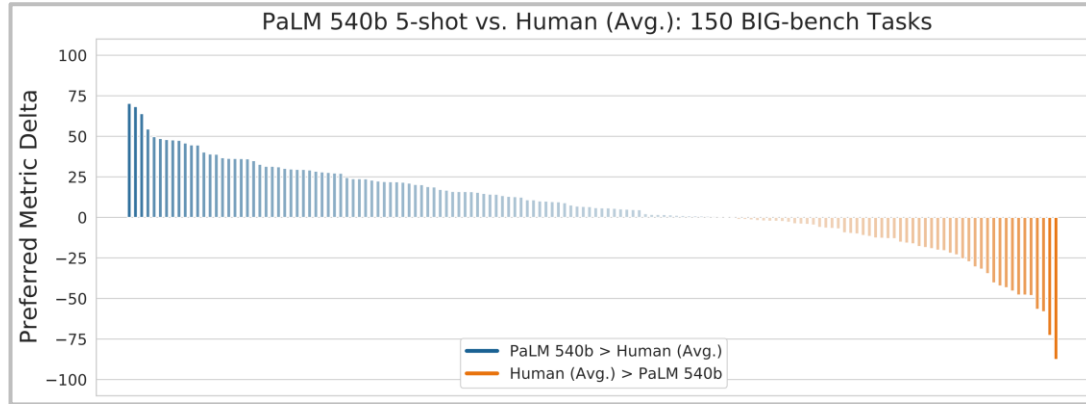


# Developing and studying instruction-following models

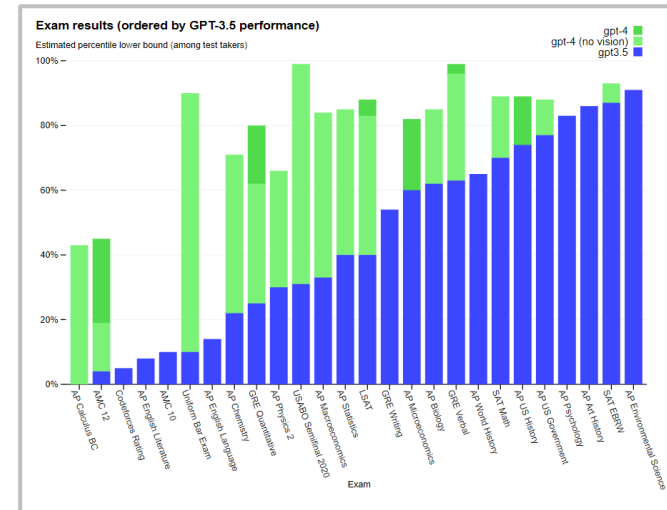
Tatsunori Hashimoto, Stanford CS

Future of Decentralization, AI, and Computing Summit

# LLMs in the spotlight



Google PaLM on BigBench



GPT4 on a range of exams

Impressive, ongoing advances in NLP and AI from large language models!

# These models are increasingly closed off

“On the competitive landscape front — it’s competitive out there,” said Sutskever. “GPT-4 is not easy to develop. It took pretty much all of OpenAI working together for a very long time to produce this thing. And there are many many companies who want to do the same thing, so from a competitive side, you can see this as a maturation of the field.”



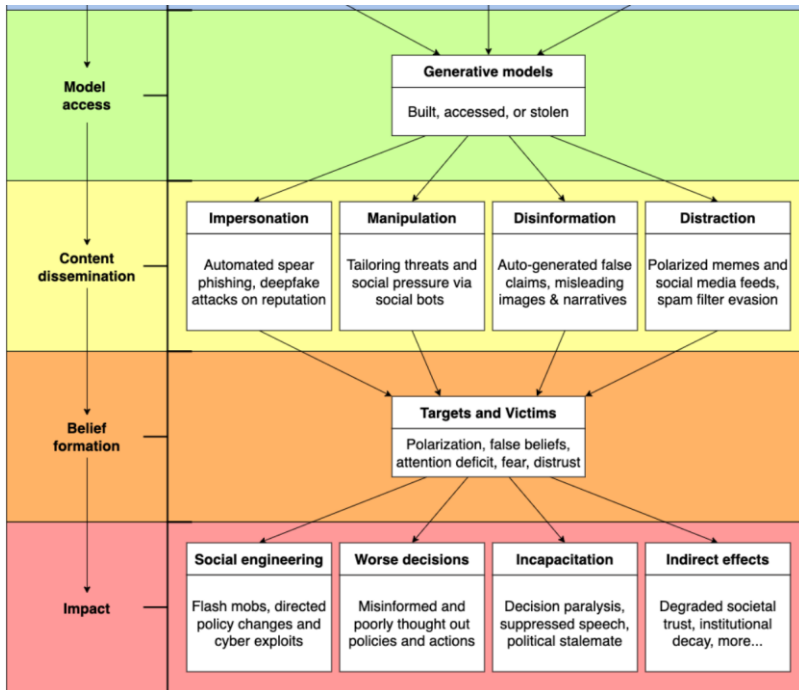
**Jan Leike** ✓ @janleike · Oct 24, 2022

I agree. While OpenAI doesn't like talking about exact model sizes / parameter counts anymore, documentation should definitely be better.

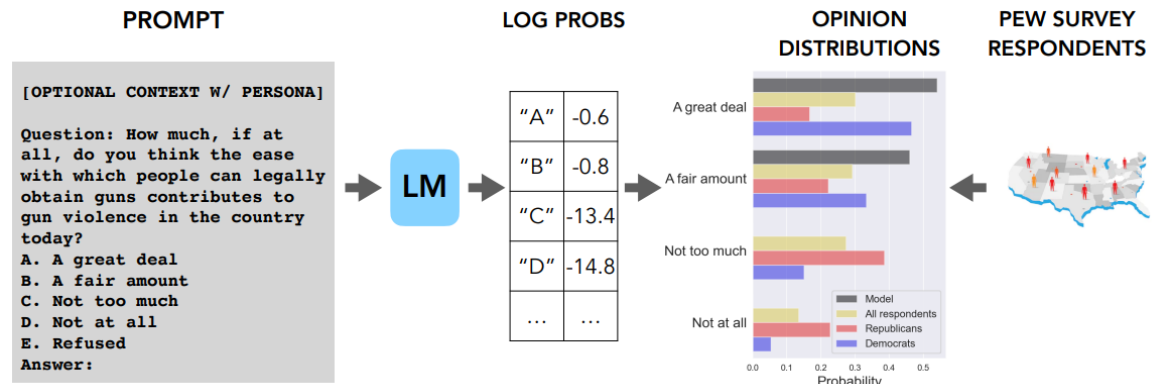
text-davinci-002 isn't the model from the InstructGPT paper. The closest to the paper is text-davinciplus-002.

	OpenAI	cohere	stability.ai	ANTHROPIC	Google	BigScience	Meta	AI21labs	ALEPH ALPHA	ELEutherAI	Totals
Draft AI Act Requirements	GPT-4	Cohere Command	Stable Diffusion v2	Claude	PaLM 2	BLOOM	LLaMA	Jurassic-2	Luminous	GPT-NeoX	
Data sources	● ○ ○ ○ ○	● ● ● ○ ○	● ● ● ● ●	○ ○ ○ ○ ○	● ● ○ ○ ○	● ● ● ● ●	● ● ● ● ●	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ● ●	22
Data governance	● ● ○ ○ ○	● ● ● ○ ○	● ● ○ ○ ○	○ ○ ○ ○ ○	● ● ● ○ ○	● ● ● ● ●	● ● ○ ○ ○	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ○ ○	19
Copyrighted data	○ ○ ○ ○ ○	○ ○ ○ ○ ○	○ ○ ○ ○ ○	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ○ ○	○ ○ ○ ○ ○	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ● ●	7
Compute	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ● ●	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ● ●	● ● ● ● ●	○ ○ ○ ○ ○	● ○ ○ ○ ○	● ● ● ● ●	17
Energy	○ ○ ○ ○ ○	● ○ ○ ○ ○	● ● ● ● ○	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ● ●	● ● ● ● ●	○ ○ ○ ○ ○	○ ○ ○ ○ ○	● ● ● ● ●	16

# Closed models are hard to study and improve



Dual-use / misuse [Kang 2023]



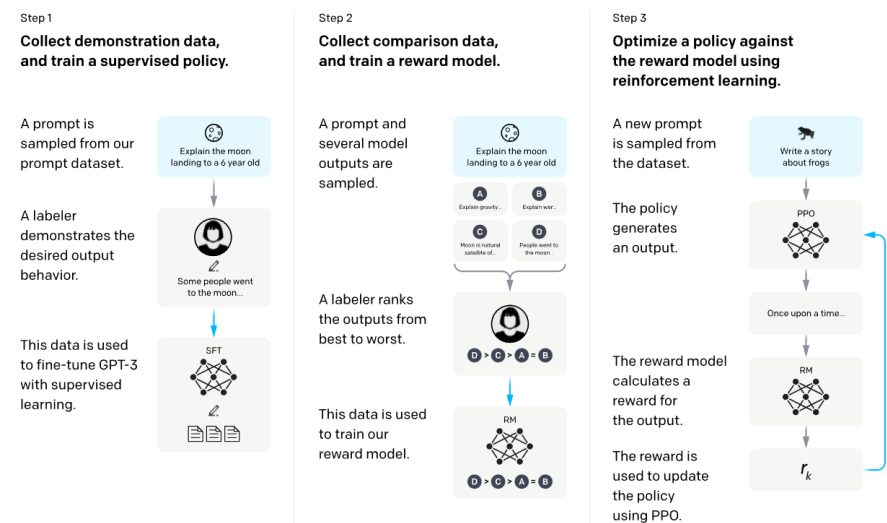
Political values / biases [Santurkar 2023]

API-only access makes it difficult to do deep analysis or propose improvements

# Reproducible low-cost environments for LLM experiments

## Reproducing instruction-following models

- **Cost** : high cost of human annotation
- **Replicability** : crowdsourcing doesn't replicate
- **Reference** : no known working PPO implementation

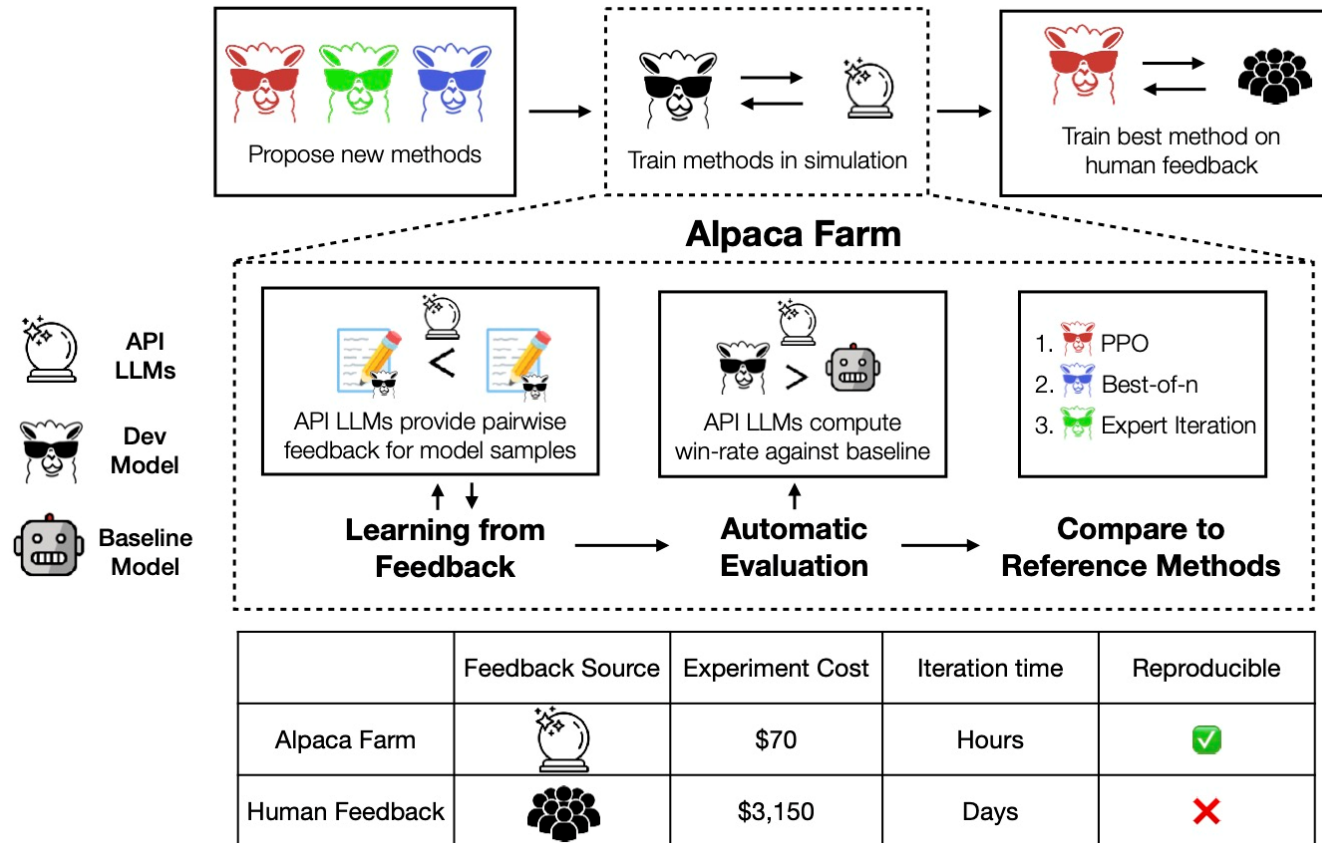


[Ouyang 2020]

- What's the impact of instruction tuning?
- Does reinforcement learning actually help?
- What changes does RL actually make?

**Why is this hard?** Figuring this out (in full) requires replicating instructGPT/chatGPT

# Alpaca trio: low-cost experiments for instruction-following



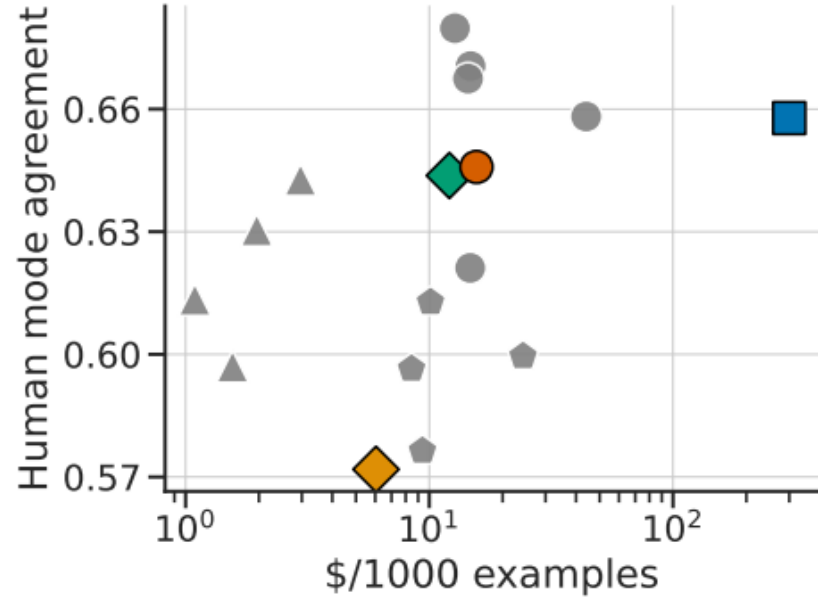
**Step 1 (SFT)** – Alpaca

**Step 2 (RLHF)** – AlpacaFarm

**Step 3 (Evals)** – AlpacaEval

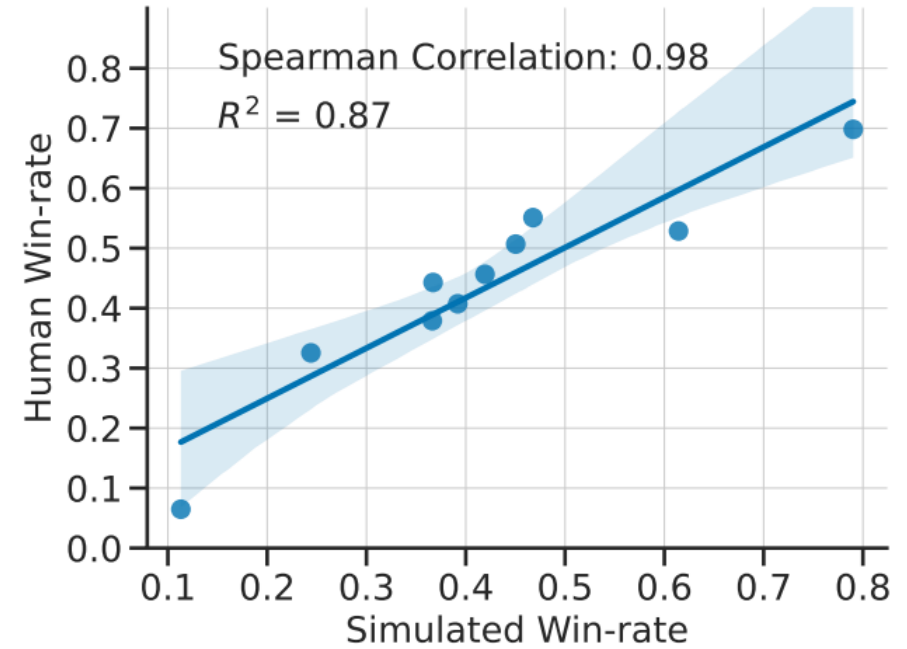
Simulating annotators (via GPT4) enables fast, low-cost prototyping and R&D of LLMs

# Validating the accuracy of simulated annotations



Annotator: ● Human  $p_{ref}$  ● Trainer  $p_{sim}^{ann}$  ● Evaluator  $p_{sim}^{eval}$  ● GPT4  $p_{sim}^{GPT4}$   
Model: ■ Human  $p_{ref}$  ◆ Simulated  $p_{sim}$  ● GPT4 ▲ ChatGPT ● Davinci003

Agreement near human inter-annotator levels



Near-perfect rank correlation at the system level

# High-performance, reference methods for RLHF

Method	Simulated win-rate (%)
GPT-4	79.0 $\pm$ 1.4
ChatGPT	61.4 $\pm$ 1.7
PPO	46.8 $\pm$ 1.8
Best-of- $n$	45.0 $\pm$ 1.7
Expert Iteration	41.9 $\pm$ 1.7
SFT 52k (Alpaca 7B)	39.2 $\pm$ 1.7
SFT 10k	36.7 $\pm$ 1.7
Binary FeedME	36.6 $\pm$ 1.7
Quark	35.6 $\pm$ 1.7
Binary Reward Conditioning	32.4 $\pm$ 1.6
Davinci001	24.4 $\pm$ 1.5
LLaMA 7B	11.3 $\pm$ 1.1

Our findings replicate RLHF's effectiveness, and these results hold outside the simulator

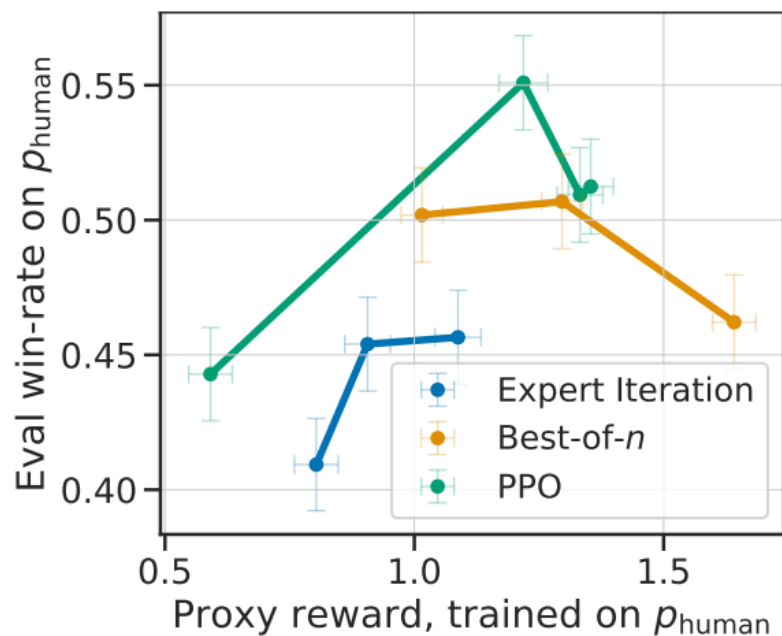


# High-performance, reference methods for RLHF

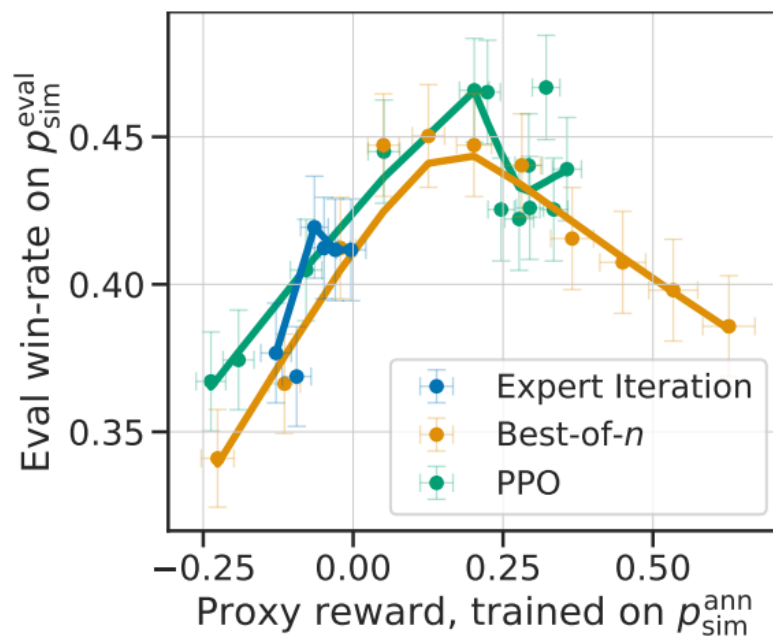
Method	Simulated win-rate (%)	Human win-rate (%)
GPT-4	79.0 ± 1.4	69.8 ± 1.6
ChatGPT	61.4 ± 1.7	52.9 ± 1.7
PPO	46.8 ± 1.8	55.1 ± 1.7
Best-of- $n$	45.0 ± 1.7	50.7 ± 1.8
Expert Iteration	41.9 ± 1.7	45.7 ± 1.7
SFT 52k (Alpaca 7B)	39.2 ± 1.7	40.7 ± 1.7
SFT 10k	36.7 ± 1.7	44.3 ± 1.7
Binary FeedME	36.6 ± 1.7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

Our findings replicate RLHF's effectiveness, and these results hold outside the simulator

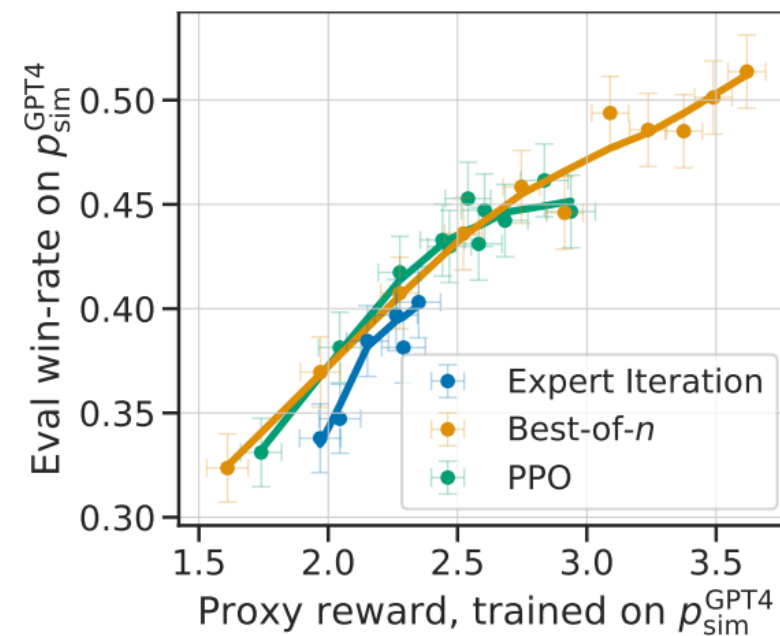
# AlpacaFarm highlights the complexity of instruction RLHF



(a) Human preferences ■



(b) AlpacaFarm ◆



(c) Single-prompt GPT-4 ●

AlpacaFarm replicates important, complex phenomena like overoptimization

# Beyond this work: LLM driven prototyping lowers the cost of R&D

## Textbooks Are All You Need

Suriya Gunasekar Yi Zhang Jyoti Aneja Caio César Teodoro Mendes  
Allie Del Giorno Sivakanth Gopi Mojan Javaheripi Piero Kauffmann  
Gustavo de Rosa Olli Saarikivi Adil Salim Shital Shah Harkirat Singh Behl  
Xin Wang Sébastien Bubeck Ronen Eldan Adam Tauman Kalai Yin Tat Lee  
Yuanzhi Li

Microsoft Research

## AlpacaEval : An Automatic Evaluator for Instruction-following Language Models

Code License [Apache 2.0](#) Data License [CC By NC 4.0](#) [python 3.10+](#) [discord server](#)

## How Far Can Camels Go? Exploring the State of Instruction Tuning on Open Resources

Yizhong Wang<sup>\*♦♦</sup> Hamish Ivison<sup>\*♦</sup> Pradeep Dasigi<sup>♦</sup> Jack Hessel<sup>♦</sup>  
Tushar Khot<sup>♦</sup> Khyathi Raghavi Chandu<sup>♦</sup> David Wadden<sup>♦</sup> Kelsey MacMillan<sup>♦</sup>  
Noah A. Smith<sup>♦♦</sup> Iz Beltagy<sup>♦</sup> Hannaneh Hajishirzi<sup>♦♦</sup>

Studying fine-tuning data

## Self-Alignment with Instruction Backtranslation

Xian Li Ping Yu Chunting Zhou Timo Schick  
Luke Zettlemoyer Omer Levy Jason Weston Mike Lewis

Meta AI

Development metrics

Caveat: development and deployment needs more than automated data/evals

Development metrics, synthetic data

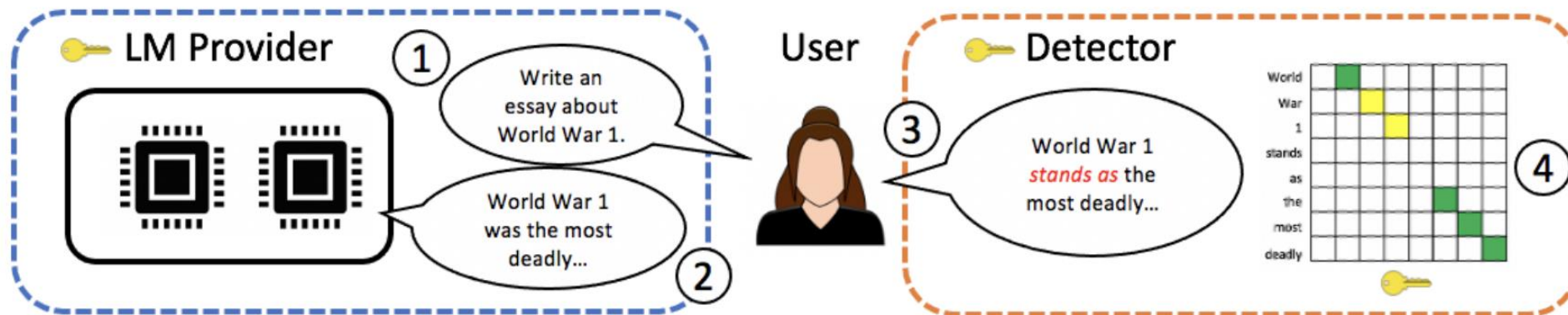


Crowdsourced data + evaluation



Live evaluation

# Case study: watermarking LLMs



Watermarking enables tracking of LLM-generated text (see Kirchenbauer et al)

## Challenges:

- Watermarks induce distortion (hard sell for LLM vendors)
- Many watermarks highly non-robust (to deletion of a few words, or cropping)

# Development of a distortion-free, robust watermark.

In recent work [Kuditipudi et al 2023], we derive a distortion free and robust watermark.

## **Generate** (for each token $y_i$ )

- Draw a random sequence  $\xi_i \in [0,1]$ , call this the key
- Sample according to  $\min_i -\log \xi_i/p_i$  (From Aaronson)

**This is distortion free** (i.e. the marginal distribution over  $\xi$  is  $p$ )

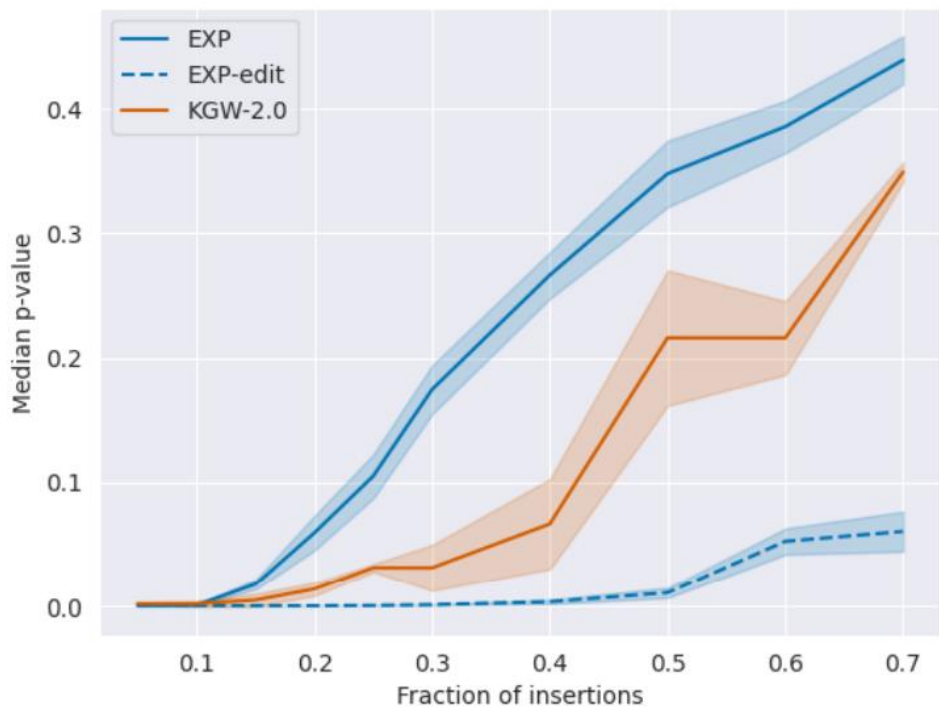
## **Detect**

- Find the min-Levenshtein cost with  $d(y, \xi) = \sum_i \log(1 - \xi_{i,y_i})$
- Compare vs the min-Levenshtein cost w/ random  $\xi$

**This is robust** (i.e. can detect under small Levenshtein edits)

# Watermarks and open models

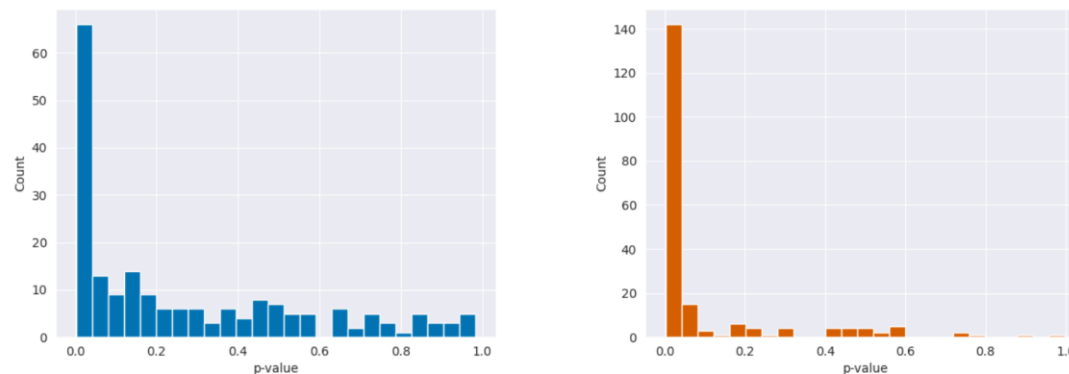
**Open models** (and access to logprobs) enable watermarking research



[Kuditipudi et al 2023]

**Open instruction-tuning models and evals lead to new open problems**

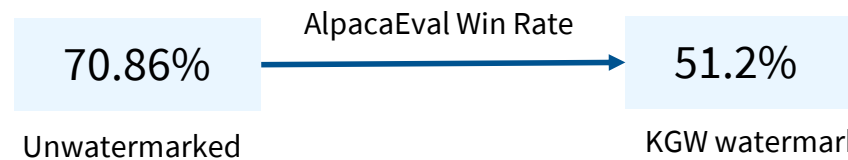
Distortion-free watermarks are weaker on instruction-tuned models



(a) EXP-edit

(b) KGW-2.0

Distortion-inducing watermarks lead to major drops in performance



[Freeman and Hashimoto, unpublished]

# Takeaways

## **Open models and trustworthiness**

Open source provides important accountability and transparency

## **Research on LLMs**

LLMs enable new research into instruction-following models

## **Enabling safer and more robust LLMs**

New innovations and interventions based on open LLMs