

The History and Development of Machine Learning

Lecture Series in Artificial Intelligence & Machine Learning

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Topics Covered in Today's Lecture

- A. Machine Learning in the Context of Artificial Intelligence (AI)
- B. The Connectionists: Artificial Neural Networks (ANN's), Machine Learning (ML) and Deep Learning (NN)
- C. Three Pillars of Machine Learning: Data, Algorithms & Processing Power
- D. Machine Learning Today: Progress, State-of-the-Art & Challenges



Part A

Machine Learning in the Context of Artificial Intelligence (AI)

What is Machine Learning?

*"... a field of study that gives **computers** the ability to learn without being explicitly programmed"*

(- Arthur Samuel, 1959)

*"... the study of **computer algorithms** that allow computer programs to automatically improve through experience"*

(- Tom Mitchell, 1997)

*If you want to learn more about ML, check out the really excellent online lectures by Andrew Ng**

* https://www.youtube.com/playlist?list=PLssT5z_DsK-h9vYZkOkYNWcItahIRJLN

Artificial Intelligence



Completing tasks which normally require human level intelligence

Machine Learning



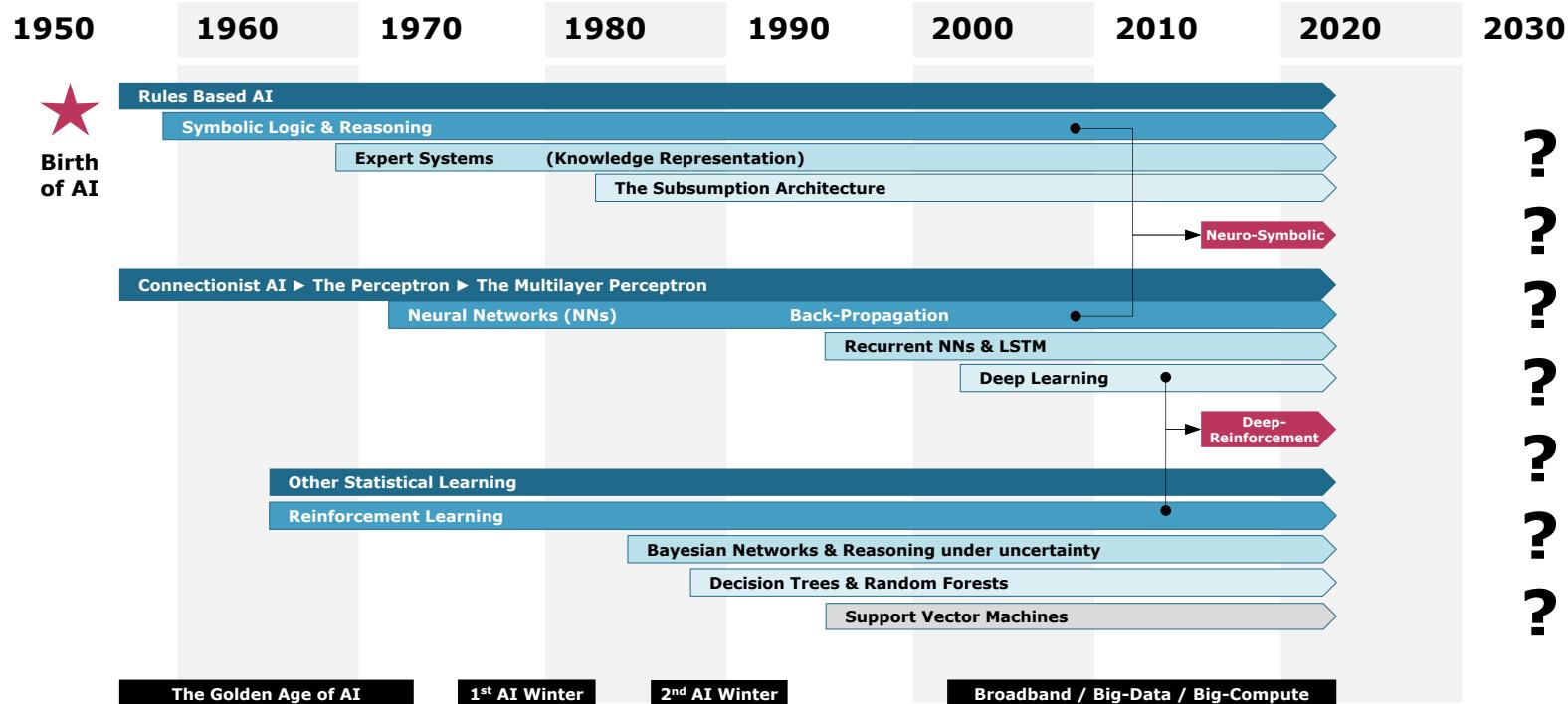
Statistical methods enabling machines improve with experience

Deep Learning



Many-layered learning-networks progressively extracting higher level features from raw input

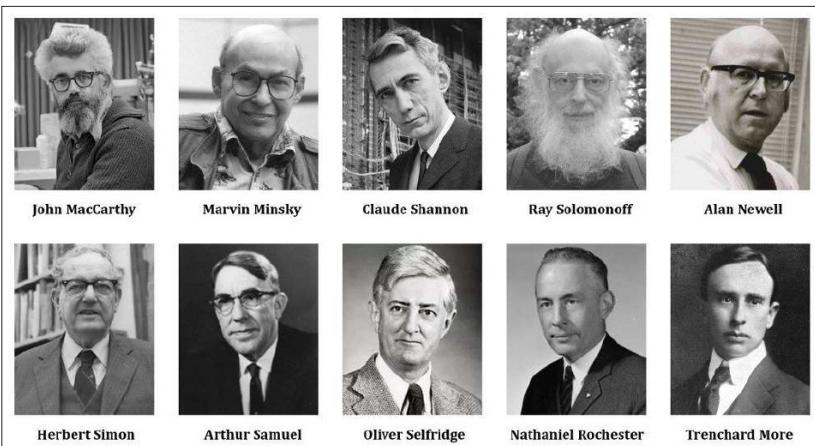
A Brief History of AI / ML



The Origins of AI

- 1945** Worlds first programmable computer: ENIAC
- 1950** Alan Turing: **The Turing Test**. Can a machine pass itself off as a human in its responses?
- 1956** **Dartmouth conference:** official birth of AI
- 1960's** The Golden Years: Interpret the human brain as a machine

Dartmouth 1956 - The Founding Fathers of AI



"The study [of AI] is to proceed on the basis of conjecture that every aspect of learning or any other feature of intelligence can be so precisely described that a machine can be made to simulate it"

The Golden Years: Logic & Reasoning

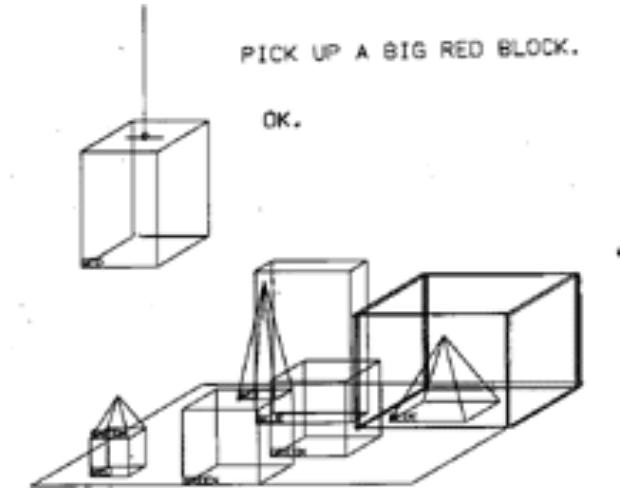
1956 Newell & Simon : 38 [Proofs](#)
from Principia Mathematica

1963 DARPA gives MIT \$2.2M for
machine aided cognition

1964 IBM [Handwriting Recognition](#)
Demo at NY World Fair
Write Date → Get Headlines
Translate English Russian texts

1967 Marvin Minsky: "Within a
generation, the problem of
creating AI will substantially be
solved"

1970



Terry Winograd (MIT): [Natural language processing](#) for moving
blocks in a Microworld

The First AI Winter

- 1970** Minsky: In 3-8 years we will have a machine with the general intelligence of an average human
- 70-73** AI mainly based on rule-based programming, **fails to deliver** on most promises
- 1973** U.S. and British Governments stop funding undirected AI research
- 74-80** The first **AI Winter**

Shakey, the First “Intelligent” Robot



The Stanford Research Institute 1966-1972

Moravec Paradox: *“It is easy to make computers exhibit adult level performance on intelligence tests or playing checkers, and difficult or impossible to give them the skills of a one-year-old when it comes to perception and mobility”*

The Second Wave: Expert Systems

1970's Research on **Expert Systems** which augments reasoning with **Knowledge**

1980's Large-scale deployment: Two thirds of Fortune 500 companies used the technology in daily business.

1985 Over \$1B Spent on AI research & development by more than 150 companies

Expert Systems: Success Criteria

Problem type criteria

task involves mostly symbolic processing;
test cases are available;
problem task is well-bounded (i.e. taking a few minutes to a few hours to solve);
task is required to be performed frequently;
written materials exist explaining the task;
task requires only cognitive skills;
experts agree on the solutions.

Expert criteria

an expert exists;
the expert is cooperative;
the expert is articulate;
the expert's knowledge is based on experience, facts and judgement;
other experts exist in the task.

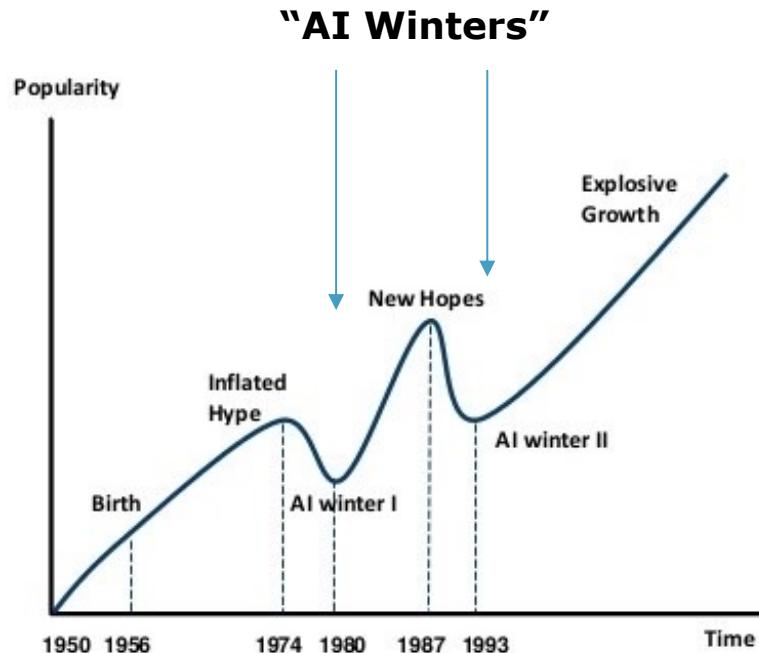
Domain area personnel criteria

a need exists for developing an expert system for that task;
the task would be provided with the necessary financial support;
top management supports the project;
the domain area personnel have realistic expectations on the use of an expert system;
users would welcome the expert system;
the knowledge is not politically sensitive or controversial.

The Second AI Winter

- 1987** Collapse of market for specialized AI hardware (LISP Machines)
- 87-89** DARPA Funding Slashed by one third
- 89-92** Most deployed systems fall into disuse

Steven Pinker "The main lesson of the first 35 years of AI research is that the hard problems are easy and the easy problems are hard"



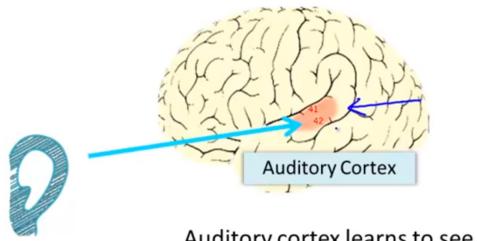
Part B

The Connectionists: Artificial Neural Networks (ANN's), Machine Learning (ML) and Deep Learning (NN)

How do Humans and Animals Learn?

There is a hypothesis that there is **one type of learning**, used by every part of the brain

Example: in animal experiments, when optic nerves are connected to the auditory cortex: the animal **learns to see!**



Auditory cortex learns to see

Example: In 1848 Phineas Gage had a 3-foot rod go through his cheekbone and out the top of his skull. He lived another 11 years and **learned to adapt** to his condition.

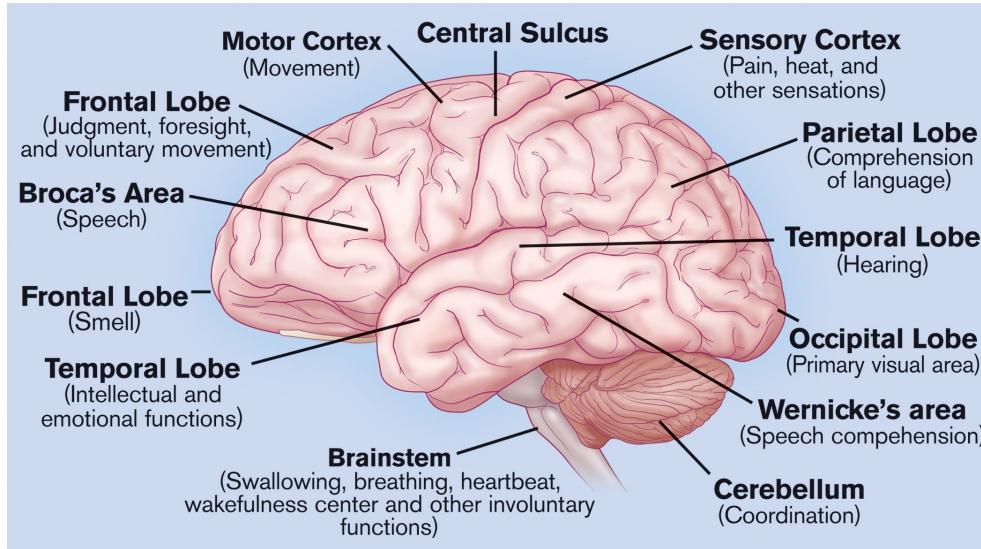


Example: Some blind people **learn to echolocate** like bats, making clicks with their mouths.



Can we explain learning by examining structures in the brain?

The Human Brain



Weight:
1.3 – 1.5kg

Neurons:
~100 Billion ($\sim 10^{11}$)

Connections: ~150 Trillion ($\sim 10^{14}$)

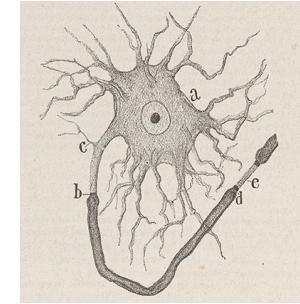
Connectivity:
Each neuron connects to 1k-10k others

All parts of the brain are made of the same neural tissue. It is a highly connected network. The original **Connectionists** believed that this was at the center of human learning and intelligence and they set out to copy it within computers.

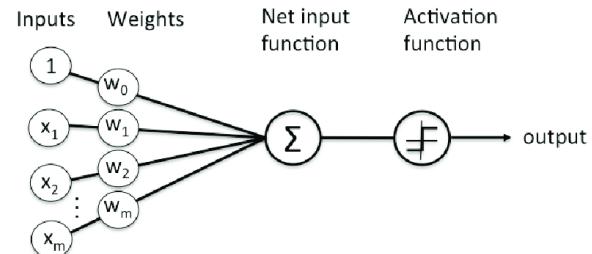
Networks that Learn

- 1887** Santiago Ramón y Cajal at Uni. Barcelona discovers **neurons** as fundamental to the nervous system
- 1943** McCulloch & Pitts **model the neuron as a logic unit**. Show that network of such neurons can do any computation.
- 1949** Donald Hebb conceives an update Rule for **learning**: *Neurons that fire together, wire together.*
- 1958** Frank Rosenblatt takes the ideas into computer research: he invents the **Perceptron**, a single layer **neural network**

Cajal's sketch of a Neuron



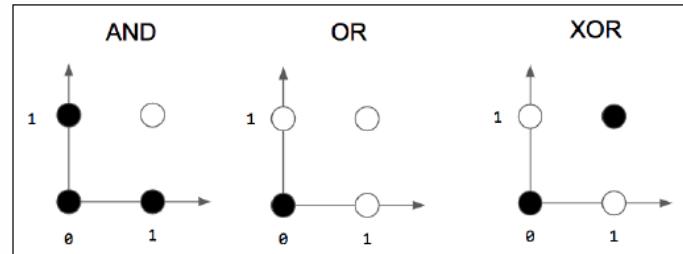
Rosenblatt's Perceptron



The Difficult Birth of Neural Networks

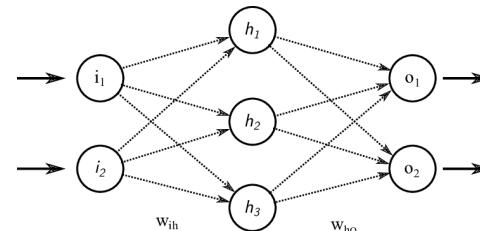
- 1969** Minsky & Papert claim much scientific writing on Perceptrons is **without scientific value**
- 70's** Rosenblatt dies. Rule-based programming dominates. Funding crashes. First AI-Winter.
- 80's** **Neural networks** show promise and make comeback. By '91 there are >10k NN researchers in the U.S. alone.
- 1987** Yann LeCun proposes modern form of **back-propagation** learning algorithm for ANNs
- 1993** The Second AI Winter! ☹

*The perceptron is a supervised binary linear classifier.
Can you separate two groups using a straight line?*



AND, OR are linearly separable; XOR is not

Neural networks with hidden layers can implement non-linear classification



Deep Learning and the AI Boom

- 2005** Geoffry Hinton exposes internal function of multi-layered Neural networks with many hidden units
- 2010** Affordable GPUs give boost to large Neural Networks
- 2015** Machines outperform humans at image recognition. Facebook launches DeepFace (9 layers, 120M params)
- 2016** AlphaGo from DeepMind beats world champion Lee Sodol at Go
- 2020** Open-AI releases GPT-3 language model with 175 Billion parameters

Turing Award 2018

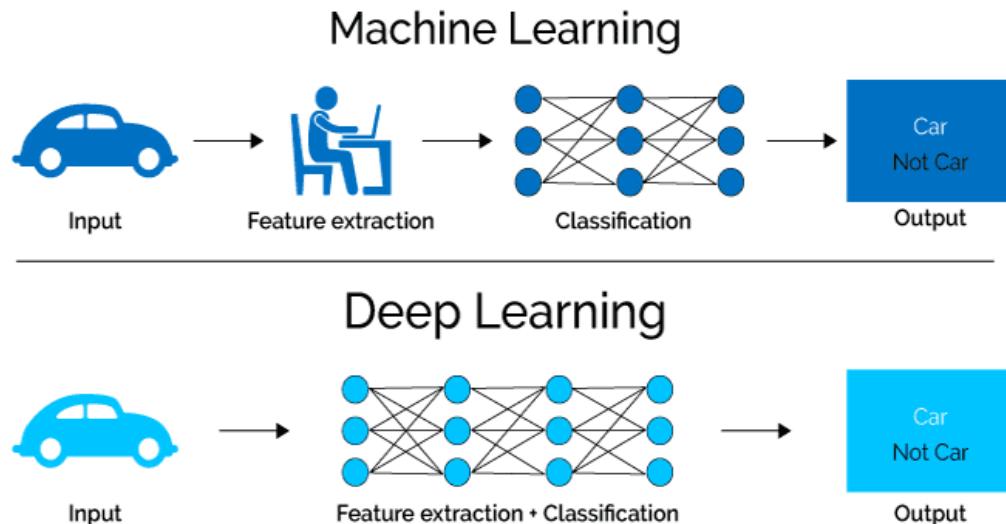


Key Contribution:
Generative Adversarial Networks

Key Contribution:
Backpropagation allows NNs discover their own internal representations of data

Key Contribution:
Convolutional Neural Networks

Deep Learning Using Many Layers



The core idea of deep learning is to exploit the ability of large neural networks to learn features within the data relevant to the task at hand

To do this we need lots of data, sophisticated algorithms and lots of processing power

PART C

Three Pillars of Machine Learning: Data, Algorithms & Processing Power

How Much Data is Generated Every Day?

- 100 Million Uploads to Instagram
- 500 Million Tweets on Twitter
- 3.5 Billion Photos Taken
- 5 Billion Web Searches
- 65 Billion Messages on Whatsapp
- 300 Billion Emails

This is mostly well known consumer data. There are also vast amounts of business data being captured in digitalization programs and other public data being captured by government agencies.

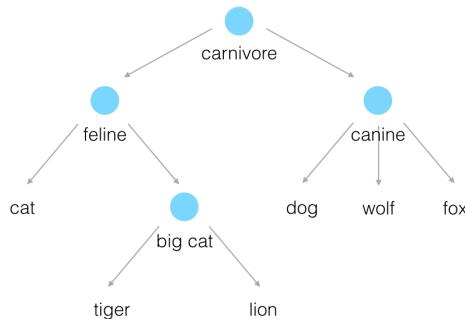
- **Machine learning algorithms can be trained to higher performance levels with labelled data.**
- **This is more expensive, and far more scarce than typical unstructured and unlabeled data**
- **But large, open-source, labelled data sets are available...**

Example: Open Source Image Data

ImageNet



- Biggest and best known, out of Stanford
- **14M labelled images**
- 1 Million images with bounding box notations
- 22k image categories,



Coco Dataset



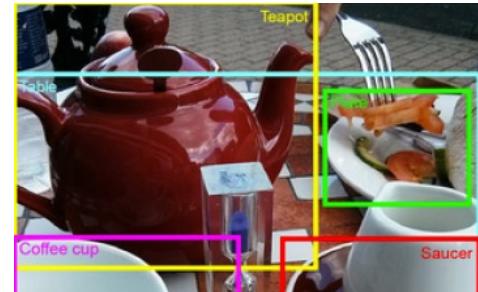
- **Common Objects in Context:** backed by Microsoft and Facebook
- A large-scale object detection, segmentation, and captioning dataset
- **~200k labelled images**



Open Images



- Released by Google
- **~9M labelled images**
- object bounding boxes
- object segmentation
- visual relationships



Open Source Algorithms Are Also Available

Tensorflow

Google's TensorFlow is JavaScript-based and comes equipped with a wide range of tools and community resources that facilitate easy training and deploying Deep Learning



TensorFlow

Pytorch

Open-source DL framework from **Facebook**. Designed to speed process from prototyping to production. It has a C++ frontend atop a Python interface



Sonnet

Developed by **DeepMind**, Sonnet is a high-level library designed for building complex neural network structures in TensorFlow.



Sonnet

Keras

Keras is fast and open source!. It can process massive volumes of data while accelerating the training time for models. Provides a Python interface to the TensorFlow library.



Keras

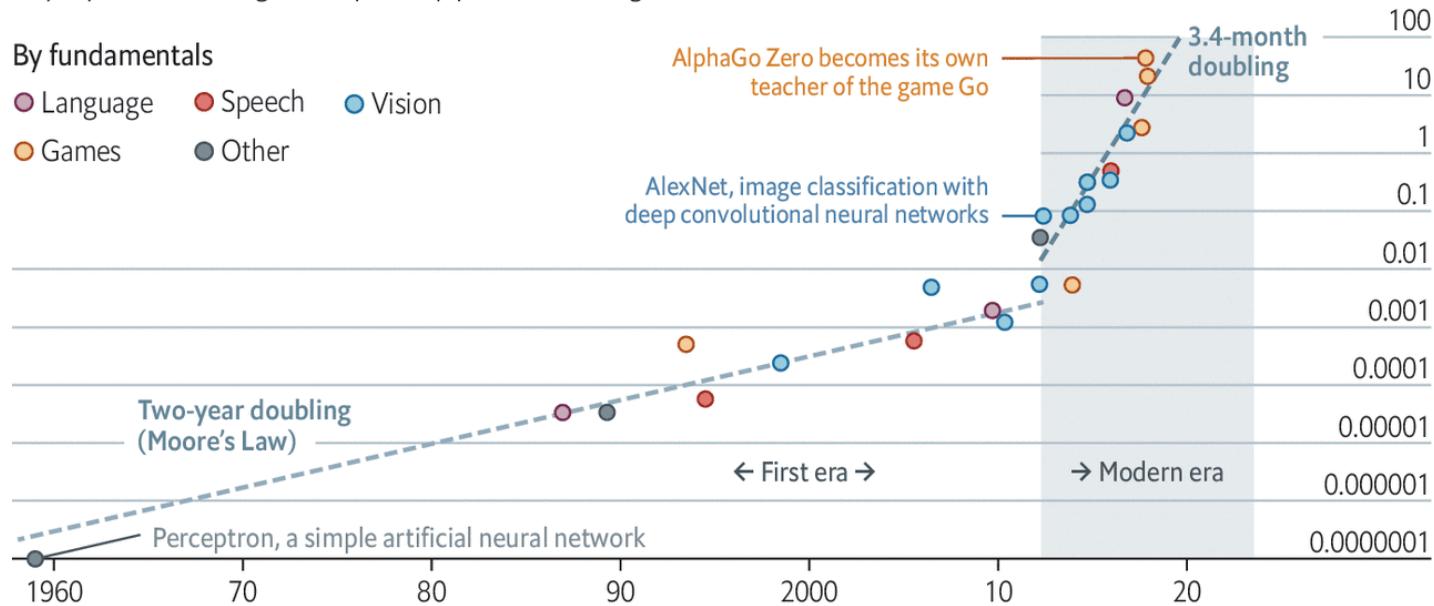
There are many more frameworks. It's worth to check around depending on the needs of your project.

Deep Learning is Hungry for Computation

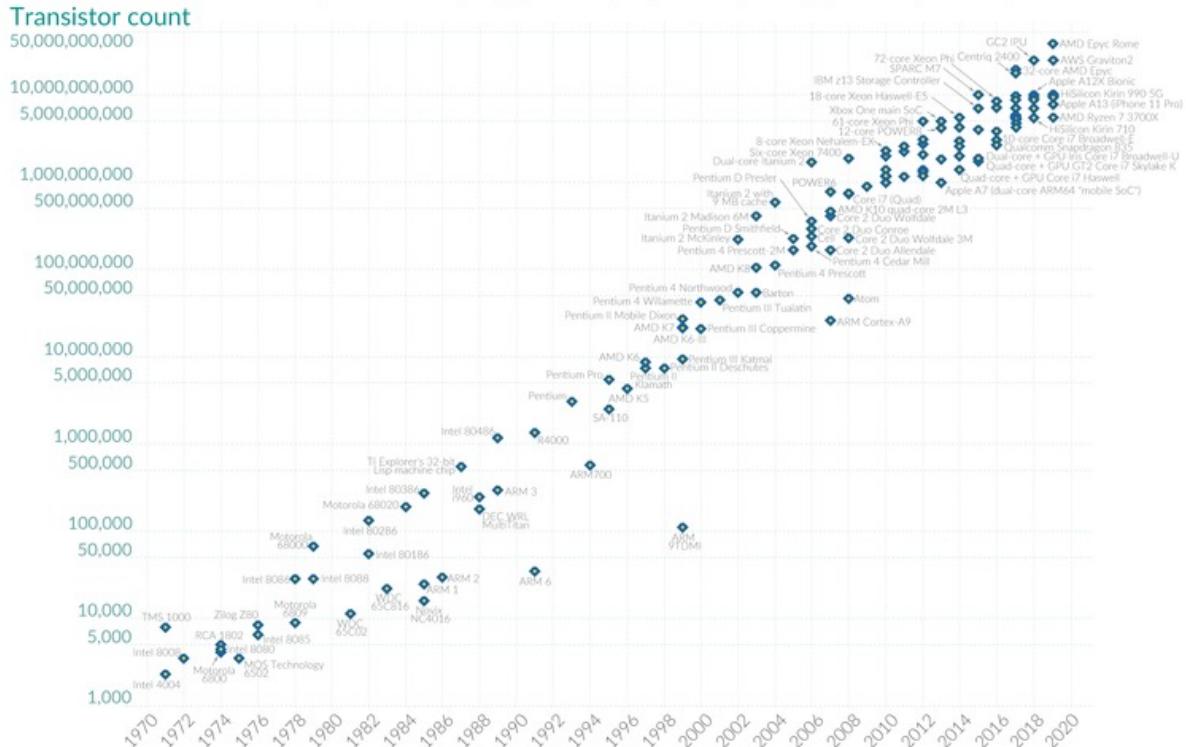
Computing power used in training AI systems
Days spent calculating at one petaflop per second*, log scale

By fundamentals

- Language ● Speech ● Vision
- Games ● Other



Luckily we have Moore's Law



Moore's law is the observation that the number of transistors in a dense integrated circuit (IC) doubles about every two years.

Various Options for Hardware Acceleration

CPU

A **Central Processing Unit** is what you will find in your laptop or PC. General purpose, not so efficient.



E.g. Intel

GPU

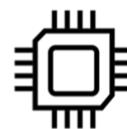
Graphics Processing Unit, well suited for tensor calculations found in neural nets. Widely used.



E.g. NVidia

FPGA

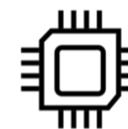
Field programmable gate array. Expensive to program, but lightning fast! Worth it for some applications.



E.g. Xilinx

ASIC

Application specific integrated circuit. Dedicated silicon. Can't be beaten for speed. Very costly!



E.g. Google TPU

Quick and cheap

Development Time

Long and expensive

Long! Runs more slowly

Execution Time

Short! Runs very fast

Graphics Processing Units (GPU's)

	Cores	Clock Speed	Memory	Price	Speed
CPU (Intel Core i7-7700k)	4 (8 threads with hyperthreading)	4.2 GHz	System RAM	\$385	~540 GFLOPs FP32
GPU (NVIDIA RTX 2080 Ti)	3584	1.6 GHz	11 GB GDDR6	\$1199	~13.4 TFLOPs FP32

CPU: Fewer cores, but each core is much faster and much more capable; great at sequential tasks

GPU: More cores, but each core is much slower and “dumber”; great for parallel tasks



VS.



Processing Power Available in the Cloud

Colab

Google Colab allows you to write and execute Python in your browser with zero configuration, free access to GPUs, and easy sharing



AWS

Amazon Web Services enables deep learning in the cloud at scale. You can quickly train custom AI models, with new algorithms.



Azure

GPUs are now part of **Microsoft**'s cloud platform, ideal for the neural networks underpinning much of modern machine learning



IBM Cloud

IBM Cloud offers GPUs on bare metal and virtual servers. Design and deploy neural networks at scale within **IBM Watson Studio**



The international cloud computing landscape is highly dynamic and changing rapidly.
Switzerland has its own national providers such as Switch.ch for universities

Part D

Machine Learning Today:
Progress, State-of-the-Art &
Challenges



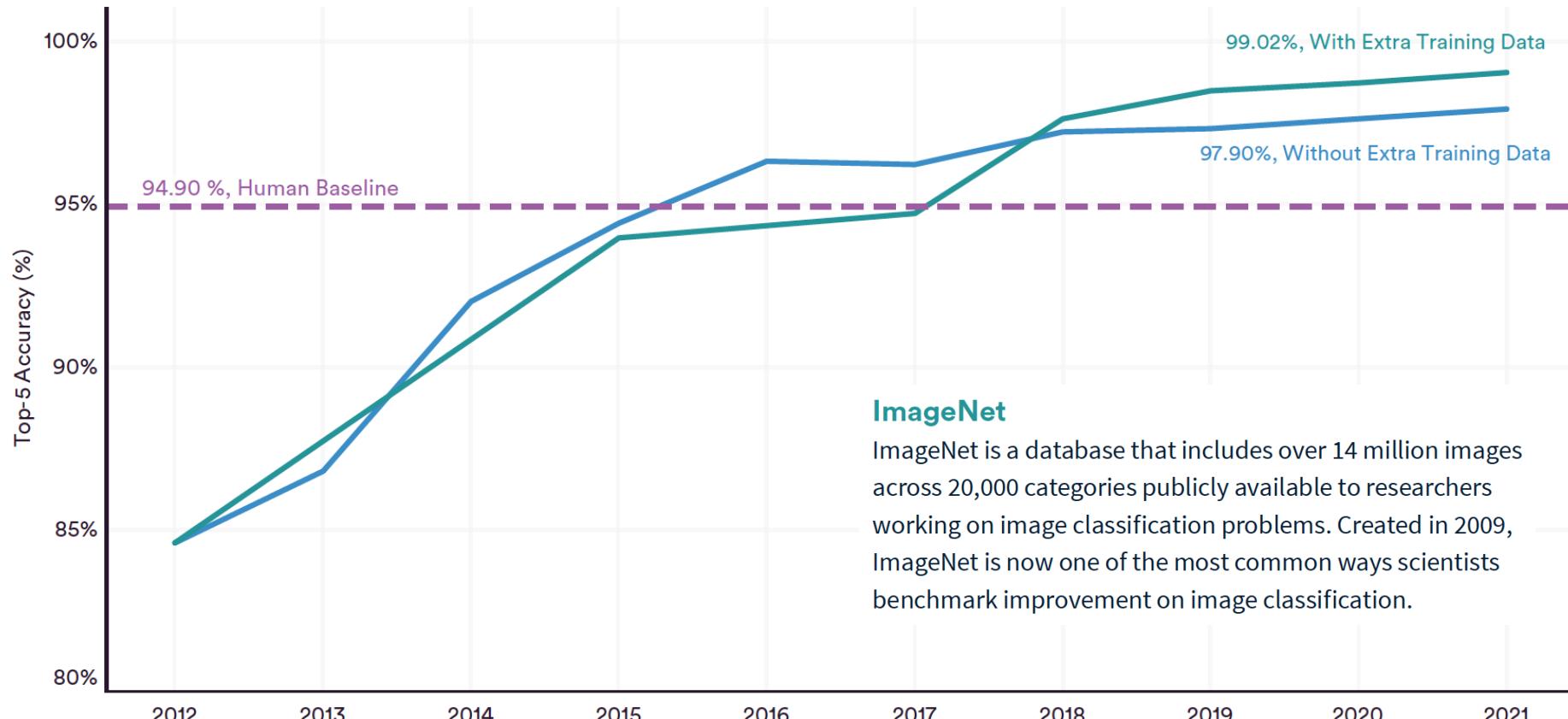
**Artificial
intelligence
is...**

the ability of machines to complete tasks ...
which normally require a human level of intelligence...
better faster and cheaper than humans can



IMAGENET CHALLENGE: TOP-5 ACCURACY

Source: Papers with Code, 2021; arXiv, 2021 | Chart: 2022 AI Index Report



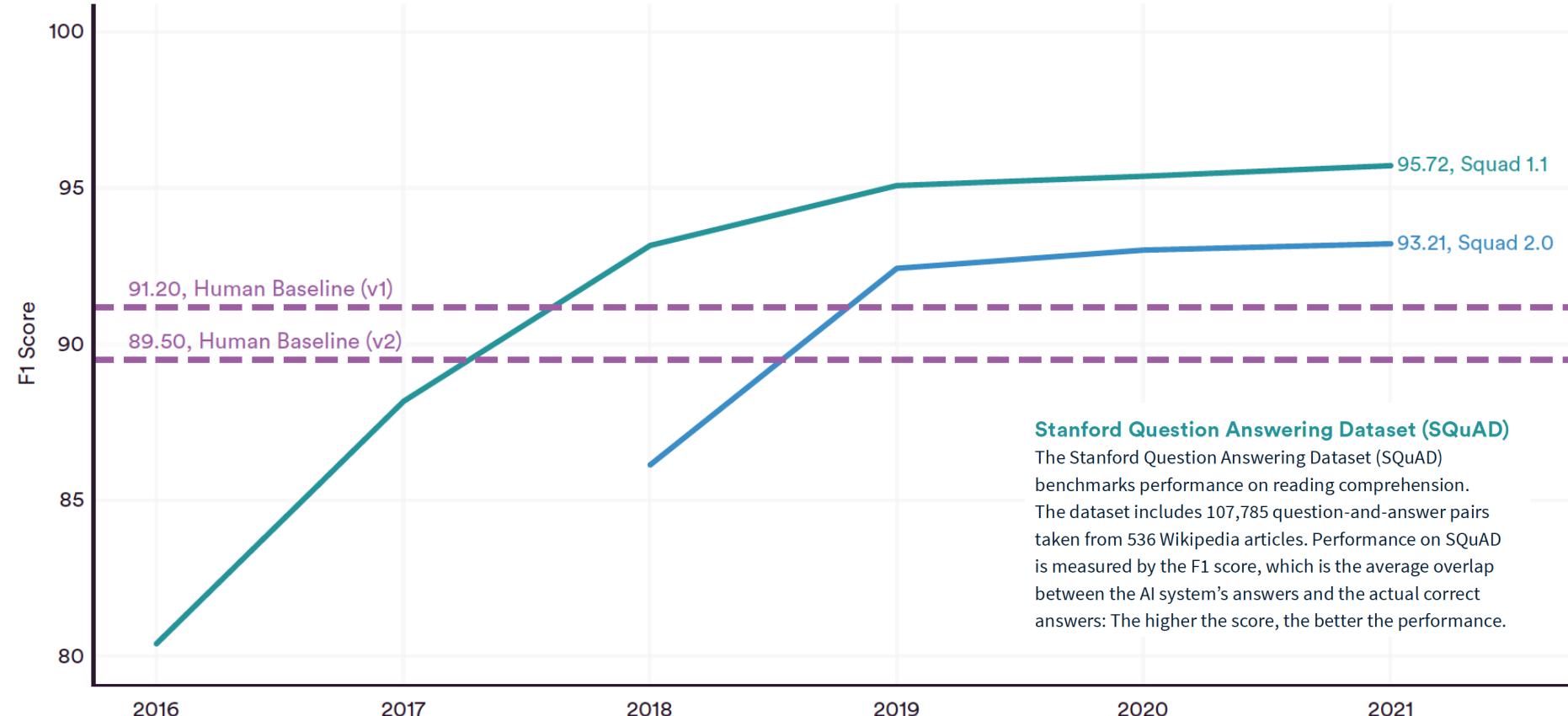
ImageNet

ImageNet is a database that includes over 14 million images across 20,000 categories publicly available to researchers working on image classification problems. Created in 2009, ImageNet is now one of the most common ways scientists benchmark improvement on image classification.

Figure 2.1.3

SQuAD 1.1 and SQuAD 2.0: F1 SCORE

Source: SQuAD 1.1 and SQuAD 2.0, 2021 | Chart: 2022 AI Index Report



Stanford Question Answering Dataset (SQuAD)

The Stanford Question Answering Dataset (SQuAD) benchmarks performance on reading comprehension. The dataset includes 107,785 question-and-answer pairs taken from 536 Wikipedia articles. Performance on SQuAD is measured by the F1 score, which is the average overlap between the AI system's answers and the actual correct answers: The higher the score, the better the performance.

Figure 2.3.4

ABDUCTIVE NATURAL LANGUAGE INFERENCE (aNLI): ACCURACY

Source: Allen Institute for AI, 2021 | Chart: 2022 AI Index Report

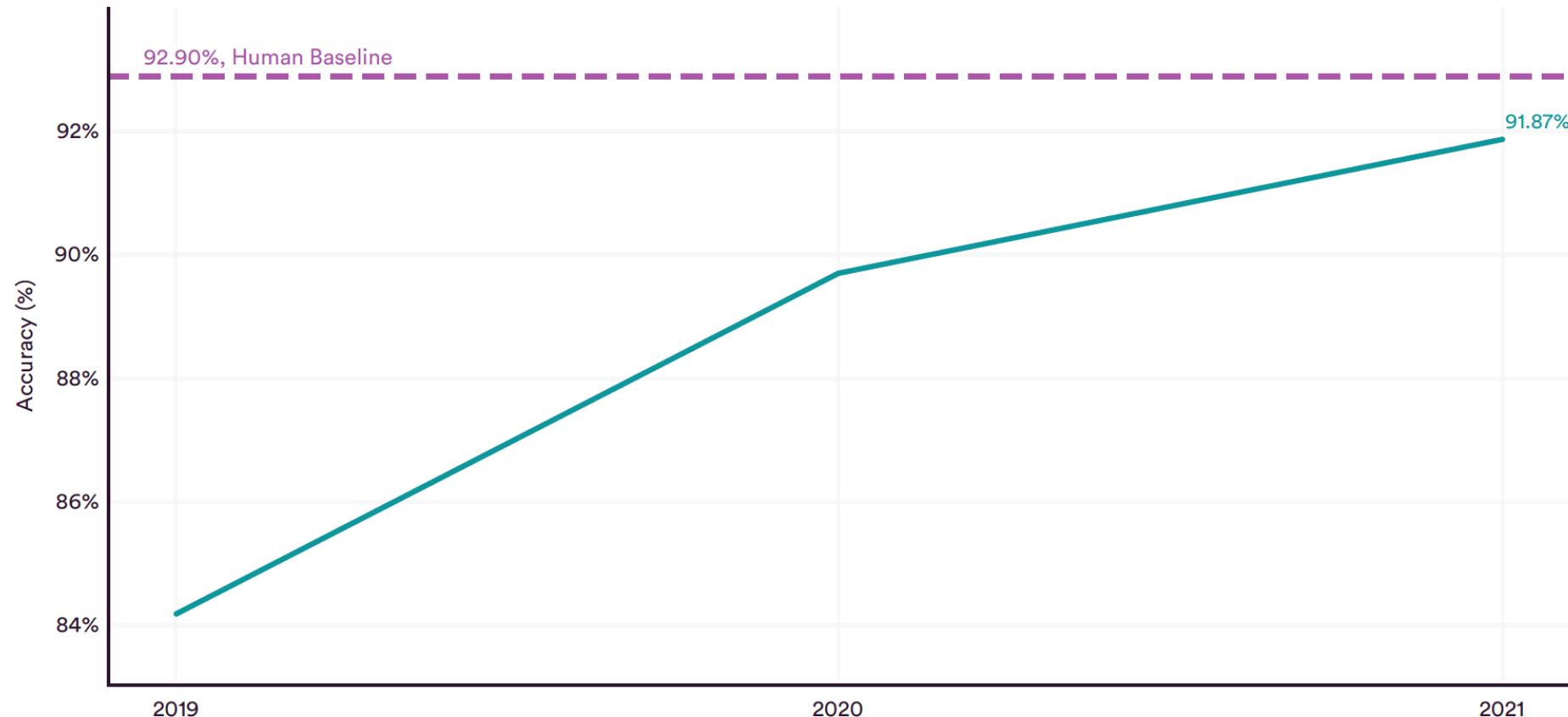


Figure 2.3.12

CHESS SOFTWARE ENGINES: ELO SCORE

Source: Swedish Computer Chess Association, 2021 | Chart: 2022 AI Index Report

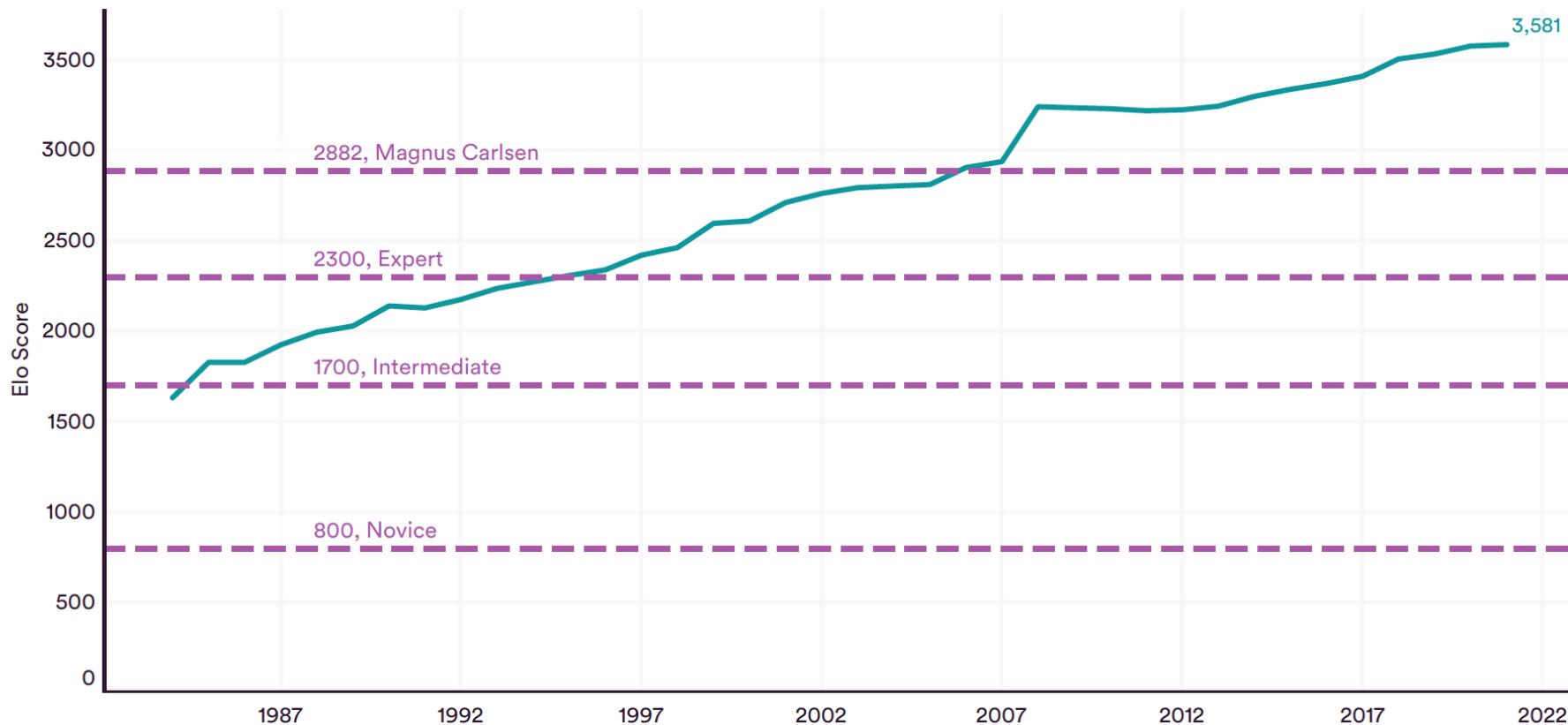


Figure 2.6.4

NUMBER of AI PUBLICATIONS in the WORLD, 2010–21

Source: Center for Security and Emerging Technology, 2021 | Chart: 2022 AI Index Report

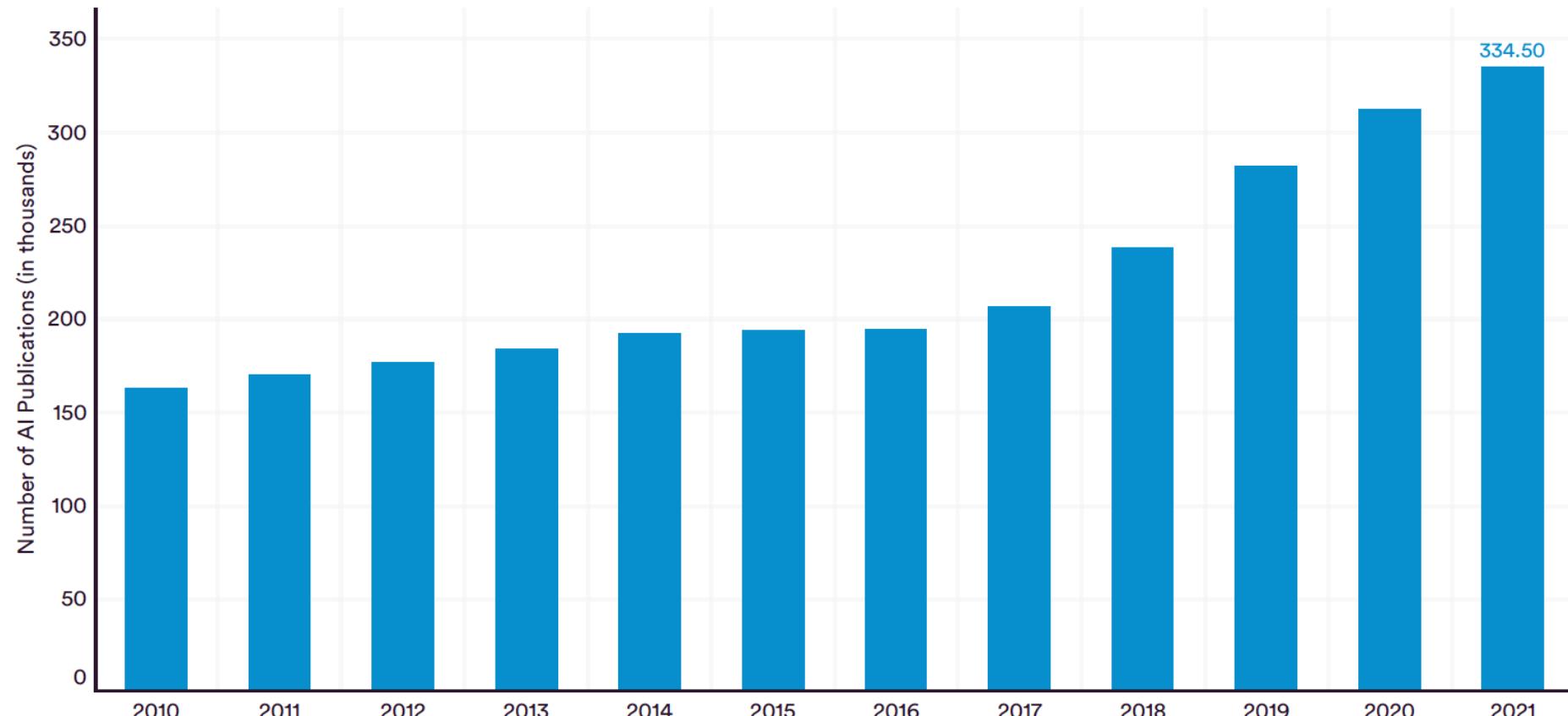


Figure 1.1.1

NUMBER of AI PATENT FILINGS, 2010–21

Source: Center for Security and Emerging Technology, 2021 | Chart: 2022 AI Index Report

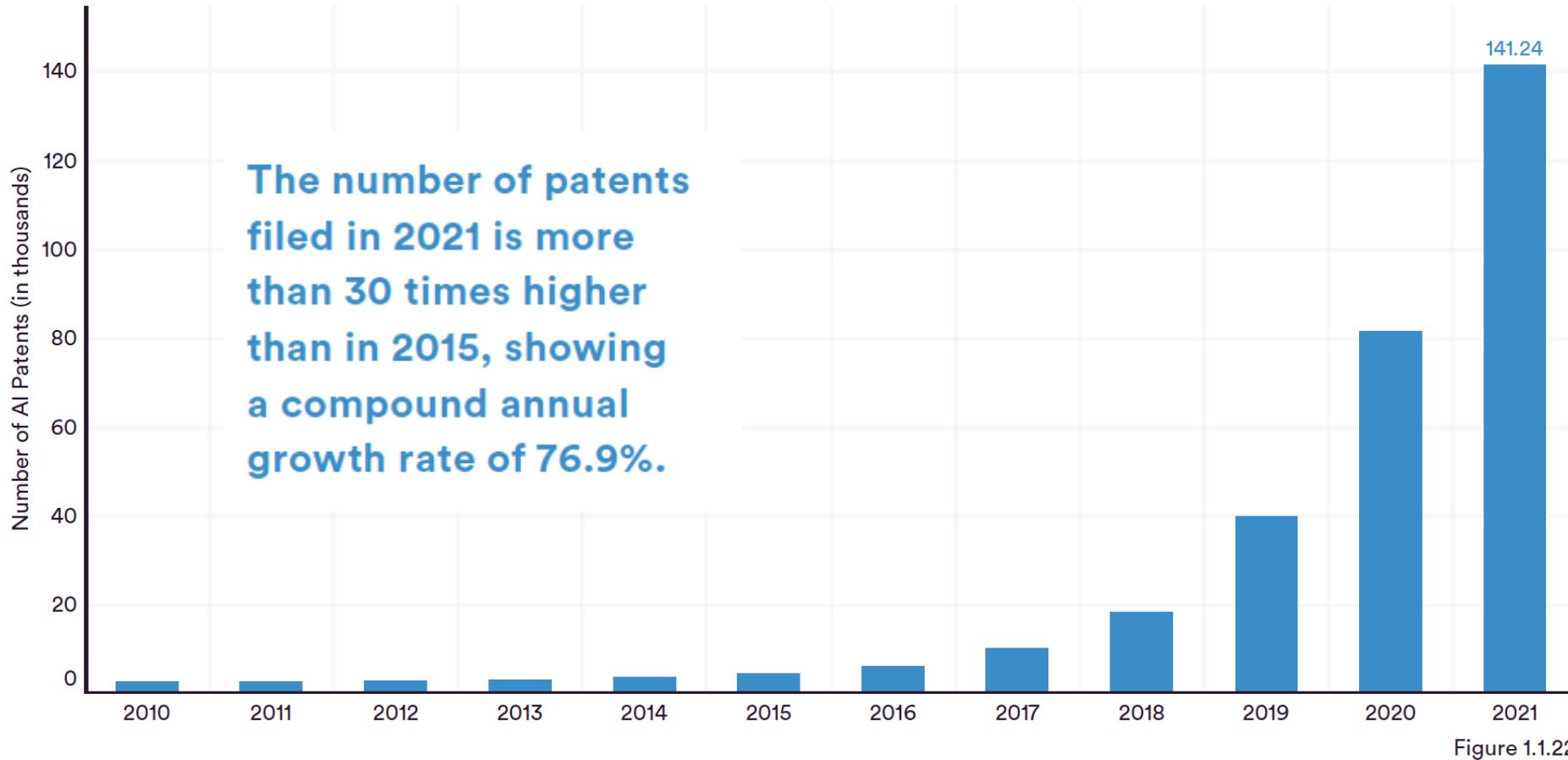
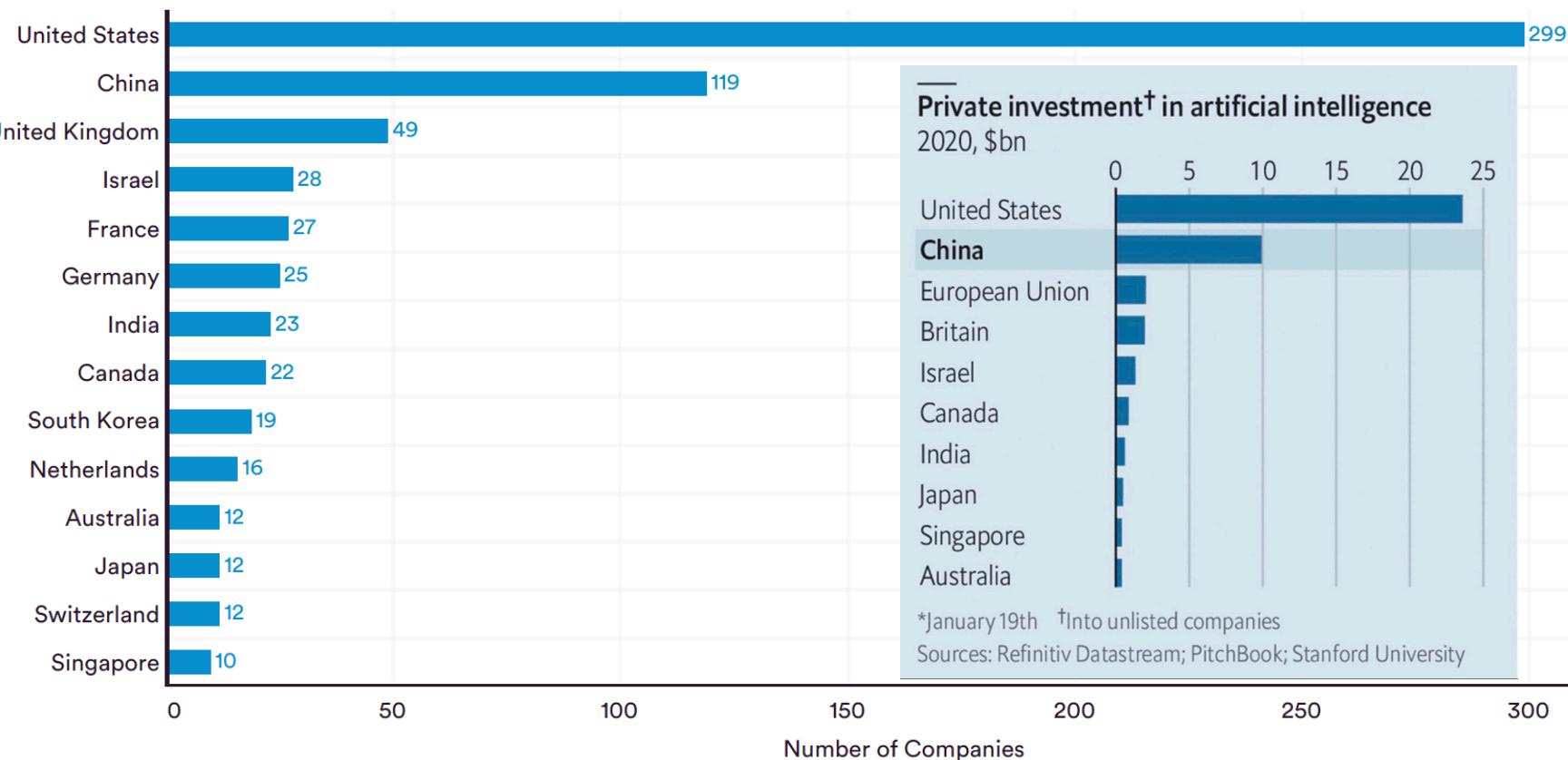


Figure 1.1.22

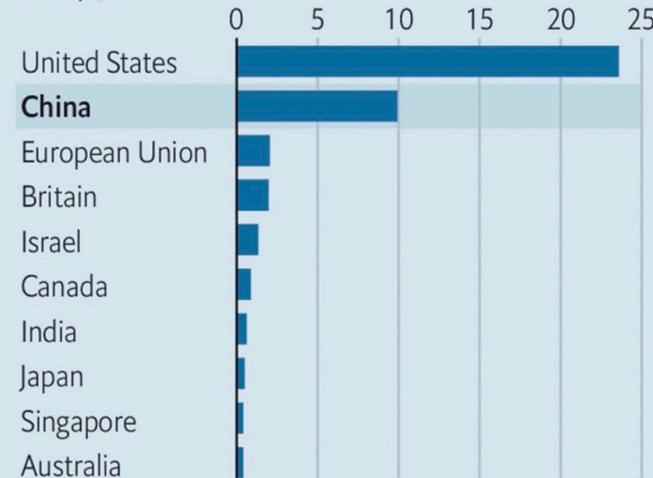
NUMBER of NEWLY FUNDED AI COMPANIES by GEOGRAPHIC AREA, 2021

Source: NetBase Quid, 2021 | Chart: 2022 AI Index Report



Private investment[†] in artificial intelligence

2020, \$bn



*January 19th †Into unlisted companies

Sources: Refinitiv Datastream; PitchBook; Stanford University

GLOBAL CORPORATE INVESTMENT in AI by INVESTMENT ACTIVITY, 2013–21

Source: NetBase Quid, 2021 | Chart: 2022 AI Index Report

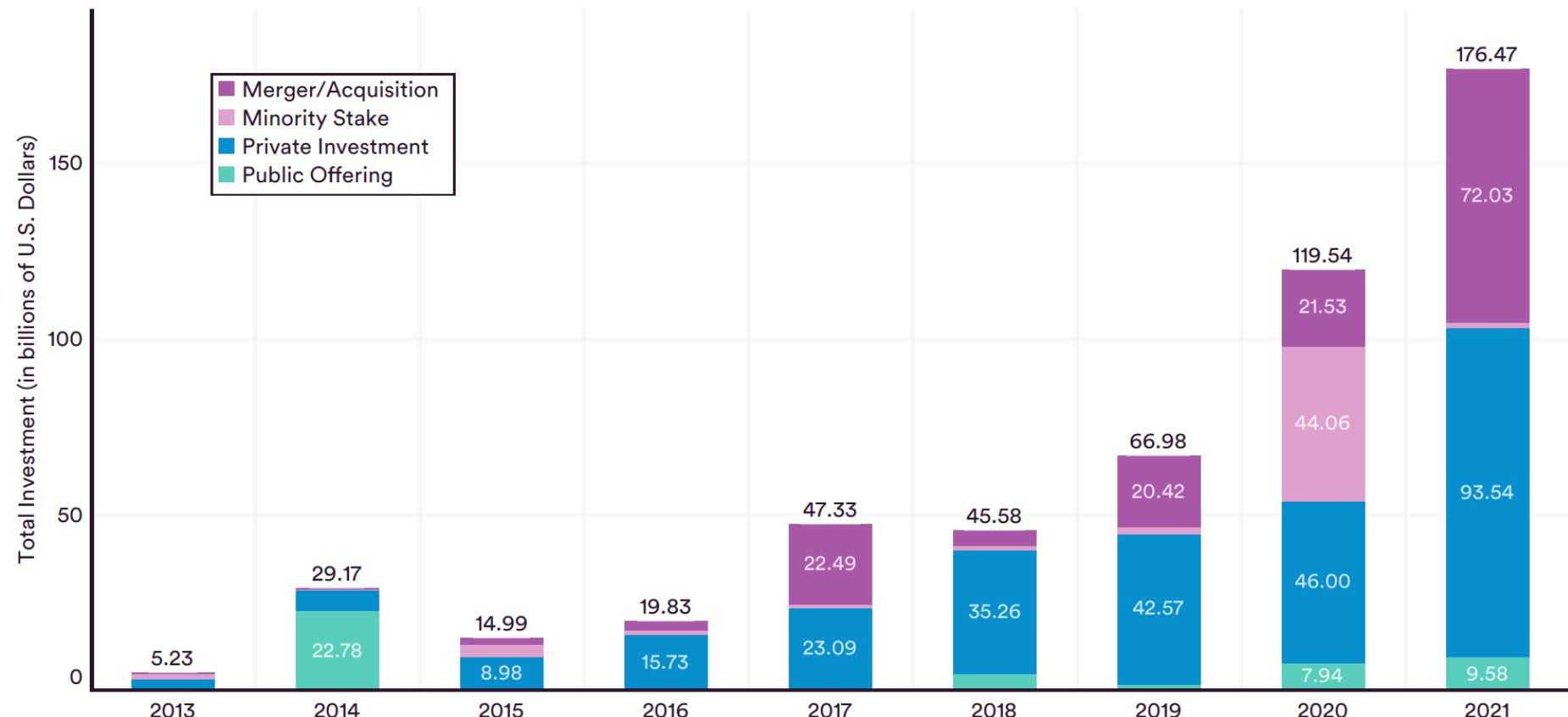


Figure 4.2.1

NUMBER of MENTIONS of AI in LEGISLATIVE PROCEEDINGS in SELECT COUNTRIES, 2021

Source: AI Index, 2021 | Chart: 2022 AI Index Report

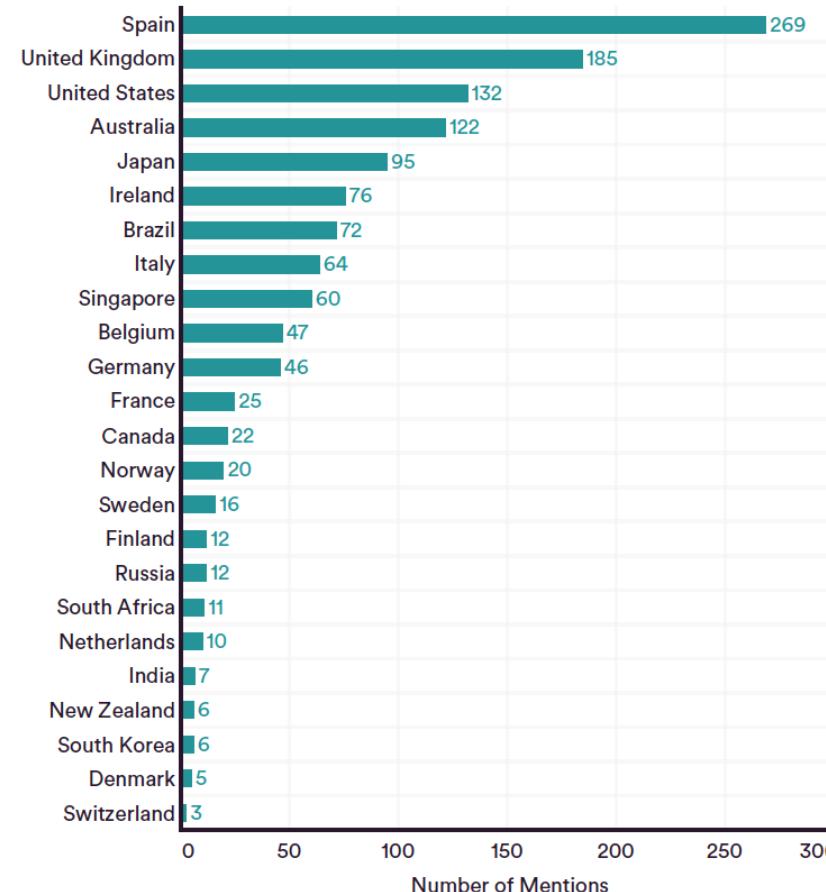


Figure 5.1.10a

NUMBER of MENTIONS of AI in LEGISLATIVE PROCEEDINGS in SELECT COUNTRIES, 2016–2021 (SUM)

Source: AI Index, 2021 | Chart: 2022 AI Index Report

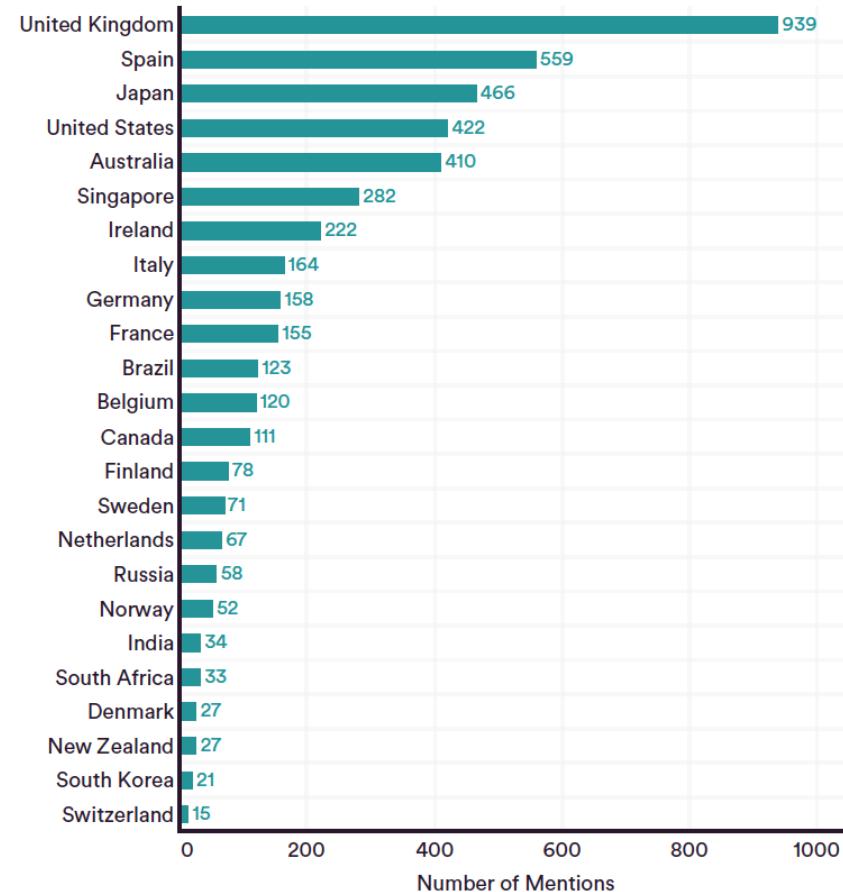


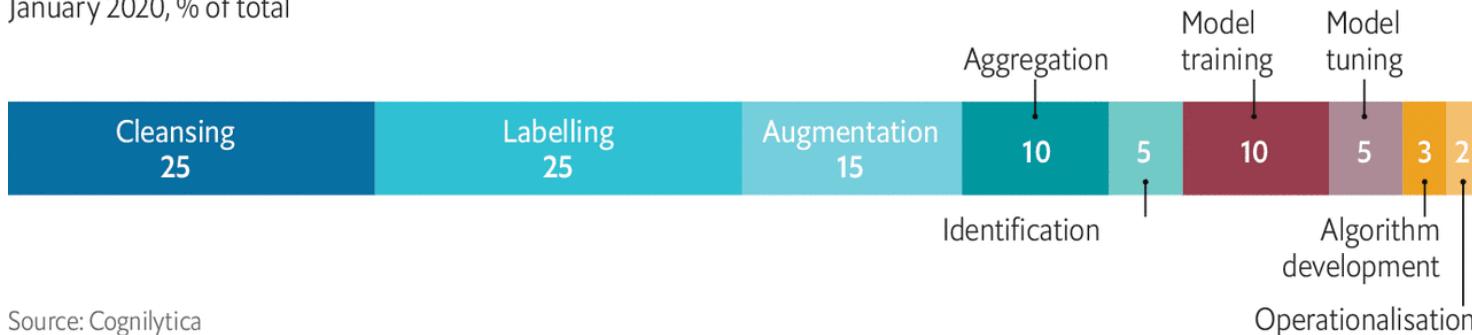
Figure 5.1.10b

ML Projects remain Challenging

More complex than it looks

Average time allocated to machine-learning project tasks

January 2020, % of total



Source: Cognilytica

- Data issues are one of the most common sticking-points in real AI projects
- Up to 80% of project time is spent on the data and < 20% on ML models!

Datasets Often Contain Inherent Bias



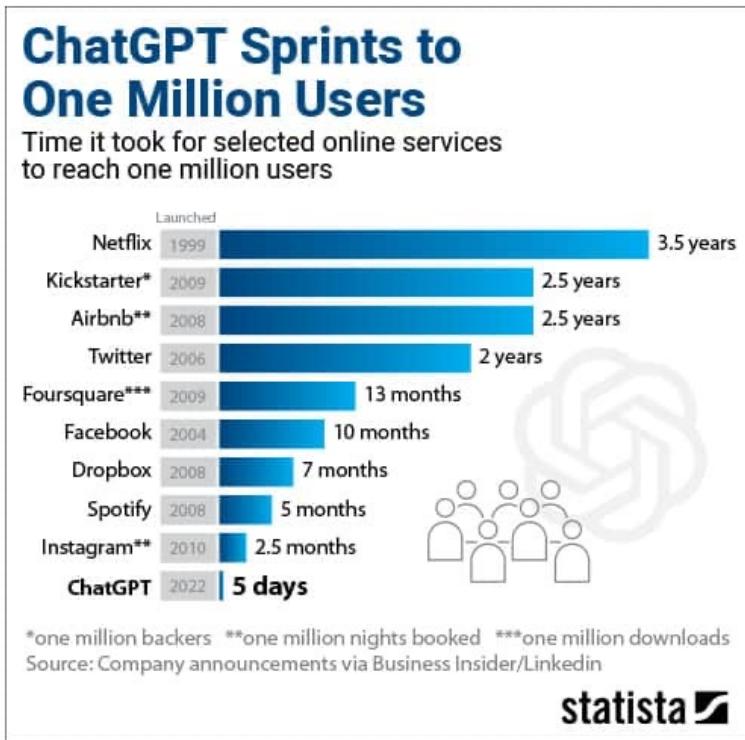
- In 2019 America's National Institute of Standards and Technology tested nearly **200 facial recognition algorithms** and found that many were significantly **less accurate at identifying black faces** than white ones.
- The problem may reflect a preponderance of white faces in their training data. A study from IBM, published in 2019 found that **over 80% of faces** in three widely used training sets **had light skin**.

Training of Large ML Models is Energy Intensive

- In 2019 researchers at Uni. Amherst estimated that training one version a big language model, could **cost as much as \$3m**.
- In 2020 an algorithm capable of learning, through trial and error, how to manipulate the pieces of a Rubik's Cube using a robotic hand consumed about **2.8 gigawatt-hours of electricity** in its training
- Facebook's head of AI, says that one round of training for the biggest models can cost "millions of dollars" in **electricity consumption**.
- Researchers estimate that the training of GPT-3, which ChatGPT is partly based on, consumed 1.3 GWh, and led to emissions of more than **550 tons of carbon dioxide equivalent**



We are at a Turning Point in the History of AI/ML

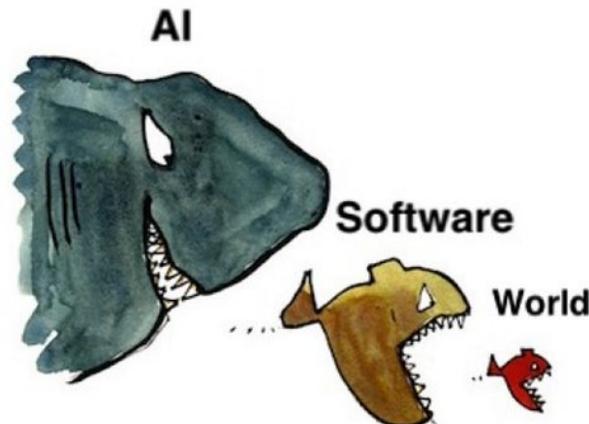


Bojan Tunguz
@tunguz

Machine Learning at Nvidia. Kaggle Quadruple Grandmaster.

...

This is insane. This is what I've been alluding to for months now. This is an epochal transformative technology that will soon touch - and radically transform - ALL knowledge work. If most of your work involves sitting in front of a computer, you will be disrupted very, very soon.



Brings risks as well as opportunities



President Biden ✅ @POTUS · Jun 21

I sat down with experts at the intersection of technology and society who provided a range of perspectives on AI's enormous promise and risks.

In seizing this moment of technological change, we also need to manage the risks.

My Administration is on it.



European Commission ✅ @EU_Commission · Sep 14

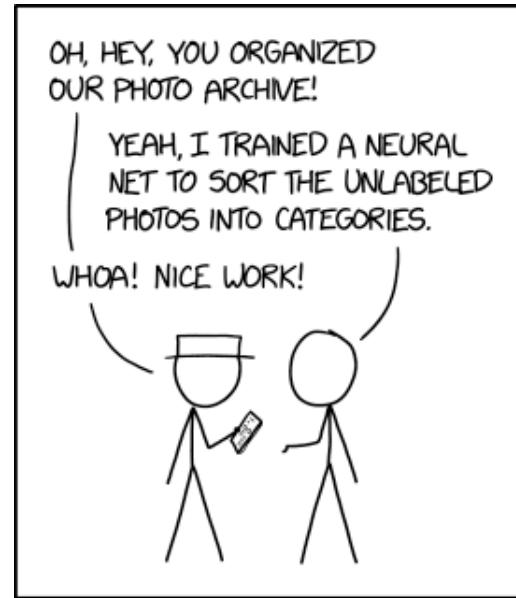
Mitigating the **risk** of extinction from **AI** should be a global priority.

And Europe should lead the way, building a new global **AI** framework built on three pillars: guardrails, governance and guiding innovation ↓



Recap of Today's Lecture

- A. Machine Learning in the Context of Artificial Intelligence (AI)
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ENGINEERING TIP:
WHEN YOU DO A TASK BY HAND,
YOU CAN TECHNICALLY SAY YOU
TRAINED A NEURAL NET TO DO IT.

Questions to Think About

- What's the difference between **AI** and Machine Learning (ML)? What's the difference between ML and **Deep Learning** (DL)? We had **Neural Nets** in the 1980s, but not DL – why not?
- The average **power consumption** of a typical adult is 100 Watts and the **brain consumes** 20% of this making the **power** of the **brain** 20W, about the same as a light-bulb. How do you think we could get modern machine learning algorithms to work at this level of efficiency?
- Deep Learning (DL) can learn from large amounts of data to **automate cognitive tasks** normally requiring a human. For example we can train a DL algorithm to screen CVs for selecting job candidates. **Can you think of any negative consequences of this?**

TO PROVE YOU'RE A HUMAN,
CLICK ON ALL THE PHOTOS
THAT SHOW PLACES YOU
WOULD RUN FOR SHELTER
DURING A ROBOT UPRISING.



Thank you! Any Questions?



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