# Alpagasus : Training A Better Alpaca with Fewer Data

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#### **ABSTRACT**

Large language models (LLMs) obtain instruction-following capability through instruction-finetuning (IFT) on supervised instruction/response data. However, widely used IFT datasets (e.g., ALPACA's 52k data) surprisingly contain many low-quality instances with incorrect or irrelevant responses, which are misleading and detrimental to IFT. In this paper, we propose a simple and effective data selection strategy that automatically identifies and removes low-quality data using a strong LLM (e.g., ChatGPT). To this end, we introduce ALPAGASUS, which is finetuned on only 9k high-quality data filtered from the 52k ALPACA data. ALPAGASUS significantly outperforms the original ALPACA as evaluated by GPT-4 on multiple test sets and its 13B variant matches > 90% performance of its teacher LLM (i.e., Text-Davinci-003) on test tasks. It also provides 5.7x faster training, reducing the training time for a 7B variant from 80 minutes (for ALPACA) to 14 minutes <sup>1</sup>. Overall, ALPAGASUS demonstrates a novel data-centric IFT paradigm that can be generally applied to instruction-tuning data, leading to faster training and better instruction-following models. Our project page is available at: https://lichang-chen.github.io/AlpaGasus/.

# 1 Introduction

Instruction fine-tuning (IFT) (Longpre et al., 2023) has been recently applied as an essential continual training stage for pre-trained large language models (LLMs) to achieve instruction-following capability (Ouyang et al., 2022b; Chen et al., 2023b), which is often attributed to aligning the models' behavior with a diverse set of human instructions and responses (Taori et al., 2023; Askell et al., 2021). The recent series of open-source, instruction-tuned models (Taori et al., 2023; Xu et al., 2023) reveal that the alignment of better IFT data could result in better instruction-following skills. For example, GPT-4-LLM (Peng et al., 2023) (with GPT-4 (OpenAI, 2023b) as its teacher) exhibits better reasoning and math ability than ALPACA (Taori et al., 2023) (with Text-davinci-003 as its teacher), though they share the same base model LLaMA (Touvron et al., 2023), demonstrating the importance of data quality.

Although stronger teachers can usually bring further improvement by providing better IFT data, their responses inevitably include incorrect or irrelevant answers to the corresponding instructions (see examples in Fig. 2), which can be misleading or detrimental to IFT. Moreover, these data also increases unnecessary training cost. Alpaca-cleaned <sup>2</sup> is the pioneer of filtering bad data in ALPACA

<sup>♦</sup> The name "ALPAGASUS" combines two words, ALPACA and Pegasus.

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<sup>&</sup>lt;sup>1</sup>We apply IFT for the same number of epochs as ALPACA(7B) but on fewer data, using 4×NVIDIA A100 (80GB) GPUs and following the original ALPACA setting and hyperparameters.

<sup>&</sup>lt;sup>2</sup>https://github.com/gururise/AlpacaDataCleaned/

dataset though it requires humans fully involved in examining and filtering the data. Nonetheless, how to automatically filter out poor-quality data from IFT datasets has not been investigated yet. A primary bottleneck is that rating the data quality usually requires expensive human labor but still may not be accurate for IFT because stronger teachers are more powerful in generating eloquent but incorrect responses that are more subtle to detect by humans.

This paper aims to bridge the gap by proposing a novel data-filtering strategy for IFT that is efficient, automatic, and accurate. Specifically, we design a prompt applied to a powerful LLM (e.g., ChatGPT) for evaluating the quality of each (instruction, input, response) tuple and then filter out the ones with scores lower than a threshold. By applying this filter to the 52k data used to train ALPACA, we find that a majority of the data suffer from low-quality issues. Using the LLM filter, IFT on a much smaller but carefully filtered subset of 9k data produces a much better model, i.e., ALPAGASUS, than the original ALPACA, as shown in Fig. 1, following exactly the same training configuration of ALPACA. This also reduces the training time from 80 minutes to merely 14 minutes on 4× NVIDIA A100 (80GB) GPUs. This discovery is inspiring, as it demonstrates that the data quality in IFT can outweigh the quantity. In addition, this shift towards prioritizing data quality presents a new and more efficient paradigm that can generally improve the fine-tuning of LLMs.

Our evaluation of the finetuned LLMs focuses on complex open-domain QA tasks, e.g., math, roleplay, and academic writings. We conduct a holistic evaluation on four different humaninstruction test sets for evaluating instructionfollowing capability, including the ones used by WizardLM (Xu et al., 2023), Vicuna (Chiang et al., 2023), Koala (Geng et al., 2023), and Self-Instruct (Wang et al., 2022). Given the notable advantages that GPT-4 judge could match with both the controlled and crowdsourced human preferences (> 80% agreement) (Zheng et al., 2023), we employ GPT-4 as our judge for the evaluation. Specifically, we apply a prompt to turn GPT-4 into a judge comparing the responses of ALPAGASUS and the original AL-PACA. In the 7B and 13B model comparisons, our ALPAGASUS performs significantly better than ALPACA on all four test sets. Moreover, we present a fine-grained evaluation of ALPA-GASUS on individual tasks including Generic,

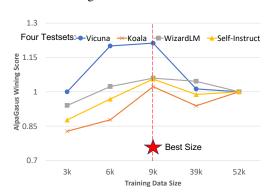


Figure 1: Performance of ALPAGASUS on four test sets when increasing its finetuning data, where the winning score is  $\frac{\#Win-\#Lose}{\#Testset}+1$  with #Testset=#Win+#Tie+#Lose to be the test set size and #Win/#Tie/#Lose to be the number of samples on which ALPAGASUS wins/draws/loses compared to ALPACA 52K.

Roleplay, Knowledge, and Commonsense from the Vicuna test set. ALPAGASUS exhibits advantages on a majority of the tasks. We also investigate the reason why ALPAGASUS loses its advantage over others on a small portion of the tasks.

To sum up, our data-filtering approach exhibits significant benefits in terms of scalability and automation. We also demonstrate that prudent management of training data quality can lead to substantial performance improvement and computation savings of IFT. In addition, our data selection and evaluation strategies can generalize to other instruction finetuning datasets and LLMs, thereby paving the way for a promising new research trajectory aimed at pragmatic LLM deployment.

#### 2 METHODOLOGY

#### 2.1 Overview

Unlike the recent work (Zhou et al., 2023), which relies on human labor to curate 1k high-quality high-quality instruction data that leads to a better fine-tuned model, we aim to avoid the expensive and time-consuming human annotation. Hence, we exploit the potential of strong LLMs to be auto-grader of the training data and then filter out the data with lower scores.

In particular, we prompt a strong API LLM, i.e., ChatGPT, to produce a score for each triplet of (instruction, input, response). The prompt is given in Fig. 3, where "dimension" denotes a user-

preferred property such as helpfulness. We then only select the triplets with scores higher than a certain threshold to fine-tune a LLaMA-series model following an existing IFT pipeline.

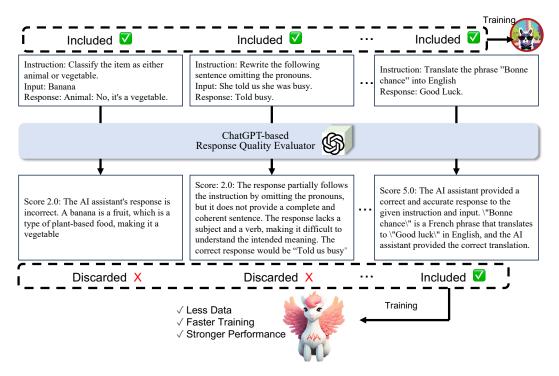


Figure 2: The fine-tuning pipeline of ALPAGASUS. We prompt ChatGPT as our auto-grader to score each training triplet on a scale of 0 to 5. We then use exactly the same instruction fine-tuning script of ALPAGA to train ALPAGASUS on the filtered data with scores higher than a threshold.

## **System Prompt:**

We would like to request your feedback on the performance of AI assistant in response to the instruction and the given input displayed following.

Instruction: [Instruction]

Input: [Input]

Response: [Response]

# **User Prompt:**

Please rate according to the [dimension] of the response to the instruction and the input. Each assistant receives a score on a scale of 0 to 5, where a higher score indicates higher level of the [dimension]. Please first output a single line containing the value indicating the scores. In the subsequent line, please provide a comprehensive explanation of your evaluation, avoiding any potential bias.

Figure 3: Prompt  $p_G$  to ChatGPT for rating and filtering training data in Eq. (1).

#### 2.2 Data Rating and Filtering

Given an IFT dataset V of triplets x =(instruction, input, response) with  $x \in V$  and an open-sourced LLM  $\theta$  (e.g., LLaMA), let  $\theta_V$  denote the finetuned  $\theta$  on V, our overarching goal is to select a subset  $S \subset V$  such that IFT on S results in a better model  $\theta_S$  than  $\theta_V$ .

In order to select S from V, we prompt an API LLM  $G(\cdot)$  (e.g., ChatGPT) as an auto-grader rating each sample  $x \in V$  by a score  $G(x, p_G)$  wherein  $p_G$  is the rating prompt in Fig. 3. We then select  $x_i$  whose score is above a certain threshold  $\tau$ , i.e.,

$$S \triangleq \{x \in V : G(x, p_G) \ge \tau\}. \tag{1}$$

We achieve  $\theta_S$  by finetuning  $\theta$  on S using an existing IFT framework. Fig. 2 illustrates the data selection pipeline.

#### 2.3 ALPAGASUS: 9K TRAINING DATA FILTERED FROM ALPACA

For "dimension" in the rating prompt  $p_G$  shown in Fig. 3, given that "accuracy" closely aligns with human expectations of LLMs' responses, we designate "accuracy" as the dimension for rating purposes. Correspondingly, we establish  $\tau$  in Eq. (1) as an accuracy threshold for the subsequent experiments. The distribution of scores in relation to the 52k Alpaca dataset is presented in Figure 4. Exploration of other dimensions will be undertaken in future studies.

In particular, we choose the threshold  $\tau=4.5$  according to the score histogram. For the ALPACA dataset V with 52,002 samples, this filtering criterion leads to a subset S of 9,229 samples  $^3$ .

## 3 EXPERIMENTAL SETUP

#### 3.1 Test Sets

Most instruction-tuned models are evaluated on one test set that might not cover sufficient diverse instructions and thus leads to a risk of biased evaluation (Chia et al., 2023). To conduct a holistic evaluation of ALPAGASUS, we curate

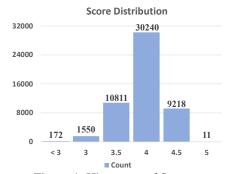


Figure 4: Histogram of Scores.

our test sets from Self-instruct (Wang et al., 2022) <sup>4</sup>, Vicuna (Chiang et al., 2023), WizardLM (Xu et al., 2023) <sup>5</sup>, and Koala (Geng et al., 2023), which together can cover more types of instructions and reduce the evaluation bias. Details of these four test sets are provided in Table 1.

# 3.2 BASELINE MODELS

We compare our ALPAGASUS with the following four recent LLMs.

ALPACA (Taori et al., 2023) is an open-sourced model developed by Stanford University through IFT of LLaMA on a training dataset of 52,002 (instruction, input, response) samples with the responses generated by Text-Davinci-003 (teacher).

TEXT-DAVINCI-003 is a recent OpenAI LLM trained with an increased emphasis on contextual understanding and response accuracy. Its proficiency in capturing complex linguistic patterns makes it a powerful teacher LLM for generating high-quality training data for finetuning LLMs such as ALPACA.

CHATGPT (OpenAI, 2023a) is an AI chatbot finetuned via reinforcement learning with human feedback (RLHF). It exhibits exceptional capability across a wide range of tasks and might be the most popular chatbot recently. Hence, it would be interesting to study to what extent ALPAGASUS can match its performance.

ChatGPT on the Alpaca-eval (Li et al., 2023) leaderboard.

Test Set	# Samples	Category
Koala	180	
Vicuna	80	$\checkmark$
WizardLM	218	$\checkmark$
Self-Instruct	252	

CLAUDE (Bai et al., 2022) is an AI chatbot developed Table 1: Four test sets used in this paper. by Anthropic. It was finetuned by RLHF to align with humans' preference on three dimensions, i.e., helpful, honest, and harmless. Claude is comparable to

<sup>&</sup>lt;sup>3</sup>52k denotes 52002 samples from the original Alpaca training set. 9k represents 9229 data samples. (either randomly sampled or filtered in our experiments)

<sup>4</sup>https://github.com/yizhongw/self-instruct/blob/main/human\_eval/user\_oriented\_instructions.jsonl

 $<sup>^5</sup> https://github.com/nlpxucan/WizardLM/blob/main/WizardLM/data/WizardLM_testset.jsonl$ 

## 3.3 EVALUATION METRICS

The evaluation of the instruction-following capability of LLMs is usually challenging due to the existence of multiple eligible responses to one instruction and the difficulty to reproduce human evaluations. In light of the recent advancements in automated evaluation (Dubois et al., 2023; Zheng et al., 2023; Chiang et al., 2023), which offer superior scalability and explainability than human studies, we also apply an API LLM  $J(\cdot)$  (e.g., GPT-4) as the judge to evaluate  $\theta_S$  and compare it with  $\theta_V$ . In particular, we apply  $J(\cdot)$  to compare the responses of  $\theta_S$  and  $\theta_V$  to each instruction z drawn from a test set D. Let  $F(z;\theta_V)$  and  $F(z;\theta_S)$  denote the two models' responses to instruction  $z \in D$ , the judge outputs a score for each response and we aim to achieve a higher score on  $\theta_S$ , i.e.,

$$J(F(z;\theta_S)) \ge J(F(z;\theta_V)) \tag{2}$$

for most  $z \in D$ . In our experiments, we include both models' responses in the input to the judge (e.g., GPT-4), followed by an instruction to the judge, which aims to rate the responses with a score between 1 and 10. Details of the input and prompt to the judge can be found in Fig. 12 in the Appendix.

Since there exists position bias within LLM judges, which refers to a phenomenon where LLM judges have tendencies to prefer specific positions over others (Wang et al., 2018; Ko et al., 2020; Wang et al., 2023), to mitigate it, we try both orders (i.e., placing ALPAGASUS's response before/after the baseline model's response) and define the final judge of "Win-Tie-Lose" to be:

- 1. Win: ALPAGASUS wins twice, or wins once and draws once.
- 2. Tie: ALPAGASUS draws twice, or wins once and loses once.
- 3. Lose: ALPAGASUS loses twice, or loses once and draws once.

To avoid cut-off responses, we allow models to generate up to 1024 tokens. For ChatGPT, Claude, and Text-Davinci-003, we set the temperature to 0.0, respectively, to reduce randomness and ensure a fair comparison.

## 4 EXPERIMENTAL RESULTS

### 4.1 QUALITY MATTERS MORE THAN QUANTITY



Figure 5: **Main results** of comparing ALPAGASUS and ALPACA on their 7B and 13B models. ALPAGASUS-9k achieves much better performance than ALPACA-52k on all four test sets: Vicuna, Koala, Self-Instruct, and WizardLM.

ALPAGASUS-9k vs. ALPACA-52k We compare ALPAGASUS and ALPACA on two sizes of models in Fig. 5. They only differ in the training data: ALPACA uses all the 52k data while ALPAGASUS only uses 9k data selected from the 52k. Their hyperparameters and training scripts are the same. As shown in the evaluation results, ALPAGASUS significantly outperforms the original ALPACA across all four test sets. This finding confirms that our training data selection approach leads to superior performance even when the selected training data are only 17.75% of the original dataset.

**Quality-Guided Filtering vs. Random Filtering** To investigate the efficacy of our data selection strategy, we compare ALPAGASUS with LLaMA models fine-tuned on a randomly sampled subset of

the ALPACA 52k data, denoted by ALPACA-9k-random in Fig. 6. Both models start from the same initial model (i.e., LLaMA) and are then finetuned on the same number of samples (i.e., 9k). They only differ in terms of the data selection criteria. In Fig. 6, we compare the two types of models under two model sizes, i.e., 7B and 13B.

ALPAGASUS-9k significantly outperforms ALPACA-9k-random, demonstrating the high quality of our selected data and their importance to the performance of IFT.

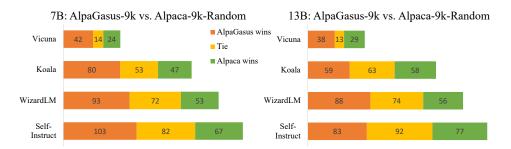


Figure 6: Comparing ALPAGASUS with LLaMA finetuned on randomly selected data.

#### 4.2 How Much Data Should Be Filtered?

Threshold  $\tau$  of data filtering. In Eq. (1), we select data with score  $\geq \tau$  and we set  $\tau = 4.5$  in our main experiments, which results in 9k out of the 52k data to finetune ALPAGASUS. To study the impact of the threshold  $\tau$  on IFT, we compare ALPAGASUS with LLaMA finetuned on 39k data selected by applying a lower threshold of  $\tau = 4.0$ . We report the comparison results in Fig. 7.

When tested on the Koala and WizardLM test sets, ALPACA-39k model outperforms the original ALPACA-52k model. However, when using the Vicuna and Self-Instruct as test sets, ALPACA-39k does not exhibit advantages over

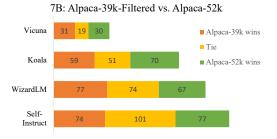


Figure 7: Comparing ALPACA-7B (39k data) with ALPACA-7B (52k data).

the original ALPACA-52k model. Hence, a loose criterion (a lower threshold) includes more data in the selected data and a model with comparable performance as the original ALPACA. However, it still performs poorer than ALPAGASUS trained on much fewer but higher-quality data, indicating the negative impact of low-quality data to IFT.

ALPAGASUS **trained on 3k/6k/9k selected data.** On the other hand, high-quality data show a positive impact on IFT. To verify this, we randomly draw 3k and 6k data from the 9k data selected for training ALPAGASUS and finetune two variants of ALPAGASUS from LLaMA using the same training script. Fig. 8 reports the evaluation results of these variants: ALPAGASUS trained on 9k data performs the best on all four test sets, indicating that more high-quality data leads to better IFT models.

Minimum training data for ALPAGASUS to match the performance of ALPACA. According to Fig. 1, ~6k high-quality data suffices to finetune LLaMA achieving similar performance as the original ALPACA.

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Figure 8: Comparing models finetuned on 3k/6k/9k high-quality data (3k and 6k data are randomly drawn from the 9k data selected for ALPAGASUS).

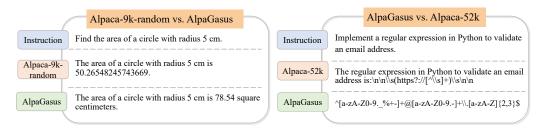


Figure 9: Case study on 13B models of ALPAGASUS and ALPACA. Left: Math capability comparison based on WizardLM test set. Right: Coding skill comparison based on Vicuna test set.

#### 5 ANALYSIS

## 5.1 CASE STUDY

Fig. 9 shows two case studies of 13B models trained on 52k data (ALPACA), 9k selected data (ALPAGASUS), and 9k randomly selected data (ALPACA-9k-random). The left case study focuses on the math capability, where ALPAGASUS can produce a correct answer while ALPACA-9k-random cannot. As the judge, GPT-4 rates the answer of ALPAGASUS by a score of 10.0 while ALPACA-9k-random receives a score of 2.0. The right case study focuses on coding skills, ALPACA-52k cannot follow the instruction but produces a regular expression to validate the website address while ALPAGASUS directly generates the correct code.

## 5.2 ANALYSIS ON WIZARDLM TEST SET

We conduct a fine-grained evaluation of ALPAGASUS on each skill/category in the WizardLM and Vicuna test sets, whose samples are split into a list of skill sets/categories and thus facilitate detailed analyses of the capabilities achieved by IFT.

ALPAGASUS-**7B(9k) vs.** ALPACA-**7B(52k).** We compare these two 7B models on the WizardLM test set and report the results in Fig. 18. Our ALPAGASUS achieves better or equally good performance than ALPACA on 22/29 skills but does not show advantages on the remaining 7 skills such as coding (e.g., code generation). To investigate the reasons, we notice that the coding categories include "python", "Java", "C++", and "C#", which indicate that we can allocate training samples regarding coding skills based on these related keywords (Appendix B). We find that our data selection/filtering, without specifying the proportions of skill categories, leads to a much higher filtering ratio of coding-related data  $\frac{718-85}{718} = 88.16\%$  than the average filtering ratio  $\frac{52002-9229}{52002} = 82.25\%$ . Hence, the resulting coding skill is weaker than other skills. This indicates the importance of keeping the training data diverse and balanced across different categories in IFT.

ALPAGASUS-13B(9k) vs. ALPACA-13B(52k). We further compare the two 13B models on the WizardLM test set with the fine-grained evaluation, as shown in Fig. 17. The observations on the 13B

models are consistent with those on the 7B models and our ALPAGASUS still outperforms ALPACA on most skills. Hence, the data quality still outweighs the data quantity when the model size increases.

#### 5.3 Analysis on Vicuna Test Set

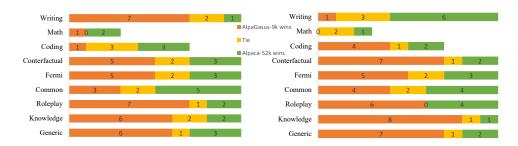


Figure 10: Fine-grained evaluation of ALPAGASUS-13B-9k vs. ALPACA-13B-52k on categories of the Vicuna test set.

Fig. 10 demonstrates the detailed analysis on Vicuna testset. ALPAGASUS-7B is better than the ALPACA-7B on the majority of the categories, including Counterfactual, Roleplay, Knowledge, and Generic, etc. Another strong point is that when the base model scales up, the conclusion still holds. (See right part of the Fig. 10)

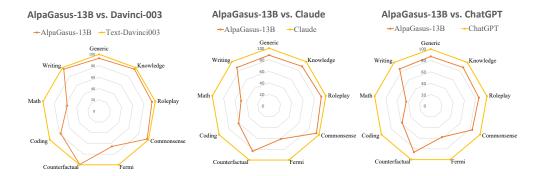


Figure 11: ALPAGASUS-13B vs. Davinci-003, Claude, and ChatGPT. ALPAGASUS achieves average 90.1% capacity of Davinci003, 81.2% of Claude and 78.4% of ChatGPT.

In Fig. 11, we compare ALPAGASUS with text-Davinci-003, ChatGPT, and Claude. The results show that ALPAGASUS-13B can achieve  $\geq 90\%$  capacity of its teacher model, text-Davinci-003. which is used to generate the ALPACA-52k instruction data.

# 6 COST SAVING

Model Size	Data Size	# GPUs	Time	Epoch	LR	Batch Size	Cost
7B	9k	4	14m	3 3	2e-5	128	\$ 4.78*
7B	52k	4	80m		2e-5	128	\$ 27.31*
13B	9k	8	1h	5	1e-5	128	\$ 40.96
13B	52k	8	5.5h	5	1e-5	128	\$ 225.28

Table 2: All the cost is estimated based on the price provided by AWS, assuming the training scripts for all models are the same (e.g., training epochs, batch size on each GPU, accumulation steps, etc.)

We compare the training cost of ALPAGASUS and ALPACA in terms of the estimated expenses for the required computation on AWS <sup>6</sup>. Table 2 reports the details of the hyperparameters for IFT and the estimated costs. Since the experiments of instruction-tuning 33B and 65B LLaMA models require more GPUs and longer training time, our data selection strategy brings more significant savings when the model size scales up.

## 7 RELATED WORK

**Open-sourced Instruction-following models.** Instruction-tuning datasets can be gathered in two ways. A number of studies (Köpf et al., 2023; Dolly, 2023; Zhou et al., 2023) utilize crowdsourcing to produce human-generated pairs of instructions and responses. This approach, while effective, can be laborious and costly. Alternatively, ALPACA (Taori et al., 2023) opens the door to create machine-generated IFT sets from the distillation of the "teacher" LLM, i.e., Text-Davinci-003. Peng et al. (2023) keep the instructions from ALPACA intact but using GPT-4 as the "teacher" LLM, which enhances model on 3H (Helpfulness, Honesty and Harmlessness) (Askell et al., 2021) alignment criteria. Vicuna (Chiang et al., 2023) is the first to adopt ShareGPT (ShareGPT, 2023) data, which is the realistic dialogue data chatting with ChatGPT shared by users. Xu et al. (2023) and Luo et al. (2023) evolve the original Alpaca instruction set and obtains more complex instructions which help better elicit the instruction-following ability of LLMs. There also exists concurrent work like Koala (Geng et al., 2023) and UltraChat (Ding et al., 2023), using dialogue & preference data as well as the adversarial prompts to conduct safe alignment.

**Data-centric AI.** Over the last decade, the realm of data-centric AI (Chu et al., 2016; Motamedi et al., 2021) has witnessed substantial progress. Central to this concept is the belief that the quality of data (Hajij et al., 2021; Zha et al., 2023; Chen et al., 2023a;c;d) warrants the same level of importance as algorithms within the AI/ML lifecycle. As noted by Chu et al. (2016), for an effective engagement with diverse types of data across various domains, data cleaning processes should exhibit a higher degree of automation and adaptability. With the advent of the Transformer architecture (Vaswani et al., 2017b), a shift in the paradigm of language models has occurred. Models such as RoBERTa (Liu et al., 2019), BERT (Vaswani et al., 2017a), and Bard <sup>7</sup> all have incorporated this effective structure, stacking varying quantities of transformer blocks to create more potent models. This marked a turning point in NLP research, signifying a heightened emphasis on data as opposed to model structure. Presently, SOTA LLMs like ChatGPT also underscore this shift toward data. They employ user data to conduct Reinforcement Learning from Human Feedback (RLHF) (Ouyang et al., 2022a; Gao et al., 2022), which further aligns with the Data-centric AI philosophy.

**Evaluation of LLMs.** Evaluating the open-ended instruction-following ability of LLMs is often neglected by previous works (Chung et al., 2022; Anil et al., 2023), though they conduct a series of benchmark evaluations centered around factuality (Hendrycks et al., 2020) and reasoning (Bisk et al., 2020) for their pre-training models. Similarly, the frameworks proposed by Liang et al. (2022) and Gao et al. (2021) focus more on the evaluation of the base models but not on the evaluation of the IFT models, where open-ended instruction-following capability are supposed to be prioritized. Since instruction-following is a general ability but the scope of benchmarks is limited, the recent works such as Koala (Geng et al., 2023), Vicuna (Chiang et al., 2023), Self-Instruct (Wang et al., 2022), and WizardLM (Xu et al., 2023) all provide the instruction sets they collected and some of them also include the categories of the instructions for the evaluation of instruction-tuned LLMs. There are also some leaderboards like Alpaca-Eval (Li et al., 2023) measuring the model's instruction-following ability. Leveraging these recent advancements, we evaluate our models on human instruction sets.

## 8 CONCLUSION

In conclusion, our study reveals that data quality is essential for IFT but existing machine-generated instruction-finetuning datasets include many low-quality data detrimental to finetuning. A major

 $<sup>^6</sup>$ https://aws.amazon.com/ec2/instance-types/p4/ a p4de.24xlarge(preview) node has 8  $\times$  80GB A100 and it costs \$40.96/h.\*: we assume the training time of using 8 GPUs is half of using 4 GPUs.

<sup>&</sup>lt;sup>7</sup>https://bard.google.com/

contribution of this paper is an efficient and automatic data selection strategy based on ratings given by a strong LLM such as ChatGPT with a carefully designed prompt. This novel approach has proven effective across public instruction-finetuning datasets and paves the way for more accurate and efficient LLM instruction-finetuning protocols. Moreover, we propose a holistic evaluation scheme comparing the instruction-following capability of two models by prompting an LLM to be a judge (e.g., GPT-4) on four test sets covering diverse test cases.

When applied to the 52k training data of ALPACA, our data selection reduces the data to just 9k but significantly improves the performance of the resulting ALPAGASUS. It also greatly shortens the training time from 80 minutes to merely 14 minutes, which is a paramount consideration in AI model development. Hence, our data filtering method paves the way for more efficient and effective IFT.

#### 9 LIMITATIONS

**Model Size.** In our experiments, we evaluated our IFT strategy by training models of two different sizes, 7B and 13B, since they are the most common sizes for recent open-source LLMs. We plan to extend this study to larger model sizes such as 33B, 65B, or even 175B, and verify whether the same conclusion still holds, i.e., a small subset of high-quality data selected by our method can improve the instruction-finetuned model. We leave analysis on the IFT of larger models as future work.

**Human Evaluations.** Our study does not rely on any human evaluation due to its expensive cost. In the future, we would like to study the difference between human feedback and LLM ratings/evaluations.

**Experiments on other IFT datasets.** Our work focuses on the IFT dataset for Alpaca. We leave exploration for other IFT datasets as future work.

#### REFERENCES

- Rohan Anil, Andrew M Dai, Orhan Firat, Melvin Johnson, Dmitry Lepikhin, Alexandre Passos, Siamak Shakeri, Emanuel Taropa, Paige Bailey, Zhifeng Chen, et al. Palm 2 technical report. *arXiv* preprint arXiv:2305.10403, 2023.
- Amanda Askell, Yuntao Bai, Anna Chen, Dawn Drain, Deep Ganguli, Tom Henighan, Andy Jones, Nicholas Joseph, Ben Mann, Nova DasSarma, et al. A general language assistant as a laboratory for alignment. *arXiv preprint arXiv:2112.00861*, 2021.
- Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, et al. Constitutional ai: Harmlessness from ai feedback. *arXiv preprint arXiv:2212.08073*, 2022.
- Yonatan Bisk, Rowan Zellers, Jianfeng Gao, Yejin Choi, et al. Piqa: Reasoning about physical commonsense in natural language. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pp. 7432–7439, 2020.
- Jiuhai Chen, Lichang Chen, and Tianyi Zhou. It takes one to tango but more make trouble? in-context training with different number of demonstrations. *arXiv* preprint arXiv:2303.08119, 2023a.
- Lichang Chen, Jiuhai Chen, Tom Goldstein, Heng Huang, and Tianyi Zhou. Instructzero: Efficient instruction optimization for black-box large language models. *arXiv preprint arXiv:2306.03082*, 2023b.
- Lichang Chen, Minhao Cheng, and Heng Huang. Backdoor learning on sequence to sequence models. *arXiv preprint arXiv:2305.02424*, 2023c.
- Lichang Chen, Heng Huang, and Minhao Cheng. Ptp: Boosting stability and performance of prompt tuning with perturbation-based regularizer. *arXiv preprint arXiv:2305.02423*, 2023d.
- Yew Ken Chia, Pengfei Hong, Lidong Bing, and Soujanya Poria. Instructeval: Towards holistic evaluation of instruction-tuned large language models. *arXiv preprint arXiv:2306.04757*, 2023.

- Wei-Lin Chiang, Zhuohan Li, Zi Lin, Ying Sheng, Zhanghao Wu, Hao Zhang, Lianmin Zheng, Siyuan Zhuang, Yonghao Zhuang, Joseph E. Gonzalez, Ion Stoica, and Eric P. Xing. Vicuna: An open-source chatbot impressing gpt-4 with 90%\* chatgpt quality, March 2023. URL https://lmsys.org/blog/2023-03-30-vicuna/.
- Xu Chu, Ihab F Ilyas, Sanjay Krishnan, and Jiannan Wang. Data cleaning: Overview and emerging challenges. In *Proceedings of the 2016 international conference on management of data*, pp. 2201–2206, 2016.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*, 2022.
- Ning Ding, Yulin Chen, Bokai Xu, Yujia Qin, Zhi Zheng, Shengding Hu, Zhiyuan Liu, Maosong Sun, and Bowen Zhou. Enhancing chat language models by scaling high-quality instructional conversations. *arXiv preprint arXiv:2305.14233*, 2023.
- Dolly. Free dolly: Introducing the world's first truly open instruction-tuned llm. Blog Post, 2023. URL https://www.databricks.com/blog/2023/04/12/dolly-first-open-commercially-viable-instruction-tuned-llm.
- Yann Dubois, Xuechen Li, Rohan Taori, Tianyi Zhang, Ishaan Gulrajani, Jimmy Ba, Carlos Guestrin, Percy Liang, and Tatsunori B Hashimoto. Alpacafarm: A simulation framework for methods that learn from human feedback. *arXiv preprint arXiv:2305.14387*, 2023.
- Leo Gao, Jonathan Tow, Stella Biderman, Sid Black, Anthony DiPofi, Charles Foster, Laurence Golding, Jeffrey Hsu, Kyle McDonell, Niklas Muennighoff, Jason Phang, Laria Reynolds, Eric Tang, Anish Thite, Ben Wang, Kevin Wang, and Andy Zou. A framework for few-shot language model evaluation, September 2021. URL https://doi.org/10.5281/zenodo.5371628.
- Leo Gao, John Schulman, and Jacob Hilton. Scaling laws for reward model overoptimization. *arXiv* preprint arXiv:2210.10760, 2022.
- Xinyang Geng, Arnav Gudibande, Hao Liu, Eric Wallace, Pieter Abbeel, Sergey Levine, and Dawn Song. Koala: A dialogue model for academic research. Blog post, April 2023. URL https://bair.berkeley.edu/blog/2023/04/03/koala/.
- Mustafa Hajij, Ghada Zamzmi, Karthikeyan Natesan Ramamurthy, and Aldo Guzman Saenz. Datacentric ai requires rethinking data notion. *arXiv preprint arXiv:2110.02491*, 2021.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. Measuring massive multitask language understanding. *arXiv preprint arXiv:2009.03300*, 2020.
- Miyoung Ko, Jinhyuk Lee, Hyunjae Kim, Gangwoo Kim, and Jaewoo Kang. Look at the first sentence: Position bias in question answering. *arXiv preprint arXiv:2004.14602*, 2020.
- Andreas Köpf, Yannic Kilcher, Dimitri von Rütte, Sotiris Anagnostidis, Zhi-Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, Richárd Nagyfi, et al. Openassistant conversations—democratizing large language model alignment. *arXiv preprint arXiv:2304.07327*, 2023.
- Xuechen Li, Tianyi Zhang, Yann Dubois, Rohan Taori, Ishaan Gulrajani, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Alpacaeval: An automatic evaluator of instruction-following models. https://github.com/tatsu-lab/alpaca\_eval, 2023.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, et al. Holistic evaluation of language models. *arXiv preprint arXiv:2211.09110*, 2022.
- Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*, 2019.

- Shayne Longpre, Le Hou, Tu Vu, Albert Webson, Hyung Won Chung, Yi Tay, Denny Zhou, Quoc V Le, Barret Zoph, Jason Wei, et al. The flan collection: Designing data and methods for effective instruction tuning. *arXiv preprint arXiv:2301.13688*, 2023.
- Ziyang Luo, Can Xu, Pu Zhao, Qingfeng Sun, Xiubo Geng, Wenxiang Hu, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. Wizardcoder: Empowering code large language models with evol-instruct, 2023.
- Mohammad Motamedi, Nikolay Sakharnykh, and Tim Kaldewey. A data-centric approach for training deep neural networks with less data. *arXiv preprint arXiv:2110.03613*, 2021.
- OpenAI. Chatgpt. https://openai.com/blog/chatgpt, 2023a.
- OpenAI. Gpt-4 technical report. arXiv, 2023b.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35: 27730–27744, 2022a.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35: 27730–27744, 2022b.
- Baolin Peng, Chunyuan Li, Pengcheng He, Michel Galley, and Jianfeng Gao. Instruction tuning with gpt-4. *arXiv preprint arXiv:2304.03277*, 2023.
- ShareGPT. Sharegpt. 2023. URL sharegpt.com.
- Rohan Taori, Ishaan Gulrajani, Tianyi Zhang, Yann Dubois, Xuechen Li, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. Stanford alpaca: An instruction-following llama model. https://github.com/tatsu-lab/stanford\_alpaca, 2023.
- Hugo Touvron, Thibaut Lavril, Gautier Izacard, Xavier Martinet, Marie-Anne Lachaux, Timothée Lacroix, Baptiste Rozière, Naman Goyal, Eric Hambro, Faisal Azhar, Aurelien Rodriguez, Armand Joulin, Edouard Grave, and Guillaume Lample. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Ł ukasz Kaiser, and Illia Polosukhin. Attention is all you need. In I. Guyon, U. Von Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett (eds.), Advances in Neural Information Processing Systems, volume 30. Curran Associates, Inc., 2017a. URL https://proceedings.neurips.cc/paper\_files/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf.
- Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. *Advances in neural information processing systems*, 30, 2017b.
- Peiyi Wang, Lei Li, Liang Chen, Dawei Zhu, Binghuai Lin, Yunbo Cao, Qi Liu, Tianyu Liu, and Zhifang Sui. Large language models are not fair evaluators. *arXiv preprint arXiv:2305.17926*, 2023.
- Xuanhui Wang, Nadav Golbandi, Michael Bendersky, Donald Metzler, and Marc Najork. Position bias estimation for unbiased learning to rank in personal search. In *Proceedings of the eleventh ACM international conference on web search and data mining*, pp. 610–618, 2018.
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A Smith, Daniel Khashabi, and Hannaneh Hajishirzi. Self-instruct: Aligning language model with self generated instructions. *arXiv preprint arXiv:2212.10560*, 2022.
- Can Xu, Qingfeng Sun, Kai Zheng, Xiubo Geng, Pu Zhao, Jiazhan Feng, Chongyang Tao, and Daxin Jiang. Wizardlm: Empowering large language models to follow complex instructions, 2023.

- Daochen Zha, Zaid Pervaiz Bhat, Kwei-Herng Lai, Fan Yang, Zhimeng Jiang, Shaochen Zhong, and Xia Hu. Data-centric artificial intelligence: A survey. *arXiv preprint arXiv:2303.10158*, 2023.
- Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. Judging llm-as-a-judge with mt-bench and chatbot arena. *arXiv preprint arXiv:2306.05685*, 2023.
- Chunting Zhou, Pengfei Liu, Puxin Xu, Srini Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, et al. Lima: Less is more for alignment. *arXiv preprint arXiv:2305.11206*, 2023.

# **APPENDIX**

## A GPT-4 EVALUATION PROMPT

We provide the detailed form of the prompt to GPT-4 used for evaluation in Fig. 12. It is the prompt for evaluation used in the original Vicuna blog <sup>8</sup>

#### **System Prompt:**

You are a helpful and precise assistant for checking the quality of the answer.

User Prompt:
[Question]
[The Start of Assistant 1's Answer]
{answer\_1}
[The End of Assistant 1's Answer]
[The Start of Assistant 2's Answer]

{answer\_2}
[The End of Assistant 2's Answer]

We would like to request your feedback on the performance of two AI assistants in response to the user question displayed above.\nPlease rate the helpfulness, relevance, accuracy, level of details of their responses. Each assistant receives an overall score on a scale of 1 to 10, where a higher score indicates better overall performance.\nPlease first output a single line containing only two values indicating the scores for Assistant 1 and 2, respectively. The two scores are separated by a space. In the subsequent line, please provide a comprehensive explanation of your evaluation, avoiding any potential bias and ensuring that the order in which the responses were presented does not affect your judgment."

Figure 12: The prompt for evaluation using GPT-4 as the judge.

# B KEYWORDS SET FOR DETAILED ANALYSIS

We use the keyword set of [Java, java, C++, c++, C#, c#, Python, python] and count the number of (instruction, input, output) tuples which contain the keyword in this set.

## C MORE EXAMPLES

We include more examples rated by the response quality evaluator, i.e., ChatGPT, in this section. The examples of Score 5.0, Score 4.5, Score 4.0, Score 3.5, Score 3.0, Score 2.5, Score 2.0 are shown in Fig. 13, Fig. 14, Fig. 15, and Fig. 16, respectively.

<sup>8</sup>https://lmsys.org/blog/2023-03-30-vicuna/

Triplet: (Instruction, Input, Response)	Score & Explanations
Instruction: Answer this true or false question: The capital of France is London. Response: False. The capital of France is Paris.	5: The AI assistant provided a correct and accurate response to the instruction and input given. It correctly identified that the statement \"The capital of France is London\" is false and provided the correct answer that the capital of France is Paris. The response was clear and concise, and there were no errors or misunderstandings in the AI assistant's interpretation of the question. Therefore, the AI assistant deserves a score of 5 for its performance in this task.
Instruction: Translate the phrase "Bonne chance" into English Response: Good luck.	5: The AI assistant provided a correct and accurate response to the given instruction and input. \"Bonne chance\" is a French phrase that translates to \"Good luck\" in English, and the AI assistant provided the correct translation. Therefore, the assistant deserves a score of 5 for its accuracy.
Instruction: Complete the following sentence given the context: Input: My grandmother always said, "An apple a day Response: keeps the doctor away.",	5: The AI assistant provided a perfect response to the given input and instruction. The response accurately completed the sentence with the correct phrase that follows \"An apple a day\". Therefore, the AI assistant deserves a score of 5 for its accuracy.",

Figure 13: The triplets (instruction, input, response) obtain Score 5.0.

#### Triplet: (Instruction, Input, Response) Score & Explanations 4.5: The response provided by the AI assistant is Instruction: Suggest ways to reduce plastic waste in everyday life. highly accurate and relevant to the given instruction. It suggests various ways to reduce plastic waste in everyday life, including using reusable items, Response: one way to reduce plastic waste in avoiding single-use containers and utensils, finding everyday life is to make the switch to reusable items. sustainable alternatives, and recycling. The only This includes bringing a reusable water bottle potential improvement could be providing more instead of buying bottled water, investing in a specific examples of sustainable alternatives to reusable coffee cup, bringing your own bags when plastic items. Overall, the response is informative shopping, and using reusable containers for storing and helpful in addressing the given instruction. and transporting food. You can also reduce the amount of plastic waste you create by avoiding or limiting the use of take-out or single-use containers, utensils and straws. Additionally, try to find sustainable alternatives to plastic items when shopping and avoid purchasing items wrapped in plastic whenever possible. Finally, make sure you recycle any plastic items you do have. Instruction: Generate a list of non-alcoholic drinks 4.5: The AI assistant provided a comprehensive list of non-alcoholic drinks that are commonly consumed. Response: \n- Fruit juices \n- Tea \n- Smoothies \n-The list includes a variety of options such as fruit Iced coffee \n- Milkshakes \n- Fizzy drinks \n- Hot juices, tea, smoothies, and fizzy drinks. However, chocolate\n- Lemonades\n- Kombucha\n- Energy there are some duplicates in the list such as drinks\n- Milkshake\n- Coconut water\n- Ginger milkshakes and iced coffee. Additionally, some of the beer \n- Ice tea \n- Sparkling water\n- Aloe vera options may not be as commonly consumed as drink\n- Vegetable juice\n others, such as kombucha and aloe vera drink. Overall, the response is accurate and provides a good range of options for non-alcoholic drinks.

Figure 14: The triplets (instruction, input, response) obtain Score 4.5.

the root causes of problems.

#### Triplet: (Instruction, Input, Response) Score & Explanations Instruction: Compare and contrast commercial banks 4.0: The response provided by the AI assistant is and investment banks. mostly accurate and relevant to the given instruction and input. It clearly explains the differences between commercial banks and investment banks, Response: Commercial banks are financial highlighting their respective roles and services. institutions that provide services to their customers, However, it could have provided more specific such as loans, deposits, and investment examples of the services offered by each type of management. Investment banks, on the other hand, bank, and could have elaborated further on the are a type of financial institution that specializes in regulations that apply to them. Overall, the response the trading of securities, such as stocks and bonds. is informative and helpful, but could benefit from The main difference between the two is that more detail. commercial banks provide services to customers, while investment banks provide services to governments, corporations, and wealthy individuals. Commercial banks are also subject to more regulations than investment banks, as they offer deposit accounts to customers. Investment banks, however, do not accept deposits from the general public and are subject to fewer regulations. Both types of banks are important for the global economy, but their roles and services are different. Instruction: Determine the application of statistics in 4.0 The AI assistant provided a fairly accurate the field of economics. response to the instruction. It correctly identified the various applications of statistics in the field of Response: Statistics is widely used in economics to economics, including market analysis, company analyze and predict markets, examine the performance evaluation, policy evaluation, and performance of companies, and evaluate economic prediction of economic growth and interest rates. policies. Statistics is used to identify trends and However, the response could have been more correlations and to measure variables such as prices detailed and provided specific examples of statistical and wages. Statistical models are also used to methods used in economics. Overall, the response predict economic growth and changes in interest was informative and provided a good overview of rates and to test the effects of regulation and the topic. taxation. Statistical tools are also used to estimate the impacts of policy changes, assess the effectiveness of government programs and identify

Figure 15: The triplets (instruction, input, response) obtain Score 4.0.

Triplet: (Instruction, Input, Response)	Score & Explanations
Instruction:\nDesign a company logo Response:\n <nooutput>\n\n</nooutput>	2.0: The AI assistant did not provide any response to the given instruction and input. Therefore, it cannot be evaluated for accuracy.
Instruction: Classify the item as either animal or vegetable. Input: Banana Response: Animal: No, it's a vegetable.	2.0: The AI assistant's response is incorrect. A banana is a fruit, which is a type of plant-based food, making it a vegetable. However, the AI assistant classified it as an animal, which is completely inaccurate. Therefore, the score is low.
Instruction: Design a poster to advertise a product. Response: No output required	2.5: The AI assistant did not provide any response to the given input, which makes it difficult to evaluate its performance accurately. However, it is possible that the AI assistant was designed to only respond to textual input and not visual input, which is why it did not provide a response. Therefore, I have given it a score of 2.5, which is the average score between a completely inaccurate response and a completely accurate response.

Figure 16: The triplets (instruction, input, response) obtain Score 2.0 and 2.5.

# D DETAILED ANALYSIS ON THE WIZARDLM TESTSET

In Fig. 19, Fig. 20, and Fig. 21, we compare AlpaGasus with text-Davinci-003, ChatGPT, and Claude, respectively. The results show that AlpaGasus-13B can achieve  $\geq 91\%$  capacity of its "teacher" model, text-Davinci-003 (all the responses in the AlpaCa-52k dataset are generated by text-Davinci-003 so we call it "teacher" LLM). The results also show that our model could achieve pretty good performance on tasks like Writing, RolePlay, Toxicity, Art, etc., while it still needs improvement on coding and math capacity when compared with stronger LLMs.

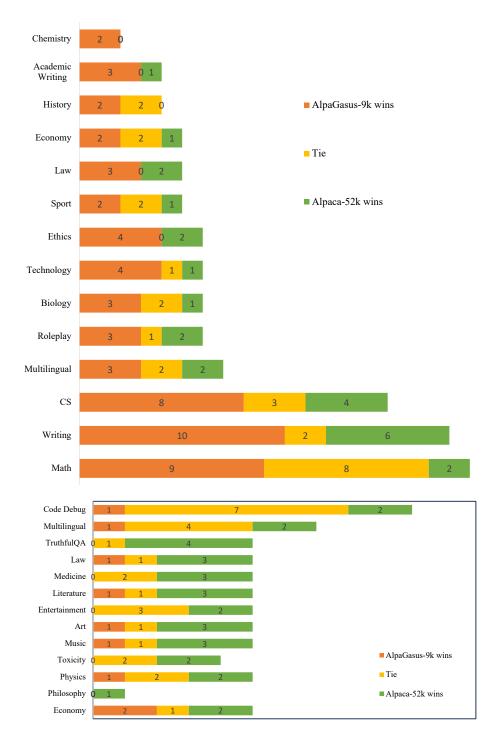


Figure 17: Fine-grained evaluation of ALPAGASUS-9k(13B) vs. ALPACA-52k(13B) on categories of the WizardLM test set.

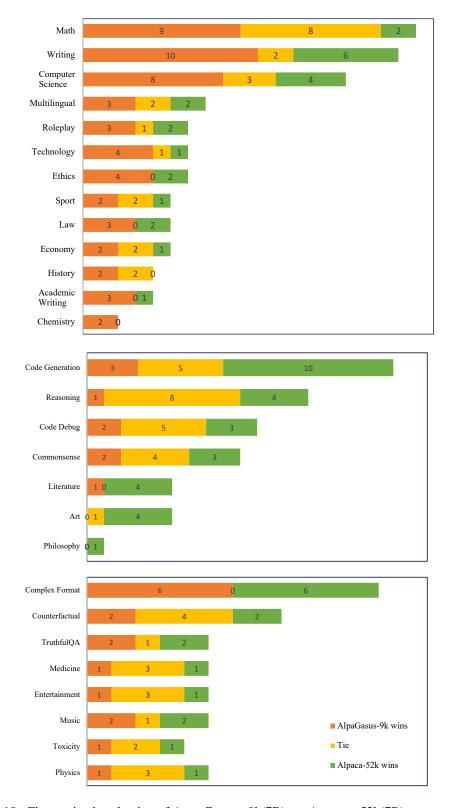


Figure 18: Fine-grained evaluation of ALPAGASUS-9k(7B) vs. ALPACA-52k(7B) on categories of the WizardLM test set.

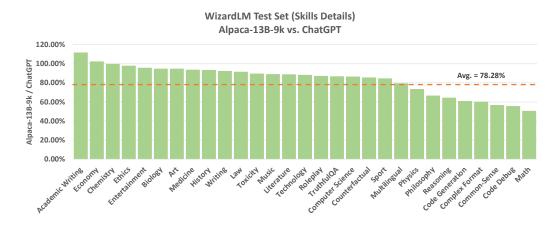


Figure 19: Compare with ChatGPT. Achieve average 78.26% capacity of ChatGPT on all 29 skills.

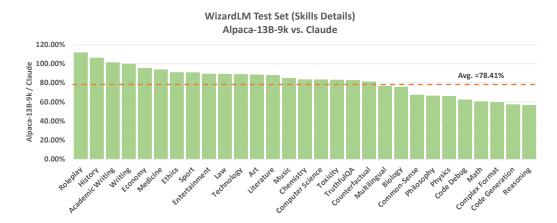


Figure 20: Compare with claude. Achieve average 78.41% capacity of ChatGPT on all 29 skills.

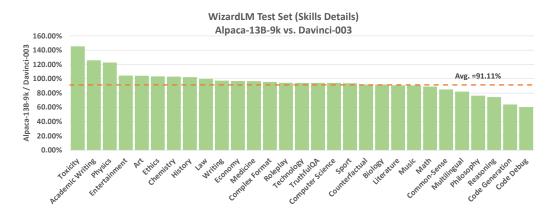


Figure 21: Compare with Davinci-003. Achieve average 91.11% capacity of ChatGPT on all 29 skills.

# E Frequently Asked Questions

#### E.1 IS THERE ANY BIAS CONTAINED IN THE EVALUATION PROMPTS?

We also try other evaluation prompts like the prompts provided in the Zheng et al. (2023), which are shown in Table 3. We apply the same rules to calculate the "Win-Tie-Lose" and show the results in Fig. 22. ALPAGASUS could still win in all the test sets.



Figure 22: The experimental results when using the evaluation prompt from Zheng et al. (2023) to judge the two responses. ALPAGASUS could still maintain its advantage.

# E.2 HAVE YOU TRIED OTHER LLM AS RESPONSE QUALITY EVALUATOR?

Yes, we also try to use Claude<sup>9</sup> as our response quality evaluator. We will analyze the scores and add supplementary materials in the next Arxiv version. Stay tuned!

System Prompt	Please act as an impartial judge and evaluate the quality of the responses provided by two AI assistants to the user question displayed below. You should choose the assistant that follows the user's instructions and answers the user's question better. Your evaluation should consider factors such as the helpfulness, relevance, accuracy, depth, creativity, and level of detail of their responses. Begin your evaluation by comparing the two responses and provide a short explanation. Avoid any positional biases and ensure that the order in which the responses were presented does not influence your decision. Do not allow the length of the responses to influence your evaluation. Do not favor certain names of the assistants. Be as objective as possible. After providing your explanation, output your final verdict by strictly following this format: "[[A]]" if assistant A is better, "[[B]]" if assistant B is better, and "[[C]]" for a tie.
Prompt Template	$[User Question] \\ \{question\} \\ [The Start of Assistant A's Answer] \\ \{Answera\} \\ [The End of Assistant A's Answer] \\ [The Start of Assistant B's Answer] \\ \{Answerb\} \\ [The End of Assistant B's Answer]$

Table 3: The GPT-4 evaluation prompt from Zheng et al. (2023).

<sup>9</sup>https://www.anthropic.com/index/introducing-claude