COS 484

Natural Language Processing

L18: Large Language Models: post-training (cont'd)

Spring 2025

Lecture plan

- **Post-training (cont’d)**
- **LLM agents** - guest lecture: Alexander Wettig

Recap: InstructGPT

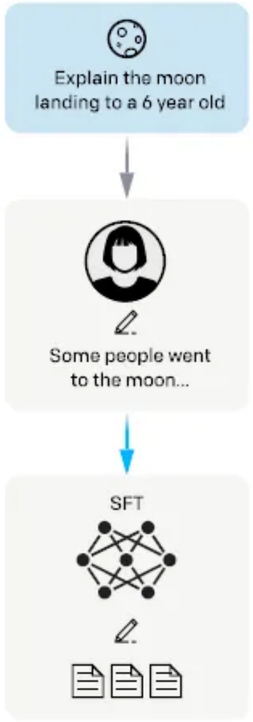
Step 1

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.



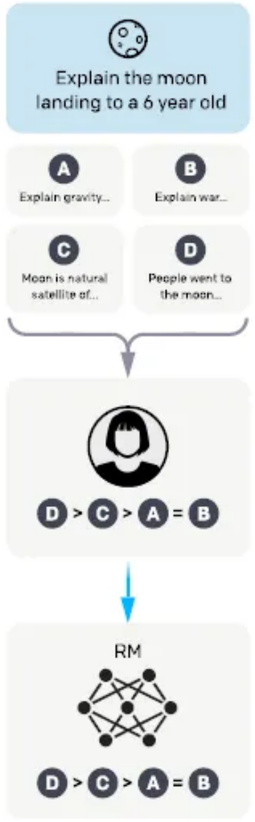
Step 2

Collect comparison data, and train a reward model.

A prompt and several model outputs are sampled.

A labeler ranks the outputs from best to worst.

This data is used to train our reward model.



Step 3

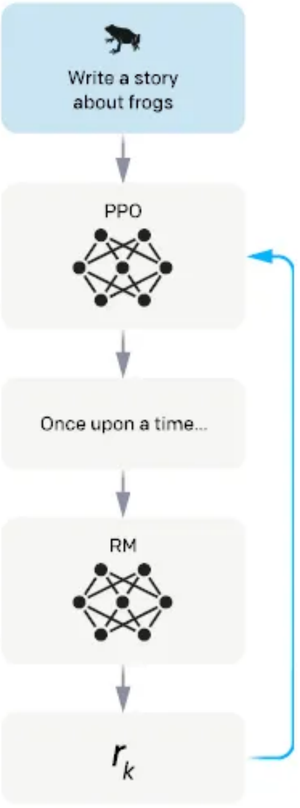
Optimize a policy against the reward model using reinforcement learning.

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.



Recap: InstructGPT

- **Step 1: supervised fine-tuning (SFT) or instruction tuning**

  13k prompts, completions are written by human labelers

  Instruction data (prompt, response): (x, y)

$$-\sum_{i=1}^{|y|} \log P(y_i \mid y_{<i}, x)$$

- **Step 2**: reward modeling (RM)

  33k prompts, K (4-9) completions sampled, human labelers provide a ranking

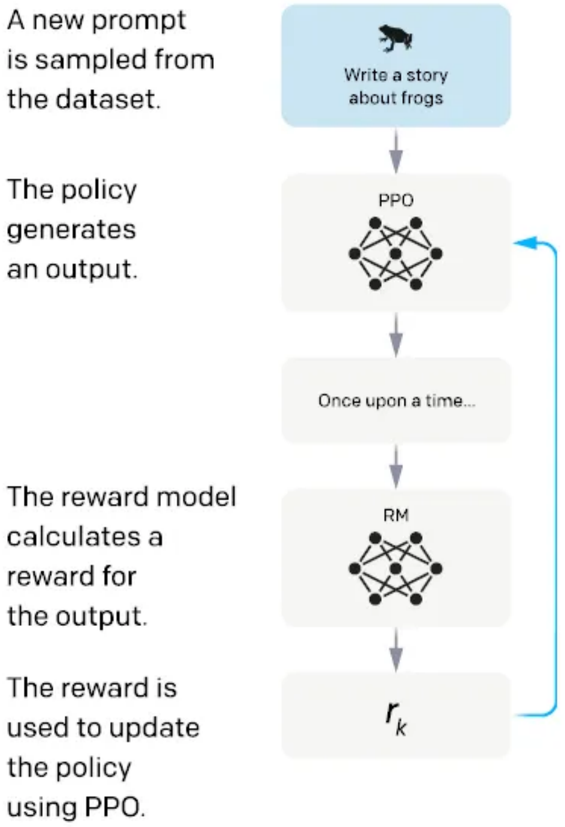
  Human preference data (prompt, winning response, losing response): (x, y_w, y_l)

$$\text{loss}(\theta) = -\frac{1}{\binom{K}{2}} E_{(x,y_w,y_l)\sim D} \left[\log\left(\sigma\left(r_\theta\left(x, y_w\right) - r_\theta\left(x, y_l\right)\right)\right)\right]$$

The RM is only 6B parameters: $R : (x, y) \rightarrow \mathbb{R}$

Recap: InstructGPT

- **Step 3:** reinforcement learning (RL)
  - **Key idea:** fine-tuning supervised policy to optimize reward (output of the RM) using PPO

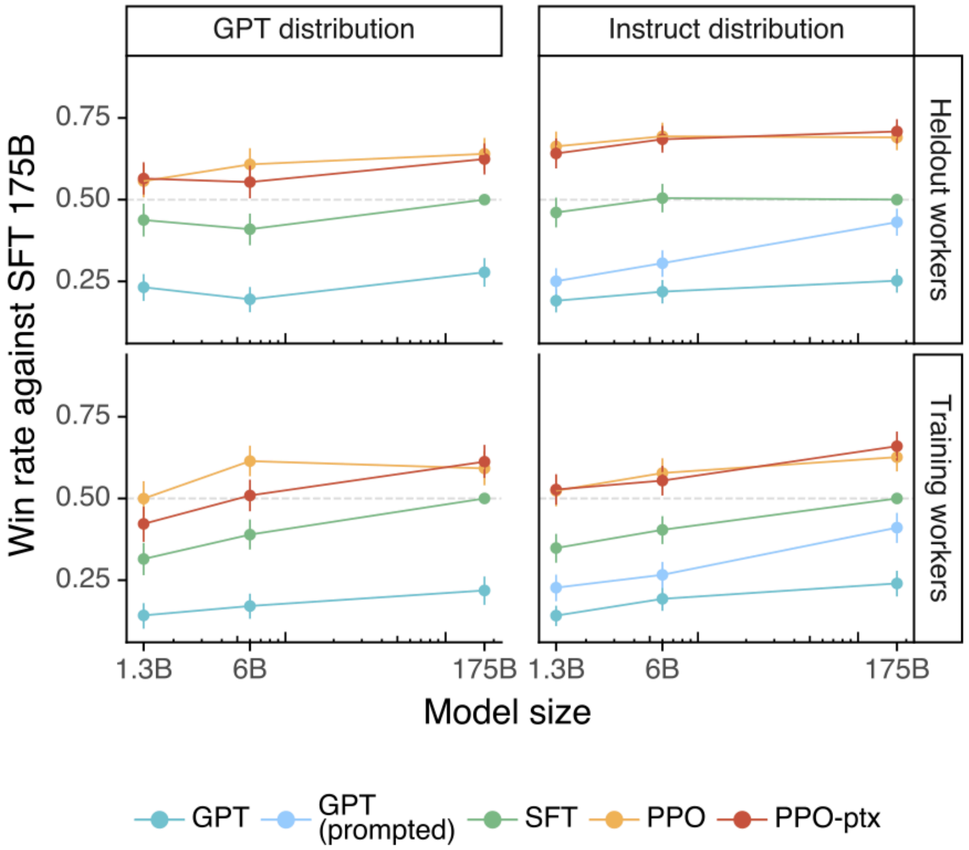


31k prompts, no human annotations involved

$$\text{objective}\,(\phi) = E_{(x,y)\sim D_{\pi_\phi^{\text{RL}}}}\left[r_\theta(x,y)\right]$$

Reminder: the goal is to build a general-purpose chat model that is aligned with human intents! (3 Hs)

Research questions



- Can we replace **human annotations** by model annotations?
- How important is **SFT**? How important is **RL**?
- Is **preference data** the key, or the **RL algorithm**? Is the architecture/size of RM important?
- How to **evaluate** these general-purpose chat models?

Reinforcement learning from AI Feedback (RLAIF)

RLAIF: first introduced by Bai et al. 2022 “Constitutional AI”

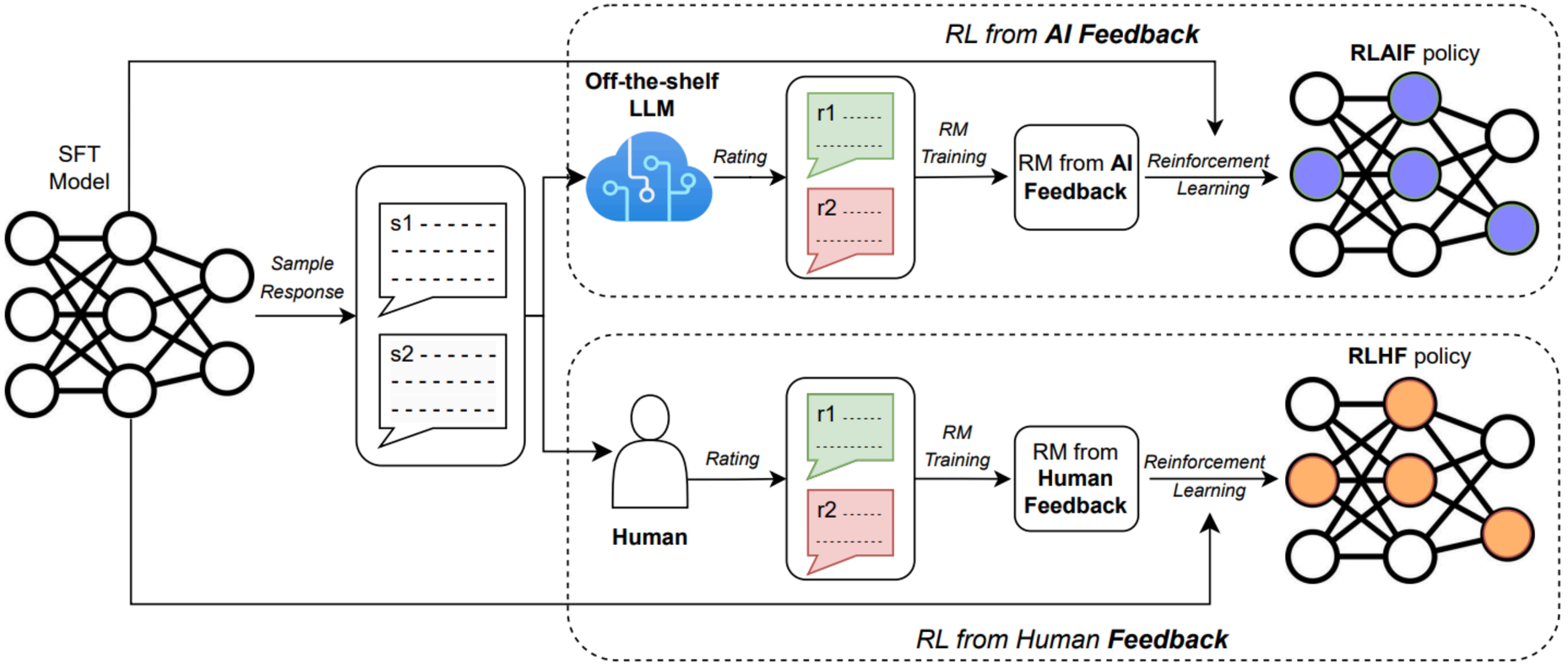
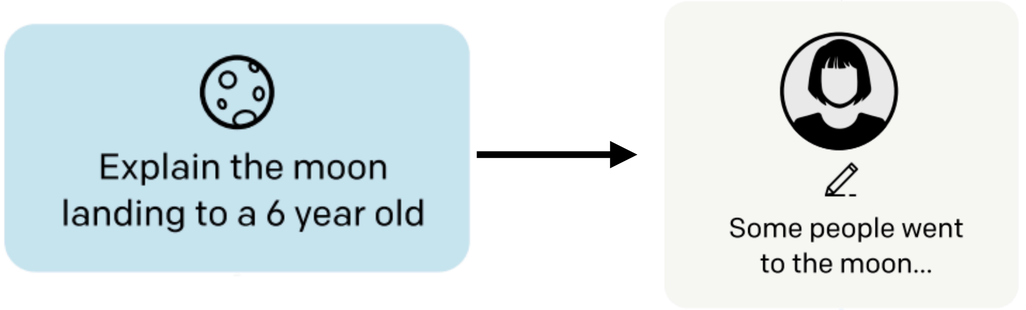


Figure: (Lee et al., 2024)

Supervised fine-tuning (SFT): open research efforts

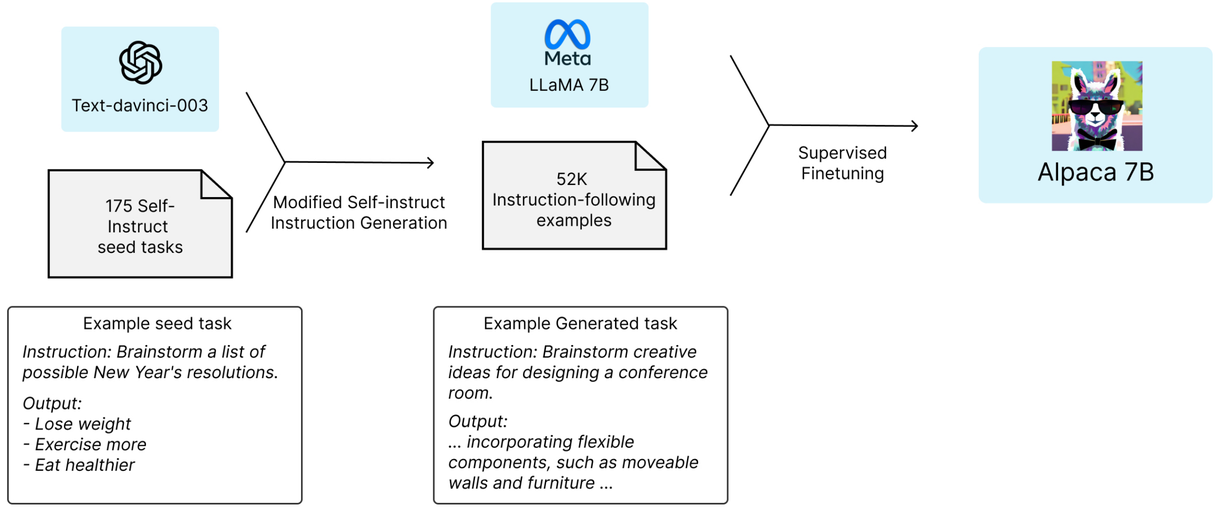
- **Data**: (**prompt**, **response**)
- **Learning**: next-token prediction



Research questions:

- How to collect **prompts**?
- How to collect **responses**? Do responses include chain-of-thought?
- How to ***combine*** *and* ***select*** these datasets for instruction tuning?

Stanford Alpaca

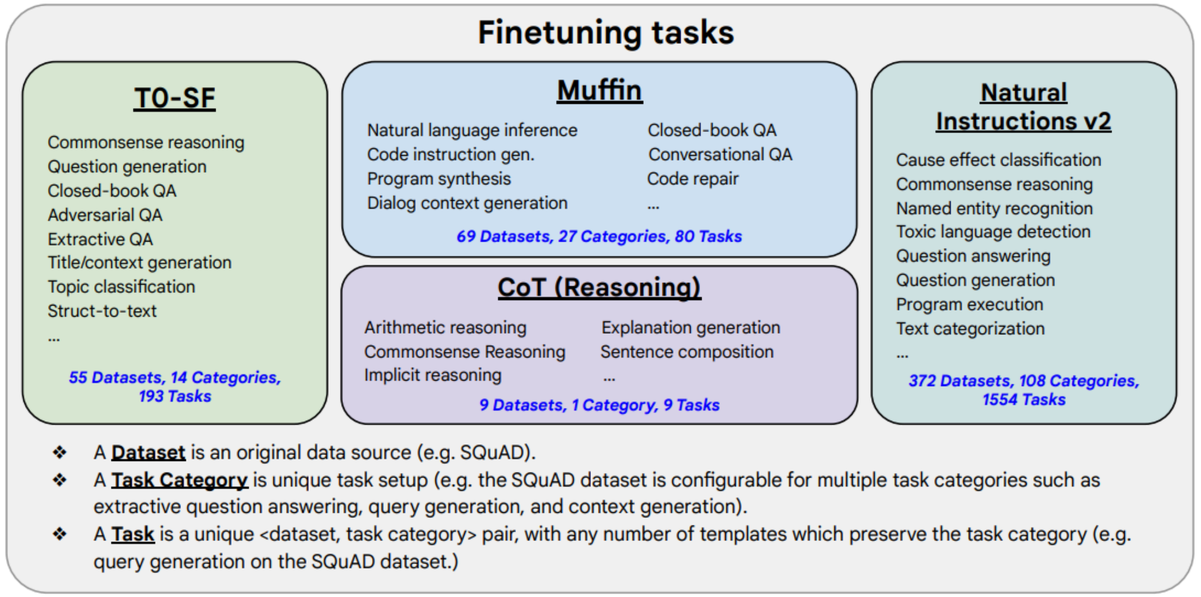


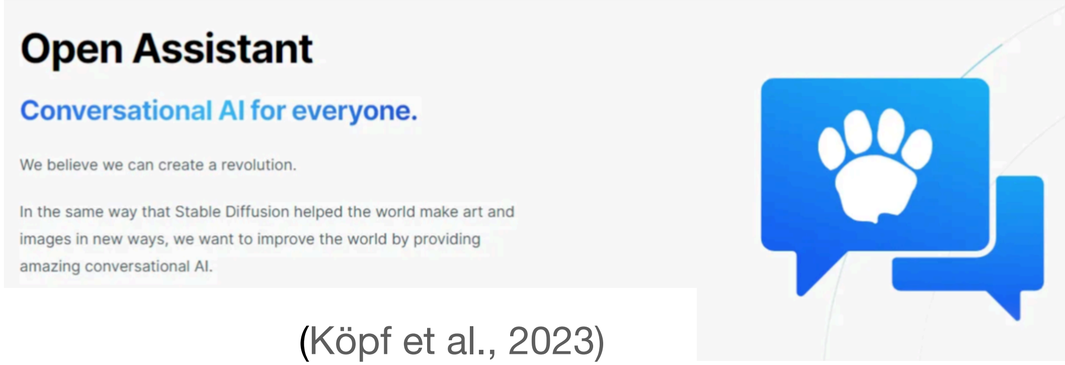
- 52K Prompts are model-generated (Self-Instruct)
- Responses are distilled from OpenAI's text-davinci-003

- 70K user-shared ChatGPT conversations
- Responses are from ChatGPT

Other SFT datasets

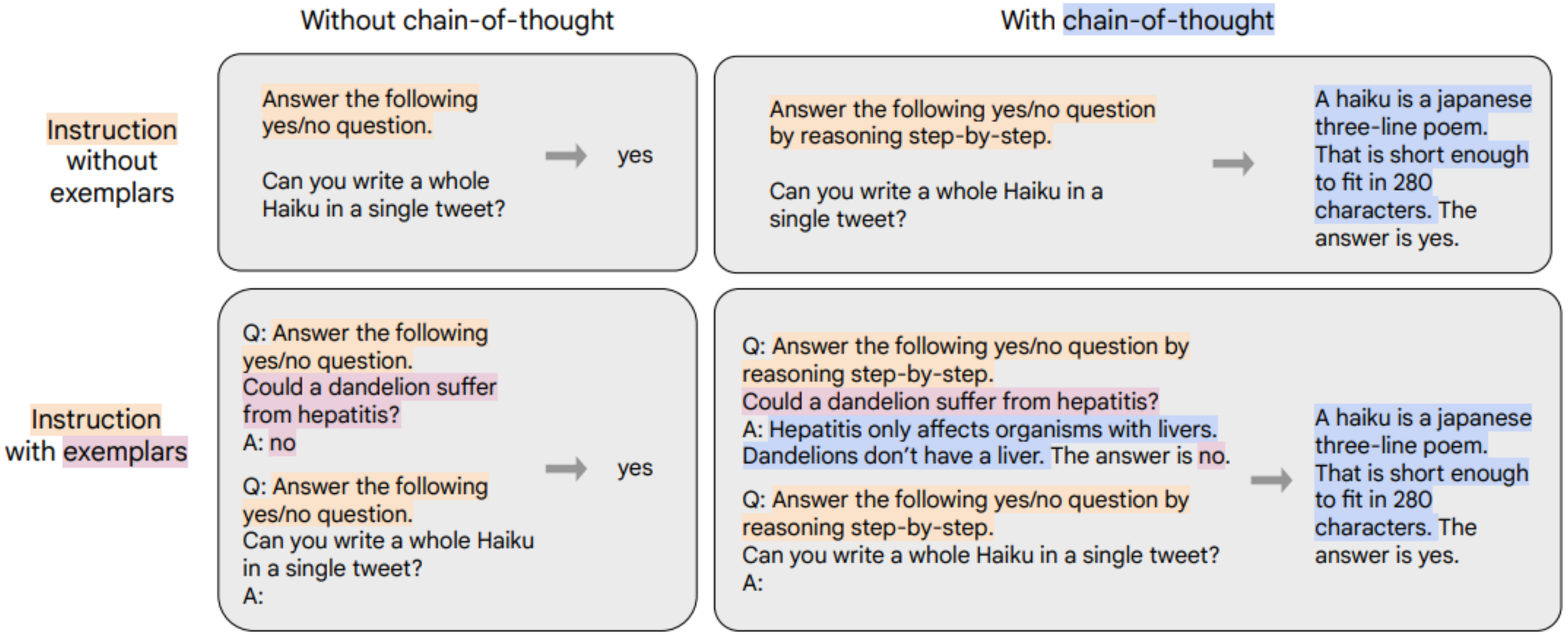
- **Repurposed from existing datasets** (w/ human-written instructions and CoT)
  - Examples: Super-NaturalInstructions, Flan V2
- **Human-written from scratch**
  - Examples: Dolly, Open Assistant





(Köpf et al., 2023)

Instruction tuning with exemplars and CoT



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

LIMA: superficial alignment hypothesis

LIMA: Less Is More for Alignment

Source	#Examples	Avg Input Len.	Avg Output Len.
Training			
Stack Exchange (STEM)	200	117	523
Stack Exchange (Other)	200	119	530
wikiHow	200	12	1,811
Pushshift r/WritingPrompts	150	34	274
Natural Instructions	50	236	92
Paper Authors (Group A)	200	40	334

1000 manually-selected examples work great!

Superficial Alignment Hypothesis: Knowledge is learned during pre-training; instruction tuning teaches models which subdistribution of formats to use

Zhou et al., 2023, LIMA: Less Is More for Alignment

An explosion of SFT datasets: "How Far Can Camels Go?"

	MMLU (factuality)	GSM (reasoning)	BBH (reasoning)	TydiQA (multilinguality)	Codex-Eval (coding)	AlpacaEval (open-ended)	Average
	EM (0-shot)	EM (8-shot, CoT)	EM (3-shot, CoT)	F1 (1-shot, GP)	P@10 (0-shot)	Win % vs Davinci-003	
Vanilla LLaMa 13B	42.3	14.5	39.3	43.2	28.6	-	-
+SuperNI	49.7	4.0	4.5	**50.2**	12.9	4.2	20.9
+CoT	44.2	40.0	41.9	47.8	23.7	6.0	33.9
+Flan V2	**50.6**	20.0	40.8	47.2	16.8	3.2	29.8
+Dolly	45.6	18.0	28.4	46.5	31.0	13.7	30.5
+Open Assistant 1	43.3	15.0	39.6	33.4	31.9	58.1	36.9
+Self-instruct	30.4	11.0	30.7	41.3	12.5	5.0	21.8
+Unnatural Instructions	46.4	8.0	33.7	40.9	23.9	8.4	26.9
+Alpaca	45.0	9.5	36.6	31.1	29.9	21.9	29.0
+Code-Alpaca	42.5	13.5	35.6	38.9	34.2	15.8	30.1
+GPT4-Alpaca	46.9	16.5	38.8	23.5	**36.6**	63.1	37.6
+Baize	43.7	10.0	38.7	33.6	28.7	21.9	29.4
+ShareGPT	49.3	27.0	40.4	30.5	34.1	**70.5**	42.0
+Human data mix.	50.2	38.5	39.6	47.0	25.0	35.0	39.2
+Human+GPT data mix.	49.3	**40.5**	**43.3**	45.6	35.9	56.5	**45.2**

Wang et al., 20223, How Far Can Camels Go? Exploring the State of Instruction Tuning on Open Resources

Data mixture of instruction tuning

TÜLU v2

- **FLAN** [Chung et al., 2022]: We use 50,000 examples sampled from FLAN v2.
- **CoT**: To emphasize chain-of-thought (CoT) reasoning, we sample another 50,000 examples from the CoT subset of the FLAN v2 mixture.
- **Open Assistant 1** [Köpf et al., 2023]: We isolate the highest-scoring paths in each conversation tree and use these samples, resulting in 7,708 examples. Scores are taken from the quality labels provided by the original annotators of Open Assistant 1.
- **ShareGPT**[2]: We use all 114,046 examples from our processed ShareGPT dataset, as we found including the ShareGPT dataset resulted in strong performance in prior work.
- **GPT4-Alpaca** [Peng et al., 2023]: We sample 20,000 samples from GPT-4 Alpaca to further include distilled GPT-4 data.
- **Code-Alpaca** [Chaudhary, 2023]: We use all 20,022 examples from Code Alpaca, following our prior V1 mixture, in order to improve model coding abilities.
- ***LIMA** [Zhou et al., 2023]: We use 1,030 examples from LIMA as a source of carefully curated data.
- ***WizardLM Evol-Instruct V2** [Xu et al., 2023]: We sample 30,000 examples from WizardLM, which contains distilled data of increasing diversity and complexity.
- ***Open-Orca** [Lian et al., 2023]: We sample 30,000 examples generated by GPT-4 from OpenOrca, a reproduction of Orca [Mukherjee et al., 2023], which augments FLAN data with additional model-generated explanations.
- ***Science literature**: We include 7,544 examples from a mixture of scientific document understanding tasks— including question answering, fact-checking, summarization, and information extraction. A breakdown of tasks is given in Appendix C.
- ***Hardcoded**: We include a collection of 140 samples using prompts such as 'Tell me about yourself' manually written by the authors, such that the model generates correct outputs given inquiries about its name or developers.

Size	Data	Average
		-
7B	ShareGPT	47.0
	V1 mix.	47.8
	V2 mix.	**54.2**
13B	V1 mix.	56.0
	V2 mix.	**60.8**
70B	V1 mix.	71.5
	V2 mix.	**72.4**

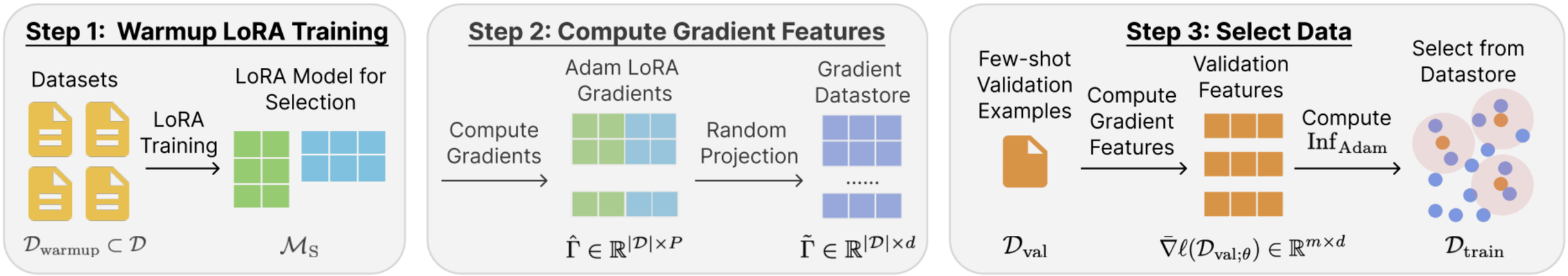
Ivison et al., 2023, Camels in a Changing Climate: Enhancing LM Adaptation with Tulu 2

How to select instruction tuning examples?

LESS: Selecting Influential Data for Targeted Instruction Tuning

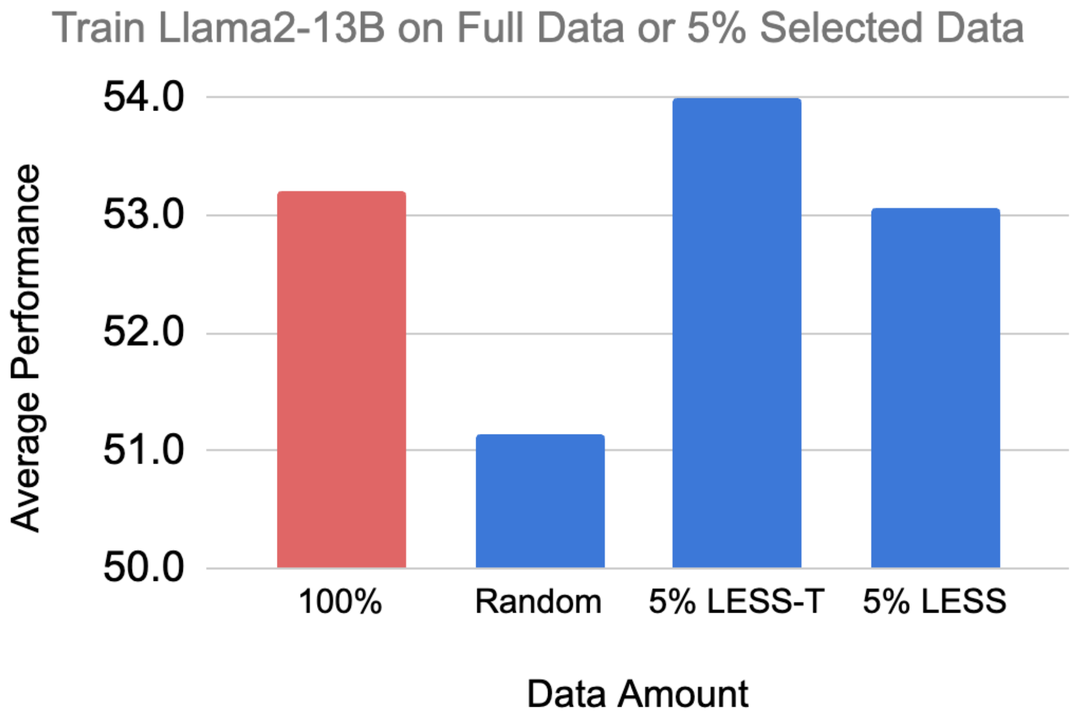
Mengzhou Xia [1 *] Sadhika Malladi [1 *] Suchin Gururangan [2] Sanjeev Arora [1] Danqi Chen [1]

- Key idea: use **influence formulation** to estimate how training examples influence models' predictions on target tasks and use it as proxy for data selection



Xia et al., 2024, LESS: Selecting Influential Data for Targeted Instruction Tuning

How to select instruction tuning examples?



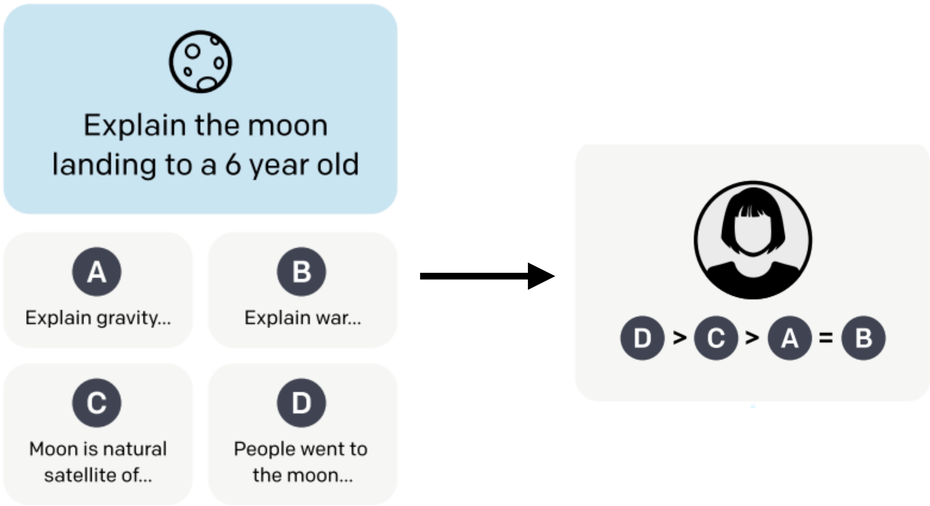
Less-T: “transfer” setting

Instruction tuning examples selected based on LLama-2-7B can be used to instruct fine-tune Mistral-7B and LLama-2-13B!

Xia et al., 2024, LESS: Selecting Influential Data for Targeted Instruction Tuning

Learning from preferences: open research efforts

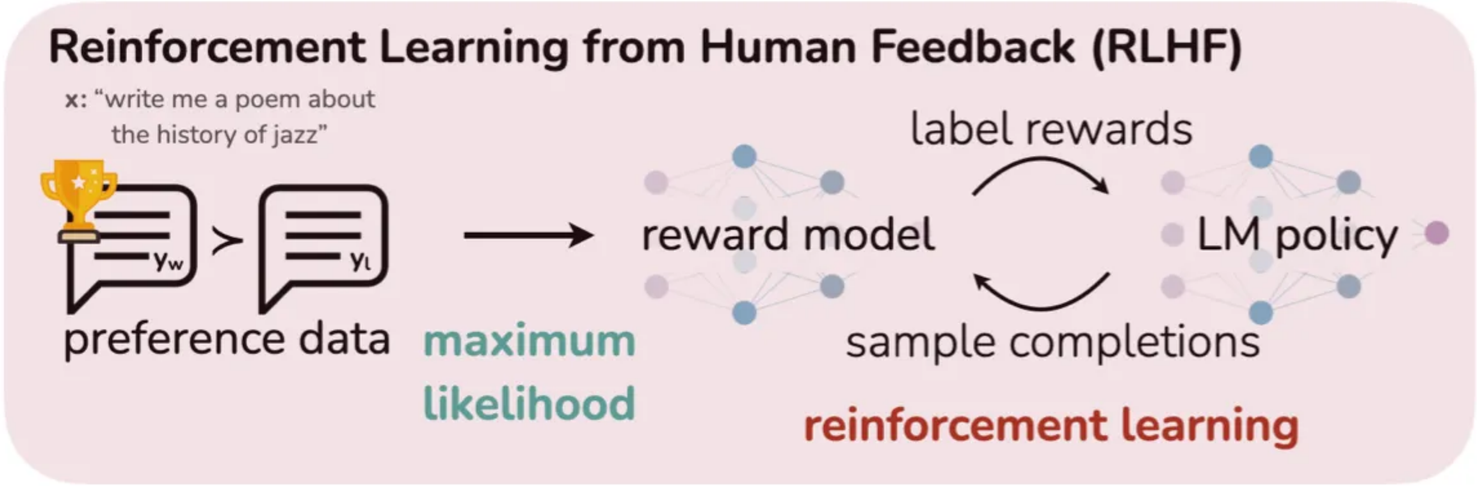
- **Data**: (**prompt**, **winning response**, **losing response**)
- **Learning:** RL (PPO) vs offline PO (DPO)



- How to get **prompts**?
- How to get **winning responses** and **losing responses**?
- How to train the reward model?
- Is RL really necessary?

Direct preference optimization (DPO)

Preference data: (**prompt**, **winning response**, **losing response**) $(x, y_w, y_l) \sim D$



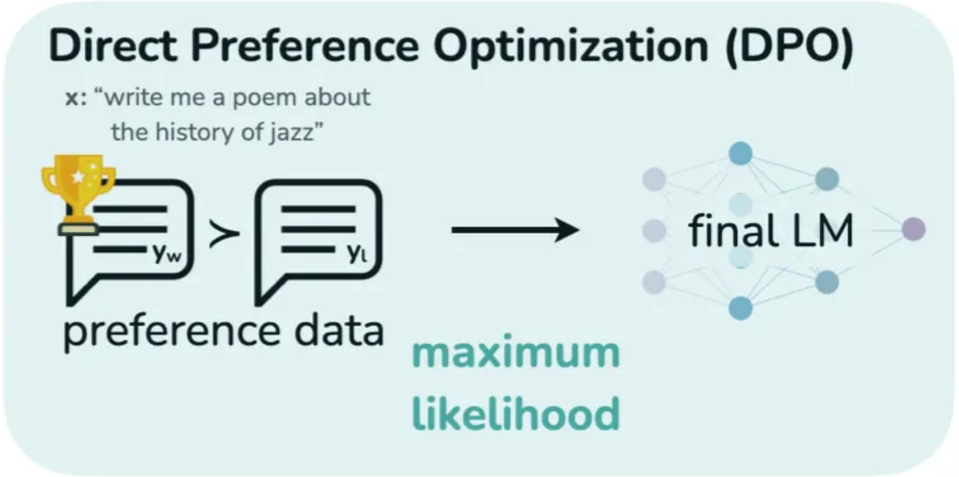
1. Optimize **reward model** over **preference data**
2. Optimize **policy model** according to the **reward model**

Next: Why not directly learn the **policy model** from **preference data**?

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

Direct preference optimization (DPO)

Preference data: (**prompt**, **winning response**, **losing response**) $(x, y_w, y_l) \sim D$



DPO objective:

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

π_{ref}: SFT model

(Reminder: we don't want the PPO model to drift away much from SFT in RLHF too)

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

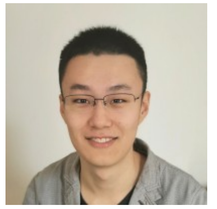
Wide use of DPO in open models

T	Model	Average	ARC	HellaSwag	MMLU	TruthfulQA	Winogrande	GSM8K
	udkai/Turdus	74.66	73.38	88.56	64.52	67.11	86.66	67.7
	fblgit/UNA-TheBeagle-7b-v1	73.87	73.04	88	63.48	69.85	82.16	66.72
	argilla/distilabeled-Marcoro14-7B-slerp	73.63	70.73	87.47	65.22	65.1	82.08	71.19
	mlabonne/NeuralMarcoro14-7B	73.57	71.42	87.59	64.84	65.64	81.22	70.74
	abideen/NexoNimbus-7B	73.5	70.82	87.86	64.69	62.43	84.85	70.36
	Neuronovo/neuronovo-7B-v0.2	73.44	73.04	88.32	65.15	71.02	80.66	62.47
	argilla/distilabeled-Marcoro14-7B-slerp-full	73.4	70.65	87.55	65.33	64.21	82	70.66
	CultriX/MistralTrix-v1	73.39	72.27	88.33	65.24	70.73	80.98	62.77
	ryandt/MusingCaterpillar	73.33	72.53	88.34	65.26	70.93	80.66	62.24
	Neuronovo/neuronovo-7B-v0.3	73.29	72.7	88.26	65.1	71.35	80.9	61.41
	CultriX/MistralTrixTest	73.17	72.53	88.4	65.22	70.77	81.37	60.73
	samir-fama/SamirGPT-v1	73.11	69.54	87.04	65.3	63.37	81.69	71.72
	SanjiWatsuki/Lelantos-DPO-7B	73.09	71.08	87.22	64	67.77	80.03	68.46

DPO
DPO (& UNA)
DPO
DPO
Merge (of DPO models)
DPO
DPO
DPO
DPO
DPO
No info but prob DPO, given Merge (incl. DPO)
DPO

Llama 3 also uses DPO instead of RL (iterative training of SFT, RM and DPO)

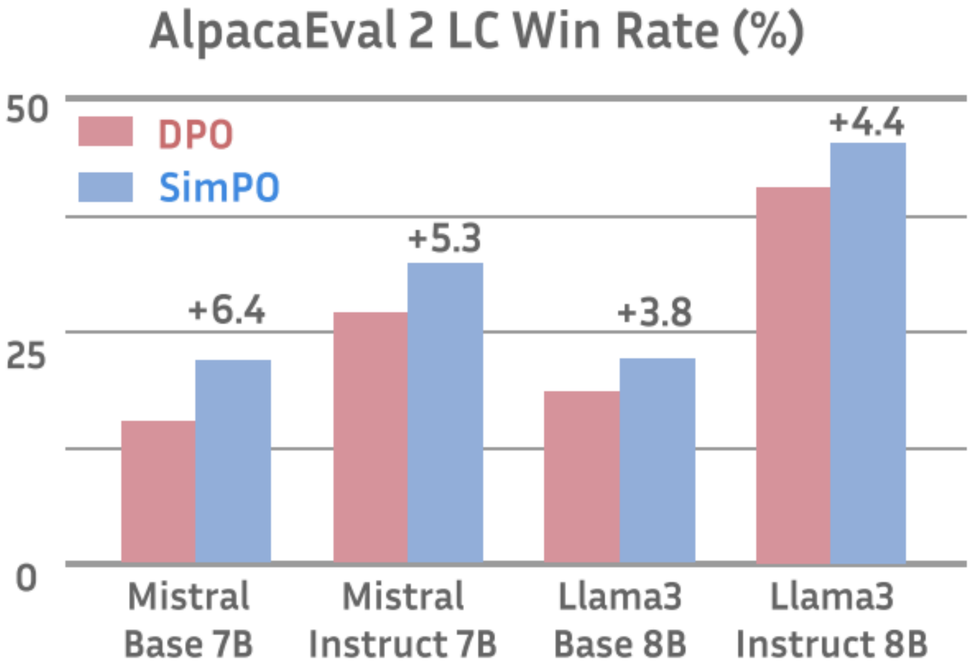
SimPO: Simple preference optimization with a reference-free reward




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

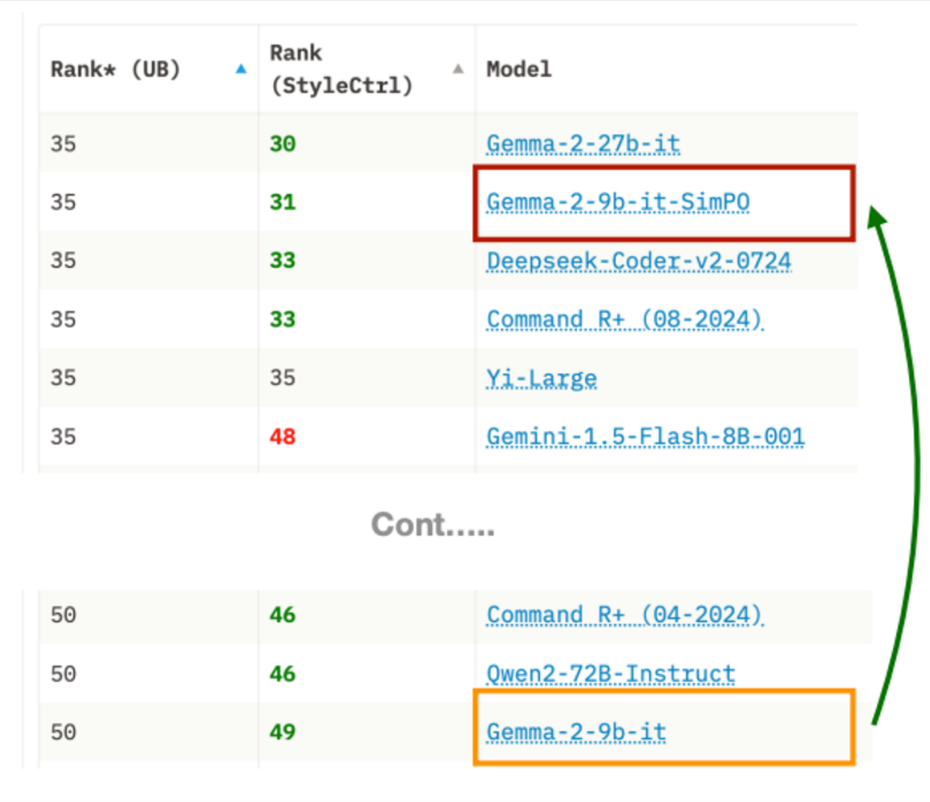
$$\mathcal{L}_{\text{SimPO}}(\pi_\theta) = -\mathbb{E}\left[\log \sigma\left(\frac{\beta}{|y_w|} \log \pi_\theta(y_w \mid x) - \frac{\beta}{|y_l|} \log \pi_\theta(y_l \mid x) - \gamma\right)\right]$$

Maybe you don’t need reference model either?



Meng et al., 2024, SimPO: Simple Preference Optimization with a Reference-Free Reward

Open models for the win



Rank* (UB)	Rank (StyleCtrl)	Model
35	30	Gemma-2-27b-it
35	31	Gemma-2-9b-it-SimPO
35	33	Deepseek-Coder-v2-0724
35	33	Command R+ (08-2024)
35	35	Yi-Large
35	48	Gemini-1.5-Flash-8B-001
Cont.....		
50	46	Command R+ (04-2024)
50	46	Qwen2-72B-Instruct
50	49	Gemma-2-9b-it

- We start from **Gemma-2-9b-it** model
  - Closed pre-training and closed RLHF
- We take **50k prompts** x from **UltraFeedback** (Cui et al., 2023) and regenerate 5 responses
- We use a reward model **ArmoRM** (Wang et al., 2024) to pick the **best** and **worst** response as **winning response** y_w, **losing response** y_l
- We train SimPO on this **on-policy** data, and obtained:

princeton-nlp/**gemma-2-9b-it-SimPO**

< 3 hours on 8 H100 GPUs!

Model: princeton-nlp/**gemma-2-9b-it-SimPO** 🏆

The strongest <10B model on Chatbot Arena, WildBench, Arena Hard, Alpaca Eval 2

Meng et al., 2024, SimPO: Simple Preference Optimization with a Reference-Free Reward

RewardBench: evaluating reward models

RewardBench: Evaluating Reward Models

Evaluating the capabilities, safety, and pitfalls of reward models

Code | Eval. Dataset | Prior Test Sets | Results | Paper | Total models: 165 | * Unverified models | ⚠️ Dataset Contamination | Last restart (PST): 22:01 PDT, 28 Mar 2025

⚠️ Many of the top models were trained on unintentionally contaminated, AI-generated data, for more information, see this gist.

🏆 RewardBench Leaderboard | 🔍 RewardBench - Detailed | Prior Test Sets | About | Dataset Viewer

Model Search (delimit with ,)

☑ Seq. Classifiers ☑ DPO ☑ Custom Classifiers ☑ Generative ☐ Prior Sets

	Model	Model Type	Score	Chat	Chat Hard	Safety	Reasoning
1	infly/INF-ORM-Llama3.1-70B	Seq. Classifier	95.1	96.6	91.0	93.6	99.1
2	ShikaiChen/LDL-Reward-Gemma-2-27B-v0.1	Seq. Classifier	95.0	96.4	90.8	93.8	99.0
3	nicolinho/QRM-Gemma-2-27B	Seq. Classifier	94.4	96.6	90.1	92.7	98.3
4	Skywork/Skywork-Reward-Gemma-2-27B-v0.2	Seq. Classifier	94.3	96.1	89.9	93.0	98.1
5	nvidia/Llama-3.1-Nemotron-70B-Reward *	Custom Classifier	94.1	97.5	85.7	95.1	98.1
6	Skywork/Skywork-Reward-Gemma-2-27B ⚠️	Seq. Classifier	93.8	95.8	91.4	91.9	96.1
7	SF-Foundation/TextEval-Llama3.1-70B * ⚠️	Generative	93.5	94.1	90.1	93.2	96.4
8	meta-metrics/MetaMetrics-RM-v1.0	Custom Classifier	93.4	98.3	86.4	90.8	98.2

Lambert et al., 2024, RewardBench: Evaluating Reward Models for Language Modeling