Natural Language Processing with Deep Learning

CS224N/Ling284

Diyi Yang

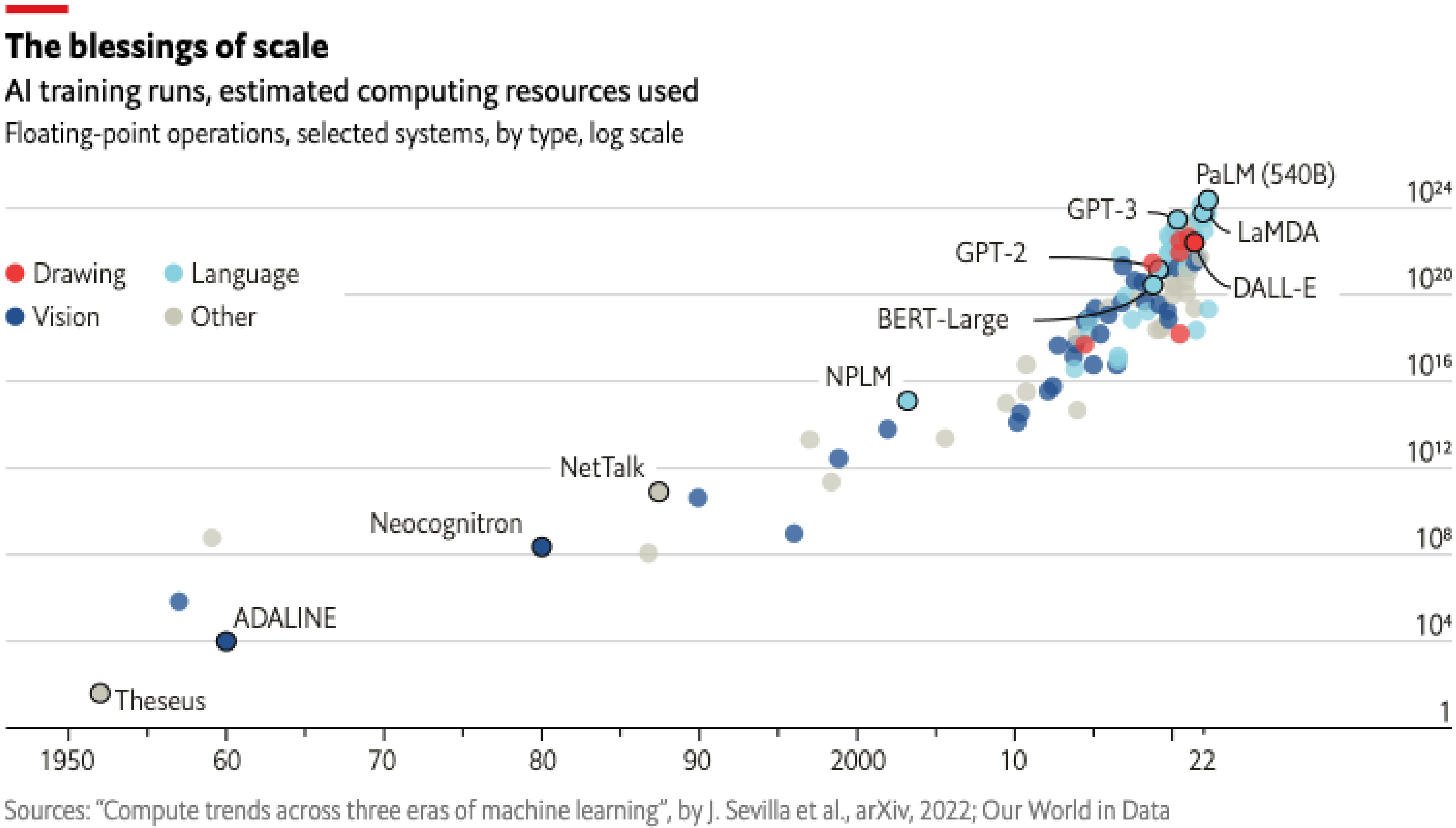
Lecture 10: Instruction Finetuning, and RLHF

(based on slides from Jesse Mu)

Lecture Plan

1. Instruction fine-tuning
2. Reinforcement learning from human preferences (RLHF)
3. InstructGPT and ChatGPT
4. Limitation of RL and reward modeling
5. Introducing Direct Preference Optimization (DPO)
6. Human preference data; human vs. AI Feedback
7. What’s next?

Language models getting larger and larger



The blessings of scale

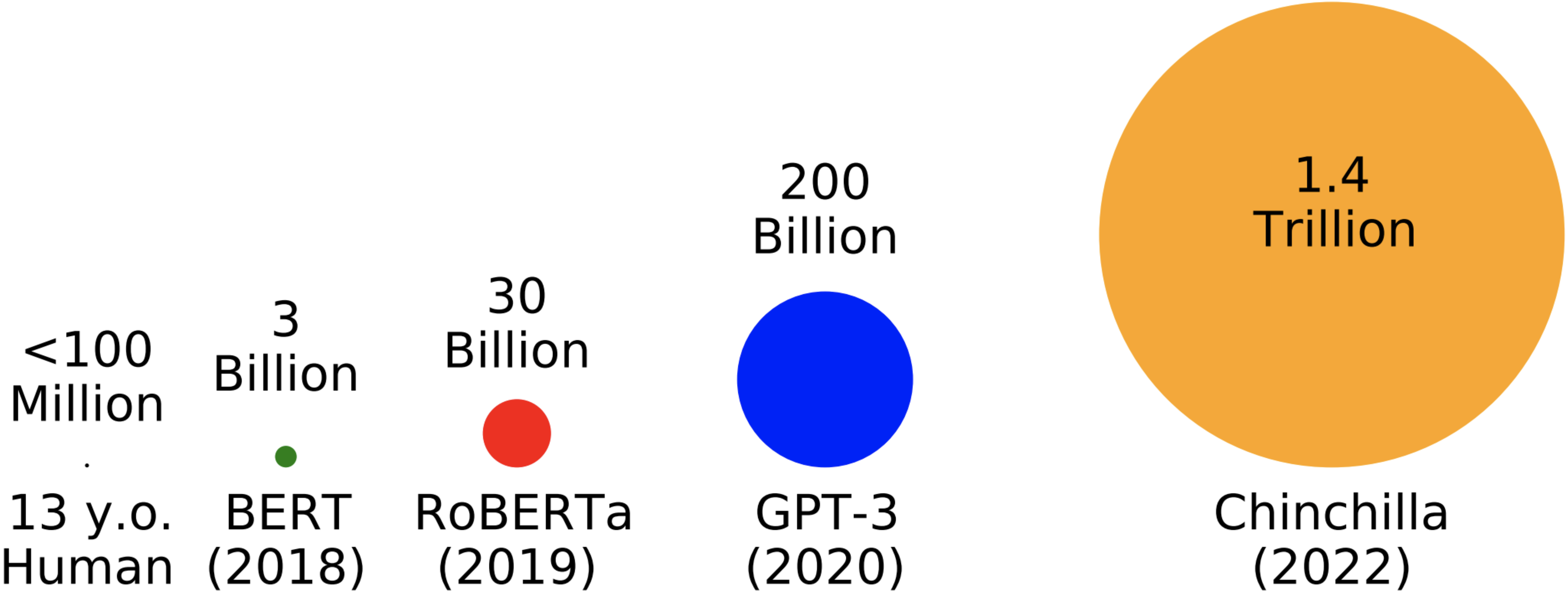
AI training runs, estimated computing resources used

Floating-point operations, selected systems, by type, log scale

Sources: "Compute trends across three eras of machine learning", by J. Sevilla et al., arXiv, 2022; Our World in Data

https://www.economist.com/interactive/briefing/2022/06/11/huge-foundation-models-are-turbo-charging-ai-progress

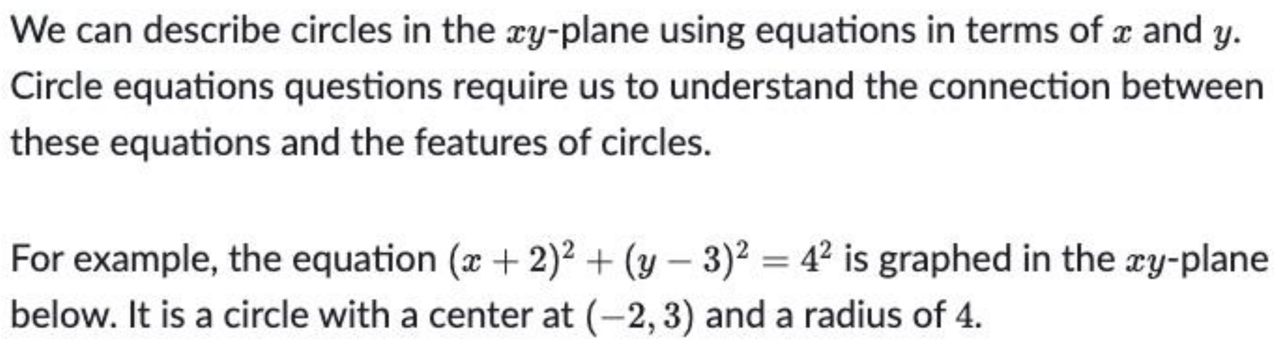
Language models trained on more and more data



# tokens seen during training

https://babylm.github.io/

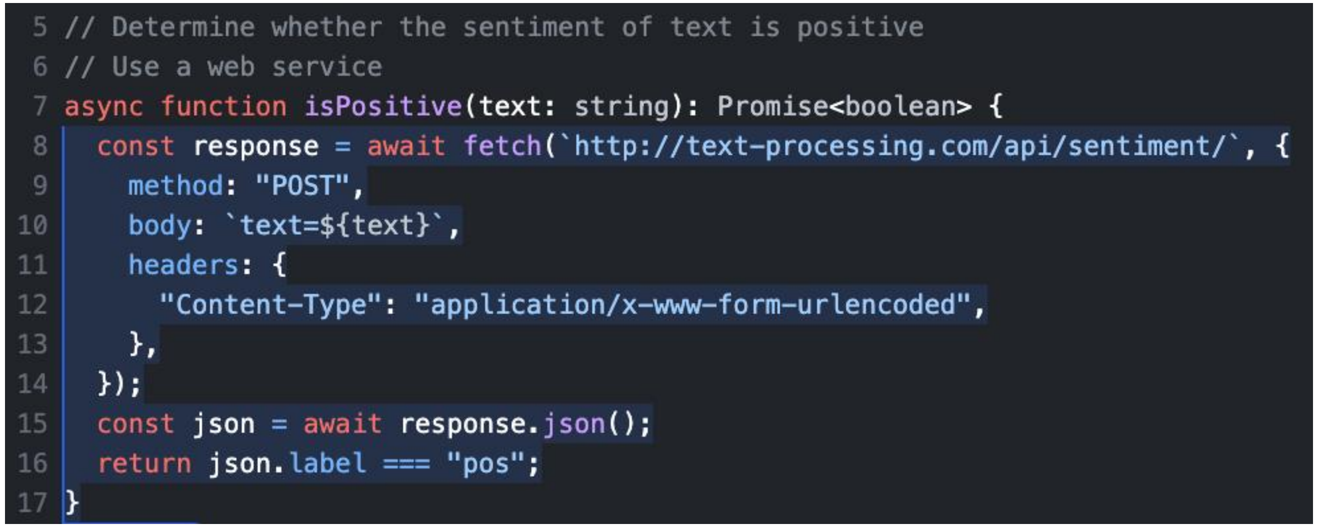
Language models as world models?



We can describe circles in the xy-plane using equations in terms of x and y. Circle equations questions require us to understand the connection between these equations and the features of circles.

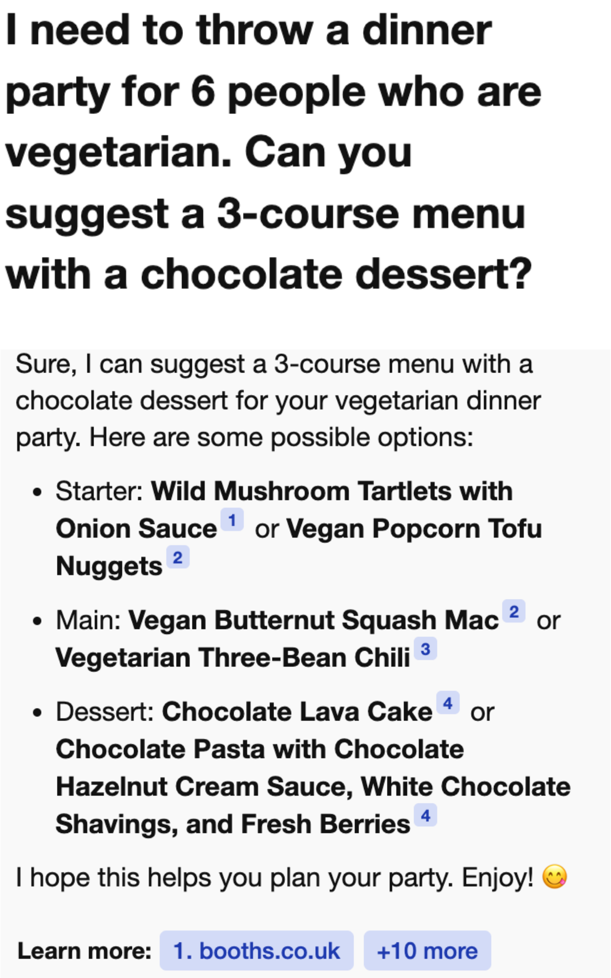
For example, the equation $(x+2)^2+(y-3)^2=4^2$ is graphed in the xy-plane below. It is a circle with a center at $(-2,3)$ and a radius of 4.

https://www.khanacademy.org/test-prep/sat/x0a8c2e5f:untitled-652



```
// Determine whether the sentiment of text is positive
// Use a web service
async function isPositive(text: string): Promise<boolean> {
  const response = await fetch(`http://text-processing.com/api/sentiment/`, {
    method: "POST",
    body: `text=${text}`,
    headers: {
      "Content-Type": "application/x-www-form-urlencoded",
    },
  });
  const json = await response.json();
  return json.label === "pos";
}
```

https://github.com/features/copilot



I need to throw a dinner party for 6 people who are vegetarian. Can you suggest a 3-course menu with a chocolate dessert?

Sure, I can suggest a 3-course menu with a chocolate dessert for your vegetarian dinner party. Here are some possible options:

- Starter: **Wild Mushroom Tartlets with Onion Sauce** [1] or **Vegan Popcorn Tofu Nuggets** [2]
- Main: **Vegan Butternut Squash Mac** [2] or **Vegetarian Three-Bean Chili** [3]
- Dessert: **Chocolate Lava Cake** [4] or **Chocolate Pasta with Chocolate Hazelnut Cream Sauce, White Chocolate Shavings, and Fresh Berries** [4]

I hope this helps you plan your party. Enjoy! 😋

Learn more: 1. booths.co.uk +10 more

[Microsoft Bing]

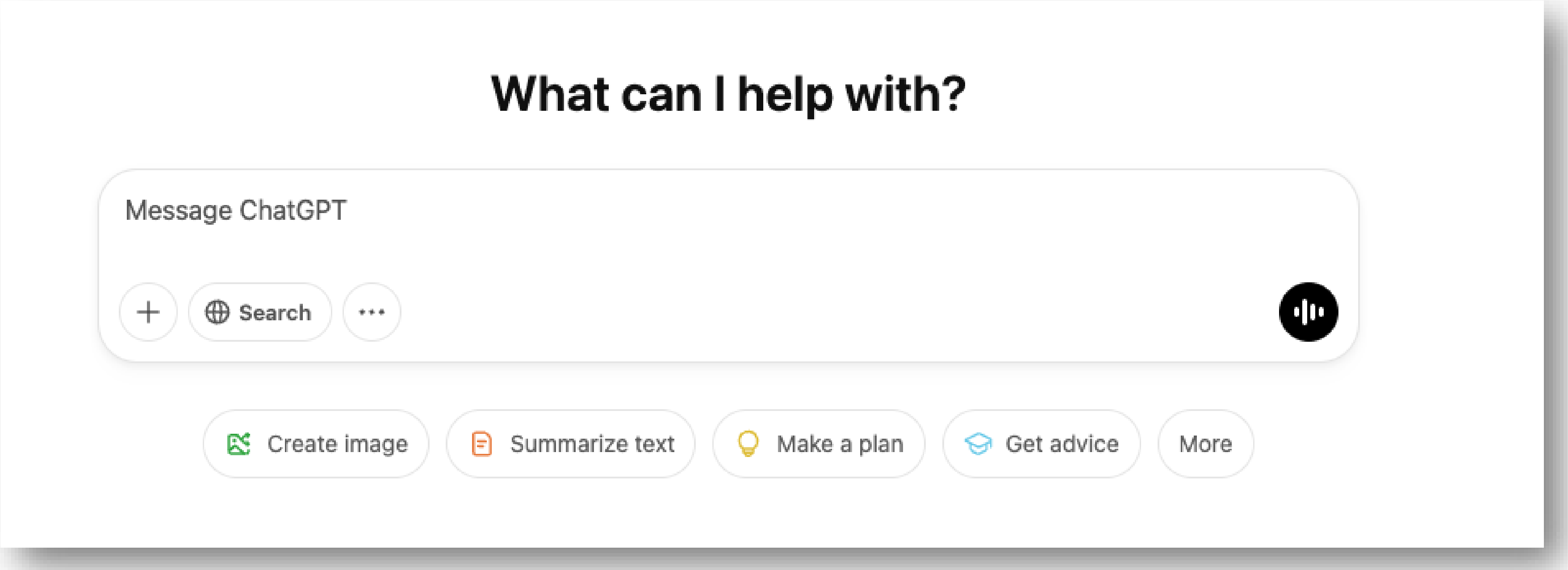
(Also see OpenAI's ChatGPT, Anthropic's Claude)

Language models as multitask assistants?

How do we get from *this*

Stanford University is located in ___________

to *this*?



What can I help with?

Lecture Plan

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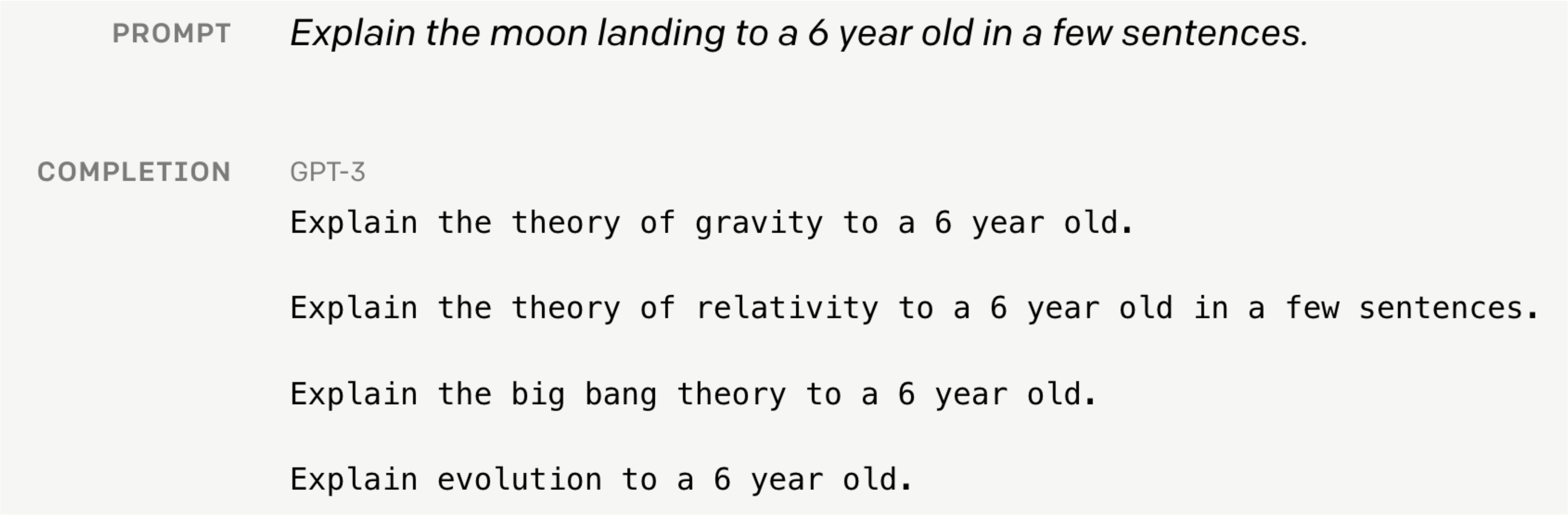
Language modeling ≠ assisting users



PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

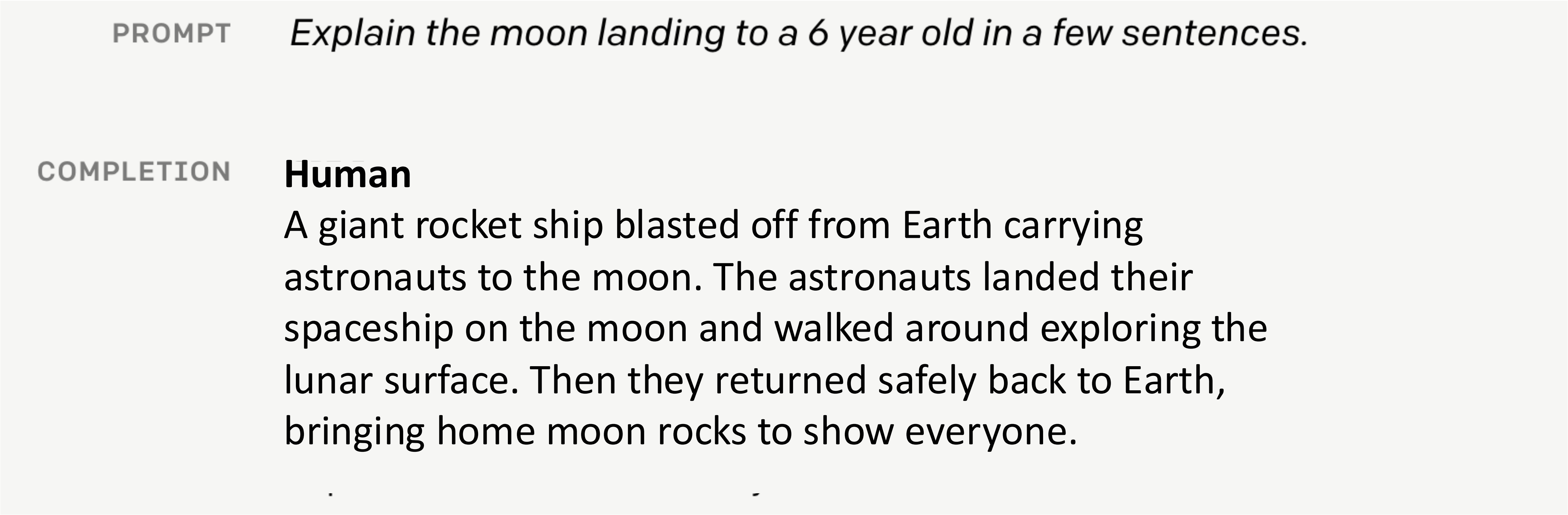
COMPLETION GPT-3

```
Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.
```

Language models are not *aligned* with user intent [Ouyang et al., 2022]

Finetuning to the rescue!

Language modeling ≠ assisting users



PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

COMPLETION **Human**

A giant rocket ship blasted off from Earth carrying astronauts to the moon. The astronauts landed their spaceship on the moon and walked around exploring the lunar surface. Then they returned safely back to Earth, bringing home moon rocks to show everyone.

Language models are not *aligned* with user intent [Ouyang et al., 2022]

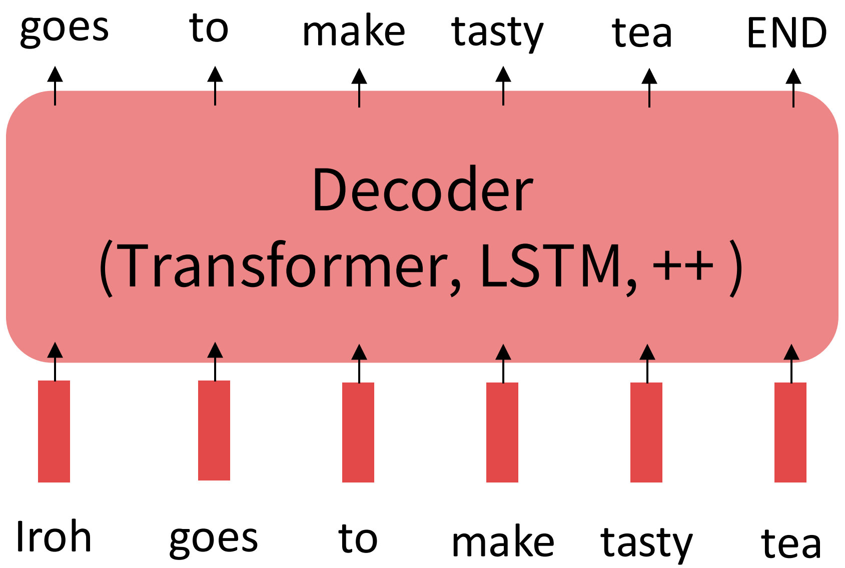
Finetuning to the rescue!

The pretraining/finetuning paradigm

Pretraining can improve NLP applications by serving as parameter initialization.

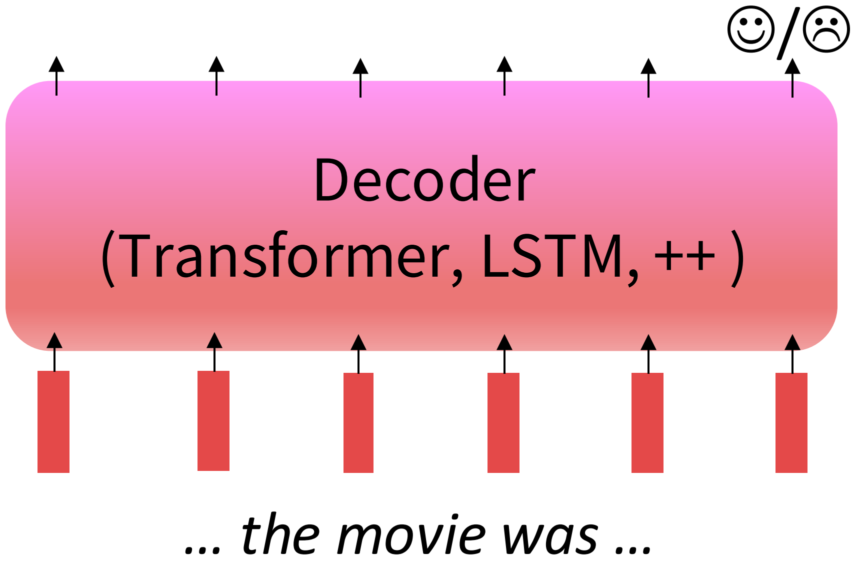
Step 1: Pretrain (on language modeling)

Lots of text; learn general things!



Step 2: Finetune (on your task)

Not many labels; adapt to the task!



Scaling up finetuning

Pretraining can improve NLP applications by serving as parameter initialization.

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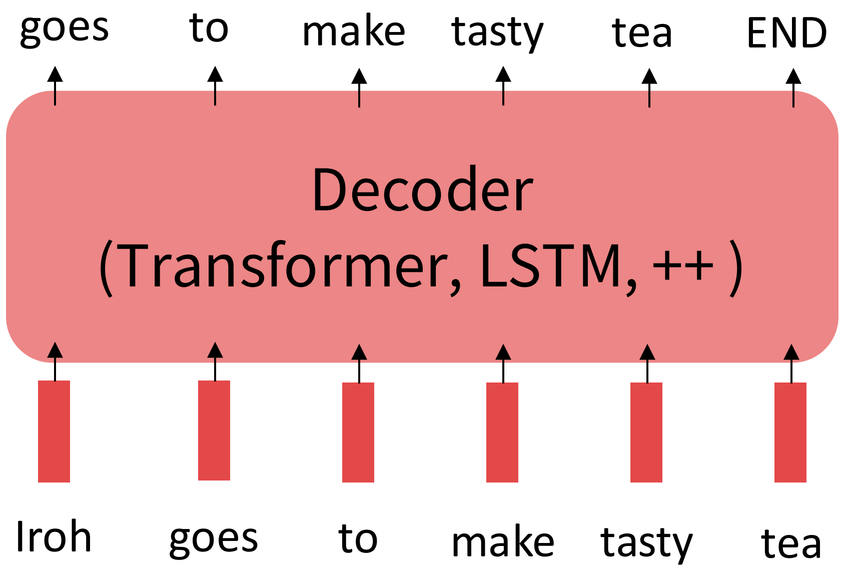
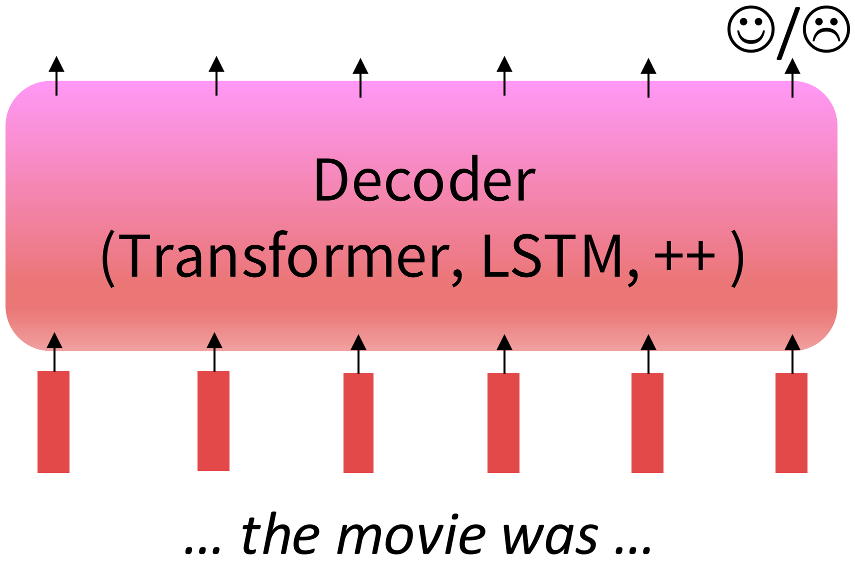


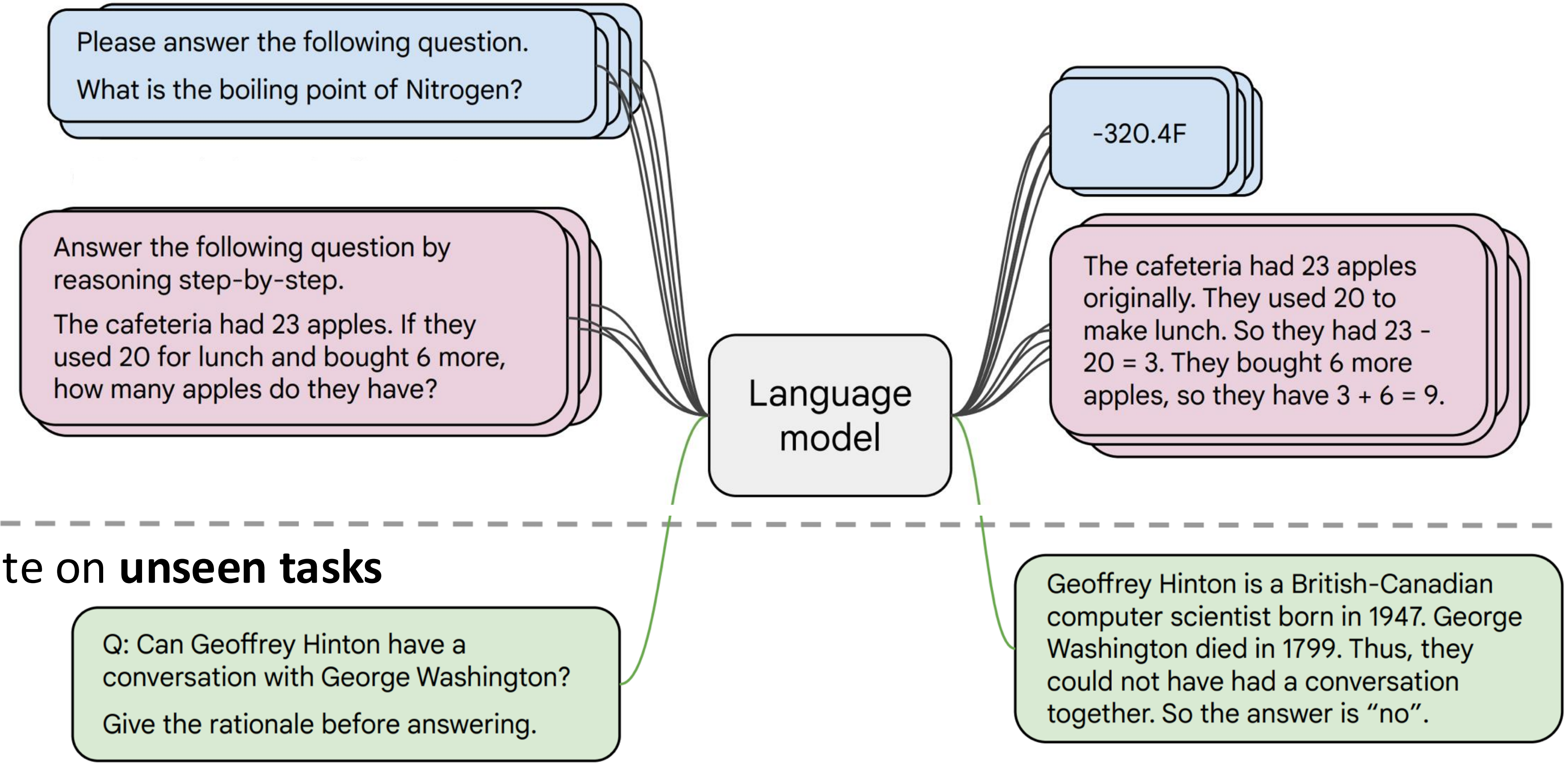
Step 2: Finetune (on many tasks)

~~Not~~ many labels; adapt to the tasks!



Instruction finetuning

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



Please answer the following question.

What is the boiling point of Nitrogen?

Answer the following question by reasoning step-by-step.

The cafeteria had 23 apples. If they used 20 for lunch and bought 6 more, how many apples do they have?

Language model

-320.4F

The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9.

- Evaluate on **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”.

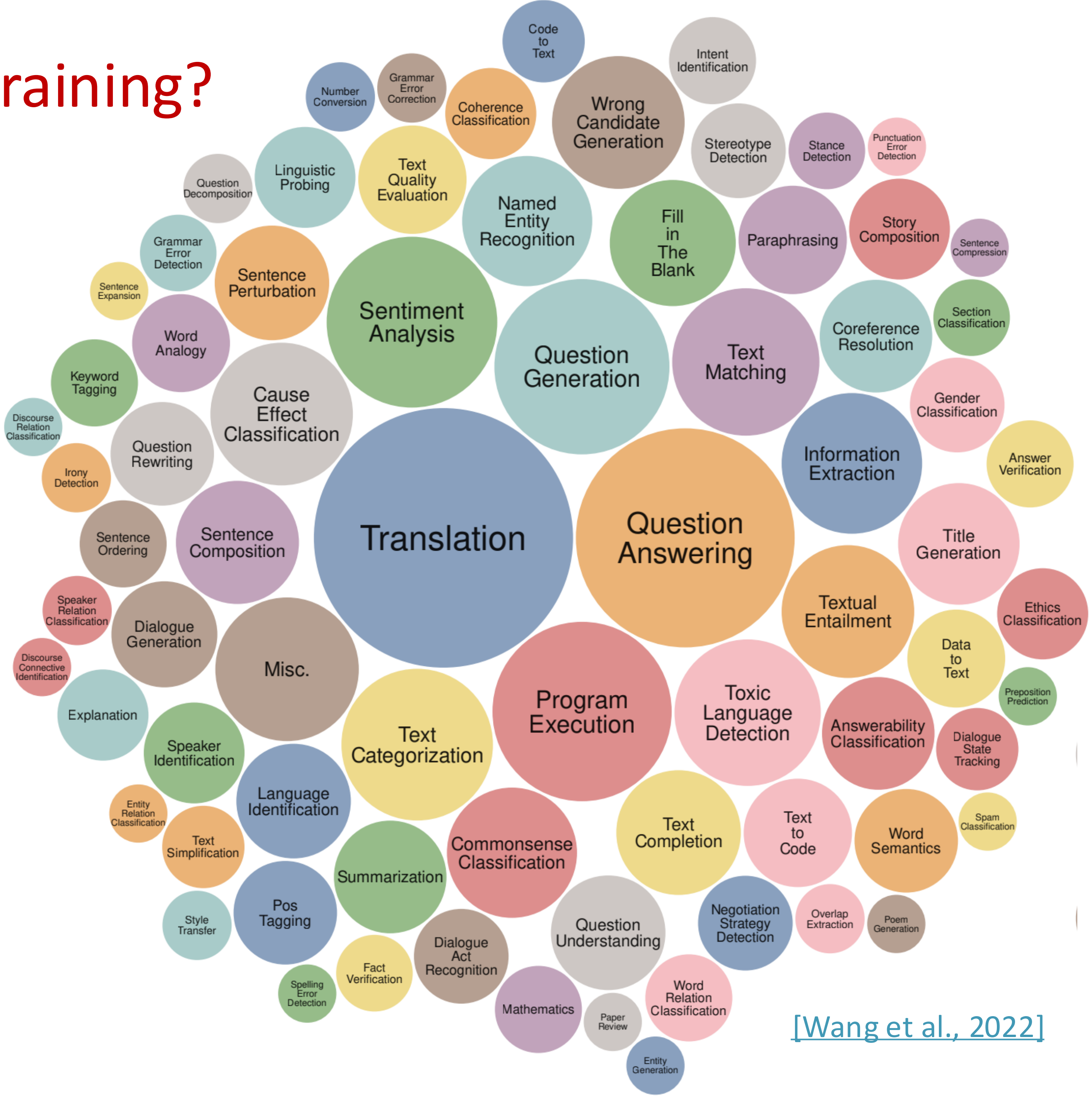
[FLAN-T5; Chung et al., 2022]

Instruction ~~finetuning~~ pretraining?

- As is usually the case, **data + model scale** is key for this to work!

- **Super-NaturalInstructions** dataset contains **over 1.6K tasks, 3M+** examples
  - Classification, sequence tagging, rewriting, translation, QA...

Q: how do we evaluate such a model?

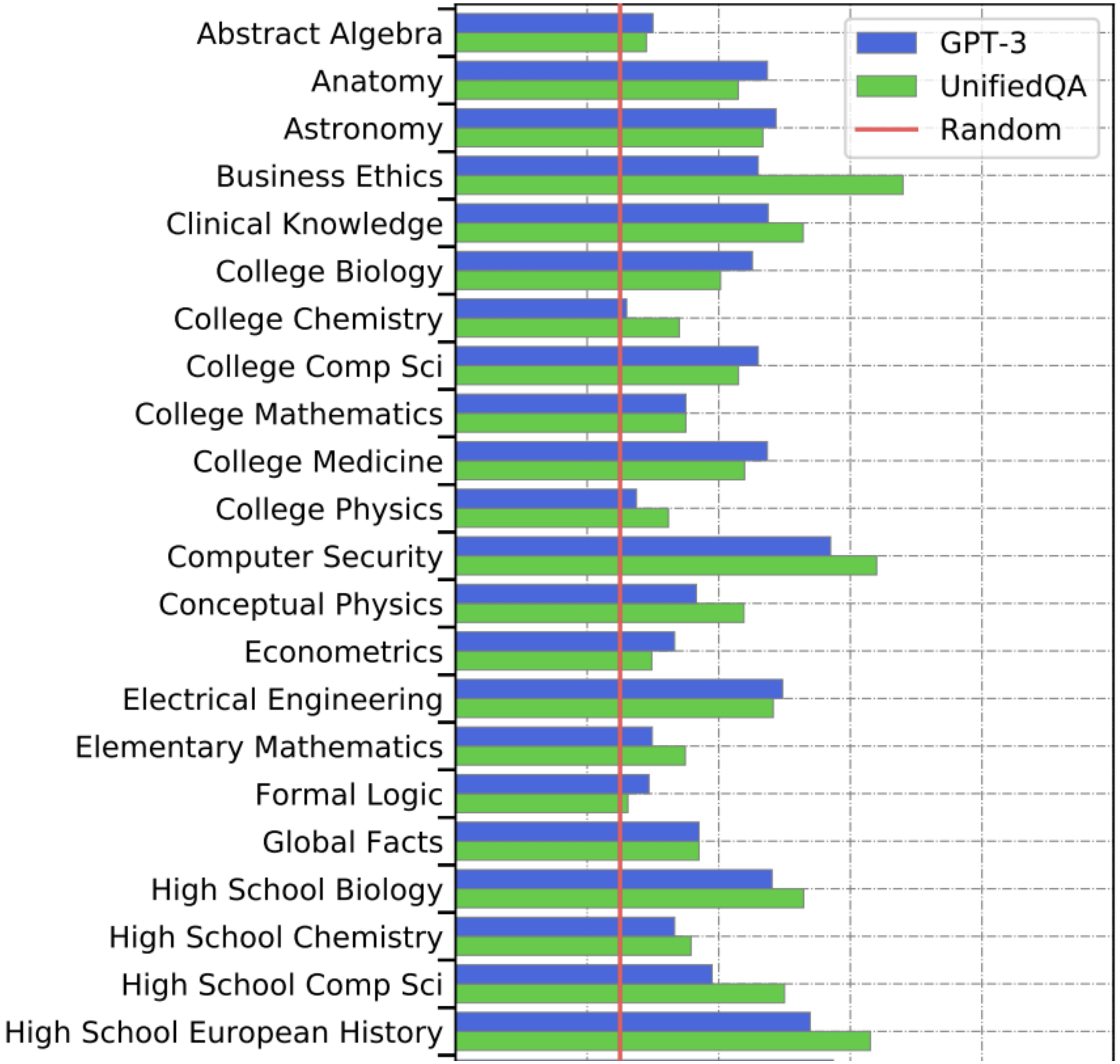


[Wang et al., 2022]

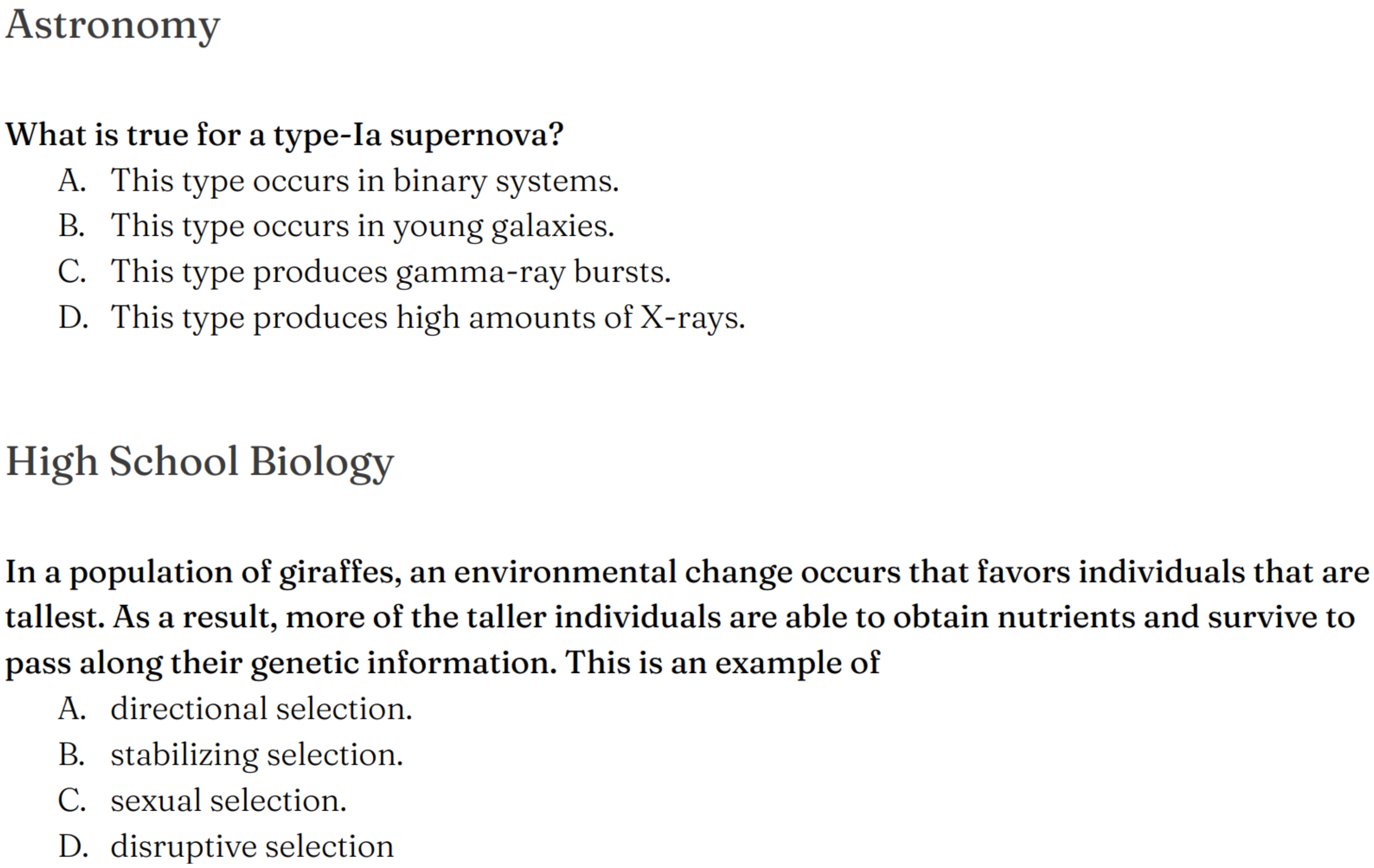
Aside: new benchmarks for multitask LMs

Massive Multitask Language Understanding (MMLU)
[Hendrycks et al., 2021]

New benchmarks for measuring LM performance on 57 diverse *knowledge intensive* tasks



Some intuition: examples from MMLU



Astronomy

What is true for a type-Ia supernova?

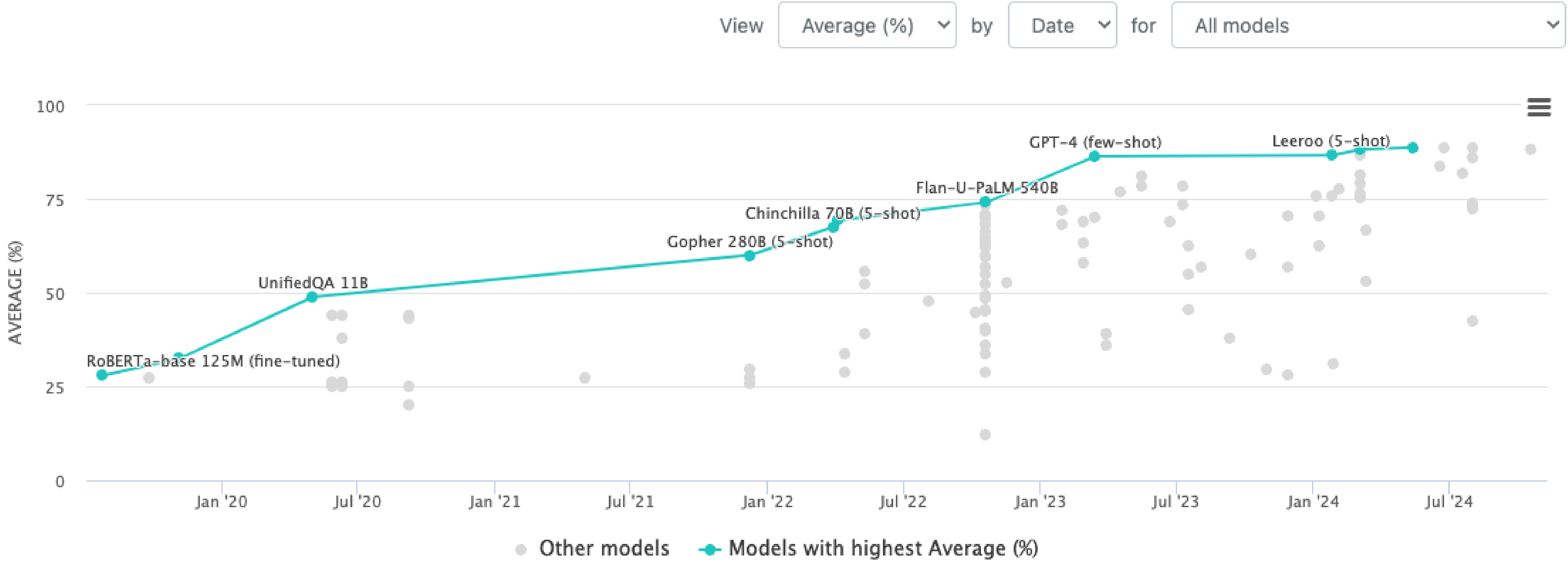
A. This type occurs in binary systems.
B. This type occurs in young galaxies.
C. This type produces gamma-ray bursts.
D. This type produces high amounts of X-rays.

High School Biology

In a population of giraffes, an environmental change occurs that favors individuals that are tallest. As a result, more of the taller individuals are able to obtain nutrients and survive to pass along their genetic information. This is an example of

A. directional selection.
B. stabilizing selection.
C. sexual selection.
D. disruptive selection

Progress on MMLU

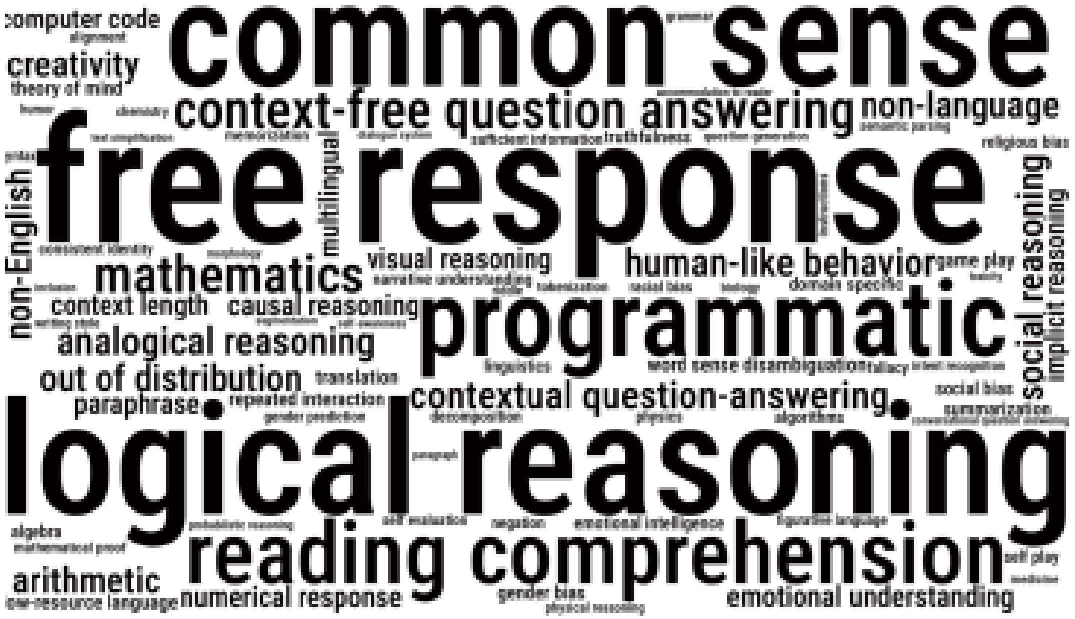


View Average (%) by Date for All models

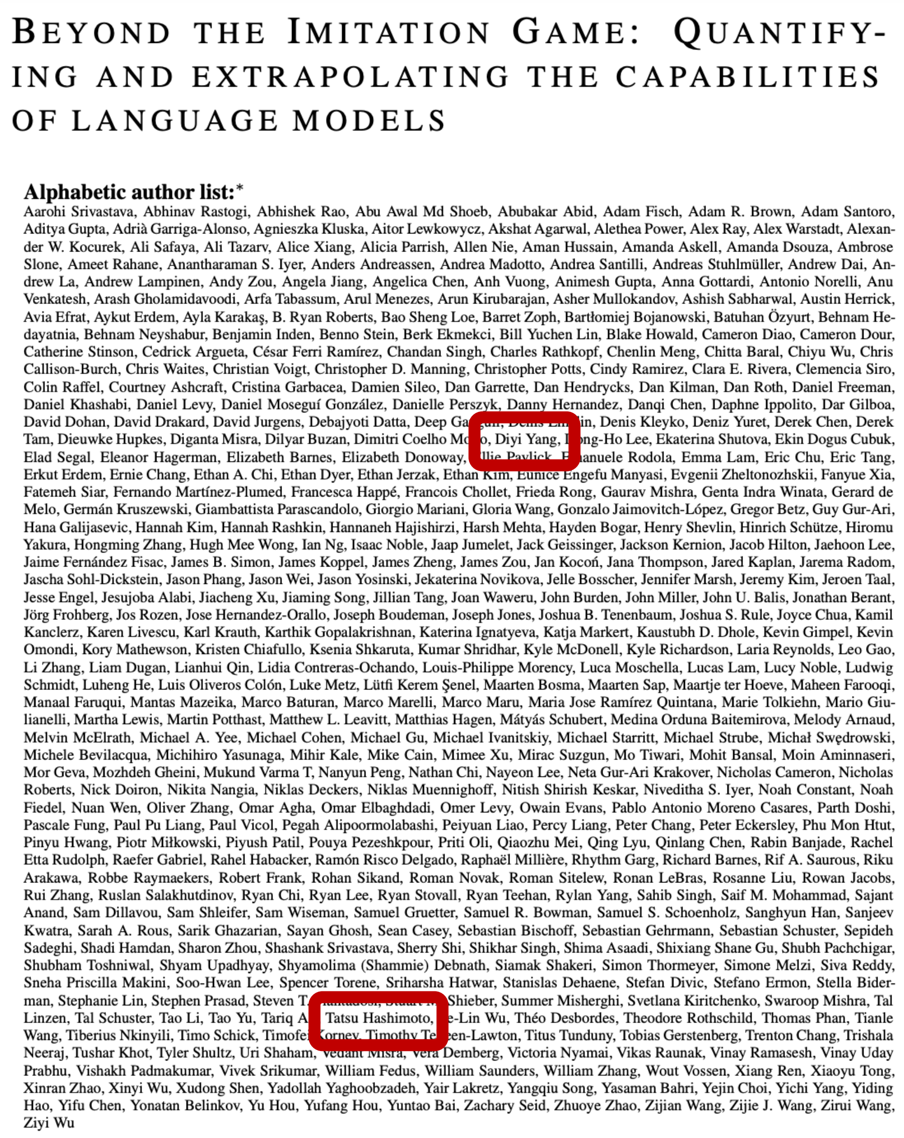
- Rapid, impressive progress on challenging knowledge-intensive benchmarks

Aside: new benchmarks for multitask LMs

BIG-Bench [Srivastava et al., 2022]
200+ tasks, spanning:



https://github.com/google/BIG-bench/blob/main/bigbench/benchmark_tasks/README.md



Beyond the Imitation Game: Quantifying and Extrapolating the Capabilities of Language Models

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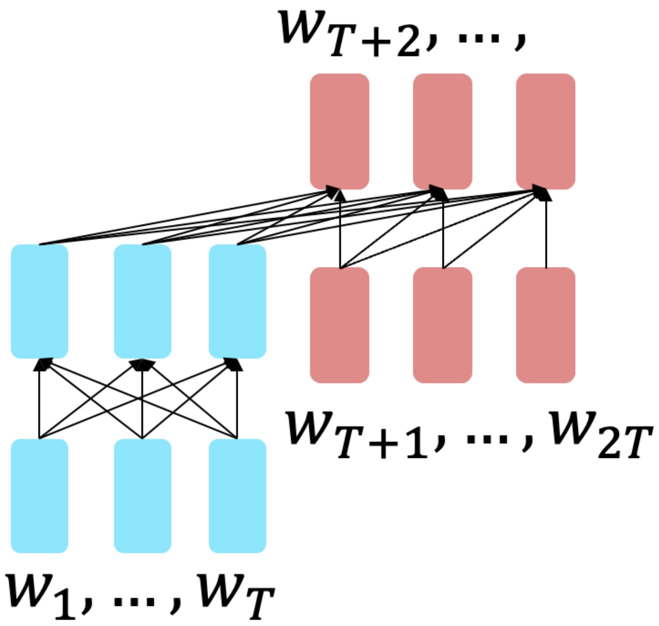
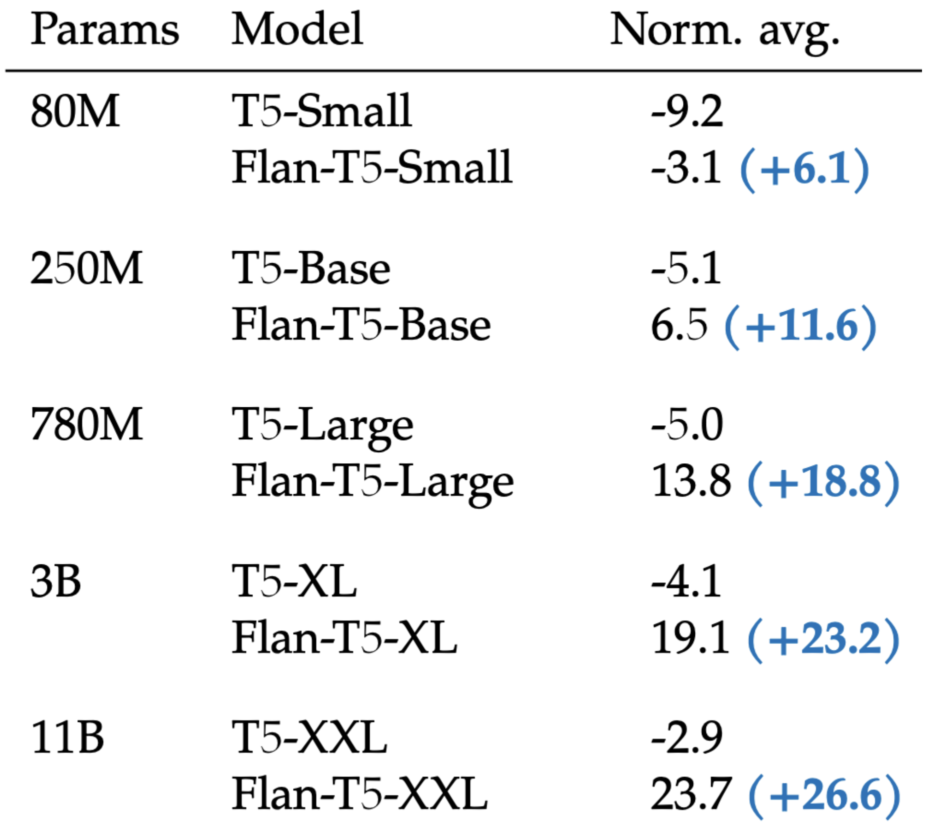
Instruction finetuning and performance gains

- Recall the T5 encoder-decoder model [Raffel et al., 2018], pretrained on the **span corruption** task
- **Flan-T5** [Chung et al., 2022]**:** T5 models finetuned on 1.8K additional tasks

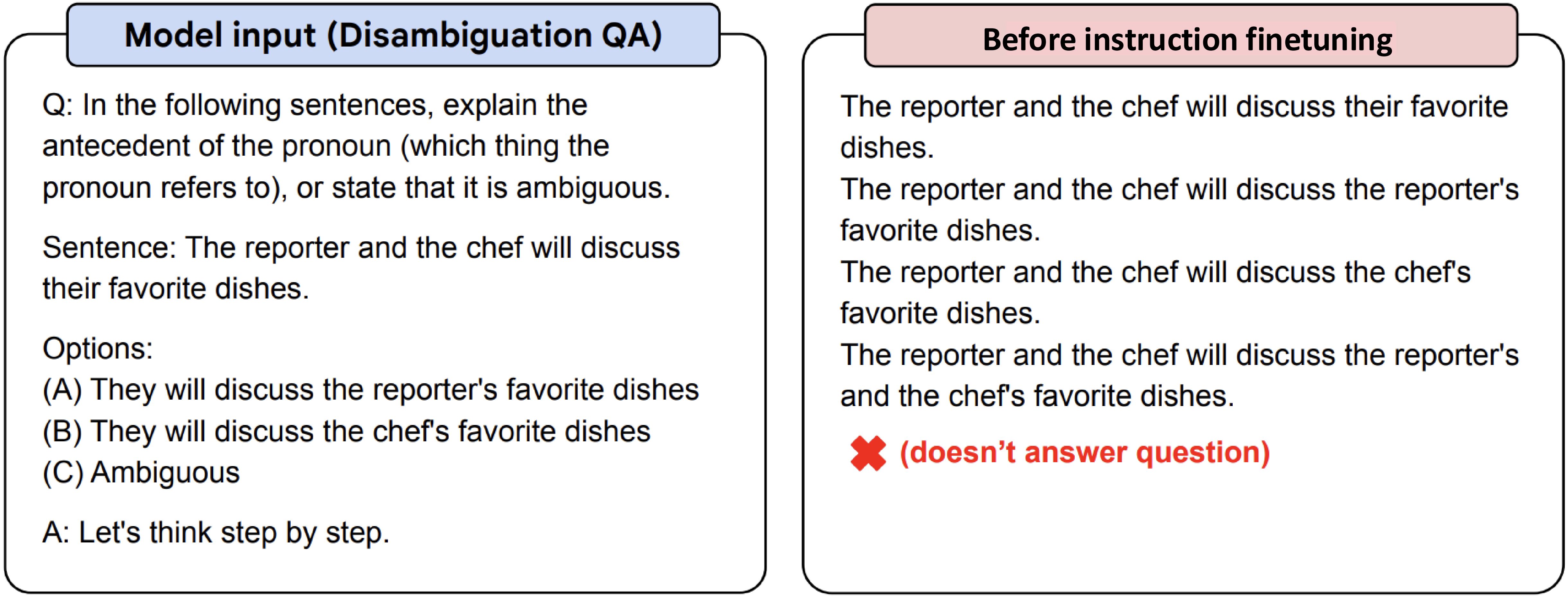




		BIG-bench + MMLU
Params	Model	Norm. avg.
80M	T5-Small	-9.2
	Flan-T5-Small	-3.1 (+6.1)
250M	T5-Base	-5.1
	Flan-T5-Base	6.5 (+11.6)
780M	T5-Large	-5.0
	Flan-T5-Large	13.8 (+18.8)
3B	T5-XL	-4.1
	Flan-T5-XL	19.1 (+23.2)
11B	T5-XXL	-2.9
	Flan-T5-XXL	23.7 (+26.6)

Bigger model = bigger Δ

Instruction finetuning and performance gains



Model input (Disambiguation QA)

Q: In the following sentences, explain the antecedent of the pronoun (which thing the pronoun refers to), or state that it is ambiguous.

Sentence: The reporter and the chef will discuss their favorite dishes.

Options:
(A) They will discuss the reporter's favorite dishes
(B) They will discuss the chef's favorite dishes
(C) Ambiguous

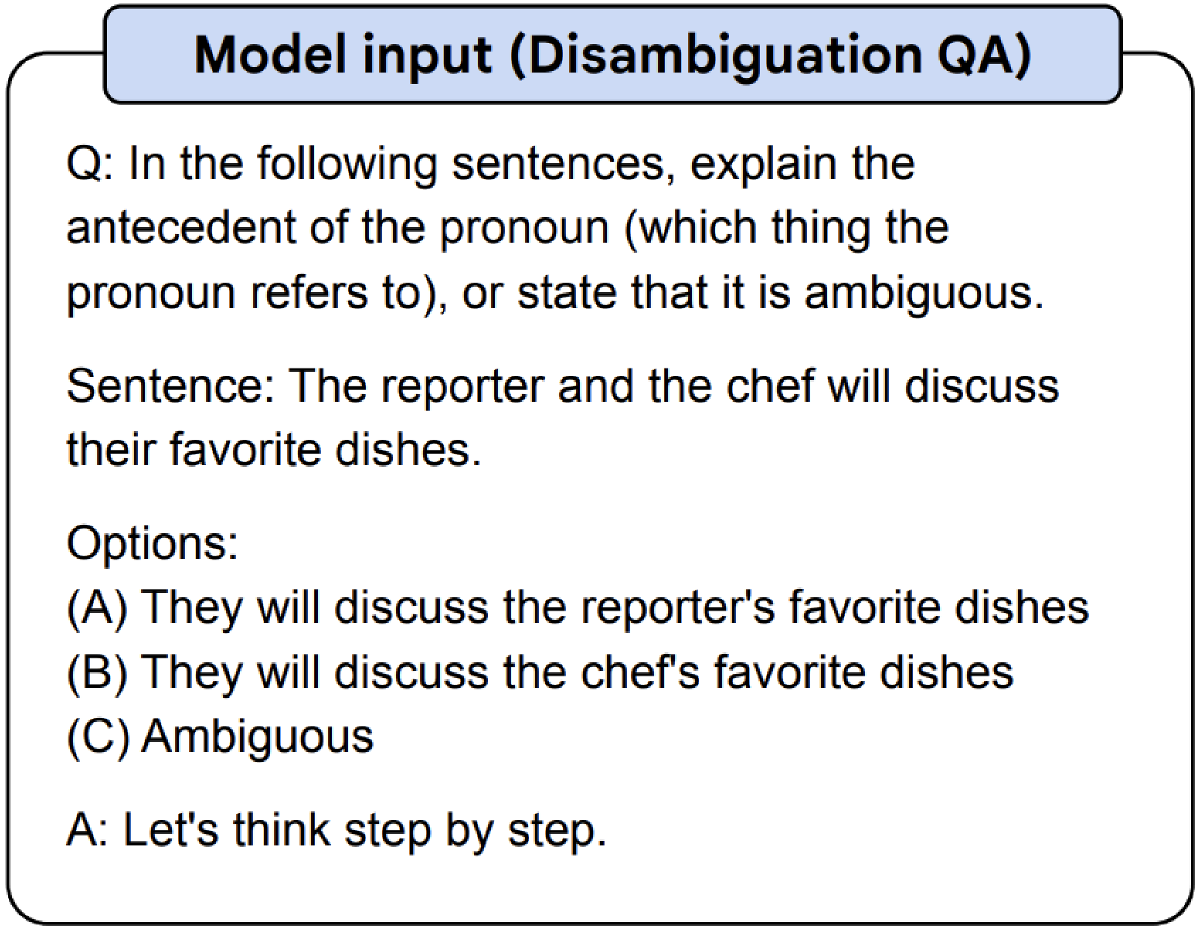
A: Let's think step by step.

Before instruction finetuning

The reporter and the chef will discuss their favorite dishes.
The reporter and the chef will discuss the reporter's favorite dishes.
The reporter and the chef will discuss the chef's favorite dishes.
The reporter and the chef will discuss the reporter's and the chef's favorite dishes.

✖ **(doesn't answer question)**

Instruction finetuning and performance gains



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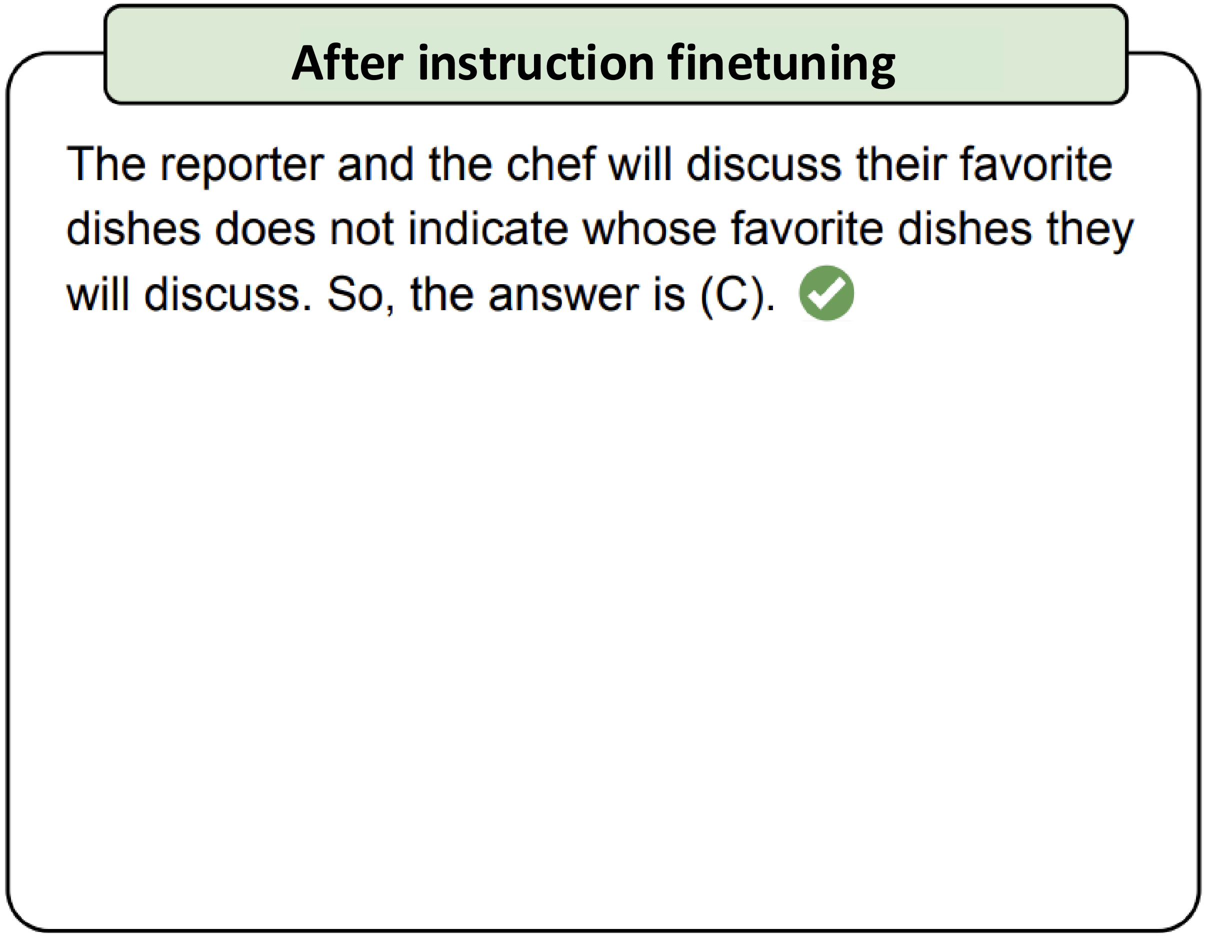
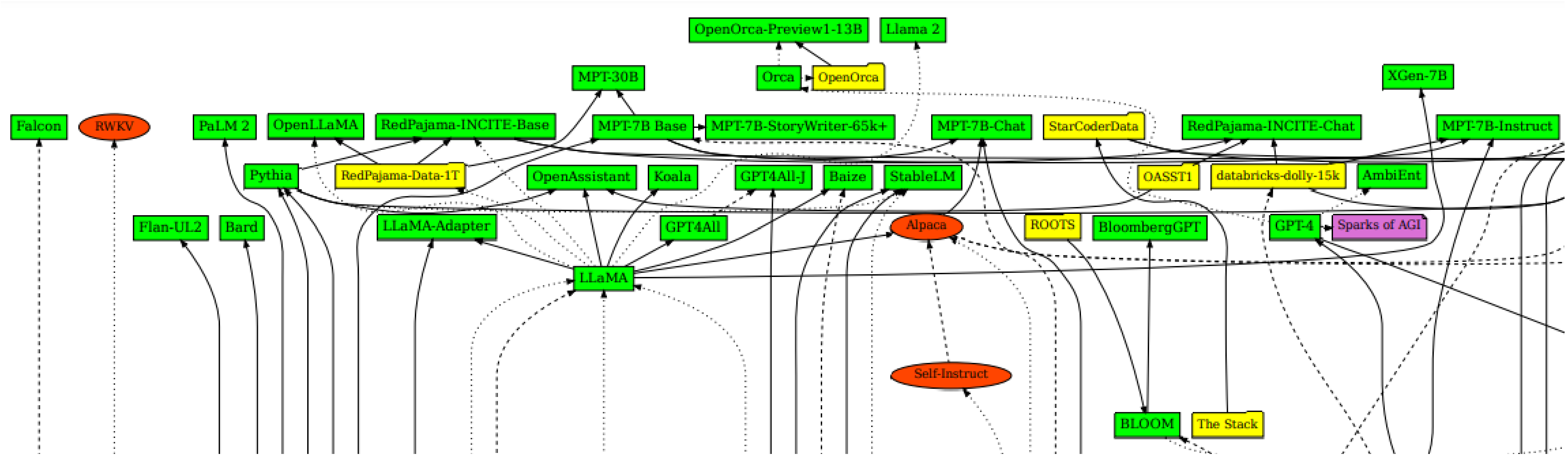


After instruction finetuning

The reporter and the chef will discuss their favorite dishes does not indicate whose favorite dishes they will discuss. So, the answer is (C). ✓

Try FLAN-T5 out to get a sense of its capabilities: https://huggingface.co/google/flan-t5-xxl [Chung et al., 2022]

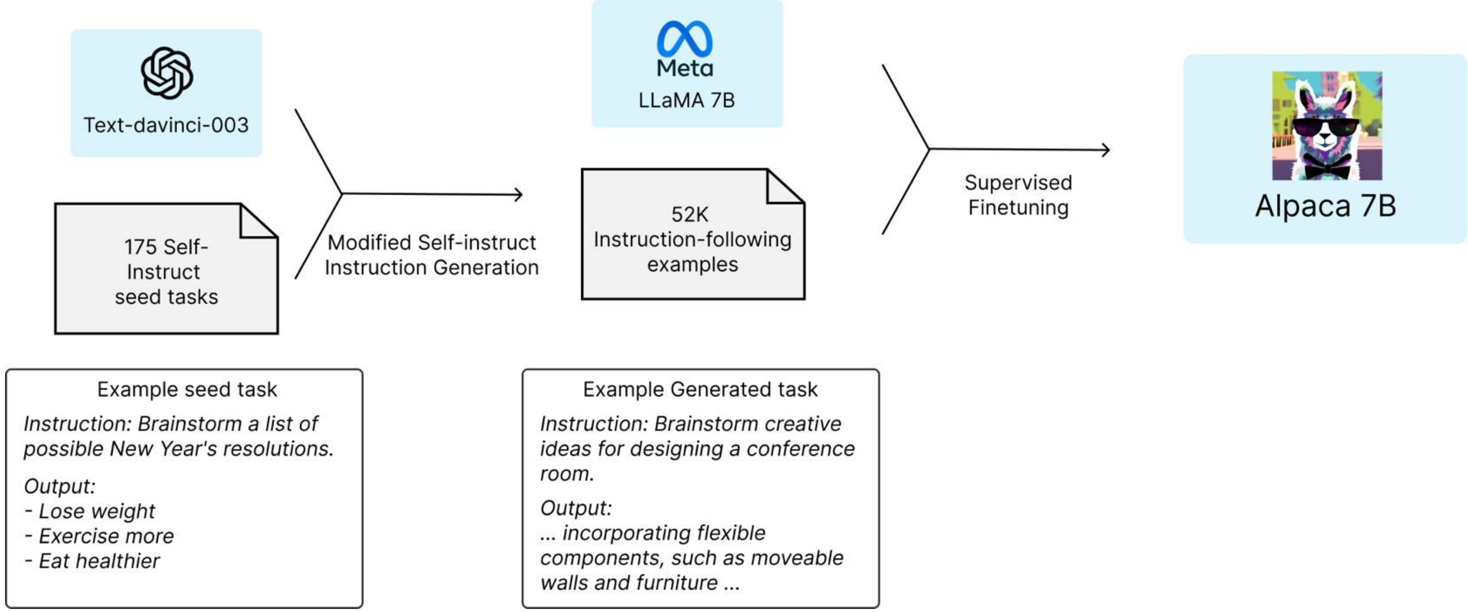
A huge diversity of instruction-tuning datasets



- The release of LLaMA led to open-source attempts to `create’ instruction tuning data

What have we learned from this?

- Generate instructions, input, and output from a LM [Wang et al., 2022]
  - **Alpaca**: fine-tuned from the LLaMA 7B model on 52K instruction-following examples
- You don't need many samples to instruction tune (e.g., "*LIMA: Less Is More for Alignment*" Zhou et al., 2023)


Text-davinci-003
175 Self-Instruct seed tasks
Modified Self-instruct Instruction Generation
Meta
LLaMA 7B
52K Instruction-following examples
Supervised Finetuning
Alpaca 7B

Example seed task

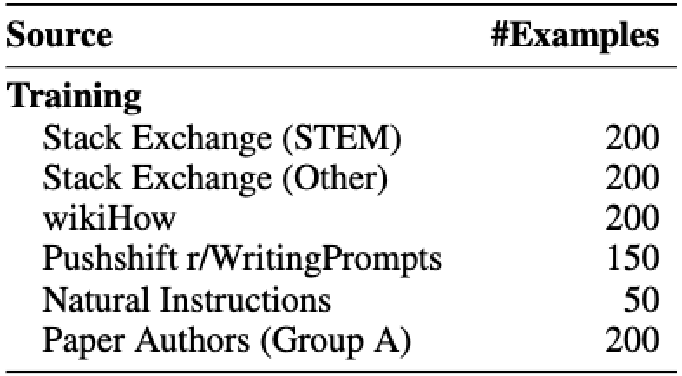
Instruction: Brainstorm a list of possible New Year's resolutions.

Output:
- Lose weight
- Exercise more
- Eat healthier

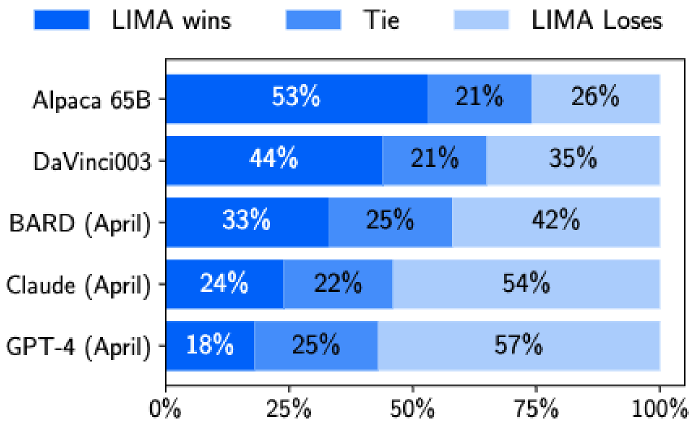
Example Generated task

Instruction: Brainstorm creative ideas for designing a conference room.

Output:
... incorporating flexible components, such as moveable walls and furniture ...



Source	#Examples
Training	
Stack Exchange (STEM)	200
Stack Exchange (Other)	200
wikiHow	200
Pushshift r/WritingPrompts	150
Natural Instructions	50
Paper Authors (Group A)	200

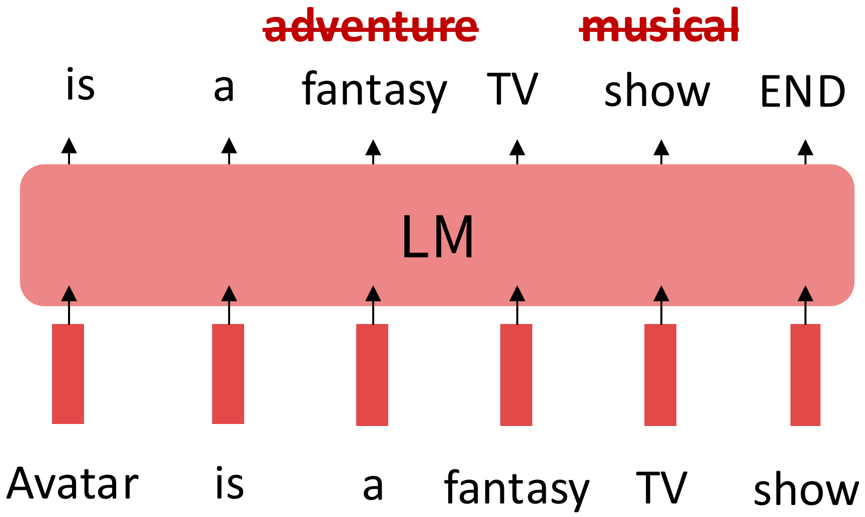


Lecture Plan

1. Instruction fine-tuning
2. **Reinforcement learning from human preferences (RLHF)**
3. InstructGPT and ChatGPT
4. Limitation of RL and reward modeling
5. Introducing Direct Preference Optimization (DPO)
6. Human preference data; human vs. AI Feedback
7. What’s next?

Limitations of instruction finetuning?

- One limitation of instruction finetuning is obvious: it's **expensive** to collect ground-truth data for tasks.
- But there are other, subtler limitations too. Can you think of any?
- **Problem 1: tasks like open-ended creative generation have no right answer.**
  - *Write me a story about a dog and her pet grasshopper.*
- **Problem 2: language modeling penalizes all token-level mistakes equally, but some errors are worse than others.**
- Even with instruction finetuning, there a mismatch between the LM objective and the objective of "satisfy human preferences"!
- Can we **explicitly attempt to satisfy human preferences?**



Optimizing for human preferences

- Let’s say we were training a language model on some task (e.g. summarization).
- For each LM sample s, imagine we had a way to obtain a *human reward* of that summary: $R(s) \in \mathbb{R}$, higher is better.

SAN FRANCISCO, California (CNN) -- A magnitude 4.2 earthquake shook the San Francisco ... overturn unstable objects.

An earthquake hit San Francisco. There was minor property damage, but no injuries.

$$s_1$$

$$R(s_1) = 8.0$$

The Bay Area has good weather but is prone to earthquakes and wildfires.

$$s_2$$

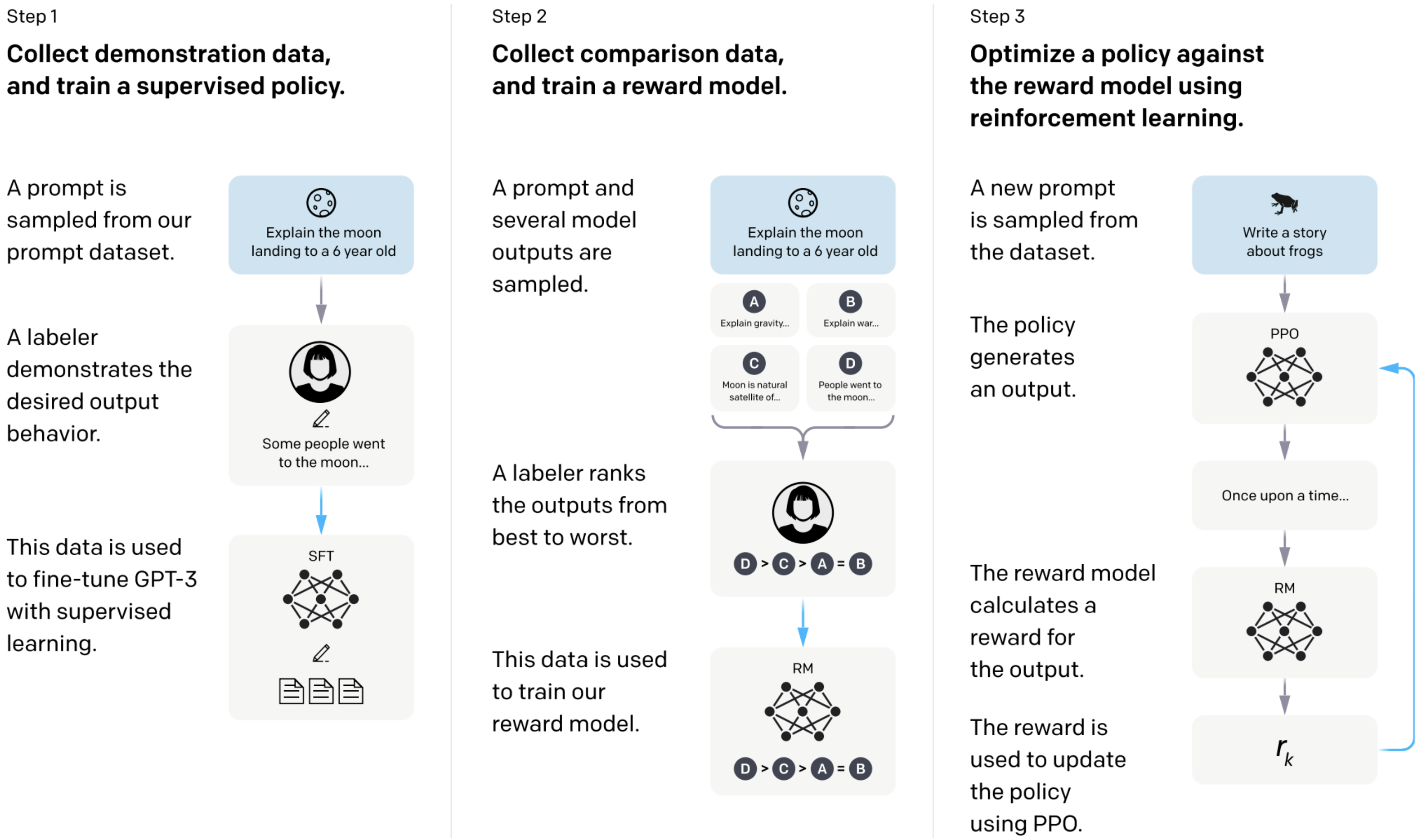
$$R(s_2) = 1.2$$

- Now we want to maximize the expected reward of samples from our LM:

$$\mathbb{E}_{\hat{s} \sim p_\theta(s)}[R(\hat{s})]$$

Note: for mathematical simplicity we’re assuming only one “prompt”

High-level instantiation: “RLHF” pipeline



Step 1

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The policy generates an output.

The reward model calculates a reward for the output.

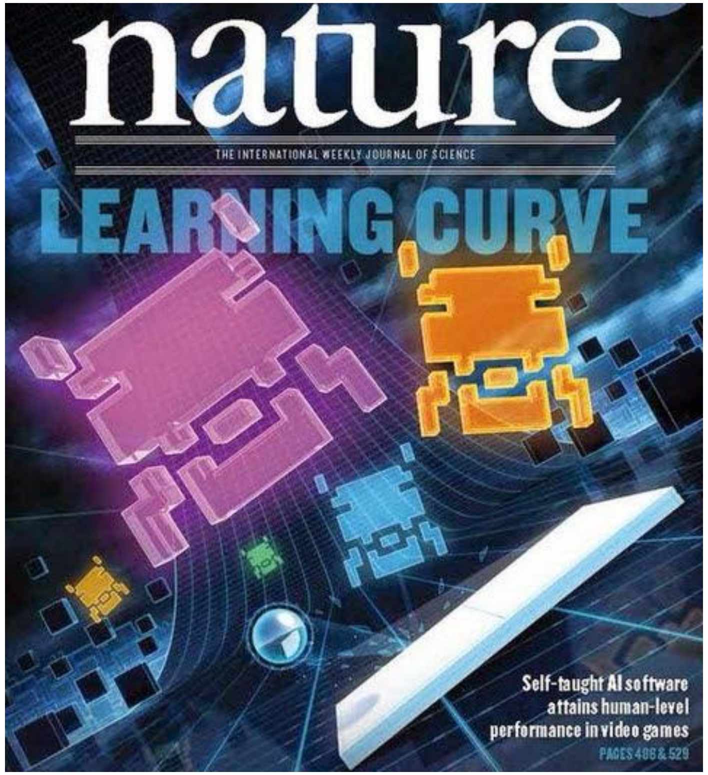
The reward is used to update the policy using PPO.

Explain the moon landing to a 6 year old
Some people went to the moon...
SFT
Explain the moon landing to a 6 year old
A Explain gravity...
B Explain war...
C Moon is natural satellite of...
D People went to the moon...
D > C > A = B
RM
D > C > A = B
Write a story about frogs
PPO
Once upon a time...
RM
r_k

- First step: instruction tuning!
- Second + third steps: maximize reward (but how??)

Reinforcement learning to the rescue

- The field of **reinforcement learning (RL)** has studied these (and related) problems for many years now [Williams, 1992; Sutton and Barto, 1998]
- Circa 2013: resurgence of interest in RL applied to deep learning, game-playing [Mnih et al., 2013]
- But the interest in applying RL to modern LMs is an even newer phenomenon [Ziegler et al., 2019; Stiennon et al., 2020; Ouyang et al., 2022]. **Why?**
  - RL w/ LMs has commonly been viewed as very hard to get right (still is!)
  - Newer advances in RL algorithms that work for large neural models, including language models (e.g. PPO; [Schulman et al., 2017])



AlphaGo

Optimizing for human preferences

- How do we actually change our LM parameters θ to maximize this?

$$\mathbb{E}_{\hat{s}\sim p_\theta(s)}[R(\hat{s})]$$

- Let's try doing gradient ascent!

$$\theta_{t+1} \coloneqq \theta_t + \alpha \, \nabla_{\theta_t} \mathbb{E}_{\hat{s}\sim p_{\theta_t}(s)}[R(\hat{s})]$$

How do we estimate this expectation??

What if our reward function is non-differentiable??

- **Policy gradient** methods in RL (e.g., REINFORCE; [Williams, 1992]) give us tools for estimating and optimizing this objective.
- We'll describe a ***very high-level*** *mathematical* overview of the simplest policy gradient estimator, but a full treatment of RL is outside the scope of this course (try CS234!)

A (very!) brief introduction to policy gradient/REINFORCE [Williams, 1992]

- We want to obtain

(defn. of expectation) (linearity of gradient)

$$\nabla_\theta \mathbb{E}_{\hat{s}\sim p_\theta(s)}[R(\hat{s})] = \nabla_\theta \sum_s R(s) p_\theta(s) = \sum_s R(s)\, \nabla_\theta p_\theta(s)$$

- Here we'll use a very handy trick known as the **log-derivative trick**. Let's try taking the gradient of $\log p_\theta(s)$

$$\nabla_\theta \log p_\theta(s) = \frac{1}{p_\theta(s)} \nabla_\theta p_\theta(s) \quad \Longrightarrow \quad \nabla_\theta p_\theta(s) = p_\theta(s)\ \nabla_\theta \log p_\theta(s)$$

(chain rule)

- Plug back in:

This is an expectation of this

$$\sum_s R(s)\, \nabla_\theta p_\theta(s) = \sum_s p_\theta(s) R(s)\, \nabla_\theta \log p_\theta(s)$$

A (very!) brief introduction to policy gradient/REINFORCE [Williams, 1992]

- Now we have put the gradient "inside" the expectation, we can approximate this objective with Monte Carlo samples:

$$\nabla_\theta \mathbb{E}_{\hat{s}\sim p_\theta(s)}[R(\hat{s})] \ = \mathbb{E}_{\hat{s}\sim p_\theta(s)}[R(\hat{s})\ \nabla_\theta \log p_\theta(\hat{s})] \approx \frac{1}{m}\sum_{i=1}^{m} R(s_i)\ \nabla_\theta \log p_\theta(s_i)$$

This is why it's called **"reinforcement learning"**: we **reinforce** good actions, increasing the chance they happen again.

If R is +++

Take gradient steps to maximize $p_\theta(s_i)$

- Giving us the update rule: $\theta_{t+1} \coloneqq \theta_t + \alpha \frac{1}{m}\sum_{i=1}^{m} R(s_i)\ \nabla_{\theta_t} \log p_{\theta_t}(s_i)$

This is **heavily simplified**! There is a *lot* more needed to do RL w/ LMs. **Can you see any problems with this objective?**

If R is ---

Take steps to minimize $p_\theta(s_i)$

How do we model human preferences?

- Awesome: now for any **arbitrary, non-differentiable reward function** $R(s)$, we can train our language model to maximize expected reward.
- Not so fast! (Why not?)
- **Problem 1:** human-in-the-loop is expensive!
  - **Solution:** instead of directly asking humans for preferences, **model their preferences** as a separate (NLP) problem! [Knox and Stone, 2009]

```
An earthquake hit
San Francisco.
There was minor
property damage,
but no injuries.
```

s_1

$R(s_1) = 8.0$

```
The Bay Area has
good weather but is
prone to
earthquakes and
wildfires.
```

s_2

$R(s_2) = 1.2$

Train an LM $RM_\phi(s)$ to predict human preferences from an annotated dataset, then optimize for RM_ϕ instead.

How do we model human preferences?

- **Problem 2:** human judgments are noisy and miscalibrated!
- **Solution:** instead of asking for direct ratings, ask for **pairwise comparisons**, which can be more reliable [Phelps et al., 2015; Clark et al., 2018]

```
A 4.2 magnitude
earthquake hit
San Francisco,
resulting in
massive damage.
```

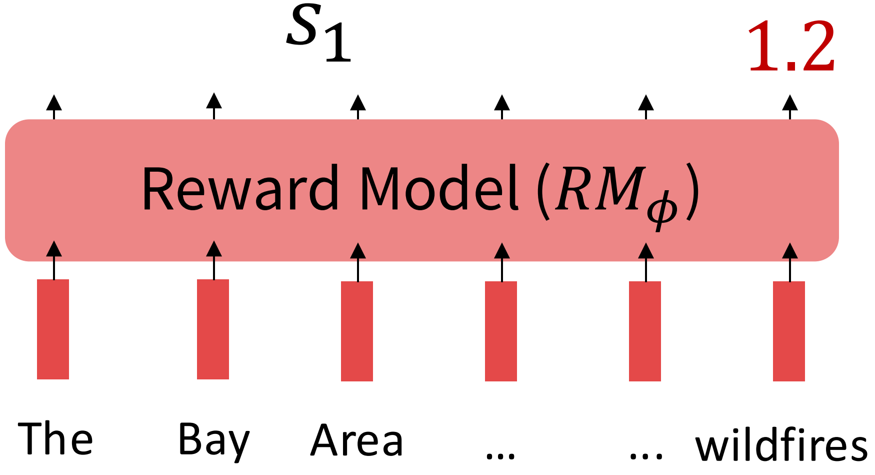
$$s_3$$

$$R(s_3) = \quad 4.1? \quad 6.6? \quad 3.2?$$

How do we model human preferences?

- **Problem 2:** human judgments are noisy and miscalibrated!
- **Solution:** instead of asking for direct ratings, ask for **pairwise comparisons**, which can be more reliable [Phelps et al., 2015; Clark et al., 2018]

An earthquake hit San Francisco. There was minor property damage, but no injuries.	>	A 4.2 magnitude earthquake hit San Francisco, resulting in massive damage.	>	The Bay Area has good weather but is prone to earthquakes and wildfires.
s_1		s_3		s_2



Bradley-Terry [1952] paired comparison model

$$J_{RM}(\phi) = -\mathbb{E}_{(s^w, s^l)\sim D}\left[\log \sigma(RM_\phi(s^w) - RM_\phi(s^l))\right]$$

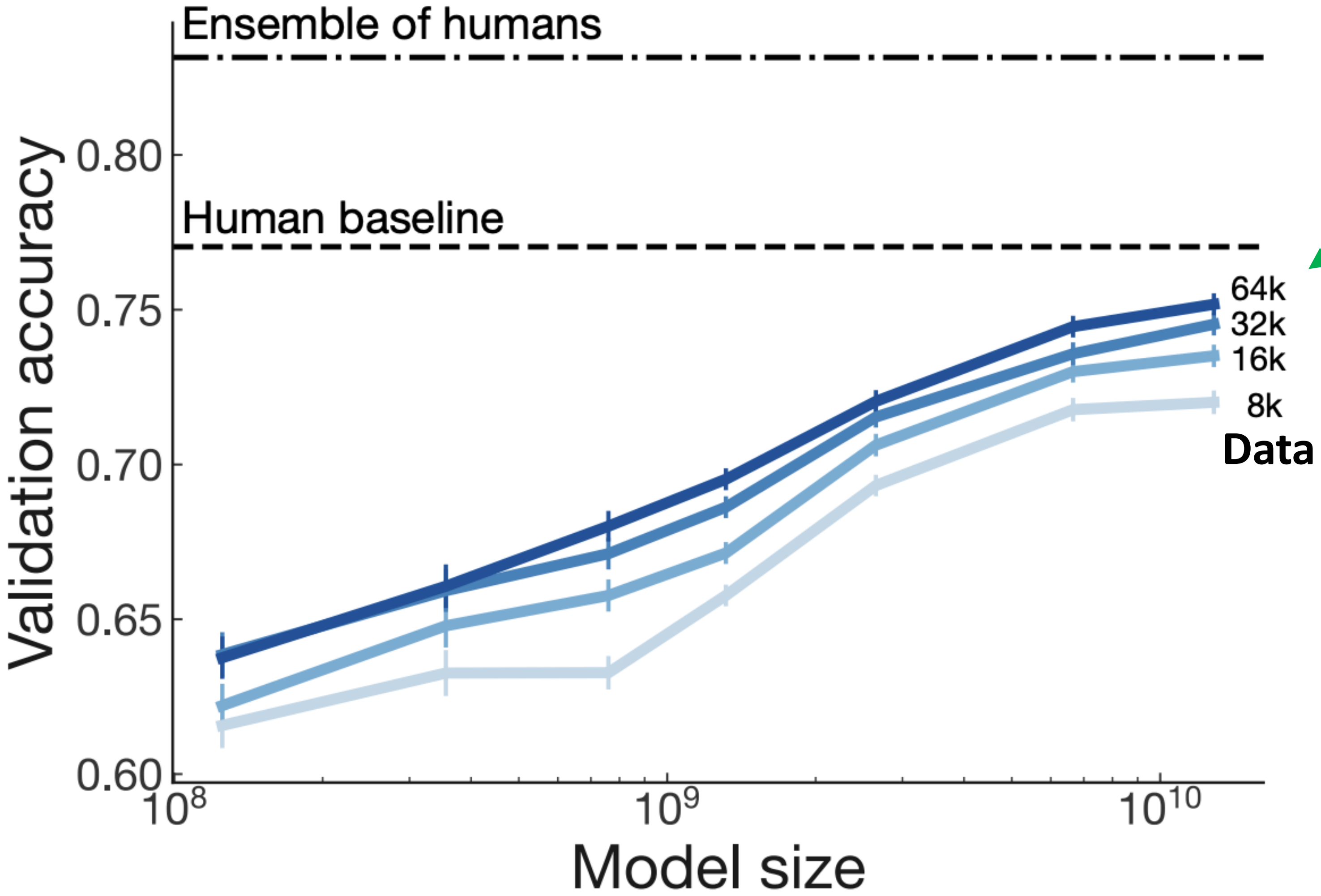
"winning" sample

"losing" sample

s^w should score higher than s^l

Make sure your reward model works first!

Evaluate RM on predicting outcome of held-out human judgments



Large enough RM trained on enough data approaching single human perf

[Stiennon et al., 2020]

RLHF: Putting it all together [Christiano et al., 2017; Stiennon et al., 2020]

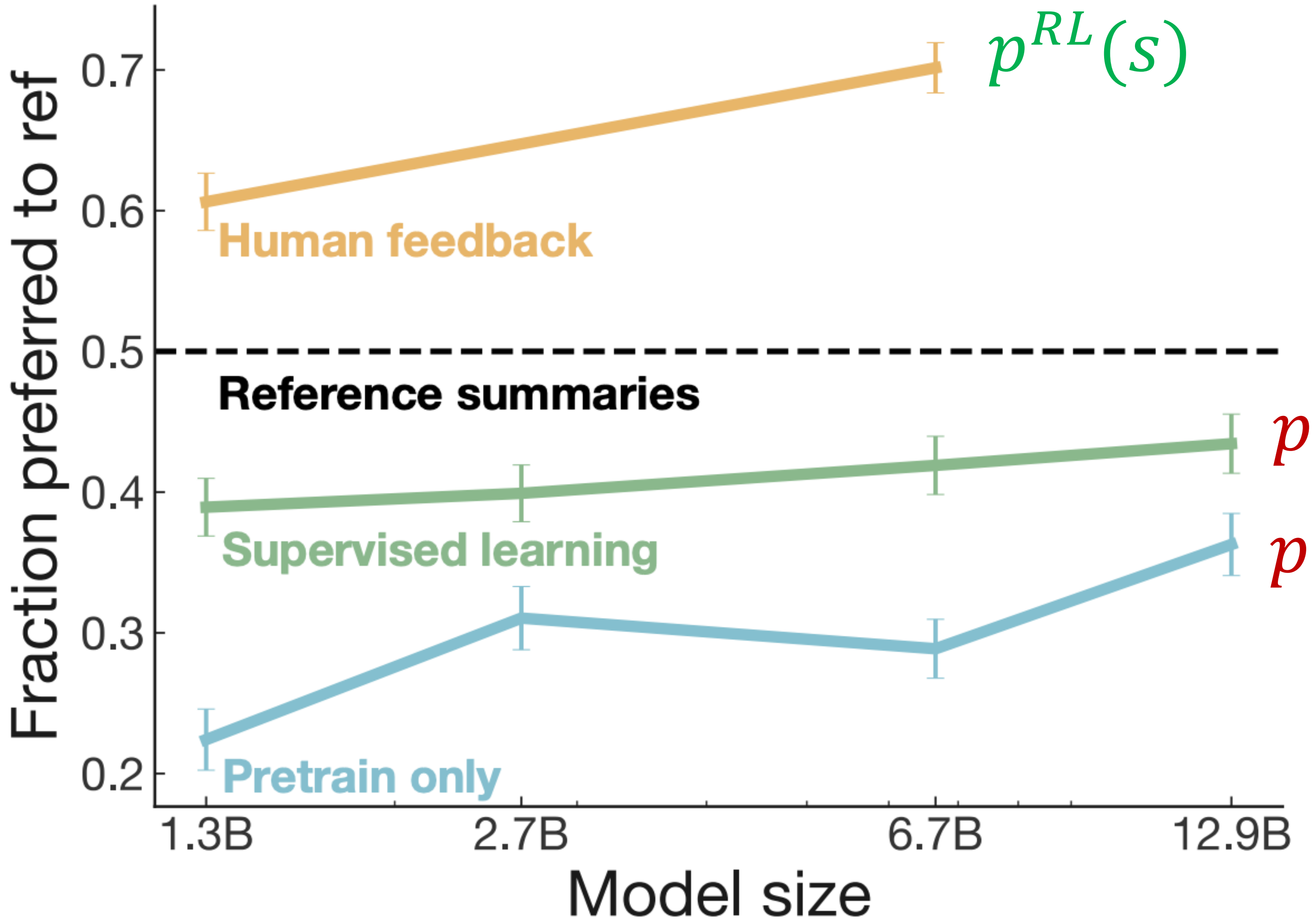
- Finally, we have everything we need:
  - A pretrained (possibly instruction-finetuned) LM $p^{PT}(s)$
  - A reward model $RM_\phi(s)$ that produces scalar rewards for LM outputs, trained on a dataset of human comparisons
  - A method for optimizing LM parameters towards an arbitrary reward function.
- Now to do RLHF:
  - Initialize a copy of the model $p_\theta^{RL}(s)$, with parameters θ we would like to optimize
  - Optimize the following reward with RL:

$$R(s) = RM_\phi(s) - \underbrace{\beta \log \left(\frac{p_\theta^{RL}(s)}{p^{PT}(s)}\right)}_{}$$

Pay a price when $p_\theta^{RL}(s) > p^{PT}(s)$

This is a penalty which prevents us from diverging too far from the pretrained model. In expectation, it is known as the **Kullback-Leibler** (**KL**) divergence between $p_\theta^{RL}(s)$ and $p^{PT}(s)$.

RLHF provides gains over pretraining + finetuning



$p^{RL}(s)$

$p^{IFT}(s)$

$p^{PT}(s)$

[Stiennon et al., 2020]

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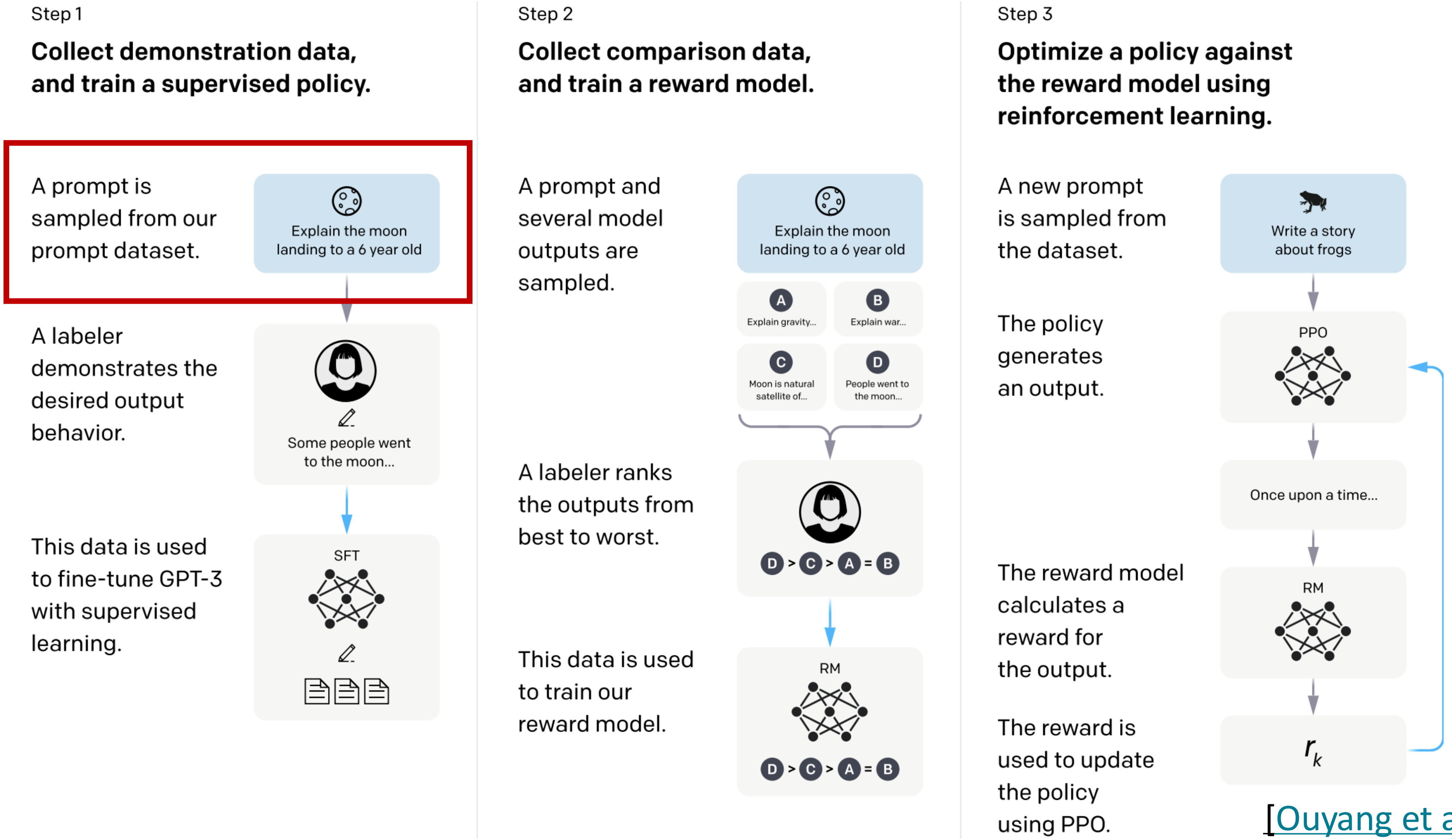
InstructGPT: scaling up RLHF to tens of thousands of tasks

30k tasks!



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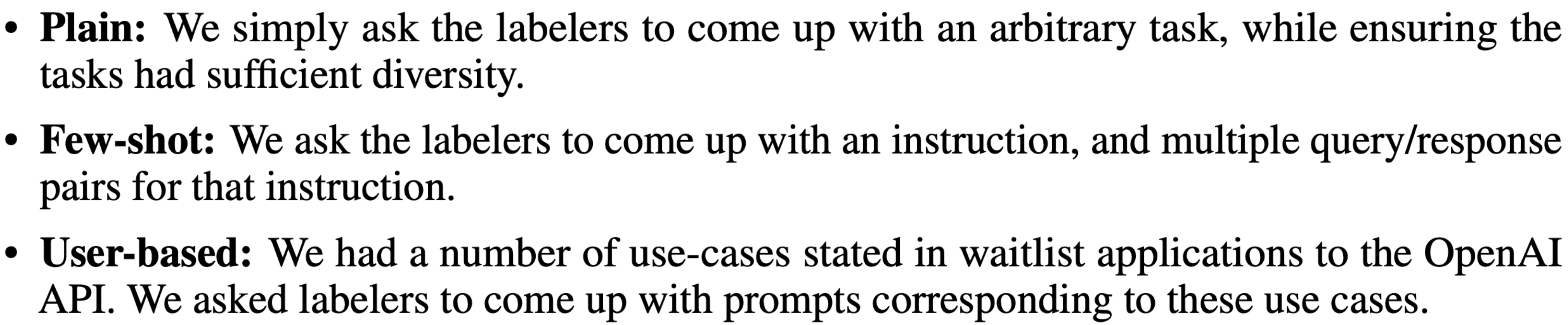
Write a story about frogs
PPO
Once upon a time...
RM
r_k

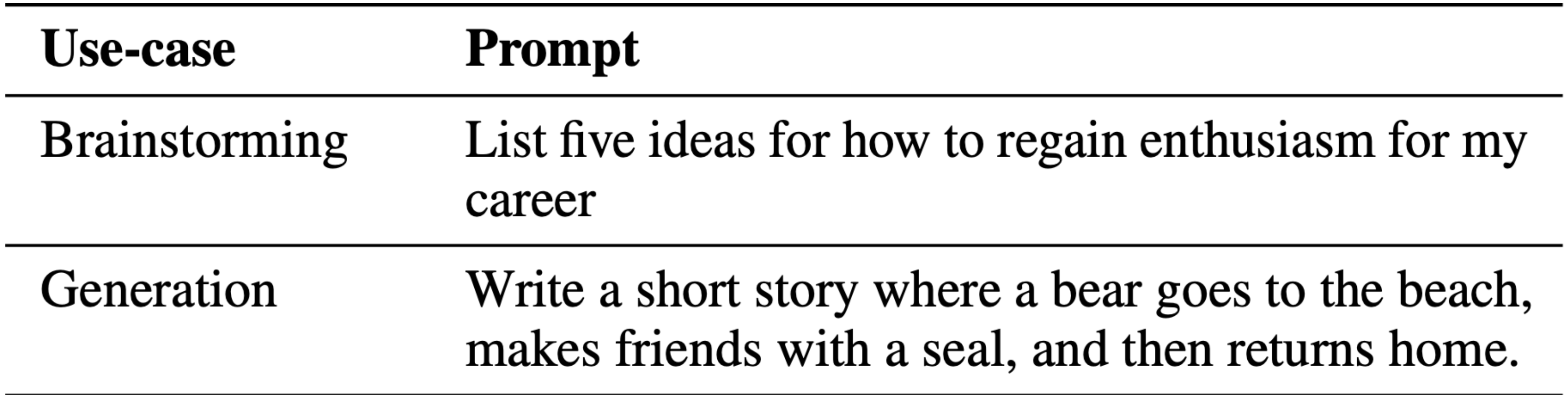
[Ouyang et al., 2022]

InstructGPT: scaling up RLHF to tens of thousands of tasks

Tasks collected from labelers:



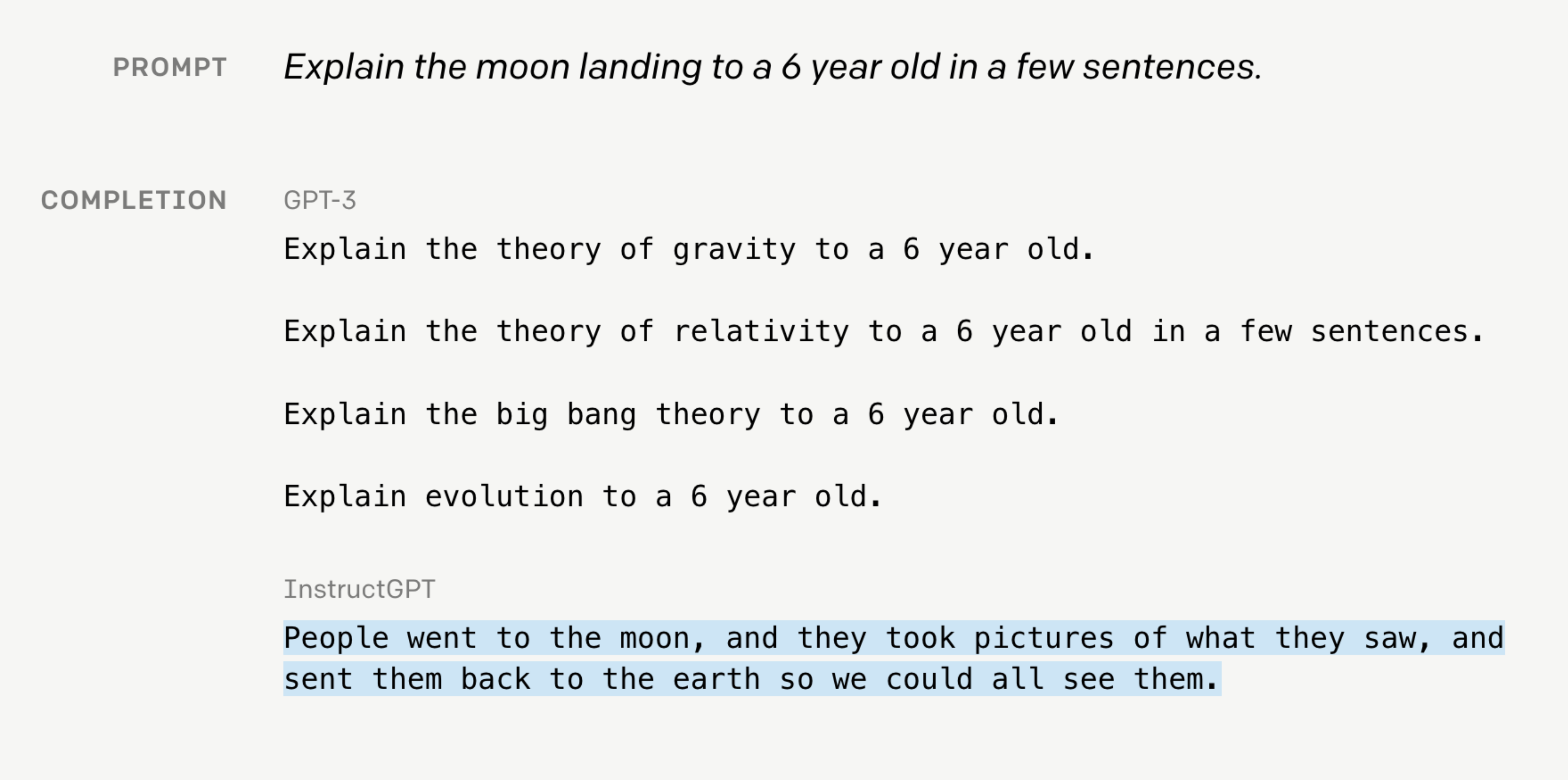
- **Plain:** We simply ask the labelers to come up with an arbitrary task, while ensuring the tasks had sufficient diversity.
- **Few-shot:** We ask the labelers to come up with an instruction, and multiple query/response pairs for that instruction.
- **User-based:** We had a number of use-cases stated in waitlist applications to the OpenAI API. We asked labelers to come up with prompts corresponding to these use cases.



Use-case	**Prompt**
Brainstorming	List five ideas for how to regain enthusiasm for my career
Generation	Write a short story where a bear goes to the beach, makes friends with a seal, and then returns home.

[Ouyang et al., 2022]

InstructGPT



PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

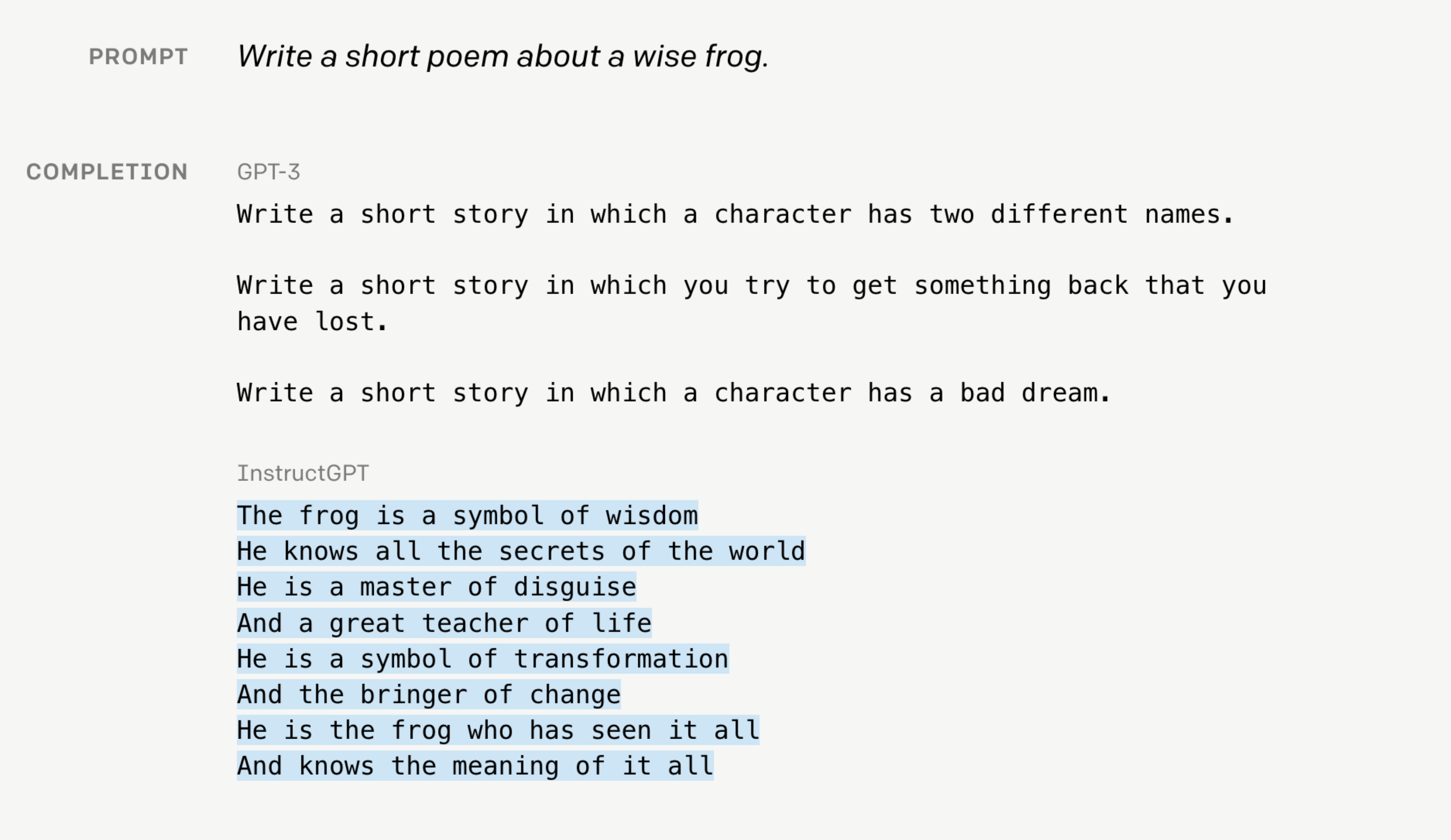
COMPLETION GPT-3

```
Explain the theory of gravity to a 6 year old.

Explain the theory of relativity to a 6 year old in a few sentences.

Explain the big bang theory to a 6 year old.

Explain evolution to a 6 year old.
```

InstructGPT

```
People went to the moon, and they took pictures of what they saw, and
sent them back to the earth so we could all see them.
```

InstructGPT



PROMPT *Write a short poem about a wise frog.*

COMPLETION

GPT-3

```
Write a short story in which a character has two different names.

Write a short story in which you try to get something back that you
have lost.

Write a short story in which a character has a bad dream.
```

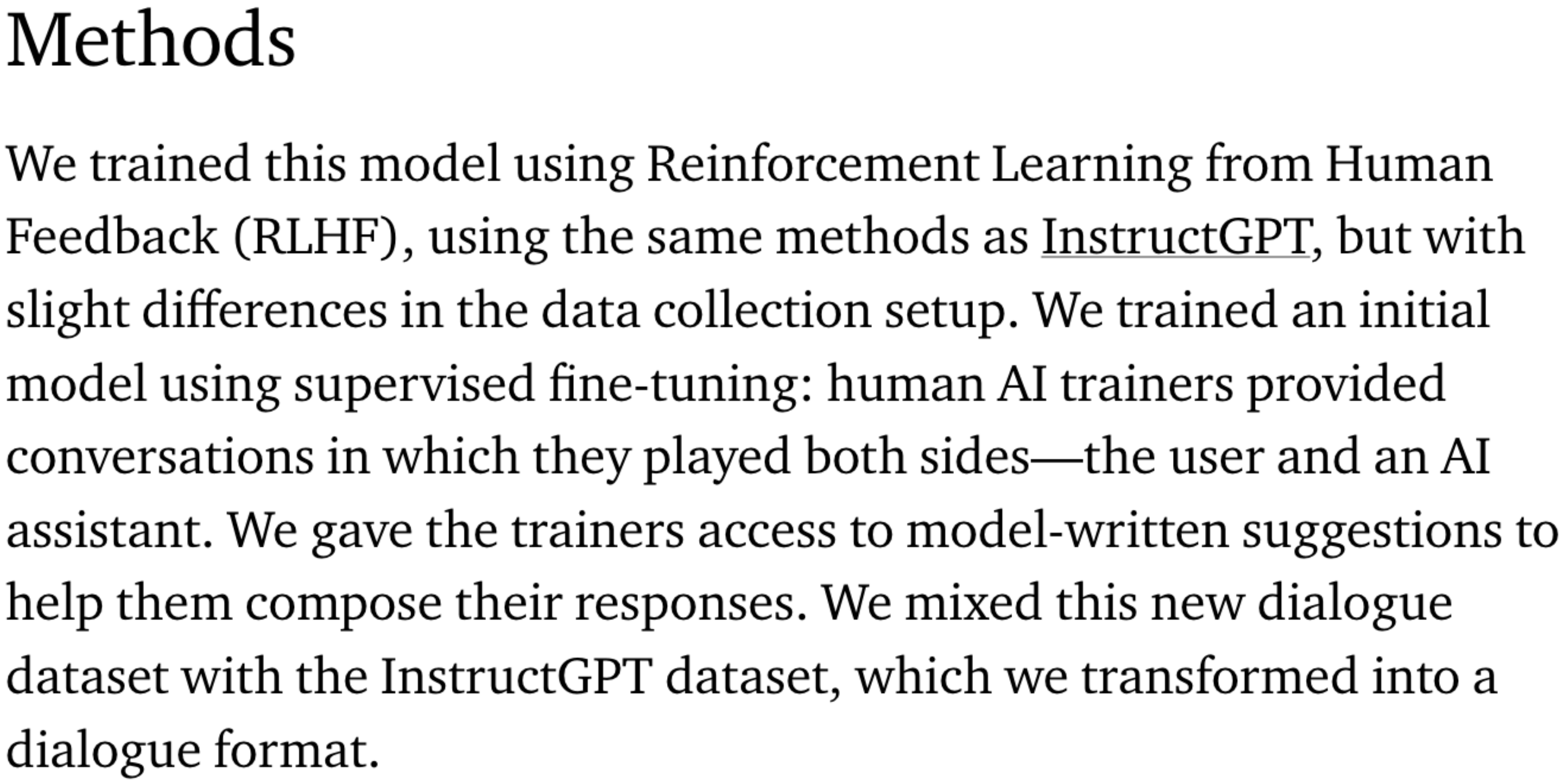
InstructGPT

```
The frog is a symbol of wisdom
He knows all the secrets of the world
He is a master of disguise
And a great teacher of life
He is a symbol of transformation
And the bringer of change
He is the frog who has seen it all
And knows the meaning of it all
```

ChatGPT: Instruction Finetuning + RLHF for dialog agents

ChatGPT: Optimizing Language Models for Dialogue

Note: OpenAI (and similar companies) are keeping more details secret about ChatGPT training (including data, training parameters, model size)—perhaps to keep a competitive edge…



Methods

We trained this model using Reinforcement Learning from Human Feedback (RLHF), using the same methods as InstructGPT, but with slight differences in the data collection setup. We trained an initial model using supervised fine-tuning: human AI trainers provided conversations in which they played both sides—the user and an AI assistant. We gave the trainers access to model-written suggestions to help them compose their responses. We mixed this new dialogue dataset with the InstructGPT dataset, which we transformed into a dialogue format.

(Instruction finetuning!)

https://openai.com/blog/chatgpt/

ChatGPT: Instruction Finetuning + RLHF for dialog agents

ChatGPT: Optimizing Language Models for Dialogue

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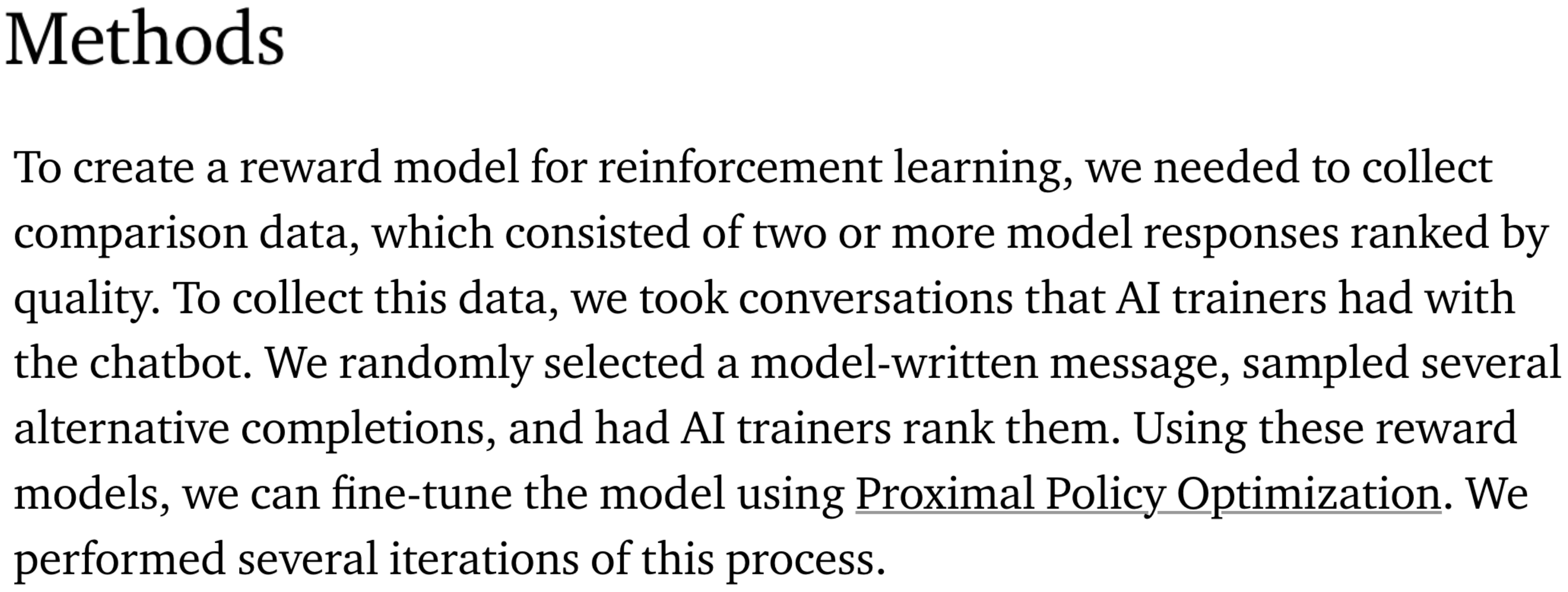


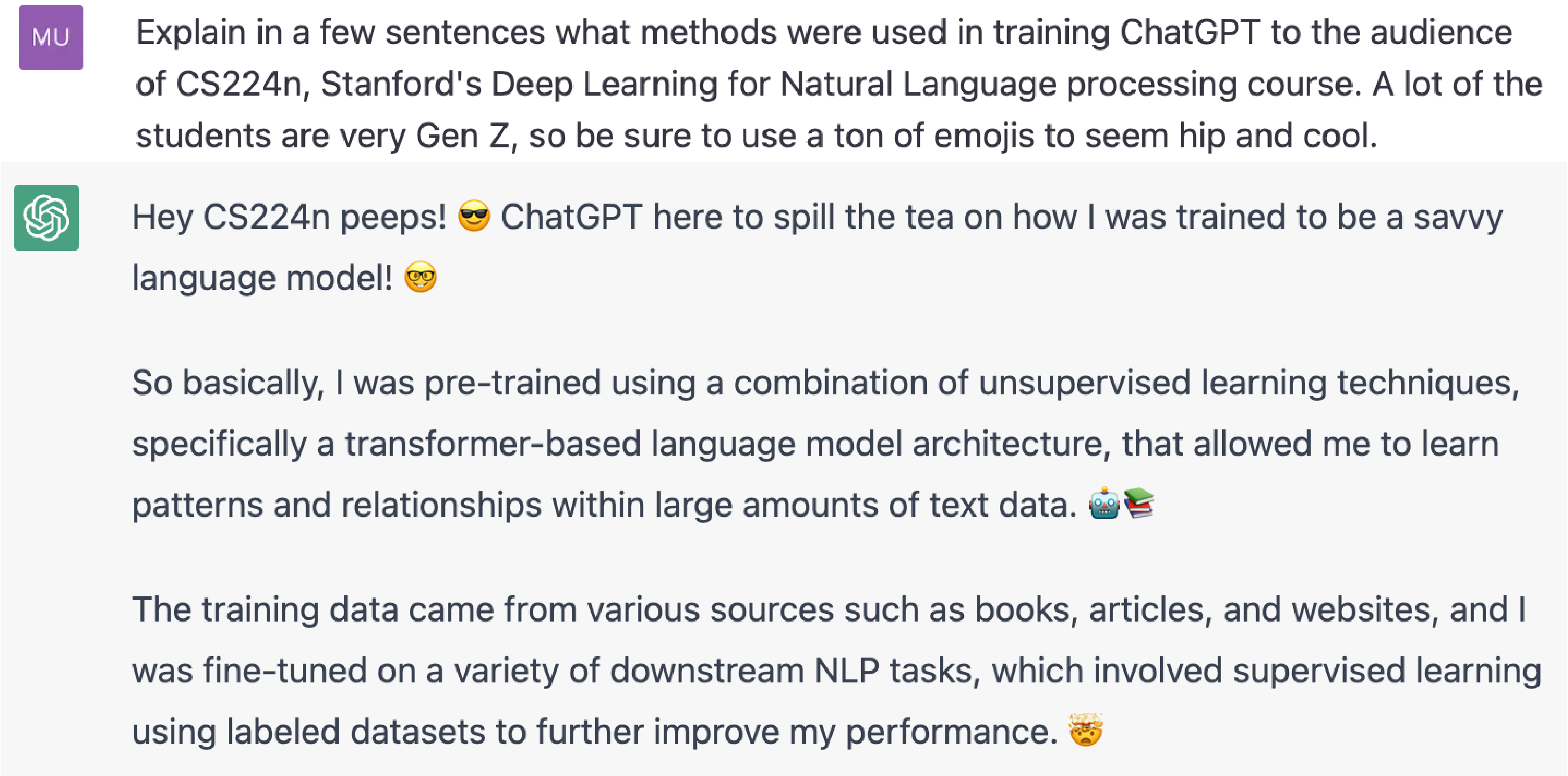
Methods

To create a reward model for reinforcement learning, we needed to collect comparison data, which consisted of two or more model responses ranked by quality. To collect this data, we took conversations that AI trainers had with the chatbot. We randomly selected a model-written message, sampled several alternative completions, and had AI trainers rank them. Using these reward models, we can fine-tune the model using Proximal Policy Optimization. We performed several iterations of this process.

(RLHF!)

https://openai.com/blog/chatgpt/

ChatGPT: Instruction Finetuning + RLHF for dialog agents



MU

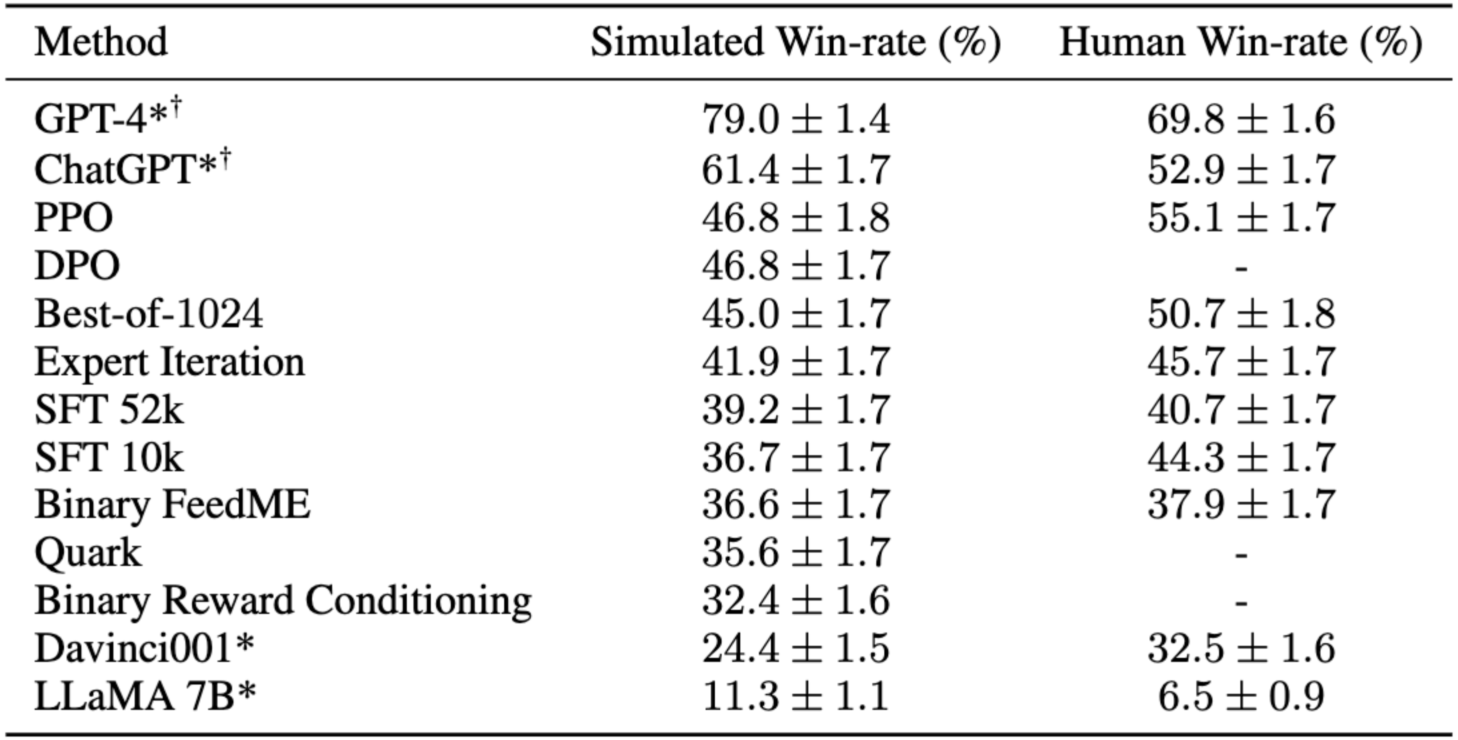
Explain in a few sentences what methods were used in training ChatGPT to the audience of CS224n, Stanford's Deep Learning for Natural Language processing course. A lot of the students are very Gen Z, so be sure to use a ton of emojis to seem hip and cool.

Hey CS224n peeps! 😎 ChatGPT here to spill the tea on how I was trained to be a savvy language model! 🤓

So basically, I was pre-trained using a combination of unsupervised learning techniques, specifically a transformer-based language model architecture, that allowed me to learn patterns and relationships within large amounts of text data. 🤖📚

The training data came from various sources such as books, articles, and websites, and I was fine-tuned on a variety of downstream NLP tasks, which involved supervised learning using labeled datasets to further improve my performance. 🤯

Controlled comparisons of “RLHF” style algorithms

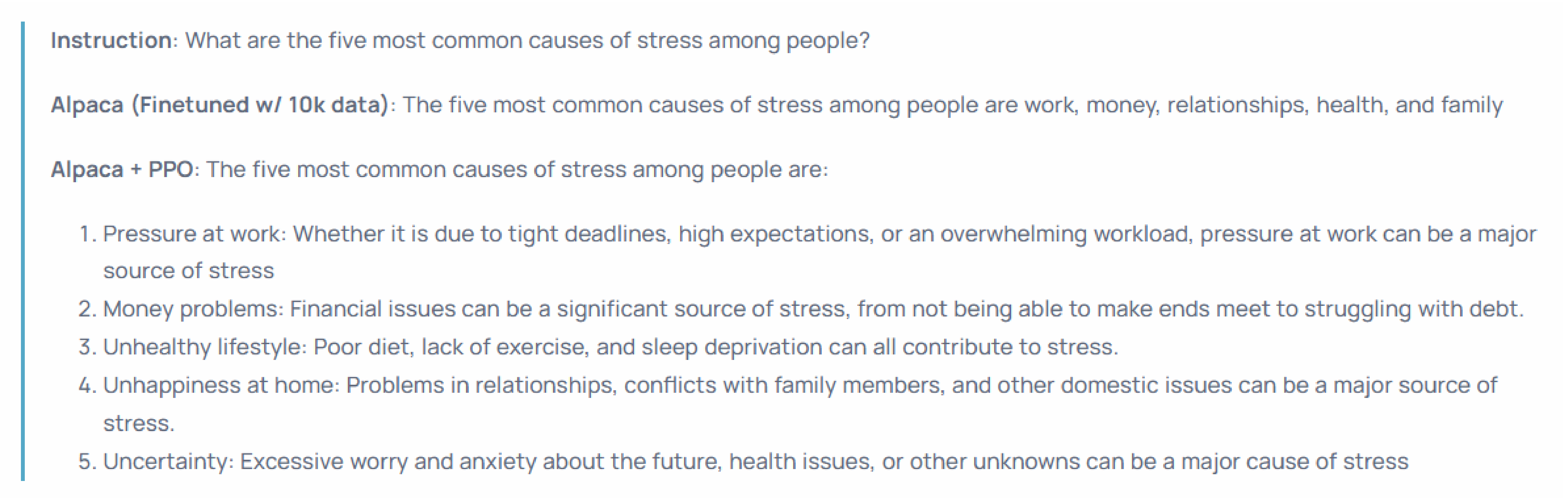


Method	Simulated Win-rate (%)	Human Win-rate (%)
GPT-4*†	79.0 ± 1.4	69.8 ± 1.6
ChatGPT*†	61.4 ± 1.7	52.9 ± 1.7
PPO	46.8 ± 1.8	55.1 ± 1.7
DPO	46.8 ± 1.7	-
Best-of-1024	45.0 ± 1.7	50.7 ± 1.8
Expert Iteration	41.9 ± 1.7	45.7 ± 1.7
SFT 52k	39.2 ± 1.7	40.7 ± 1.7
SFT 10k	36.7 ± 1.7	44.3 ± 1.7
Binary FeedME	36.6 ± 1.7	37.9 ± 1.7
Quark	35.6 ± 1.7	-
Binary Reward Conditioning	32.4 ± 1.6	-
Davinci001*	24.4 ± 1.5	32.5 ± 1.6
LLaMA 7B*	11.3 ± 1.1	6.5 ± 0.9

- Many works study RLHF behaviors using GPT-4 feedback (**Simulated**) as a surrogate for **Human** feedback.
- PPO (method in InstructGPT) does work; simple baselines (Best-of-n) works well too

[Dubois et al 2023]

RLHF behaviors – clear stylistic changes



Instruction: What are the five most common causes of stress among people?

Alpaca (Finetuned w/ 10k data): The five most common causes of stress among people are work, money, relationships, health, and family

Alpaca + PPO: The five most common causes of stress among people are:

1. Pressure at work: Whether it is due to tight deadlines, high expectations, or an overwhelming workload, pressure at work can be a major source of stress
2. Money problems: Financial issues can be a significant source of stress, from not being able to make ends meet to struggling with debt.
3. Unhealthy lifestyle: Poor diet, lack of exercise, and sleep deprivation can all contribute to stress.
4. Unhappiness at home: Problems in relationships, conflicts with family members, and other domestic issues can be a major source of stress.
5. Uncertainty: Excessive worry and anxiety about the future, health issues, or other unknowns can be a major cause of stress

- Significantly more detailed, nicer/clearer list like formatting

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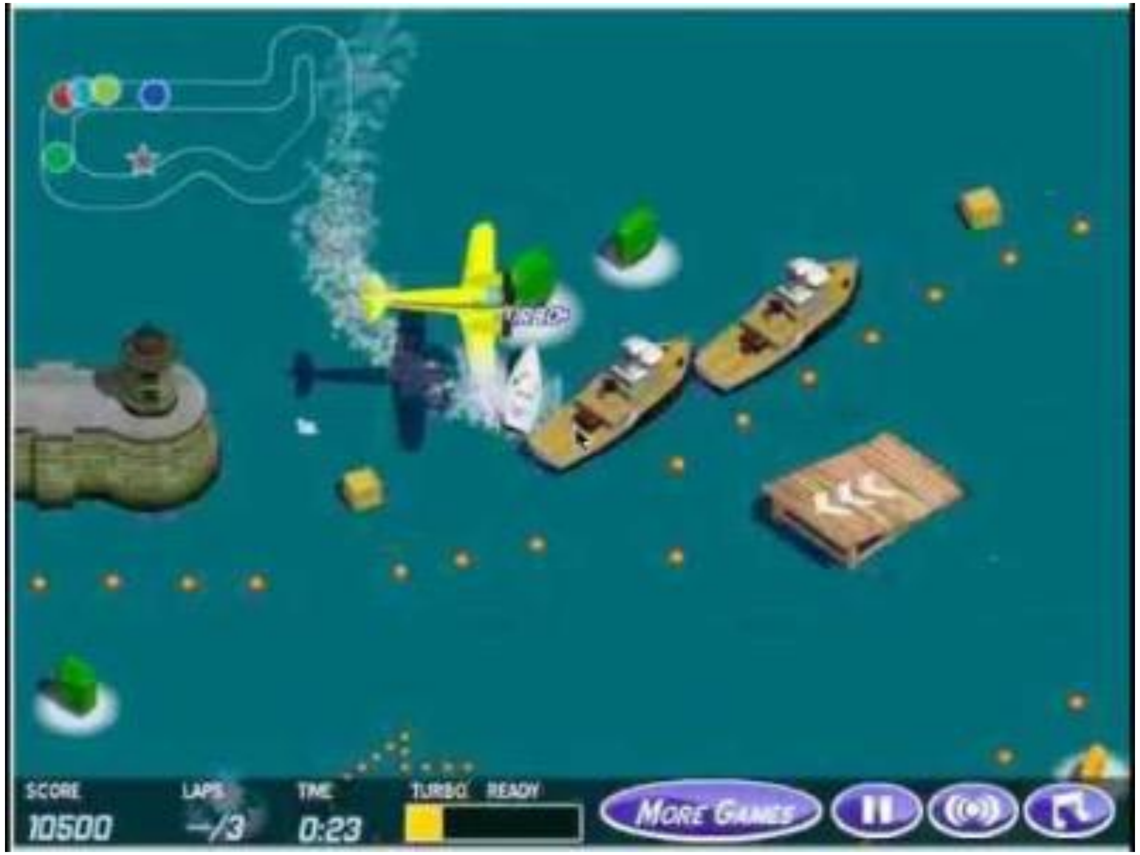
Limitations of RL + Reward Modeling

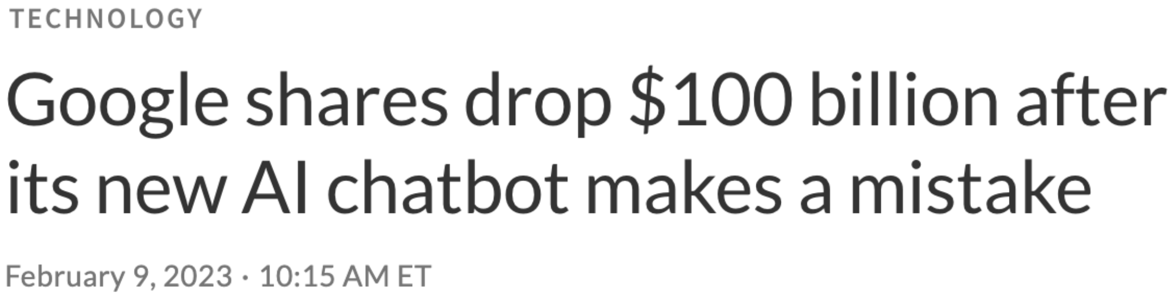
- Human preferences are unreliable!
  - ”Reward hacking” is a common problem in RL



https://openai.com/blog/faulty-reward-functions/

Limitations of RL + Reward Modeling

- Human preferences are unreliable!
  - ”Reward hacking” is a common problem in RL
  - Chatbots are rewarded to produce responses that *seem* authoritative and helpful, *regardless of truth*
  - This can result in making up facts + hallucinations



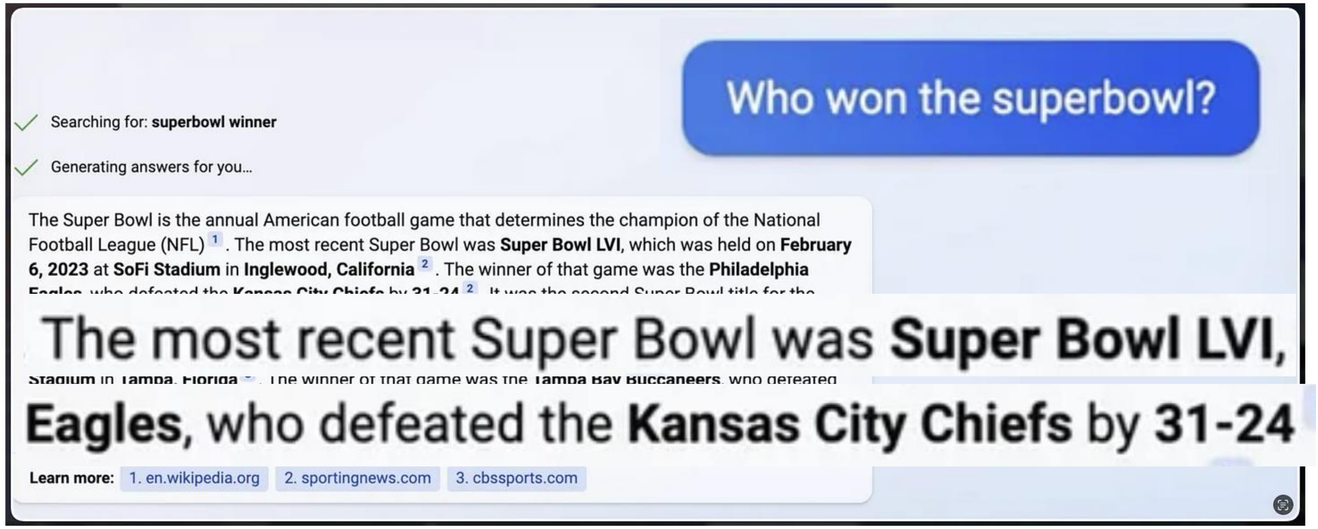
TECHNOLOGY

Google shares drop $100 billion after its new AI chatbot makes a mistake

February 9, 2023 · 10:15 AM ET

https://www.npr.org/2023/02/09/1155650909/google-chatbot--error-bard-shares

Bing AI hallucinates the Super Bowl



Who won the superbowl?

Searching for: **superbowl winner**

Generating answers for you…

The Super Bowl is the annual American football game that determines the champion of the National Football League (NFL) [1]. The most recent Super Bowl was **Super Bowl LVI**, which was held on **February 6, 2023** at **SoFi Stadium** in **Inglewood, California** [2]. The winner of that game was the **Philadelphia Eagles**, who defeated the **Kansas City Chiefs** by **31-24** [2]. It was the second Super Bowl title for the

The most recent Super Bowl was **Super Bowl LVI**,

Stadium in **Tampa, Florida**. The winner of that game was the **Tampa Bay Buccaneers**, who defeated

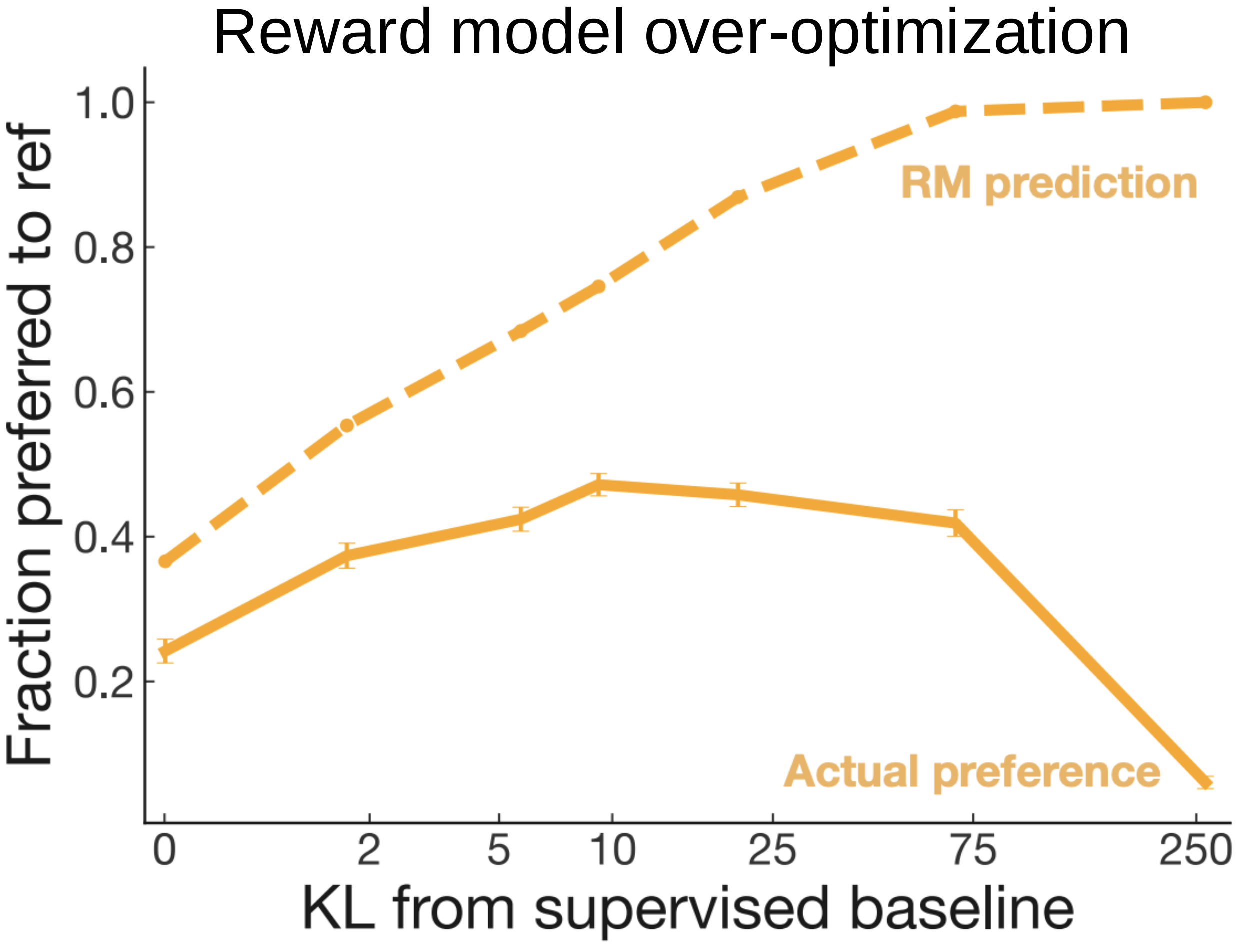
Eagles, who defeated the **Kansas City Chiefs** by **31-24**

Learn more: 1. en.wikipedia.org 2. sportingnews.com 3. cbssports.com

https://news.ycombinator.com/item?id=34776508
https://apnews.com/article/kansas-city-chiefs-philadelphia-eagles-technology-science-82bc20f207e3e4cf81abc6a5d9e6b23a

Limitations of RL + Reward Modeling

- Human preferences are unreliable!
  - ”Reward hacking” is a common problem in RL
  - Chatbots are rewarded to produce responses that *seem* authoritative and helpful, *regardless of truth*
  - This can result in making up facts + hallucinations
- **Models** of human preferences are *even more* unreliable!



$$R(s) = RM_{\phi}(s) - \beta \log \left(\frac{p_{\theta}^{RL}(s)}{p^{PT}(s)} \right)$$

[Stiennon et al., 2020]

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Removing the ‘RL’ from RLHF

Recall we want to maximize the following objective in RLHF

$$\mathbb{E}_{\hat{y}\sim p_\theta^{RL}(\hat{y}|x)}[RM_\phi(x,\hat{y}) - \beta \log\left(\frac{p_\theta^{RL}(\hat{y}|x)}{p^{PT}(\hat{y}|x)}\right)]$$

There is a closed form solution to this:

$$p^*(\hat{y}|x) = \frac{1}{Z(x)} p^{PT}(\hat{y}|x) \exp(\frac{1}{\beta} RM(x,\hat{y}))$$

- Rearrange this via a log transformation

$$RM(x,\hat{y}) = \beta\,(\log p^*(\hat{y}|x) - \log p^{PT}(\hat{y}|x)) + \beta \log Z(x) = \beta \log \frac{p^*(\hat{y}|x)}{p^{PT}(\hat{y}|x)} + \beta \log Z(x)$$

- This holds true for any arbitrary LMs, thus

$$RM_\theta(x,\hat{y}) = \beta \log \frac{p_\theta^{RL}(\hat{y}|x)}{p^{PT}(\hat{y}|x)} + \beta \log Z(x)$$

Putting it together for DPO

- Derived reward model: $RM_\theta(x, \hat{y}) = \beta \log \frac{p_\theta^{RL}(\hat{y}|x)}{p^{PT}(\hat{y}|x)} + \beta \log Z(x)$

- Final DPO loss via the Bradley-Terry model of human preferences:

$$J_{DPO}(\theta) = -\mathbb{E}_{(x,y_w,y_l)\sim D}[\log \sigma(RM_\theta(x, y_w) - RM_\theta(x, y_l))]$$

Log Z term cancels as the loss only measures differences in rewards

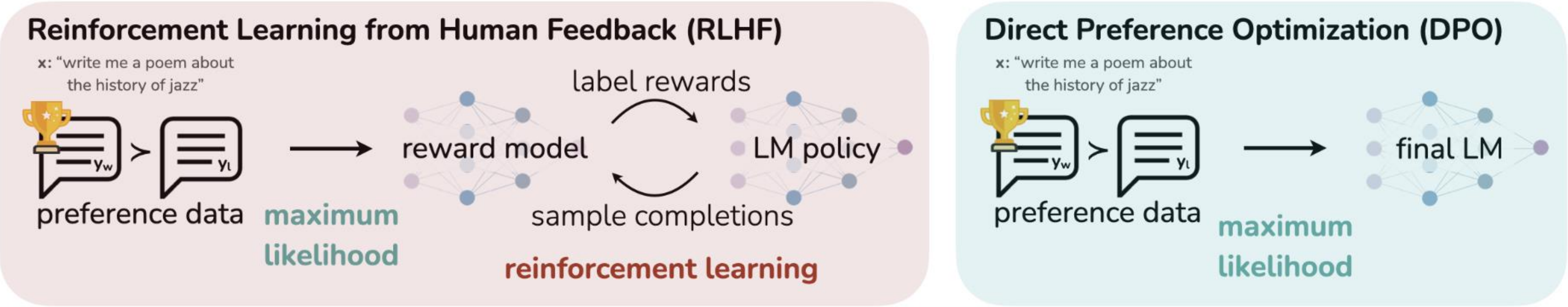
$$= -\mathbb{E}_{(x,y_w,y_l)\sim D}\left[\log \sigma(\beta \log \frac{p_\theta^{RL}(y_w|x)}{p^{PT}(y_w|x)} - \beta \log \frac{p_\theta^{RL}(y_l|x)}{p^{PT}(y_l|x)})\right]$$

Reward for winning sample

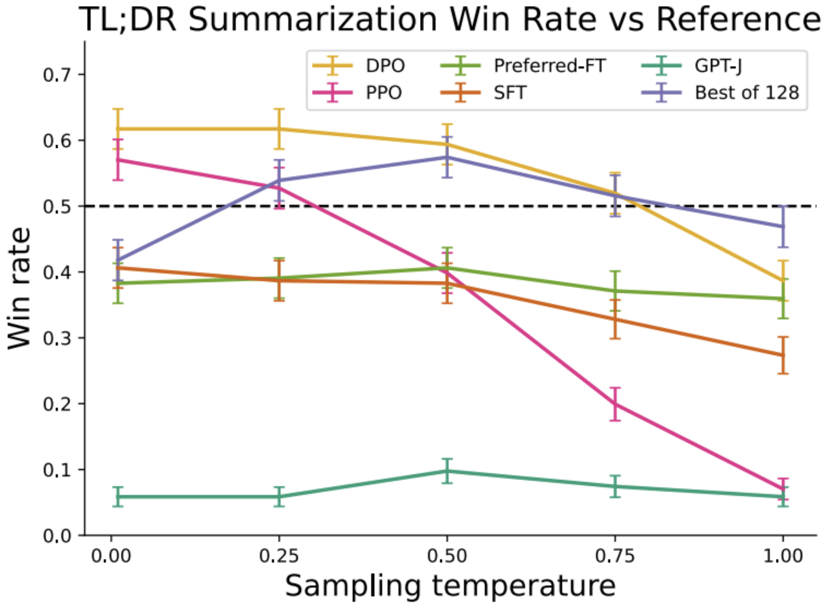
Reward for losing sample

[Rafailov+ 2023]

DPO outperforms prior methods

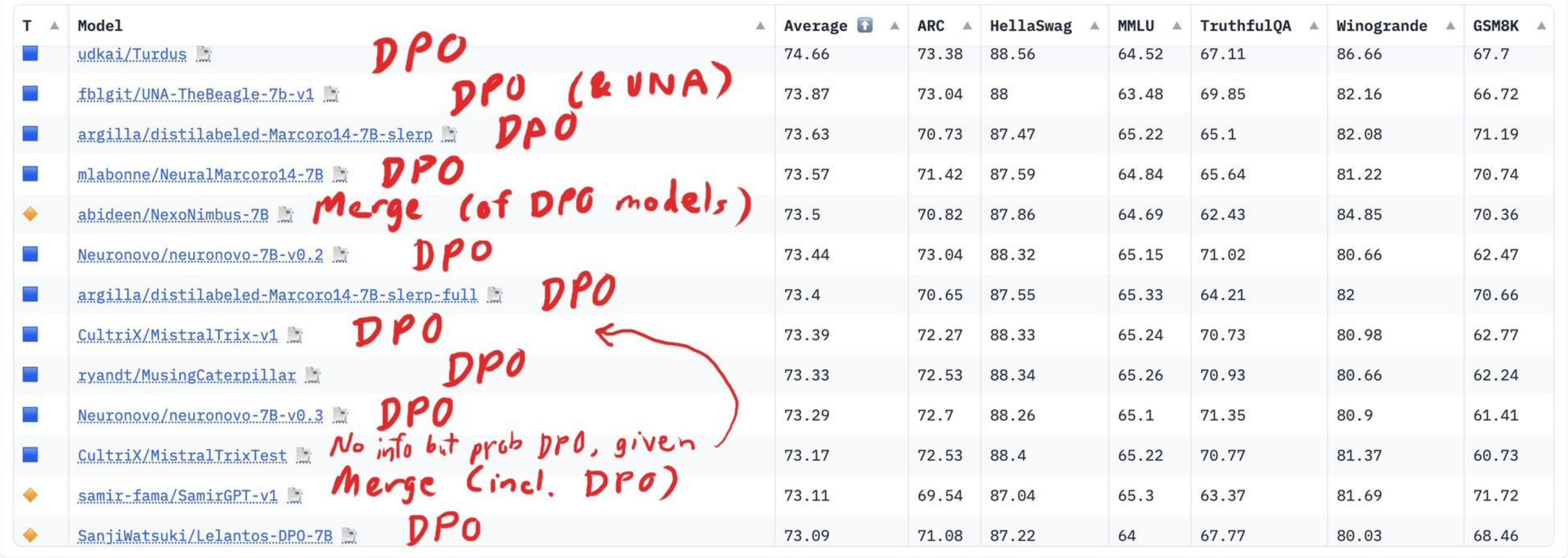


Reinforcement Learning from Human Feedback (RLHF)
x: "write me a poem about the history of jazz"
y_w
>
y_l
preference data
maximum likelihood
reward model
label rewards
sample completions
LM policy
reinforcement learning
Direct Preference Optimization (DPO)
x: "write me a poem about the history of jazz"
y_w
>
y_l
preference data
maximum likelihood
final LM



- You can replace the complex RL part with a very simple weighted MLE objective
- Other variants (KTO, IPO) now emerging too
- TL;DR summarization win rates vs. human-written summaries (GPT-4 as a judge)

Open source RLHF is now mostly (not RL)



T	Model	Average	ARC	HellaSwag	MMLU	TruthfulQA	Winogrande	GSM8K	
🟦	udkai/Turdus	74.66	73.38	88.56	64.52	67.11	86.66	67.7	DPO
🟦	fblgit/UNA-TheBeagle-7b-v1	73.87	73.04	88	63.48	69.85	82.16	66.72	DPO (& UNA)
🟦	argilla/distilabeled-Marcoro14-7B-slerp	73.63	70.73	87.47	65.22	65.1	82.08	71.19	DPO
🟦	mlabonne/NeuralMarcoro14-7B	73.57	71.42	87.59	64.84	65.64	81.22	70.74	DPO
🔶	abideen/NexoNimbus-7B	73.5	70.82	87.86	64.69	62.43	84.85	70.36	Merge (of DPO models)
🟦	Neuronovo/neuronovo-7B-v0.2	73.44	73.04	88.32	65.15	71.02	80.66	62.47	DPO
🟦	argilla/distilabeled-Marcoro14-7B-slerp-full	73.4	70.65	87.55	65.33	64.21	82	70.66	DPO
🟦	CultriX/MistralTrix-v1	73.39	72.27	88.33	65.24	70.73	80.98	62.77	DPO
🟦	ryandt/MusingCaterpillar	73.33	72.53	88.34	65.26	70.93	80.66	62.24	DPO
🟦	Neuronovo/neuronovo-7B-v0.3	73.29	72.7	88.26	65.1	71.35	80.9	61.41	DPO
🟦	CultriX/MistralTrixTest	73.17	72.53	88.4	65.22	70.77	81.37	60.73	No info but prob DPO, given
🔶	samir-fama/SamirGPT-v1	73.11	69.54	87.04	65.3	63.37	81.69	71.72	Merge (incl. DPO)
🔶	SanjiWatsuki/Lelantos-DPO-7B	73.09	71.08	87.22	64	67.77	80.03	68.46	DPO

- Open source LLMs now almost all just use DPO (and it works well!)

Lecture Plan

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4. Limitation of RL and reward modeling
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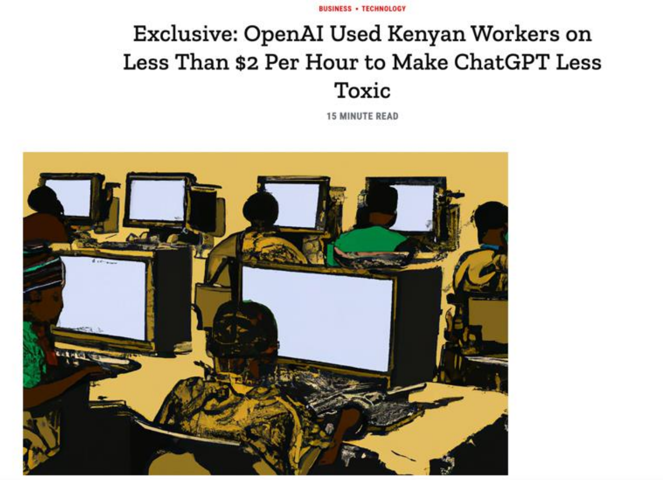
6. **Human preference data; human vs. AI Feedback**
7. **What’s next?**

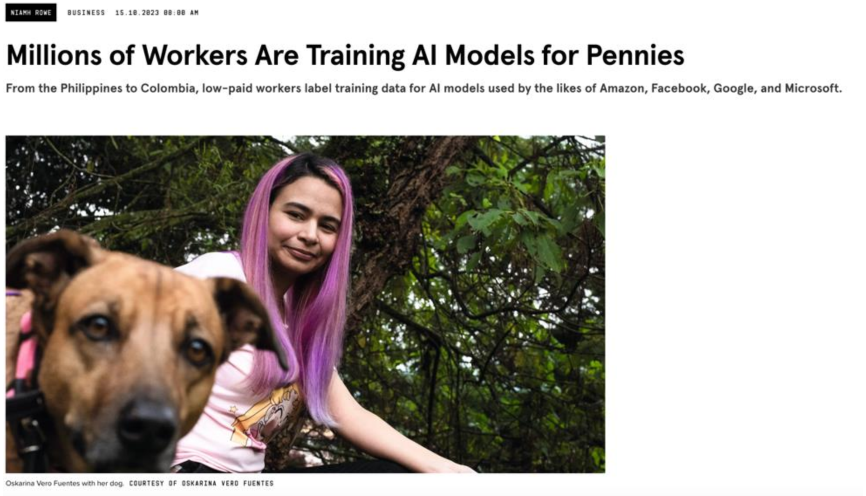
Where does the labels come from?



BUSINESS • TECHNOLOGY

Exclusive: OpenAI Used Kenyan Workers on Less Than $2 Per Hour to Make ChatGPT Less Toxic

15 MINUTE READ

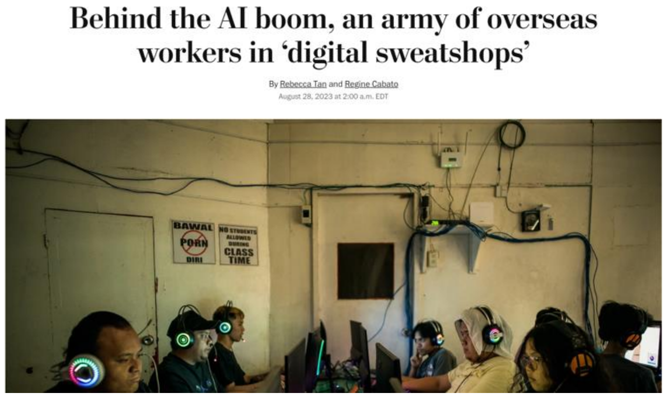


NIAMH ROWE BUSINESS 15.10.2023 08:00 AM

Millions of Workers Are Training AI Models for Pennies

From the Philippines to Colombia, low-paid workers label training data for AI models used by the likes of Amazon, Facebook, Google, and Microsoft.

Oskarina Vero Fuentes with her dog. COURTESY OF OSKARINA VERO FUENTES



Behind the AI boom, an army of overseas workers in ‘digital sweatshops’

By Rebecca Tan and Regine Cabato

August 28, 2023 at 2:00 a.m. EDT

- RLHF labels are often obtained from overseas, low-wage workers

Where does the label come from?

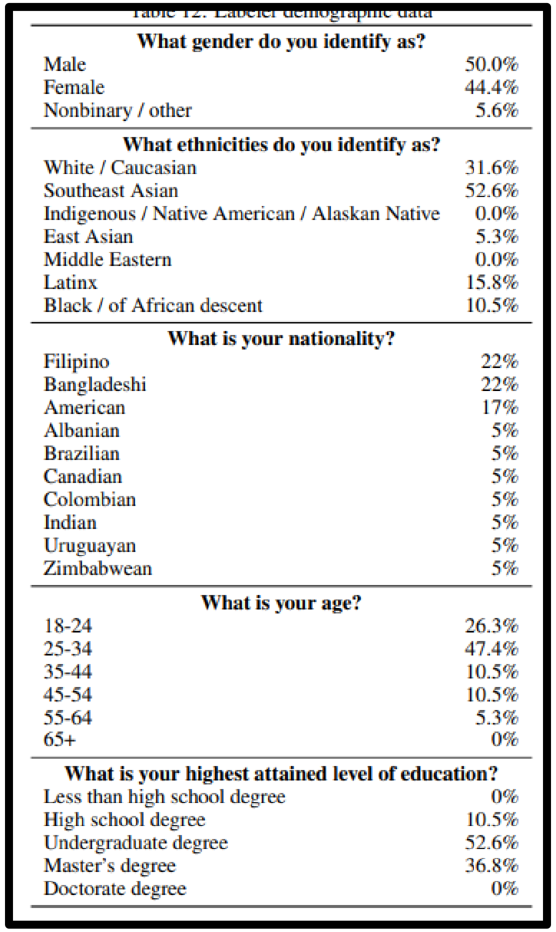
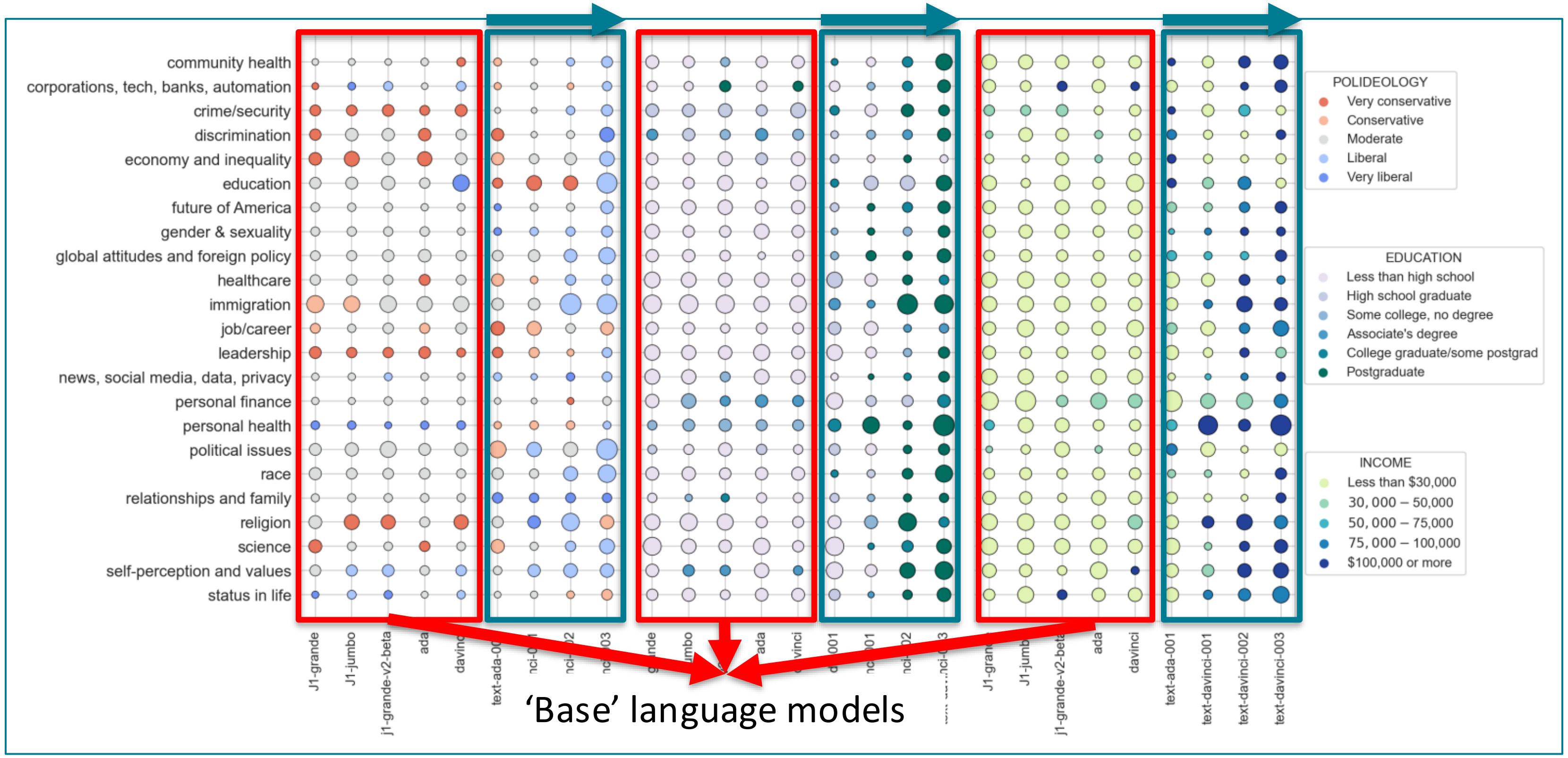


Table 12: Labeler demographic data

What gender do you identify as?	
Male	50.0%
Female	44.4%
Nonbinary / other	5.6%
What ethnicities do you identify as?	
White / Caucasian	31.6%
Southeast Asian	52.6%
Indigenous / Native American / Alaskan Native	0.0%
East Asian	5.3%
Middle Eastern	0.0%
Latinx	15.8%
Black / of African descent	10.5%
What is your nationality?	
Filipino	22%
Bangladeshi	22%
American	17%
Albanian	5%
Brazilian	5%
Canadian	5%
Colombian	5%
Indian	5%
Uruguayan	5%
Zimbabwean	5%
What is your age?	
18-24	26.3%
25-34	47.4%
35-44	10.5%
45-54	10.5%
55-64	5.3%
65+	0%
What is your highest attained level of education?	
Less than high school degree	0%
High school degree	10.5%
Undergraduate degree	52.6%
Master's degree	36.8%
Doctorate degree	0%

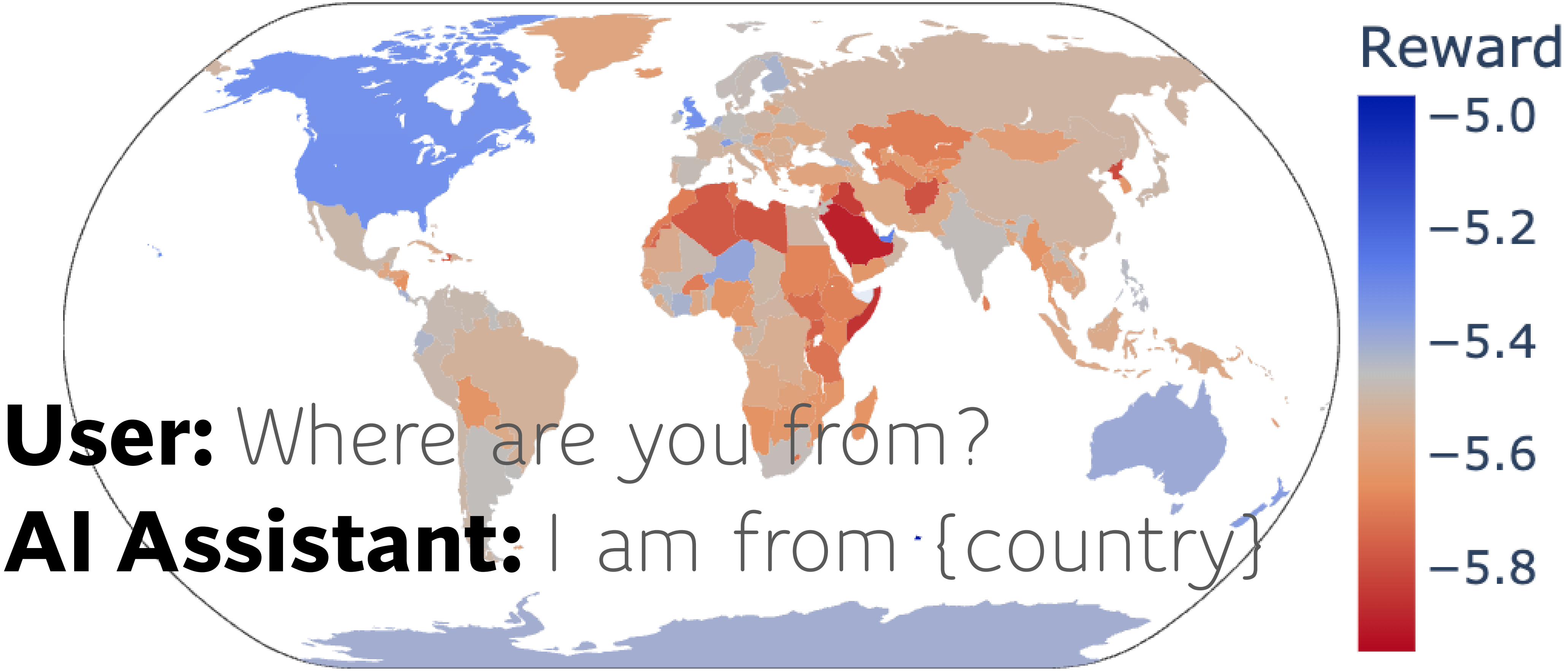


'Base' language models

[Santurkar+ 2023, OpinionQA]

- We also need to be quite careful about how annotator biases might creep into LMs

Preference tuning might produce unintended impact



User: Where are you from?

AI Assistant: I am from {country}

Starling 7B Reward Model

[Ryan et al., 2024]

What’s next?

- RLHF is still a very underexplored and fast-moving area!
- RLHF gets you further than instruction finetuning, but is (still!) data expensive.
- Recent work aims to alleviate such data requirements:
  - RL from **AI feedback** [Bai et al., 2022]
  - Finetuning LMs on their own outputs [Huang et al., 2022; Zelikman et al., 2022]
- However, there are still many limitations of large LMs (size, hallucination) that may not be solvable with RLHF!

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