

# Large Language Models: Revisiting Few Mysteries

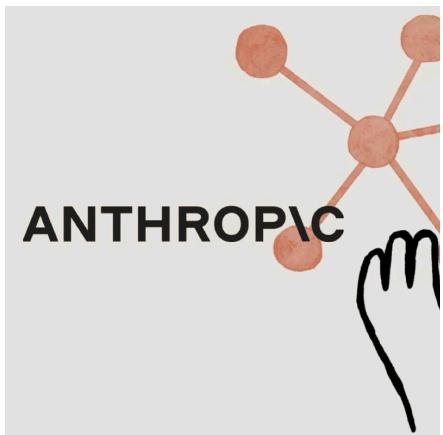
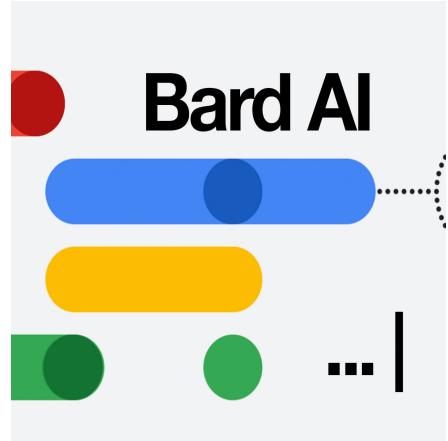
Daniel Khashabi



JOHNS HOPKINS  
UNIVERSITY

Please don't hesitate to  
stop me and ask questions.

# The success we dreamed of



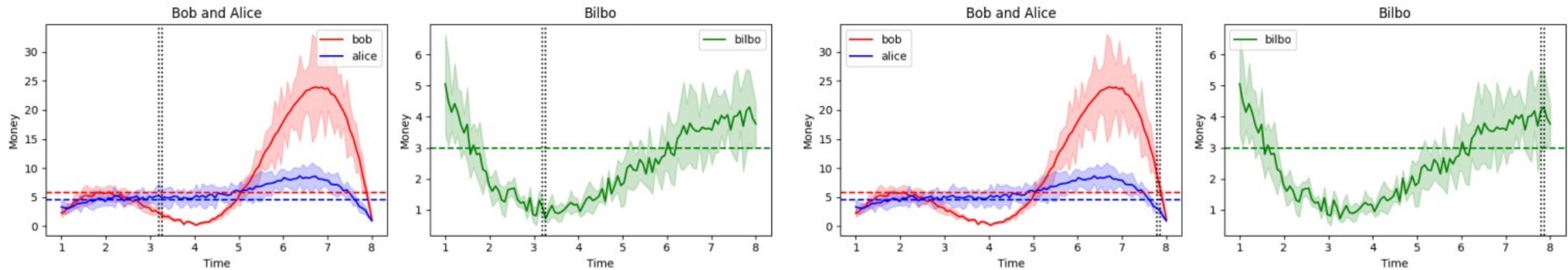
Language models that are remarkably capable at solving many important NLP benchmarks.

# The success we dreamed of

**Prompt:** Can you generate a pyplot for the following data:  $x = [1, 3, 5, 6, 8]$ ,  $y1 = [2, 3, 5, 18, 1]$ ,  $y2 = [3, 5, 6, 8, 1]$ ,  $y3 = [5, 1, 2, 3, 4]$ ,  $y4 = [9, 7, 2, 3, 1]$ . I want  $y1, y2$  to be in the same plot, but  $y3$  is in another plot next to that plot,  $y4$  is in below. I want the legend of  $y1$  to be "bob",  $y2$  to be "alice",  $y3$  to be "bilbo",  $y4$  to be "allie". I want the  $x$ -axis to be labeled with "time" and  $y$  axis to be labeled with "money". I want to add a 10 %-40% random error bar to each curve, through all times (including non-integers). I want smoothed curves to show the plot, and smoothed error bar. Do not use linear interpolation, use smooth interpolation! I want to also add some small zig-zag to the smoothed curve to make it look more real. I want to put a baseline as the mean of each line. I want to put a pie chart below indicating the fraction of the four people in each time step. I also want an animation to show how the fractions are changing in the pie chart in \*\*continuous time\*\*. Interpolate the missing fractions! I also want vertical line animation in other three plots to match the pie chart. I want the fanciest things. Please add as many fancy things as possible.

Here is a possible code to generate a pyplot for the following data, with some comments to explain the steps:

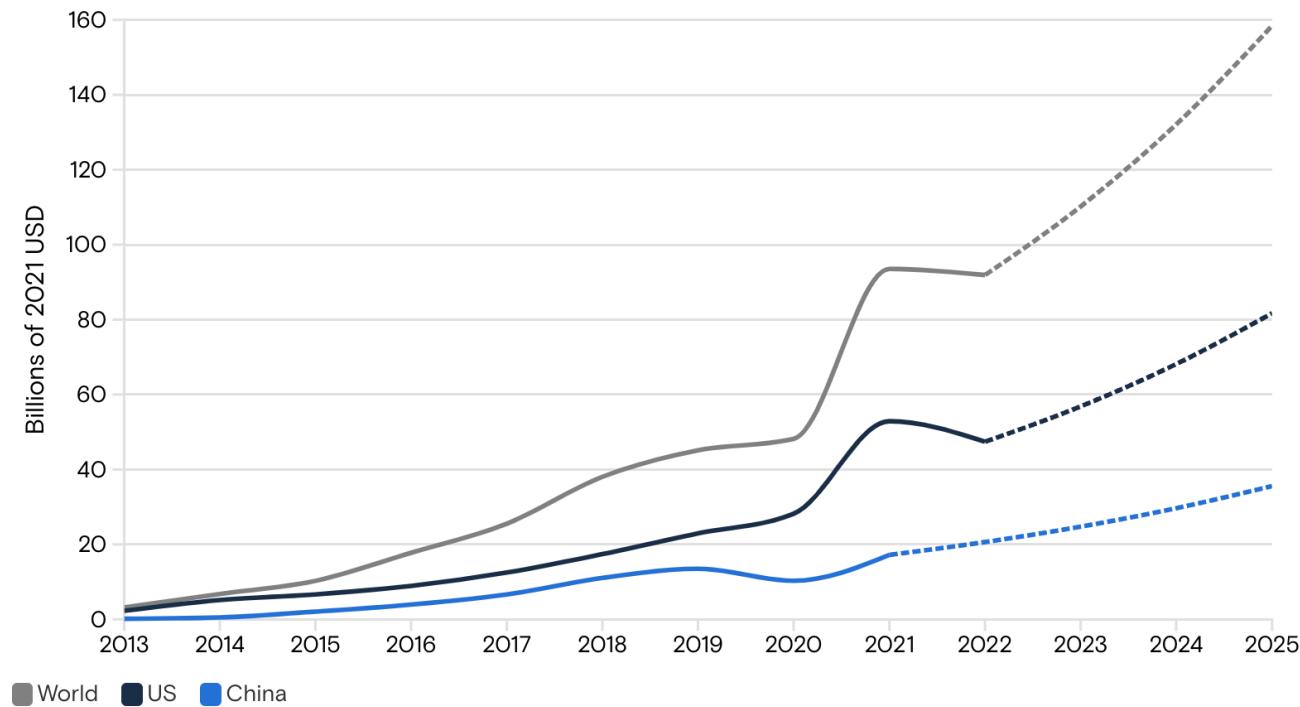
**GPT-4:** [We give two snapshots from the animation resulting from the produced code]



# Accelerated Industrialization of AI

**AI investment is likely to grow in the next three years**

Private AI investment (dotted lines show GS revenue projections\*)

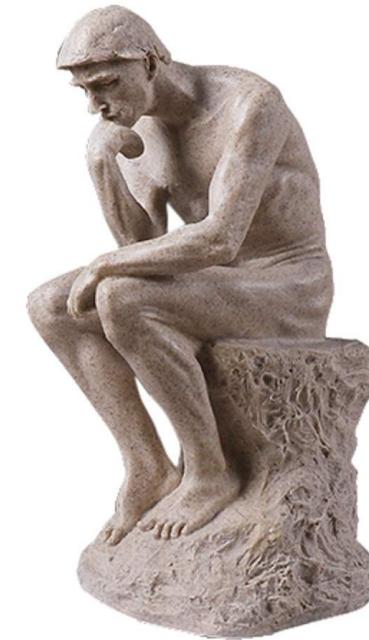
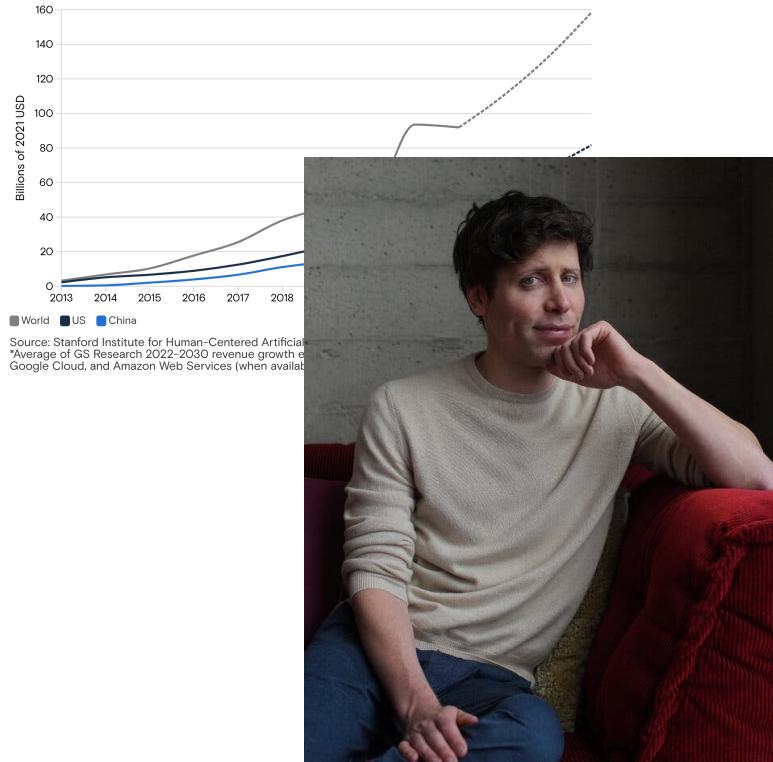


Source: Stanford Institute for Human-Centered Artificial Intelligence, Goldman Sachs Research ·  
\*Average of GS Research 2022–2030 revenue growth estimates for Microsoft Azure, NVIDIA,  
Google Cloud, and Amazon Web Services (when available)

**Goldman  
Sachs**

# Accelerated Industrialization of AI

**AI investment is likely to grow in the next three years**  
Private AI investment (dotted lines show GS revenue projections\*)



Accelerated industrialization of AI based on market competition  
entails diverging missions.

# Remarkable progress but many questions remain open.



- Questions about
  - optimality of architectures,
  - limits of their controllability,
  - scope of machine innovations,
  - effective interaction with humans, . . .
- **Today:** Revisit two interrelated technological pieces that deserve further deliberation.



# Today

- Revisiting ...

In-Context  
Learning

Alignment  
of chatbots



# Today

- Revisiting ...

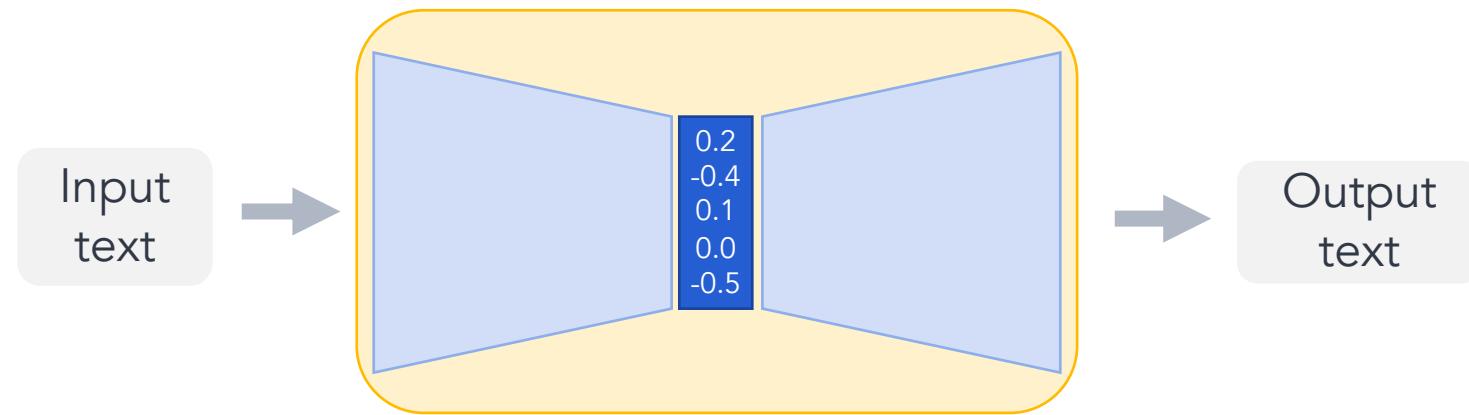
In-Context  
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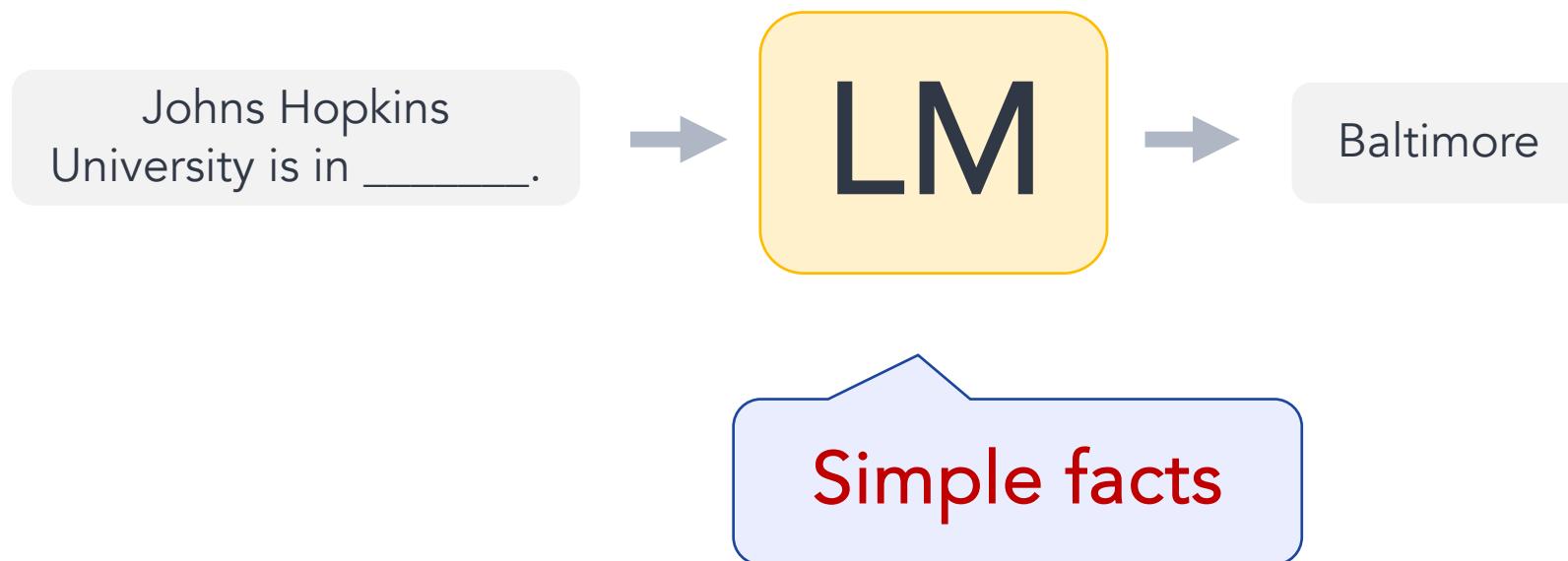
# Language Models



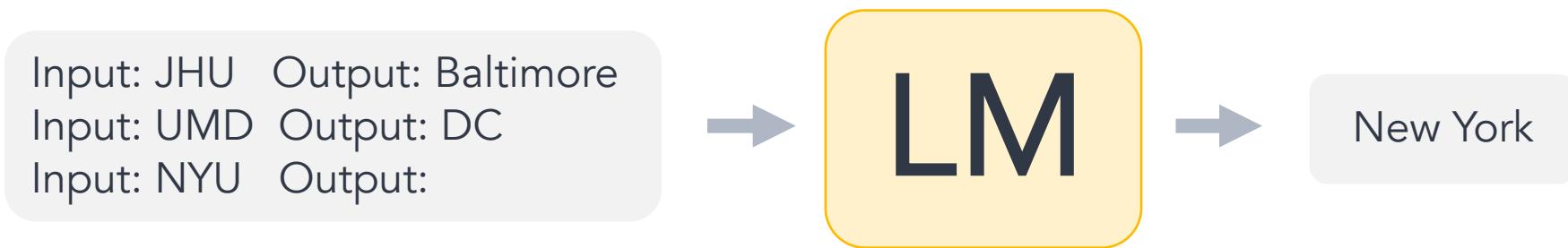
# Language Models



# Language Models

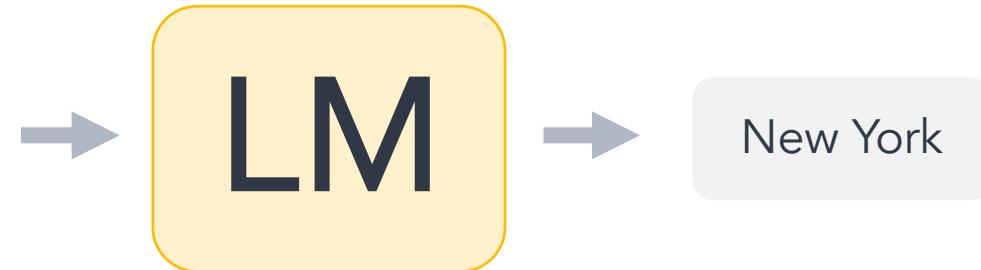


# In-context learning emerges from pre-training

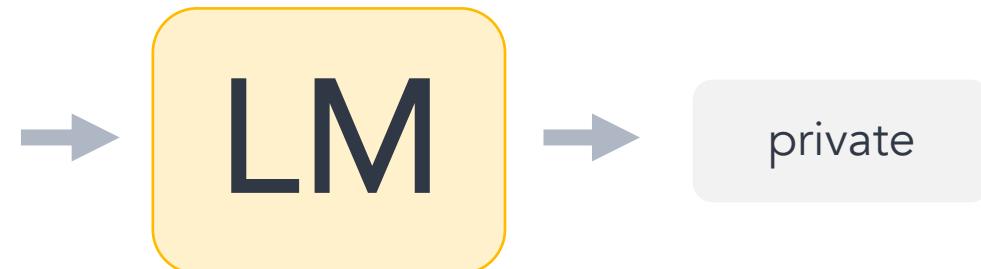


# In-context learning emerges from pre-training

Input: JHU Output: Baltimore  
Input: UMD Output: DC  
Input: NYU Output:

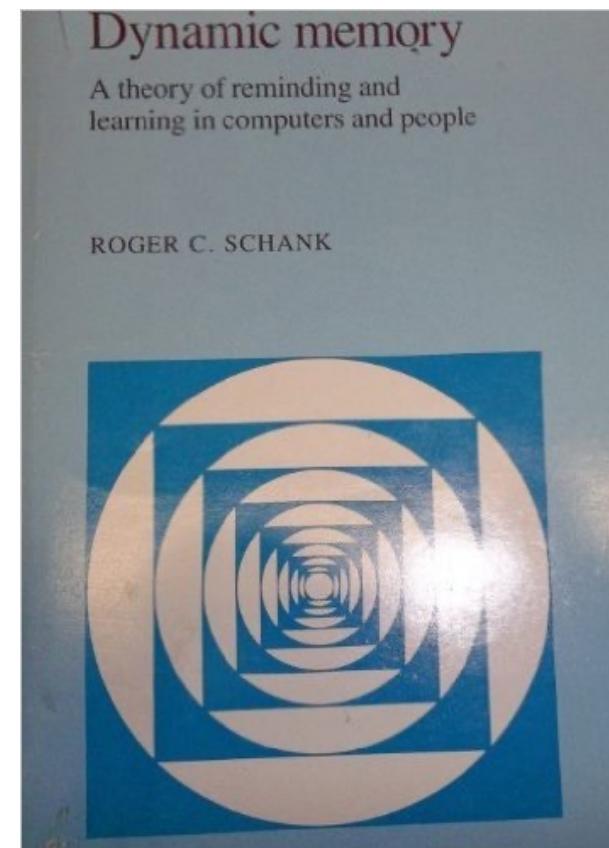
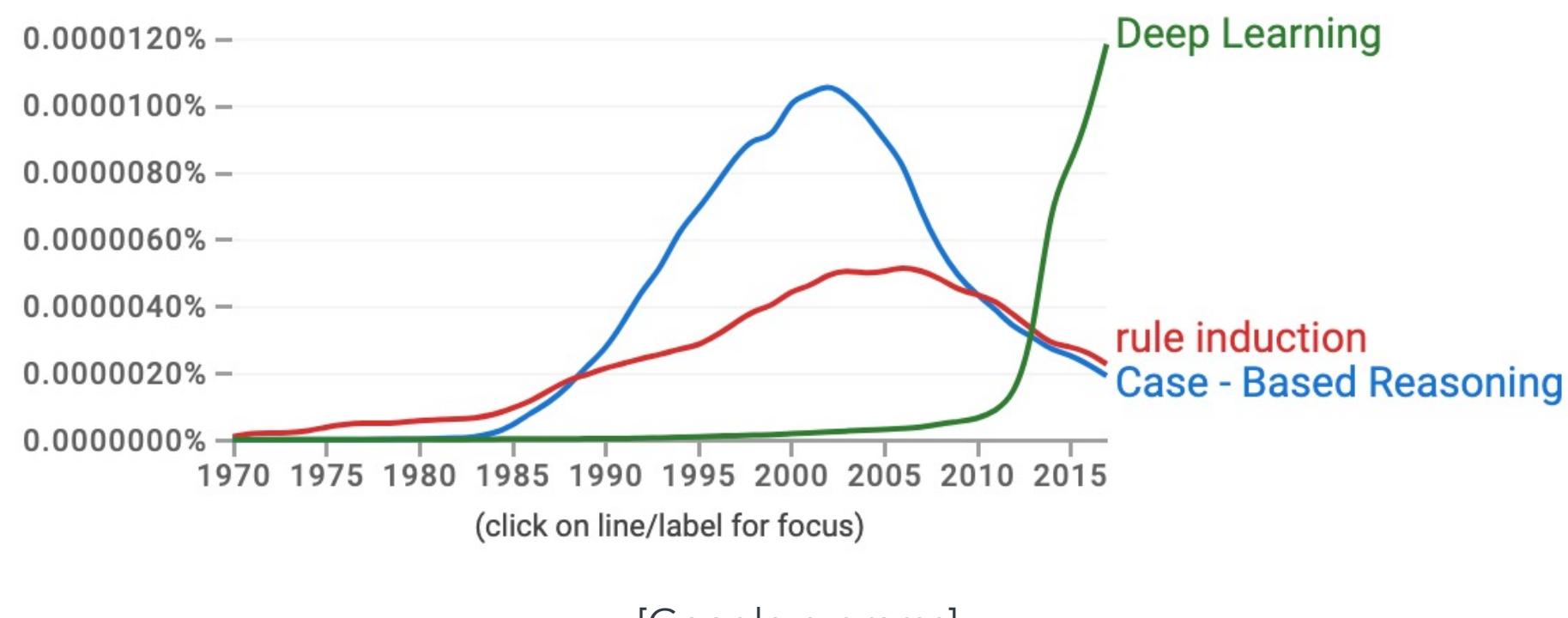


Input: JHU Output: private  
Input: UMD Output: public  
Input: NYU Output:



# This is an old dream come true!

Case-based reasoning, rule-induction, dynamic memory, analogical reasoning, ...



# In-context learning: well-studied yet **elusive**.

- What we understand:
  - ICL improves with scale. [Brown et al. 2020; Srivastava et al. 2023]
  - ICL is brittle. [Min et al., 2022; Mishra et al., 2022]
  - ICL as a probabilistic inference. [Muller et al. 2021; Xie et al. 2021]
- Still no framework that fully explains and predicts its nuts and bolts.

# Explaining ICL via Gradient Descent

- Is it possible that ICL is secretly executing GD during inference?
- We have known GD for a long time.



Transformers Learn In-Context by Executing Gradient Descent

Johannes von Oswald<sup>1,2</sup> Eyvind Niklasen<sup>1</sup>  
Alexander Mordvintsev<sup>2</sup> Andrew Ng<sup>1</sup>

ICML

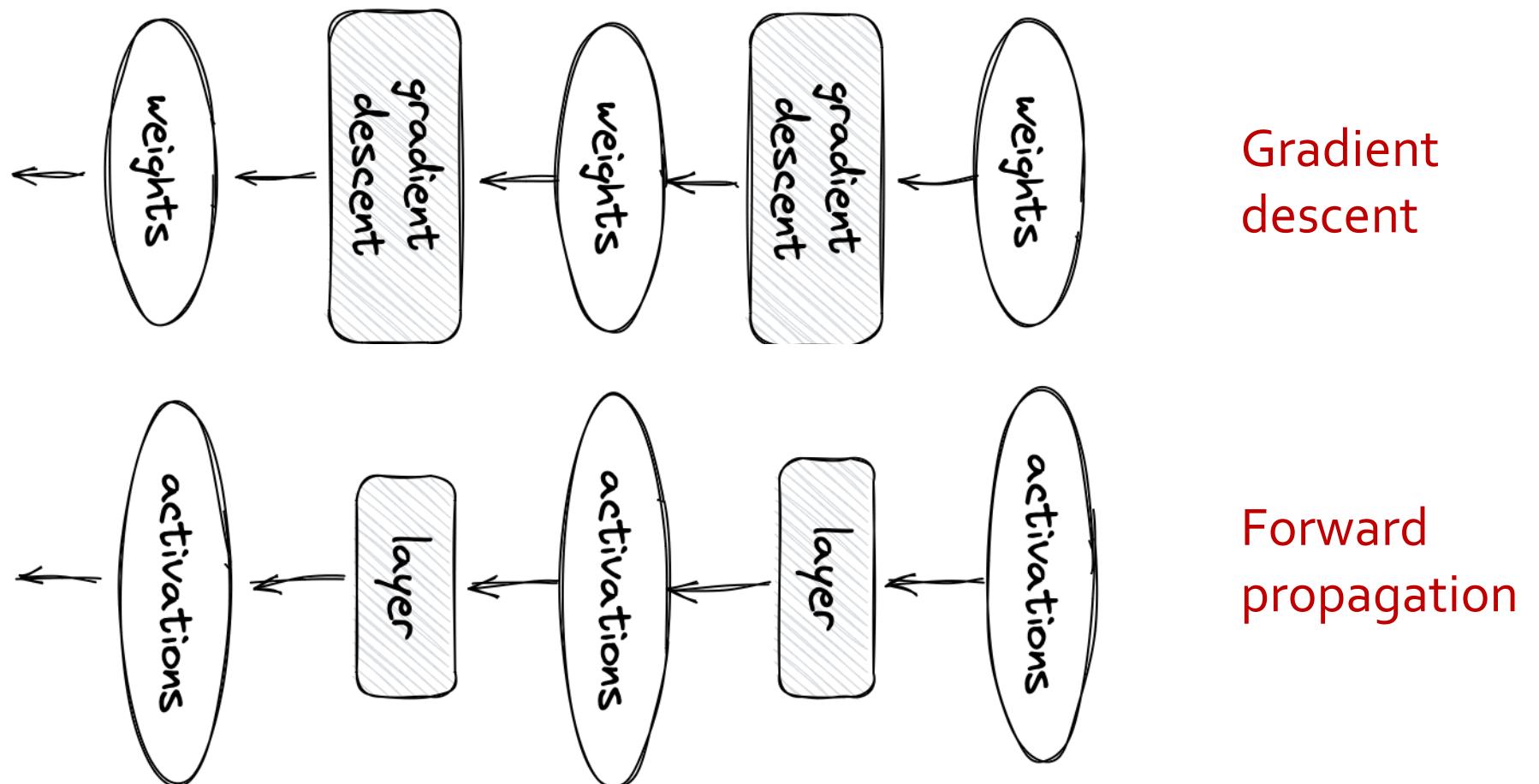
RITHM IS IN-CONTEXT LEARN-  
WITH LINEAR MODELS

Ekin Akyürek<sup>1,2,a</sup> Dale Schuurmans<sup>1</sup> Jacob Andreas<sup>\*2</sup> Tengyu Ma<sup>\*1,3,b</sup> Denny Zhou<sup>\*1</sup>

Dai et al. 2022; Garg et al. 2022; Zhang et al. 2023;  
Ahn et al. 2023; Raventos et al. 2023; Li et al. 2023; Guo et al. 2023; ...

ICLR 2023

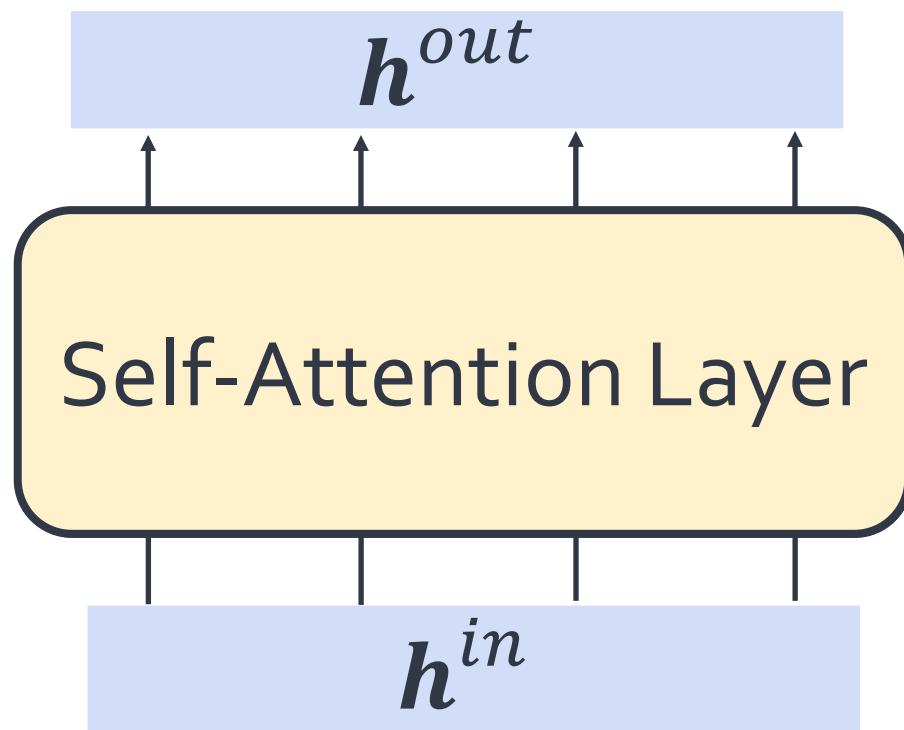
Basic idea: gradient computation in forward process



(photo credit: Blaine on lesswrong)

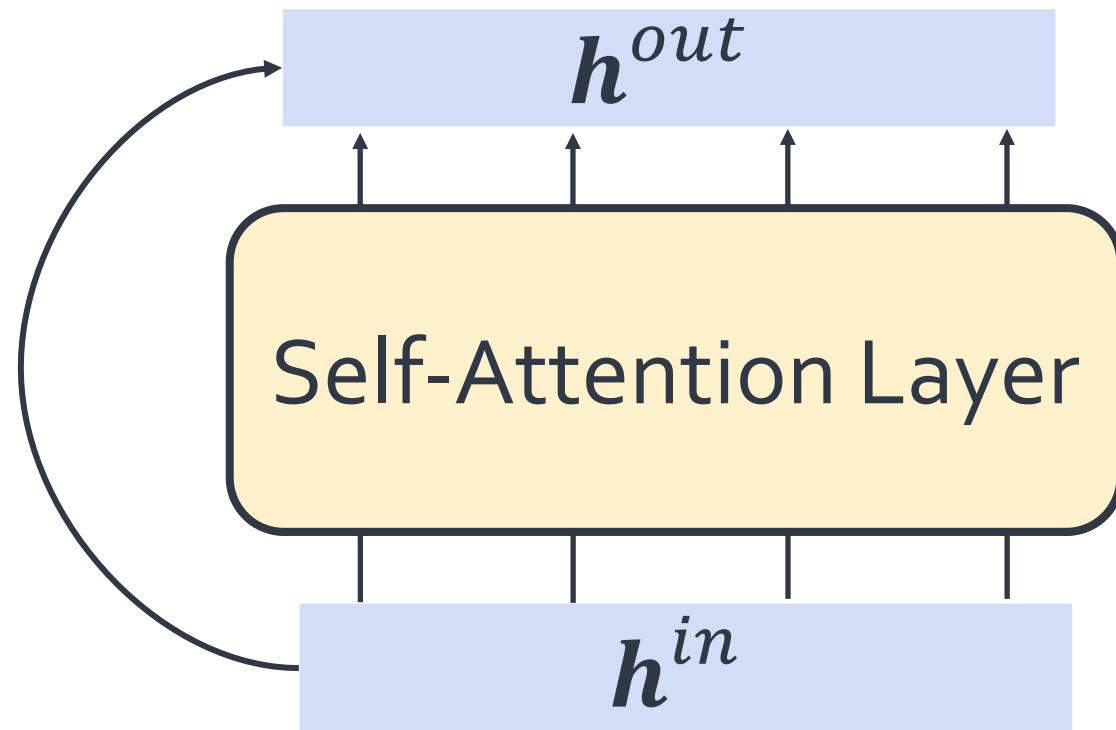
# A Self-Attention (SA) Layer

$$\mathbf{h}^{out} = \text{SA}(\mathbf{h}^{in}; \mathbf{W}_q, \mathbf{W}_k, \mathbf{W}_v)$$



# A Self-Attention (SA) Layer

$$h^{out} = h^{in} + \text{SA}(h^{in}; W_q, W_k, W_v)$$



# A SA Layer vs. a GD update

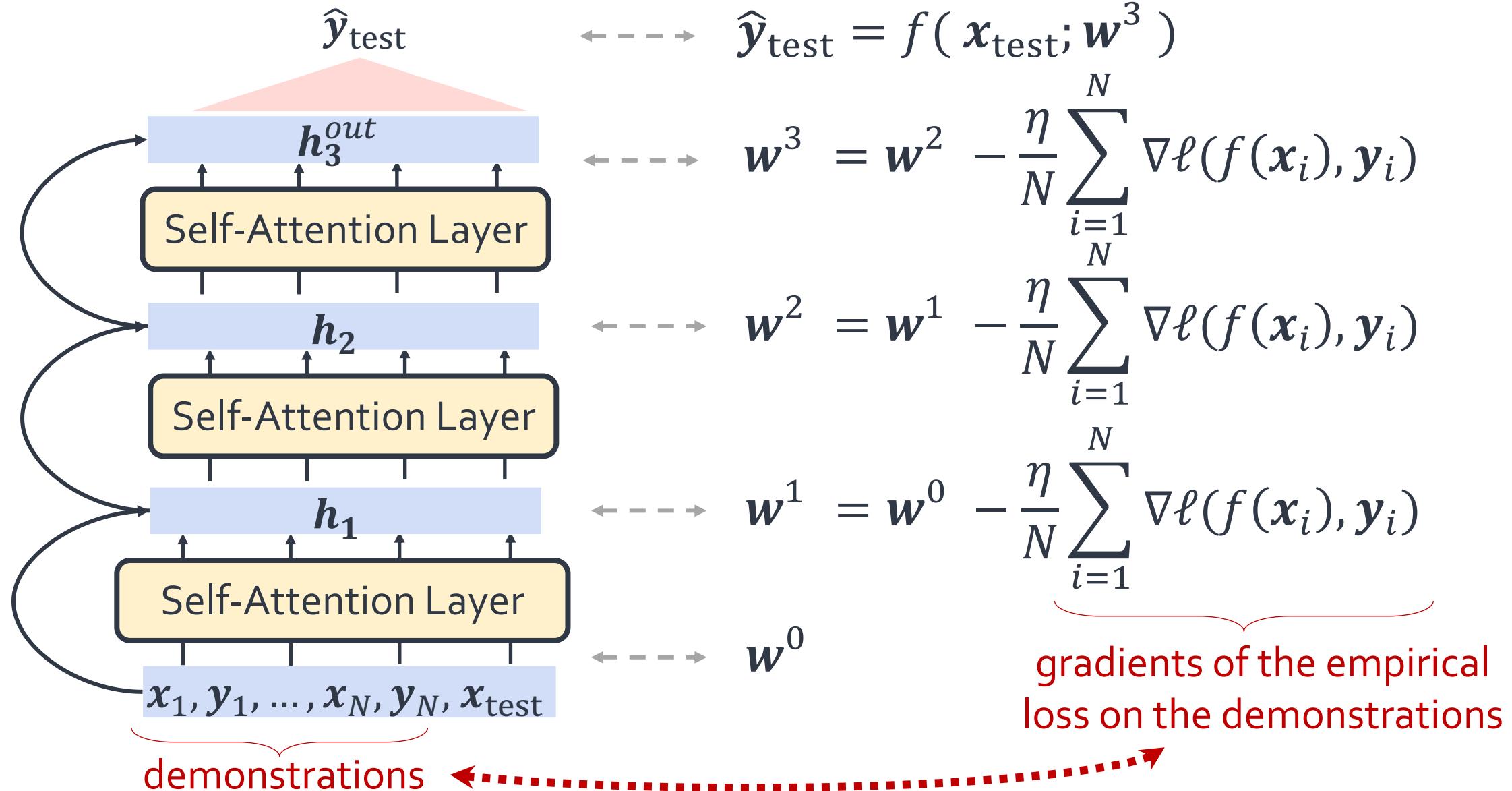
$$\mathbf{h}^{out} = \mathbf{h}^{in} + \underbrace{\text{SA}(\mathbf{h}^{in}; W_q, W_k, W_v)}$$

Each layer simulate an implicit gradient update?

$$\mathbf{w}^{t+1} = \mathbf{w}^t - \eta \times \nabla \mathcal{L}$$

# Results: Transformers **can** implement GD

*!= does*



# Results: Transformers **can** implement GD

Theorem [von Oswald et al., among others]: There exists self-attention weights that, ICL simulates GD, for a fixed well-defined task family.

How strong of a claim are we making here?  
**Do they hold in real practice?**

What existing work shows:



Theorem [von Oswald et al., among others]: There exists self-attention weights that, ICL simulates GD, for a fixed well-defined task family.

Ǝ

Do the existing results generalize to realistic settings?

What is more interesting and **realistic**:



Hypothesis [ICL $\approx$ GD hypothesis]: For any pre-trained Transformer weights , ICL is equivalent to GD, for any well-defined task family.

forall

# Do Pretrained Transformers Really Learn In-Context by Gradient Descent?

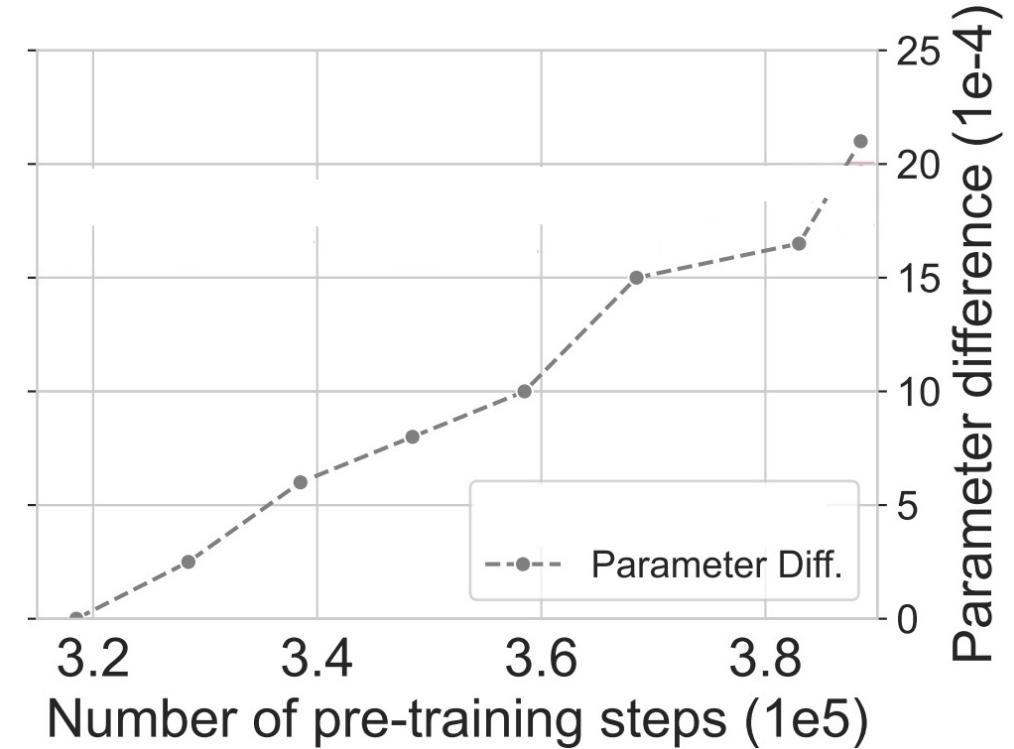
Lingfeng Shen, Aayush Mishra, Daniel Khashabi



<https://arxiv.org/abs/2310.08540>

# How realistic is it to prove $\text{ICL} \approx \text{GD}$ for **fixed** weights?

- GPT-J's ICL ability does not change much over time during training, while the parameters change steadily.
- There are **many** ICL-inducing parameters.



Therefore, to prove  $\text{ICL} \approx \text{GD}$  hypothesis,  
showing it for **a single choice of parameters** is **not** enough.

# ICL vs GD: End task comparison

Input: Rookie Taylor Wins Playoff at Tahoe  
Output:

LM

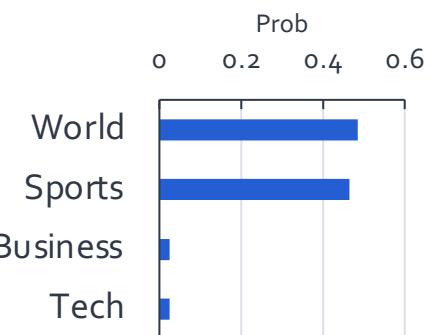
Possible values:  
World, Sports, Business, Tech



**demonstrations**  
Input: Apple recalls 15in PowerBook batteries  
Output: Tech  
Input: Major attack by rebels on Nepalese town  
Output: World  
...  
Input: Rookie Taylor Wins Playoff at Reno-Tahoe  
Output:

In-context

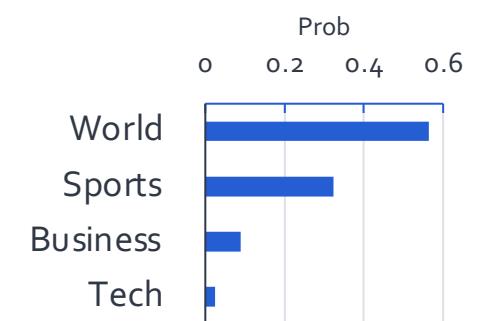
LM



Input: Rookie Taylor Wins Playoff at Tahoe  
Output:

Gradient-descent

LM



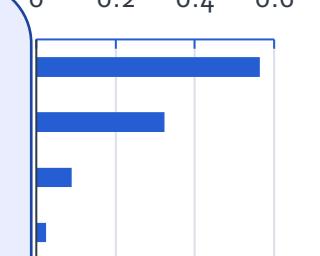
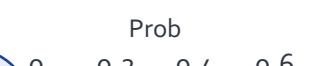
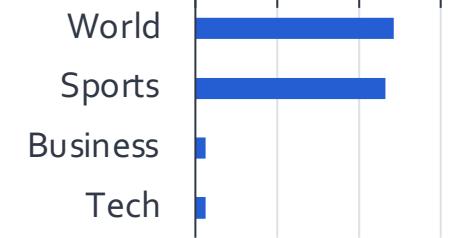
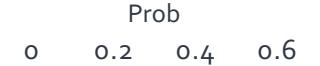
# ICL vs GD: End task comparison

demonstrations

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...  
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**Output:**



Possible values:  
World, Sports, Business, Tech



**Input:**  
**Output:**

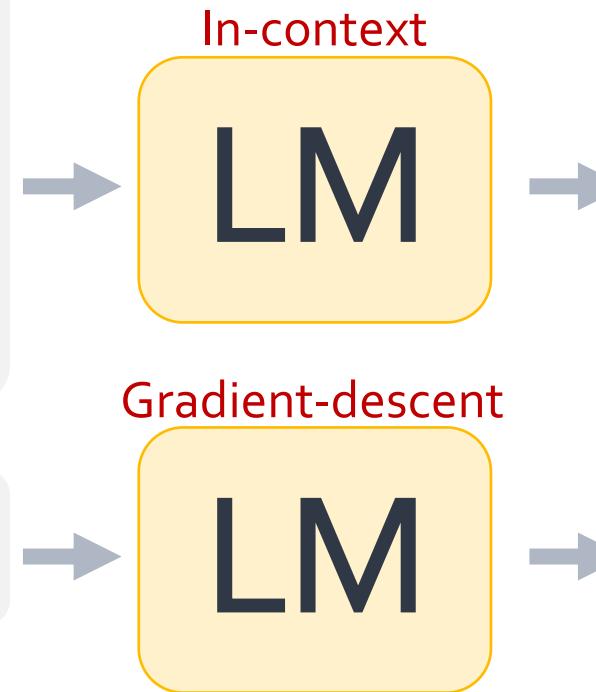
**Hypothesis:** If two adaptation algorithms consistently lead to the **same distribution** on **any tasks**, they must be **equivalent**.

# ICL vs GD: End task comparison

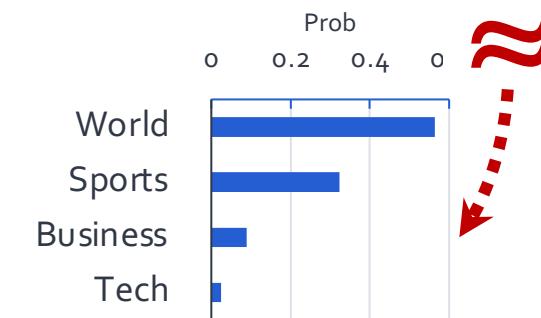
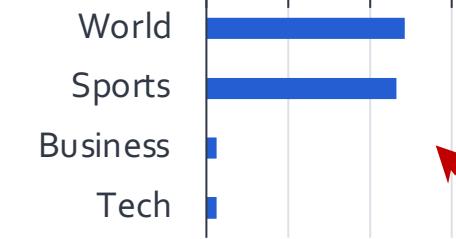
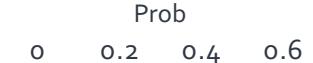
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Possible values:  
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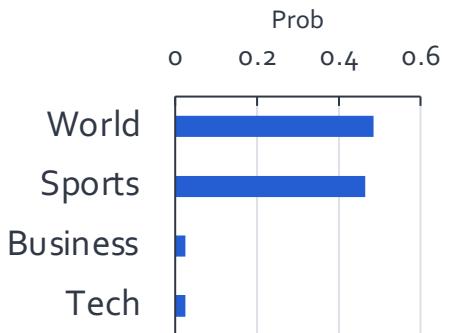


Can we take this  
as an evidence for ICL  $\approx$ GD?

Full distributions over vocabulary are quite different!

In-context

LM



In-context

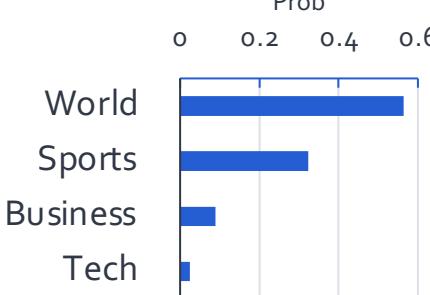
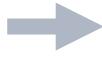


Gradient-descent



Gradient-descent

LM



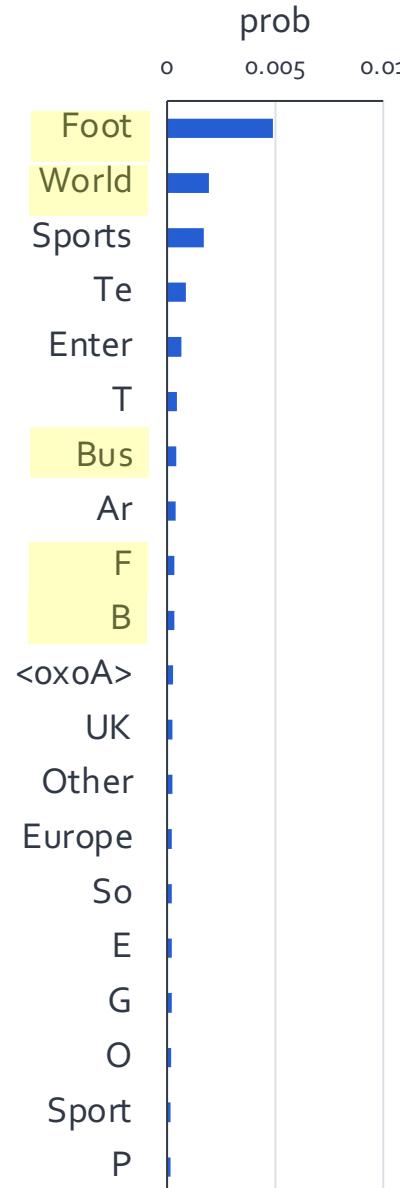
ICL vs GD modify LLM distributions **differently.**

**Overlap( $k$ ):** % commonality across  
top- $k$  tokens of two distributions

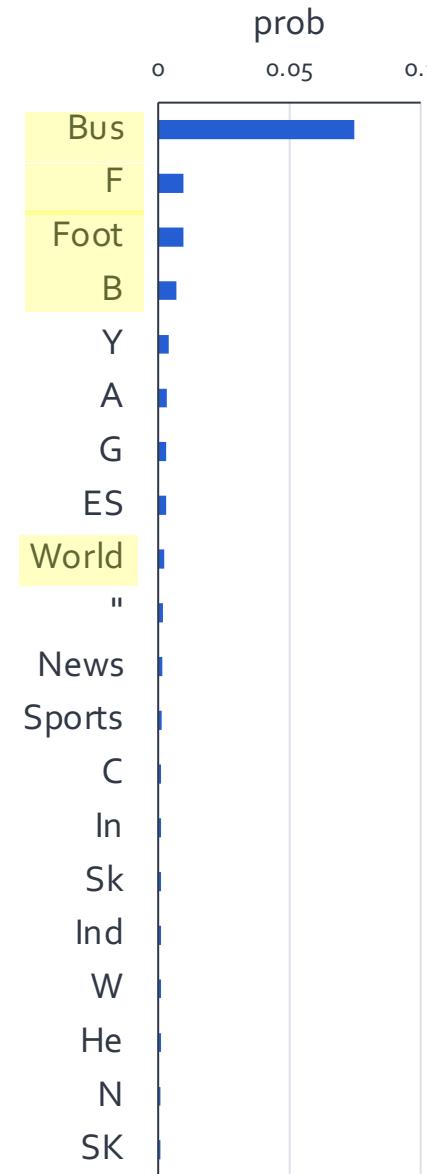
Overlap( $k=10$ )=50%

top- $k$

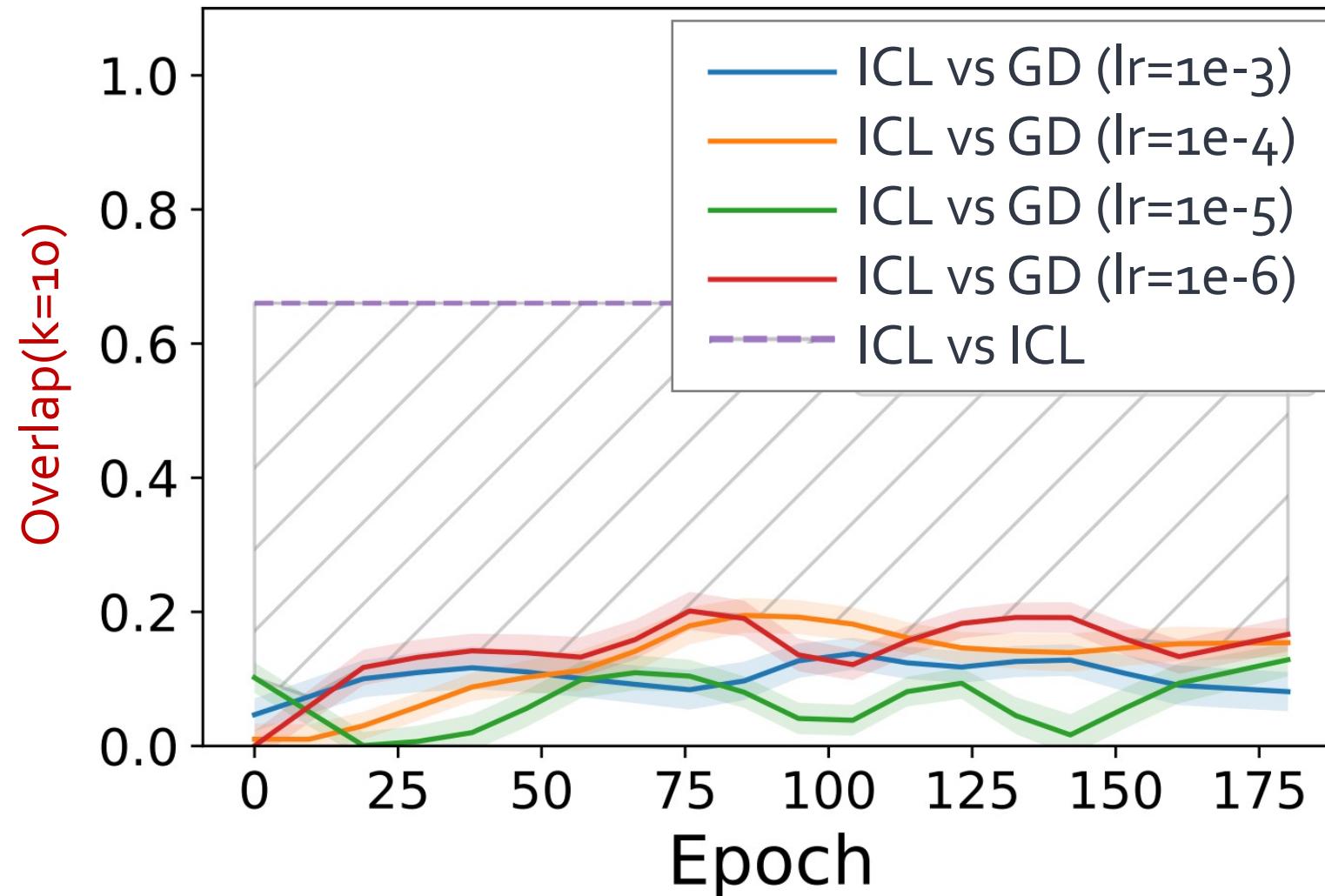
In-context



Gradient-descent



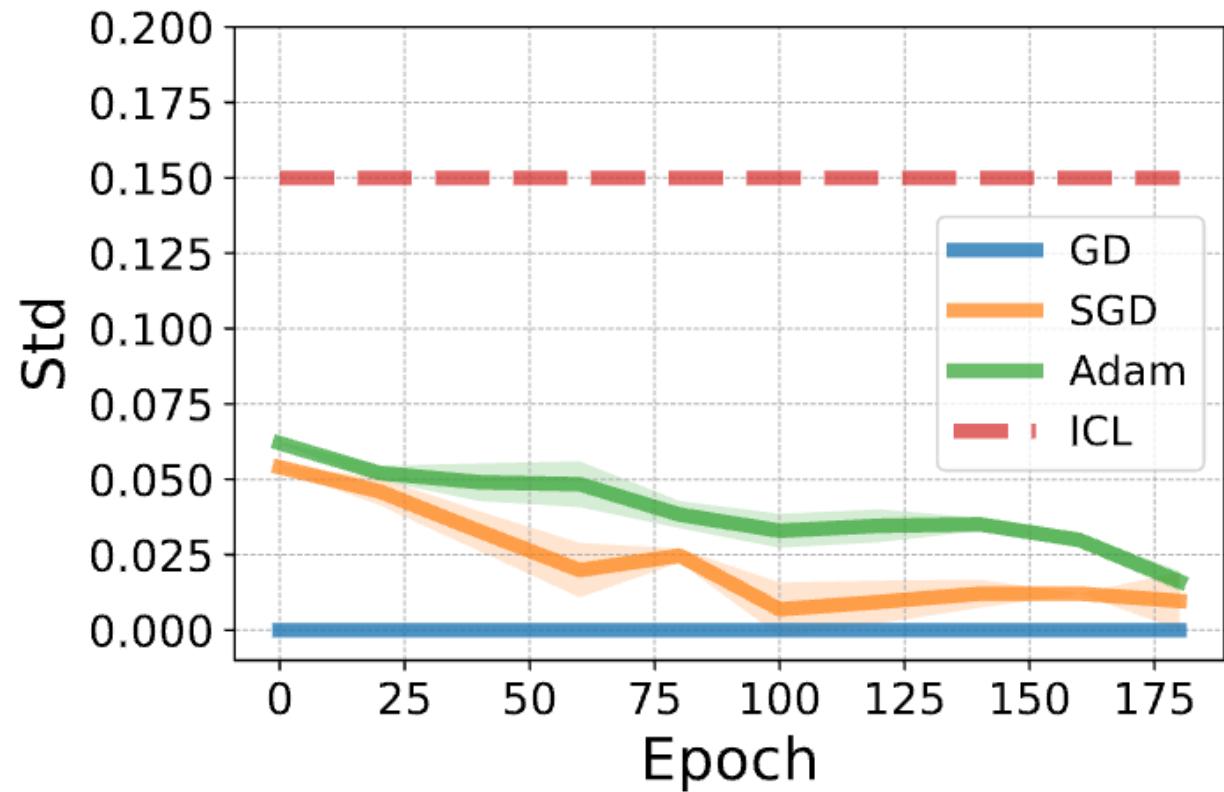
ICL vs GD modify LLM distributions differently.



# ICL vs GD have different order-sensitivity.

- Prior research has demonstrated that ICL is **highly sensitive** to the order of in-context sample [Lu et al. 2022].
- GD and its variants is **more order-stable** (less STD).

Standard deviation token probabilities, for different choices of demonstrations.



# Summary Thus Far

- The explanations of ICL based on GD are quite intriguing — do they hold in practice?
- In practice, we did **not** see any evidence that ICL simulates GD.
  - See the paper for more arguments and analysis.
- Note, we're **not** refuting it. It's left open for future research.
  - Deep inside, I believe that there must be a connection between ICL and optimization algorithms — we're just not looking at it right.

# ICL remains understudied and elusive.

- ICL is the most **important & mysterious** phenomenon.
  - ... we **don't** know how to explain it.
  - ... and we are getting used to it.
- Many open problems:
  - Under what conditions does it emerge? (e.g., distributional properties)
  - Does ICL need natural language? Can it emerge, e.g., on brain signals?

# ICL is likely what makes “alignment” effective.

- The success of LLMs in following instructions can be viewed from the lens of ICL.
- Being able to make LLMs adapt to various in-context demonstration was an early sign that **LLMs can be controlled**.
- To understand **limits** of controlling LLMs, we must understand limits of ICL.



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- Revisiting ...

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Alignment  
of chatbots



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# Language Modeling ≠ Following User Intents

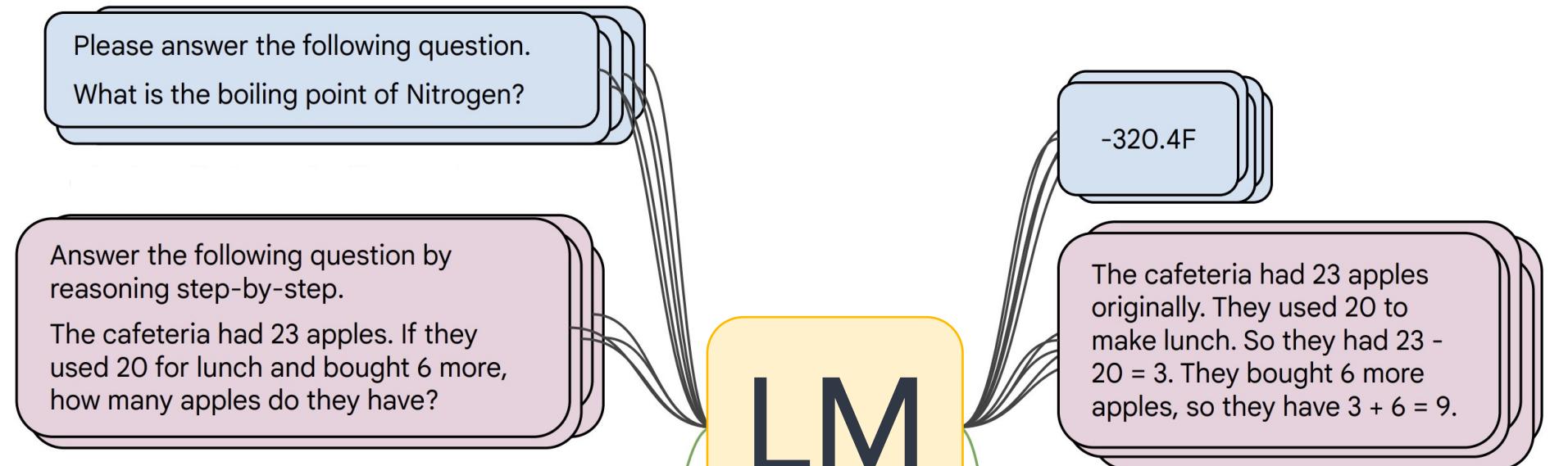


LMs are not “aligned” with **user intents** [Ouyang et al., 2022].

How do we “align” LMs with our articulated intents?

# Approach 1: Behavior Cloning (Supervised Learning)

1. Collect examples of (instruction, output) pairs across many tasks and finetune an LM



2. Evaluate LM on unseen tasks

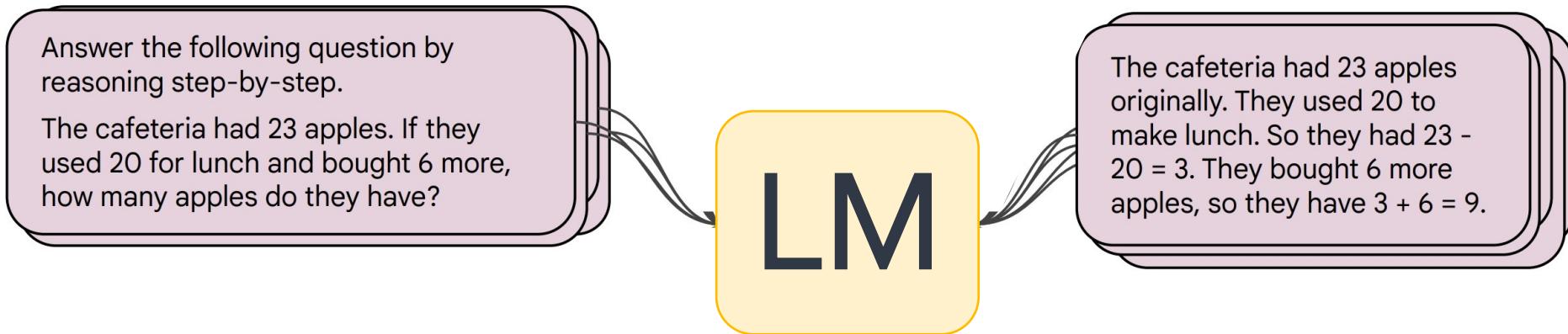
*Inference: generalization to unseen tasks*

Q: Can Geoffrey Hinton have a conversation with George Washington?  
Give the rationale before answering.

Geoffrey Hinton is a British-Canadian computer scientist born in 1947. George Washington died in 1799. Thus, they could not have had a conversation together. So the answer is "no".

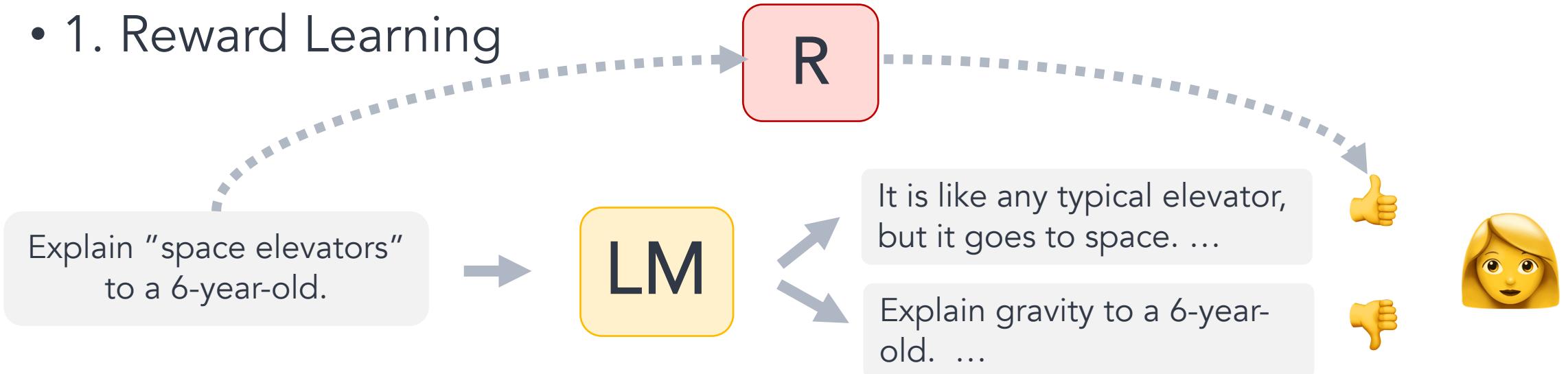
# Approach 1: Behavior Cloning (Supervised Learning)

- Incentivizes word-by-word rote learning => **limits creativity**
- => The resulting models' **generality/creativity** is bounded by that of **their supervision data**.

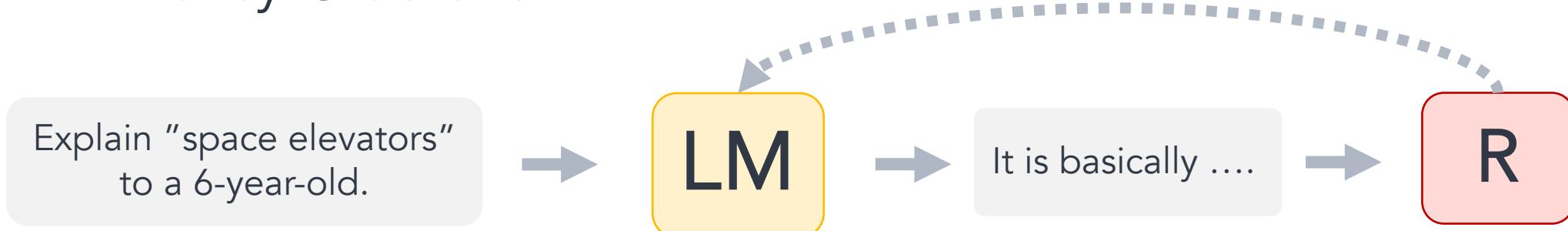


# Approach 2: RL w/ Ranking Feedback (RLHF)

- 1. Reward Learning



- 2. Policy Gradient



# The overall recipe :

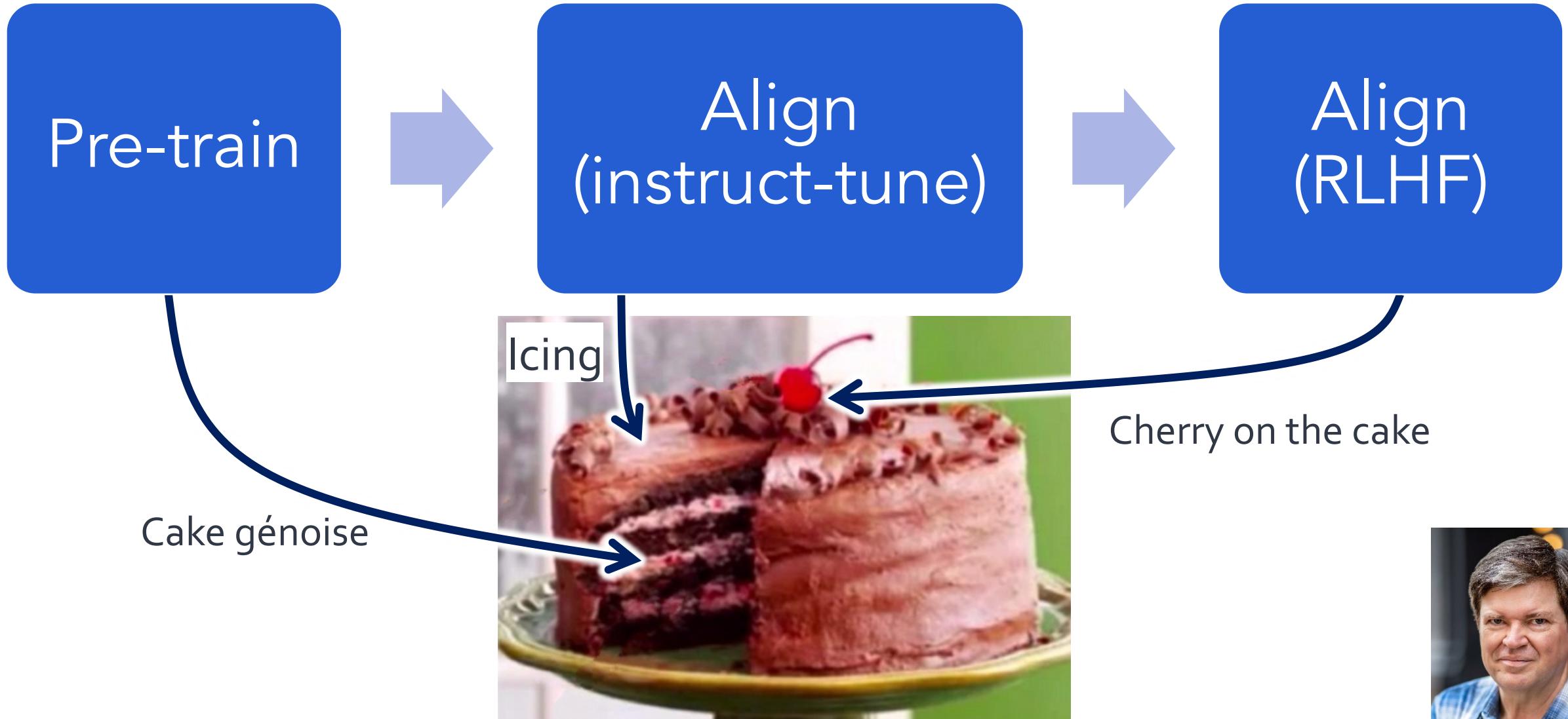


# The overall recipe :



# The overall recipe 🧑‍🍳:

## Yann's Three-layered cake



# Are these steps equally important?



# Are these steps equally important?



Who should care?

1. **Product designers:** If you have \$X million to build your best chatbot, how would you allocate it?
2. **Scientists:** Fundamentally, is this the ultimate pipeline?

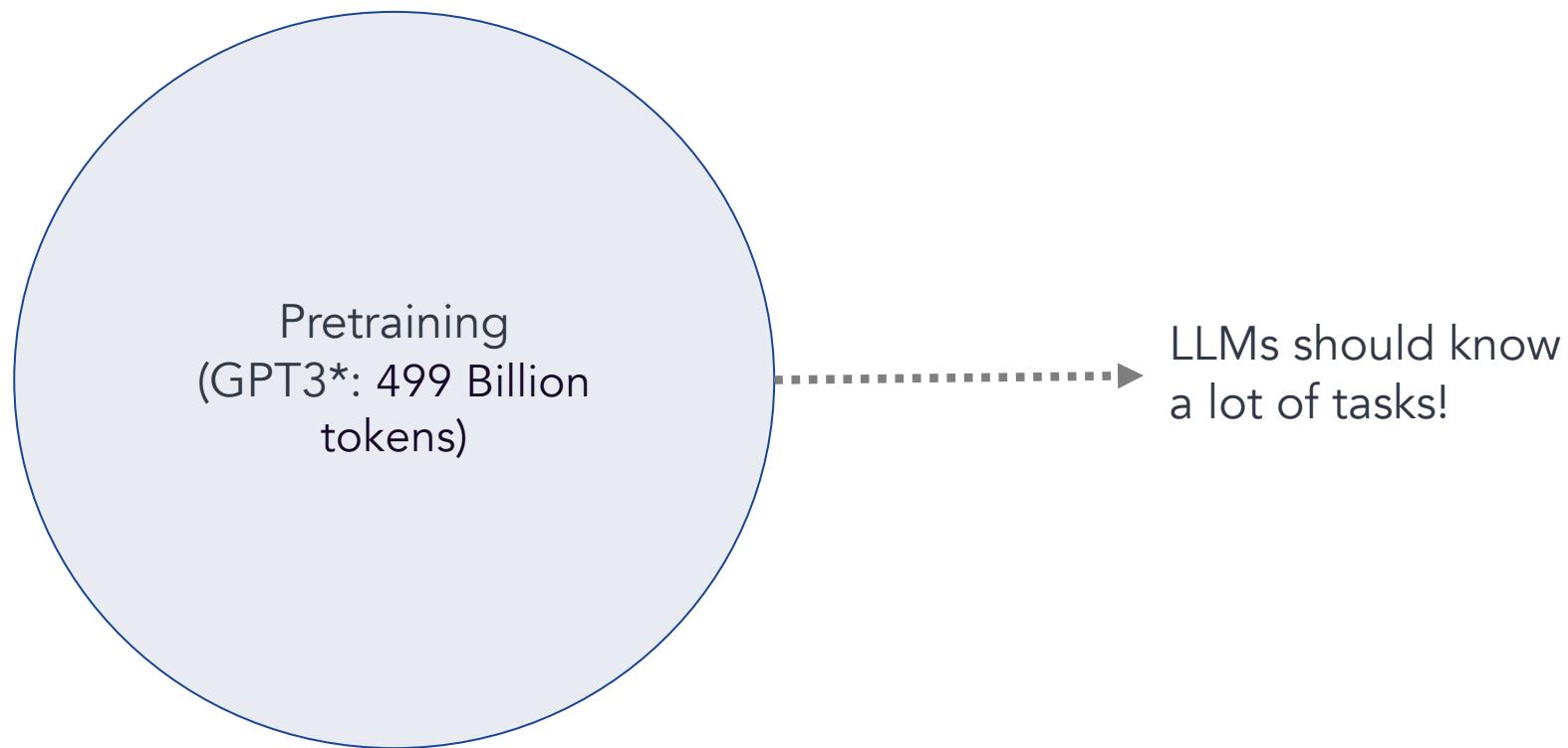
# Are these steps equally important?



How far can we **reduce** the human annotations?

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- Idea: we can **bootstrap “instruction”** from off-the-shelf LMs.
  - LMs have seen humans talk about their needs and goals.

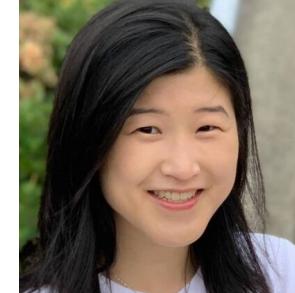


Self-Instruct:

Warning: the paper  
is a year old!!

# Aligning Language Models w/ Self-Generated Instructions

Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu,  
Noah A. Smith, Daniel Khashabi, Hannaneh Hajishirzi



<https://arxiv.org/abs/2212.10560>

# Get humans to write “seed” tasks



- I am planning a 7-day trip to Seattle. Can you make a detailed plan for me?
- Is there anything I can eat for breakfast that doesn't include eggs, yet includes protein and has roughly 700-1000 calories?
- Given a set of numbers find all possible subsets that sum to a given number.
- Give me a phrase that I can use to express I am very happy.

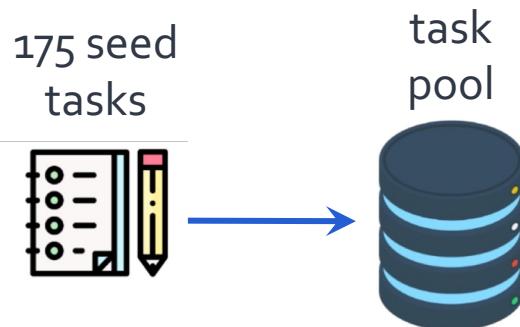
175 seed  
tasks



# Put them your task bank



- I am planning a 7-day trip to Seattle. Can you make a detailed plan for me?
- Is there anything I can eat for breakfast that doesn't include eggs, yet includes protein and has roughly 700-1000 calories?
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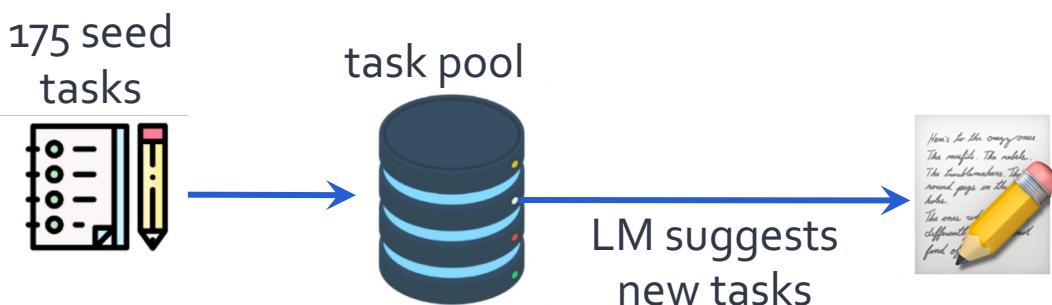
# Sample and get LLM to expand it

- I am planning a 7-day trip to Seattle. Can you make a detailed plan for me?
- Is there anything I can eat for breakfast that doesn't include eggs, yet includes protein and has roughly 700-1000 calories?
- Given a set of numbers find all possible subsets that sum to a given number.
- Give me a phrase that I can use to express I am very happy.

LM

Pre-trained, but **not aligned yet**

- Create a list of 10 African countries and their capital city?
- Looking for a job, but it's difficult for me to find one. Can you help me?
- Write a Python program that tells if a given string contains anagrams.



# Get LLM to answers the new tasks

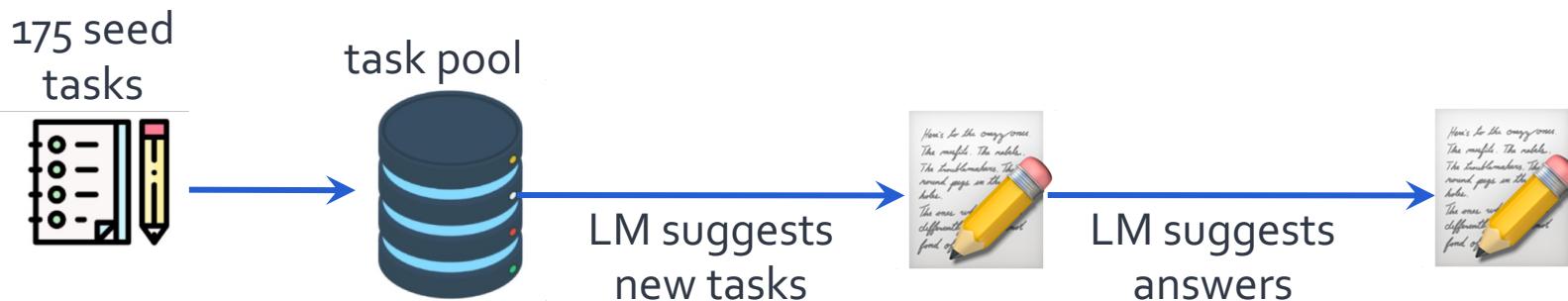
- Task: Convert the following temperature from Celsius to Fahrenheit.
- Input: 4 °C
- Output: 39.2 °F
- Task: Write a Python program that tells if a given string contains anagrams.

LM

Pre-trained, but **not aligned yet**

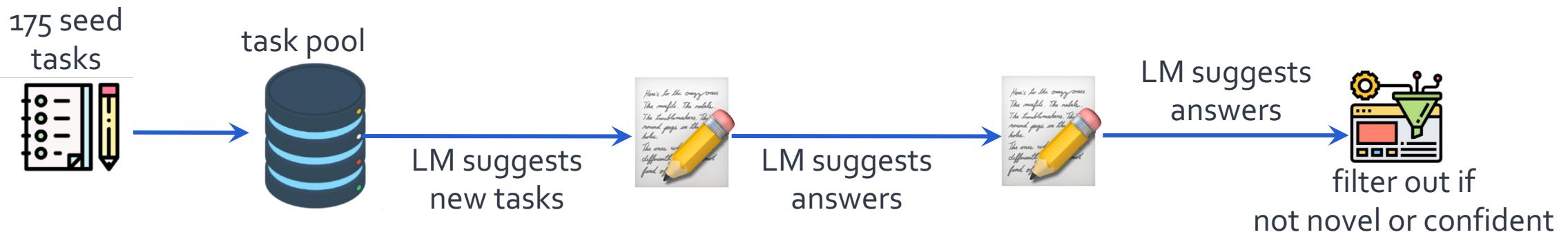
- Input: -
- Output:  

```
def isAnagram(str1, str2): ...
```



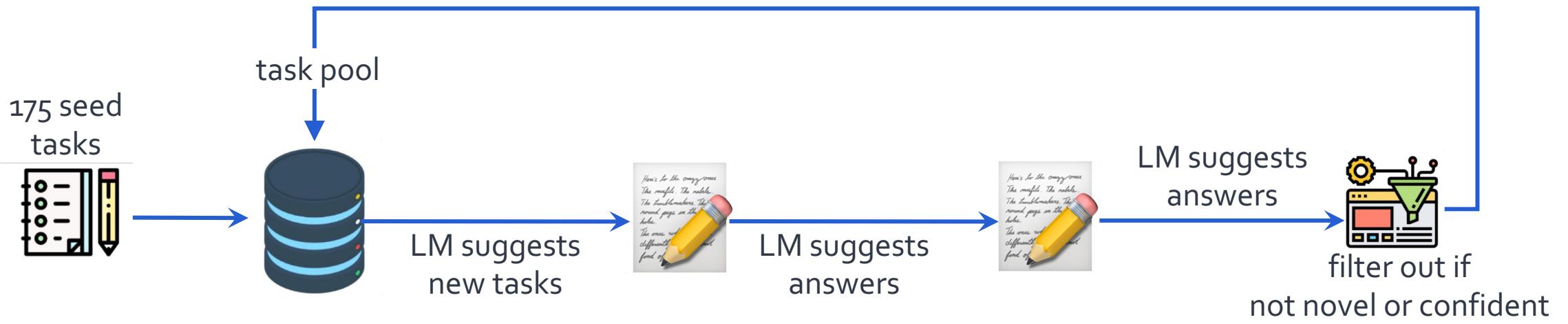
# Filter tasks

- Drop tasks if LM assigns **low probability** to them.
- Drop tasks if they have a **high overlap** with one of the existing tasks in the task pool.
  - Otherwise, common tasks become more common — **tyranny of majority**.



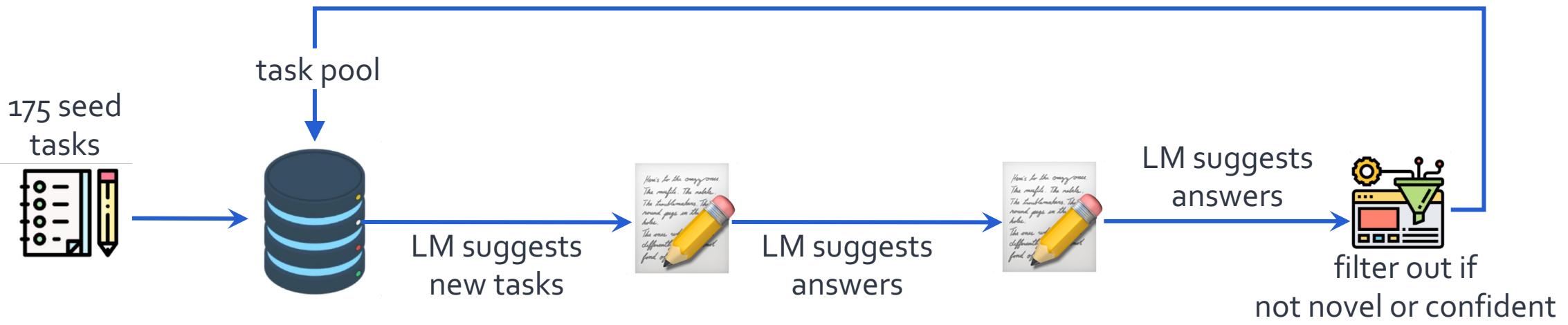
# Close the loop

- Add the filtered tasks to the task pool.
- Iterate this process (generate, filter, add) until yield is near zero.



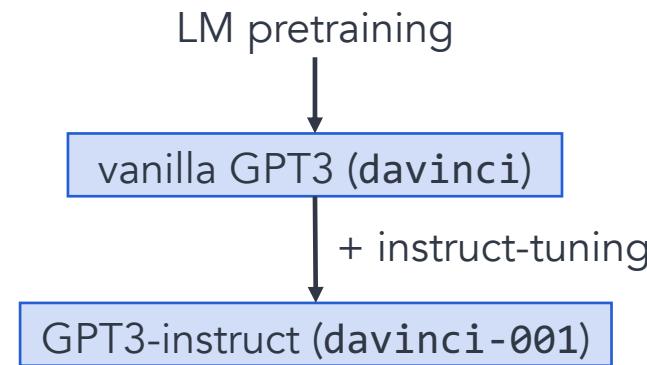
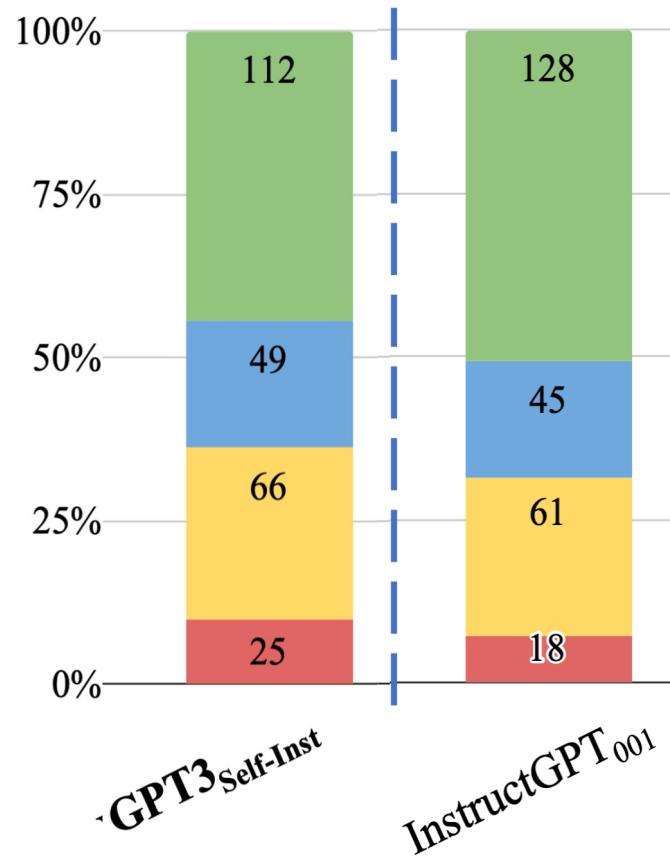
# Self-Instructing GPT3 (base version)

- **Generate:**
  - GPT3 (“davinci” engine).
  - We generated 52K instructions and 82K instances.
  - API cost ~\$600
- **Align:**
  - We finetuned GPT3 with this data via OpenAI API (2 epochs). \*\*
  - API cost: ~\$338 for finetuning



# Evaluation on User-Oriented Instructions

- A: correct and satisfying response
- B: acceptable response with minor imperfections
- C: responds to the instruction but has significant errors
- D: irrelevant or invalid response



Diverse, “self-instruct” data ~ thousands of human-written data

# Summary Thus Far

- There is a lot of room to reduce the reliance on **human** annotations in the “alignment” stage.
  - Well-read LLMs know a lot of our needs and demands.
  - Magic of “in-context learning” can surface these.
- Self-Instruct: Rely on creativity induced by LLMs themselves.
  - Lots of open-source adoption, but that’s not the point ...

# The weight of “alignment” step

Fundamentally, what is the role of post hoc alignment (step #2/3)?



It's playing a **small** role —  
**Lightly modify** LM so it  
can articulate its **existing**  
knowledge of tasks.

(+ put guardrails for what it can articulate)



It's playing a **big** role —  
**Teaching** LM knowledge  
of **new** tasks.

# Implications for how to invest

Fundamentally, what is the role of post hoc alignment (step #2/3)?



Make it more efficient, possibly with minimal human labor.

It's playing a **small** role —  
Lightly modify LM so it can articulate its **existing** knowledge of tasks.  
(+ put guardrails for what it can articulate)

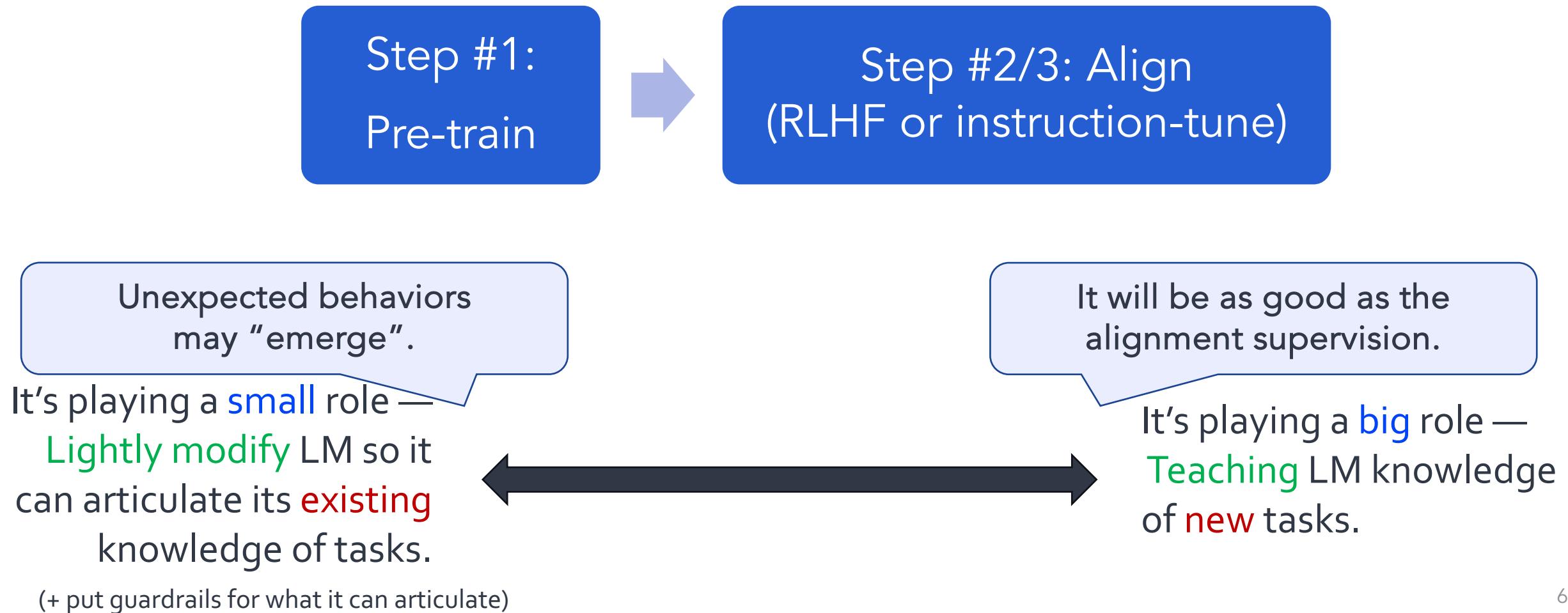
Step #2/3: Align  
(RLHF or instruction-tune)

It ought to be annotation-intensive to teach the necessary knowledge.

It's playing a **big** role —  
Teaching LM knowledge of **new** tasks.

# Implications for what comes out

Fundamentally, what is the role of post hoc alignment (step #2/3)?



# The weight of “alignment” step: My 2 cents

- Most of the heavy lifting is done via **pre-training (unlabeled)**.
- Alignment to “instructions” (tuning/RLHF) is a **light touch** on LLMs.
  - Can (and should) be done more **efficiently**.

It's playing a **small** role —  
Lightly modify LM so it  
can articulate its **existing**  
knowledge of tasks.



(+ put guardrails for what it can articulate)

It's playing a **big** role —  
Teaching LM knowledge  
of **new** tasks.

# RLHF is patchwork for lack of grounding

- RLHF teach LMs (ground) the communicative **intent** of users.
  - For example, what is **intended** by “summarize”? The act of producing a summary grounded in the human concept of “summary”.
- Not a panacea, but a short-term “band-aid” solution.



# Alignment as a social process

- Can alignment emerge as a social experience?
- Internet also captures a subset of the world's interactive experiences.



# The future is a cheesecake

- Future: A **unifying process** that **encompasses** various steps that are done separately today.
- The margins between alignment stages are getting **murkier**.
  - Using model itself for feedback and verification
  - Alignment during pre-training (Korbak et al. 2023)
  - Building bridges between supervised learning and RL (see DPO vs. RLHF)
  - ...



# The future is a cheesecake

- Future: A **unifying process** that **encompasses** various steps that are done separately today.
- Yann's framework was good for **getting a system off the ground**.
- Now that we are moving to **interactive setups**, alignment and pre-training will be a **continual process**. Systems that :
  - Adaptively change to our needs and habits;
  - Seamlessly pick up on implicit reward;
  - ....



Thanks!