RLHF and Instruction-tuning

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CS 288

With lots of credits to Jesse Mu and Stanford CS224N

Few-shot Learning Thus Far

- Thus far, we have talked about using LMs “out-of-the-box” for few-shot
  - surprising emergent property

Questions:

- Can we directly train models to do few-shot learning?
- Can we directly train models to follow arbitrary user instructions?
- Can we directly train models to obey toxicity & safety constraints?

Lecture Overview

- Instruction Finetuning
- Reinforcement Learning from Human Feedback (RLHF)
- Open challenges with RLHF

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Language modeling ≠ assisting users

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Explain the theory of gravity to a 6 year old.

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Finetuning to the rescue!

Language modeling ≠ assisting users

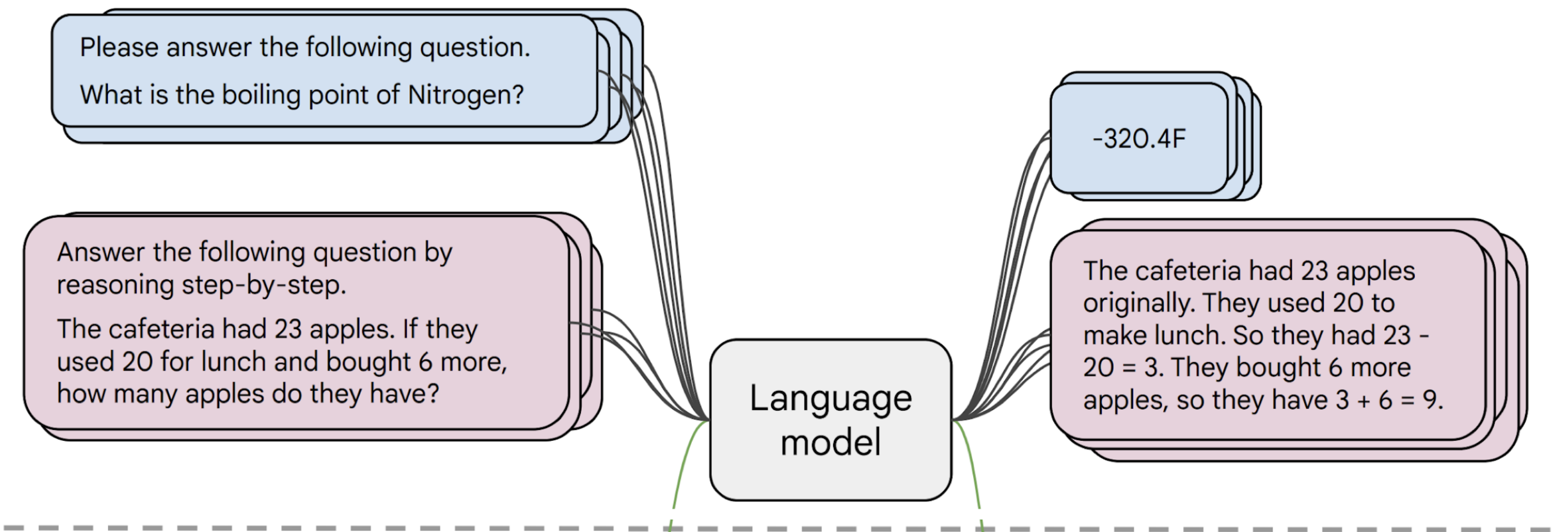
PROMPT *Explain the moon landing to a 6 year old in a few sentences.*

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!

Instruction Finetuning

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



- Evaluate on **unseen tasks**

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

Scaling Up Instruction Finetuning

[Wang et al., 2022]

Aside: new benchmarks for multitask LMs

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

BEYOND THE IMITATION GAME: QUANTIFYING AND EXTRAPOLATING THE CAPABILITIES OF LANGUAGE MODELS

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Aside: new benchmarks for multitask LMs

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

Kanji ASCII Art to Meaning

This subtask converts various kanji into ASCII art and has the language model guess their meaning from the ASCII art.

```
.......#.......
.......#.......
.#############.
.....#####.....
....##.#.##....
..###..#...##..
.##....#....###
...#...#..##...
...##.....##...
###############
...##.....##...
..####...####..
.######.####.#.
##.##..##.##..#
...##.....##...
```

Gains from Instruction Finetuning

- Lots of models based on finetuning T5
  - Flan-T5
  - Tk-Instruct
  - T0
  - ....

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

Qualitative Results

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)

Highly recommend trying FLAN-T5 out to get a sense of its capabilities:
https://huggingface.co/google/flan-t5-xxl

[Chung et al., 2022]

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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).

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Lecture Plan: From Language Models to Assistants

1. **Instruction finetuning**
   - + Simple and straightforward, generalize to unseen tasks
   - – ?
   - – ?
2. **Reinforcement Learning from Human Feedback (RLHF)**
3. **What's next?**

Limitations of instruction finetuning?

- **Problem 1:** it's expensive to collect ground-truth data for tasks
  - *Provide me five active research areas in April 2023 for LLMs*
- **Problem 2:** tasks like open-ended creative generation have no right answer.
  - *Write me a story about a dog and her pet grasshopper.*
- **Problem 3:** Even with instruction tuning, you are not directly "maximizing human preferences"

- Can we **explicitly attempt to satisfy human preferences?**

Lecture Overview

- Instruction Finetuning
- **Reinforcement Learning from Human Feedback (RLHF)**
- Open challenges with RLHF

Optimizing for human preferences

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```
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

$$R(s_2) = 1.2$$

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

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

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

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

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If R is +++

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

We **reinforce** good actions, increasing the chance they happen again.

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.

d.

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  - **Solution:** instead of directly asking humans for preferences, **model their preferences** as a separate (NLP) problem! [Knox and Stone, 2009]

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s_1	s_2
An earthquake hit San Francisco. There was minor property damage, but no injuries.	The Bay Area has good weather but is prone to earthquakes and wildfires.
$R(s_1) = 8.0$	$R(s_2) = 1.2$

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.
```

$$s_3$$

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

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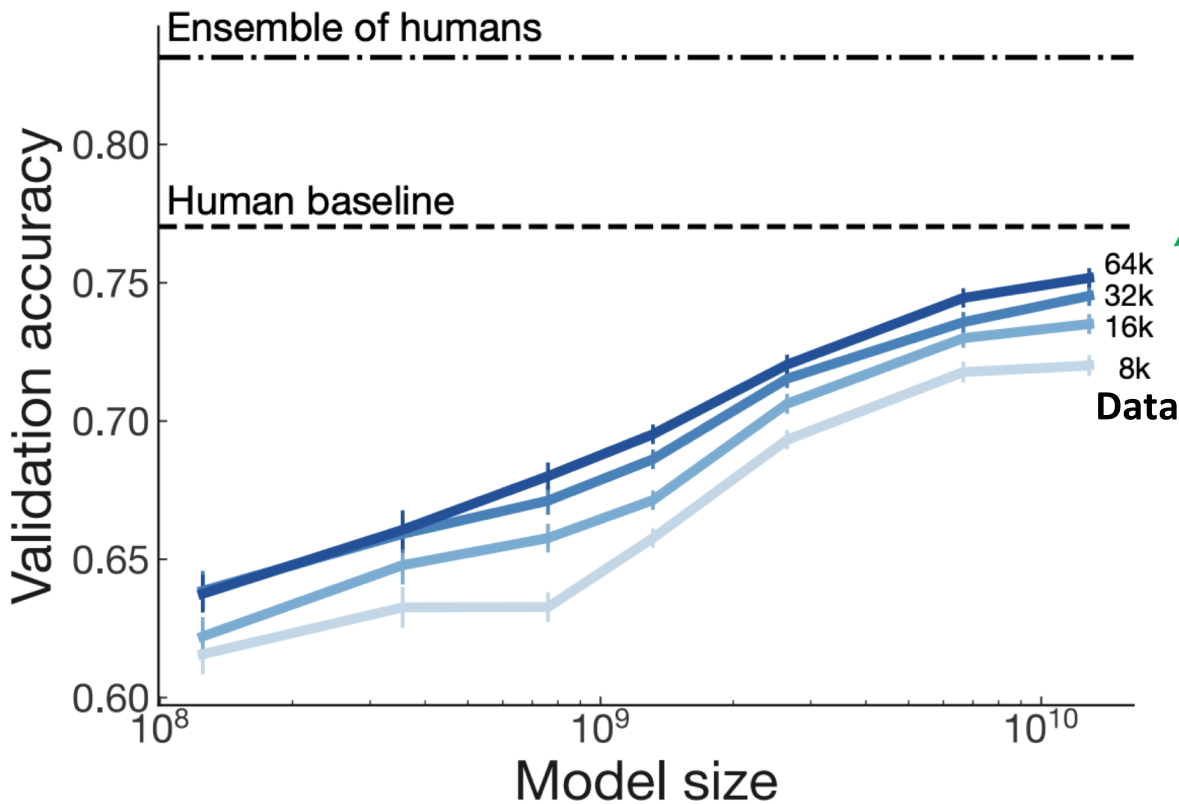
s_1		s_3		s_2
An earthquake hit San Francisco. There was minor property damage, but no injuries.	>	A 4.2 magnitude earthquake hit San Francisco, resulting in massive damage.	>	The Bay Area has good weather but is prone to earthquakes and wildfires.

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.

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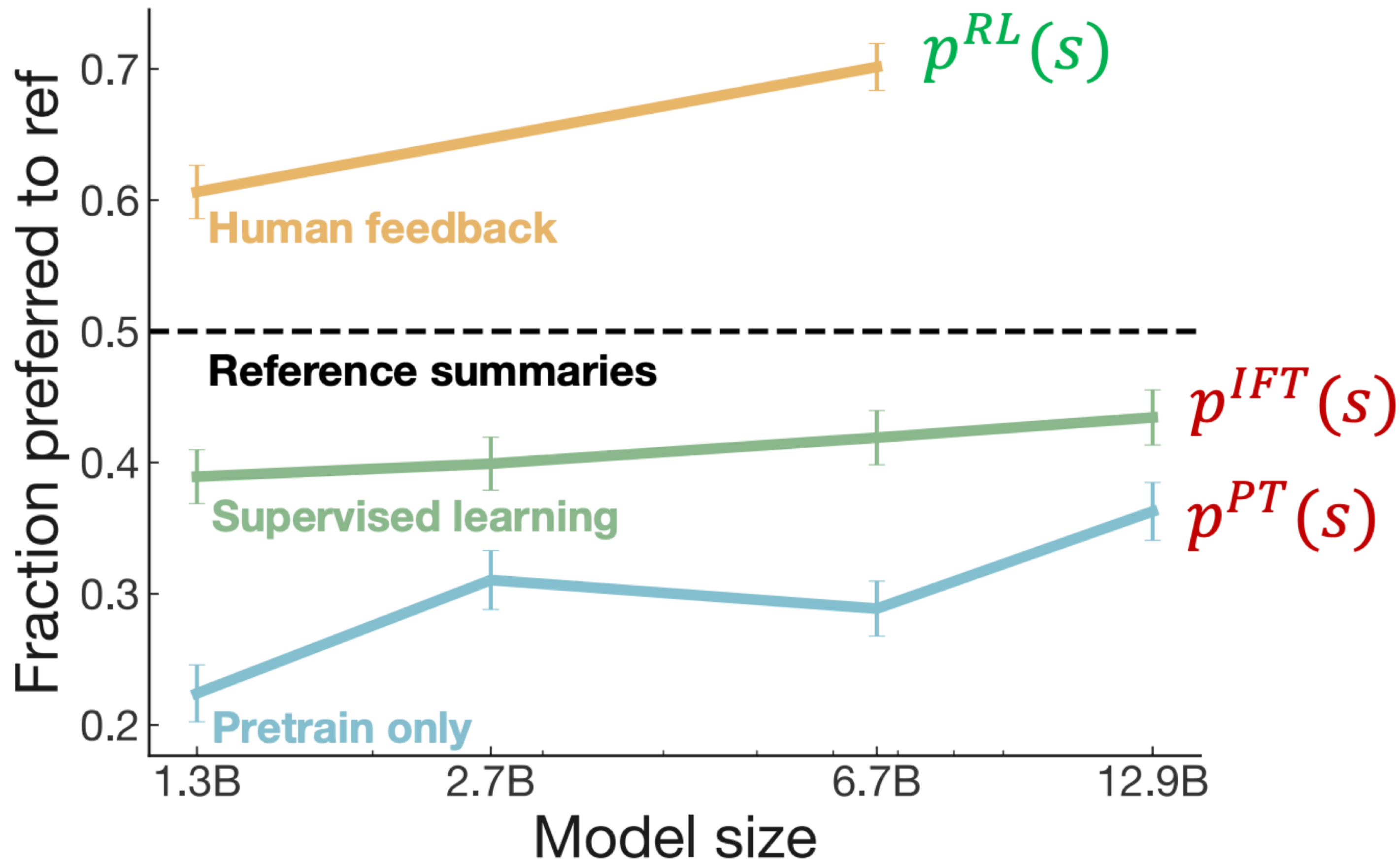
  - A reward model $RM_\phi(s)$ that produces scalar rewards for LM outputs, trained on a dataset of human comparisons
  - A method for optimizing LM parameters towards an arbitrary reward function.
- Now to do RLHF:
  - Initialize a copy of the model $p_\theta^{RL}(s)$, with parameters θ we would like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

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

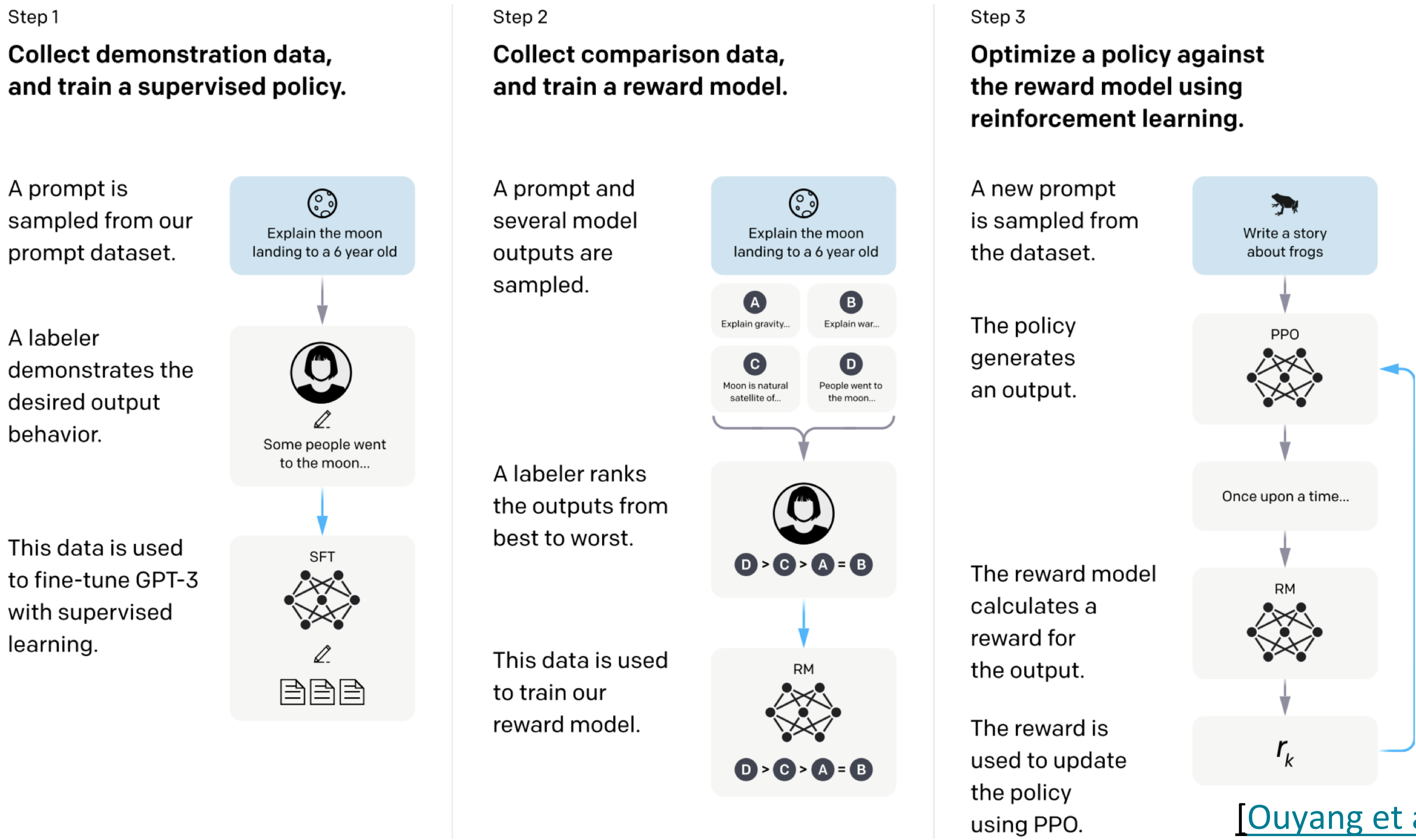
Pay a price when $p_\theta^{RL}(s) > p^{PT}(s)$

RLHF provides gains over pretraining + finetuning



[Stiennon et al., 2020]

InstructGPT: scaling up RLHF to tens of thousands of tasks



[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

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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/

Lecture Overview

- Instruction Finetuning
- Reinforcement Learning from Human Feedback (RLHF)
- **Open challenges with RLHF**

Limitations of RL + Reward Modeling

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

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

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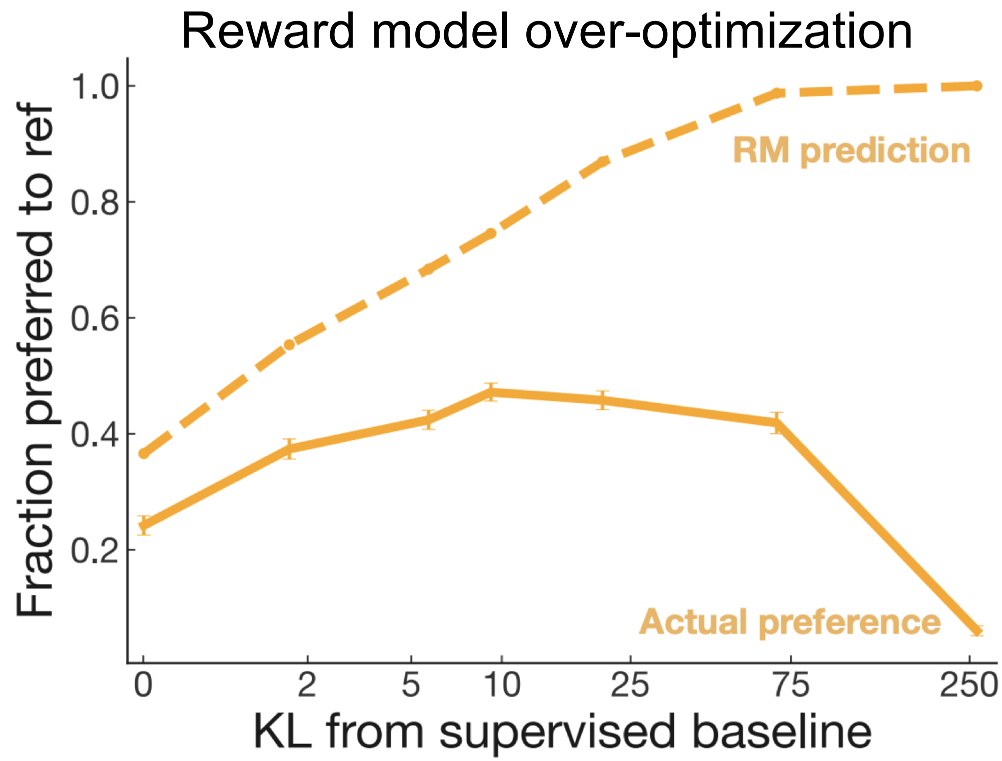
  - Chatbots are rewarded to produce responses that *seem* authoritative and helpful, *regardless of truth*
  - This can result in making up facts + hallucinations

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]