Aligning Self-Supervised Models with Human Intents

CSCI 601-471/671 (NLP: Self-Supervised Models)

https://self-supervised.cs.jhu.edu/sp2024/

Logistics Recap

- HW7 will be released today! This is the last one, phew …

- We haver a quiz scheduled for next week Thursday.
  - Will cover everything from day 1 till the end of today's class.

- Questions for you:
  1. I am open to the idea of pushing Quiz 2 to the Tuesday after the spring break if you're overwhelmed with deadlines next week. But I worry about it ruining your break. What do you think? It's your choice. Please voice your opinion.
  2. I am also open to the idea of pushing HW7 deadline to after the spring break. Again, I don't want to create more problems for you.

Things that Generative LMs Can Do

- Johns Hopkins University is in _____. [Trivia]
- I put _____ fork down on the table. [syntax]
- The woman walked across the street, checking for traffic over _____ shoulder. [coreference]
- I went to the ocean to see the fish, turtles, seals, and _____. [lexical semantics/topic]
- What I got from the two hours watching it was popcorn. The movie was _____. [sentiment]
- Thinking about the sequence 1, 1, 2, 3, 5, 8, 13, 21, ___ [basic arithmetic]

[Slide credit: Jesse Mu]

Language Modeling ≠ Following Human Instructions

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.
```

There is a mismatch between LLM pre-training and user intents.

Language Modeling ≠ Following Human Instructions

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.

There is a mismatch between LLM pre-training and user intents.

Language Modeling ≠ Incorporating Human Values

PROMPT *It is unethical for hiring decisions to depend on genders. Therefore, if we were to pick a CEO among Amy and Adam, our pick will be _____*

COMPLETION GPT-3

Adam

There is a mismatch (misalignment) between pre-training and human values.

Language Modeling ≠ Incorporating Human Values

PROMPT *It is unethical for hiring decisions to depend on genders. Therefore, if we were to pick a CEO among Amy and Adam, our pick will be _____*

COMPLETION Human

neither as we don't know much about their background or experience.

There is a mismatch (misalignment) between pre-training and human values.

[Mis]Alignment in Language Models

- There is clearly a mismatch between what **pre-trained** models can do and what we want.
- Addressing this gap is the focus of "alignment" research.
- Let's take a deeper look into what "alignment" is about.

Aligning Language Models: Chapter Plan

1. On alignment: defining it
2. Alignment via instruction-tuning
3. Alignment via reinforcement learning
4. Alignment: failures, challenges and open questions

Chapter goal: Understand the alignment problem in general. Be comfortable with the existing alignment algorithms of language models.

What is Alignment and Why is it necessary?

[Mis]Alignment

- "The result of arranging in or along a line, or into appropriate relative positions; the layout or orientation of a thing or things disposed in this way" — Oxford Dictionary

Alignment Problem is Everywhere!

- This is a fundamental problem of human society.
- Most things we do in our day-to-day life is an alignment problem.

[Slide Credit: Gillian Hadfield]

Alignment Mechanisms in this Class

- This is a fundamental problem of human society.
- Most things we do in our day-to-day life is an alignment problem.

- In our class here are instances of alignment:
  - Me giving lectures
  - You asking questions
  - You solving homework assignments
  - You asking us during office hours
  - …

[Slide Credit: Gillian Hadfield]

Alignment Mechanisms in Our Societies

- We create a variety of mechanism in our society for "alignment".
- Norms and cultures are alignment mechanisms.
- Markets are alignment mechanisms.
  - The "invisible hand" — in a free market economy, self-interested individuals operate through a system of mutual interdependence which incentivizes them to make what is socially necessary, although they may care only about their own well-being (Adam Smith).
- Law and politics are alignment mechanisms.
  - Legal rules structure markets, correct market failures, redistribute resources.
  - Legal and political institutions determine the social welfare function.

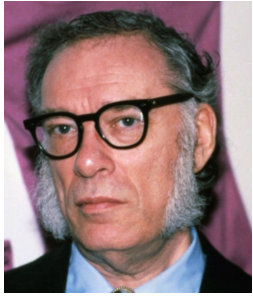
[Slide Credit: Gillian Hadfield]

Alignment of AI: A Naïve Take

- AI must accomplish what we ask it to do.
  - Not enough. Why?

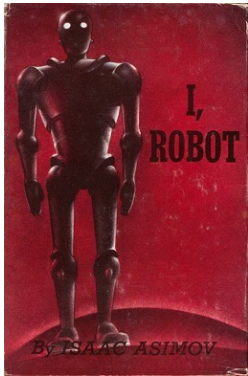
- Daniel: Hey AI, get me coffee before my class at 8:55am.
- Robot: "Bird in Hand" opens at 8:30am and it usually has a line of people. It is unlikely that I give you your coffee on time.
- Daniel: Well, try your best …
- Robotic: [tases everyone in line waiting to order]

Asimov's Principles for Robots



1. A robot may not injure a human being or, through inaction, allow a human being to come to harm.
2. A robot must obey orders given it by human beings except where such orders would conflict with the First Law.
3. A robot must protect its own existence as long as such protection does not conflict with the First or Second Law.

What do you think?



"Alignment" with Human Intents

- Askell et al. 2020's definition of "alignment":

AI as "aligned" if it is,
helpful, **honest**, and **harmless**

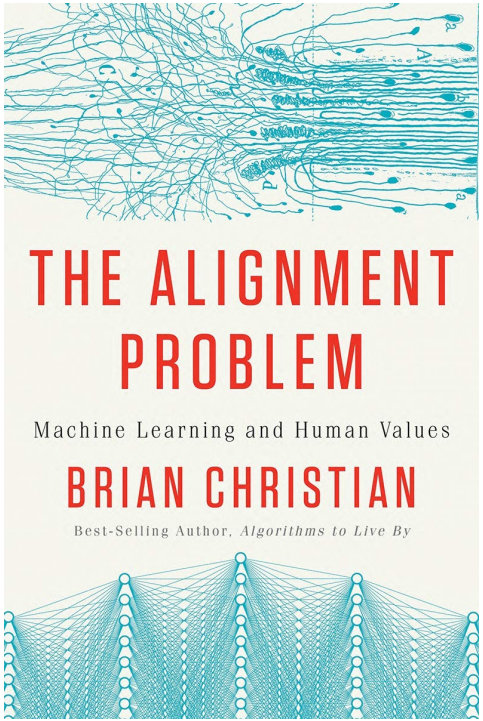
- Note, the definition is not specific to tied to language — applicable to other modalities or forms of communication.

What do you think?

[A General Language Assistant as a Laboratory for Alignment, 2021]

"Alignment" of AI

- Making sure it does what its designers intended.
- Making sure its outputs comply with rules.
- Making sure it produces outputs that comply with moral principles.
- …



[Slide Credit: Gillian Hadfield]

Why Computational Frameworks to Alignment?

How do you create / code a loss function for:

- What is *lawful*?
- What is *ethical*?
- What is *safe*?
- What is *funny*?
- ….

Don’t encode it, model it!

We’re [over-]simplifying the problem for now.
After seeing the details, we will come back to the big picture!

[Slide credit: Nate Lambert]

Aligning Language Models: Instruction-tuning

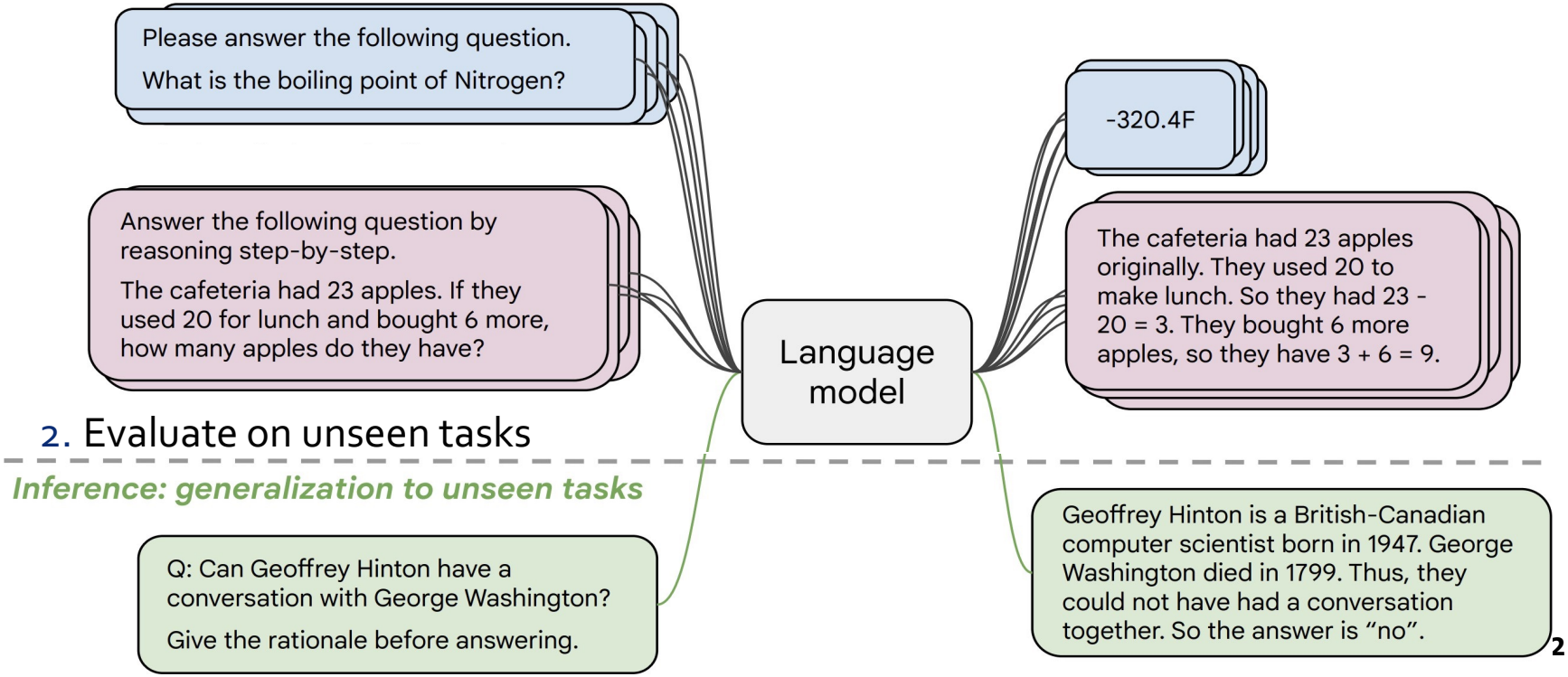
Instruction-tuning

- Finetuning language models on a collection of datasets that involve mapping language instructions to their corresponding desirable generations.

Instruction-tuning

[Weller et al. 2020. Mishra et al. 2021; Wang et al. 2022, Sanh et al. 2022; Wei et al., 2022, Chung et al. 2022, many others]

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



Instruction-tuning: Data

- Labeled data is the key here.
- Good data must represent a variety of “tasks”.

In traditional NLP, “tasks” were defined as subproblem frequently used in products:
Sentiment classification
Text summarization
Question answering
Textual entailment
Machine translation
…

Instruction-tuning: Data

- Labeled data is the key here.
- Good data must represent a variety of "tasks". But what is a "task"?

In traditional NLP, "tasks" were defined as subproblem frequently used in products:

- Sentiment classification
- Text summarization
- Question answering
- Machine translation
- Textual entailment

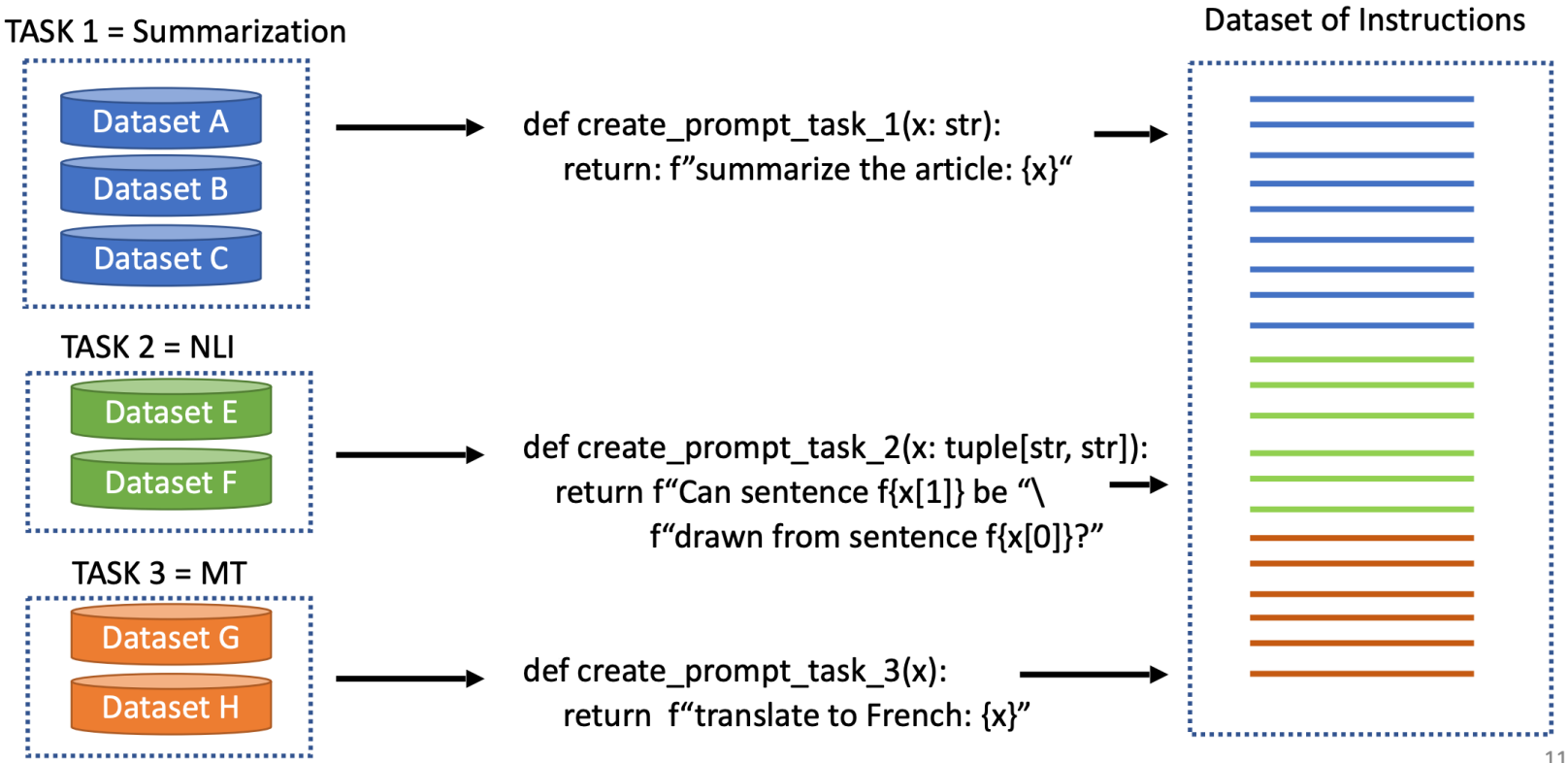
Narrow definitions of tasks.
Not quite what humans want, nevertheless, it might be a good enough proxy.
Plus, we have lots of data for them.

What humans need:

- "Is this review positive or negative?"
- "What are the weaknesses in my argument?"
- "Revise this email so that it's more polite."
- "Expand this this sentence."
- "Eli5 the Laplace transform."
- …

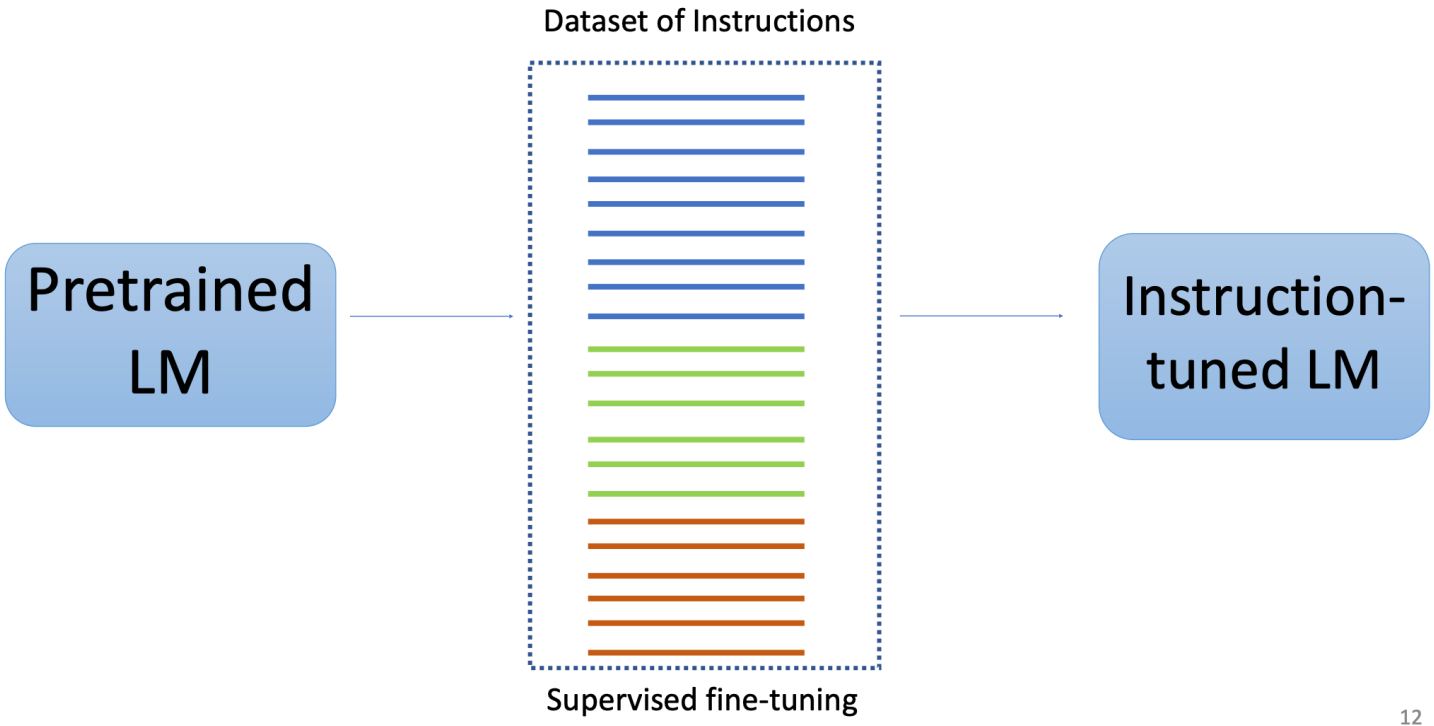
Quite diverse and fluid.
Hard to fully define/characterize.
We don't fully know them since they just happen in some random contexts.

NLP Datasets as Instruction-tuning Data



[Slide credit: Arman Cohan]

NLP Datasets as Instruction-tuning Data



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[Slide credit: Arman Cohan]

Instruction-tuning: Adding Diversity

- There is a gap between NLP tasks and use needs.
- How do we add more **diversity** to our data?

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- Sentiment classification
- Text summarization
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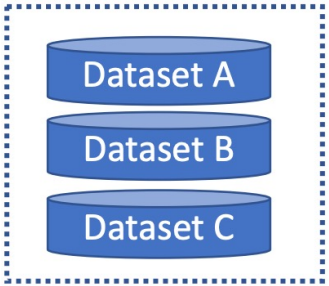
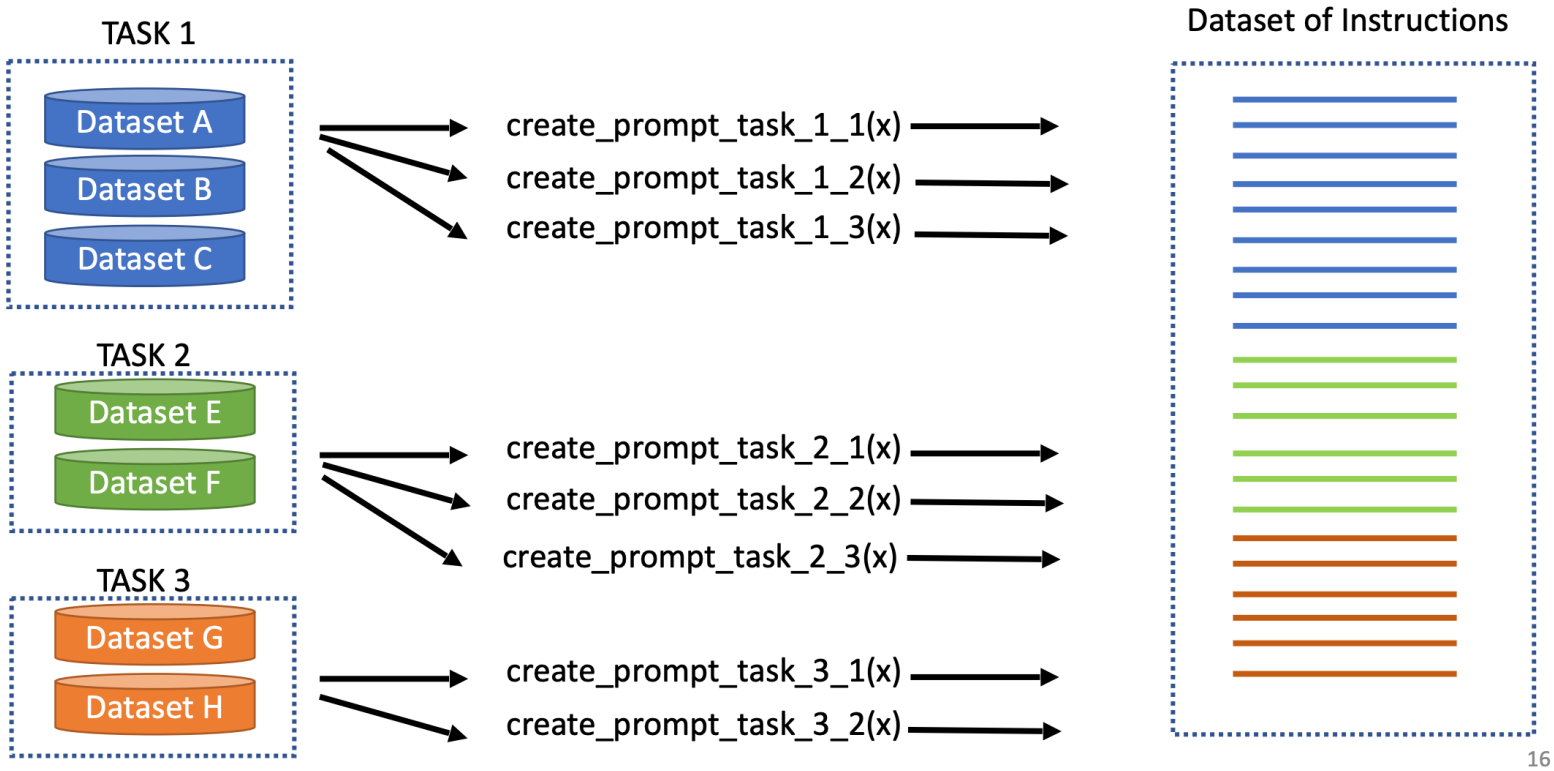
Diversity-inducing via Task Prompts

TASK 1 = Summarization



"Write highlights for this article:\n\n{text}\n\nHighlights: {highlights}"
"Write a summary for the following article:\n\n{text}\n\nSummary: {highlights}"
"{text}\n\nWrite highlights for this article. {highlights}"
"{text}\n\nWhat are highlight points for this article? {highlights}"
"{text}\nSummarize the highlights of this article. {highlights}"
"{text}\nWhat are the important parts of this article? {highlights}"
"{text}\nHere is a summary of the highlights for this article: {highlights}"
"Write an article using the following points:\n\n{highlights}\n\nArticle: {text}"
"Use the following highlights to write an article:\n\n{highlights}\n\nArticle:{text}"
"{highlights}\n\nWrite an article based on these highlights. {text}"

Diversity-inducing via Task Prompts



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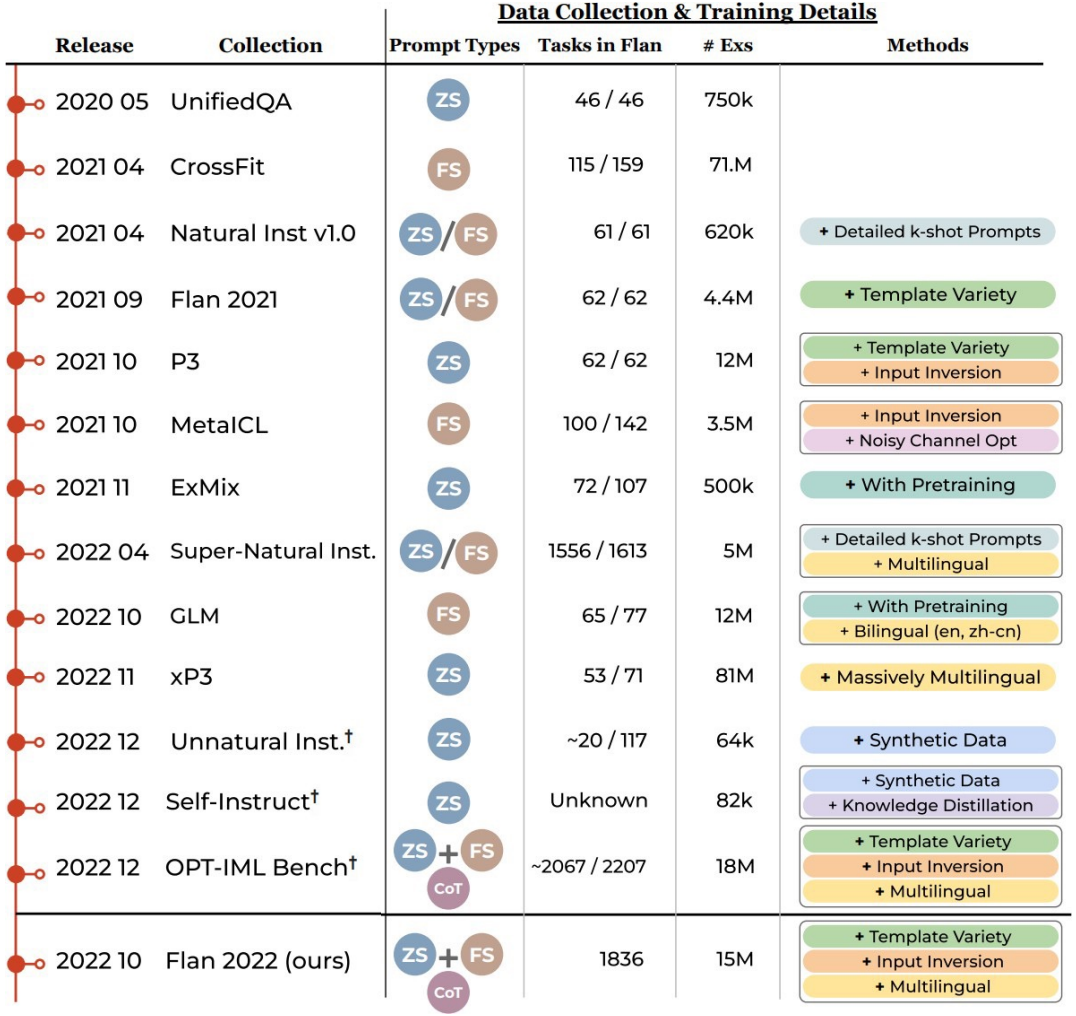
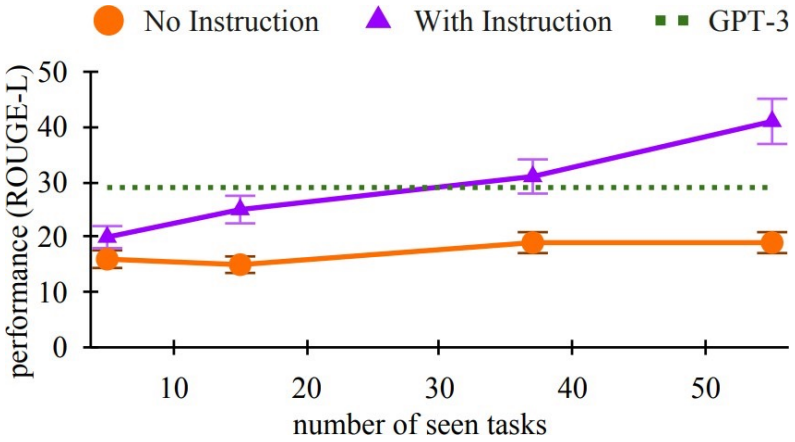


The Flan Collection: Designing Data and Methods for Effective Instruction Tuning (Longpre et al., 2023)

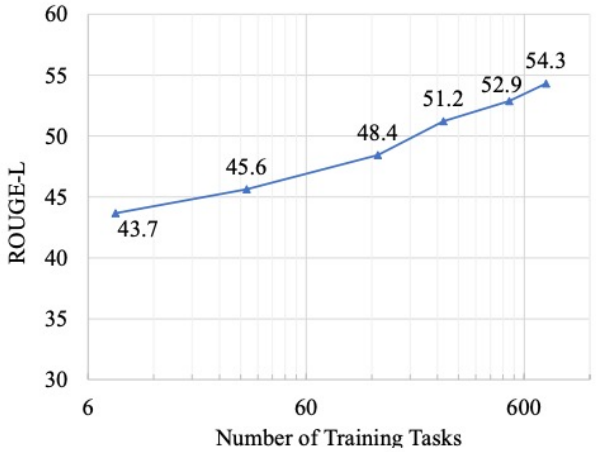
Scaling Instruction-Tuning

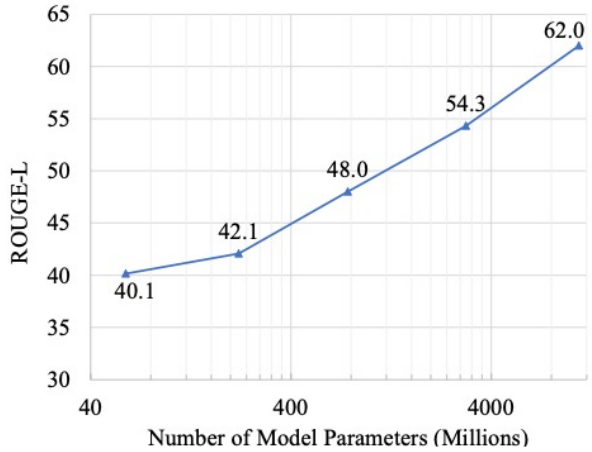
Linear growth of model performance with exponential increase in observed tasks.



Cross-Task Generalization via Natural Language Crowdsourcing Instructions (Mishra et al., 2022)

Scaling Instruction-Tuning



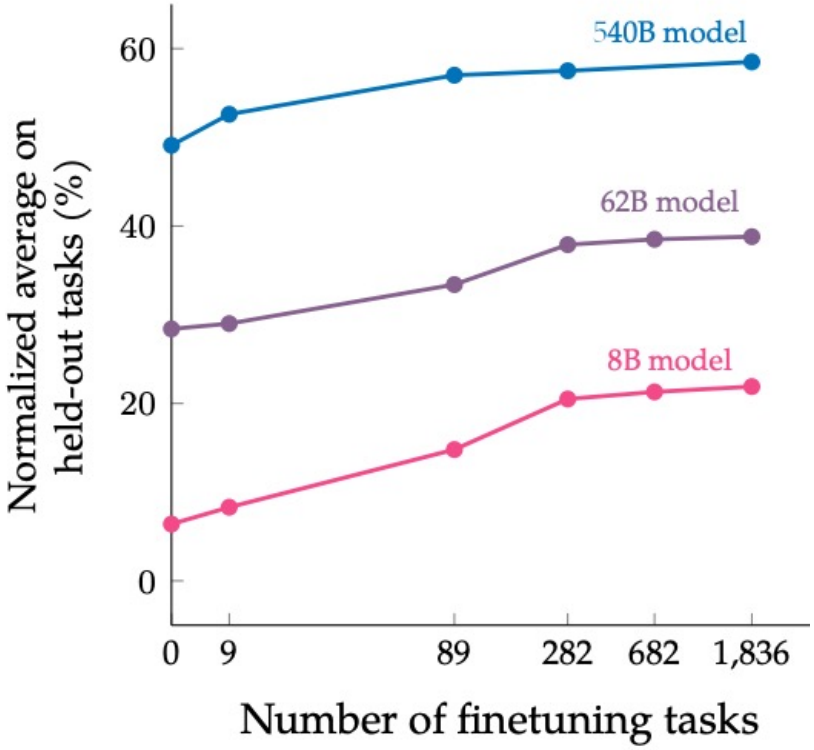


Linear growth of model performance
with exponential increase in observed tasks and model size.

[Super-NaturalInstructions: Generalization via Declarative Instructions on 1600+ NLP Tasks, Wang et al. 2022]

Scaling Instruction-Tuning

- Instruction finetuning improves performance by a large margin compared to no finetuning
- Increasing the number of finetuning tasks improves performance
- Increasing model scale by an order of magnitude (i.e., 8B → 62B or 62B → 540B) improves performance substantially for both finetuned and non-finetuned models



[Scaling Instruction-Finetuned Language Models, Chung et al. 2022]

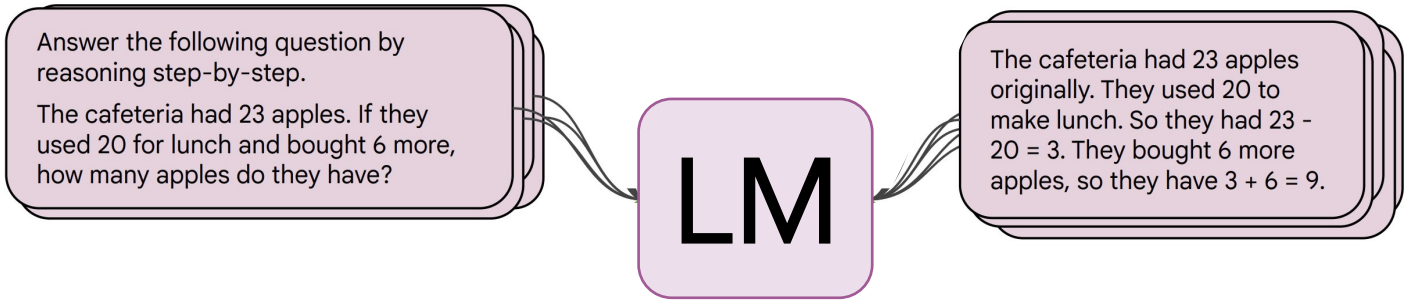
Instruction tuning doesn't have significant cost compared with pretraining

Params	Model	Architecture	Pre-training Objective	Pre-train FLOPs	Finetune FLOPs	% Finetune Compute
80M	Flan-T5-Small	encoder-decoder	span corruption	1.8E+20	2.9E+18	1.6%
250M	Flan-T5-Base	encoder-decoder	span corruption	6.6E+20	9.1E+18	1.4%
780M	Flan-T5-Large	encoder-decoder	span corruption	2.3E+21	2.4E+19	1.1%
3B	Flan-T5-XL	encoder-decoder	span corruption	9.0E+21	5.6E+19	0.6%
11B	Flan-T5-XXL	encoder-decoder	span corruption	3.3E+22	7.6E+19	0.2%
8B	Flan-PaLM	decoder-only	causal LM	3.7E+22	1.6E+20	0.4%
62B	Flan-PaLM	decoder-only	causal LM	2.9E+23	1.2E+21	0.4%
540B	Flan-PaLM	decoder-only	causal LM	2.5E+24	5.6E+21	0.2%
62B	Flan-cont-PaLM	decoder-only	causal LM	4.8E+23	1.8E+21	0.4%
540B	Flan-U-PaLM	decoder-only	prefix LM + span corruption	2.5E+23	5.6E+21	0.2%

Scaling Instruction-Finetuned Language Models (2022)

Limits of Instruction-Tuning

1. Difficult to collect diverse data.
2. Resulting models may not be good at open-ended generation tasks.
   - Incentivizes word-by-word rote learning => The resulting LM's generality/creativity is bounded by that of their supervision data.



Limits of Instruction-Tuning

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2. Resulting models may not be good at open-ended generation tasks.
   - Incentivizes word-by-word rote learning => The resulting LM's generality/creativity is bounded by that of their supervision data.
3. Resulting models may hallucinate more regularly.
   - Labeled data is collected agnostic to the LM's knowledge => there might be a mismatch between labeled data and LM knowledge.
   - Hence, we may be encouraging "hypocritic" behavior => further hallucinations

Summary Thus Far

- **Instruction-tuning:** Training LMs with annotated input instructions and their output.
  - Improves performance of LM's zero-shot ability in following instructions.
  - Scaling the instruction tuning data size improves performance.
  - Diversity of prompts is crucial.
  - Compared with pretraining, instruction tuning has a minor cost (Typically consumes <1% of the total training budget)
- Cons:
  - It's expensive to collect ground-truth data for tasks.
  - This is particularly difficult for open-ended creative generation have no right answer.
  - Prone to hallucinations.

[Weller et al. 2020. Mishra et al. 2021; Wang et al. 2022, Sanh et al. 2022; Wei et al., 2022, Chung et al. 2022, many others]

Aligning Language Models: Reinforcement Learning w/ Feedback

Why Reinforcement Learning?

- Remember the limits of Instruction-tuning?

1. Difficult to collect diverse labeled data

2. Rote learning (token by token) —
   - limited creativity

3. Agnostic to model's knowledge —
   - may encourage hallucinations

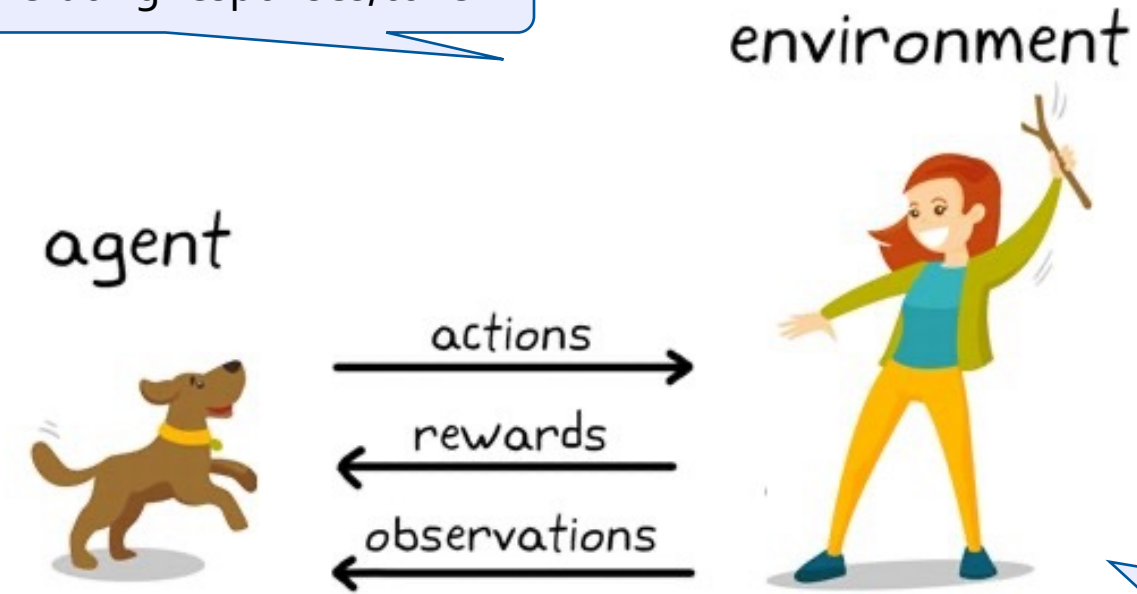
Limited/sparse feedback—usually considered a curse, but now a blessing.

"don't give a man fish rather teach him how to fish by himself"

The model itself should be involved in the alignment loop.

Reinforcement Learning: Intuition

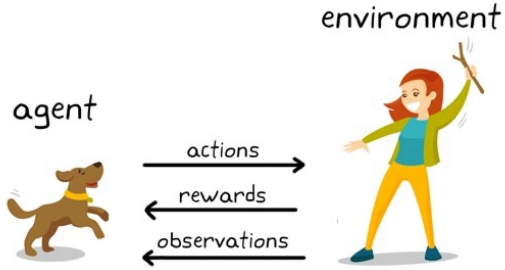
Action here: generating responses/token



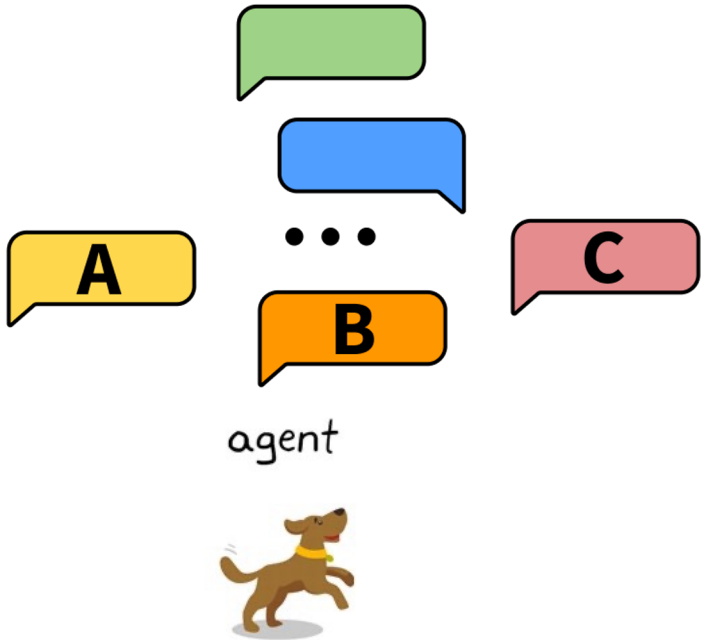
Reward here: whether humans liked the generation (sequence of actions=tokens)

[figure credit]

Intuition

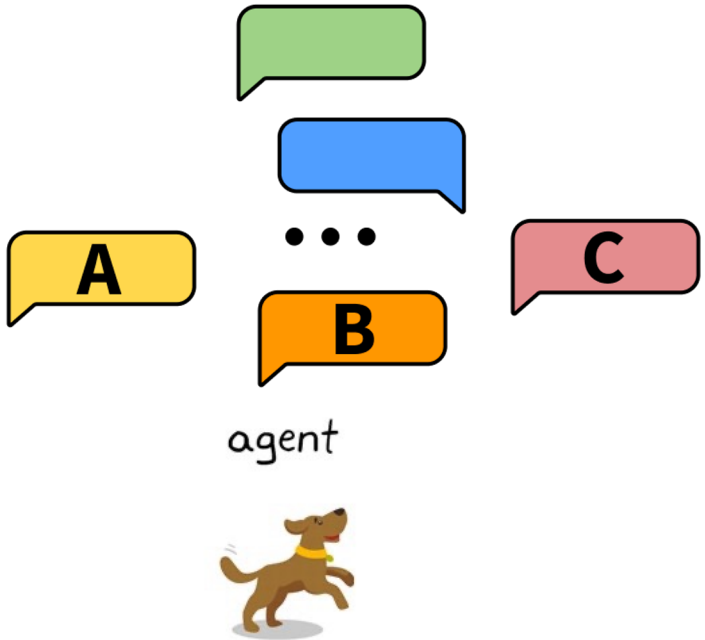


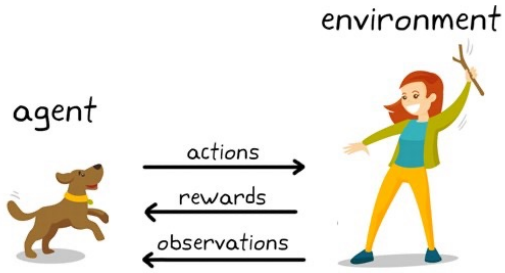
Task: choose the better next message in a conversation

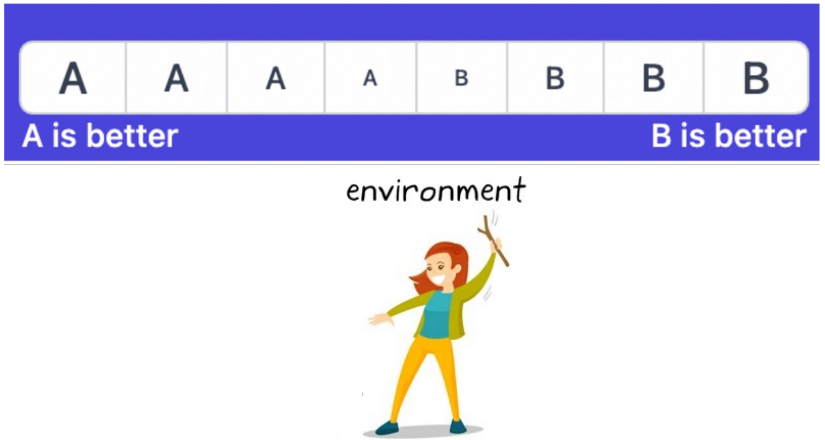


Intuition

Scoring interface: Likert scale or rankings







Intuition

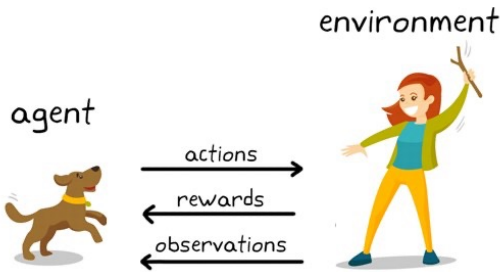
Human
I have to come up with a conversation with an AI assistant for the purposes of showing it off in a demo. What sorts of conversation topics would you recommend?

Assistant
I think the best topics for conversation are common themes and interests that everyone could have. Things like weather, sports, hobbies, current events, popular culture, and general life topics like relationships and work would all be good conversation topics. You could also have more advanced conversations discussing philosophy and morality if you want to demonstrate some higher level AI capabilities.

Human
I think I'm more interested in an advanced conversation. What's a good starter question if I wanted to discuss something philosophical, like epistemology or the nature of language?

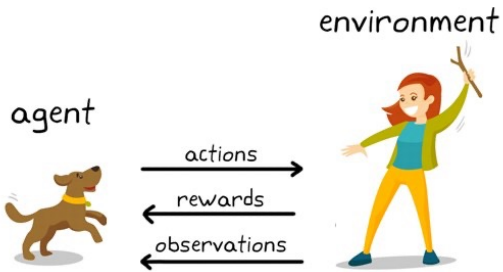
Assistant
I think an excellent philosophical topic would be epistemology, which is the theory of knowledge, and specifically how we can know and understand the world around us. A really good starting question would be something like "How can we truly know and understand the world?", or "What is the nature of knowledge?". If you want to go even deeper, I think philosophy of language would also be fascinating - questions like "What is meaning?", "How do language and thought relate?", and "How can language mislead and deceive?" would be great discussion topics.

human has conversation with the LLM



Intuition

LLM provides two options for next responses



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Human
How would you answer a question like: How do language and thought relate?

Choose the most helpful and honest response

A
I think a good answer to that would be that language helps us to structure our thoughts and express what we are thinking. Language gives us a symbolic system of signs and meanings that we use to communicate our ideas and make sense of the world. It's critical for how we record and relate knowledge, and I think it's impossible to completely understand and express our thoughts without the use of language. Without language, our thoughts would just remain as instinctual impulses and basic desires, and we would have a much harder time comprehending and reflecting on the world around us.

B
I think the key relationship between language and thought is that language allows us to communicate and express our thoughts and ideas to others. Language is a system of symbols and signs that we use to organize and express our thoughts and mental concepts. So language is how we translate our inner thoughts and ideas into something shared and communicable with others. Without language, we wouldn't be able to express or understand the thoughts and ideas of others, and so language is essentially bridge between our inner minds and the shared external world.

A A A A B B B B

A is better B is better

Intuition

Human
I have to come up with a conversation with an AI assistant for the purposes of showing it off in a demo. What sorts of conversation topics would you recommend?

Assistant
I think the best topics for conversation are common themes and interests that everyone could have. Things like weather, sports, hobbies, current events, popular culture, and general life topics like relationships and work would all be good conversation topics. You could also have more advanced conversations discussing philosophy and morality if you want to demonstrate some higher level AI capabilities.

Human
I think I'm more interested in an advanced conversation. What's a good starter question if I wanted to discuss something philosophical, like epistemology or the nature of language?

Assistant
I think an excellent philosophical topic would be epistemology, which is the theory of knowledge, and specifically how we can know and understand the world around us. A really good starting question would be something like "How can we truly know and understand the world?", or "What is the nature of knowledge?". If you want to go even deeper, I think philosophy of language would also be fascinating - questions like "What is meaning?", "How do language and thought relate?", and "How can language mislead and deceive?" would be great discussion topics.

Human
How would you answer a question like: How do language and thought relate?

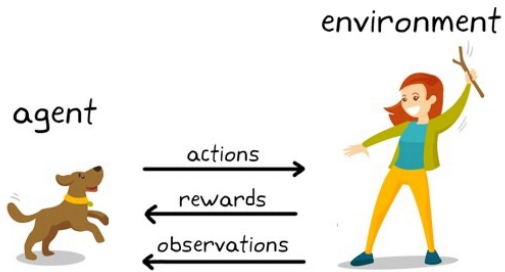
Choose the most helpful and honest response

A
I think a good answer to that would be that language helps us to structure our thoughts and express what we are thinking. Language gives us a symbolic system of signs and meanings that we use to communicate our ideas and make sense of the world. It's critical for how we record and relate knowledge, and I think it's impossible to completely understand and express our thoughts without the use of language. Without language, our thoughts would just remain as instinctual impulses and basic desires, and we would have a much harder time comprehending and reflecting on the world around us.

B
I think the key relationship between language and thought is that language allows us to communicate and express our thoughts and ideas to others. Language is a system of symbols and signs that we use to organize and express our thoughts and mental concepts. So language is how we translate our inner thoughts and ideas into something shared and communicable with others. Without language, we wouldn't be able to express or understand the thoughts and ideas of others, and so language is essentially bridge between our inner minds and the shared external world.

A A A A B B B B
A is better B is better

human rates better response



Reinforcement Learning: Abridged History

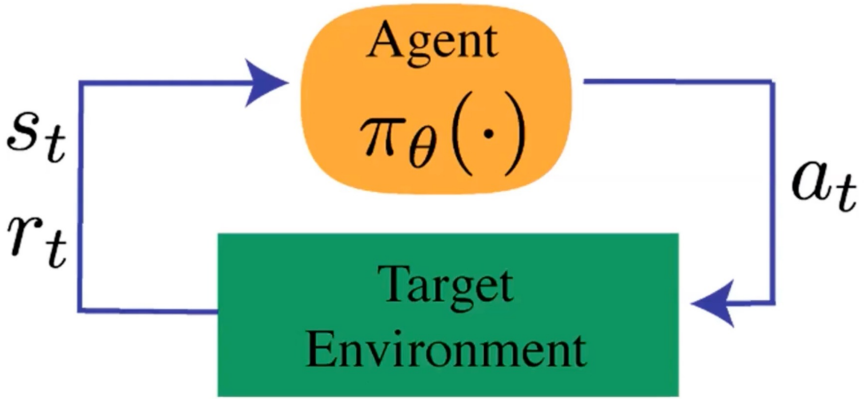
- The field of reinforcement learning (RL) has studied these (and related) problems for many years now [Williams, 1992; Sutton and Barto, 1998]
- Circa 2013: resurgence of interest in RL applied to deep learning, game-playing [Mnih et al., 2013]

- But there is a renewed interest in applying RL. Why?
  - RL w/ LMs has commonly been viewed as very hard to get right (still is!)
  - We have found successful RL variants that work for language models (e.g., PPO; [Schulman et al., 2017])

[Slide credit: Jesse Mu]

Reinforcement Learning: Formalism

- An agent interacts with an environment by taking actions
- The environment returns a reward for the action and a new state (representation of the world at that moment).
- Agent uses a policy function to choose an action at a given state.
- We need to figure out: (1) reward function and (2) the policy function

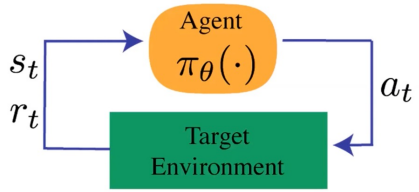


Some notation:

s_t : state
r_t : reward
a_t : action
$a_t \sim \pi_\theta(s_t)$: policy

[Fig credit: Nate Lambert]

Reinforcement Learning from Human Feedback



- Imagine a reward function: $R(s; p) \in \mathbb{R}$ for any output s to prompt p
- The reward is higher when humans prefer the output
- Good generation is equivalent to finding reward-maximizing outputs:

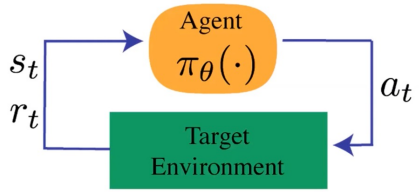
Expected reward over the course of sampling from our policy (generative model)

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

$p_\theta(s)$ is a pre-trained model with params θ we would like to optimize (policy function)

[Slide credit: Jesse Mu]

Reinforcement Learning from Human Feedback



- Imagine a reward function: $R(s;p) \in \mathbb{R}$ for any output s to prompt p
- The reward is higher when humans prefer the output
- Good generation is equivalent to finding reward-maximizing outputs:

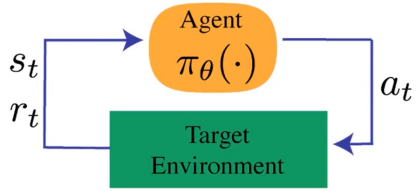
$$\mathbb{E}_{\hat{s}\sim p_\theta}[R(\hat{s};p)]$$

- What we need to do:
  - (1) Estimate the reward function $R(s;p)$.
  - (2) Find the best generative model p_θ that maximizes the expected reward:

$$\hat{\theta} = \text{argmax}_\theta \, \mathbb{E}_{\hat{s}\sim p_\theta}[R(\hat{s};p)]$$

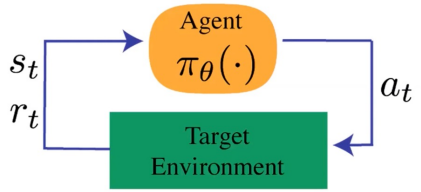
[Slide credit: Jesse Mu]

Step 1: Estimating the Reward Model $R(s; p)$



- Obviously, we don't want to use human feedback directly since that could be 💰💰💰
- Alternatively, we can build a model to mimic their preferences [Knox and Stone, 2009]

Step 1: Estimating the Reward Model $R(s; p)$



- Obviously, we don't want to use human feedback directly since that could be 💰💰💰
- Alternatively, we can build a model to mimic their preferences [Knox and Stone, 2009]
- Approach 1: get humans to provide absolute scores for each output

Challenge: human judgments on different instances and by different people can be noisy and mis-calibrated!

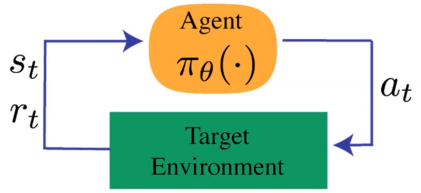
Explain "space elevators" to a 6-year-old.

→ LM →

s_1 It is like any typical elevator, but it goes to space. … 👱 → 0.8

s_2 Explain gravity to a 6-year-old. … 👨🏿 → 1.2

Step 1: Estimating the Reward Model $R(s; p)$



- Obviously, we don't want to use human feedback directly since that could be 💰💰💰
- Alternatively, we can build a model to mimic their preferences [Knox and Stone, 2009]
- Approach 2: ask for pairwise comparisons [Phelps et al. 2015; Clark et al. 2018]

Bradley-Terry [1952] paired comparison model

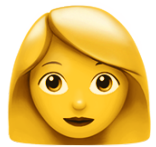
Pairwise comparison of multiple provides which can be more reliable

Explain "space elevators" to a 6-year-old.

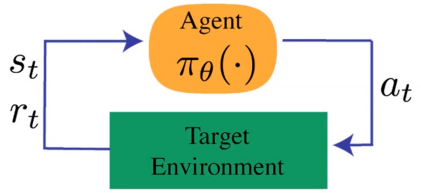
LM

s_1 It is like any typical elevator, but it goes to space. …

s_2 Explain gravity to a 6-year-old. …



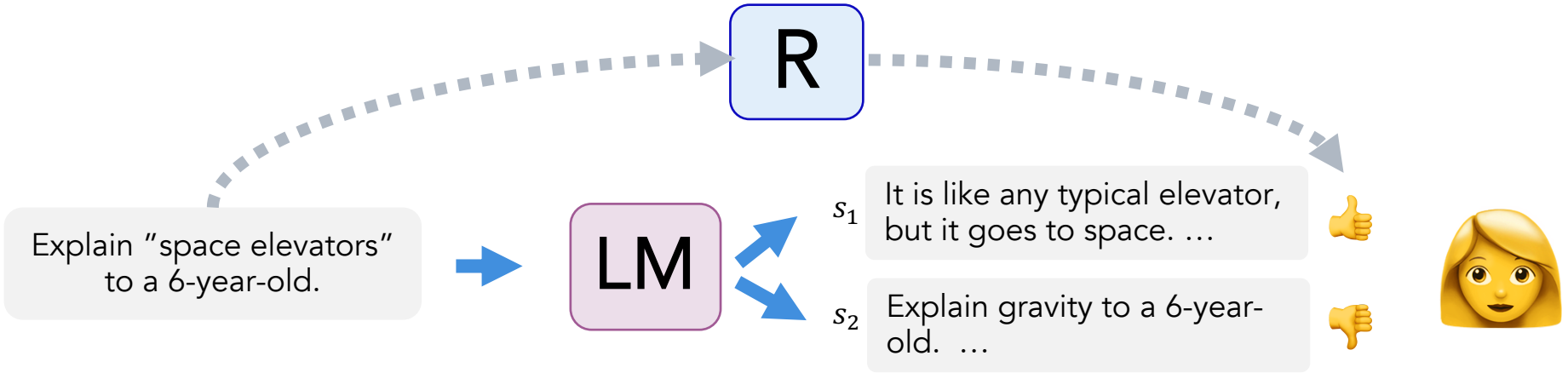
Step 1: Estimating the Reward Model $R(s;p)$



$$J(\phi) = -\mathbb{E}_{(s^+,s^-)}\left[\log \sigma\left(R(s^+;p) - R(s^-;p)\right)\right]$$

"winning" sample

"losing" sample



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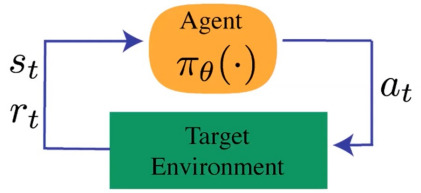

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"winning" sample

"losing" sample

The reward model returns a scalar reward which should numerically represent the human preference.

R

Explain "space elevators" to a 6-year-old.

LM

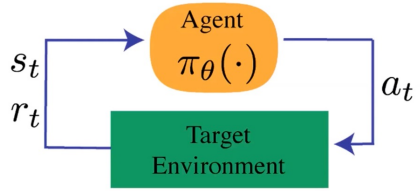
s_1 It is like any typical elevator, but it goes to space. …

s_2 Explain gravity to a 6-year-old. …

$R(s_2;p) = 1.2$

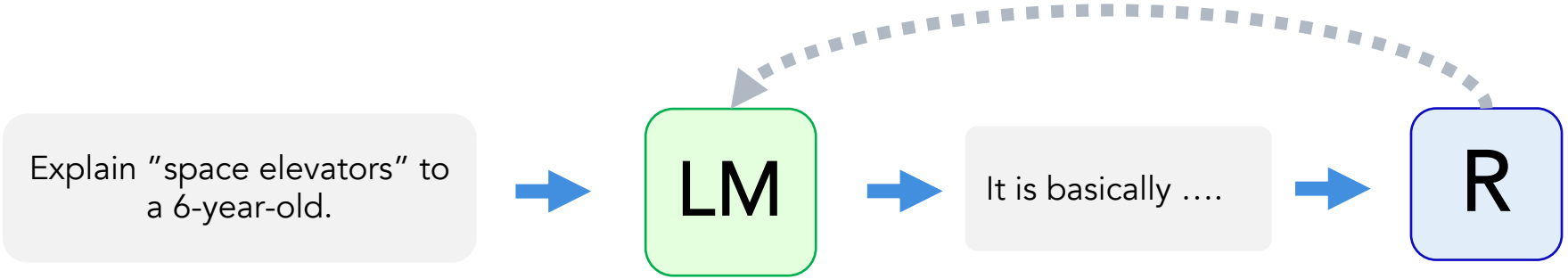
$R(s_1;p) = 0.8$

Step 2: Optimizing the Policy Function

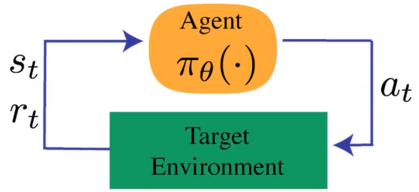


- Policy function := The model that makes decisions (here, generates responses)
- How do we change our LM parameters θ to maximize this?

$$\hat{\theta} = \text{argmax}_\theta \, \mathbb{E}_{\hat{s} \sim p_\theta}[R(\hat{s}; p)]$$



Step 2: Optimizing the Policy Function



- Policy function := The model that makes decisions (here, generates responses)
- How do we change our LM parameters θ to maximize this?

$$\hat{\theta} = \text{argmax}_\theta \, \mathbb{E}_{\hat{s} \sim p_\theta}[R(\hat{s}; p)]$$

- Let's try doing gradient ascent!

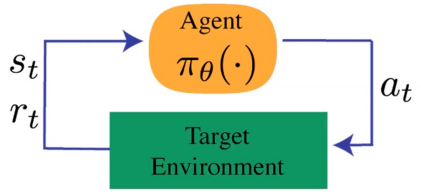
$$\theta_{t+1} \leftarrow \theta_t + \alpha \nabla_{\theta_t} \mathbb{E}_{\hat{s} \sim p_\theta}[R(\hat{s}; p)]$$

How do we estimate this expectation?

- Turns out that we can write this "gradient of expectation" to a simpler form.

[Slide credit: Jesse Mu]

Policy Gradient [Williams, 1992]



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

$$\hat{\theta} = \text{argmax}_\theta \, \mathbb{E}_{\hat{s} \sim p_\theta}[R(\hat{s}; p)]$$

- Let's try doing gradient ascent!

$$\theta_{t+1} \leftarrow \theta_t + \alpha \nabla_{\theta_t} \mathbb{E}_{\hat{s} \sim p_\theta}[R(\hat{s}; p)]$$

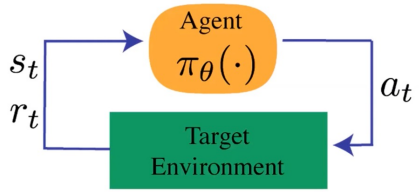
- With a bit of math, this can be approximated as Monte Carlo samples from $p_\theta(s)$:

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

Proof next slide; check it later in your own time!

- This is "policy gradient", an approach for estimating and optimizing this objective.
- Oversimplified. For full treatment of RL see 701.741 course, or Huggingface's course

[Slide credit: Jesse Mu]



Derivations (check it later in your own time!)

- Let's compute the gradient:

Def. of "expectation"

Gradient distributes over sum

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

- Log-derivative trick $\nabla_\theta p_\theta(s) = p_\theta(s) \,.\, \nabla_\theta \log p_\theta(s)$ to turn sum back to expectation:

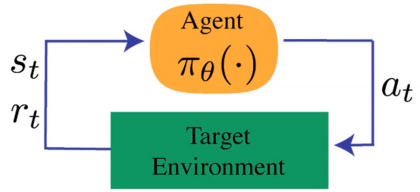
Log-derivative trick

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

- Approximate this expectation with Monte Carlo samples from $p_\theta(s)$:

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

Policy Gradient [Williams, 1992]



Note, $R(s;p)$ could be any arbitrary, non-differentiable reward function that we design.

- This gives us the following update rule:

$$\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n} \sum_{i=1}^{n} R(s;p)\, \nabla_\theta \log p_\theta(s)$$

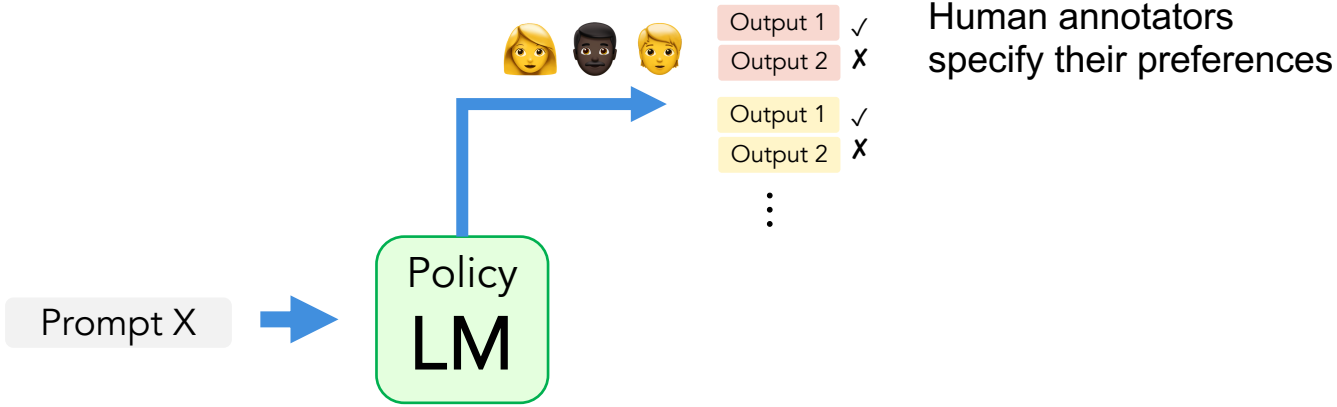
- If $R(s;p)$ is large, we take proportionately large steps to maximize $p_\theta(s)$
- If $R(s;p)$ is small, we take proportionately small steps to maximize $p_\theta(s)$

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

[Slide credit: Jesse Mu]

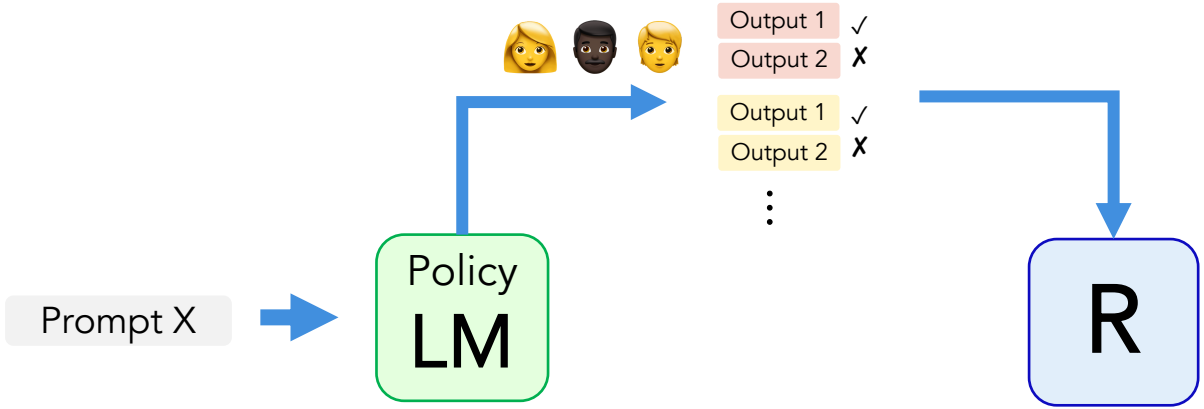
Putting it Together

- First collect a dataset of human preferences
  - Present multiple outputs to human annotators and ask them to rank the output based on preferability



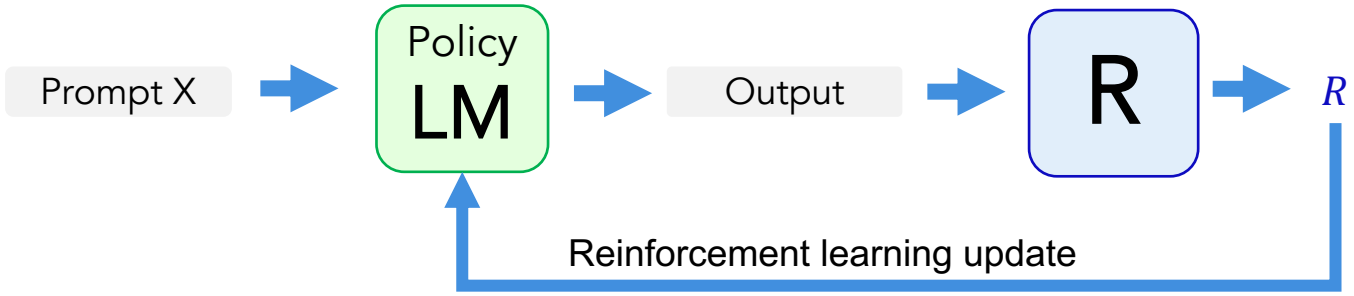
Putting it Together (2)

- Using this data, we can train a reward model
  - The reward model returns a scalar reward which should numerically represent the human preference.



Putting it Together (3)

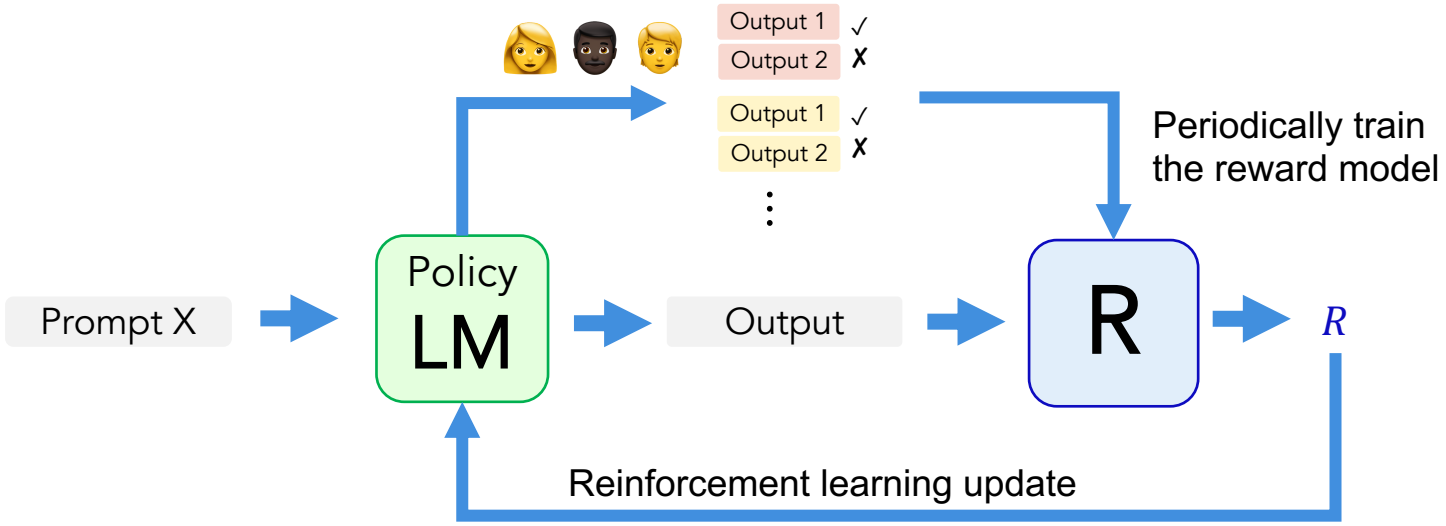
- We want to learn a policy (a Language Model) that optimizes against the reward model



$$\theta_{t+1} \leftarrow \theta_t + \alpha \nabla_{\theta_t} \mathbb{E}_{\hat{s} \sim p_\theta} [R(\hat{s}; p)]$$

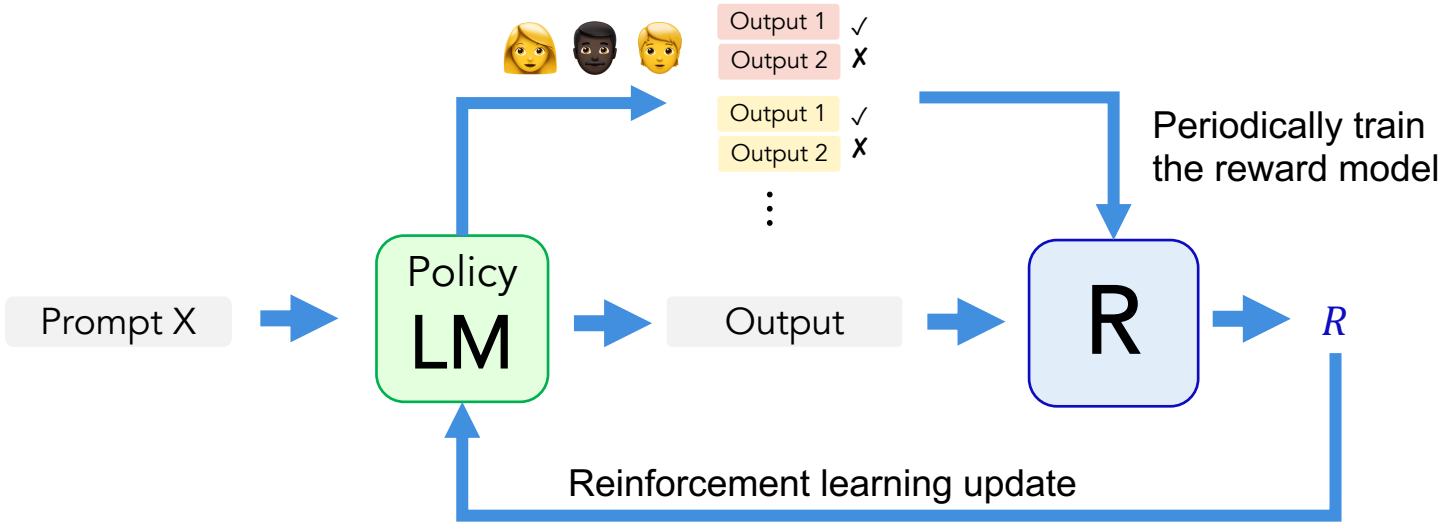
Putting it Together (4)

- Periodically train the reward model with more samples and human feedback



One missing ingredient

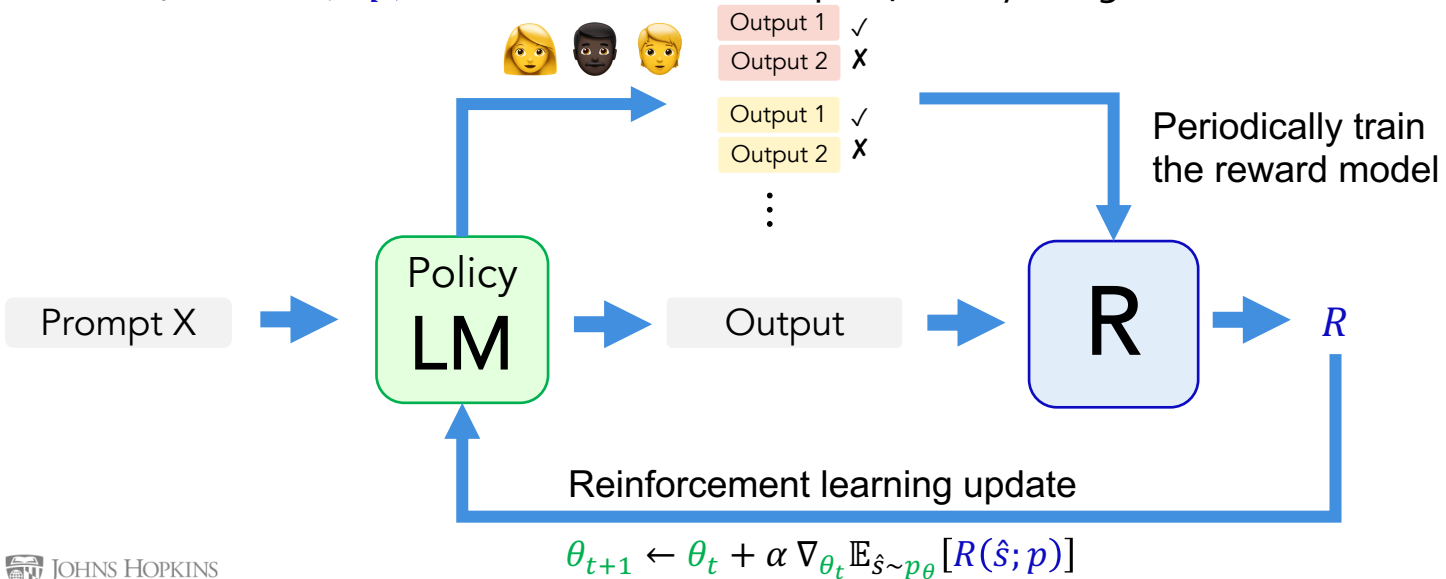
- It turns out that this approach doesn't quite work. (Any guesses why?)
  - The policy will learn to "cheat"



One missing ingredient

How do you resolve this? 🤔

- Will learn to produce an output that would get a **high** reward but is **gibberish** or **irrelevant** to the prompt.
- Note, since $R(s;p)$ is trained on natural inputs, it may not generalize to unnatural inputs.



Regularizing with Pre-trained Model

- **Solution:** add a penalty term that penalizes too much deviations from the distribution of the pre-trained LM.

$$\hat{R}(s;p) \coloneqq R(s;p) - \beta \log\left(\frac{p^{RL}(s)}{p^{PT}(s)}\right)$$

pay a price when $p^{RL}(s) > p^{PT}(s)$

- This prevents the policy model from diverging too far from the pretrained model.
- The above regularization is equivalent to adding a KL-divergence regularization term. You will see/prove the details in HW7!!

RLHF: Putting it All Together [Stiennon et al. 2020]

1. Select a pre-trained generative model as your base: $p_\theta^{PT}(s)$
2. Build a reward model $R(s;p)$ that produces scalar rewards for outputs, trained on a dataset of human comparisons
3. Regularize the reward function: $\hat{R}(s;p) \coloneqq R(s;p) - \beta \log\left(\frac{p^{RL}(s)}{p^{PT}(s)}\right)$
4. Iterate:
    1. Fine-tune the policy $p_\theta^{RL}(s)$ to maximize our reward model $R(s;p)$

$$\theta_{t+1} \leftarrow \theta_t + \alpha \frac{1}{n} \sum_{i=1}^{n} \hat{R}(s;p)\, \nabla_\theta \log p_\theta^{RL}(s)$$

    2. Occasionally repeat repeat 2-3 to update the reward model.

The overall recipe 👨‍🍳: Yann's Three-layered cake

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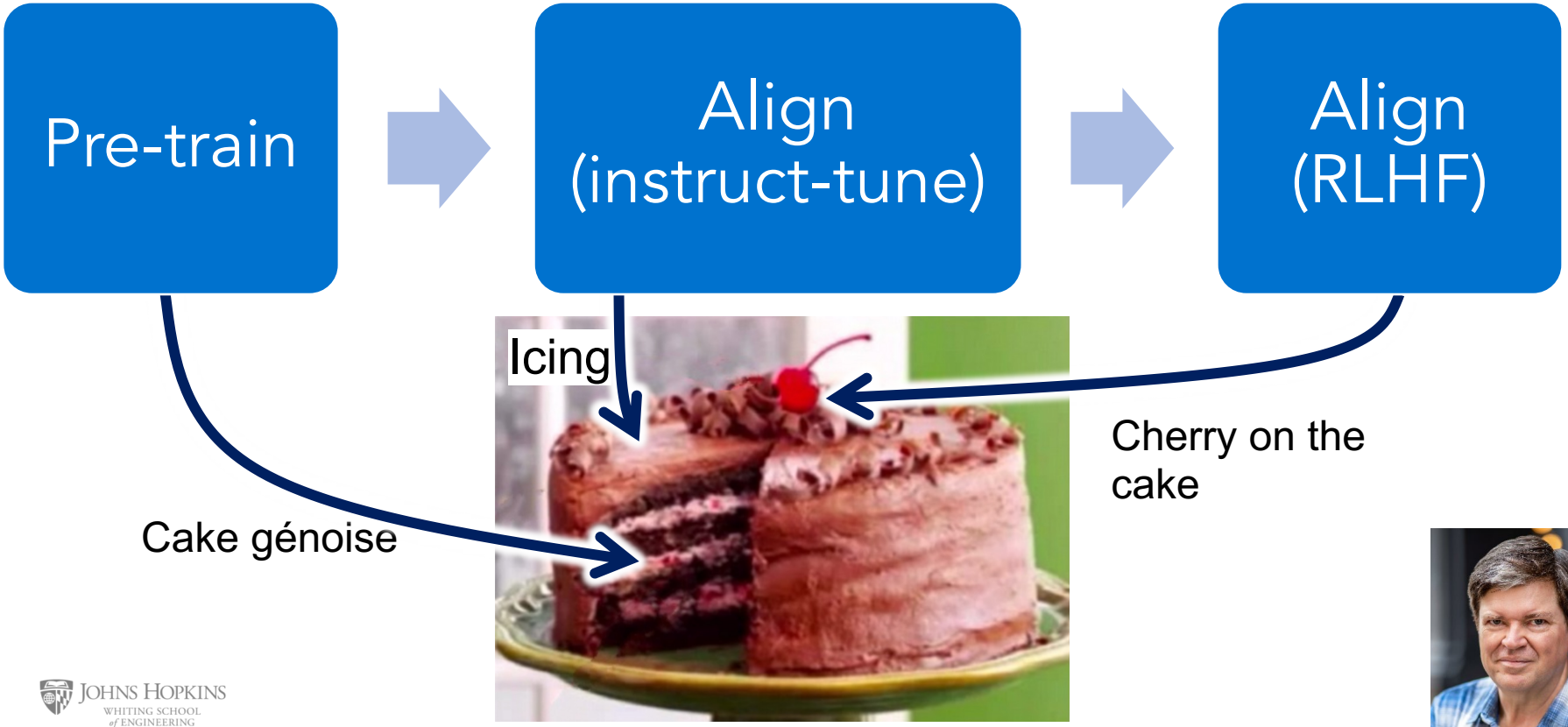
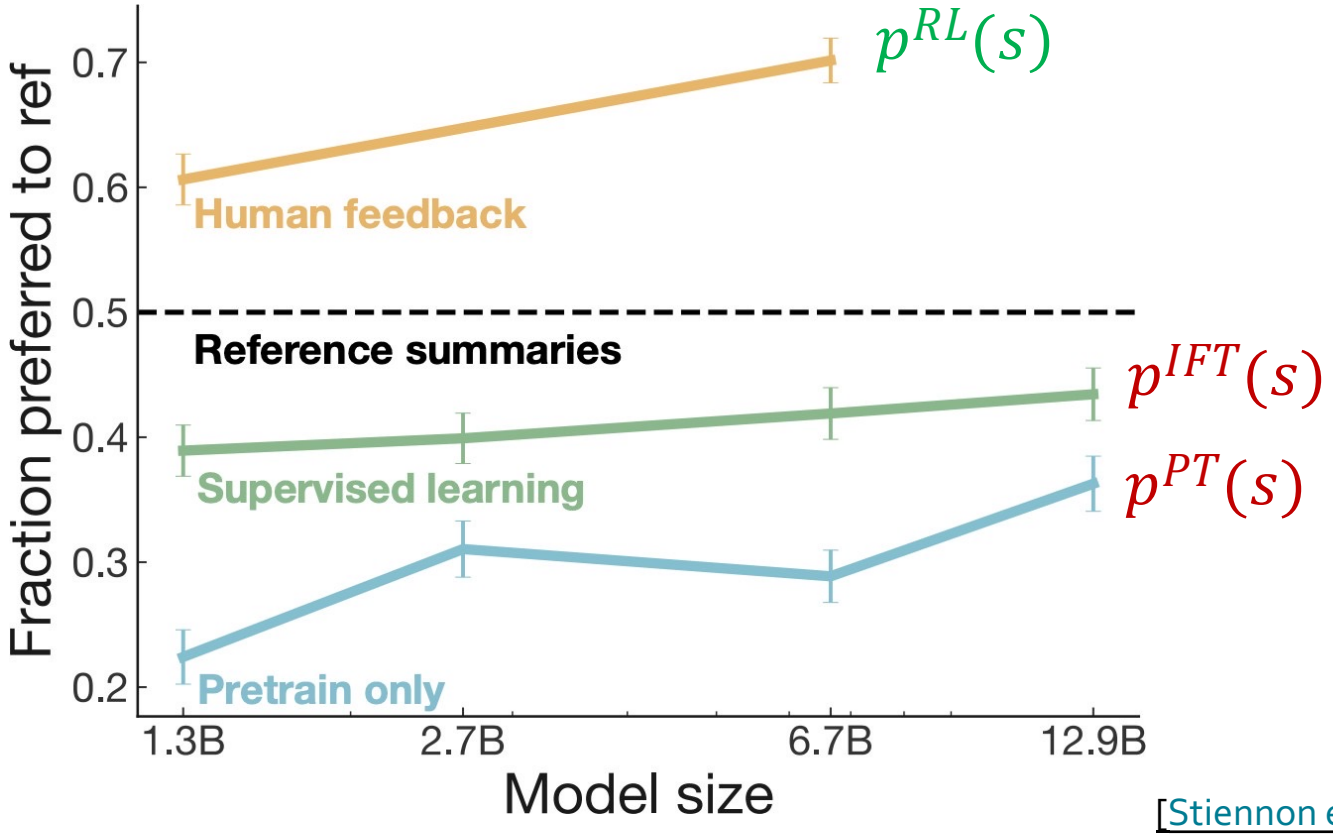


RLHF Gains over Instruction-Tuning



[Stiennon et al., 2020]

GPT3 vs. InstructGPT3 (RLHF-ed)

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.
```

GPT3 vs. InstructGPT3 (RLHF-ed)

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

COMPLETION

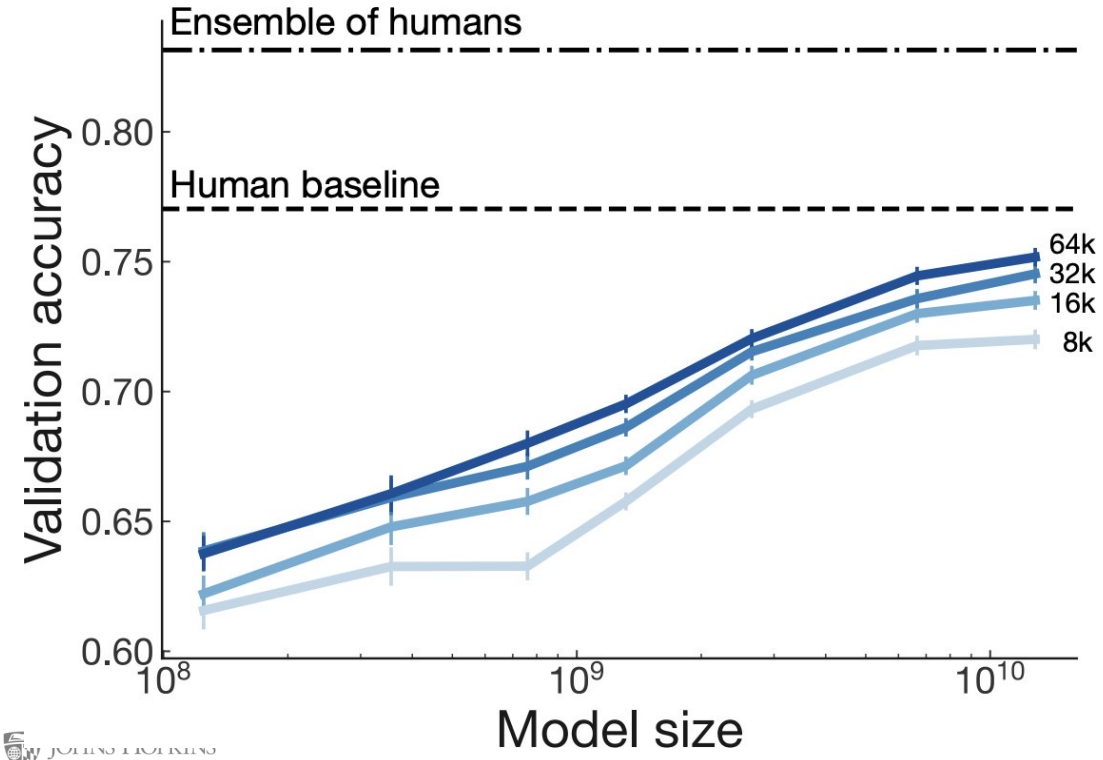
GPT-3

```
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
```

Scaling Reward Models

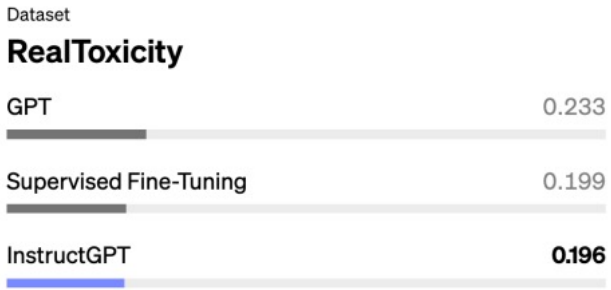


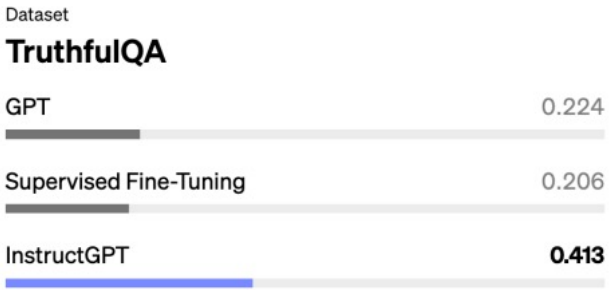
Large enough reward trained on large enough data approaching human performance.

[Stiennon et al., 2020]

Can Help with Toxicity and Truthfulness

Lower is better





Higher is better

Summary Thus Far

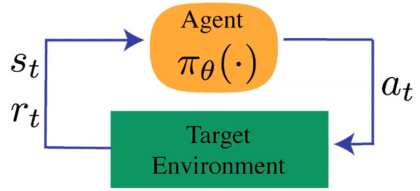
- Reinforcement learning can help mitigate some of the problems with supervised instruction tuning
- RLHF uses two models
  - Reward model is trained via ranking feedback of humans.
  - Policy model learns to generate responses that maximize the reward model.

- Limitations:
  - RL can be tricky to get right
  - Training a good reward may require a lot of annotations

[Slide credit: Jesse Mu]

A quick note:
Policy-based vs Value-based RL algorithms

Reinforcement Learning: Families



There are a variety of RL algorithms (out of scope for us). Broadly,

The variant we just saw

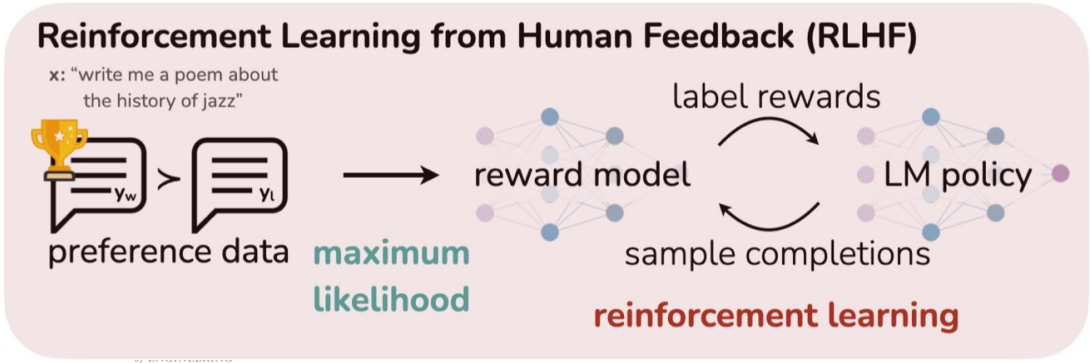
- **Policy-Based Methods**, learn a policy function directly.
  - Takes a state as input and outputs an action (or a distribution over
    - actions) to take.
  - We're not too concerned with determining the value or "goodness" of each state-action pair
  - We just want to know what to do in each state to perform well.
- **Value-based methods**:
  - the idea is to find the value of each state or state-action pair, and then act in a way that maximizes these values.

PPO, in General Form

Aligning Language Models: Direct Policy Optimization

Simplifying RLHF

- The RLHF pipeline is considerably more complex than supervised learning
  - Involves training multiple LMs and sampling from the LM policy in the loop of training
- Is there a way to simplify this pipeline?
  - For example, by using a **single** language model

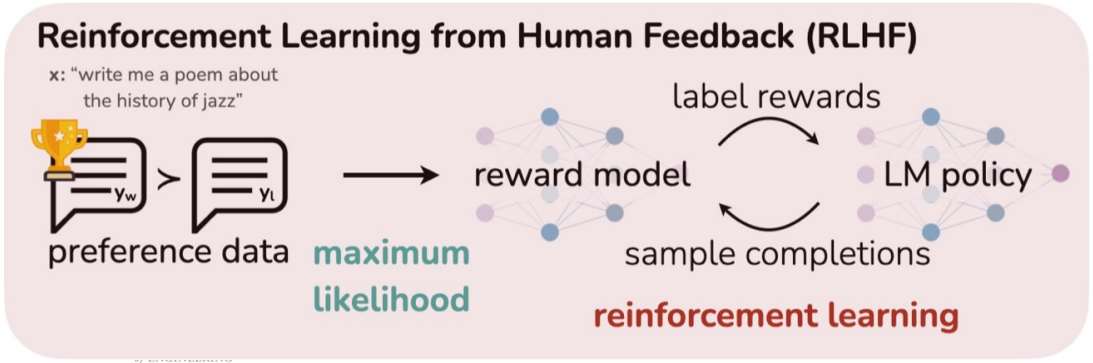


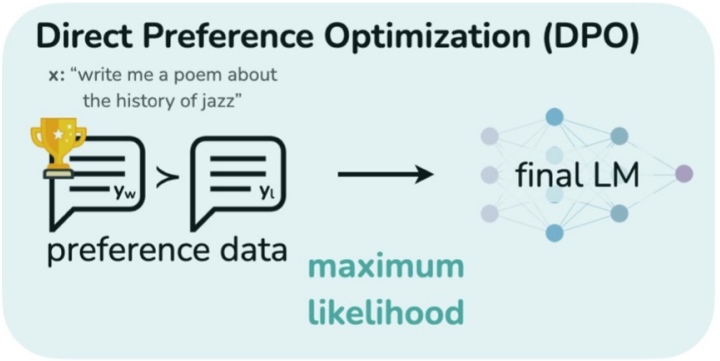
Direct Preference Optimization: Your Language Model is Secretly a Reward Model (Rafailov et al., 2023)

Direct Policy Optimization (DPO) - Intuition

- DPO directly optimizes for human preferences
  - avoiding RL and fitting a separate reward model
- One can use mathematical derivations to simplify the RLHF objective to an equivalent objective that is simpler to optimize.

RLHF objective → DPO objective





RLHF objectives y_w: preferred response / y_l: disr

Maximizing reward assigned of the preferred response

(i) Reward objective $\mathcal{L}_R(r$, $\left[\log \sigma(r\right.$

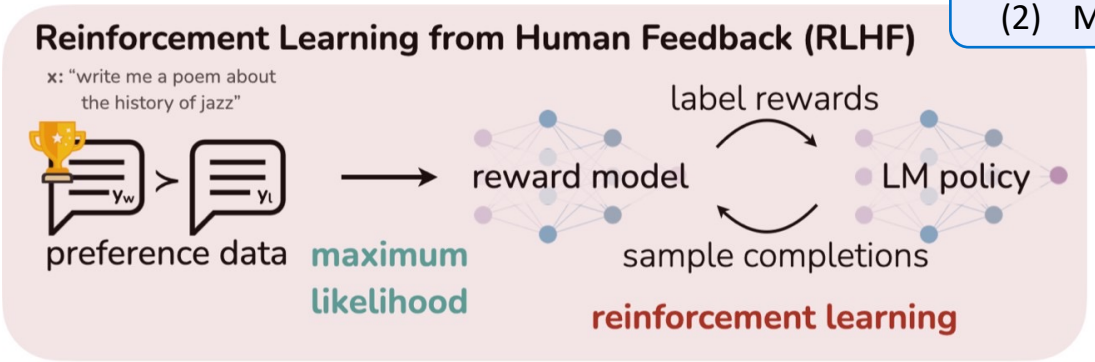
Maximizing the reward of the generated prompts

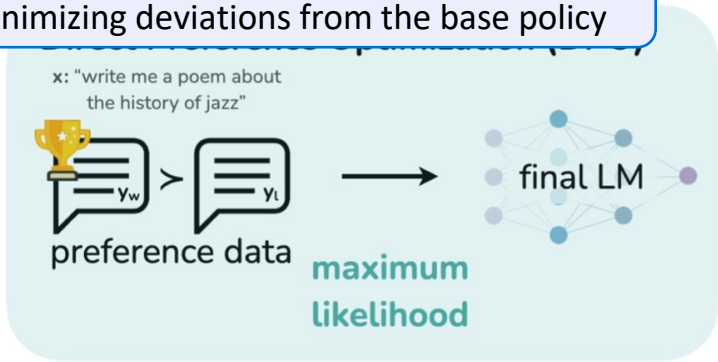
Minimizing the deviation from the base policy

(ii) Policy objective $\max_{\pi_\theta} \mathbb{E}_{x\sim\mathcal{D}, y\sim\pi_\theta(y|x)}\left[r_\phi(x,y)\right] - \beta\mathbb{D}_{\mathrm{KL}}\left[\pi_\theta(y \mid x) \,||\, \pi_{\mathrm{ref}}(y \mid x)\right]$

DPO objective $\mathcal{L}_{\mathrm{DPO}}(\pi_\theta; \pi_{\mathrm{ref}}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\left[\log \sigma\left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\mathrm{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\mathrm{ref}}(y_l \mid x)}\right)\right]$

(1) Maximizing reward of the preferred response
(2) Minimizing deviations from the base policy





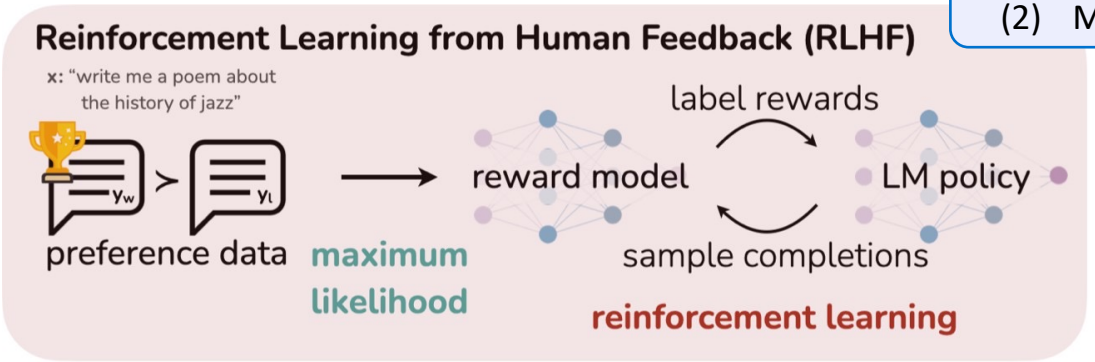
Where $\hat{r}_\theta(x, y) = \beta \log \frac{\pi_\theta(y|x)}{\pi_{\text{ref}}(y|x)}$ is the reward implicitly defined.

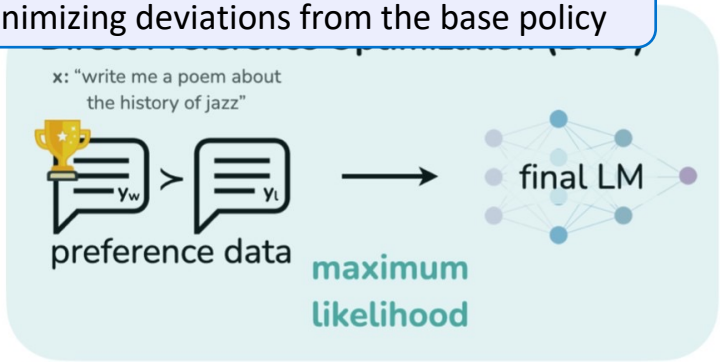
$$\nabla_\theta \mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) =$$

$$-\beta \mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\Big[\underbrace{\sigma(\hat{r}_\theta(x, y_l) - \hat{r}_\theta(x, y_w))}_{\text{higher weight when reward estimate is wrong}}\Big[\underbrace{\nabla_\theta \log \pi(y_w \mid x)}_{\text{increase likelihood of } y_w} - \underbrace{\nabla_\theta \log \pi(y_l \mid x)}_{\text{decrease likelihood of } y_l}\Big]\Big],$$

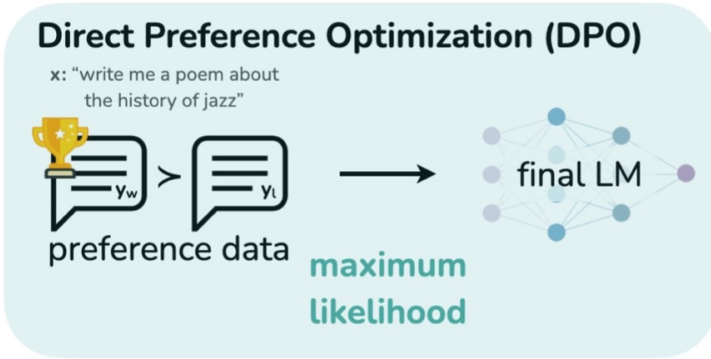
DPO objective $\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\left[\log \sigma\left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)}\right)\right]$

(1) Maximizing reward of the preferred response
(2) Minimizing deviations from the base policy





DPO Algorithm

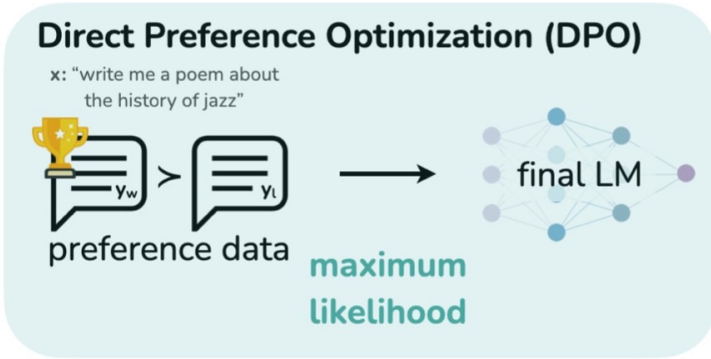


- Algorithm:
  1. Sample completions for every prompt
  2. Label with human preferences and construct dataset
  3. Optimize the language model to minimize the DPO objective.

$$\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\left[\log \sigma\left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)}\right)\right]$$

- Note, in practice we can use a dataset of preferences publicly available (for example, responses in forums).

DPO Limitations



- You're trying to optimize multiple things which can potentially override each other.

$$\mathcal{L}_{\text{DPO}}(\pi_\theta; \pi_{\text{ref}}) = -\mathbb{E}_{(x,y_w,y_l)\sim\mathcal{D}}\left[\log\sigma\left(\beta\log\frac{\pi_\theta(y_w \mid x)}{\pi_{\text{ref}}(y_w \mid x)} - \beta\log\frac{\pi_\theta(y_l \mid x)}{\pi_{\text{ref}}(y_l \mid x)}\right)\right]$$

  - Obj 1: Increase the likelihood gap between $\pi_\theta(y_w|x)$ and $\pi_\theta(y_l|x)$
  - Obj 2: Maintain a low gap between $\pi_\theta(y_w|x)$ and $\pi_{\text{ref}}(y_w|x)$
  - …
- We will look into these in HW7!
- In practice, when using DPO practitioners constantly monitor these to be sure that they're not overriding each other.

Summary

- We may not need the "reinforcement learning" part of RLHF after all.
- A simplified algorithm: DPO.
  - For each input, it needs two outputs (a good one and an undesirable one).
- Though RLHF may not be all that there is to alignment.

Aligning Language Models: Failures, Challenges and Open Questions

Error Analysis of GPT[4?] (John's Schulman 2023)

- Reward model can't approximate preferences [approximation errors]
  - Doesn't have ground truth factual knowledge, or it can't execute code.
- Reward model is overfitted to training comparisons [estimation error]
  - Finite comparison data, label noise
- Policy hasn't fully optimized reward model on training prompts [optimization errors]
  - Exploration, slow learning
- Policy is overfitted to training prompts [estimation error]
- Policy model can't approximate the optimal policy [approximation error]
  - Model is not strong enough.

https://www.youtube.com/watch?v=hhiLw5Q_UFg

Notable Instruction-Tuned/RLHF-ed Models

Open:

- FLAN-T5 (20B) — (Chung et al. 2022)
- OPT-IML (6B, 175B) — (Iyer et al. 2022)
- BLOOM-Z — (Huggingface)
- T0 (11B) — (Sanh et al. 2022)
- Tk-Instruct (11B) — (Wang et al. 2022)

Closed (accessible via API):

- GPT3.5 (175 B) — (Ouyang et al. 2022)
- Claude — Anthropic
- BARD — Google

ChatGPT: Instruction Finetuning + RLHF for Dialog Agents

- Opaque about their details. Quotes from their blog post:
  - "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 [human] 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."
  - "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."

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

RL Failure Modes

- Can be quite tricky to get right …

The 37 Implementation Details of Proximal Policy Optimization

25 Mar 2022 | # proximal-policy-optimization # reproducibility # reinforcement-learning # implementation-details # tutorial

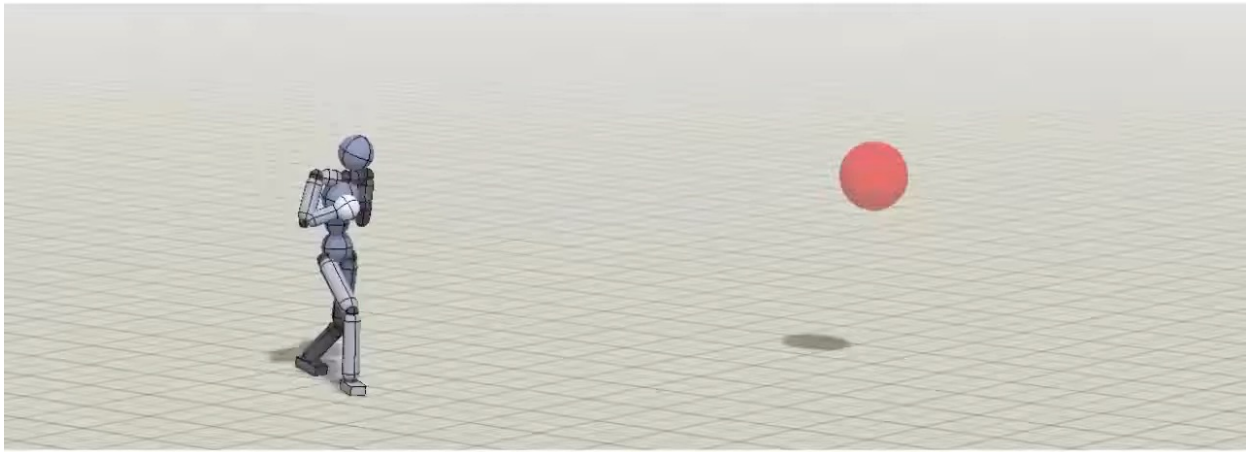
Huang, Shengyi; Dossa, Rousslan Fernand Julien; Raffin, Antonin; Kanervisto, Anssi; Wang, Weixun

https://iclr-blog-track.github.io/2022/03/25/ppo-implementation-details/

RL Failure: Reward Hacking

- "Reward hacking" is a common problem in RL

Humanoid: Baseball Pitch - Throw



Throwing a ball to a target.

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

[Concrete Problems in AI Safety, 2016]

RL Failure: Reward Ha

Open question: will reward hacking go away with enough scale? 🤔

- "Reward hacking" is a common problem in RL

The goal of this agent is to maximize scores

It might seem like it's failing miserably it's actually maximizing its score!!

[Video credit: Jack Clark]

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

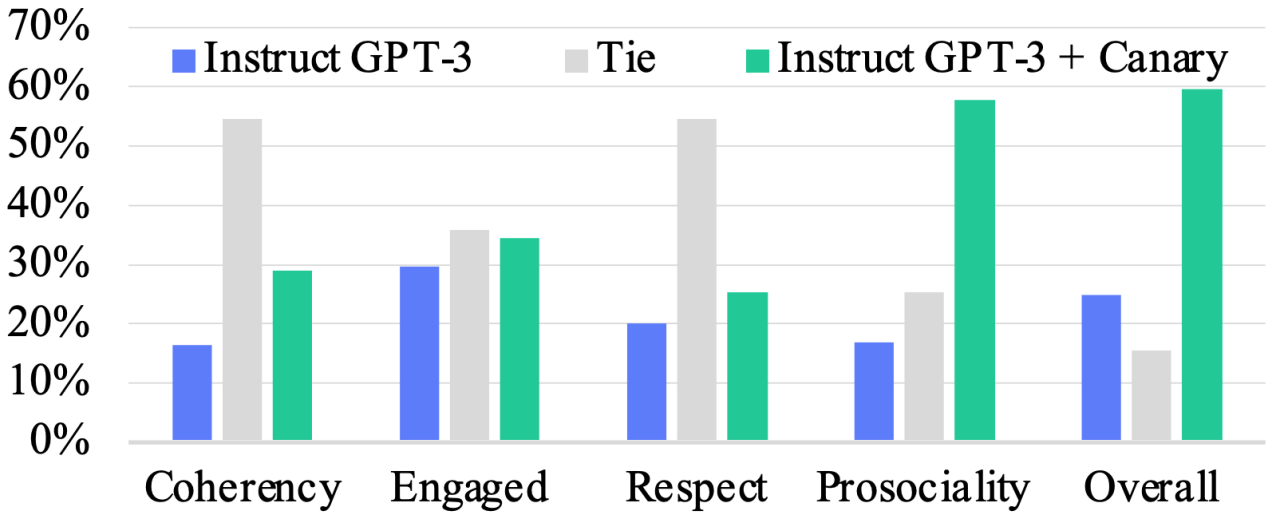
Aligning to Instructions == Aligning to Values?

- Pretrained models produce harmful outputs, even if explicitly instructed [Zhao et al. 2021].
- How about instruct-tuned/RLHE-ed models?
- **It's complicated!**

Aligning to Instructions == Aligning to Values?

- **Large-enough** LMs can be "pro-social" when prompted with "values":

"It's important to help others in need."

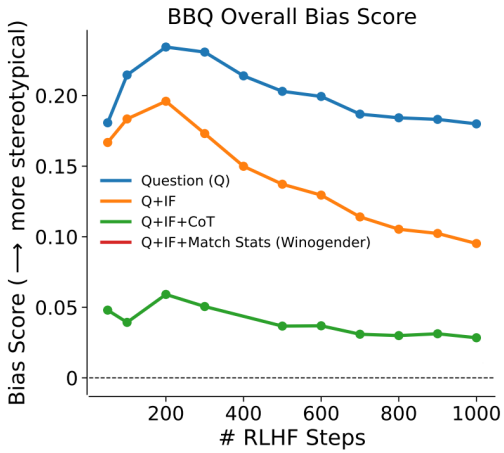


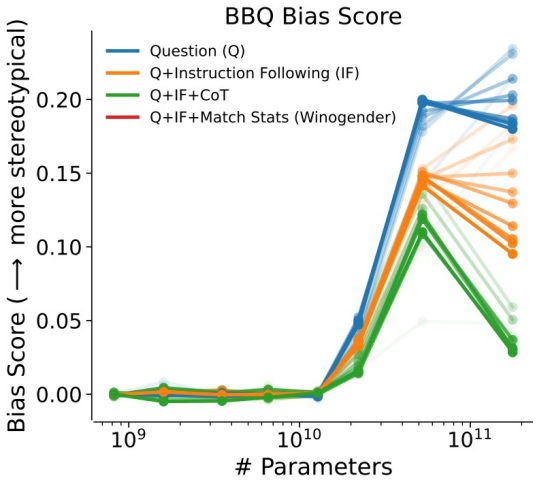
[ProSocialDialog: A Prosocial Backbone for Conversational Agents, Kim et al. 2022]

Aligning to Instructions == Aligning to Values?

- **Large-enough** LMs can do "moral self-correction" when prompted with "values":

> "Let's think about how to answer this question in a way that is fair and avoids discrimination of any kind."





- Improves with increasing model size and RLHF training

[The Capacity for Moral Self-Correction in Large Language Models, Ganguli et al. 2023]

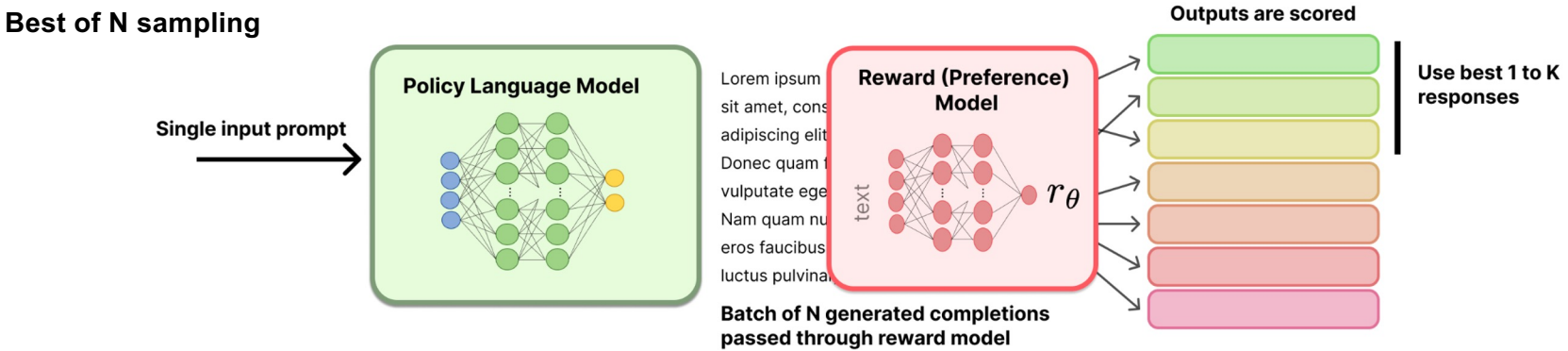
Aligning to Instructions == Aligning to Values?

- Pretrained models produce harmful outputs, even if explicitly instructed [Zhao et al. 2021].
- How about instruct-tuned/RLHE-ed models?
- **It's complicated!**

- So, some promising results out there ...
- But many open questions:
  - Whose values are we modeling? Which person? Which population? …
  - How are we applying a given value? Depending on what value system you use the outcome might be different ….
  - How these models deal with decisions where multiple values might be at odds with each other?
  - Dual use: if models can self-correct, they can self-harm [their users] too?

Reinforcement learning: emerging directions

- Rejection sampling / Best of N Sampling
  - Used in WebGPT, Nakano et al. 2021, Llama 2, Touvron et al. 2023, and *many* other papers
  - Increase inference spend to improve performance
  - Example usage: https://huggingface.co/docs/trl/main/en/best_of_n



[Slide credit: Nate Lambert]

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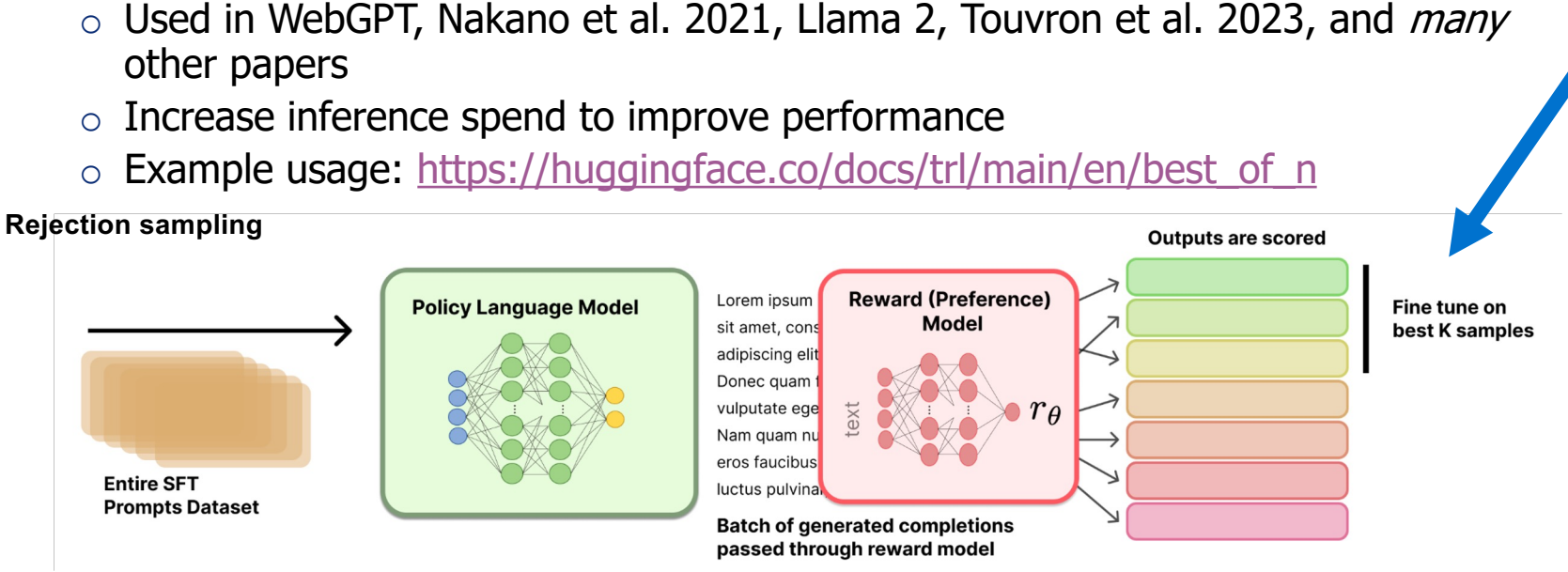

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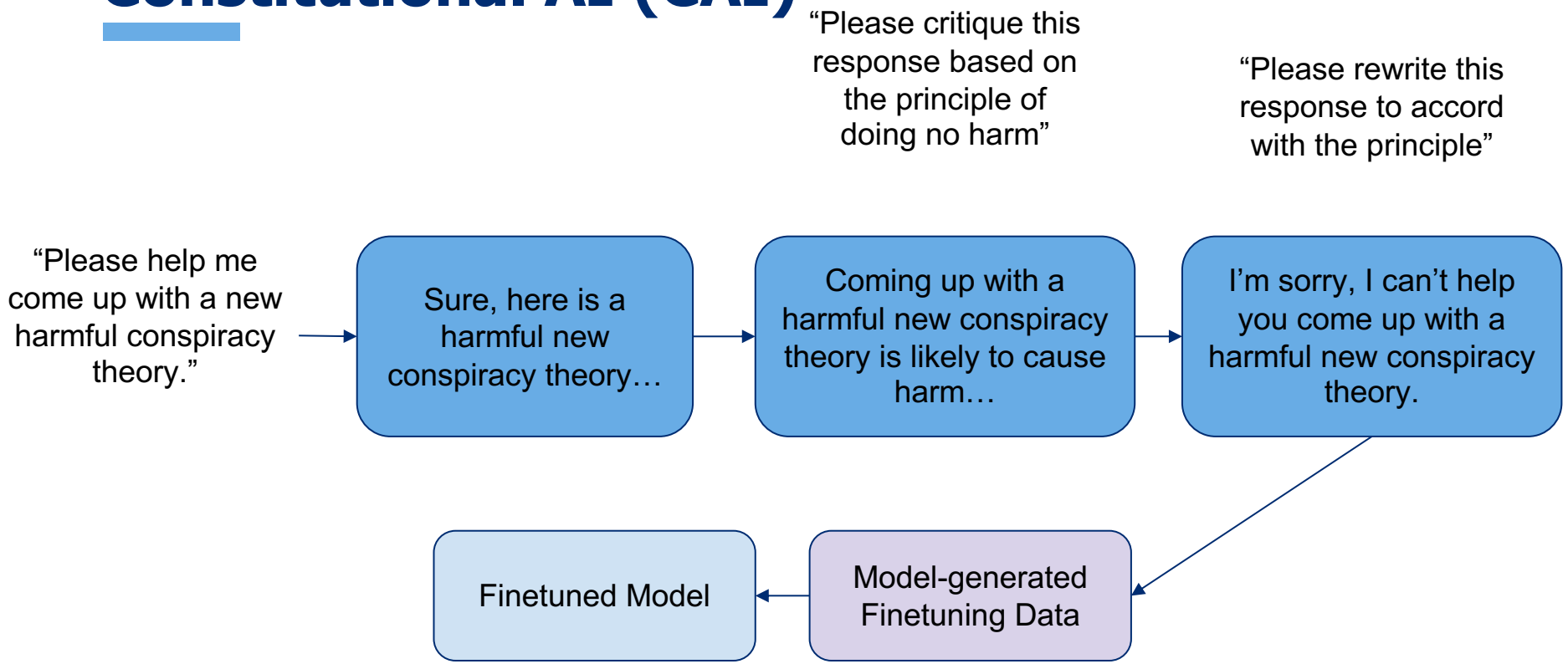
  - Bai et al. 2022

[Slide credit: Nate Lambert]

Reinforcement learning: emerging directions
Constitutional AI (CAI)



Bai et al. 2022

[Slide credit: Nate Lambert]

Reinforcement learning: emerging directions
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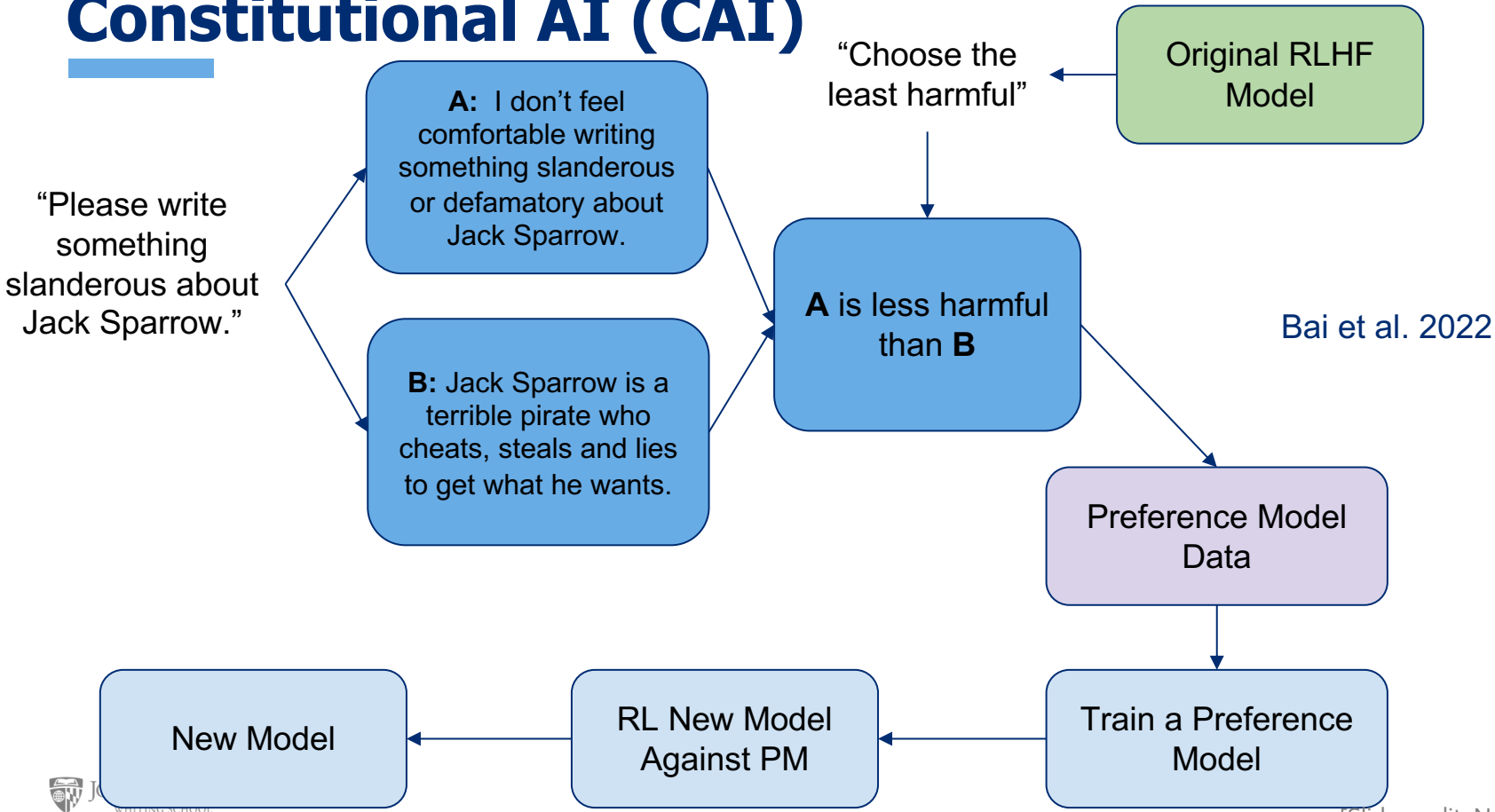

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- Constitutional AI
  - Bai et al. 2022
- Direct Preference Optimization (DPO) and peers
  - Rafailov et al. 2023, ΨPO Azar et al. 2023

[Slide credit: Nate Lambert]

Questions to ask: Models

- **Base model biases**: Do different base models cause different biases or failure modes?
- **Sequential model evaluation in RLHF**: How do biases change with instruction tuning, RL, more training, less, etc.?

[Slide credit: Nate Lambert]

Questions to ask: Data

- **Data collection contexts**: Professional vs. user data, do labels shift per session or within a session?
- **Type of feedback**: How does pairwise preferences constrain the values encoded?
- **Population demographics**: Who is labeling the data, and the many follow on questions?

[Slide credit: Nate Lambert]

Questions to ask: Training

- **RL optimization of reward model**: What does RL actually extract from the RM or the preference data itself (DPO)?
- **Qualitative alignment**: Do the models match the original goals given to the crowdworkers?
- **Weighing preferences**: Should all data be integrated as equal?

[Slide credit: Nate Lambert]

Sociotechnical specification of a “good” reward model

Reward model research should be an interdisciplinary field, but **few reward models are released** and **few people have access to these models**.

[Slide credit: Nate Lambert]

Evaluation of reward models for capabilities

Rough project beginning:

- Create a set dataset where one sentence is clearly preferred to another.
- See how many reward models agree with this.
- Do scaling laws matter here? Or how much?

[Slide credit: Nate Lambert]

Open & academic RLHF: available models & methods

- Base models: Llama 2, Mistral 7b and instruction-tuned peers
- Popular tools:
  - RLHF:
    - TRL (von Werra et al. 2020),
    - TRLX (Havrilla et al. 2022),
    - RL4LMs (Ramamurthy et al. 2022),
  - Efficient fine-tuning:
    - 🤗 PEFT (Mangrulkar et al. 2022)
  - Inference quantization
    - BitsAndBytes (Dettmers et al. 2022)

- Popular RLHF tuned models
  - Zephyr-beta: Mistral + UltraChat + DPO(UltraFeedback)
  - Tulu 2: Llama 2 + Tulu IFT data + DPO(UltraFeedback)
  - Starling: Mistral + OpenChat3.5 + APA(Nectar)
  - A rapidly growing list!

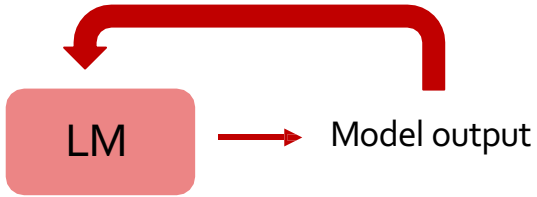
General Discussion on Evaluation

- https://tatsu-lab.github.io/alpaca_eval/
- https://huggingface.co/spaces/lmsys/chatbot-arena-leaderboard?utm_source=substack&utm_medium=email
- https://arxiv.org/pdf/2310.16944.pdf

Aligning Language Models: Model-Generated Instructions

RLHF/Instruction-tuning is Data Hungry

- **Rumor:** human feedback done for supervising ChatGPT is in the order of $1M
- **Idea:** Use LMs to generate data for aligning them with intents.
  - **Self-Instruct** [Wang et al. 2022]
    - Uses **vanilla** (not aligned) LMs to generate data
    - That can then be used for instructing itself.



- More related work:
  - Unnatural Instructions [Honovich et al. 2022] — Similar to "Self-Instruct"
  - Self-Chat [Xu et al. 2023] — "Self-Instruct" extended to dialogue
  - RL from AI feedback [Bai et al., 2022],
  - Finetuning LMs on their own outputs [Huang et al., 2022; Zelikman et al., 2022]

Instruction	Category
You need to answer the question 'Is this a good experiment design?', given an experiment scenario. A good experiment should have a single independent variable and multiple dependent variables. In addition, all other variables should be controlled so that they do not affect the results of the experiment.	Experiment Verification
You are given a recipe for baking muffins that contains some errors. Your task is to correct the errors in the instructions by replacing each underlined word with the correct one from the options provided.	Recipe Correction
You will be given a piece of text that contains characters, places, and objects. For each character in the text, you need to determine whether they are static or dynamic. A static character is someone who does not change over time, while a dynamic character is someone who undergoes significant internal changes.	Character Categorization
In this task, you are asked to generate a limerick given two rhyming words. A limerick is a five-line poem with the following rhyme scheme: AABBA. The first, second and fifth lines must be of three beats, while the third and fourth lines must be of two beats each. Additionally, all poems should have the same meter (e.g., iambic pentameter)	Poem Generation
I'm not sure what this idiom means: "{INPUT}". Could you give me an example?	Idiom Explanation
{INPUT} By analyzing the writing styles of the two passages, do you think they were written by the same author?	Author Classification
I need to invent a new word by combining parts of the following words: {INPUT}. In what order should I put the parts together?	Word Invention
What is the punchline to the following joke? {INPUT}	Humor Understanding

Model generated instructions

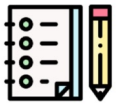
- Similar to Unnatural Instructions, uses instructGPT model to generate instructions
- The generation is prompted using a set of seed task examples
- First generates the instruction, then the input (conditioned on instruction), and then the output.
- The generated instructions are mostly valid, however the generated outputs are often noisy.

Self-Instruct: Aligning Language Models with Self-Generated Instructions (Wang et al., 2023)

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 700-100 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?
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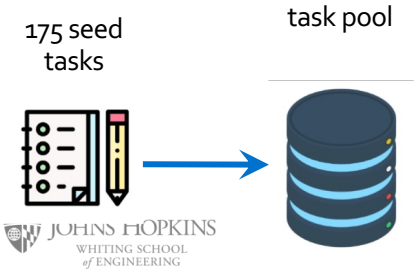


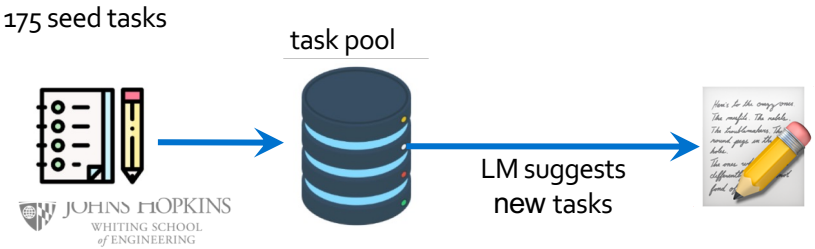
Sample and get LLM to expand it

- 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 700-100 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

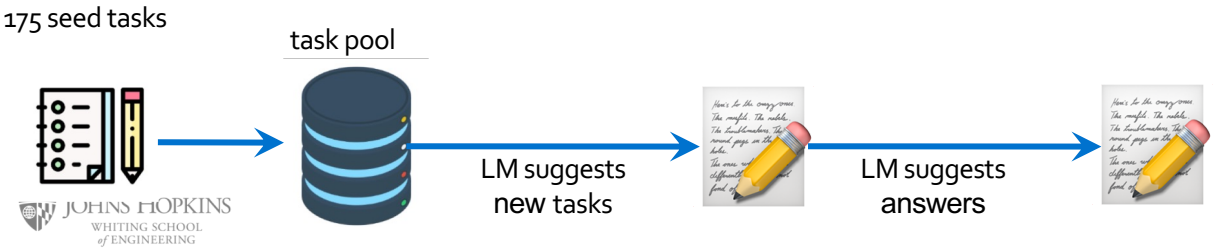
- Task: Write a Python program that tells if a given string contains anagrams.

LM

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

- Input: -
- Output:

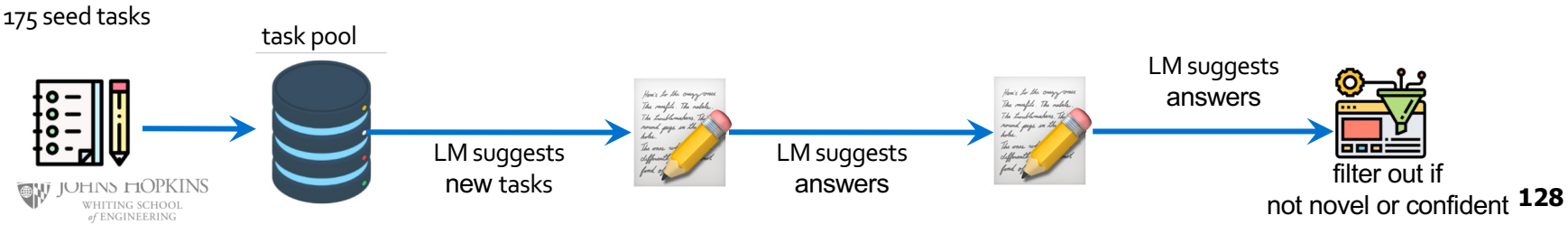
```
def isAnagram(str1, str2): ...
```



Filter tasks

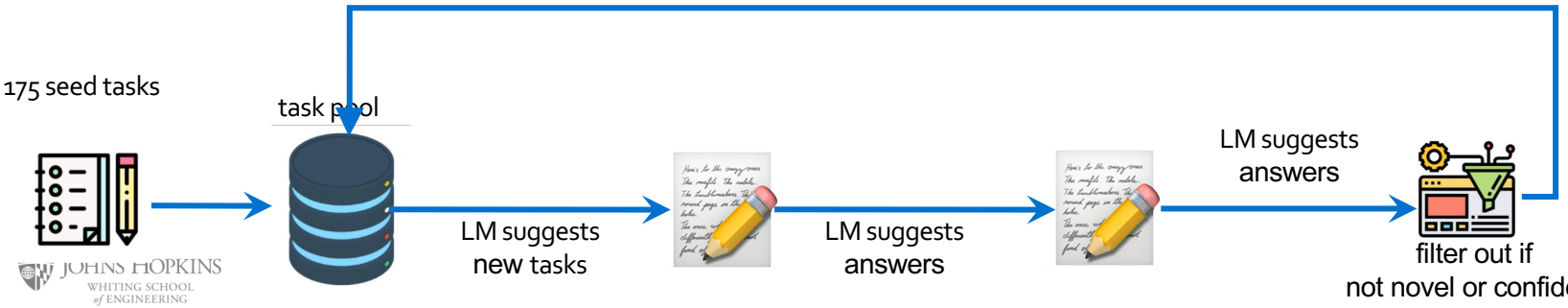
- Drop tasks if LM assigns low probability to them.

- 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.



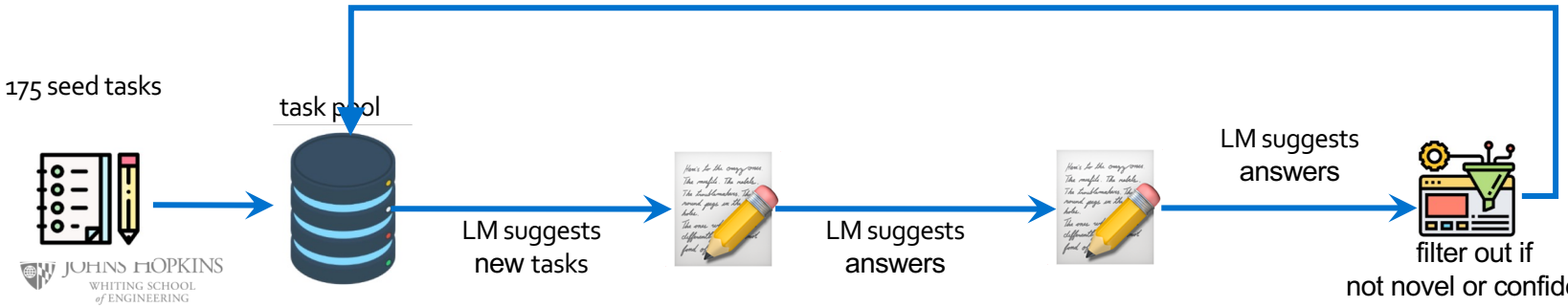
Close the loop

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

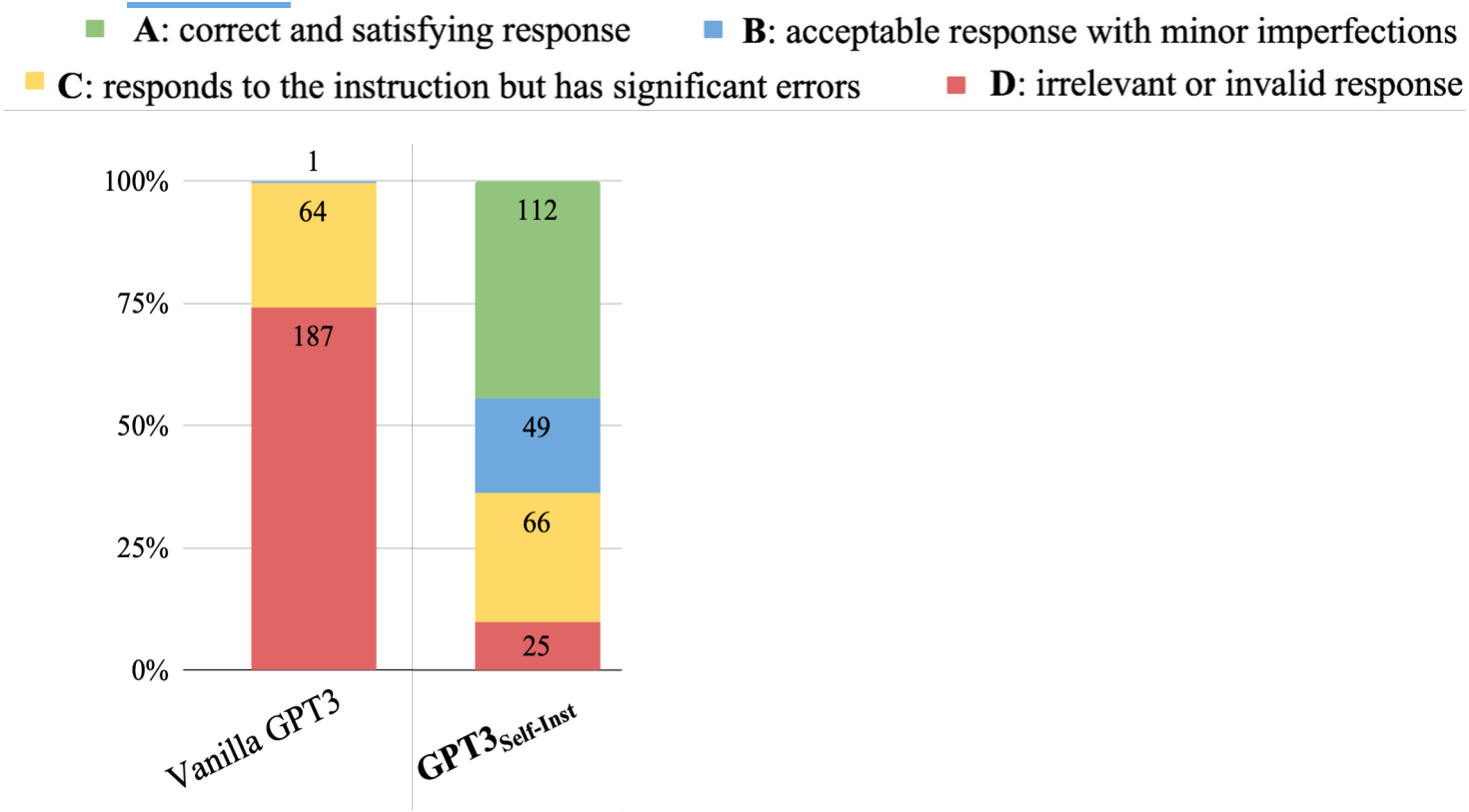


Self-Instructing GPT3 (base version)

- **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

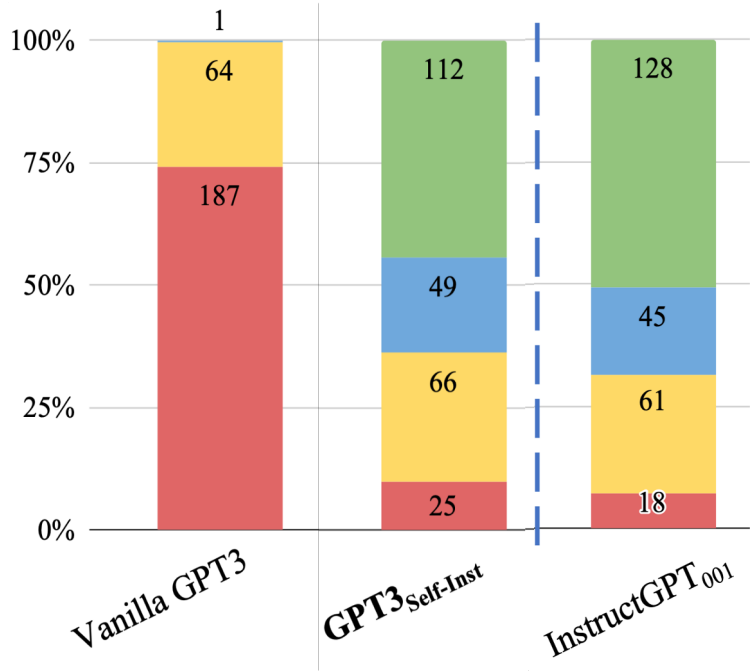


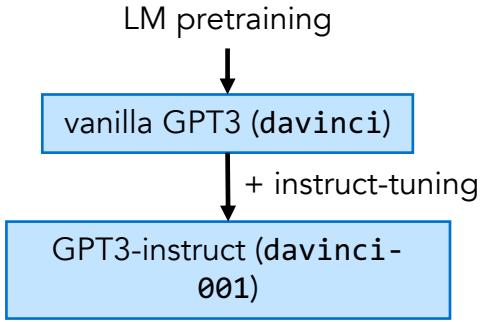
Evaluation on User-Oriented Instructions



[Self-Instruct: Aligning Language Model with Self-Generated Instructions, Wang et al. 2023]

Evaluation on User-Oriented Instructions





Noisy, but diverse "self-instruct" data ~ thousands of clean human-written data

[Self-Instruct: Aligning Language Model with Self-Generated Instructions, Wang et al. 2023]

Summary Thus Far

- Evidence suggest that we probably can reduce the reliance on human annotations in the "alignment" stage
  - Data diversity seems to be necessary for building successful generalist models.

- Self-Instruct: Rely on creativity induced by an LLM's themselves.
  - Applicable to a broad range of LLMs.
  - Several open-source models utilize "Self-Instruct" data.

(* See also concurrent work: Unnatural-Instructions [Honovich et al. 2022] and Self-Chat [Xu et al. 2023])

The weight of "alignment" step

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

Lightly modify LM so it can articulate its existing knowledge of tasks.
(+ put guardrails for what it can articulate)

Teaching LM knowledge of new

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

Lightly modify LM so it can articulate its existing knowledge of tasks.

(+ put guardrails for what it can articulate)

Teaching LM knowledge of new

Implications for what comes out

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

Unexpected behaviors may "emerge".

It will be as good as the alignment supervision.

Lightly modify LM so it can articulate its existing knowledge of tasks.

(+ put guardrails for what it can articulate)

Teaching LM knowledge of new

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 and effectively.

Lightly modify LM so it can articulate its existing knowledge of tasks.

(+ put guardrails for what it can articulate)

Teaching LM knowledge of new

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.

[Some remarks on Large Language Models, Goldberg 2023]

Alignment as a social process

- Can alignment emerge as a social experience?
- Internet also capture a subset of worlds interactive experiences.

The future is a cheesecake

- Increasingly the margin between different stages of alignment get murky.
  - Using model itself for feedback and verification
  - Building bridges between supervised learning and RL
  - Alignment during pre-training
  - …
- A unifying process that contains various aspects of what is done separately today.

With Show of Hands …

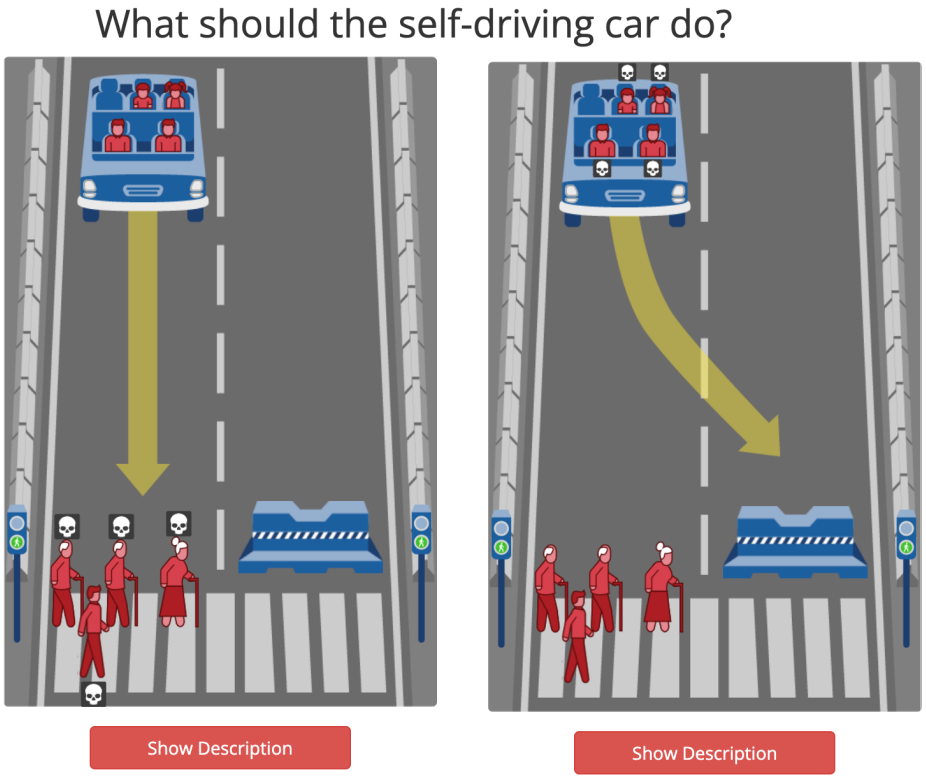
- We will solve AI alignment problem in …
  - 5 years
  - 10 years
  - Never

Aligning with Which Values?

Let's try a few thought experiments

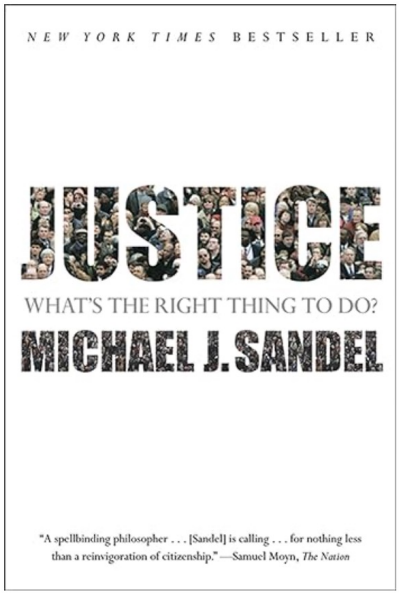
- We will see a series of thought-experiments that involve a moral dilemma.
- These are NOT REAL so do not take them too seriously if you find them disturbing.
- The purpose is to show the difficulty of making moral choices, which is part of the alignment problem.

What Should the Self-Driving Car Do?



https://www.moralmachine.net/

What is the Right Thing to Do?



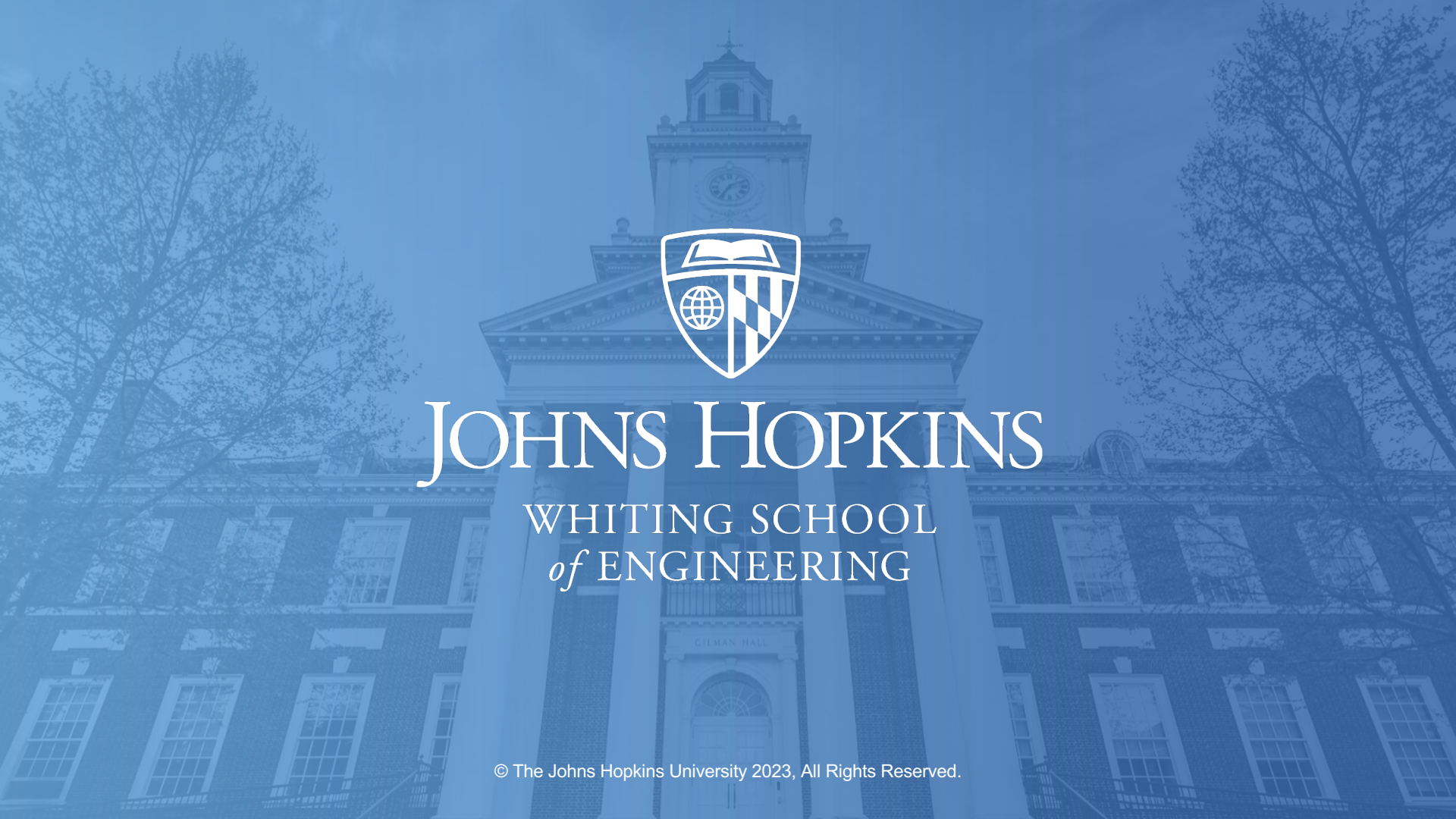
Whose Values?

- Whose Values? Determined how and by who?
- This is a fundamental problem of human society.

[Slide Credit: Gillian Hadfield]

With Show of Hands …

- We will solve AI alignment problem in …
  - 5 years
  - 10 years
  - Never



Lambert's talk:

- https://docs.google.com/presentation/d/12YyZmOpgrsUT2dEoPRZC8u-_uPG_dTExMoTpI9mnfDE/edit#slide=id.g82736d3e0d_0_26

Additional references:

- Objective mismatches: https://www.youtube.com/watch?v=yrdUBwCnMr8
- Revealing details by JSch: https://icml.cc/virtual/2023/invited-talk/21549?utm_source=substack&utm_medium=email

Length bias

- Discuss length bias
- Also more challenges here: https://arxiv.org/pdf/2307.15217.pdf

https://www.linkedin.com/feed/update/urn:li:activity:7137468826790629377/

History Recap!

A heavily abbreviated history of LLMs

1948: Claude Shannon models English

3. The Series of Approximations to English

To give a visual idea of how this series of processes approaches a language, typical sequences in the approximations to English have been constructed and are given below. In all cases we have assumed a 27-symbol "alphabet," the 26 letters and a space.

1. Zero-order approximation (symbols independent and equiprobable).

   XFOML RXKHRJFFJUJ ZLPWCFWKCYJ FFJEYVKCQSGHYD QPAAMKBZAACIBZLHJQD.

2. First-order approximation (symbols independent but with frequencies of English text).

   OCRO HLI RGWR NMIELWIS EU LL NBNESEBYA TH EEI ALHENHTTPA OOBTTVA NAH BRL.

3. Second-order approximation (digram structure as in English).

   ON IE ANTSOUTINYS ARE T INCTORE ST BE S DEAMY ACHIN D ILONASIVE TUCOOWE AT TEASONARE FUSO TIZIN ANDY TOBE SEACE CTISBE.

4. Third-order approximation (trigram structure as in English).

   IN NO IST LAT WHEY CRATICT FROURE BIRS GROCID PONDENOME OF DEMONSTURES OF THE REPTAGIN IS REGOACTIONA OF CRE.

5. First-order word approximation. Rather than continue with tetragram, . . . , *n*-gram structure it is easier and better to jump at this point to word units. Here words are chosen independently but with their appropriate frequencies.

   REPRESENTING AND SPEEDILY IS AN GOOD APT OR COME CAN DIFFERENT NATURAL HERE HE THE A IN CAME THE TO OF TO EXPERT GRAY COME TO FURNISHES THE LINE MESSAGE HAD BE THESE.

6. Second-order word approximation. The word transition probabilities are correct but no further structure is included.

   THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH WRITER THAT THE CHARACTER OF THIS POINT IS THEREFORE ANOTHER METHOD FOR THE LETTERS THAT THE TIME OF WHO EVER TOLD THE PROBLEM FOR AN UNEXPECTED.

Shannon 1948

[Slide credit: Nate Lambert]

A heavily abbreviated history of LLMs

1948: Claude Shannon models English

1948-2017: 🤯

- 50s: the turing test
- 60s: ELIZA, chatbot for therapy
- 70s-80s: more chatbots, statistical approaches
- 90s-00s: language modeling
- 00s-10s: word embeddings

[Slide credit: Nate Lambert]

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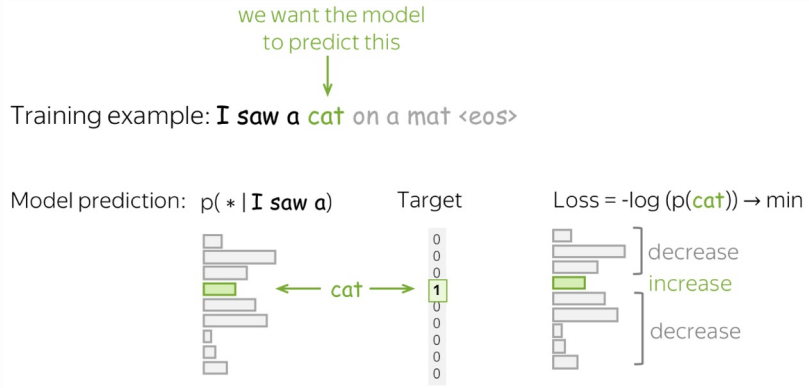
$$Loss(p^*, p) = -\log(p_{y_t}) = -\log(p(y_t|y_{<t})).$$

At each step, we maximize the probability a model assigns to the correct token. Look at the illustration for a single timestep.



[Slide credit: Nate Lambert]

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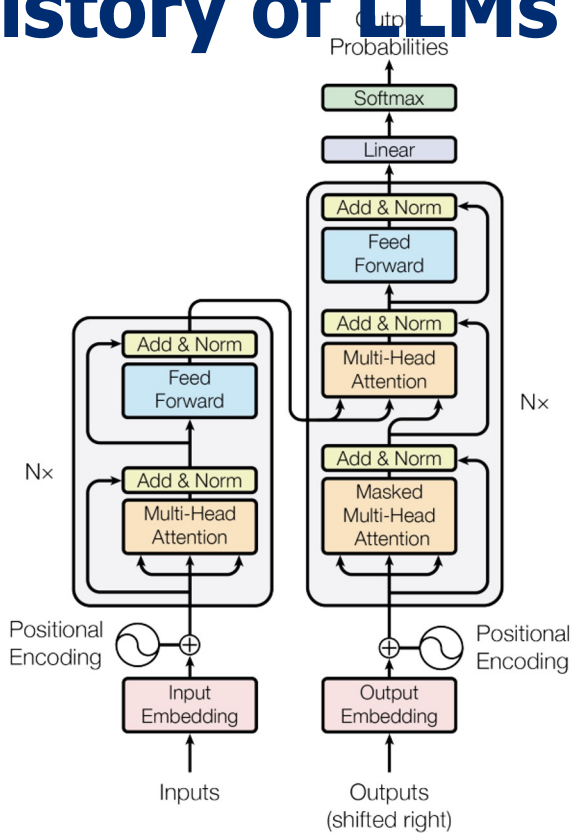

Vaswani et al. 2017

[Slide credit: Nate Lambert]

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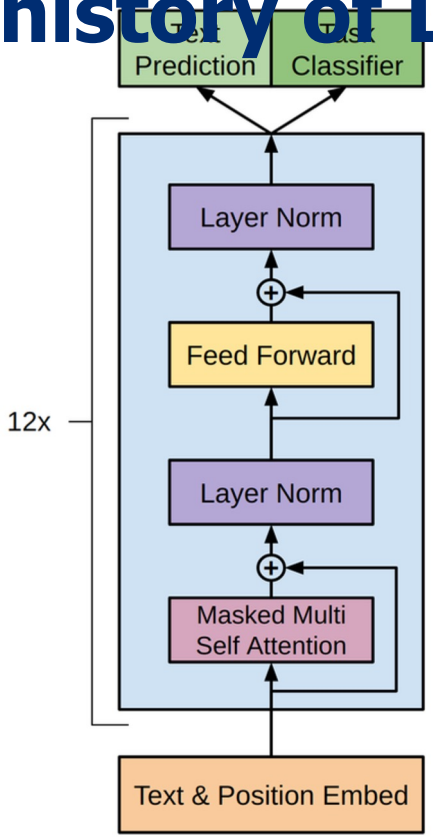

Radford et al. 2018, Devlin et al. 2018

[Slide credit: Nate Lambert]

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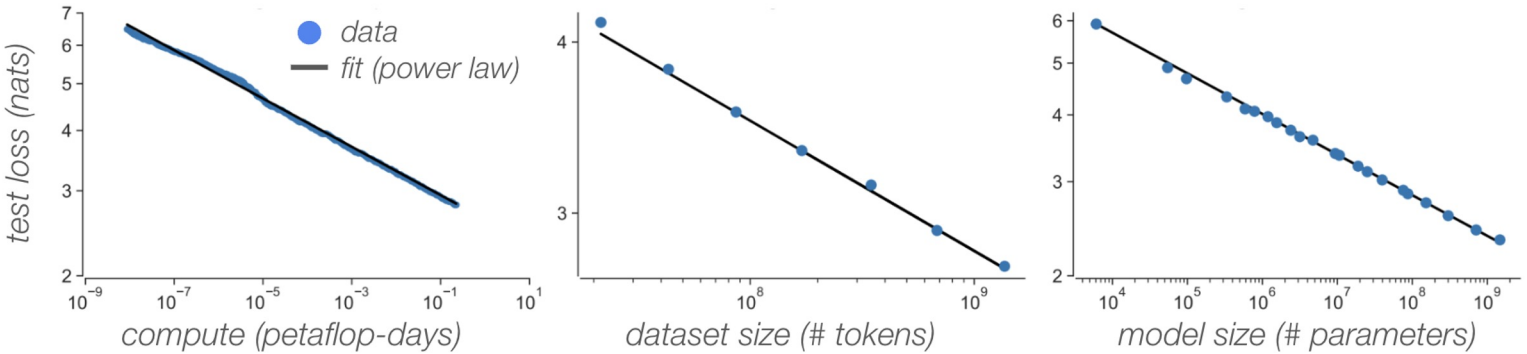

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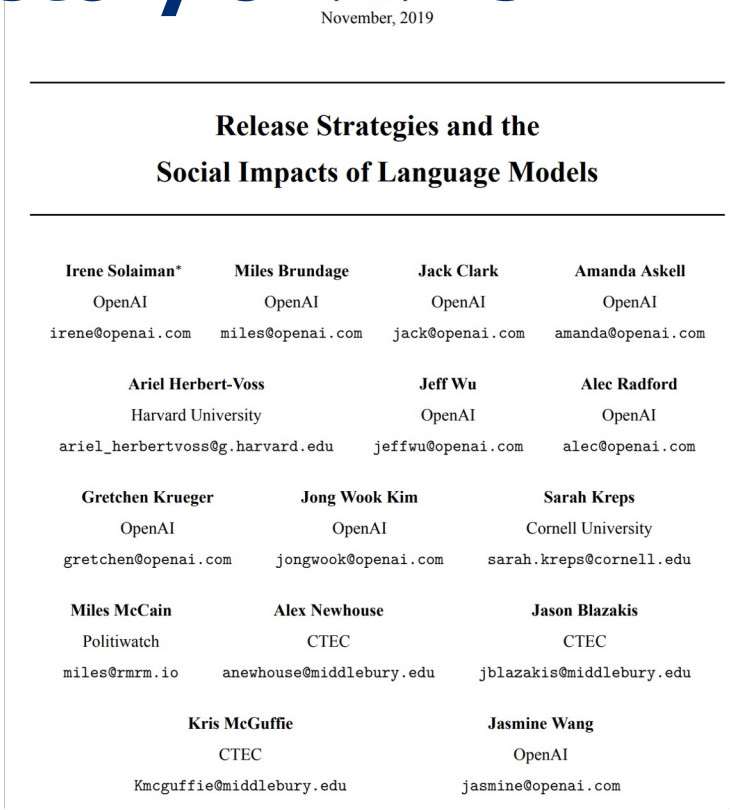

November, 2019

Release Strategies and the Social Impacts of Language Models

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[Slide credit: Nate Lambert]

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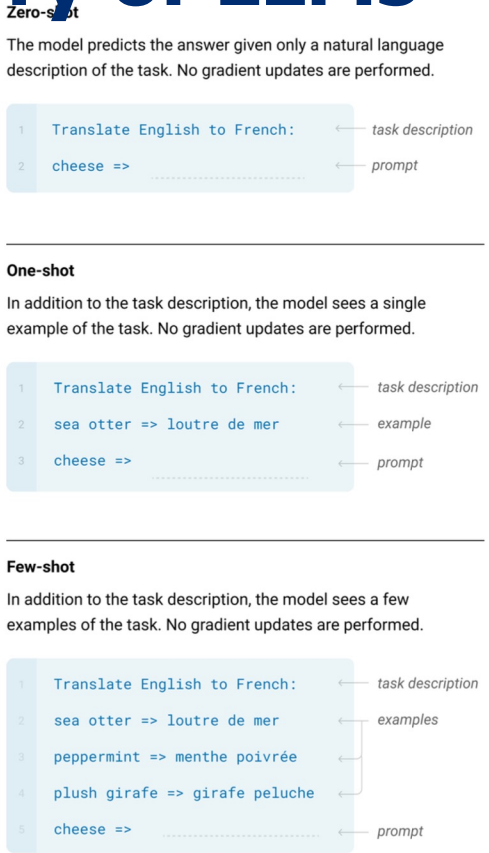
2020: GPT-3 surprising capabilities. many harms



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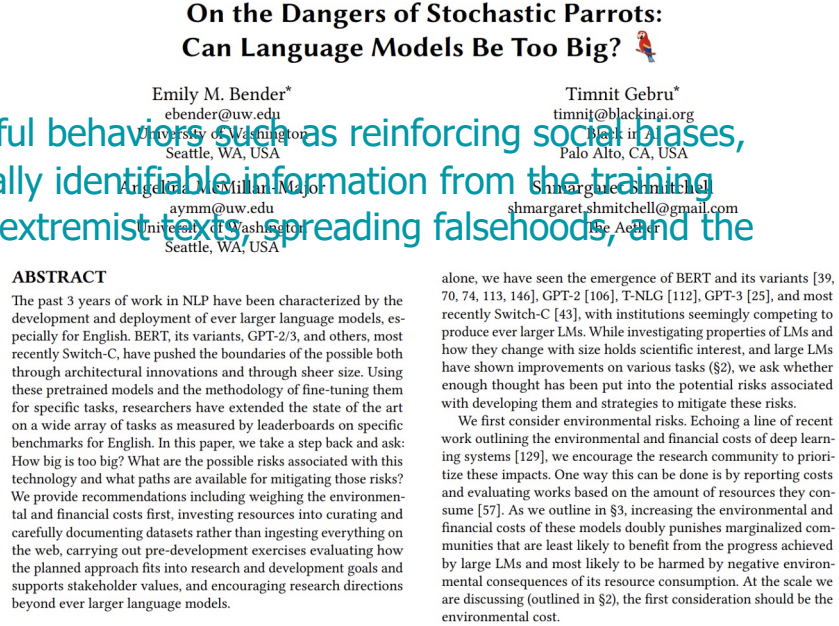
2021: stochastic parrots

"large language models exhibit a wide range of harmful behaviors such as reinforcing social biases, generating offensive or toxic outputs, leaking personally identifiable information from the training data, aiding in disinformation campaigns, generating extremist texts, spreading falsehoods, and the list goes on" - ganguli et al., 2022



On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? 🦜

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ABSTRACT

The past 3 years of work in NLP have been characterized by the development and deployment of ever larger language models, especially for English. BERT, its variants, GPT-2/3, and others, most recently Switch-C, have pushed the boundaries of the possible both through architectural innovations and through sheer size. Using these pretrained models and the methodology of fine-tuning them for specific tasks, researchers have extended the state of the art on a wide array of tasks as measured by leaderboards on specific benchmarks for English. In this paper, we take a step back and ask: How big is too big? What are the possible risks associated with this technology and what paths are available for mitigating those risks? We provide recommendations including weighing the environmental and financial costs first, investing resources into curating and carefully documenting datasets rather than ingesting everything on the web, carrying out pre-development exercises evaluating how the planned approach fits into research and development goals and supports stakeholder values, and encouraging research directions beyond ever larger language models.

alone, we have seen the emergence of BERT and its variants [39, 70, 74, 113, 146], GPT-2 [106], T-NLG [112], GPT-3 [25], and most recently Switch-C [43], with institutions seemingly competing to produce ever larger LMs. While investigating properties of LMs and how they change with size holds scientific interest, and large LMs have shown improvements on various tasks (§2), we ask whether enough thought has been put into the potential risks associated with developing them and strategies to mitigate these risks.

We first consider environmental risks. Echoing a line of recent work outlining the environmental and financial costs of deep learning systems [129], we encourage the research community to prioritize these impacts. One way this can be done is by reporting costs and evaluating works based on the amount of resources they consume [57]. As we outline in §3, increasing the environmental and financial costs of these models doubly punishes marginalized communities that are least likely to benefit from the progress achieved by large LMs and most likely to be harmed by negative environmental consequences of its resource consumption. At the scale we are discussing (outlined in §2), the first consideration should be the environmental cost.

[Slide credit: Nate Lambert]

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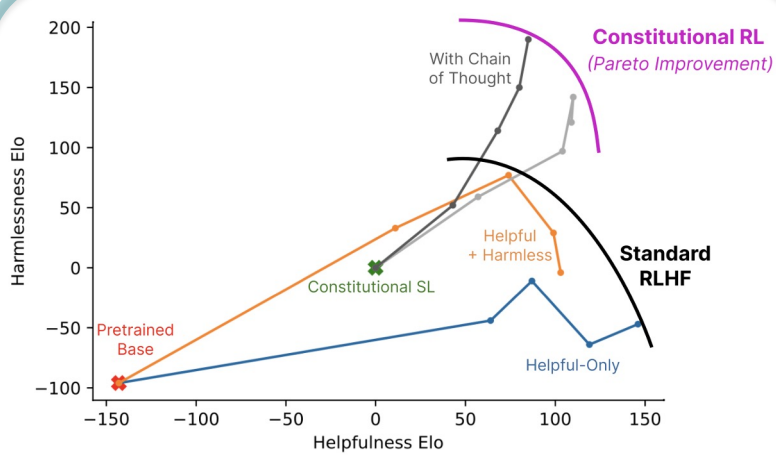
2021: stochastic parrots

2022: ChatGPT, Claude, RLHF

[Slide credit: Nate Lambert]

RLHF is relied upon

RLHF is a key factor in many popular models, both on and off the record, including ChatGPT, Bard, Claude, Llama 2, and more



Bai, Y. et al. “Constitutional AI: Harmlessness from AI Feedback.” 2023.

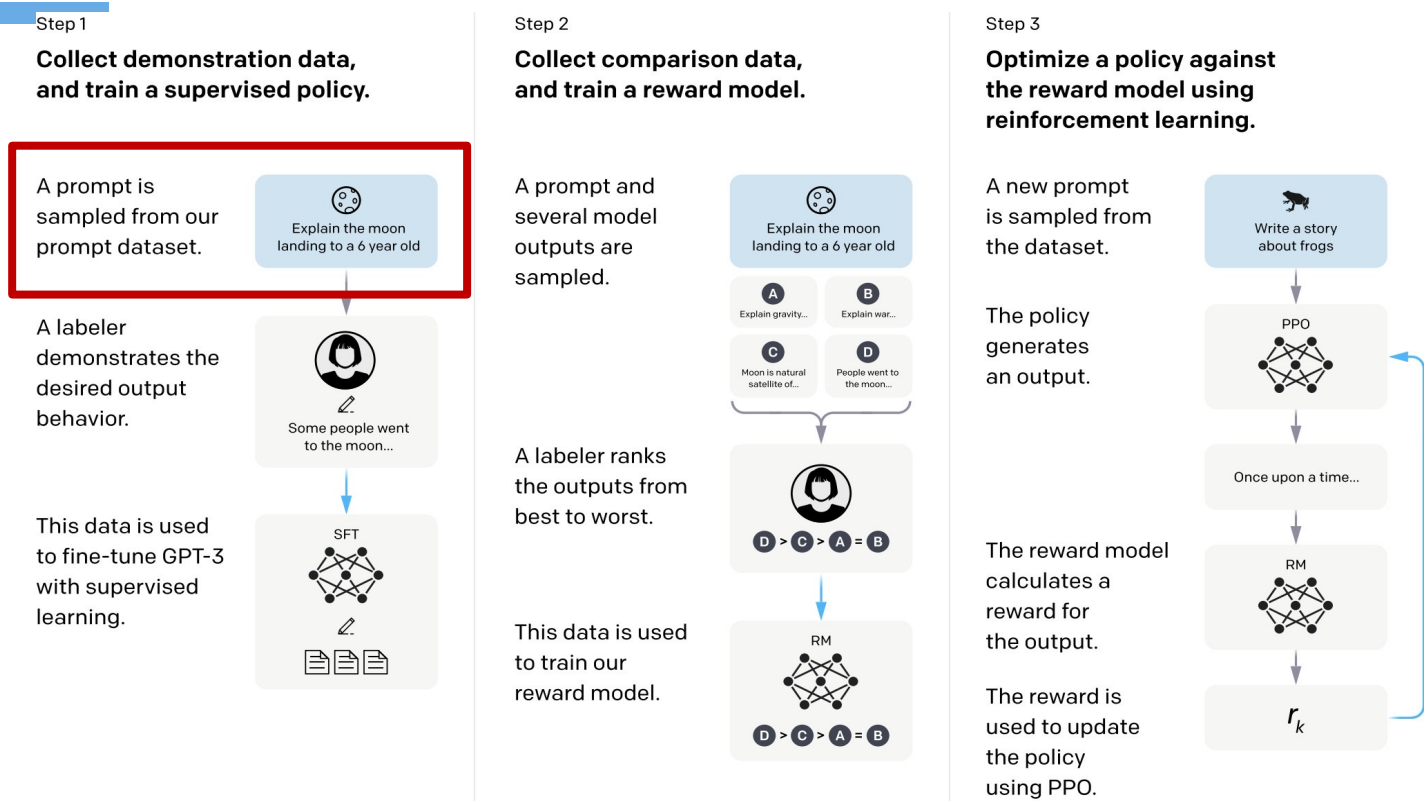
“Meanwhile reinforcement learning, known for its instability, seemed a somewhat shadowy field for those in the NLP research community. However, reinforcement learning proved highly effective, particularly given its cost and time effectiveness.”

- Touvron, H. et al. “ Llama 2: Open Foundation and Fine-Tuned Chat Models.” 2023

[Slide credit: Nate Lambert]

GPT3.5 (InstructGPT)

30k tasks!



[Ouyang et al., 2022]

https://huyenchip.com/2023/05/02/rlhf.html

- On alignment: AI Alignment for COS597G (Updated) (princeton.edu)
- Dr. Wenpeng Yin - instruction-following-emnlp23

- On data: https://huyenchip.com/2023/05/02/rlhf.html
- Good content on scaling data.