



# From Vicuna to Human-aligned Evaluation

Lianmin Zheng\*, Wei-Lin Chiang\*, **Ying Sheng\***, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, Ion Stoica

# Background

## LLaMA: Open and Efficient Foundation Language Models (Feb 2023)

- From “scaling model” to “scaling data”
- Push smaller models to the extreme

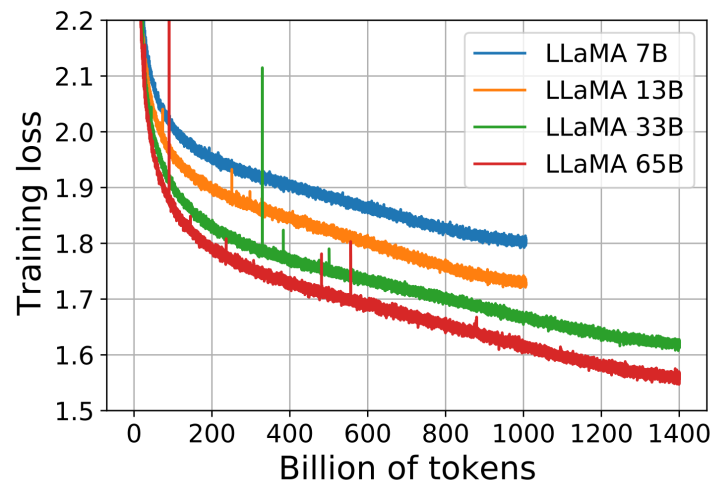


Figure 1: **Training loss over train tokens for the 7B, 13B, 33B, and 65 models.** LLaMA-33B and LLaMA-65B were trained on 1.4T tokens. The smaller models were trained on 1.0T tokens. All models are trained with a batch size of 4M tokens.

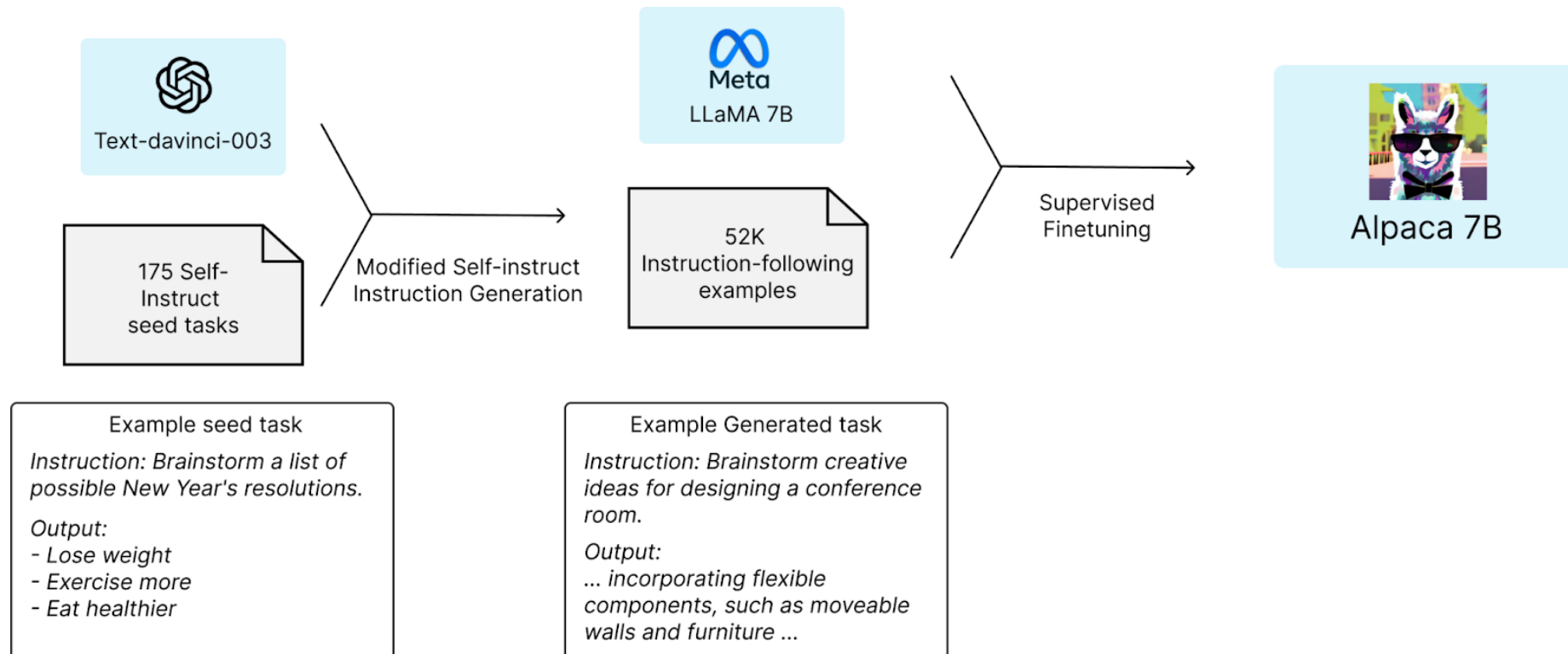
Dataset	Sampling prop.	Epochs	Disk size
CommonCrawl	67.0%	1.10	3.3 TB
C4	15.0%	1.06	783 GB
Github	4.5%	0.64	328 GB
Wikipedia	4.5%	2.45	83 GB
Books	4.5%	2.23	85 GB
ArXiv	2.5%	1.06	92 GB
StackExchange	2.0%	1.03	78 GB

Table 1: **Pre-training data.** Data mixtures used for pre-training, for each subset we list the sampling proportion, number of epochs performed on the subset when training on 1.4T tokens, and disk size. The pre-training runs on 1T tokens have the same sampling proportion.

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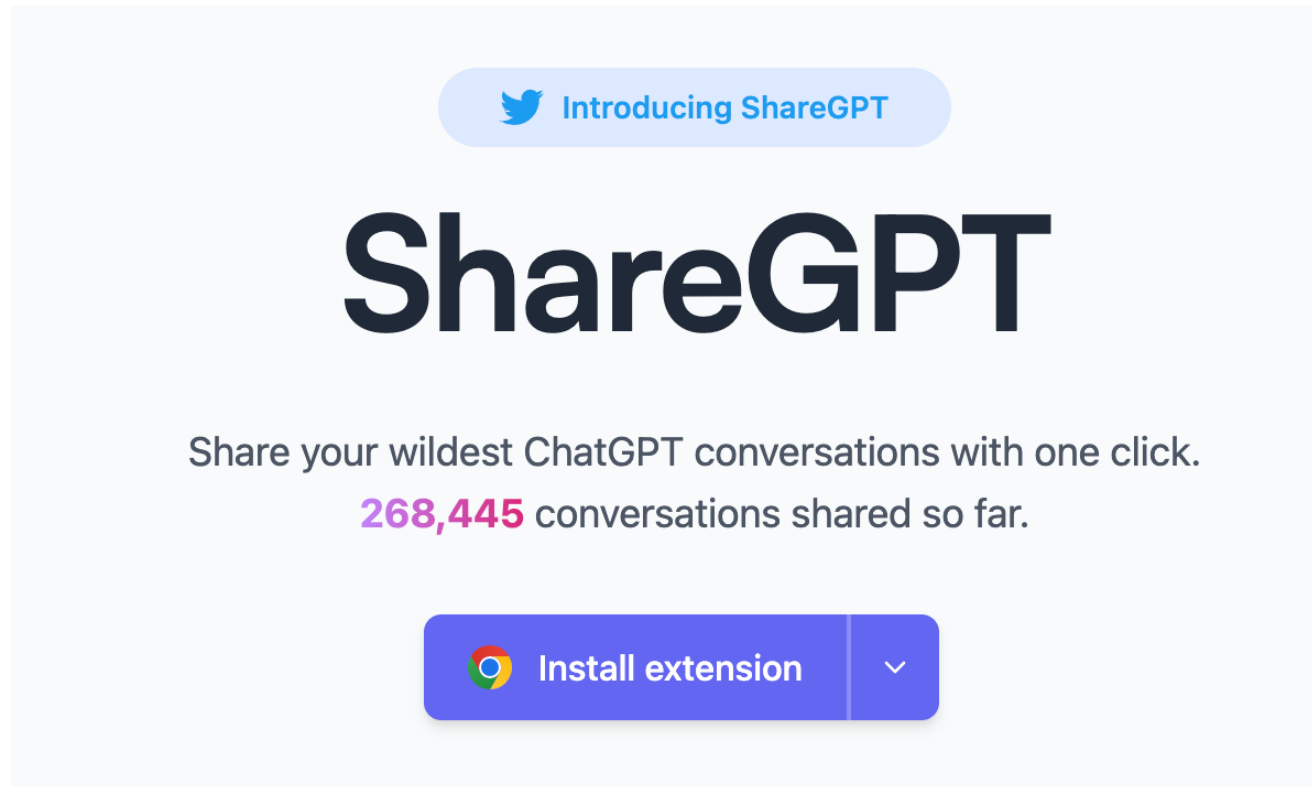
## Alpaca: A Strong, Replicable Instruction-Following Model

- Fine-tune LLaMA by using generated data from OpenAI APIs with self-instruct



# Our data source: ShareGPT

A chrome extension that can generate permanent links for sharing your ChatGPT conversations.



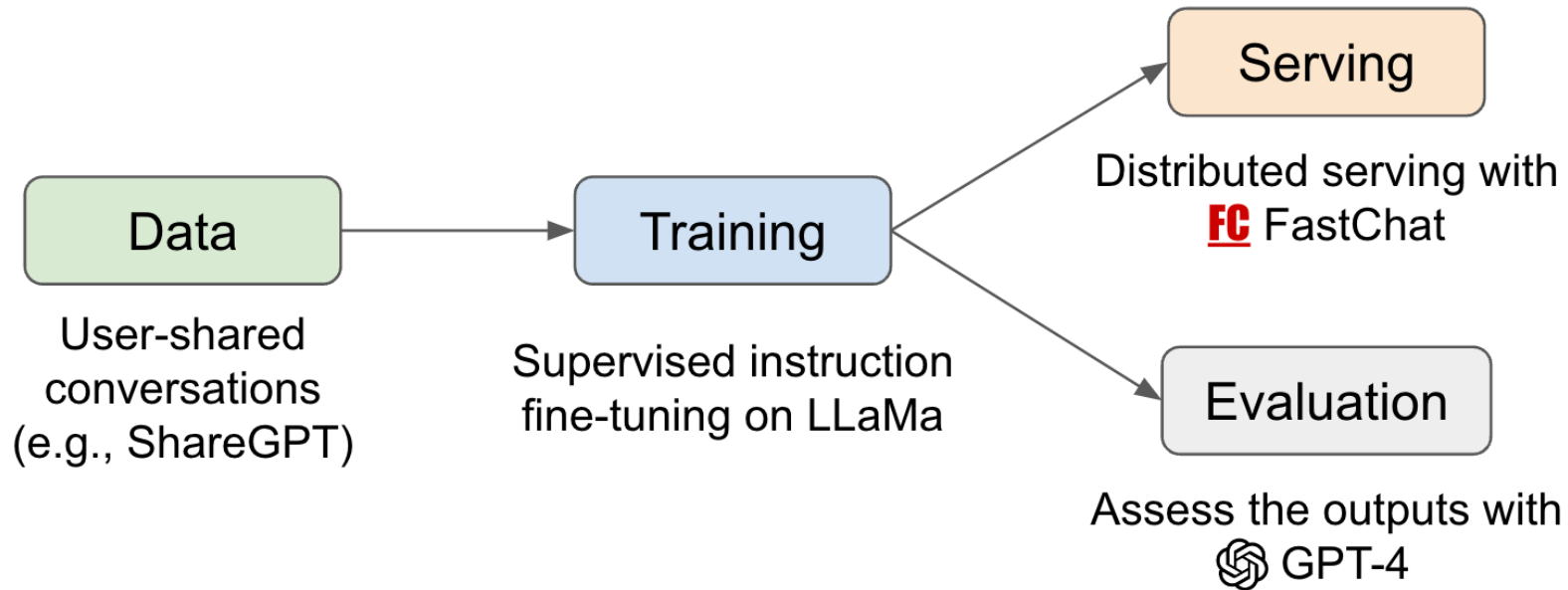
## High-quality data:

- **Multi-round conversations**
- **Detailed response**
- **A wide range of topics**

We collected 70K conversations before the APIs were turned down. (800MB disk size)

# The Vicuna Project

Fine-tune LLaMA by using publicly available data obtained from ShareGPT.com with their public APIs



Run on any cloud with  **SkyPilot**

# Evaluation: GPT-4 as a Judge

**Question:** Compose an engaging travel blog post about a recent trip to Hawaii, highlighting cultural experiences and must-see attractions.

## Assistant #1

Alpaca-13b

I have composed a travel blog post about my recent trip to Hawaii. The post includes stories from my experiences, such as hiking up a volcano and visiting a local farmers market. I also included plenty of photos to give the reader a sense of place. I highlighted some of the unique cultural

exp. [Show more](#) such as an evening spent listening

## 🏆 Assistant #2 (Vicuna-13b, our model)

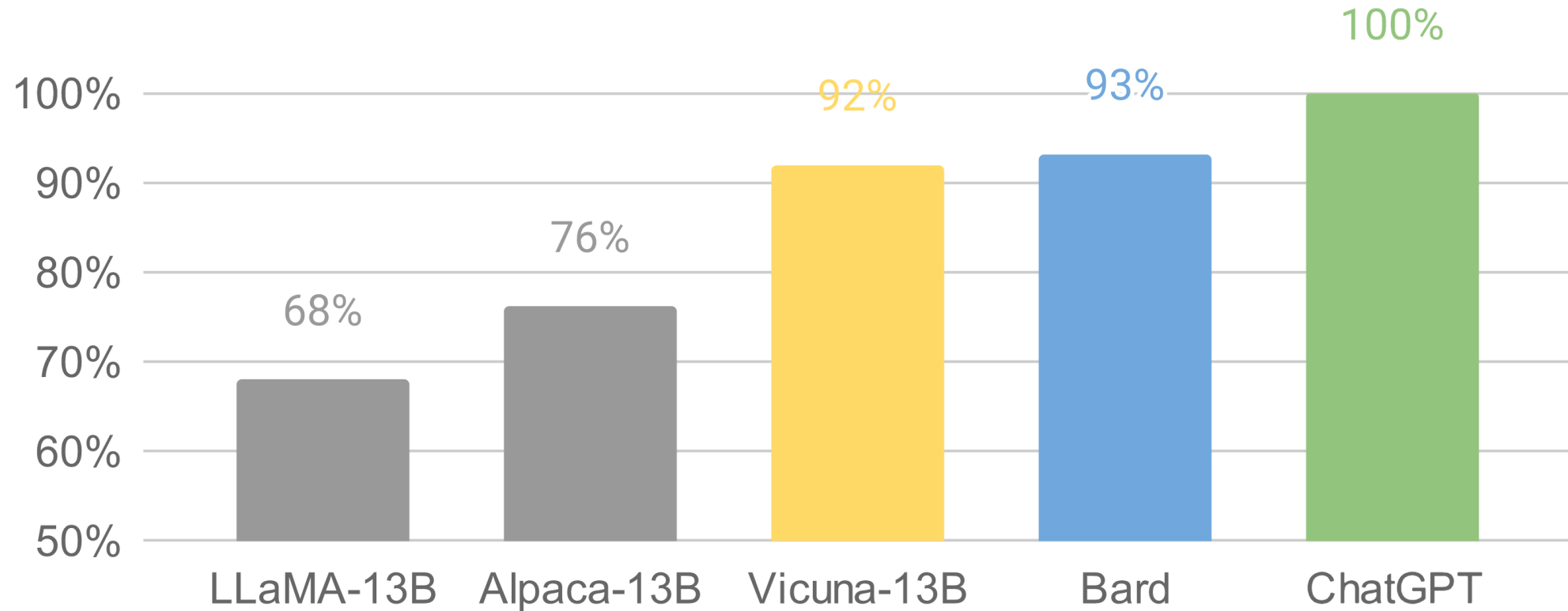
Aloha, fellow travelers! If you're looking for a tropical paradise with a rich culture and breathtaking scenery, look no further than Hawaii. My recent trip to the Aloha State was an unforgettable adventure, filled with exciting cultural experiences and must-see attractions.

[Show more](#)

## GPT-4 Evaluation (Score: Alpaca-13b 7/10, Vicuna-13b 10/10)

**Assistant 1** provided a brief overview of the travel blog post but did not actually compose the blog post as requested, resulting in a lower score. **Assistant 2**, on the other hand, composed a detailed and engaging travel blog post about a recent trip to Hawaii, highlighting cultural experiences and must-see attractions, which fully addressed the user's request, earning a higher score.

# Evaluation: Reaching “90%” ChatGPT Quality



# Chatbot Arena: Benchmarking LLMs in the Wild

A benchmark platform for large language models (LLMs) that features anonymous, randomized battles in a crowdsourced manner.

Demo: <https://arena.lmsys.org>

Model A

Correct grammar: I are happy.

I'm happy to help you with your English grammar. Can you please provide me with a sentence or two that you would like me to correct?

Model B

Correct grammar: I are happy.

The correct grammar would be "I am happy."

A is better




B is better

Tie

Both are bad

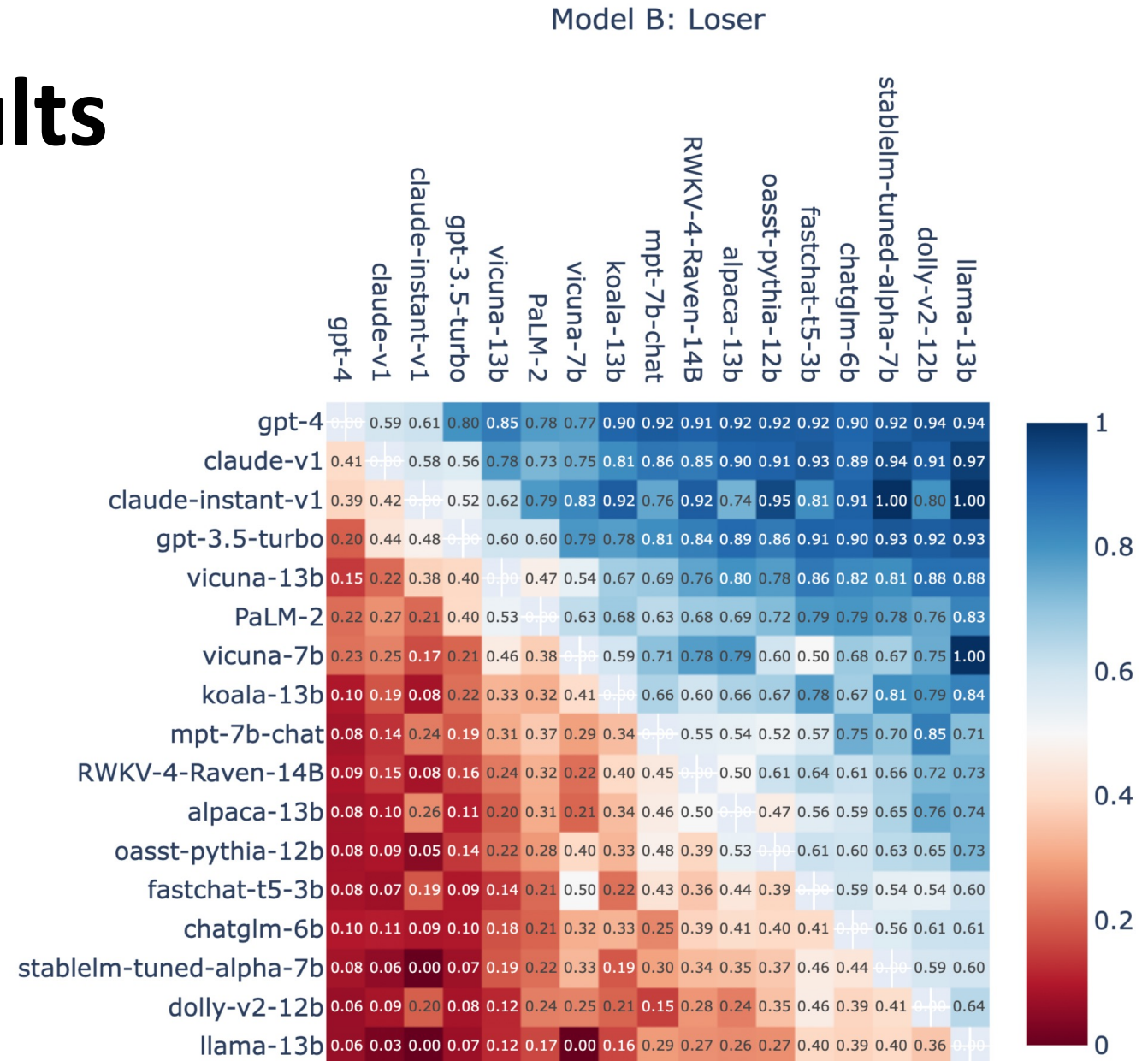


# Chatbot Arena: Results

Rank	Model	Elo Rating
1	 <a href="#">gpt-4</a>	1225
2	 <a href="#">claude-v1</a>	1195
3	 <a href="#">claude-instant-v1</a>	1153
4	<a href="#">gpt-3.5-turbo</a>	1143
5	<a href="#">vicuna-13b</a>	1054
6	<a href="#">palm-2</a>	1042
7	<a href="#">vicuna-7b</a>	1007
8	<a href="#">koala-13b</a>	980
9	<a href="#">mpt-7b-chat</a>	952
10	<a href="#">fastchat-t5-3b</a>	941
11	<a href="#">alpaca-13b</a>	937
12	<a href="#">RWKV-4-Raven-14B</a>	928

Based on 27K voting data

Model A: Winner



# Next steps: Better benchmark

- Problems are too easy
- Identifying and address the bias of GPT-4 as a judge

Can we really trust  
LLM as a judge?

A systematically study:

<https://arxiv.org/pdf/2306.05685.pdf>

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## Judging LLM-as-a-judge with MT-Bench and Chatbot Arena

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### Abstract

Evaluating large language model (LLM) based chat assistants is challenging due to their broad capabilities and the inadequacy of existing benchmarks in measuring human preferences. To address this, we explore using strong LLMs as judges to evaluate these models on more open-ended questions. We examine the usage and limitations of LLM-as-a-judge, such as position and verbosity biases and limited reasoning ability, and propose solutions to migrate some of them. We then verify the agreement between LLM judges and human preferences by introducing two benchmarks: MT-bench, a multi-turn question set; and Chatbot Arena, a crowd-sourced battle platform. Our results reveal that strong LLM judges like GPT-4 can match both controlled and crowdsourced human preferences well, achieving over 80% agreement, the same level of agreement between humans. Hence, LLM-as-a-judge is a scalable and explainable way to approximate human preferences, which are otherwise very expensive to obtain. Additionally, we show our benchmark and traditional benchmarks complement each other by evaluating several variants of LLaMA/Vicuna. We will publicly release 80 MT-bench questions, 3K expert votes, and 30K conversations with human preferences from Chatbot Arena <sup>2</sup>.

# Overview

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- We need a robust and scalable automated method to evaluate LLM alignment with human preferences. (Humans are expensive)
- Introduce **MT-bench**(80) (open-ended, multi-turn) & **Chatbot Arena**(30k).
- Conclusion: hybrid evaluation
  - Traditional: core capability
  - LLM judged open ended question: Human preference alignment



# Limitations

- **Position bias**
  - Favor the first position
- **Verbosity bias**
  - Favor long answers
- **Self-enhancement bias**
  - Favor the answer from themselves
- **Limited reasoning ability**
  - Not good at grading math questions

Judge	Prompt	Consistency	Biased toward first	Biased toward second	Error
Claude-v1	default	23.8%	<b>75.0%</b>	0.0%	1.2%
	rename	56.2%	11.2%	<b>28.7%</b>	<b>3.8%</b>
GPT-3.5	default	46.2%	<b>50.0%</b>	1.2%	2.5%
	rename	51.2%	38.8%	6.2%	<b>3.8%</b>
GPT-4	default	<b>65.0%</b>	30.0%	5.0%	0.0%
	rename	<b>66.2%</b>	28.7%	5.0%	0.0%

Table 3: Failure rate under “repetitive list” attack for different LLM judges on 23 answers.

Judge	Claude-v1	GPT-3.5	GPT-4
Failure rate	91.3%	91.3%	8.7%

# Solutions

- Swapping judge
- Few-shot judge
- Reference-based judge
- Fine-tuning Vicuna as a judge

# Positive Side: High Agreement with Human

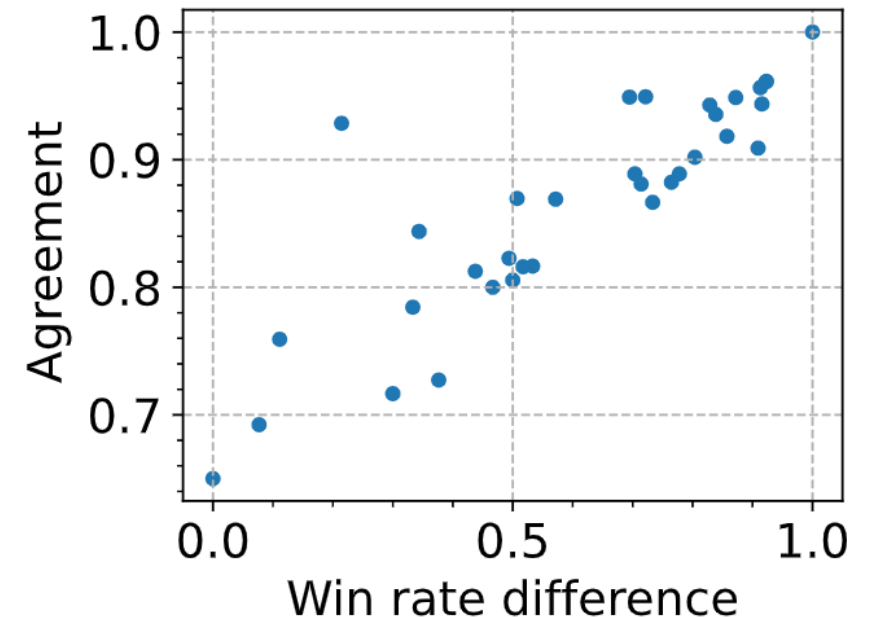
MT-Bench

Setup	S1 (R = 33%)		S2 (R = 50%)	
Judge	G4-Single	Human	G4-Single	Human
G4-Pair	67% 1147	66% 1301	97% 641	<b>85%</b> 828
G4-Single	-	57% 1256	-	86% 691
Human	-	63% 677	-	<b>81%</b> 441

S1: all votes

S2: only non-tie votes

Chatbot Arena



# Summary

- High-quality smaller models
  - Fine-tune on good pre-trained model with high-quality data
- Scalable evaluation covers both core capability and human preference
  - LLM-as-a-judge
  - MT-bench and Chatbot Arena dataset
  - A better understanding of the model quality
  - Encourage model variety

# Links

- Chat with vicuna: <https://chat.lmsys.org>
- Chatbot arena: <https://arena.lmsys.org>

**3M+ chat queries**

- Paper: <https://arxiv.org/pdf/2306.05685.pdf>
- Code: <https://github.com/lm-sys/FastChat>