Machine learning for physicists

PHYS-467

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TAs: Freya Behrens, Fabrizio Boncoraglio, Alessandro Sinibaldi, Gabriele Farné; AE: Gopal Dahale, Margarita Sagitova






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Organisation

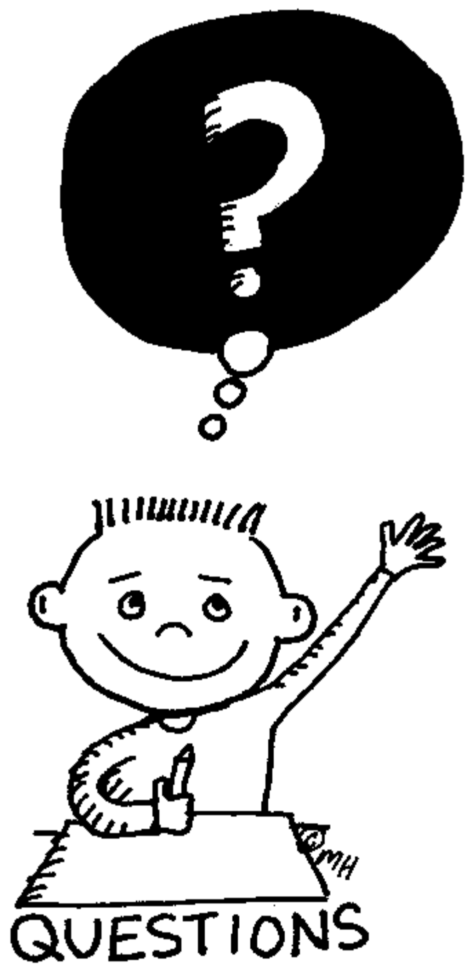
- Lecture (Fr 8h15-10h00, CE 1 4).
- Exercises (Fr 10h15-12h00, CE 1 4, with your own laptops). As (or more) important as the lecture.
- Lectures are recorded and put on Mediaspace. Link: https://mediaspace.epfl.ch/channel/PHYS-467%2BMachine%2Blearning%2Bfor%2Bphysicists/30395 (includes lectures from previous years)
- Exercises are not recorded. Solutions and notebooks are published on Moodle.
- All key information and lecture notes on Moodle https://moodle.epfl.ch/course/view.php?id=16718
- Q&A during lectures and exercises. Q&A ok by mail to TAs, preferably on Moodle.
- Language: English. Feel free to ask your questions in French.

How will you be evaluated?

- 50%: 2-3 graded exercises during the semester to be done at home within 2 weeks time. Mainly coding, in a Jupyter notebook. Solved individually. All material used (codes, books, articles, chatGPT) must be duly cited along with the names of everyone you discussed the content with. Unnecessarily verbose answers will be penalized. To be uploaded on Moodle.

- 50%: Final exam (3h) during the exam season. Questions on concepts, some calculations, and question on pieces of code from the exercises. No computer on the final exam. An A4 page (one side) of personal notes (either handwritten or at least 10pt font).

Question on the organization?



What will you learn?

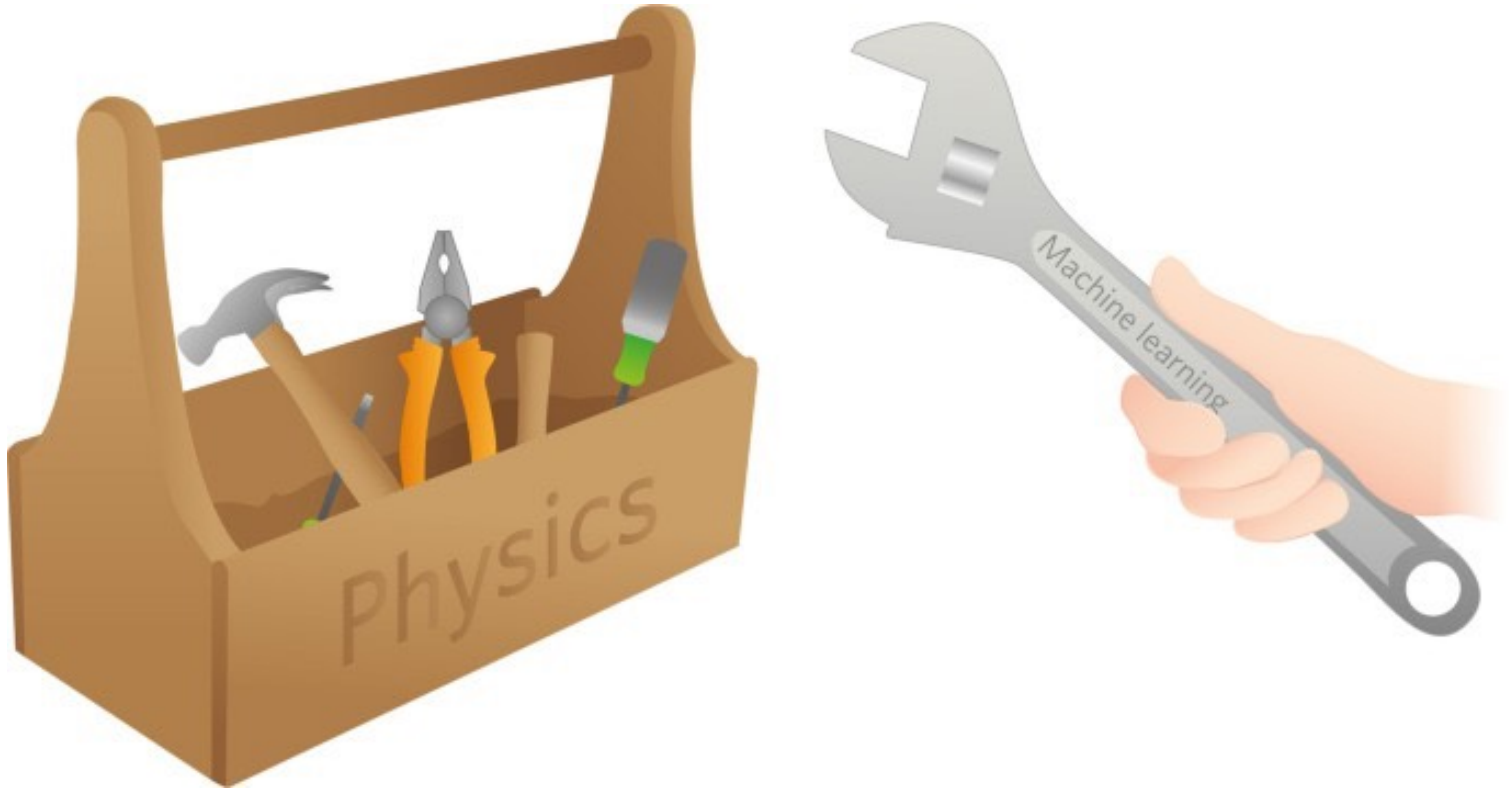
- Programming in Python (if that is new for you).
- Machine learning as a tool for physics and sciences helping us to extract information from data.
- Think about physics/science in a data-oriented manner.
- Foundations and principles of machine learning methods. Starting with linear regression and ending with state-of-the-art systems such as transformers.
- How to start thinking about AI as an object of study.

Why should physics master students study machine learning?

ChatGPT: “Machine learning is now a standard **tool in physics**—used to analyze experiments, speed up simulations, and discover new materials. At the same time, it is an **object of physics** itself: learning dynamics, phase transitions, and high-dimensional phenomena connect directly to concepts you already know from statistical physics. This course gives you both: practical skills and a new frontier where physics contributes to the foundations of learning.”

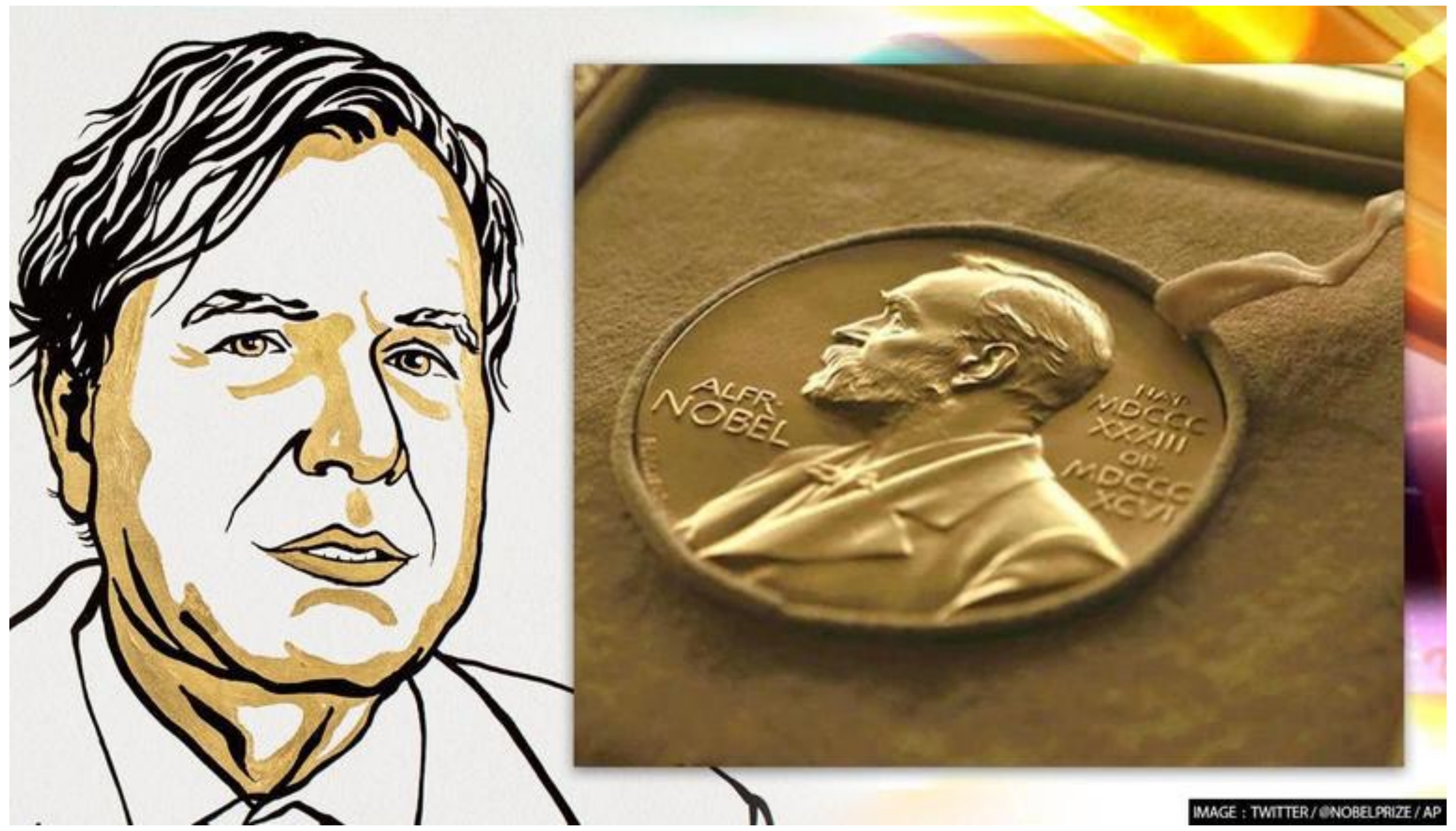
AI = “new” tool in the box

- AI/ML is a powerful tool for physics. Part of AI4Science.
- AI/ML is developed and used in all areas of physics. Notably active in astrophysics, high-energy physics, condensed matter, quantum technology physics, plasma etc.



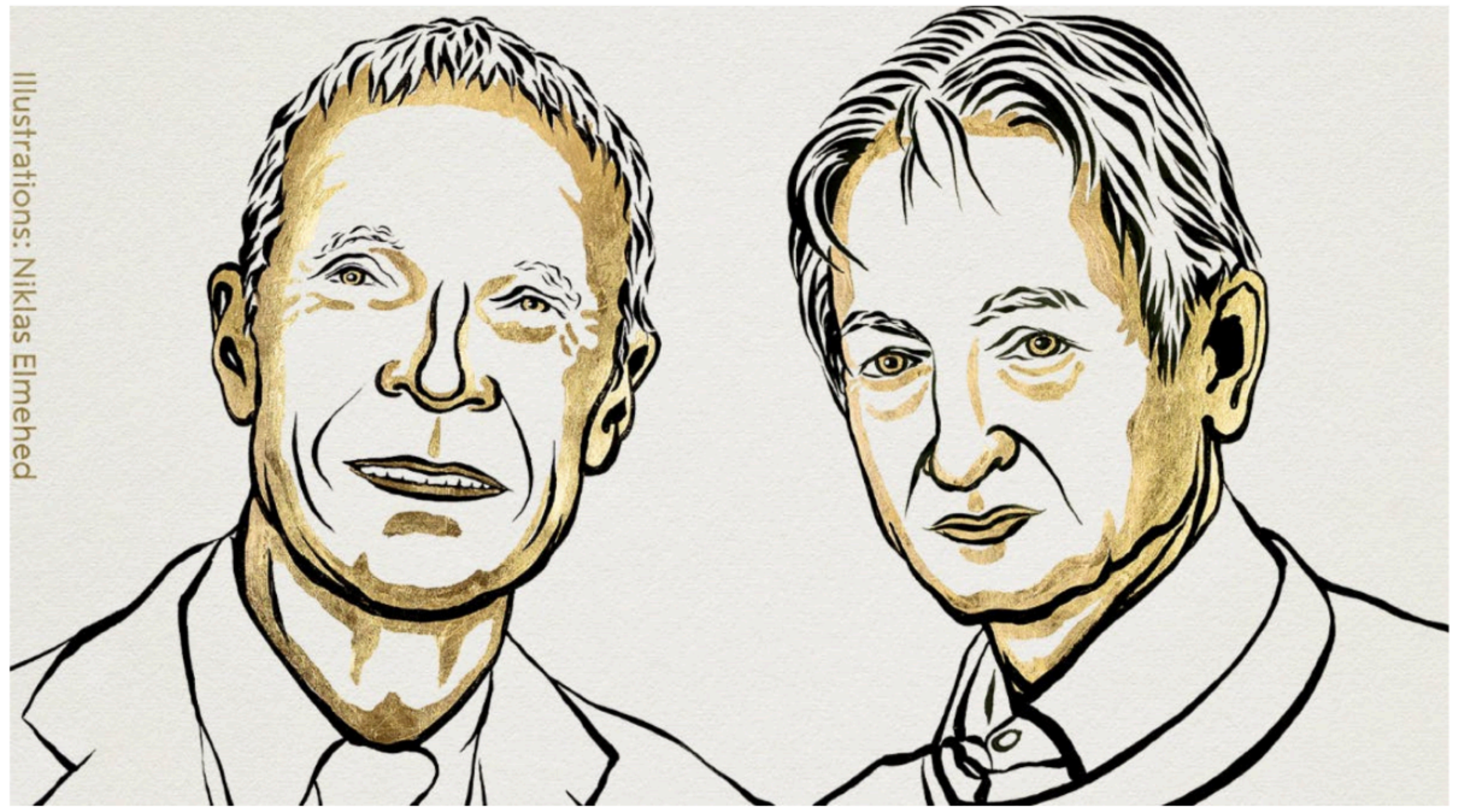
Last two Nobel Prizes in theoretical physics

2021



“Giorgio Parisi's discoveries make it possible to understand and describe many different and apparently entirely random complex materials and phenomena, not only in physics but also in other, very different areas, such as mathematics, biology, neuroscience and **machine learning**.”

2024



“This year’s two Nobel Laureates in Physics, John Hopfield and Geoffrey Hinton, have used tools from physics to develop methods that are the foundation of today’s powerful **machine learning**.

Parenthesis about the status of AI

Progress in AI is astonishing—a game-changing economic and societal force.

ChatGPT's IQ is 155. Einstein's Was 160. Predicting GPT-5

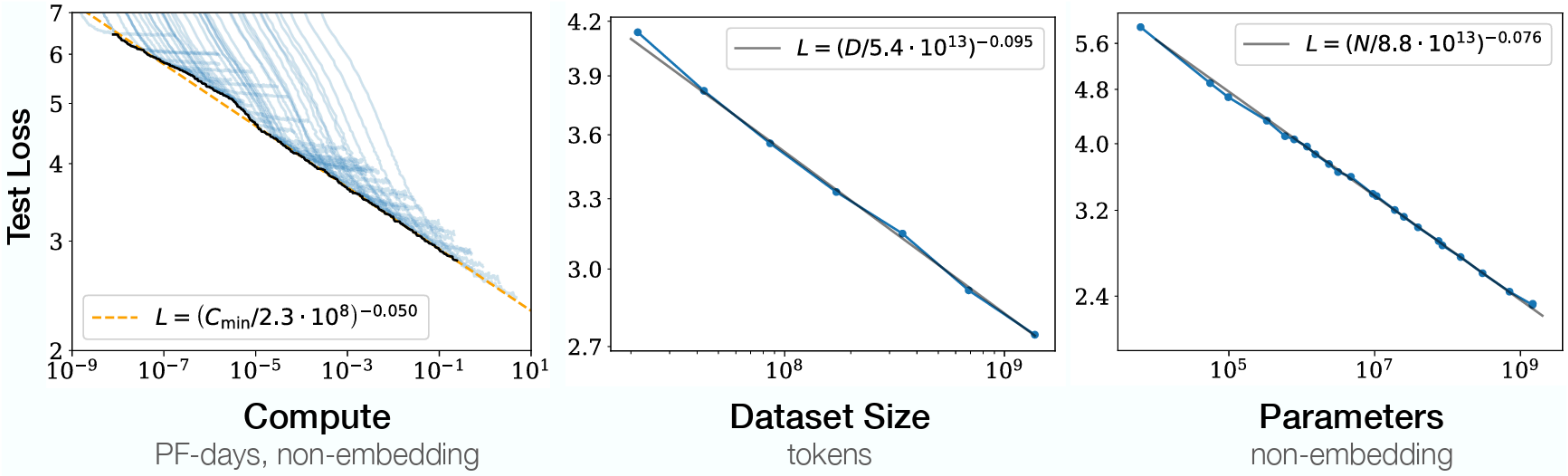
GPT-4 got 10X smarter than 3.5 in just a matter of months and without many changes.

Marko Vidrih · Follow
Published in GoPenAI · 3 min read · Jan 16, 2024

How was this success achieved?

Scaling drives AI forward ...

- More compute (GPUs), larger datasets, more trainable parameters.
- **Scaling-laws are the key drive of current AI industry.**



Kaplan et al.'20

... but cost pulls AI back!

Fundamental questions

Is scaling the only way to go?

Evidence that current AI is far from cost-optimal:

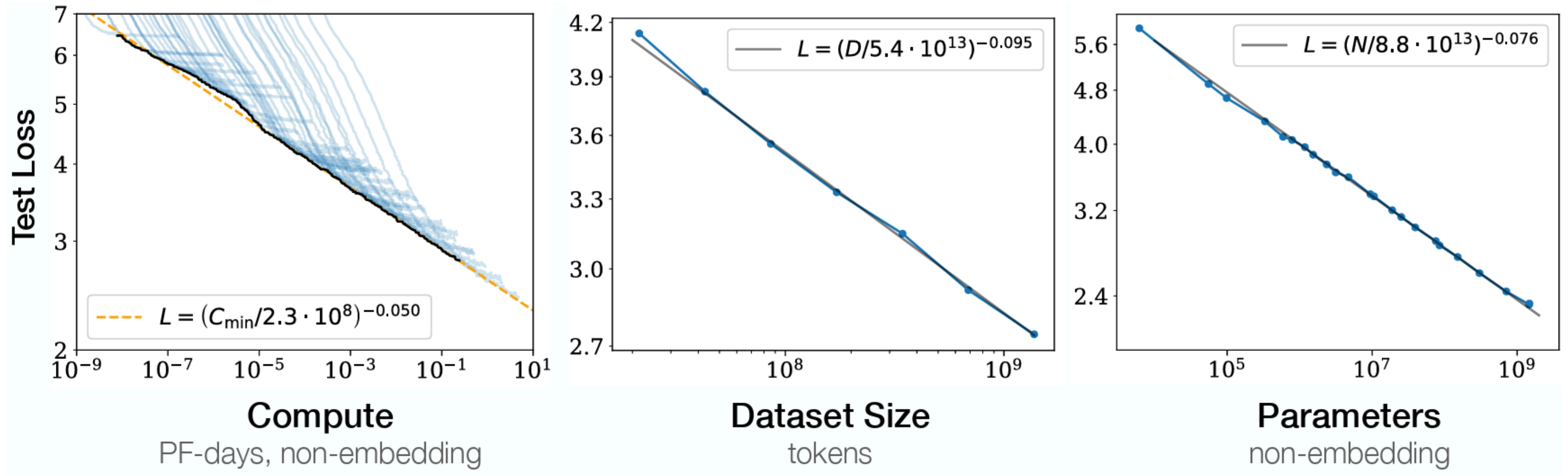
- Human brains function with a fraction of the energy and data.
- In December 2024, DeepSeek V3 cut training-costs 20 times.

What are the fundamental limits of learning?

(Imposed by statistical & computational constraints)

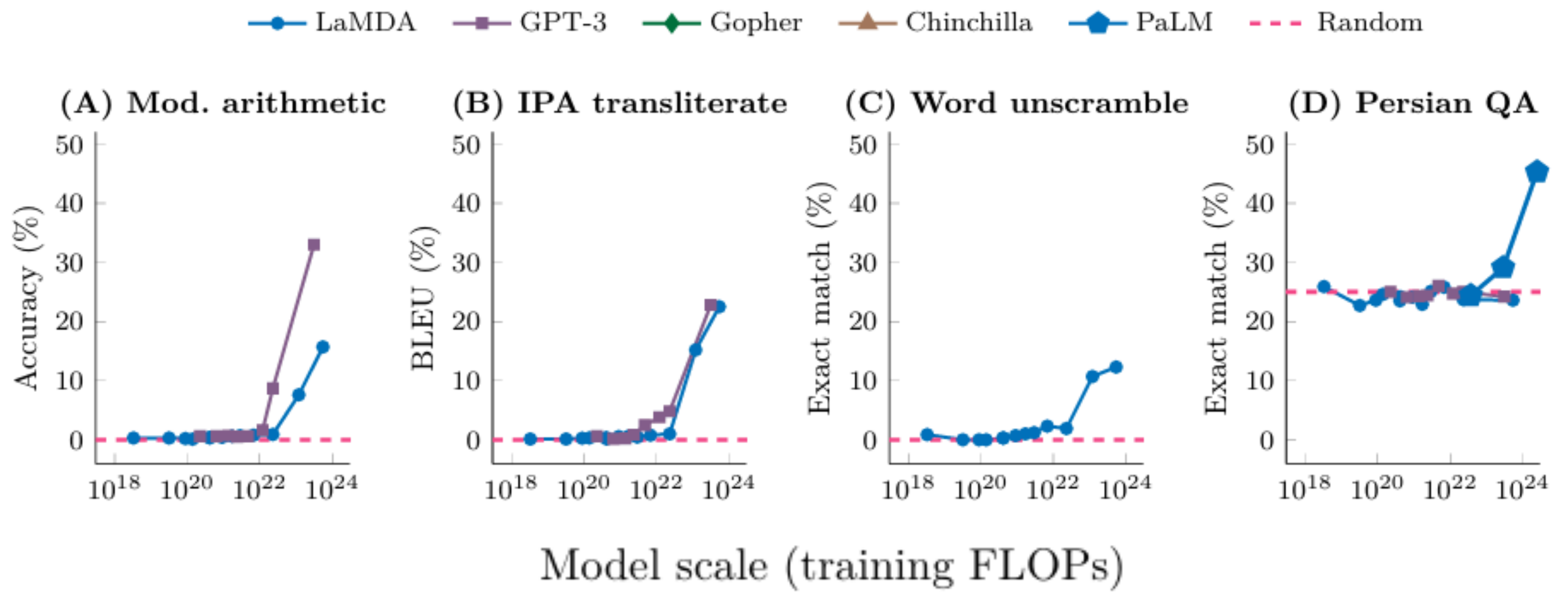
Scaling brings more questions ….

Kaplan et al.'20



- **Performance follows scaling laws.**

  ➡ Can we derive the exponents?



Wei et al.'22

- **Capabilities emerge with scale.**

  ➡ Is this a phase transition?

- **The curse of dimensionality =** training neural networks is NP-hard (Blum, Rivest'89).

  ➡ Can we characterize when hardness can be avoided?

Steam Engine	Artificial Intelligence
Denis Papin (1679) – pressure cooker → beautiful demonstration of the principle. Lacked industrial use.	
Thomas Newcomen (1712) – “atmospheric engine” → first widely deployed technology, but inefficient.	
James Watt (1760s) – key engineering improvements → universally applicable, launched Industrial Revolution.	
Sadi Carnot (1824) – thermodynamics: theory of heat engine efficiency, understanding principles and limits.	
Maxwell, Gibbs, Boltzmann (late 19th c.) – development of statistical physics, general laws beyond technology.	

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The spirit of the lecture “pragmatic version”

Way to think about it: “Physics bachelor lecture on electromagnetism is to iPhone16 what this lecture is to ChatGPT.”

$$\nabla \cdot \mathbf{E} = \frac{\rho}{\varepsilon_0}$$

$$\nabla \cdot \mathbf{B} = 0$$

$$\nabla \times \mathbf{E} = -\frac{\partial \mathbf{B}}{\partial t}$$

$$\nabla \times \mathbf{B} = \mu_0 \mathbf{j} + \frac{1}{c^2}\frac{\partial \mathbf{E}}{\partial t}$$