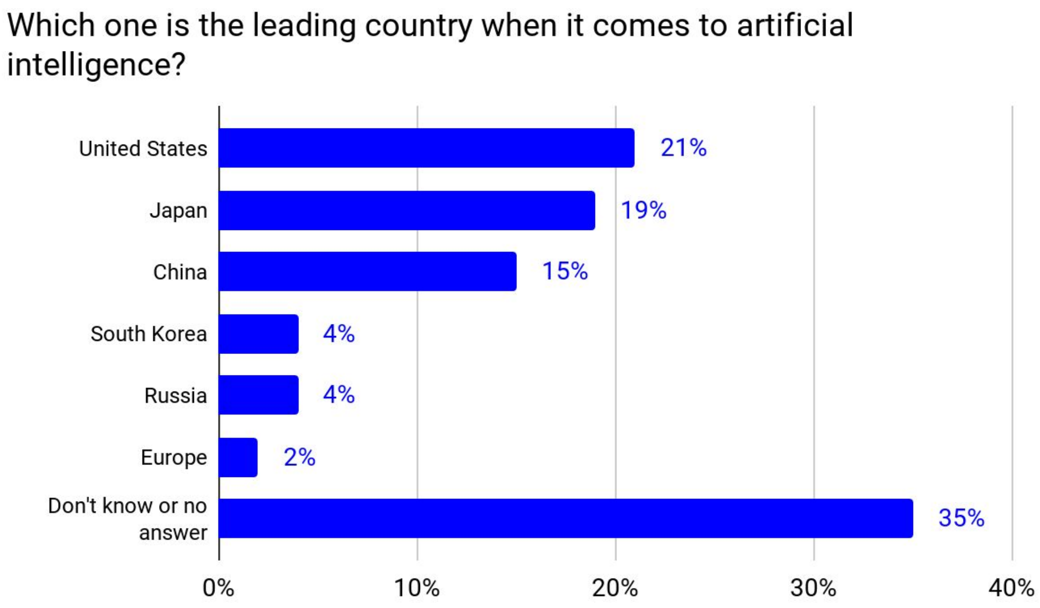
Public Attitudes to Automation: Brookings Institute

- **...and should be regulated by government**



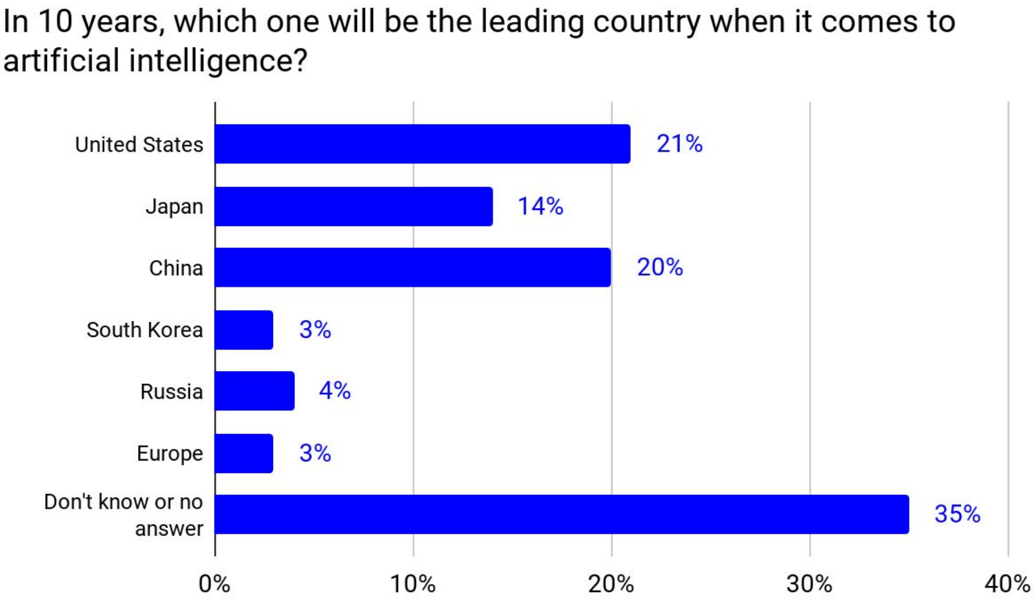
Public Attitudes to Automation: Brookings Institute

- **While Americans believe the US is currently the world leader in AI…**



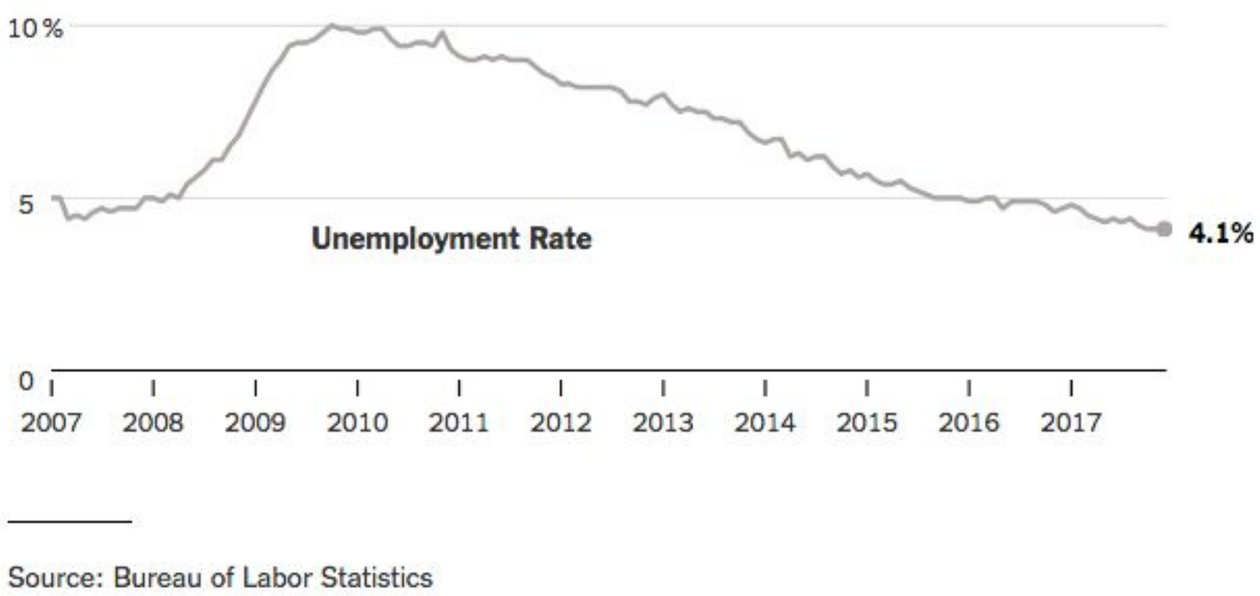
Public Attitudes to Automation: Brookings Institute

- **...China will close the gap over the next ten years**



How is the US labour market actually changing?

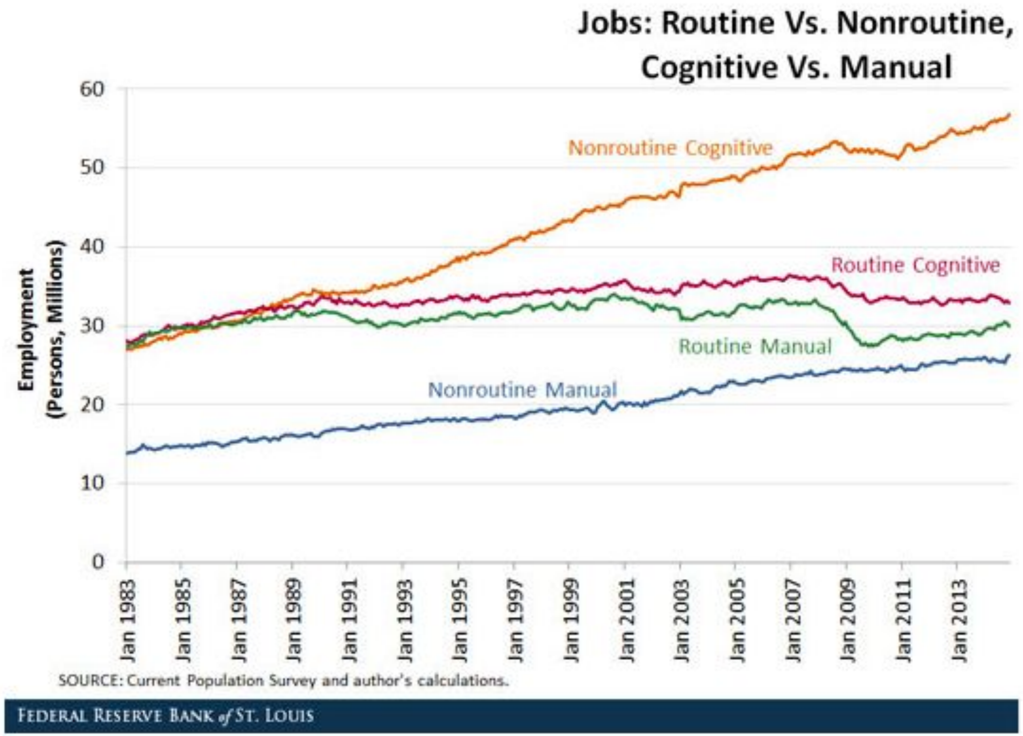
- **Despite increased automation the US unemployment rate is at a 17 year low**



The New York Times

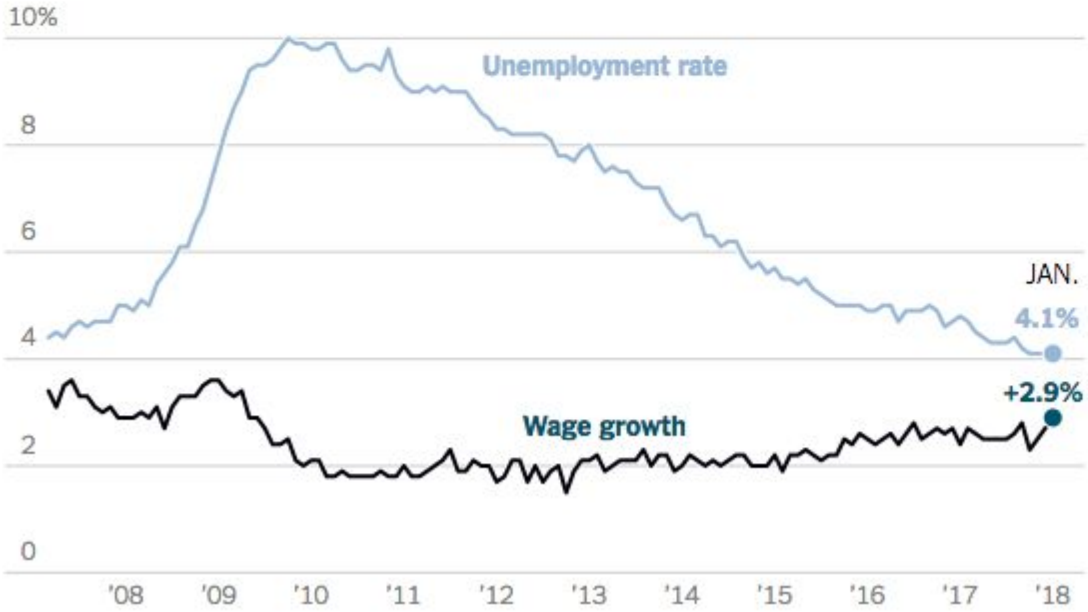
More broadly, how is the US labour market actually changing?

- **Routine jobs have stagnated**



How is the US labour market actually changing?

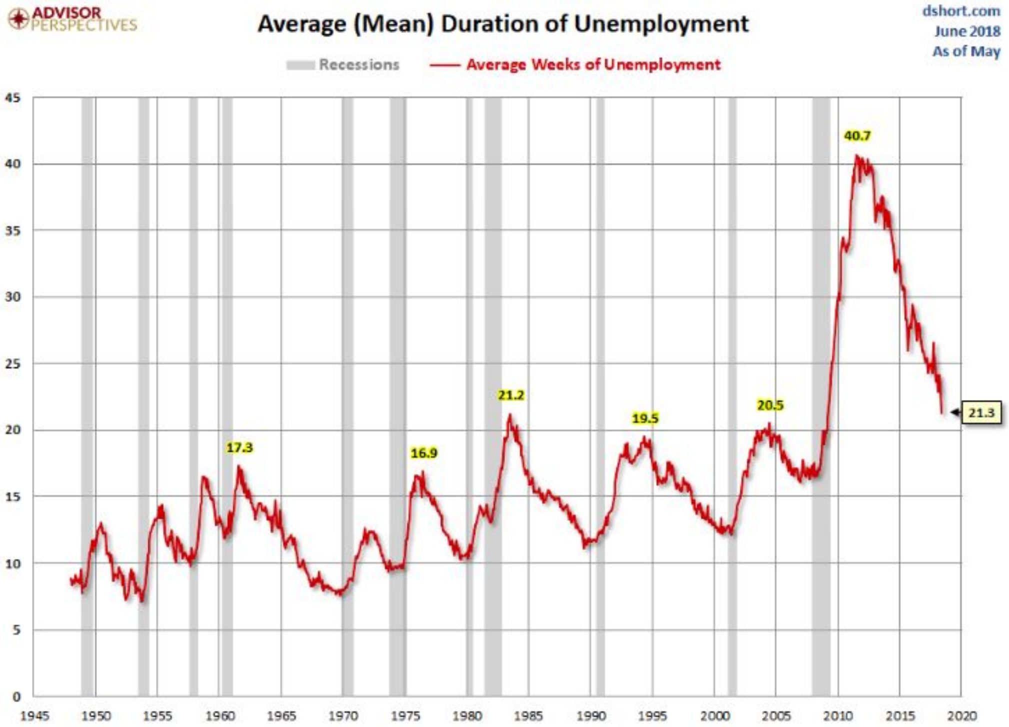
- Wages have lagged the increase in jobs



The New York Times

How is the US labour market actually changing?

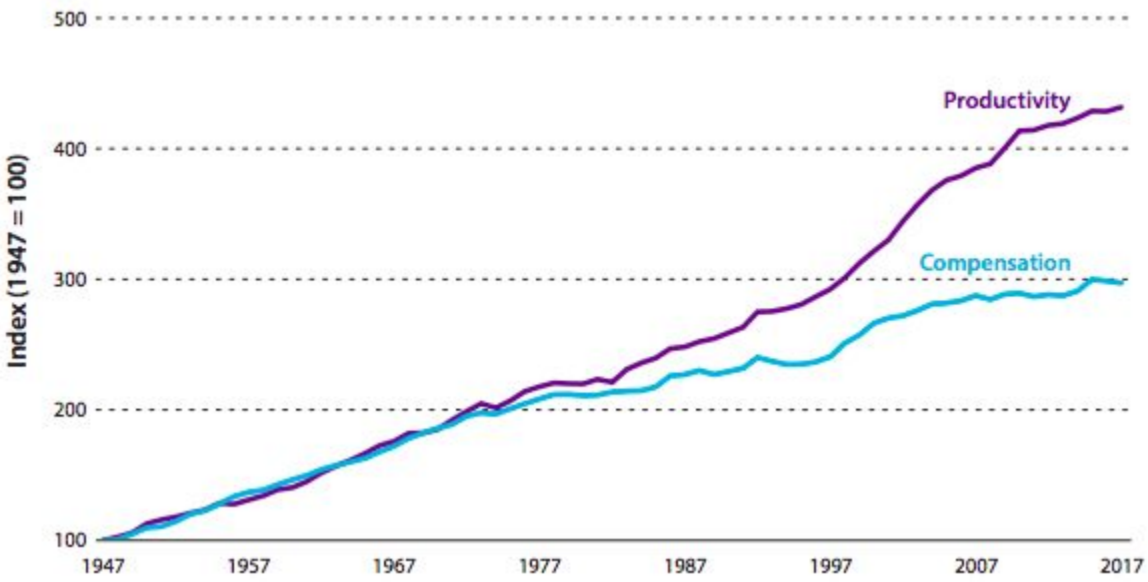
- Since 2010 there has been a marked change in how long unemployment lasts for



How is the US labour market actually changing?

- **Labour productivity and hourly compensation have diverged**

Real Labor Productivity and Hourly Compensation, 1947–2017



THE BROOKINGS INSTITUTE

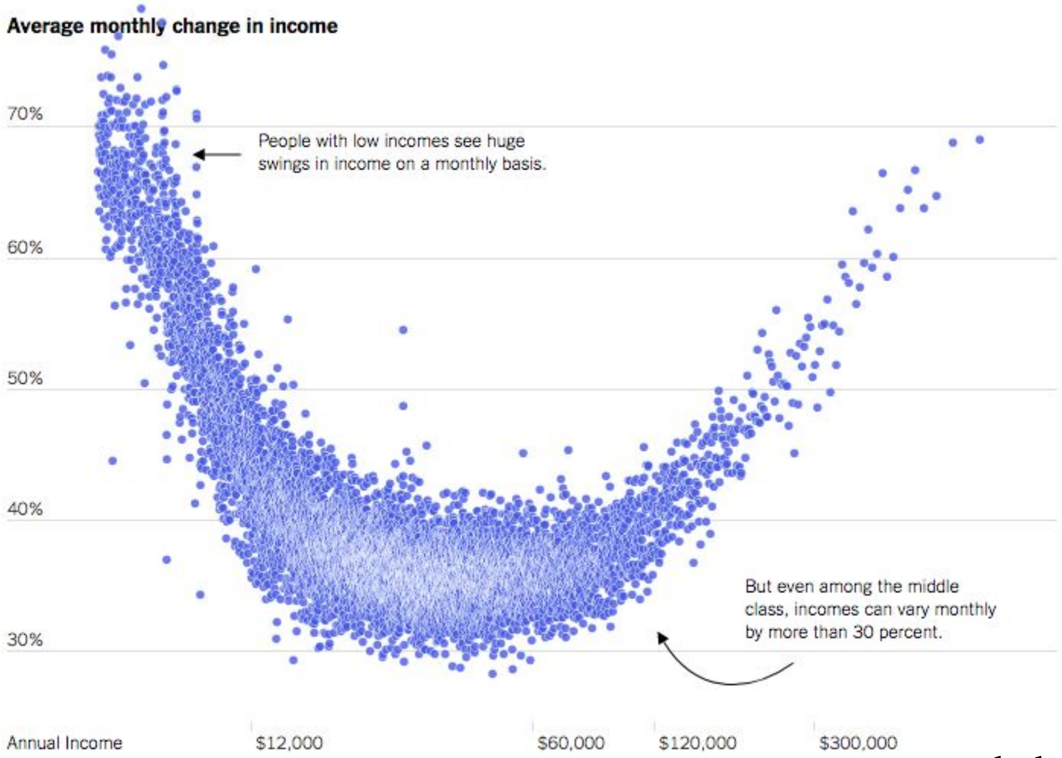
How is the US labour market actually changing?

- **Labour's share of income has been declining steadily**

THE BROOKINGS INSTITUTE

How is the US labour market actually changing?

- **Workers are experiencing greater income volatility**



The New York Times

How much of this is due to automation?

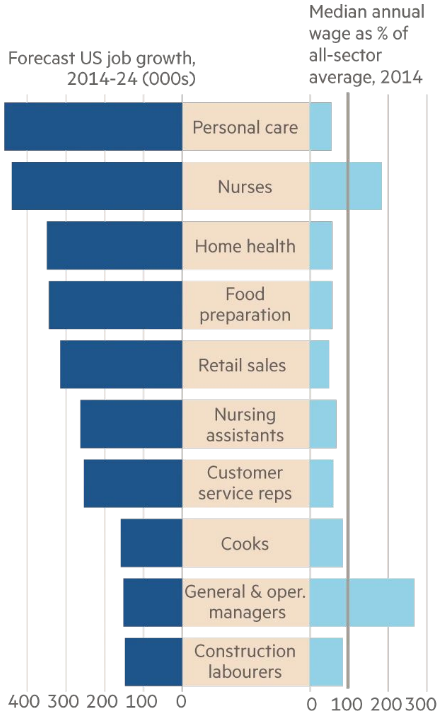
- **It's hard to say for now.** There are many confounding factors including globalisation/offshoring, reduced unionisation, increased financialisation of the economy, increased consolidation, and demographic shifts.

- **There are two poles of thought on how machine learning will affect the labour market:**

  ➔ **"Don't worry" - Historically technology has been a net job creator and it won't be different this time.** Machine learning will create more jobs than it destroys and like previous industrial revolutions, most of those jobs will be new ones that we can't imagine today. Yes, we got Automated Teller Machines at banks, but we also got many new jobs that replaced the bank teller jobs that were lost.

  ➔ **"Worry" - This time it's different.** In previous industrial revolutions we automated human muscular power and somewhat routine cognitive skills. With increasingly advanced machine learning we will replicate more and more of human intelligence, reducing the number of well paid jobs and adding fewer jobs than are destroyed.

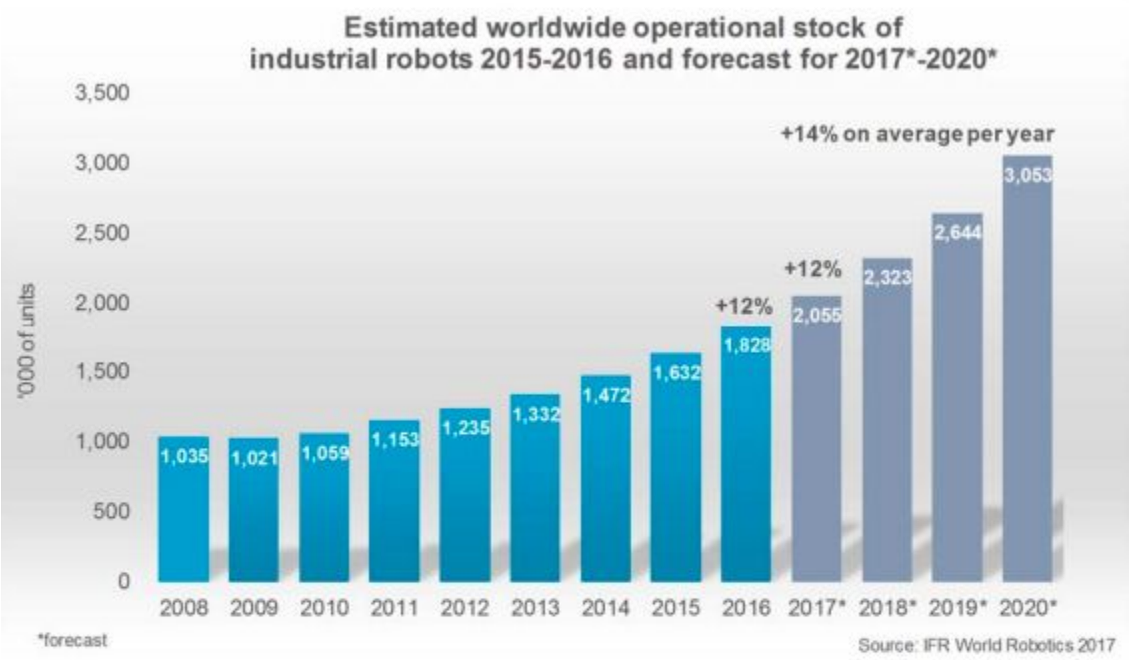
For now, many new jobs are relatively low paid



Source: A Turner, 'Capitalism in an Age of Robots' (Institute for New Economic Thinking, 2018)
© FT

It is also still early, there are only 2 million industrial robots in the world

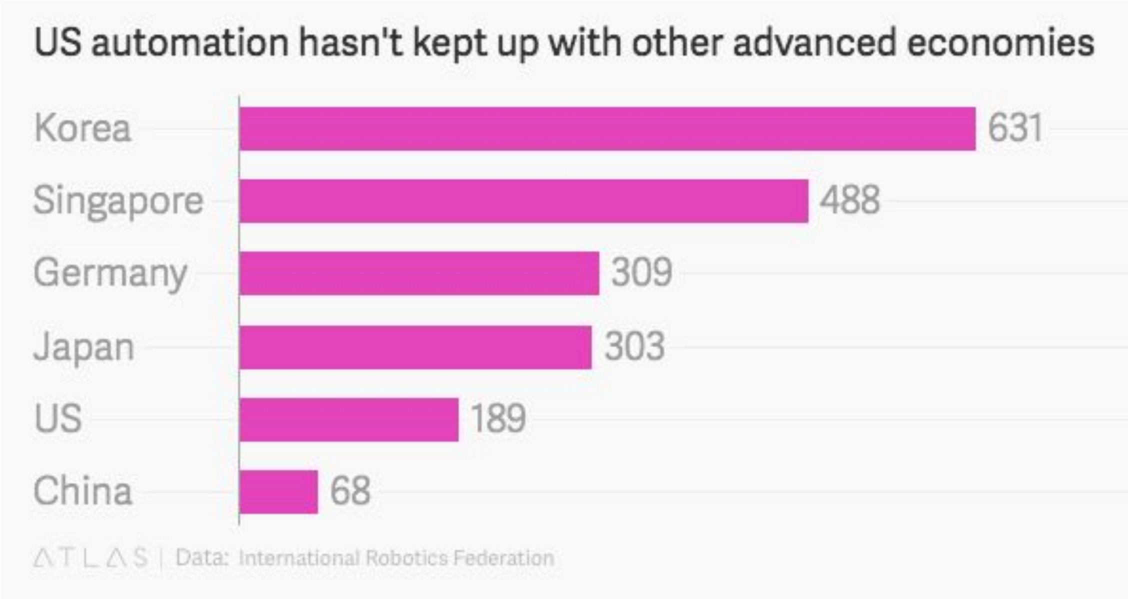
- Install base growing 12% year-on-year



IFR International Federation of Robotics

There are fewer robots in U.S. factories compared to other advanced economies

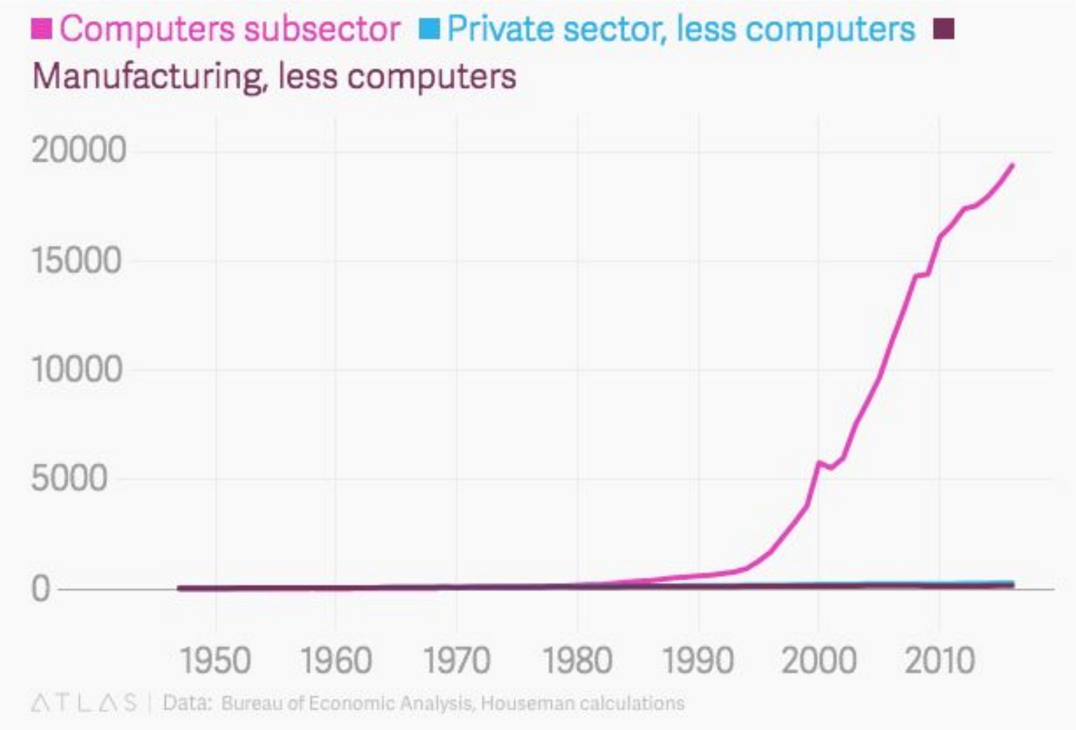
Robots per 10000 manufacturing employees



QUARTZ

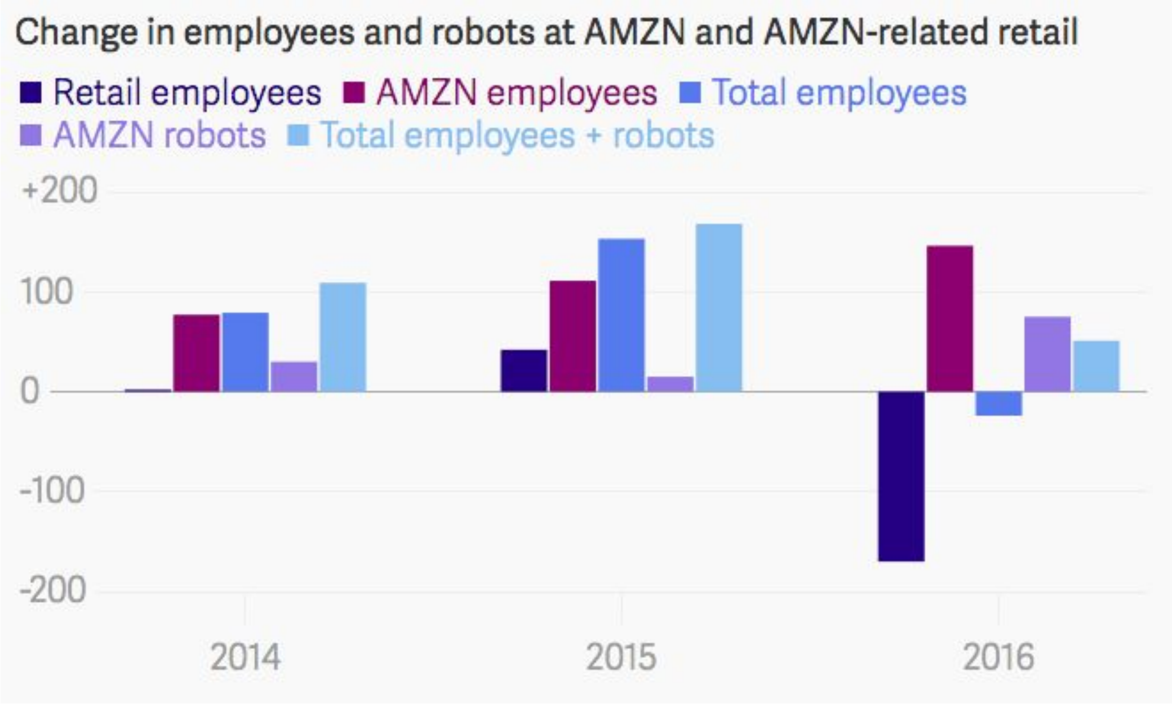
Do huge productivity gains in the computer sector mask stagnation in U.S. manufacturing?

Real output growth for manufacturing with and without the computers subsector



QUARTZ

One recent piece of analysis found that while Amazon is rapidly hiring people and robots, taken as a whole retail is losing jobs



QUARTZ

If automation does reduce net employment and/or wages what new policies will emerge?

Universal Basic Income (UBI) or Basic Income

➔ Has received substantial media coverage over the past years. We review various trials that are now being rolled out

Universal Basic Services (UBS)

➔ A less mainstream idea that was recently fleshed out by the Institute for Global Prosperity at UCL. We highlight the proposal as an interesting new alternative or complement to UBI.

Basic Income trials roll out

‘Basic Income’ aims to mitigate technological unemployment with guaranteed payments to cover basic needs

- ➔ **Finland’s** basic income trial is running with 2,000 randomly selected participants receiving €560 per month. Will conclude in December 2018. Analysis of the effects will take place in 2019.
- ➔ **Ontario** basic income pilot began enrolling participants in April 2018. Will be restricted to 4,000 lower income participants.
- ➔ Five municipal experiments in the **Netherlands** with basic income commenced in late 2017.
- ➔ **Barcelona** launched B-MINCOME experiment in October 2017 with 2000 low income households.
- ➔ US Charity GiveDirectly launched trial in **Kenya** in November 2017. More than 21,000 people will eventually receive some type of cash transfer, with more than 5,000 receiving a long-term basic income.
- ➔ Y Combinator research published proposal for randomised control trial with 3000 adults in the **United States**

Universal Basic Services proposed by UCL researchers

- **‘Universal Basic Services’ (UBS) would build on existing state provision of services**

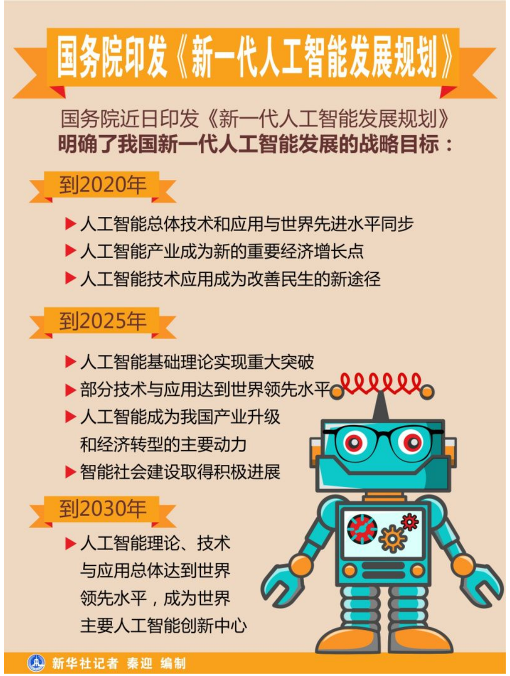
  Seeks to expand public services (e.g. a National Health Service) to other major categories of consumer spend (transport, food, shelter). Interesting model for countries with a meaningful welfare state.

+ 4 UBS	Shelter	Food	Transport	Information	UBS TOTAL
Definition	1.5 million new social housing units @ zero rent + Council Tax exemptions + utilities	Food insecurity 1.8 billion meals (7 meals/week)	Free local public transport	Basic cell phone, home Internet, BBC TV license	
Cost	£13.0 Bn	£4.0 Bn	£5.2 Bn	£19.9 Bn	£42.16 Bn
D1 effect	£39.48 / week	£24.88 / week	£2.44 / week	£5.43 / week	£83.23 / week
User value	£86.87 / week	£12.96 / week	£21.20 / week	£5.43 / week	£126.46 / week
UBI equiv	£3.85 / week	£1.19 / week	£1.54 / week	£5.88 / week	£12.47 / week

AI Nationalism: flurry of National AI strategies announced

China 2030 (announced July 2017)

- ➔ Partly a reaction to Obama White House report on AI (in 2016)
- ➔ New state funded $2.1 billion AI park in Beijing
- ➔ Call for researchers to be making major breakthroughs by 2025
- ➔ By 2030, China will “become the world’s premier artificial intelligence innovation center and foster a new national leadership and establish the key fundamentals for an economic great power.”
- ➔ Baidu announces new lab in collaboration with Chinese government
- ➔ Goal: to build a $150 billion AI industry by 2030



AI Nationalism: flurry of National AI strategies announced

French AI Strategy (announced March 2018)

- “My goal is to recreate a European sovereignty in AI” - Macron
- €1.5 billion committed over 5 years
- New AI research centres in Paris opened by Facebook, Google, Samsung, DeepMind, Fujitsu
- Plan to open up of data collected by state-owned organizations such as France’s centralized healthcare system
- Separately, France announces that foreign takeovers of AI companies will be subject to government approval

AI Nationalism: flurry of National AI strategies announced

South Korea (announced March 2016 & May 2018)

- ➔ Expands the existing 2016 AI plan to $2 billion through 2022
- ➔ Announces 6 new AI institutes
- ➔ Plan to award 4,500 domestic AI scholarships by 2022
- ➔ $1 billion fund for semiconductors through 2029
- ➔ Overall goal to reach “the global top 4 by 2022”

AI Nationalism: flurry of National AI strategies announced

European Commission plan (announced April 2018)

- ➔ Called for €20 billion investment
- ➔ Pledged to increase spending to €1.5 billion through 2020 via EU research programme Horizon 2020
- ➔ Commits to presenting ethical guidelines on AI by end 2018
- ➔ Plan to update rules on use of public sector data to train ML systems

AI Nationalism: flurry of National AI strategies announced

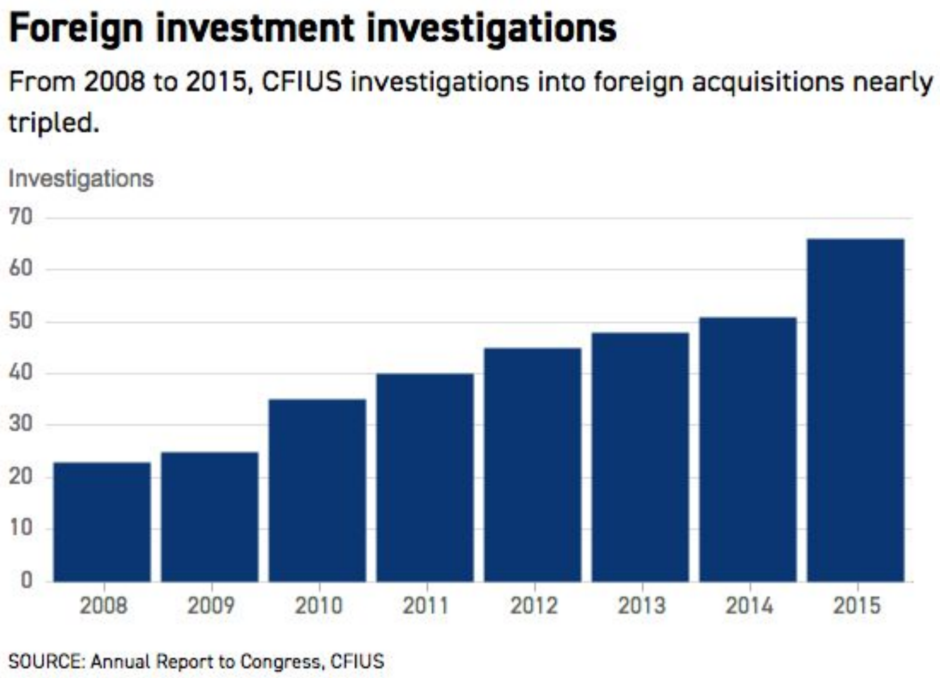
U.K. AI Sector Deal (announced April 2018)

- ➔ Government committed to train 8000 computer science teachers and fund 1000 AI-related PhDs by 2025
- ➔ £603 million in newly allocated government funding and £300 million in matched private sector funding
- ➔ Investment of £93 million in robotics and AI in extreme environments challenge (for use in industries like nuclear energy and space)

For now, US leads China on almost every measure other than data

Main Driver in AI	Proxy Measure(s)	China	USA
Hardware	Int'l market share of semiconductor prod. (2015)	4% of world	50% of world
	Financing for FPGA chip-makers (2017)	USD 34.4 million (7.6% of world)	USD 192.5 million (42.4% of world)
Data[a]	Mobile users (2016)[b]	1.4 billion (20.0% of world)	416.7 million (5.5% of world)
Research and Algorithms	Number of AI experts	39, 200 (13.1% of world)	78,700 (26.2% of world)
	Percentage of AAAI Conference Presentations (2015)[c]	20.5% of world	48.4% of world
Commercial AI Sector	Proportion of world's AI companies (2017)	23%	42%
	Total investments in AI companies (2012-2016)	USD 2.6 billion (6.6% of world)	USD 17.2 billion (43.4%)
	Total global equity funding to AI startups (2017)	48% of world	38% of world

America increasingly using the Committee on Foreign Investment in the United States (CFIUS) to scrutinise foreign acquisitions



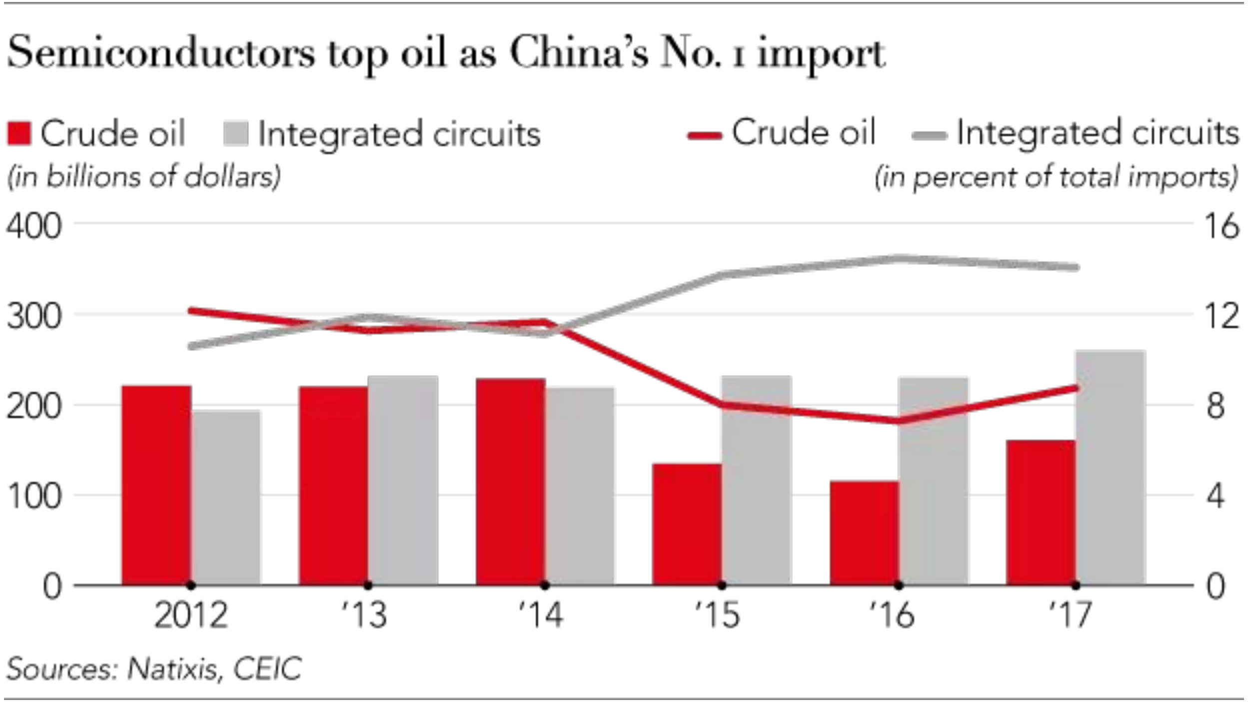
CFIUS used to block two key semiconductor acquisitions in the last year

Trump Blocks Broadcom's Bid for Qualcomm

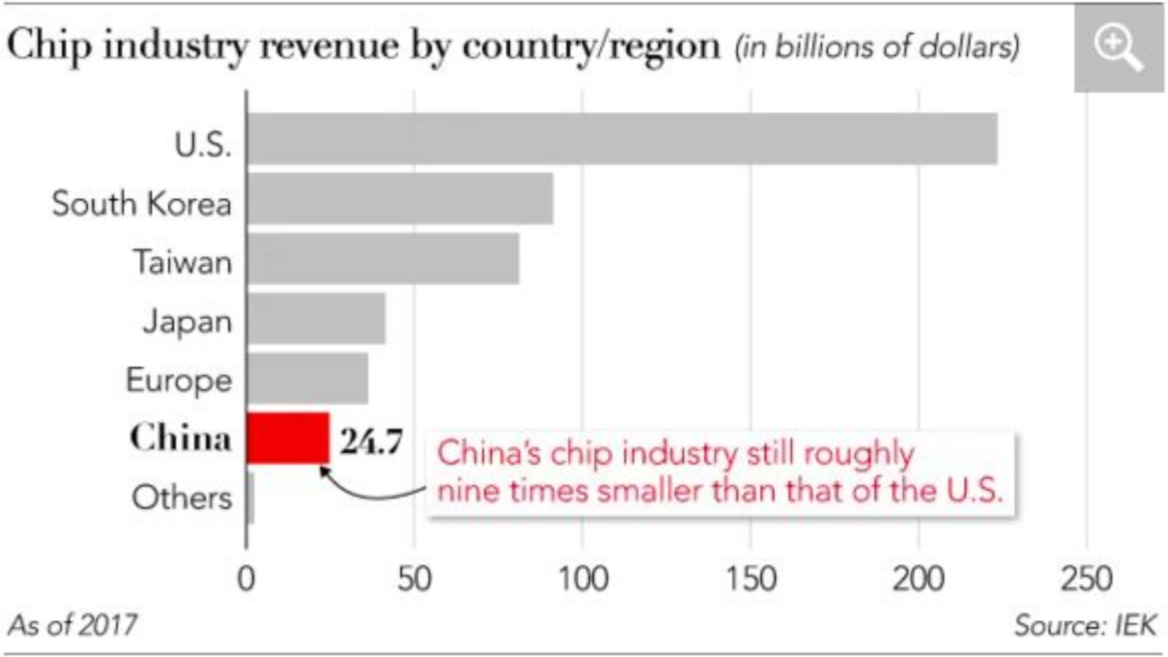
Trump Blocks China-Backed Bid to Buy U.S. Chip Maker

Lattice Semiconductor offices in San Jose, Calif., in 2007. President Trump prevented the acquisition of Lattice by an investor group with ties to Beijing. Eugene Zelenko

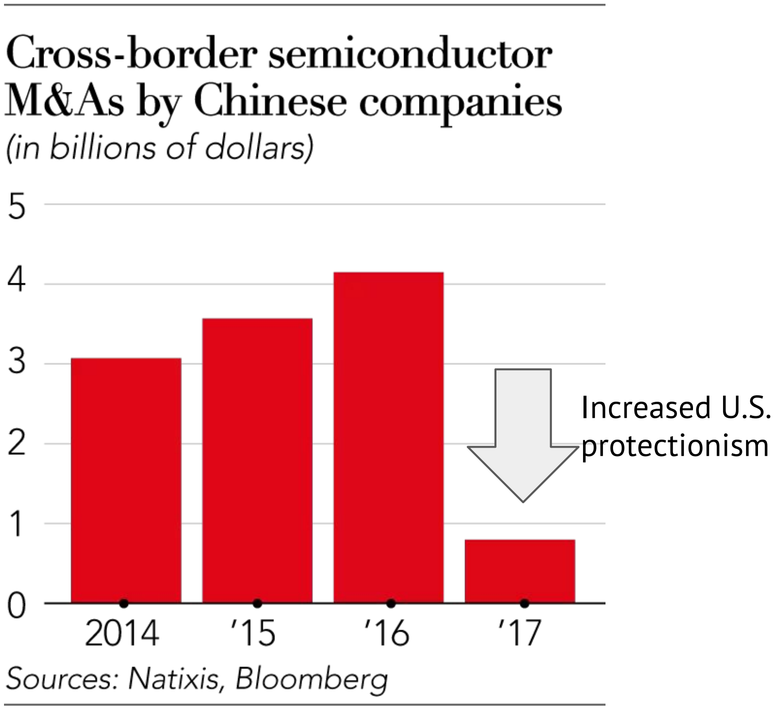
Why: China's annual imports of semiconductors have risen to $260 billion



Why: China's semiconductor industry is small compared to that of the U.S.



Why: China has been actively acquiring foreign semiconductor companies



Fake views: Generating synthetic video is getting cheaper, easier and more realistic

- ➔ This has very significant implications for enabling those who are engaged in producing disinformation and propaganda.

Section 5: Predictions

8 predictions for the next 12 months

1. A lab located in China makes a significant research breakthrough.
2. DeepMind has a breakthrough result successfully applying RL to learn how to play Starcraft.
3. Deep learning continues to dominate the discussion without major alternatives appearing.
4. The first therapeutic drug discovered using machine learning produces positive results in trials.
5. Chinese and American headquartered technology companies make acquisitions of machine learning companies based in Europe totalling over $5b.
6. The government of an OECD country blocks the acquisition of a leading machine learning company (defined as valuation >$100m) by a US or Chinese headquartered technology company.
7. Access to Taiwanese and South Korean semiconductor companies becomes an explicit part of the trade war between America and China.
8. A major research institution “goes dark” by refraining from publishing key work in the open due to geopolitical concerns.

Section 6: Conclusion

Thanks!

Congratulations on making it to the end! Thanks for reading.

In this report, we set out to capture a snapshot of the exponential progress in the field of machine learning, with a focus on developments in the past 12 months. We believe that AI will be a force multiplier on technological progress in our world, and that wider understanding of the field is critical if we are to navigate such a huge transition.

We tried to compile a snapshot of all the things that caught our attention in the last year across the range of machine learning research, commercialisation, talent and the emerging politics of AI.

Thanks to Mary Meeker for the inspiration.

We would appreciate any and all feedback on how we could improve this report further. Thanks again for reading!

Nathan Benaich (@nathanbenaich) and Ian Hogarth (@soundboy)

Conflicts of interest

The authors declare a number of conflicts of interest as a result of being investors and/or advisors, personally or via funds, in a number of private and public companies whose work is cited in this report. This concerns the following companies:

Startups

GTN.ai, TwentyBN, Kheiron Medical, Accelerated Dynamics, Avidbots, Optimal Labs, Ravelin, Tractable, LabGenius, and Mapillary.

Public companies

Alphabet, NVIDIA, Facebook, Microsoft, Intel, Baidu, Amazon, and Alibaba.

State of AI

June 29, 2018