Deep Learning

Lecture 0: Introduction

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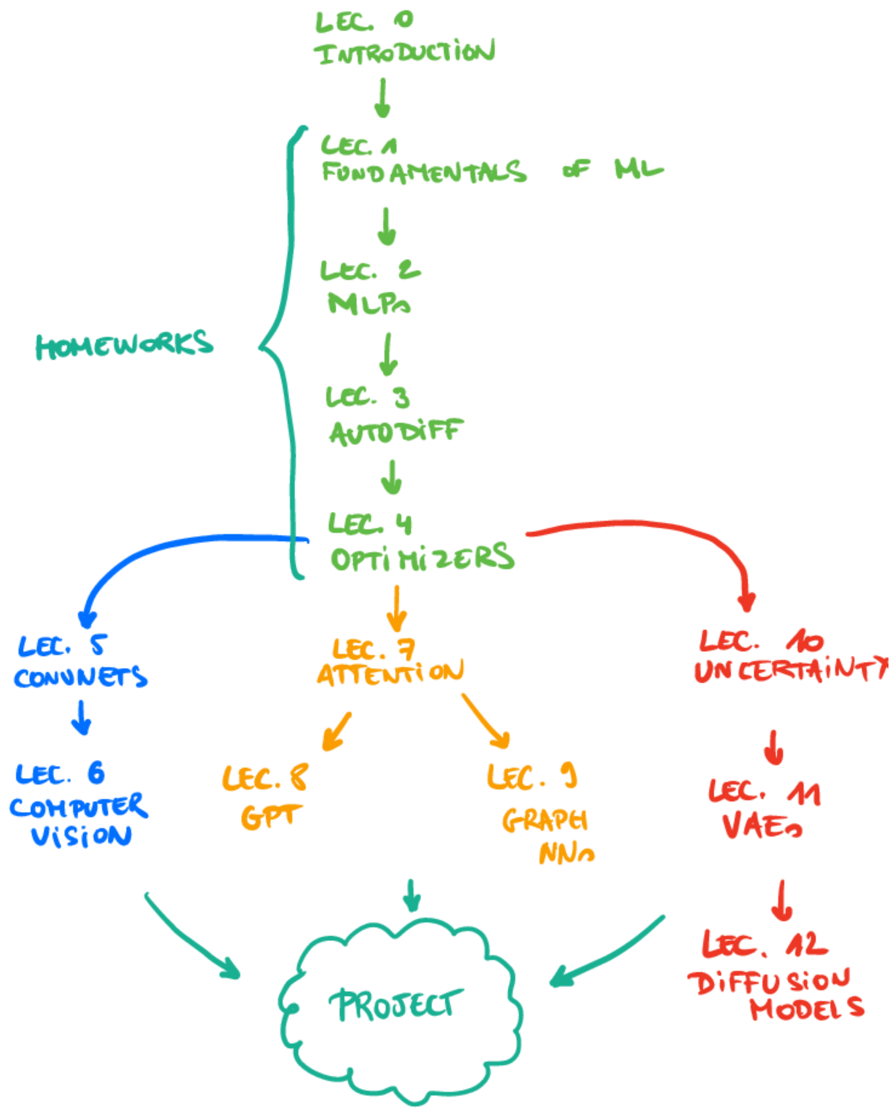
Today

- Course outline
- Introduction to deep learning
- Fundamentals of machine learning

Outline

- Lecture 1: Fundamentals of machine learning
- Lecture 2: Multi-layer perceptron
- Lecture 3: Automatic differentiation
- Lecture 4: Training neural networks
- Lecture 5: Convolutional neural networks
- Lecture 6: Computer vision
- Lecture 7: Attention and transformer networks
- Lecture 8: GPT
- Lecture 9: Graph neural networks
- Lecture 10: Uncertainty
- Lecture 11: Auto-encoders and variational auto-encoders
- Lecture 12: Score-based diffusion models


LEC. 0
INTRODUCTION
LEC. 1
FUNDAMENTALS OF ML
LEC. 2
MLPs
LEC. 3
AUTODIFF
LEC. 4
OPTIMIZERS
HOMEWORKS
LEC. 5
CONVNETS
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COMPUTER VISION
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ATTENTION
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GPT
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DIFFUSION MODELS
PROJECT

My mission

By the end of this course, you will have a strong and comprehensive understanding of deep learning.

You will learn how to design deep neural networks for various advanced probabilistic inference tasks and how to train them.

The models covered in this course have broad applications in artificial intelligence, engineering, and science.

Why learning?

What do you see?

Sheepdog or mop?

—
Credits: Karen Zack, 2016.

Chihuahua or muffin?

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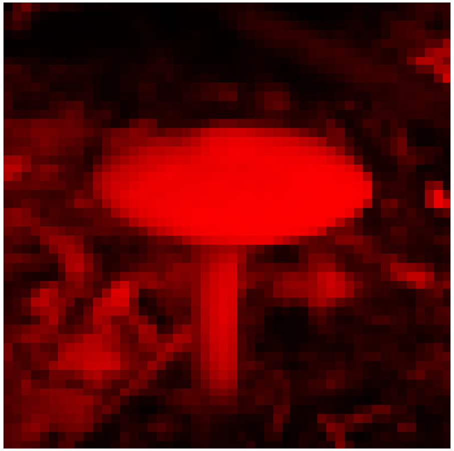
Credits: Karen Zack. 2016.

The (human) brain is so good at interpreting visual information that the gap between raw data and its semantic interpretation is difficult to assess intuitively.

This is a mushroom.

This is a mushroom.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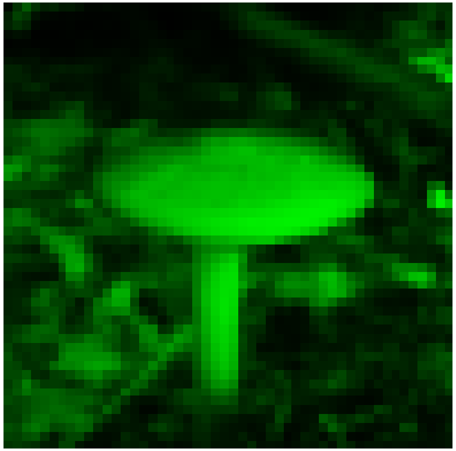
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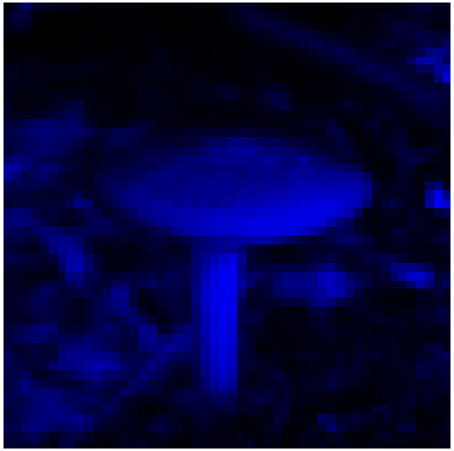

This is a mushroom.

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        [0.2509804 , 0.1882353 , 0.20392157, 1.        ],
        [0.4117647 , 0.34117648, 0.37254903, 1.        ],
        ...,
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        [0.16470589, 0.18039216, 0.12156863, 1.        ],
        [0.18039216, 0.18039216, 0.14117648, 1.        ]],

       [[0.1254902 , 0.11372549, 0.09411765, 1.        ],
        [0.2901961 , 0.2509804 , 0.24705882, 1.        ],
        [0.21176471, 0.2       , 0.20392157, 1.        ],
        ...,
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        [0.16470589, 0.20784314, 0.11764706, 1.        ]],

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        [0.0627451 , 0.08235294, 0.05098039, 1.        ],
        [0.14117648, 0.2       , 0.09803922, 1.        ]],

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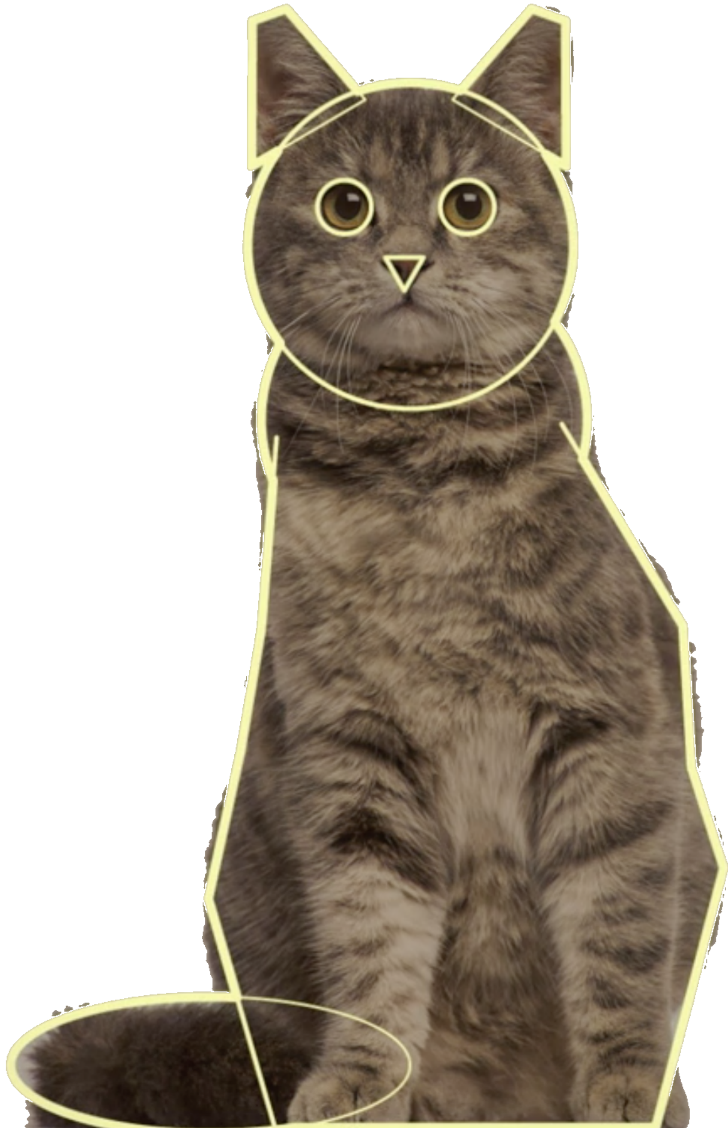
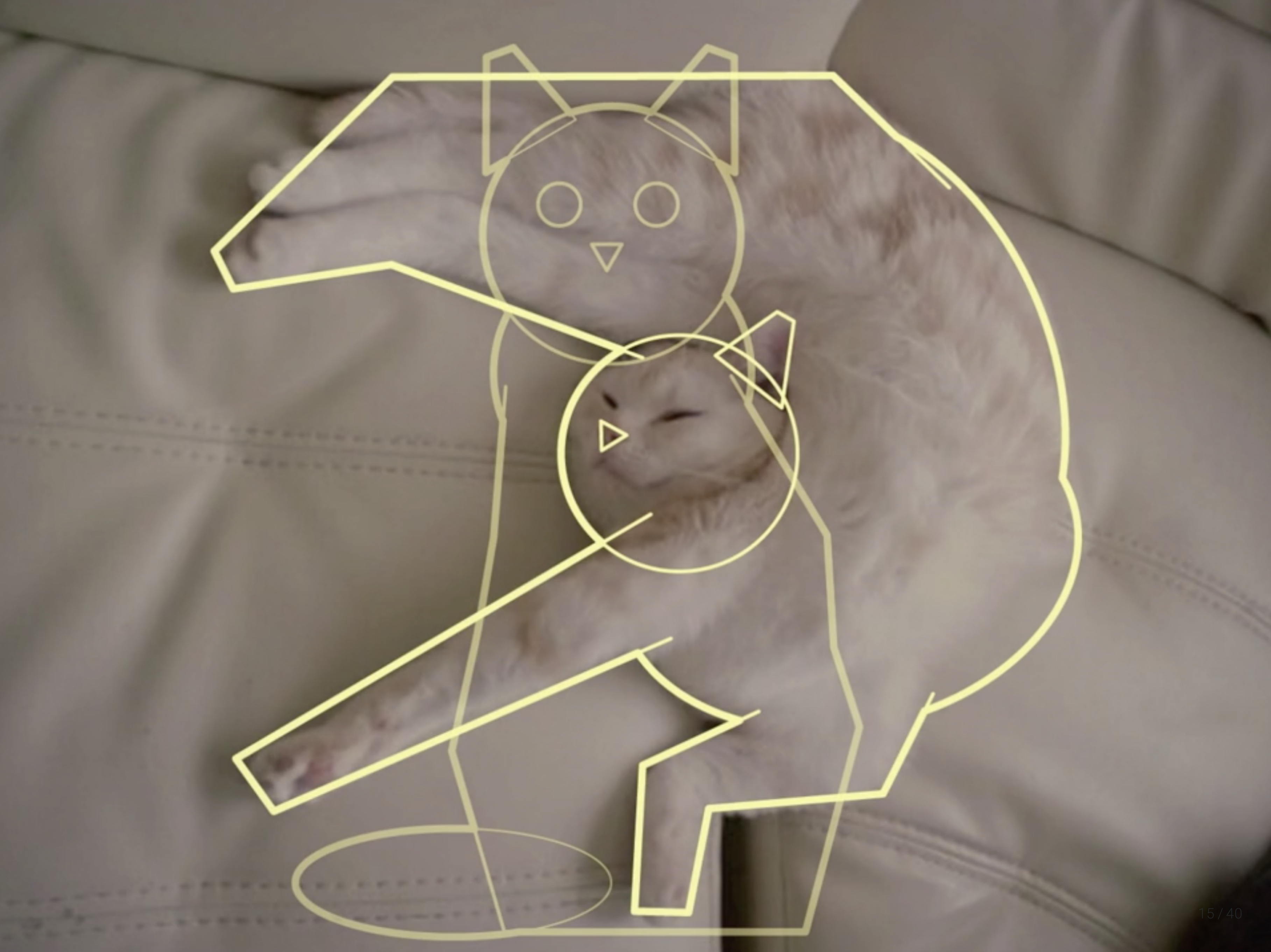
This is a mushroom.

Writing a computer program that sees?





To extract semantic information, we need models with high complexity **that cannot be manually designed**.

However, we can write a program that learns the task of extracting semantic information.

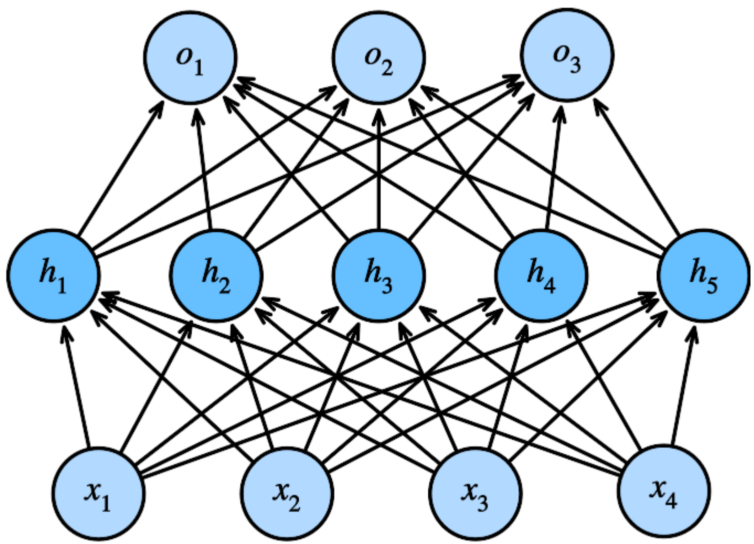
The **machine learning approach** consists in:

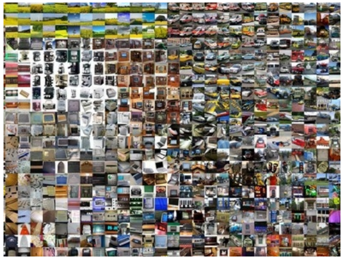
- defining a parametric model
- optimizing its parameters, by "making it work" on the training data.

The deep learning revolution

Deep learning **scales up** the statistical and machine learning approaches by

- using larger models known as neural networks,
- training on larger datasets,
- using more compute resources.



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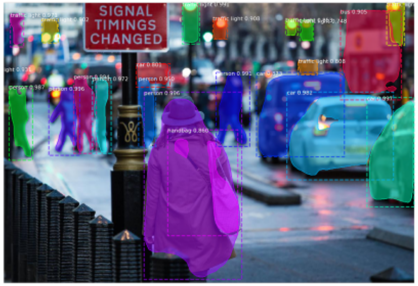
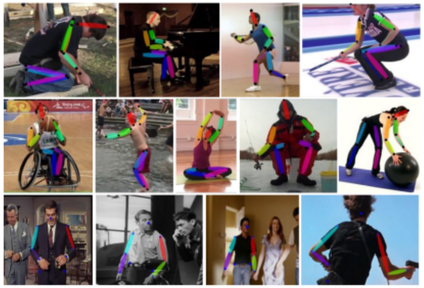
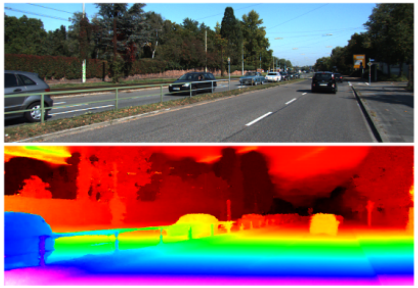
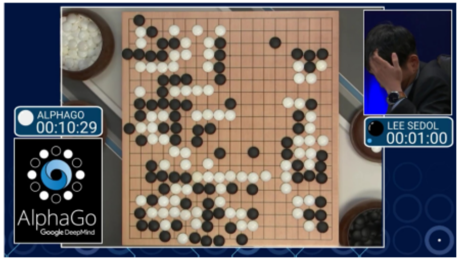
Specialized neural networks can be trained achieve super-human performance on many complex tasks that were previously thought to be out of reach for machines.









I: Jane went to the hallway.
I: Mary walked to the bathroom.
I: Sandra went to the garden.
I: Daniel went back to the garden.
I: Sandra took the milk there.
Q: Where is the milk?
A: garden

(Top) Scene understanding, pose estimation, geometric reasoning.
(Bottom) Planning, Image captioning, Question answering.

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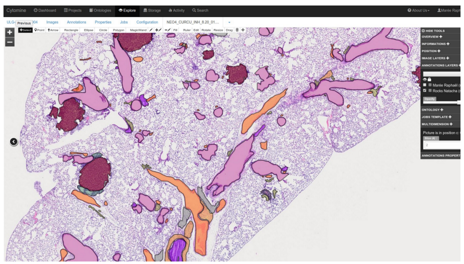
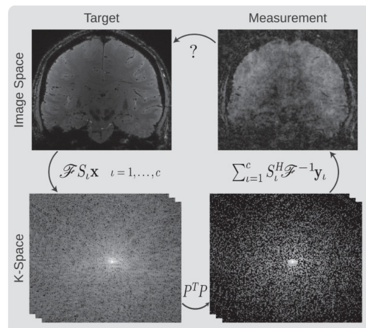
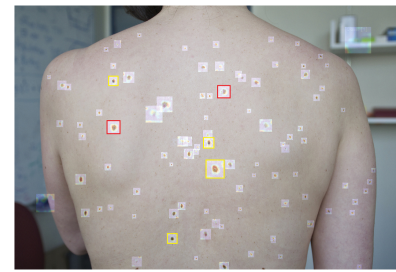
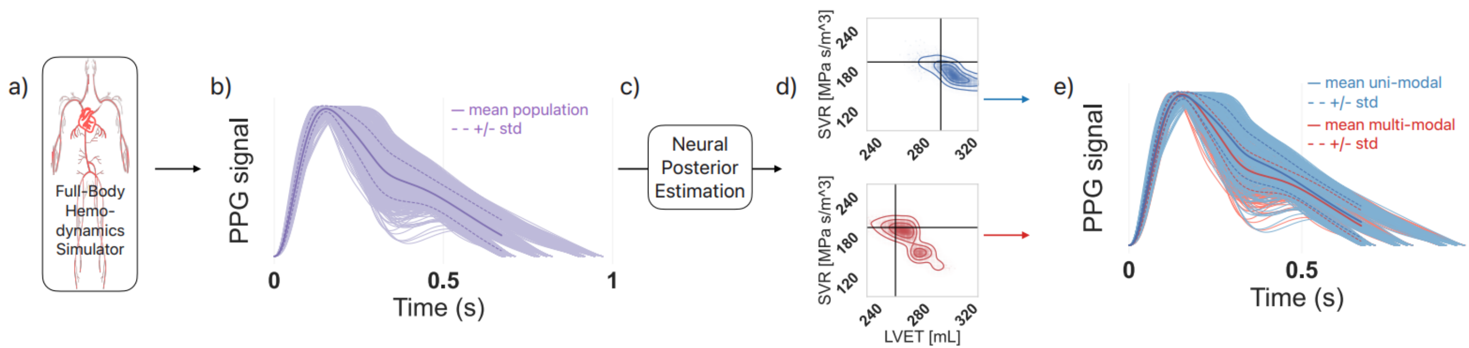
Credits: François Fleuret, 2023.

Neural networks form **primitives** that can be transferred to many domains.

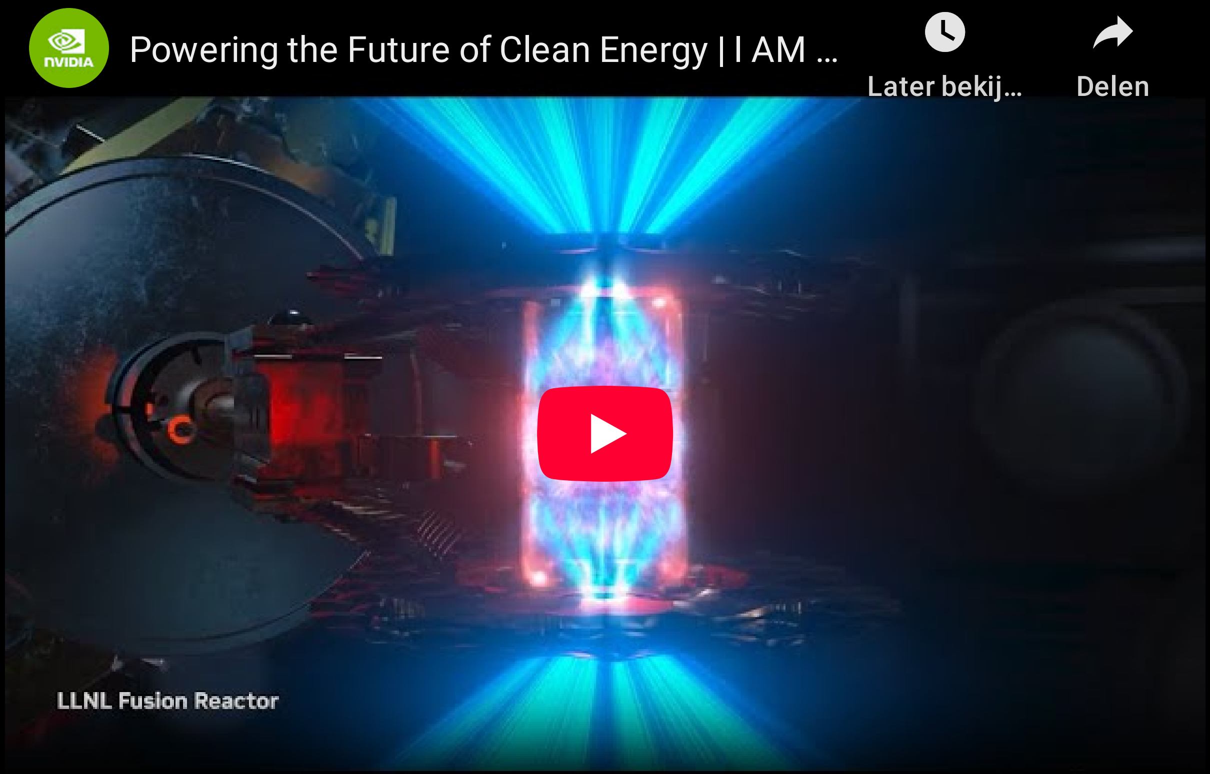








(Top) Analysis of histological slides, denoising of MRI images, nevus detection.
(Bottom) Whole-body hemodynamics reconstruction from PPG signals.



Powering the future of clean energy (NVIDIA, 2023)

How AI is advancing medicine (Google, 2023)

Building autonomous cars (Waymo, 2022)

The breakthrough

Attention Is All You Need

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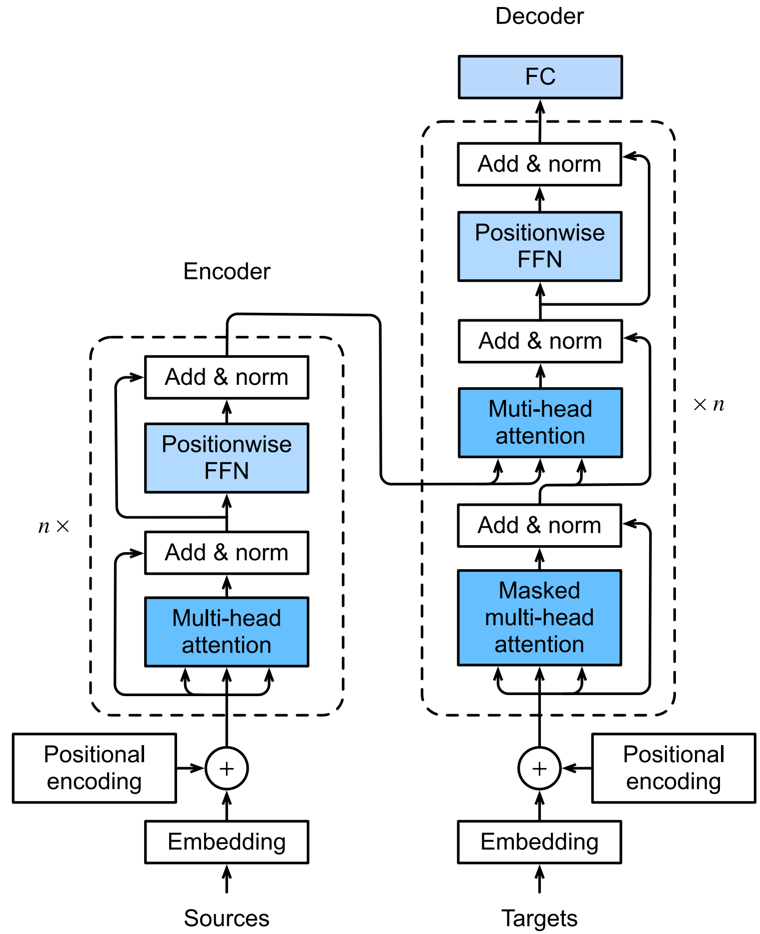
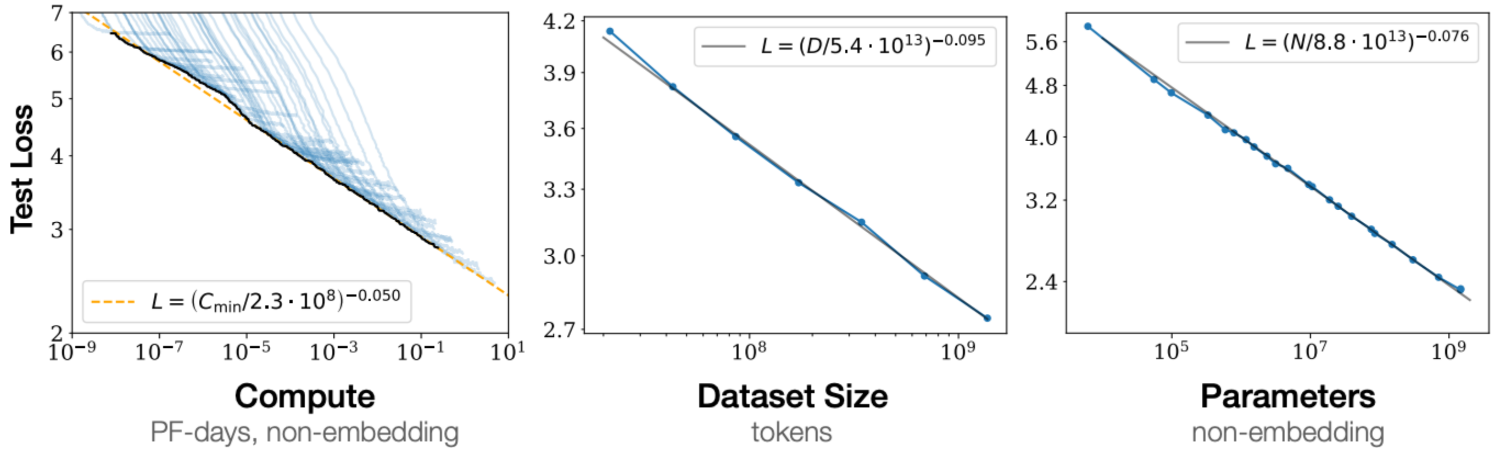
Abstract

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks that include an encoder and a decoder. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles, by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

Vaswani et al., 2017.

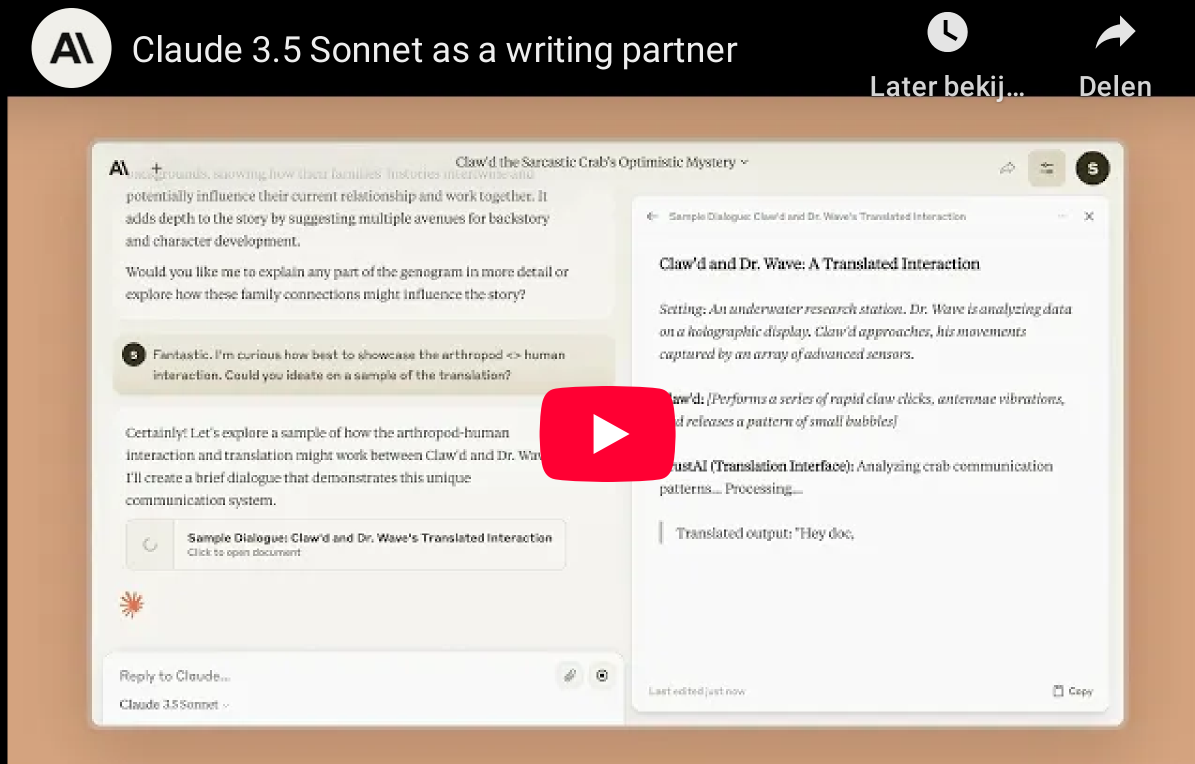




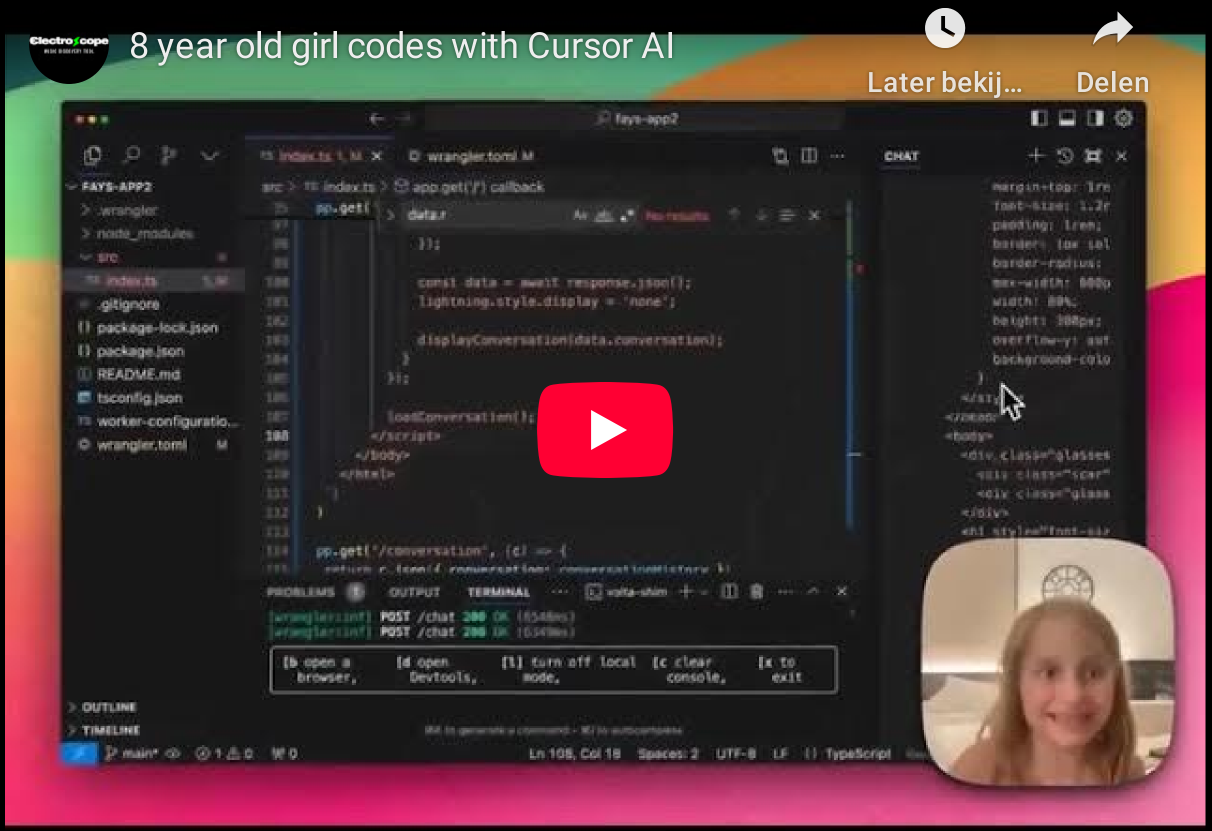
A brutal simplicity:

- The more data, the better the model.
- The more parameters, the better the model.
- The more compute, the better the model.

Scaling up further to gigantic models, datasets, and compute resources keeps pushing the boundaries of what is possible, **with no sign of slowing down**.



Conversational AI assistants (Anthropic, 2024)



Code assistants (Cursor, 2024)

Not just text, but also images and sounds.

With great power comes great responsibility.

Risks

The report classifies risks associated with general-purpose AI into three categories:

1. Risks from **malicious use** (scams, manipulation, cyberattacks, biological/chemical attacks)
2. Risks from **malfunctions** (hallucinations, biases, loss of control)
3. **Systemic** risks (labour market risks, global R&D divide, power concentration)

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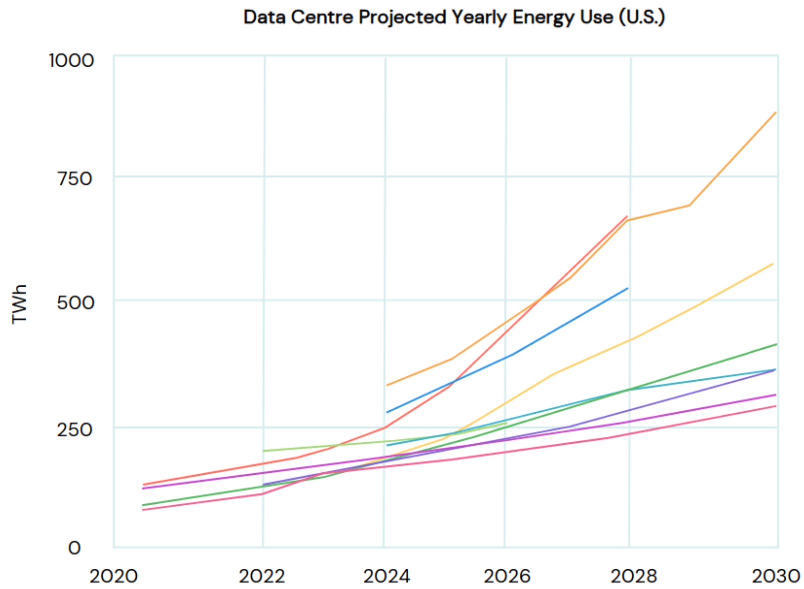
Credits: Bengio et al., 2025 (arXiv:2501.17805).



Environmental impacts

"AI is a moderate but rapidly growing contributor to global environmental impacts through energy use and greenhouse gas (GHG) emissions. Current estimates indicate that **data centres and data transmission account for an estimated 1% of global energy-related GHG emissions, with AI consuming 10–28% of data centre energy capacity**. AI energy demand is expected to grow substantially [...]"

—
Credits: Bengio et al., 2025 (arXiv:2501.17805).

The Impact of Generative AI on Critical Thinking: Self-Reported Reductions in Cognitive Effort and Confidence Effects From a Survey of Knowledge Workers

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Abstract

The rise of Generative AI (GenAI) in knowledge workflows raises questions about its impact on critical thinking skills and practices. We survey 319 knowledge workers to investigate 1) when and how they perceive the enaction of critical thinking when using GenAI, and 2) when and why GenAI affects their effort to do so. Participants shared 936 first-hand examples of using GenAI in work tasks. Quantitatively, when considering both task- and user-specific factors, a user's task-specific self-confidence and confidence in GenAI are predictive of whether critical thinking is enacted and the effort of doing so in GenAI-assisted tasks. Specifically, higher confidence in GenAI is associated with less critical thinking, while higher self-confidence is associated with more critical thinking. Qualitatively, GenAI shifts the nature of critical thinking toward information verification, response integration, and task stewardship. Our insights reveal new design challenges and opportunities for developing GenAI tools for knowledge work.

Confidence Effects From a Survey of Knowledge Workers. In *CHI Conference on Human Factors in Computing Systems (CHI '25), April 26–May 01, 2025, Yokohama, Japan.* ACM, New York, NY, USA, 23 pages. https://doi.org/10.1145/3706598.3713778

1 Introduction

Generative AI (**GenAI**) tools, defined as any *"end user tool [...] whose technical implementation includes a generative model based on deep learning"*,[1] are the latest in a long line of technologies that raise questions about their impact on the quality of human thought, a line that includes writing (objected to by Socrates), printing (objected to by Trithemius), calculators (objected to by teachers of arithmetic), and the Internet.

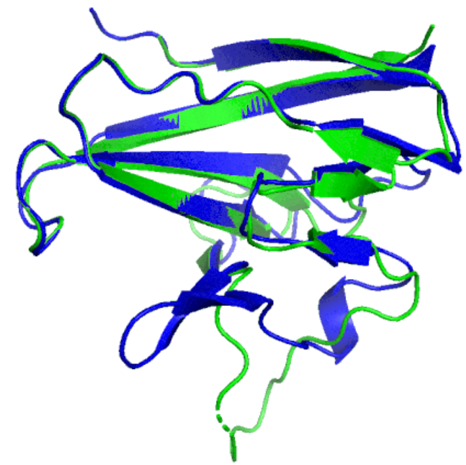
Such consternation is not unfounded. Used improperly, technologies can and do result in the deterioration of cognitive faculties that ought to be preserved. As Bainbridge [7] noted, a key irony of automation is that by mechanising routine tasks and leaving

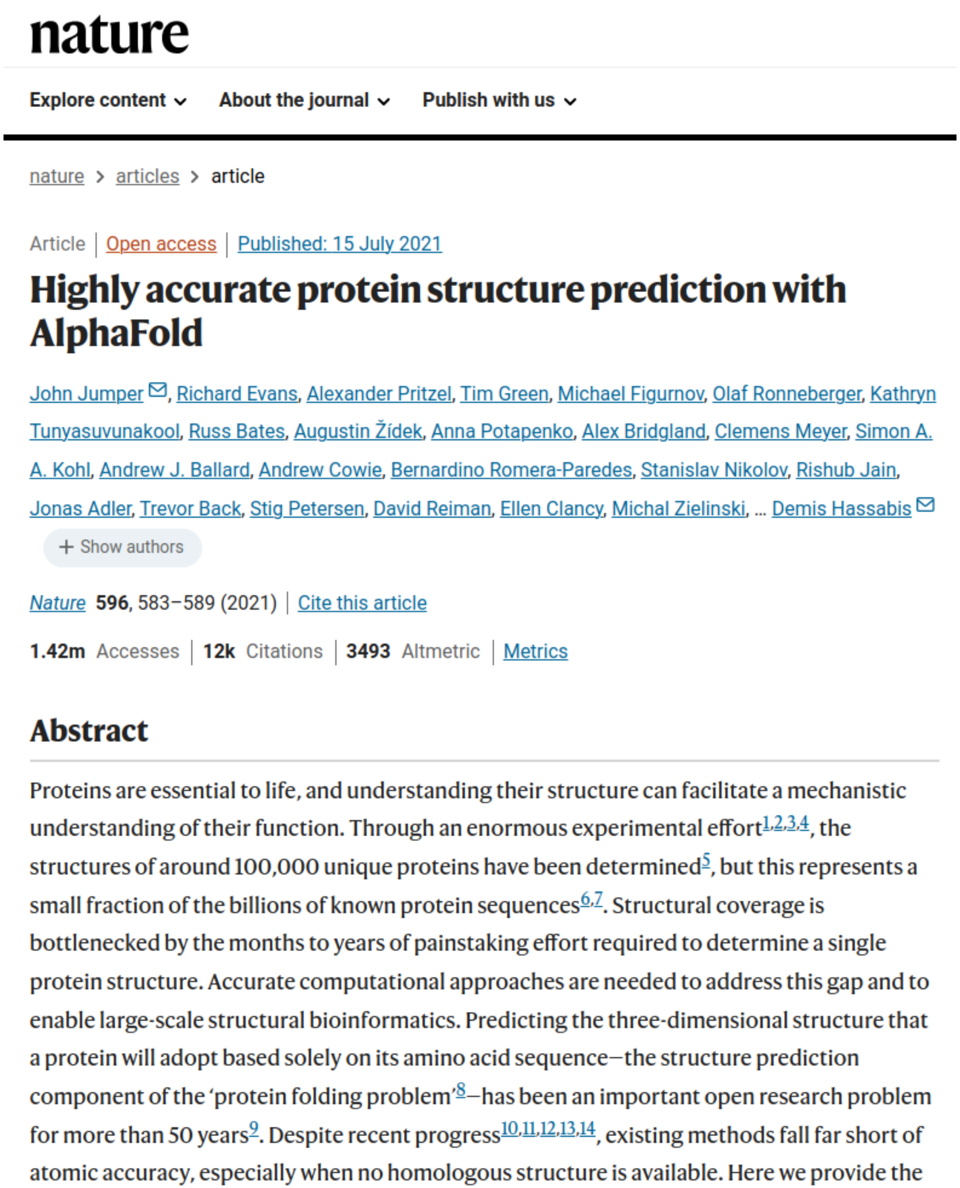
Dumb and dumber

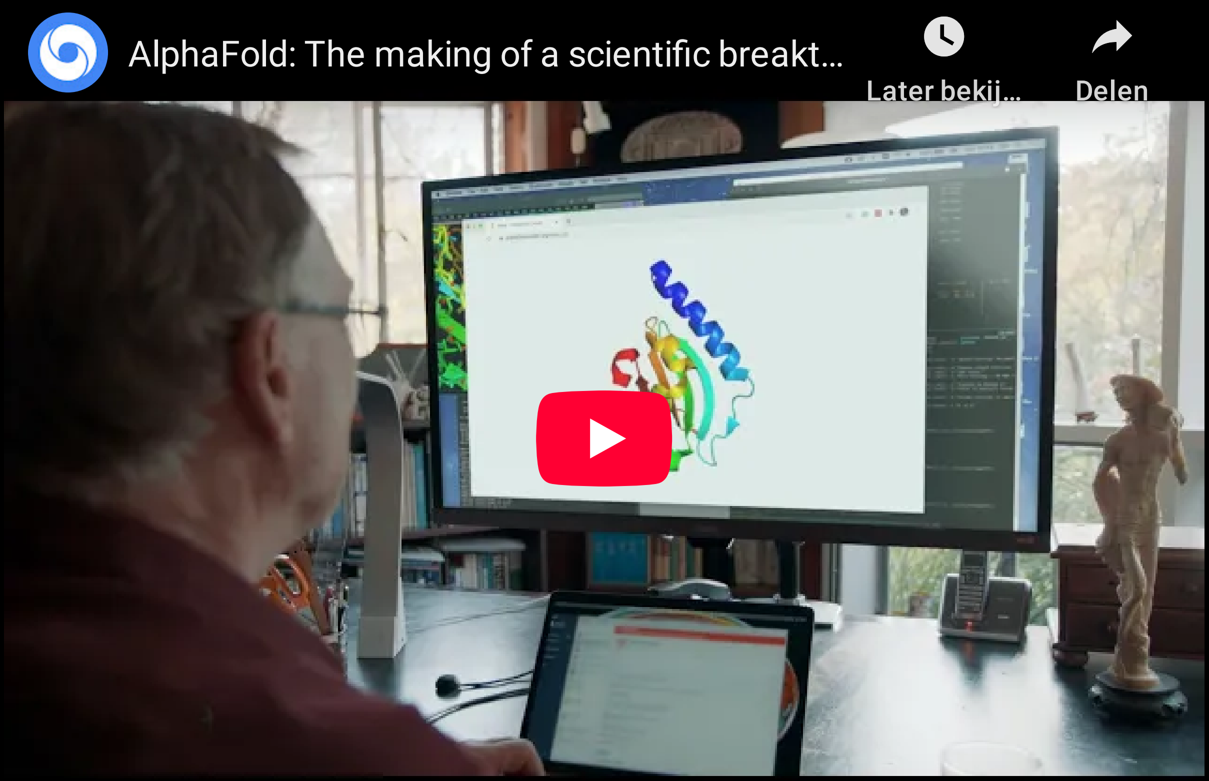
"When people rely on generative AI, **their effort shifts toward verifying that an AI's response is good enough to use, instead of using higher-order critical thinking skills** like creating, evaluating, and analyzing information. If humans only intervene when AI responses are insufficient then workers are deprived of routine opportunities to practice their judgment and strengthen their cognitive musculature, **leaving them atrophied and unprepared** [...]."

Deep learning can also **solve problems that no one could solve before**.

AlphaFold: From a sequence of amino acids to a 3D structure







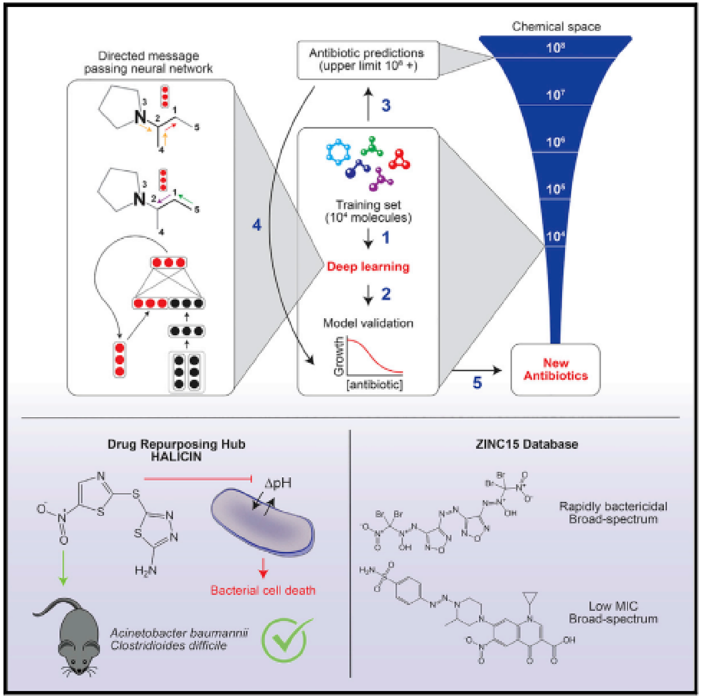
AI for Science (Deepmind, AlphaFold, 2020)

Drug discovery with graph neural networks

Cell

A Deep Learning Approach to Antibiotic Discovery

Graphical Abstract



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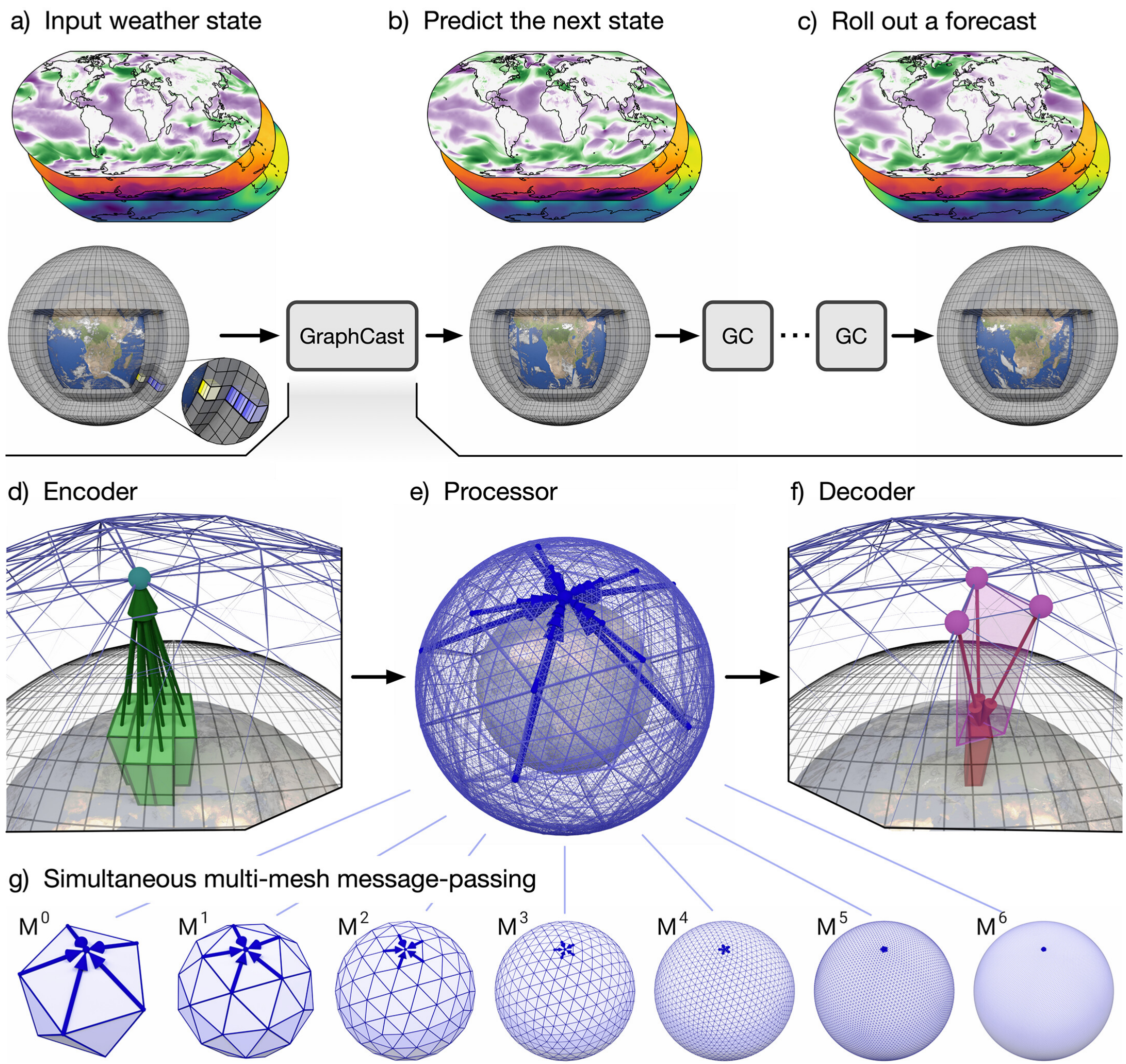
In Brief

A trained deep neural network predicts antibiotic activity in molecules that are structurally different from known antibiotics, among which Halicin exhibits efficacy against broad-spectrum bacterial infections in mice.

GraphCast: fast and accurate weather forecasts



For the last forty years we have programmed computers; for the next forty years we will train them.

Chris Bishop, 2020.

The end.