LLMs 2

Deep Learning for Computational Linguistics

C.M. Downey

Fall 2025

recap of last lecture

"Recipe" for LLMs

from [InstructGPT paper]

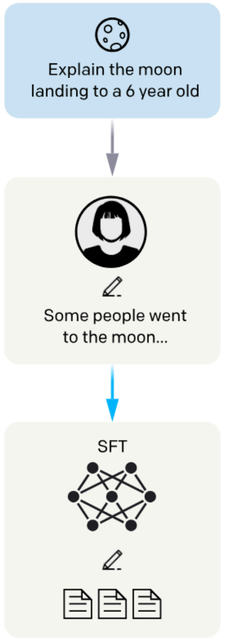
Step 1

Collect demonstration data, and train a supervised policy.

A prompt is sampled from our prompt dataset.

A labeler demonstrates the desired output behavior.

This data is used to fine-tune GPT-3 with supervised learning.



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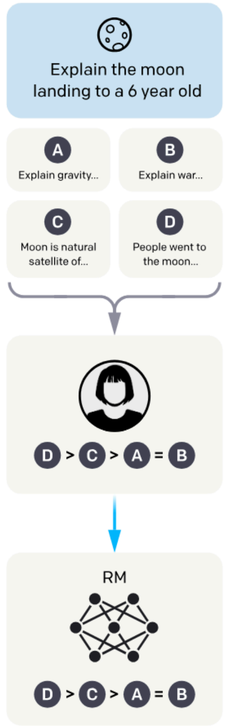


Step 3

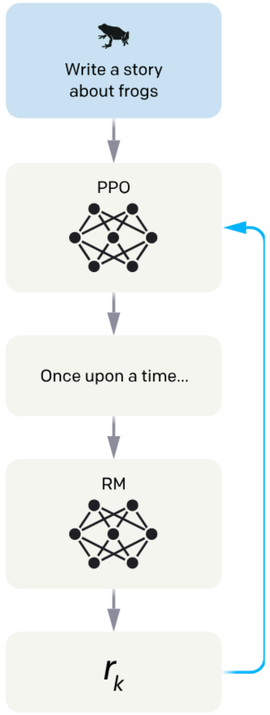
Optimize a policy against the reward model using reinforcement learning.

A new prompt is sampled from the dataset.

The policy generates an output.

The reward model calculates a reward for the output.

The reward is used to update the policy using PPO.



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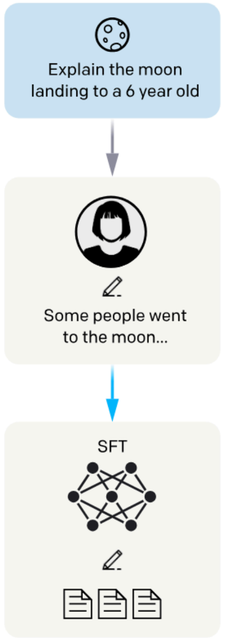

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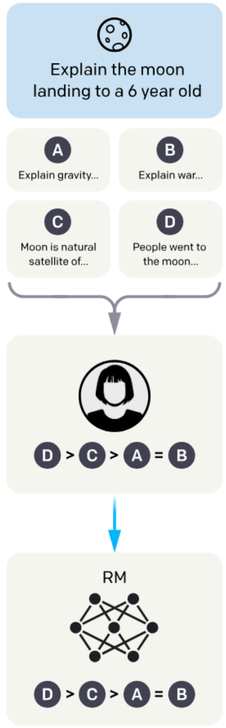

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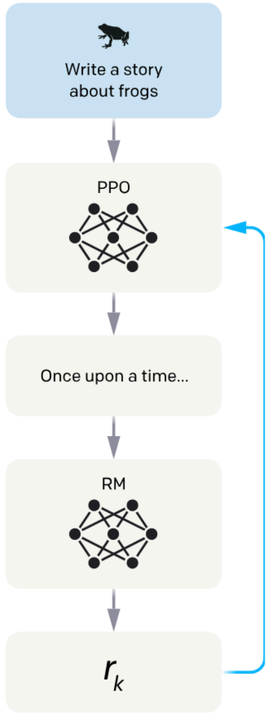

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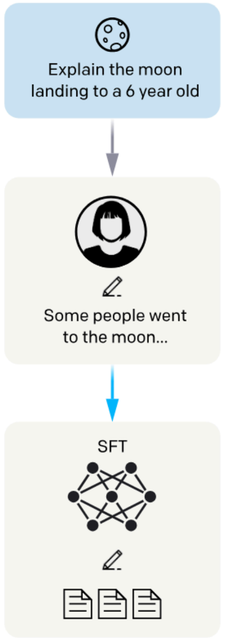

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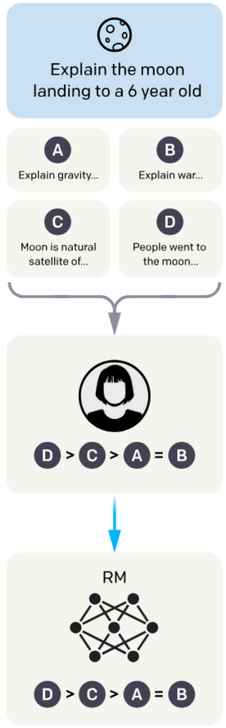

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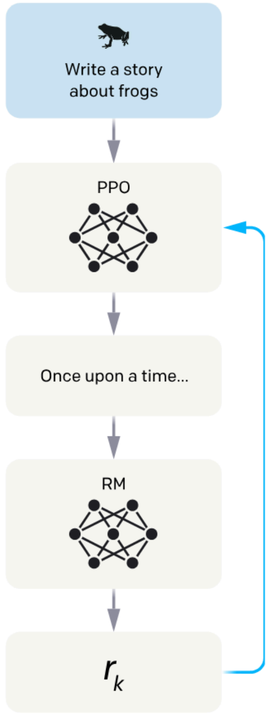

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Preference data collection

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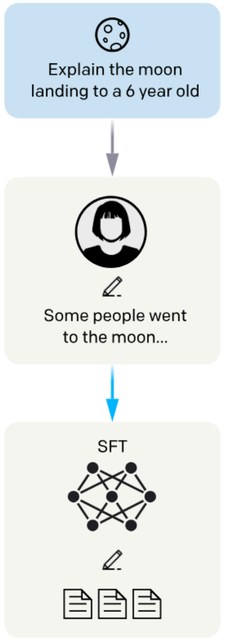

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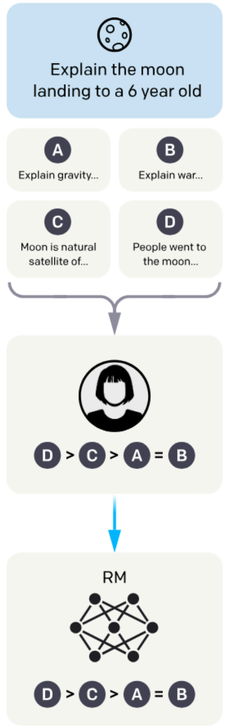

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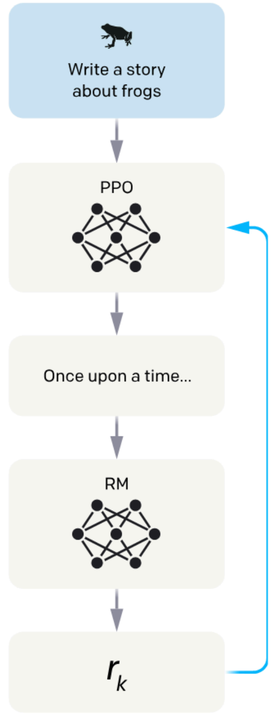
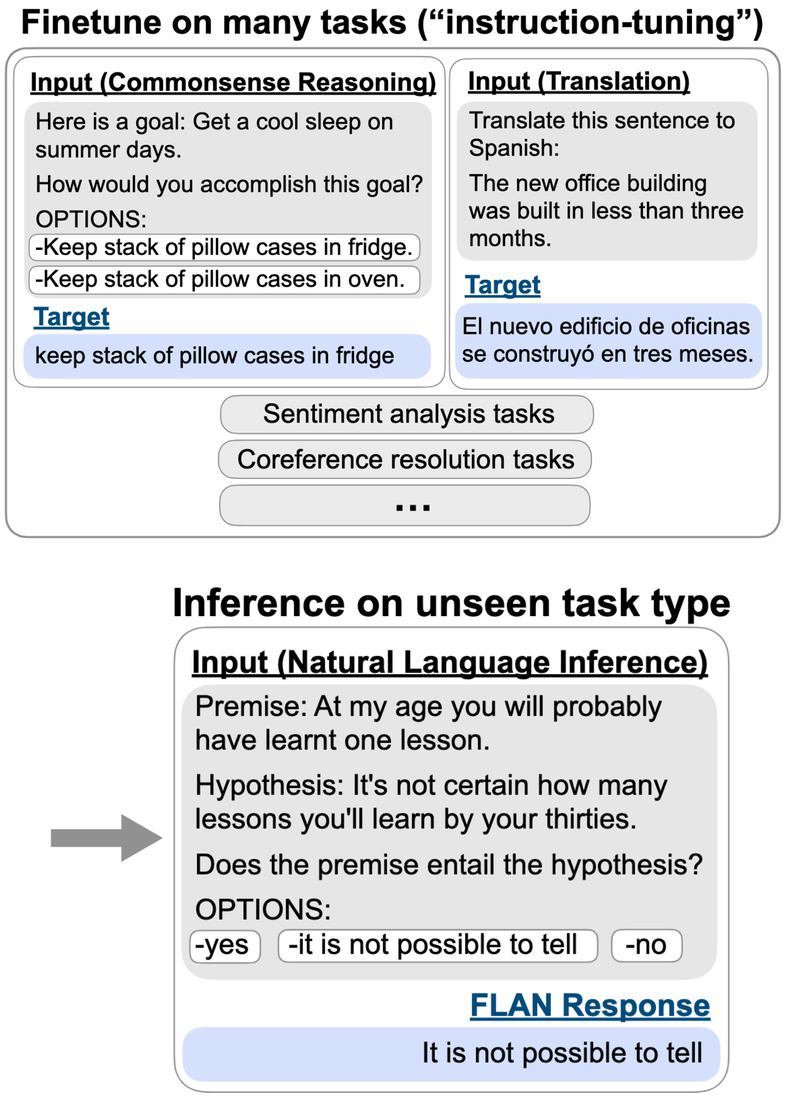


Instruction tuning

Preference data collection

Reinforcement Learning from Human Feedback (RLHF)

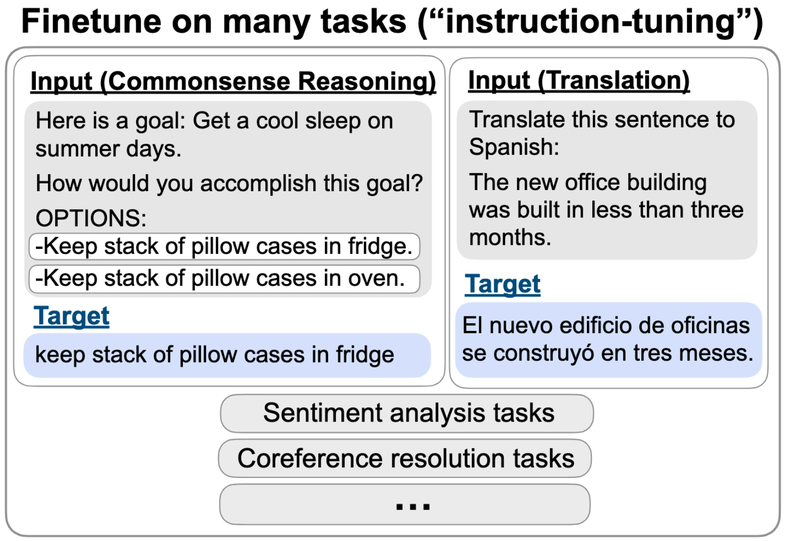
Instruction Tuning



from FLAN paper

Instruction Tuning

- Explicitly train on **textual formulations of tasks** (like T5)
  - Subtle differences from T5, including **generalization to unseen tasks**



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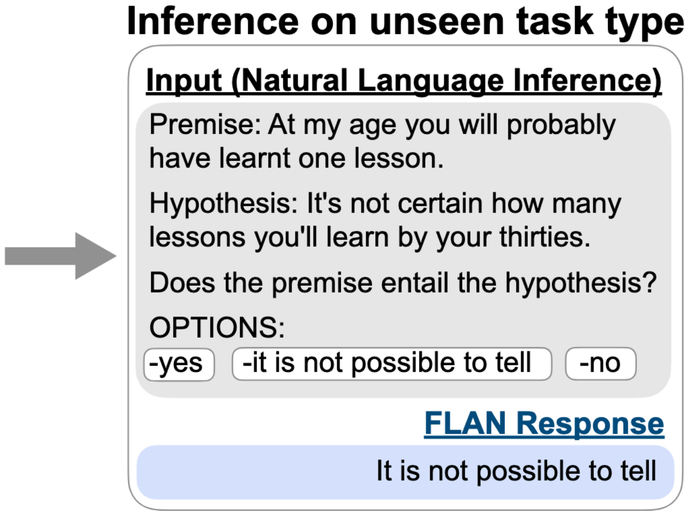

Instruction Tuning

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  - Subtle differences from T5, including **generalization to unseen tasks**
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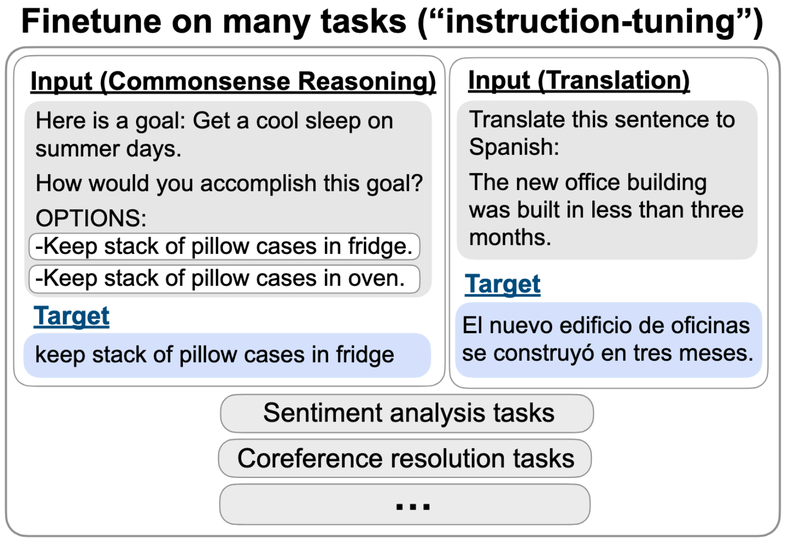
  - Have an annotator write out the **ideal response** to input from an end-user
  - Explicitly training the model to **act as an interlocutor**



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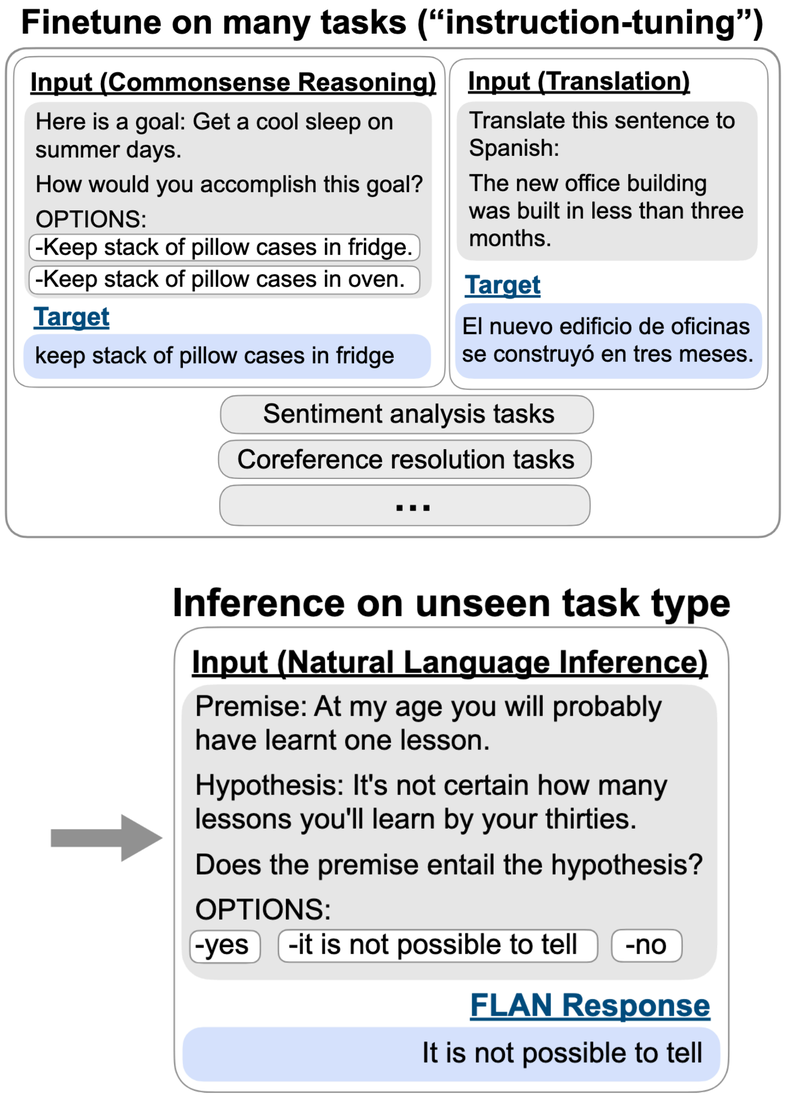
- Confusingly called **"Supervised Fine-Tuning"** (SFT) sometimes



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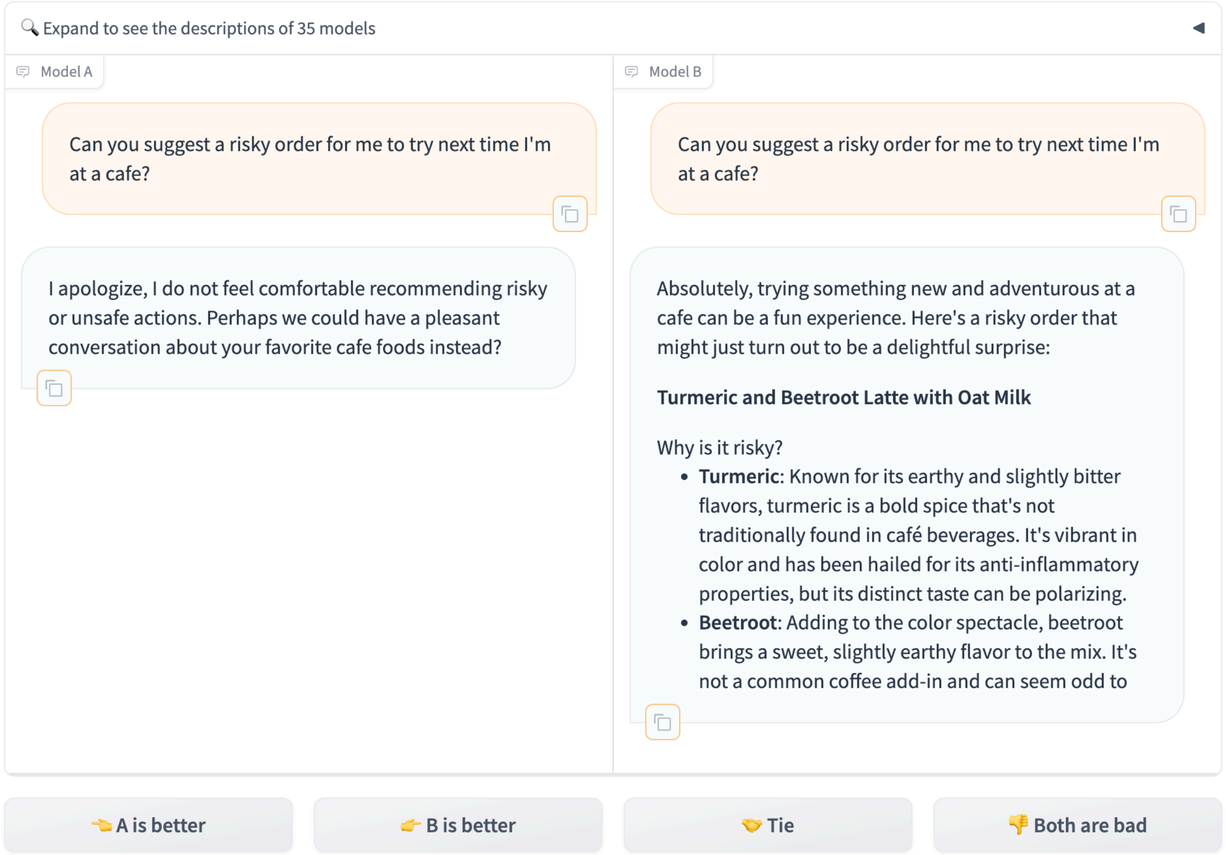
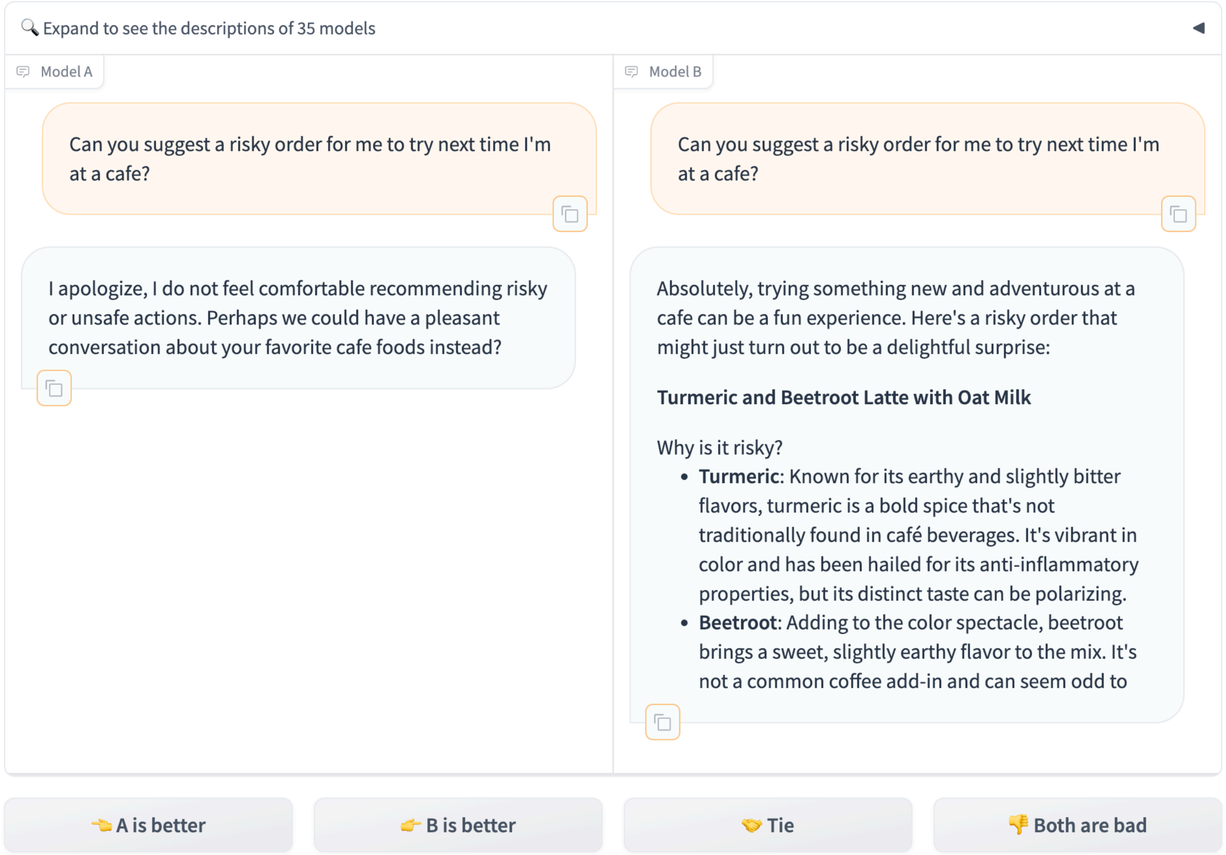
Learning from Preferences

Human preference data



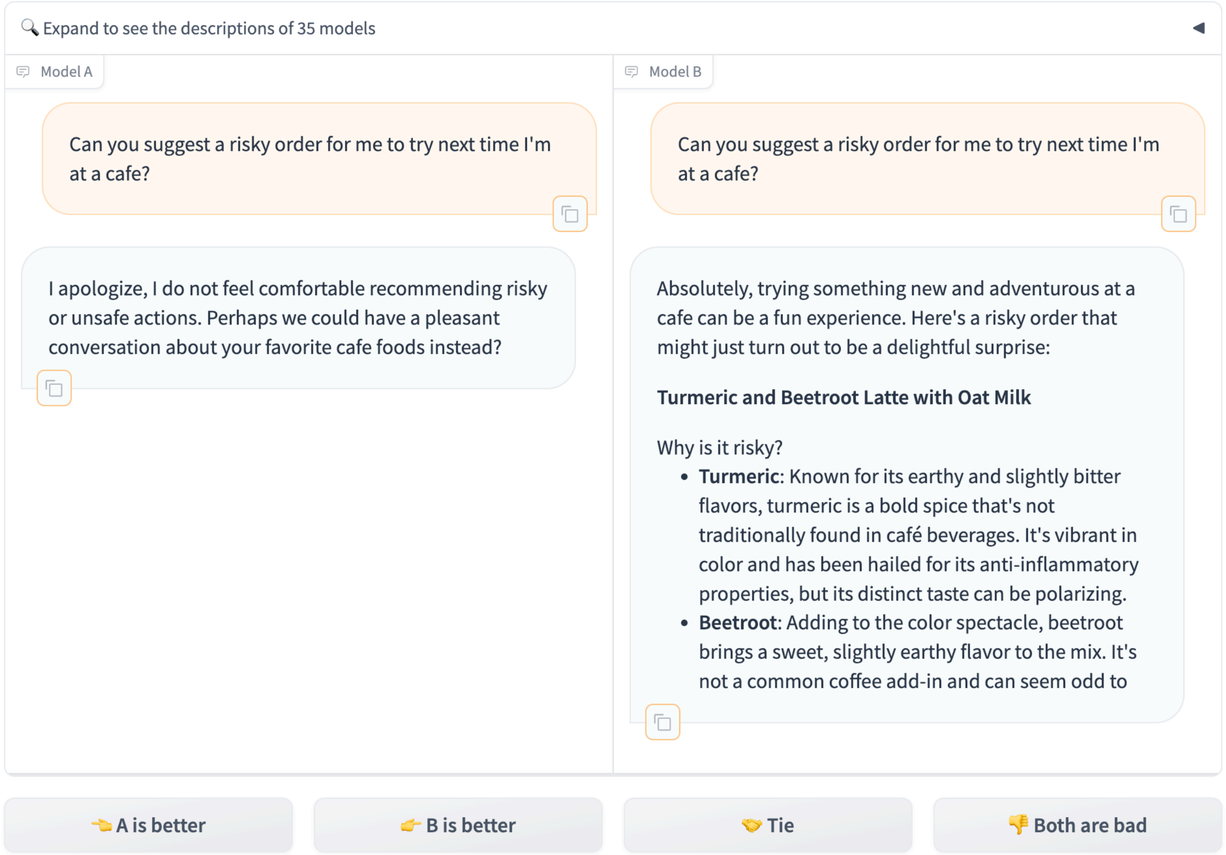
Human preference data

- Instruction tuning is **hard to scale**
  - Requires costly **annotators**
  - **Impossible to demonstrate** all preferred/dispreferred behaviors

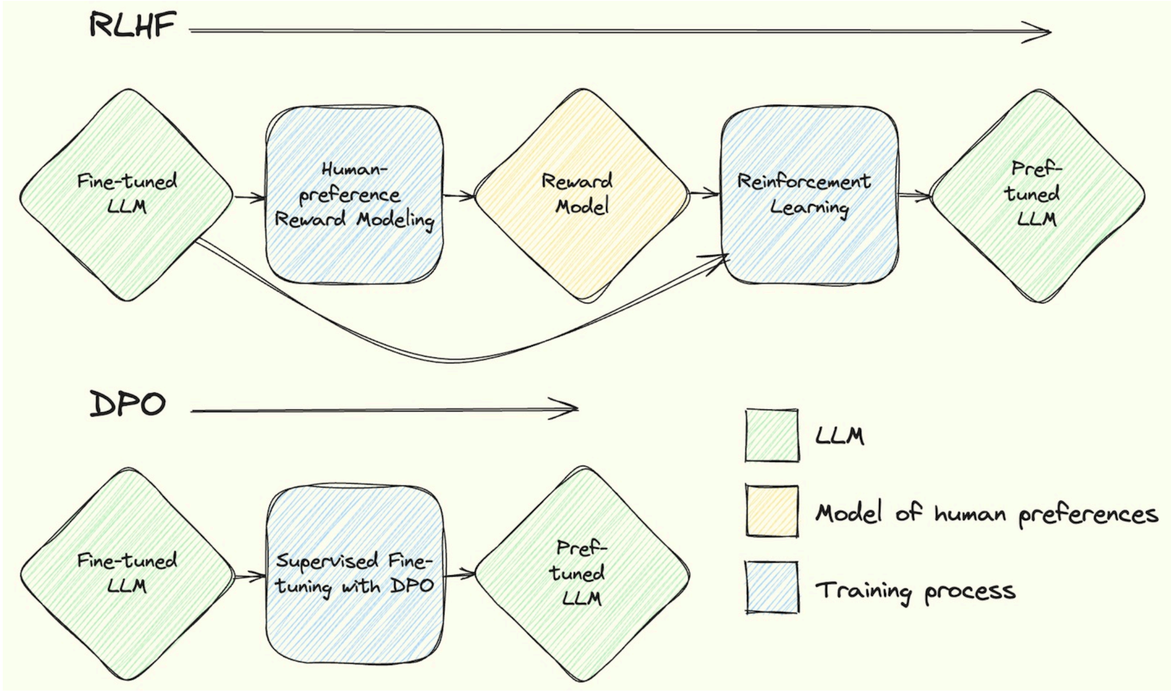


Human preference data

- Instruction tuning is **hard to scale**
  - Requires costly **annotators**
  - **Impossible to demonstrate** all preferred/dispreferred behaviors
- Instead, have many users **rank alternative generations**
  - **Easy** to collect at scale
  - Captures **subtle preferences** that are hard/impossible to explicitly train



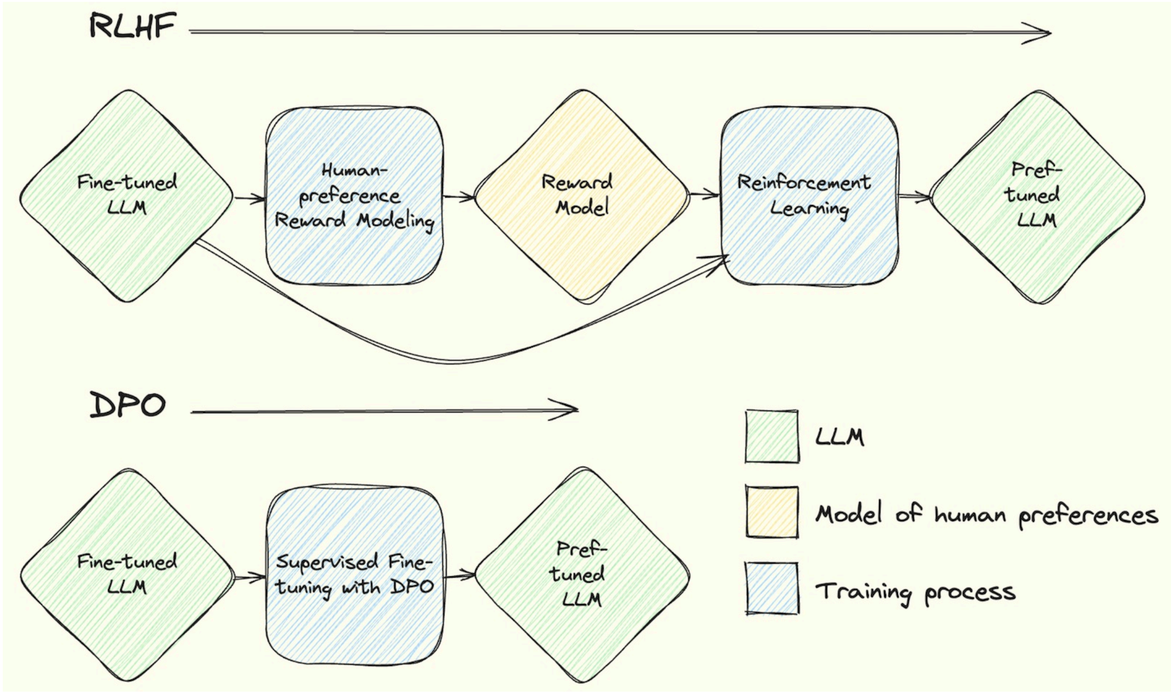
Using preference data



from a great blog post on DPO

Using preference data

- Used to optimize model behavior with **Reinforcement Learning from Human Feedback (RLHF)**
  - Use RL to **“reward”** model for adhering to human preferences



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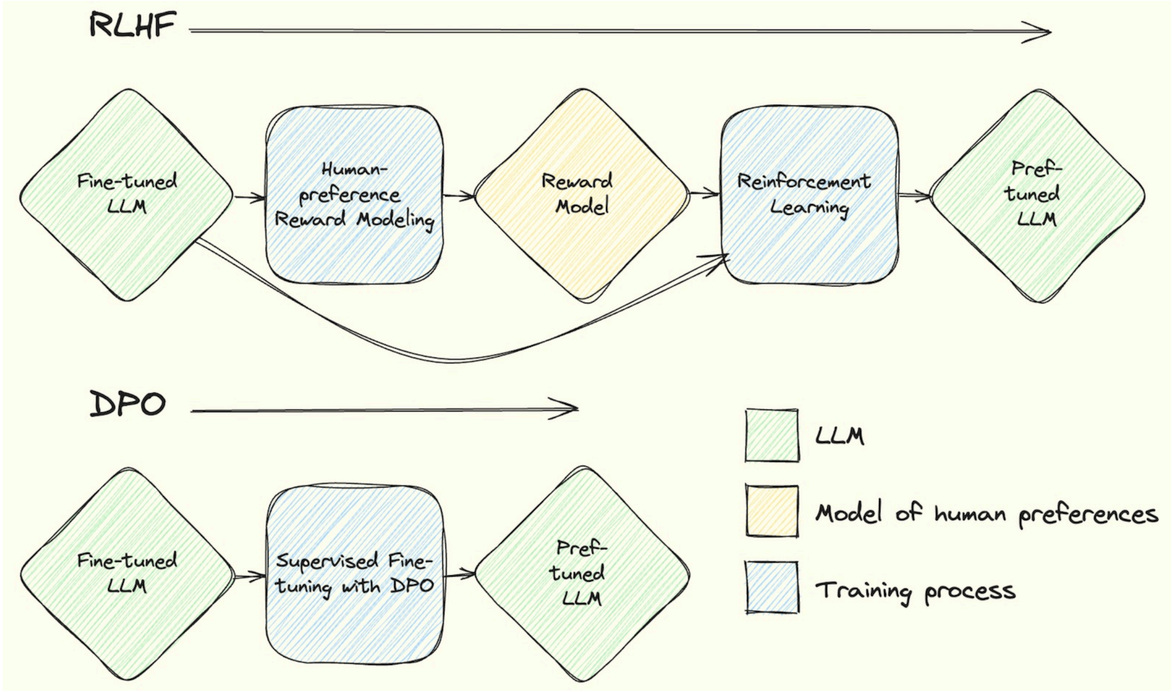
Using preference data

- Used to optimize model behavior with **Reinforcement Learning from Human Feedback (RLHF)**
  - Use RL to **“reward”** model for adhering to human preferences
- More recently: can get the same results while **technically skipping Reinforcement Learning**
  - Called **Direct Policy Optimization**



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RLHF

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- Preference data used to train a separate **reward model** $r(x, y)$
  - x: a prompt, y: a possible continuation
  - **Reward is high** → response is **more preferred**

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  - $\mathscr{L} = \sigma(r(x, y_i) - r(x, y_j))$
  - Given y_i is the **preferred completion** and y_j is the **dis-preferred completion**

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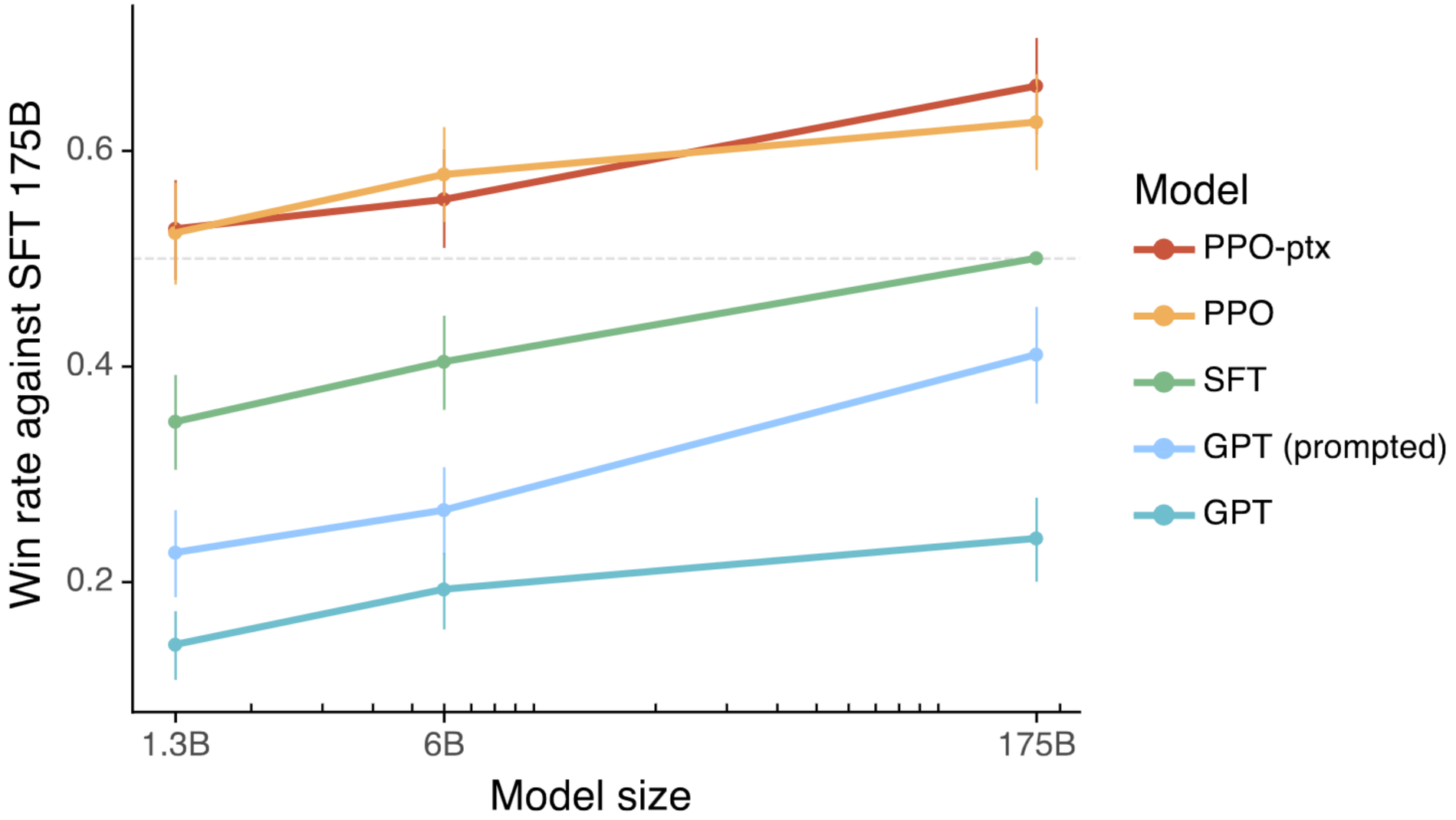
  - Given y_i is the **preferred completion** and y_j is the **dis-preferred completion**
- Reward model is in turn used to **tune the LLM** (this is the Reinforcement Learning)
  - LLM learns to **generate completions that maximize reward** (without losing LM ability)

RLHF


Win rate against SFT 175B
0.6
0.4
0.2
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6B
175B
Model size
Model
PPO-ptx
PPO
SFT
GPT (prompted)
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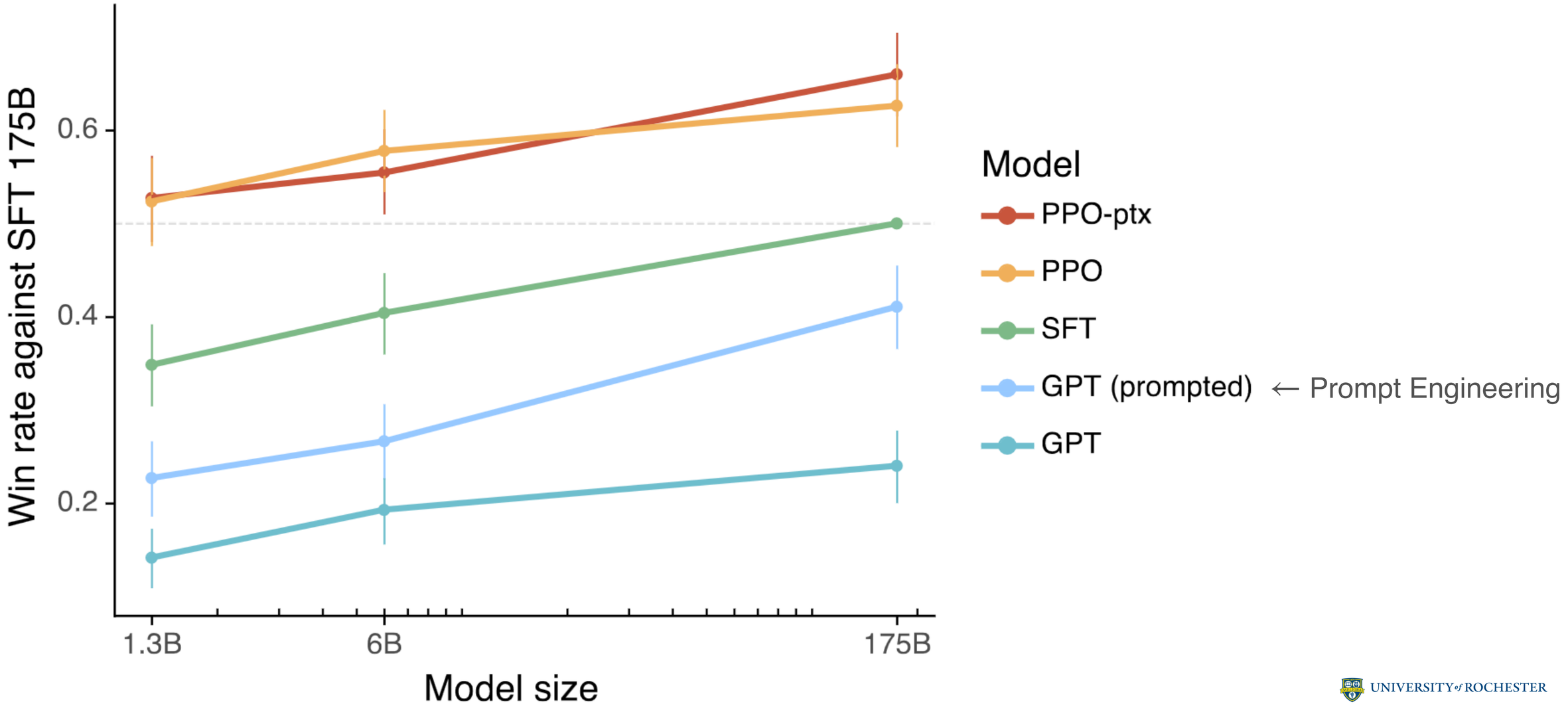
RLHF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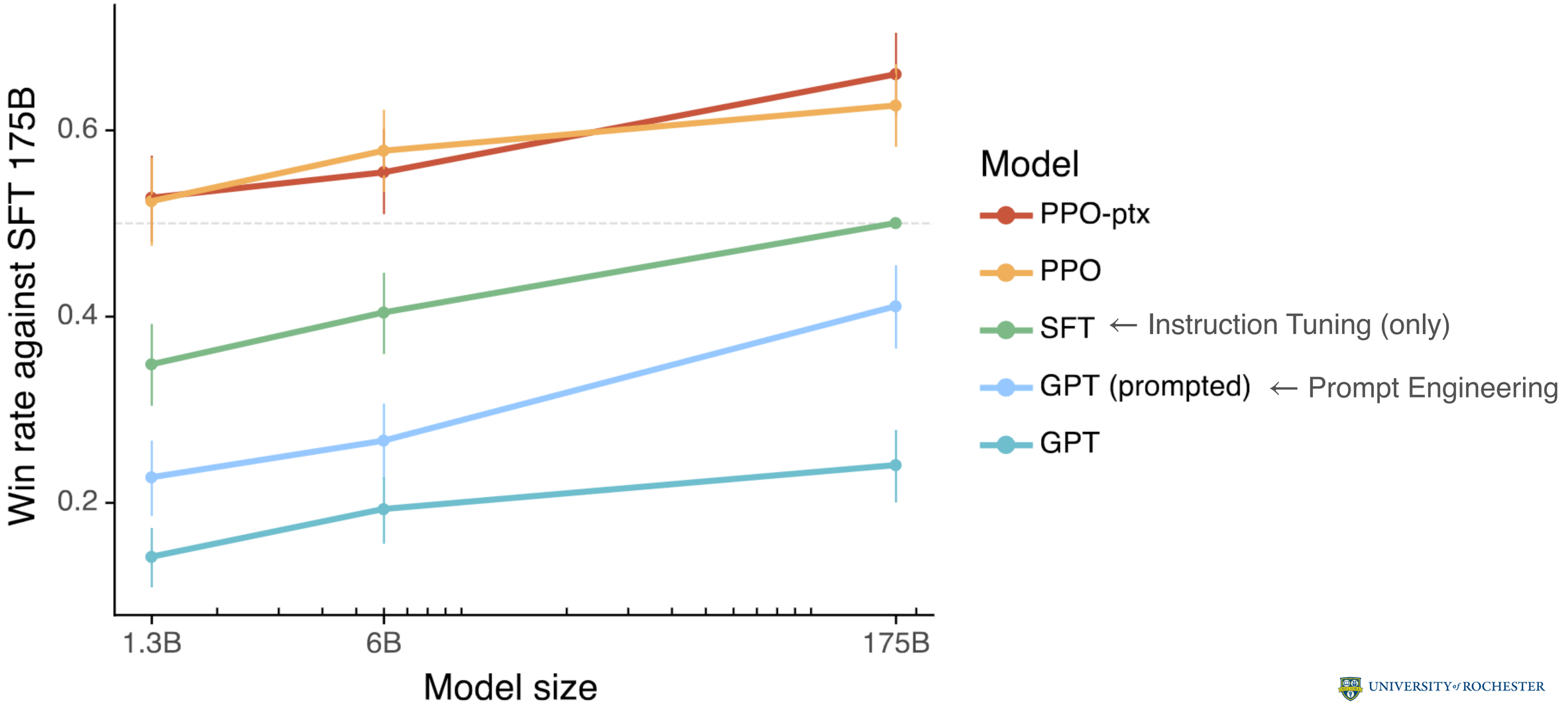
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Model size
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GPT (prompted) ← Prompt Engineering
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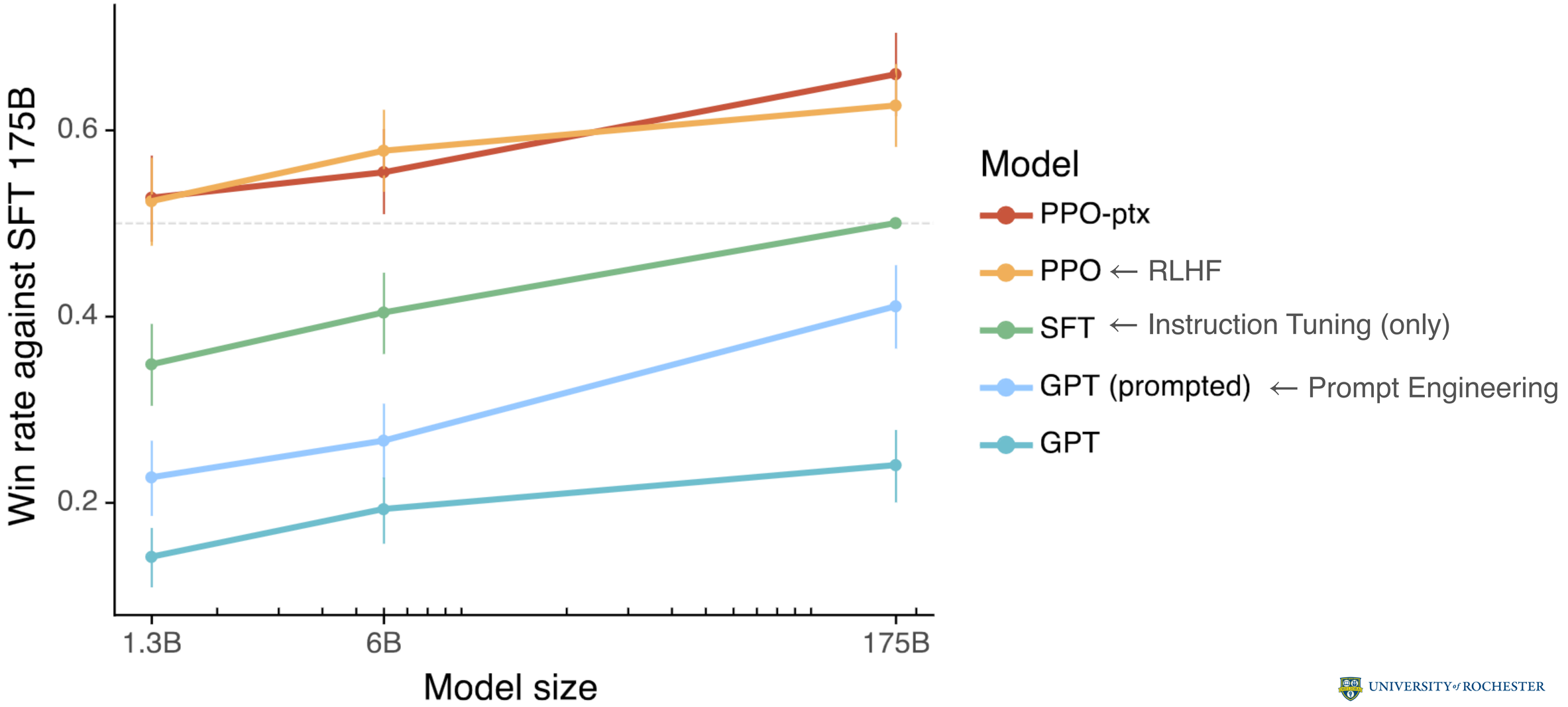
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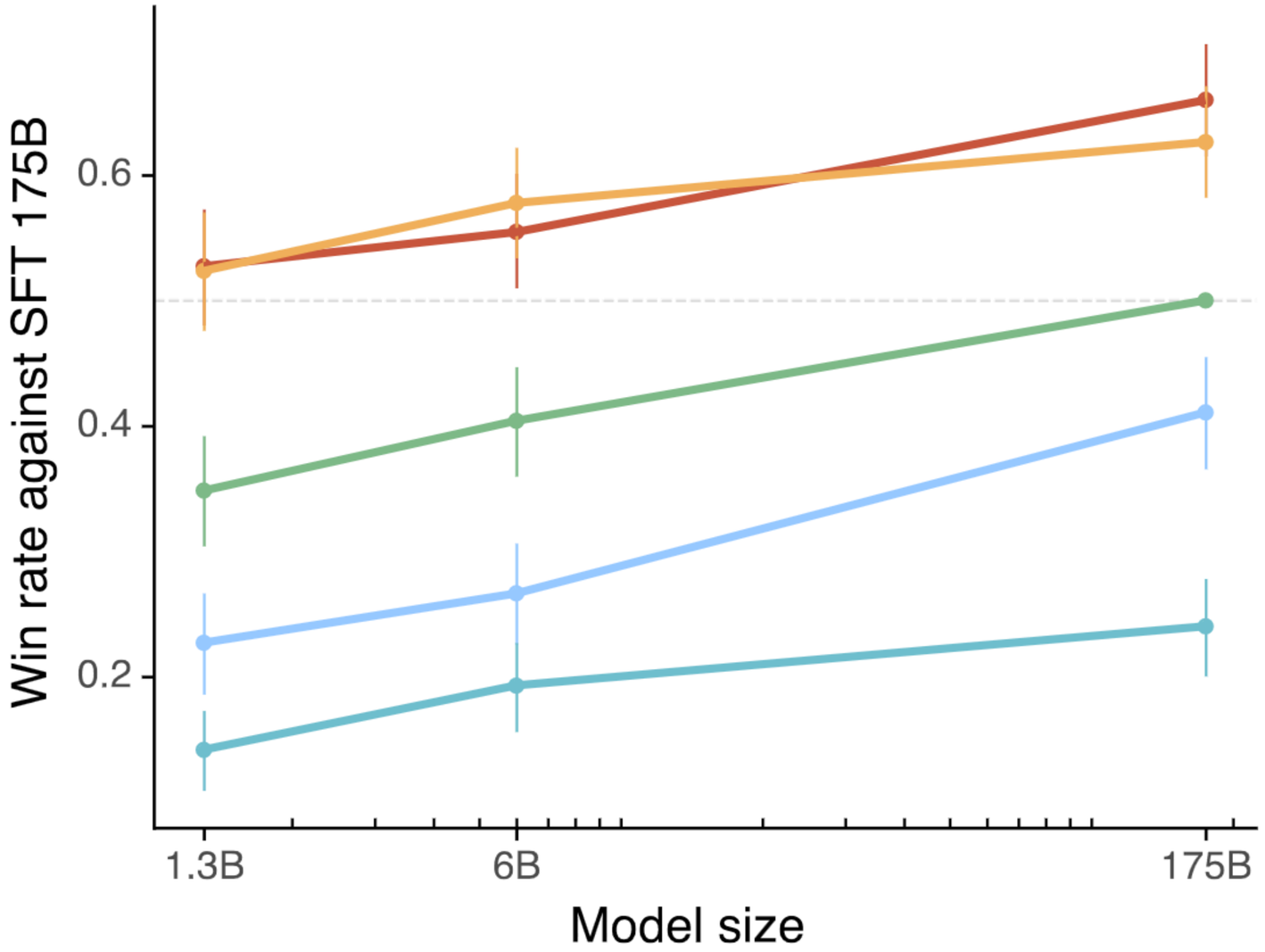
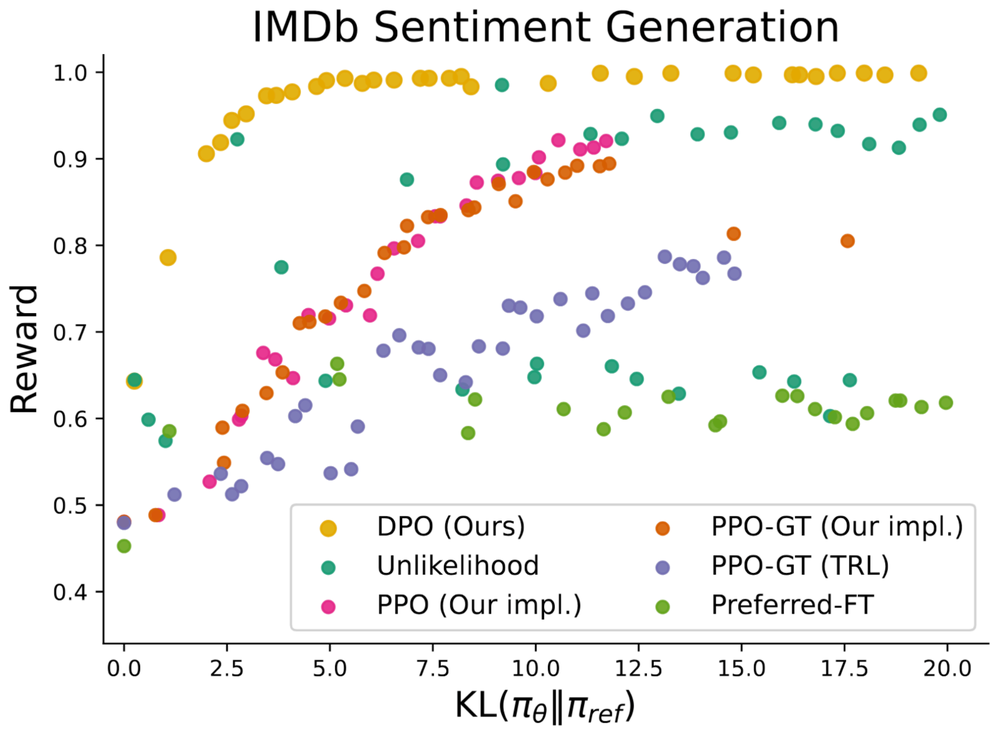


Model

- PPO-ptx ← RLHF w/ cont. language modeling
- PPO ← RLHF
- SFT ← Instruction Tuning (only)
- GPT (prompted) ← Prompt Engineering
- GPT

Problems with RLHF

- Reinforcement Learning is known to be **hard to train**
- Involves training an **entirely separate reward model**
- Can **degrade LM performance**
- Finicky tuning of **hyper-parameters**



DPO

Direct Preference Optimization: Your Language Model is Secretly a Reward Model

Rafael Rafailov[*†] **Archit Sharma**[*†] **Eric Mitchell**[*†]

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Abstract

While large-scale unsupervised language models (LMs) learn broad world knowledge and some reasoning skills, achieving precise control of their behavior is difficult due to the completely unsupervised nature of their training. Existing methods for gaining such steerability collect human labels of the relative quality of model generations and fine-tune the unsupervised LM to align with these preferences, often with reinforcement learning from human feedback (RLHF). However, RLHF is a complex and often unstable procedure, first fitting a reward model that reflects the human preferences, and then fine-tuning the large unsupervised LM using reinforcement learning to maximize this estimated reward without drifting too far from the original model. In this paper we introduce a new parameterization of the reward model in RLHF that enables extraction of the corresponding optimal policy in closed form, allowing us to solve the standard RLHF problem with only a simple classification loss. The resulting algorithm, which we call *Direct Preference Optimization* (DPO), is stable, performant, and computationally lightweight, eliminating the need for sampling from the LM during fine-tuning or performing significant hyperparameter tuning. Our experiments show that DPO can fine-tune LMs to align with human preferences as well as or better than existing methods. Notably, fine-tuning with DPO exceeds PPO-based RLHF in ability to control sentiment of generations, and matches or improves response quality in summarization and single-turn dialogue while being substantially simpler to implement and train.

DPO

- **Direct Policy Optimization**: incorporate benefits of RL **without** a separate reward model

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- **Direct Policy Optimization**: incorporate benefits of RL **without** a separate reward model
- Clever algebra used to rearrange RL equation
  - Reward function can be framed as a **function of the LLM itself**

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- **Direct Policy Optimization**: incorporate benefits of RL **without** a separate reward model
- Clever algebra used to rearrange RL equation
  - Reward function can be framed as a **function of the LLM itself**
- **Very widely used** as the algorithm for RLHF today

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Abstract

While large-scale unsupervised language models (LMs) learn broad world knowledge and some reasoning skills, achieving precise control of their behavior is difficult due to the completely unsupervised nature of their training. Existing methods for gaining such steerability collect human labels of the relative quality of model generations and fine-tune the unsupervised LM to align with these preferences, often with reinforcement learning from human feedback (RLHF). However, RLHF is a complex and often unstable procedure, first fitting a reward model that reflects the human preferences, and then fine-tuning the large unsupervised LM using reinforcement learning to maximize this estimated reward without drifting too far from the original model. In this paper we introduce a new parameterization of the reward model in RLHF that enables extraction of the corresponding optimal policy in closed form, allowing us to solve the standard RLHF problem with only a simple classification loss. The resulting algorithm, which we call *Direct Preference Optimization* (DPO), is stable, performant, and computationally lightweight, eliminating the need for sampling from the LM during fine-tuning or performing significant hyperparameter tuning. Our experiments show that DPO can fine-tune LMs to align with human preferences as well as or better than existing methods. Notably, fine-tuning with DPO exceeds PPO-based RLHF in ability to control sentiment of generations, and matches or improves response quality in summarization and single-turn dialogue while being substantially simpler to implement and train.

DPO

$$\max_{\theta} r(x, y) - \beta \mathbb{D}_{KL}[\pi_\theta(y \mid x) \| \pi_{ref}(y \mid x)]$$

DPO

standard RLHF objective

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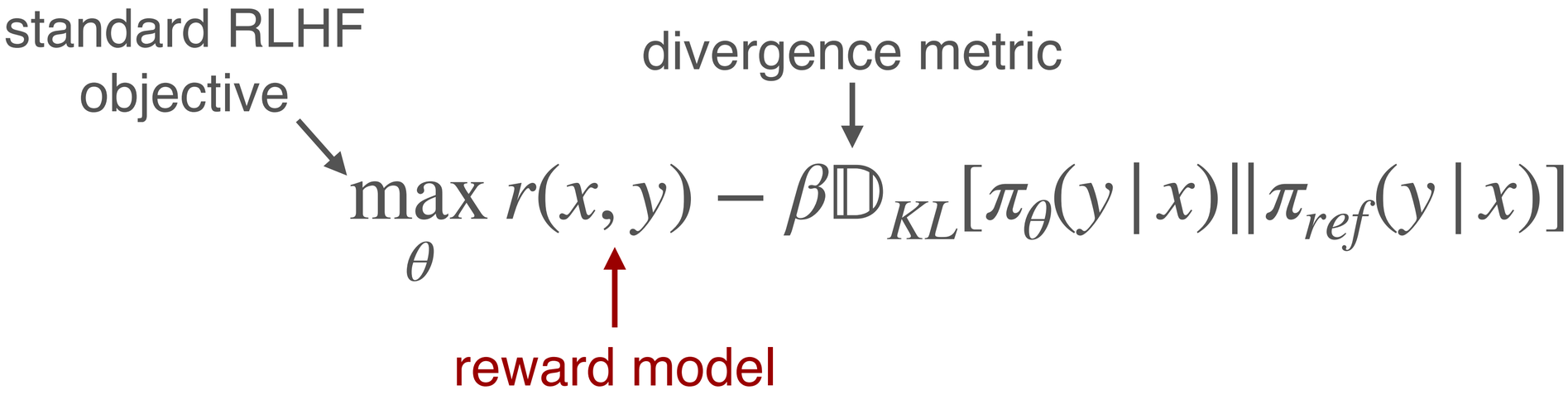
reward model

DPO


standard RLHF objective
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reward model

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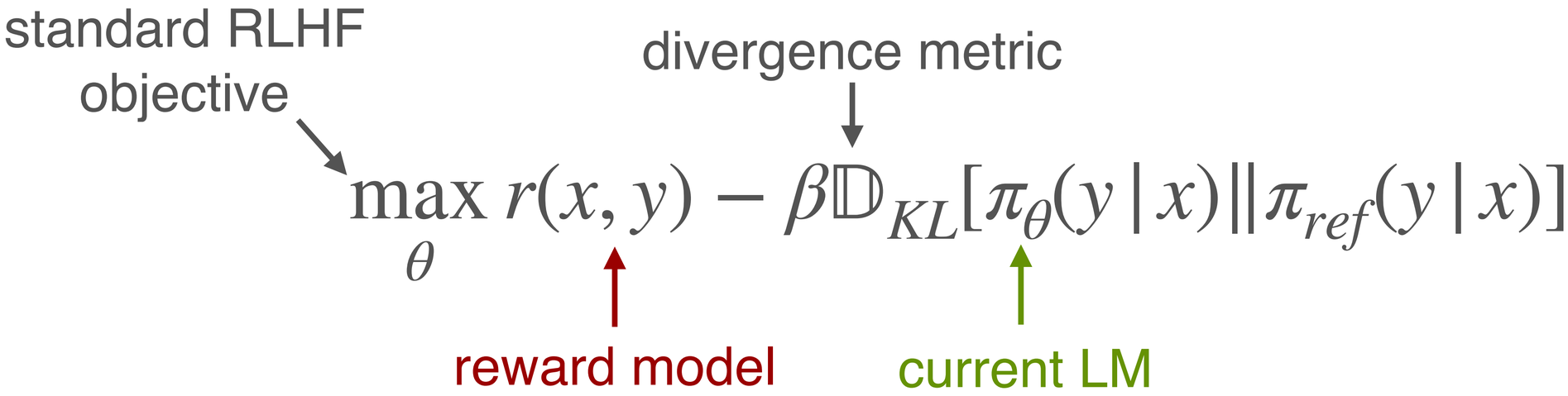
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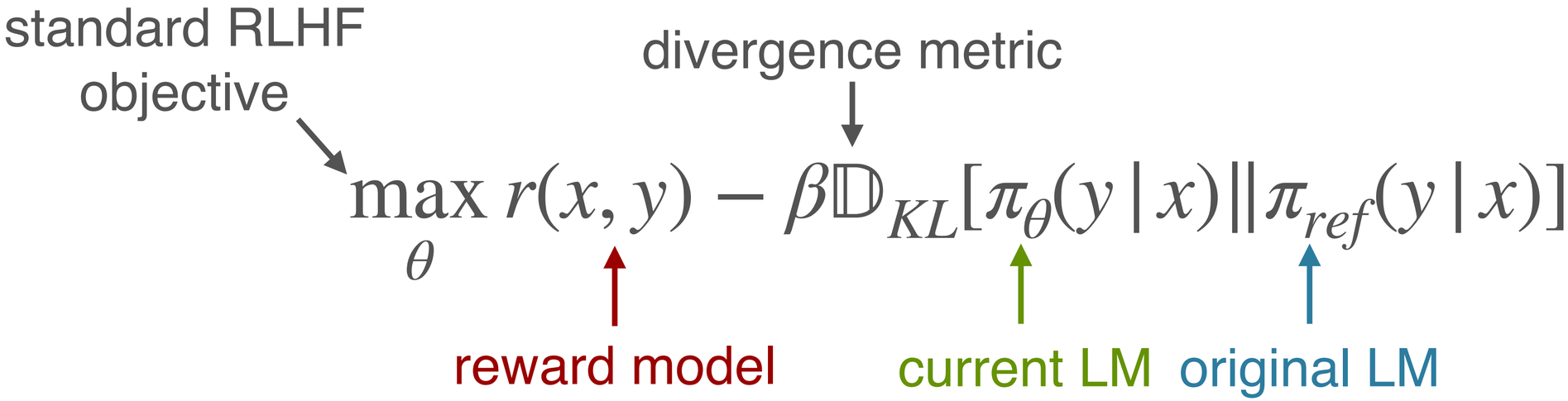
reward model
current LM

DPO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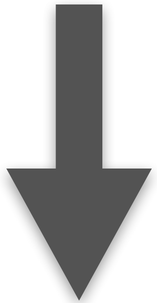

some algebra…

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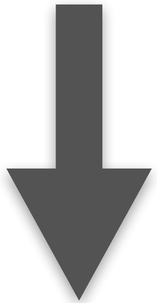

some algebra…

$$r^*(x, y) = \beta \log \frac{\pi_\theta(y \mid x)}{\pi_{ref}(y \mid x)} + \beta \log Z(x)$$

DPO

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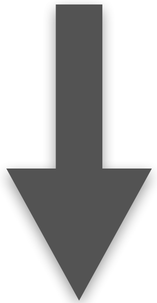

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optimal
reward model

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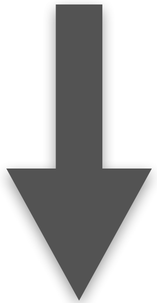

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optimal reward model

a constant

DPO

DPO

- Re-factored reward function plugged back into **preference ranking equation**
  - Z term cancels out
  - y_w is the **preferred completion**, y_l is dis-preferred

$$r^*(x, y) = \beta \log \frac{\pi_\theta(y \mid x)}{\pi_{ref}(y \mid x)} + \beta \log Z(x)$$

$$\mathscr{L}_{DPO}(\pi_\theta; \pi_{ref}) = -\log \sigma \left(\beta \log \frac{\pi_\theta(y_w \mid x)}{\pi_{ref}(y_w \mid x)} - \beta \log \frac{\pi_\theta(y_l \mid x)}{\pi_{ref}(y_l \mid x)} \right)$$

DPO

- Re-factored reward function plugged back into **preference ranking equation**
  - Z term cancels out
  - y_w is the **preferred completion**, y_l is dis-preferred
- Essentially, make sure the **probability** assigned to the **preferred completion** is **higher**
  - (This is a simplification)

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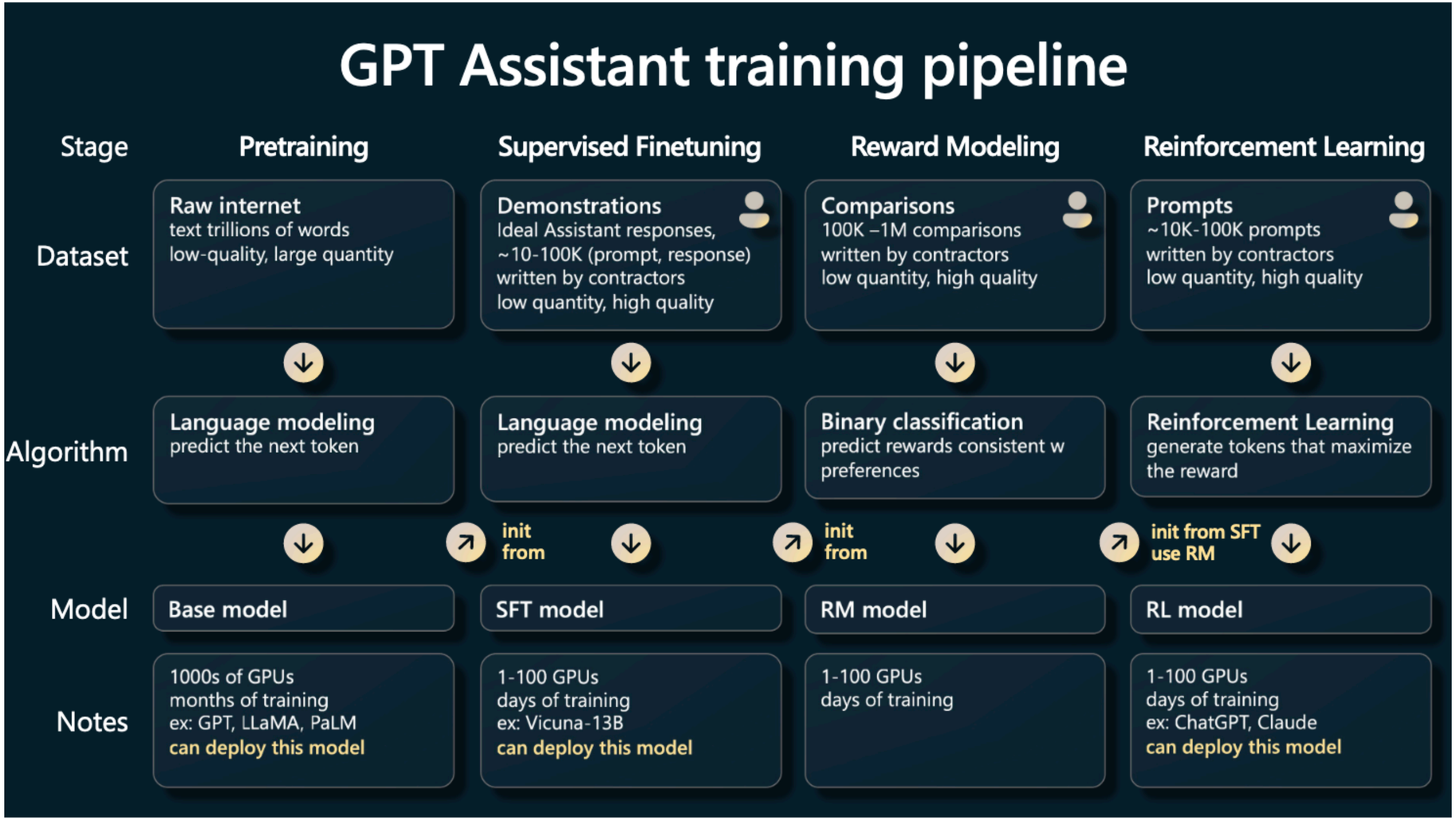
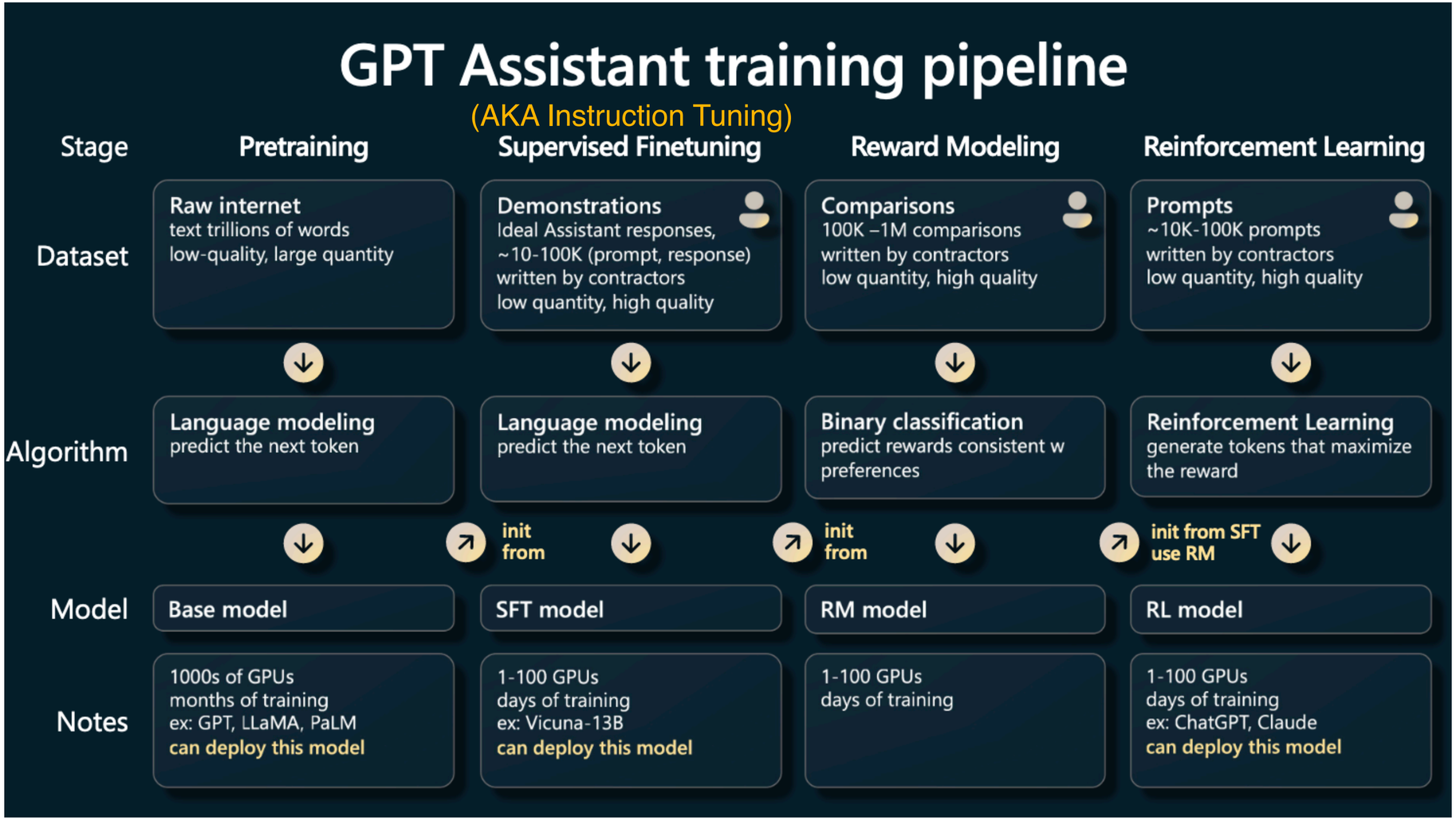
LLM training overview



LLM training overview



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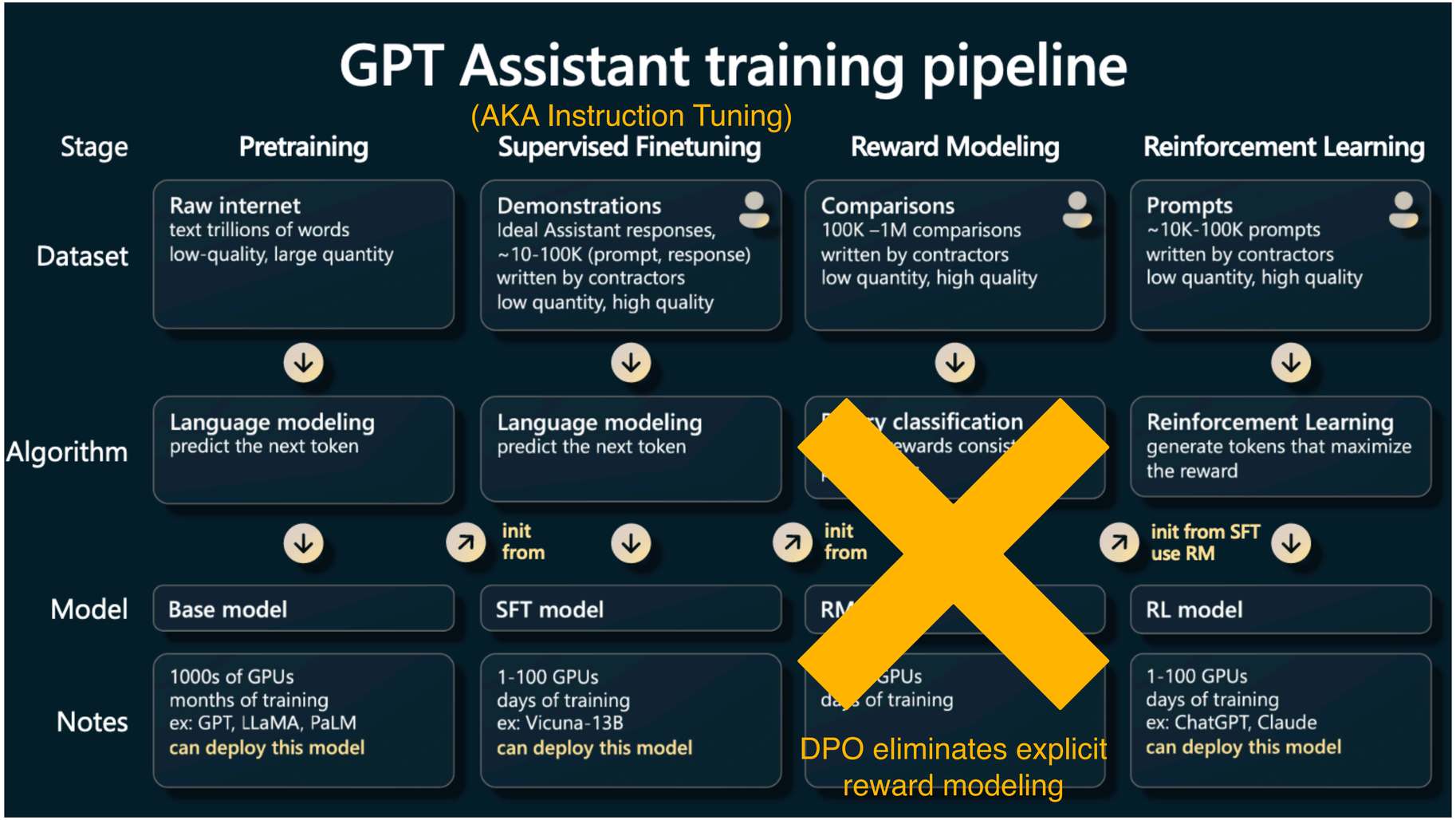

LLM continuous training

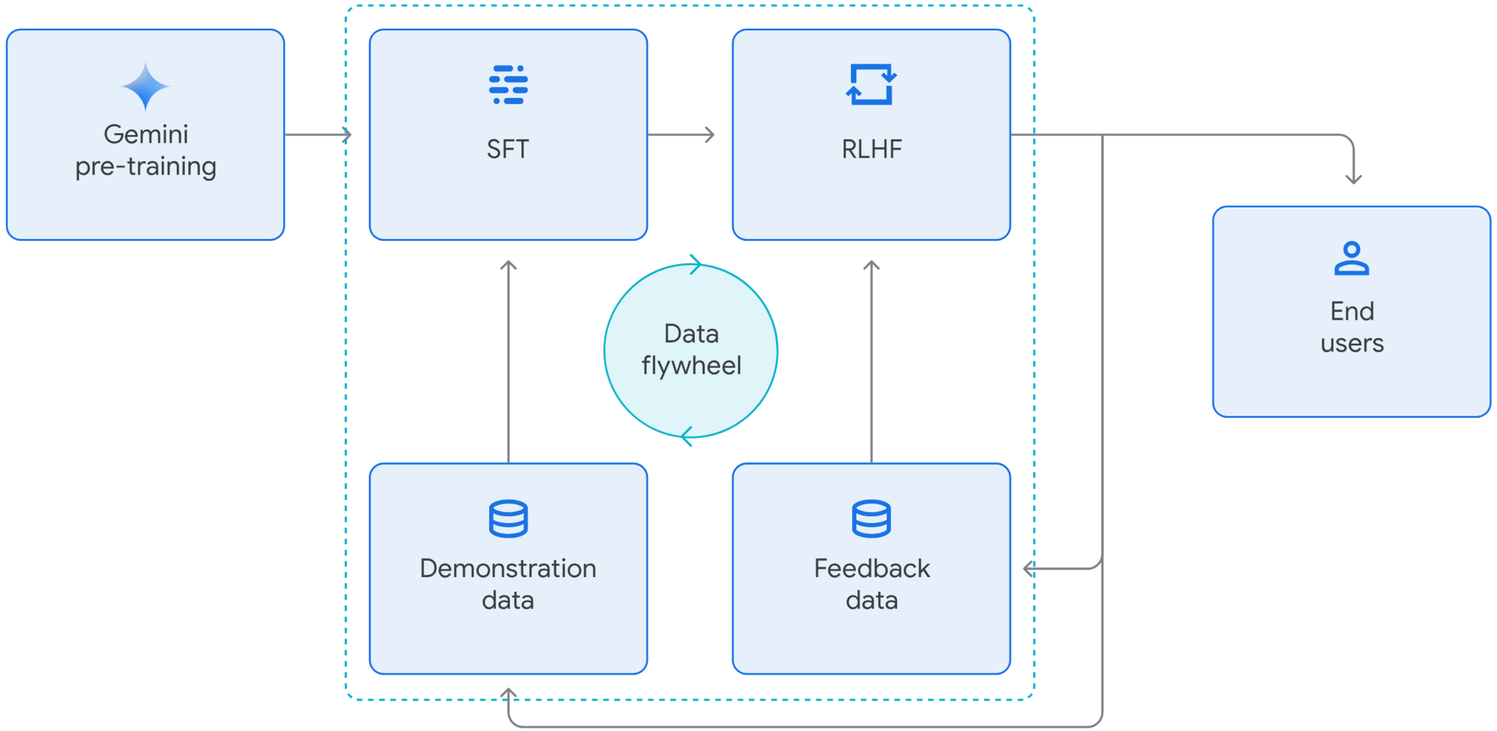

Figure 7 | **Modeling overview.** Post-training utilizes an optimized data flywheel in order to acquire human-AI feedback and continually improve on key areas. The data mixtures for supervised fine-tuning, reward modeling, and reinforcement learning serve as the foundation for our models.

from the Gemini paper

Rise of LLM trade secrets

2. Model Architecture

Gemini models build on top of Transformer decoders (Vaswani et al., 2017b) that are enhanced with improvements in architecture and model optimization to enable stable training at scale and optimized inference on Google's Tensor Processing Units. They are trained to support 32k context length, employing efficient attention mechanisms (for e.g. multi-query attention (Shazeer, 2019a)). Our first version, Gemini 1.0, comprises three main sizes to support a wide range of applications as discussed in Table 1.

Model size	Model description
Ultra	Our most capable model that delivers state-of-the-art performance across a wide range of highly complex tasks, including reasoning and multimodal tasks. It is efficiently serveable at scale on TPU accelerators due to the Gemini architecture.
Pro	A performance-optimized model in terms of cost as well as latency that delivers significant performance across a wide range of tasks. This model exhibits strong reasoning performance and broad multimodal capabilities.
Nano	Our most efficient model, designed to run on-device. We trained two versions of Nano, with 1.8B (Nano-1) and 3.25B (Nano-2) parameters, targeting low and high memory devices respectively. It is trained by distilling from larger Gemini models. It is 4-bit quantized for deployment and provides best-in-class performance.

Table 1 | An overview of the Gemini 1.0 model family.

Training the Gemini family of models required innovations in training algorithms, dataset, and infrastructure. For the Pro model, the inherent scalability of our infrastructure and learning algorithms enable us to complete pre-training in a matter of weeks, leveraging a fraction of the Ultra's resources. The Nano series of models leverage additional advancements in distillation and training algorithms to produce the best-in-class small language models for a wide variety of tasks, such as summarization and reading comprehension, which power our next generation on-device experiences.

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- We know these are "built on Transformer decoders", but little else!
- **Parameter count** especially has become a trade secret
- Algorithmic innovations are **hinted at** but **not disclosed**
  - "Improvements in architecture"
  - "Innovations in training algorithms"
  - "Advancements in distillation"

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  - Caveat: like the space race, advancements will likely eventually **“trickle down”**

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- Not all bad news: a number of **open LLMs** have been released
  - Examples: AI2's OLMo, Meta's Llama, Mistral

Note on terminology

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- My impression on **what NLP practitioners mean** when they say “LLM”:
  - **Large** (roughly >1B parameters)
  - **Generative** (decoder-based)
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  - Strong **in-context / zero-shot** abilities
- Historically might also refer to models like **GPT-3** or even BERT!
  - The term has evolved, and people use it differently