

WizardLM: EMPOWERING LARGE PRE-TRAINED LANGUAGE MODELS TO FOLLOW COMPLEX INSTRUCTIONS

Can Xu^{1*} Qingfeng Sun^{1*} Kai Zheng^{1*} Xiubo Geng¹ Pu Zhao¹

Jiazhan Feng^{2†} Chongyang Tao¹ Qingwei Lin¹ Daxin Jiang^{1‡}

¹Microsoft

²Peking University

{caxu, qins, zhengkai, xigeng, puzhao, chongyang.tao, qlin, djiang}@microsoft.com

{fengjiazhan}@pku.edu.cn

ABSTRACT

Training large language models (LLMs) with open-domain instruction following data brings colossal success. However, manually creating such instruction data is very time-consuming and labor-intensive. Moreover, humans may struggle to produce high-complexity instructions. In this paper, we show an avenue for creating large amounts of instruction data with varying levels of complexity using LLM instead of humans. Starting with an initial set of instructions, we use our proposed *Evol-Instruct* to rewrite them step by step into more complex instructions. Then, we mix all generated instruction data to fine-tune LLaMA. We call the resulting model *WizardLM*. Both automatic and human evaluations consistently indicate that *WizardLM* outperforms baselines such as Alpaca (trained from Self-Instruct) and Vicuna (trained from human-created instructions). The experimental results demonstrate that the quality of instruction-following dataset crafted by *Evol-Instruct* can significantly improve the performance of LLMs.

1 INTRODUCTION

Large-scale language models (LLMs) have become the go-to approach for numerous natural language processing tasks (Brown et al., 2020; Ouyang et al., 2022; Touvron et al., 2023). LLMs are trained on large volumes of text data to predict the subsequent tokens, enabling them to generate coherent and fluent text in response to various inputs. However, these models often struggle to follow instructions or goals specified by users, which limits their usefulness and applicability in real-world scenarios.

The NLP community has recently witnessed many endeavors to train LLMs to follow instructions better and be more helpful (Zhao et al., 2023; He et al., 2023; Guo et al., 2023; Li et al., 2023b). Initial attempts (Aribandi et al., 2022; Wei et al., 2021; Xu et al., 2022; Sanh et al., 2022; Chung et al., 2022) to train instruction-following language models are based on a collection of various NLP tasks, with a small amount of hand-written instructions. These closed-domain instructions suffer from two main drawbacks: first, all the samples in an NLP dataset share only a few common instructions, severely limiting their diversity; second, the instructions usually only ask for one task. But in real life, human instructions often have multiple and varied task demands. By using open-domain instruction data generated by real human users, OpenAI’s LLMs (e.g., InstructGPT (Ouyang et al., 2022) and ChatGPT¹) have achieved great success. These open-domain instructions can fully unleash the unlimited potential of LLMs (Luo et al., 2023; Ma et al., 2023; Hu et al., 2023; Zhu et al., 2023) and enable them to perform more complex and diverse tasks. However, using humans to create open-domain instruction datasets like OpenAI did will encounter the following challenges. The whole annotating process is extremely expensive and time-consuming (Kopf et al., 2023; Chen et al., 2023; Sun et al., 2023; Yuan et al., 2023). On the other hand, the difficulty level distribution of human-created instructions is skewed towards being easy or moderate, with fewer difficult ones (according

* Equal contribution.

† Work done during the internship at Microsoft.

‡ Corresponding author.

¹<https://chat.openai.com/>

to the difficulty statistics of ShareGPT (Chiang et al., 2023) from Figure 5a). Human annotators are prone to fatigue and cannot sustain high-intensity work to produce a sufficient proportion of high-difficulty instructions (Zhang et al., 2023; Xiao et al., 2023; Manakul et al., 2023; Zhong et al., 2023). Based on these issues, developing an automatic method that can mass-produce open-domain instructions (especially the more difficult ones) at a relatively low cost becomes the key to further advancing instruction-tuned language models (Bao et al., 2023; Liu et al., 2023; Bian et al., 2023; Cabannes et al., 2023).

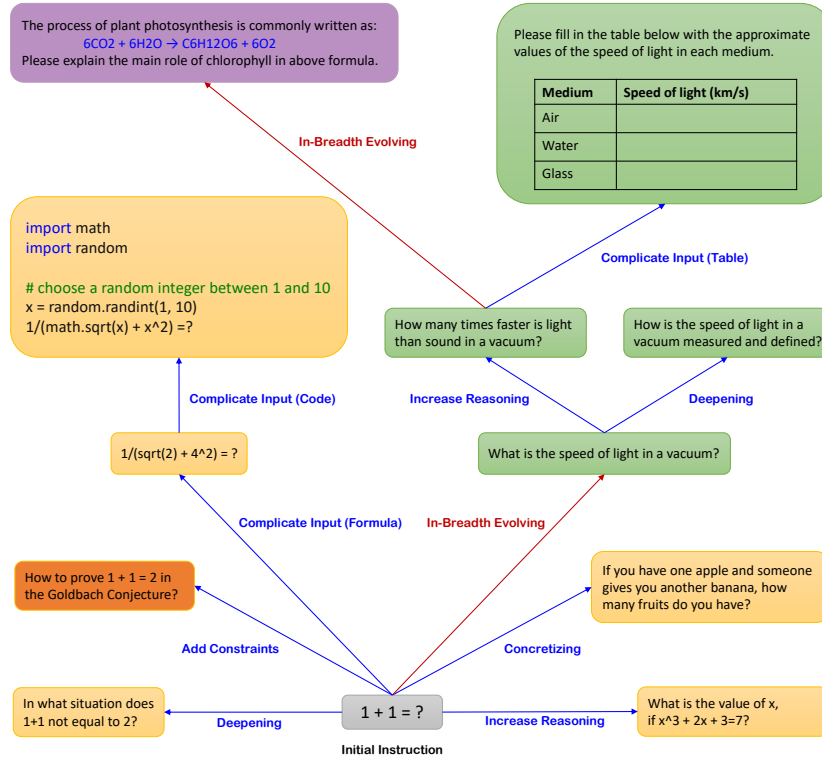


Figure 1: Running Examples of *Evol-Instruct*.

In this work, we introduce *Evol-Instruct*, a novel method using LLMs instead of humans to automatically mass-produce open-domain instructions of various difficulty levels, to improve the performance of LLMs. Figure 1 shows the running examples of *Evol-Instruct*. Starting from a simple initial instruction “ $1+1=?$ ”, our method randomly selects In-depth Evolving (blue direction line) or In-breadth Evolving (red direction line) to upgrade the simple instruction to a more complex one or create a new one (to increase diversity). The In-depth Evolving includes five types of operations: add constraints, deepening, concretizing, increase reasoning steps, and complicate input. The In-breadth Evolving is mutation, i.e., generating a completely new instruction based on the given instruction. These six operations are implemented by prompting an LLM with specific prompts. Since the evolved instructions are generated from LLMs, sometimes the evolving will fail. We adopt an instruction eliminator to filter the failed instructions, which is called Elimination Evolving. We repeat this evolutionary process for several rounds to obtain enough instruction data containing various complexities.

In order to verify the effectiveness of *Evol-Instruct* and whether the instructions it creates for fine-tuning surpass those created by humans, we evolve the instructions from Alpaca (Taori et al., 2023) data (created by machine), fine-tune the LLaMA (Touvron et al., 2023) model, and comprehensively compare the fine-tuned model *WizardLM* with Vicuna (Chiang et al., 2023) trained on ShareGPT (instructions are created by human). Alpaca data has a total of $52k$ samples and is generated using self-instruct (Wang et al., 2022a) from only 175 human-created seed instructions. We choose Alpaca data as the initial data for evolution, which can ensure that the training instructions of *WizardLM* have almost no direct human participation in annotations. We execute four epochs of evolution

using OpenAI ChatGPT API² and finally obtain 250k instructions. To ensure a fair comparison with Vicuna’s 70k real user data, we sampled 70k from the full 250k data and fine-tuned the LLaMA 13B model. Because the original Alpaca data only has 52k samples, we used its self-instruct method to generate an additional 18k data, and retrained the LLaMA 13B model with its code³ to get Alpaca 13B as our baseline. Due to the low proportion of difficult instructions in the previous instruction-following test dataset, we manually created a new difficulty-balanced test dataset, named *WizardEval*. We evaluate Alpaca, Vicuna, ChatGPT, and WizardLM on a wide range of LLM benchmarks (covering reasoning, code, mathematics, general conversation, etc.). Our main findings are as follows:

- We introduce *Evol-Instruct*, a novel approach that enhances the performance of the open-source LLMs by a large margin via automatically mass-producing open-domain instructions of various topics and difficulty levels.
- We develop *WizardLM* model, which significantly surpasses typical open-source LLMs such as Alpaca and Vicuna in a series of benchmarks. Notably, *WizardLM* outperforms baselines by a substantial margin in terms of code, math, GPT-4 and human evaluations.
- We have undertaken a preliminary investigation that underscores the importance of instruction complexity in attaining outstanding performance in supervised fine-tuning large pre-trained language models.

2 RELATED WORK

Closed domain instruction tuning Early instruction-following training work (Wei et al., 2021; Longpre et al., 2023) concerns cross task generalization in LMs, where LMs are fine-tuned on a broad range of public NLP datasets and evaluated on a different set of NLP tasks. T5 Raffel et al. (2020) made the earliest attempt by training natural language processing (NLP) tasks such as question answering, document summarization, and sentiment classification together using a unified text-to-text format. Works such as FLAN Wei et al. (2021), ExT5 Aribandi et al. (2022), T0 Sanh et al. (2022), and KnowDA Wang et al. (2022c) increased the number of NLP tasks to around one hundred, with several instructions carefully designed for each task de Wynter et al. (2023); Svikhushina & Pu (2023); Huang et al. (2023); Yue et al. (2023). Furthermore, works such as ZeroPrompt Xu et al. (2022) and FLAN-T5 Chung et al. (2022) raised the number of tasks to the thousands. These studies consistently show that fine-tuning LMs with diverse NLP task instructions enhances their performance on new tasks. However, LLMs trained with these closed-form instructions (i.e., instructions are often only for a single NLP task, and the input data form is simple) tend to fail in real-world user scenarios.

Open domain instruction tuning Our work belongs to this research line. OpenAI has hired many annotators and written many instructions with corresponding correct responses. These human-created instructions have diverse forms and rich task types. Based on this dataset, OpenAI trained GPT-3 Brown et al. (2020) into InstructGPT Ouyang et al. (2022), which can process a variety of real user instructions and led to the success of ChatGPT. Orca Mukherjee et al. (2023) learns not only the superficial response text from LLMs, but also captures complex reasoning process signals. Since these outstanding works from OpenAI were not open-sourced, Alpaca Taori et al. (2023) and Vicuna Chiang et al. (2023) subsequently actively explored open-domain instruction fine-tuning based on the open-source LLM LLaMA Touvron et al. (2023). Alpaca used a dataset of 50k instructions generated from a limited (e.g., 175 samples) seed set of manually-written instructions. Our work is different from InstructGPT and Vicuna in that we use AI-generated data for instruction fine-tuning. Unlike Alpaca’s self-instruct Wang et al. (2022a) generation method, *Evol-Instruct* can control the difficulty and complexity level of the generated instructions.

3 APPROACH

In this section, we elaborate on the details of the proposed *Evol-Instruct*. As illustrated in Figure 2, the pipeline mainly contains two components: Instruction Evolver and Instruction Eliminator. The

²[gpt-3.5-turbo from https://oai.azure.com/portal](https://oai.azure.com/portal)

³https://github.com/tatsu-lab/stanford_alpaca

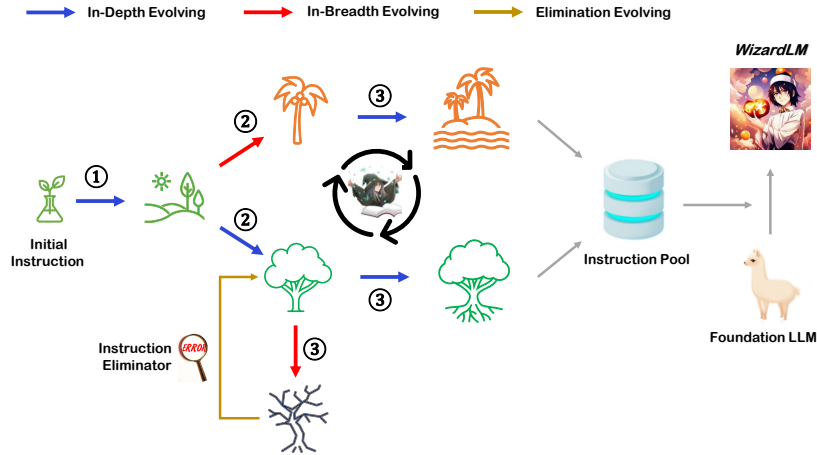


Figure 2: Overview of *Evol-Instruct*

details of these components will be presented in Sec. 3.2 and instruction fine-tuning method will be described in Sec. 3.3.

3.1 DEFINITION OF INSTRUCTION DATA EVOLUTION

We start the evolution from a given initial instruction dataset $D^{(0)} = (I_k^{(0)}, R_k^{(0)})_{1 \leq k \leq N}$, where $I_k^{(0)}$ is the k -th instruction in $D^{(0)}$, $R_k^{(0)}$ is the corresponding response for the k -th instruction, and N is the number of samples in $D^{(0)}$. In each evolution, we upgrade all the $I^{(t)}$ in $D^{(t)}$ to $I^{(t+1)}$ by prompting a LLM with *Evol-Instruct* prompt, and then use the LLM to generate corresponding responses R^{t+1} for the newly evolved I^{t+1} . Thus, we obtain an evolved instruction dataset D^{t+1} . By iteratively performing M evolutions, we can sequentially obtain M evolution datasets $[D^{(1)} \dots D^{(M)}]$. Our work focuses on open-domain instruction data, where instructions have varying inputs and tasks without a clear distinction between the instruction part and the input.

3.2 AUTOMATIC INSTRUCTION DATA EVOLUTION

Our pipeline for instruction evolution consists of three steps: 1) instruction evolving, 2) response generation, and 3) elimination evolving, i.e., filtering instructions that fails to evolve.

Instruction Evolution. We found that LLMs can make given instructions more complex and difficult using specific prompts. Additionally, they can generate entirely new instructions that are equally complex but completely different. Using this discovery, we can iteratively evolve an initial instruction dataset, improving difficulty level and expanding its richness and diversity. We initiate the instruction pool with the given initial instruction dataset $D^{(0)}$. In each evolution epoch, upgraded instructions from the previous epoch are taken out from the pool. Then we leverage the instruction evolver to evolve each fetched instruction, and the instruction eliminator to check whether the evolution fails. Successful evolved instructions are added to the pool, while unsuccessful ones are placed back as they are, with the hope of upgrading them successfully in the next evolution epoch.

Instruction Evolver. The Instruction Evolver is an LLM that uses *Evol-Instruct* prompts to evolve instructions, with two types: in-depth evolving and in-breadth evolving.

In-Depth Evolving enhances instructions by making them more complex and difficult through five types of prompts: add constraints, deepening, concretizing, increased reasoning steps, and complicating input. The core part of In-Depth Evolving’s prompt is “Your objective is to rewrite a given prompt into a more complex version to make those famous AI systems (e.g., ChatGPT and GPT4 (OpenAI, 2023)) a bit harder to handle. But the rewritten prompt must be reasonable, understood, and responded to by humans”. We require the LLM to create challenging instructions that are reasonable and not arbitrarily imagined by AI. A gradual difficulty increase is necessary to avoid

filling the instruction set with extremely complex instructions, which would harm the generalization performance of trained models. To control difficulty increase, we make each evolution "a bit harder" and restrict adding a maximum of 10 to 20 words. Among the five mentioned evolving, all can be implemented without any in-context examples except for complicating input. We show the prompt of add constraints as follows (the prompts of deepening, concretizing and increased reasoning steps will be detailed in the Appendix A-C).

Example 3.1: Prompt for Adding Constraints of In-Depth Evolving

I want you act as a Prompt Rewriter.
 Your objective is to rewrite a given prompt into a more complex version to make those famous AI systems (e.g., ChatGPT and GPT4) a bit harder to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.
 Your rewriting cannot omit the non-text parts such as the table and code in #Given Prompt#. Also, please do not omit the input in #Given Prompt#.
 You SHOULD complicate the given prompt using the following method:
Please add one more constraints/requirements into #Given Prompt#

You should try your best not to make the #Rewritten Prompt# become verbose, #Rewritten Prompt# can only add 10 to 20 words into #Given Prompt#. '#Given Prompt#', '#Rewritten Prompt#', 'given prompt' and 'rewritten prompt' are not allowed to appear in #Rewritten Prompt#

#Given Prompt#:
 {Here is instruction.}
#Rewritten Prompt#:

For complicating input, we will use in-context demonstration. Due to the lengthy demonstrations, we will provide a brief template below, with the full prompt detailed in the Appendix D.

Example 3.2: Prompt for Complicating Input of In-Depth Evolving

I want you act as a Prompt Rewriter.

Your objective is to rewrite a given prompt into a more complex version to make those famous AI systems (e.g., ChatGPT and GPT4) a bit harder to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

You must add [XML data] format data as input data in [Rewritten Prompt]

#Given Prompt#:
 {Here is instruction of Example 1.}
#Rewritten Prompt#:
 {Here is rewritten instruction of Example 1.}

... N -1 Examples ...

You must add [#Given Dataformat#] format data as input data in [Rewritten Prompt]

#Given Prompt#:
 {Here is instruction of Example N.}
#Rewritten Prompt#:

In-Breadth Evolving aims to enhance topic coverage, skill coverage, and overall dataset diversity. Open-domain instruction finetune datasets (e.g., Alpaca, ShareGPT, etc.) are typically small in scale, lacking topic and skill diversity. To solve this problem, we designed a prompt to generate a completely new instruction based on the given instruction, requiring the new instruction to be more long-tailed. Our In-Breadth Evolving prompt is as follows:

Example 3.3: Prompt for In-Breadth Evolving

I want you act as a Prompt Creator.
 Your goal is to draw inspiration from the #Given Prompt# to create a brand new prompt.
 This new prompt should belong to the same domain as the #Given Prompt# but be even more rare.
 The LENGTH and difficulty level of the #Created Prompt# should be similar to that of the #Given Prompt#.
 The #Created Prompt# must be reasonable and must be understood and responded by humans.

‘#Given Prompt#’, ‘#Created Prompt#’, ‘given prompt’ and ‘created prompt’ are not allowed to appear in #Created Prompt#.

#Given Prompt#:
 {Here is instruction.}
#Created Prompt#:

Response Generation. We use the same LLM as for evolving to generate the corresponding responses for the evolved instructions. The generation prompt is “{Here is instruction.}”, we feed it into the request of the ChatGPT-3.5 and parse the returned text body as the response.

Elimination Evolving. We classify the following four situations as instruction evolution failure:

1. The evolved instruction does not provide any information gain compared to the original one. We use ChatGPT to make this determination, details please refer to Appendix G.
2. The evolved instruction makes it difficult for the LLM to generate a response. We found that when the generated response contains “sorry” and is relatively short in length (i.e., less than 80 words), it often indicates that the LLM struggles to respond to the evolved instruction. So we can use this rule to make a judgment.
3. The response generated by the LLM only contains punctuation and stop words.
4. The evolved instruction obviously copies some words from the evolving prompt, such as “given prompt”, “rewritten prompt”, “#Rewritten Prompt#”, etc.

3.3 FINETUNING THE LLM ON THE EVOLVED INSTRUCTIONS

Once all evolutions are done, we will merge the initial instruction dataset with evolved instruction data from all epochs and randomly shuffle the samples to create the fine-tuning dataset. This processing ensures even distribution of instructions of varying difficulty levels in the dataset, maximizing model fine-tuning smoothness. To prove that the performance gain is not due to the increased amount of data after merging, but from our proposed novel method *Evol-Instruct*, we randomly sample an equal amount of data the same with training baselines (e.g., Vicuna) from this merged data as our final fine-tuning data. We choose Vicuna’s prompt as the prompt for our fine-tuning, the specific format is “A chat between a curious user and an artificial intelligence assistant. The assistant gives helpful, detailed, and polite answers to the user’s questions. USER: Hi ASSISTANT: Hello. USER: Who are you? ASSISTANT: I am WizardLM”

4 EXPERIMENT

We assess *WizardLM*, Alpaca, Vicuna, and ChatGPT using both automatic and human evaluations.

4.1 BASELINES

(1) **ChatGPT** is an AI chatbot developed by OpenAI that can interact with users in a natural and engaging way. It is built on top of LLMs like GPT-3.5 and GPT-4, trained on vast internet text data.

(2) **Alpaca** is an open-source instruction-following model developed by Stanford University. For a fair comparison, we expanded the number of instructions from 52k to 70k using self-Instruct adopted by Alpaca and replaced the original Davinci-003 responses with ChatGPT’s responses. We re-trained Alpaca 13B from LLaMA 13B (Touvron et al., 2023) based on this new Alpaca data.

(3) **Vicuna** is based on LLaMA and fine-tuned on 70k user-shared conversations collected from ShareGPT. It is one of the most advanced and versatile open instruction-following models available today. We use the 13B-v1.1 model from FastChat ⁴.

(4) Open-source models trained from Llama 13B, including **Baize** (Xu et al., 2023), **CAMEL** (Li et al., 2023a), and **Tulu** (Wang et al., 2023)

⁴<https://github.com/lm-sys/FastChat>

4.2 EXPERIMENT DETAIL

To construct the dataset, we initialize it with the 52k instruction dataset of Alpaca and iteratively perform M evolutions, where $M = 4$. For each instruction in each round of evolution, we randomly select one evolving prompt from total six prompts (i.e., five from in-depth evolving and one from in-breadth evolving) with equal probability. We execute above process using Azure OpenAI ChatGPT API⁵. Then, we leverage ChatGPT to generate responses. Finally, we obtain 250k instructions. For a fair comparison, we randomly sample 70k data from 250k data with equal probability as the final training data for *WizardLM*, the same as the amount of training data for Vicuna. We use a temperature of 1 to generate response and set the maximum number of tokens for generation to 2048. Additionally, we set the frequency penalty to zero and top-p to 0.9. Totally, we request the API 52k $\times 4 \times 3 = 624k$ times to construct the full dataset. We use pre-trained LLaMA 13B (Touvron et al., 2023) to initialize our model. We adopt Adam optimizer with an initial learning rate of 2×10^{-5} , a maximum number of tokens 2048, and the batch size is 4 for each GPU. We train our model on 8 V100 GPUs with Deepspeed Zero-3 for 140 hours on 3 epochs. For inference, we use greedy search for *WizardLM* and baseline models, and set the maximum generation length to 2048.

4.3 AUTOMATIC EVALUATION

To present a comprehensive overview of the performance of our *WizardLM*, we conduct a comparative comparison between our model and the established baselines across a range of LLM benchmarks.

OpenLLM Leaderboard of HuggingFace (Beeching et al., 2023) includes MMLU (Hendrycks et al., 2020), ARC (Clark et al., 2018), HellaSwag (Zellers et al., 2019), and TruthfulQA (Lin et al., 2022). MMLU consists of a range of multiple-choice academic questions. ARC is a set of grade-school science questions. HellaSwag is a test of commonsense inference. TruthfulQA measures a model’s propensity to reproduce falsehoods. We adopt the evaluate code (Gao et al., 2021) from OpenLLM.

Code Generation We use the extensively utilized HumanEval (Chen et al., 2021) benchmark consisting of 164 coding problems to evaluate LLMs’ code writing capabilities at the function level by reporting the pass@1 metric.

Math Reasoning We use GSM8k (Cobbe et al., 2021) to evaluate mathematical abilities of models, GSM8k contains 1319 grade school math test data. We adopt 4-shot testing and report pass@1.

GPT-4 Evaluation We employ two widely recognized GPT-4 evaluation benchmarks, including AlpacaEval (Li et al., 2023c) and MT-Bench (Zheng et al., 2023). We also use GPT-4 to judge LLMs on our following proposed WizardEval.

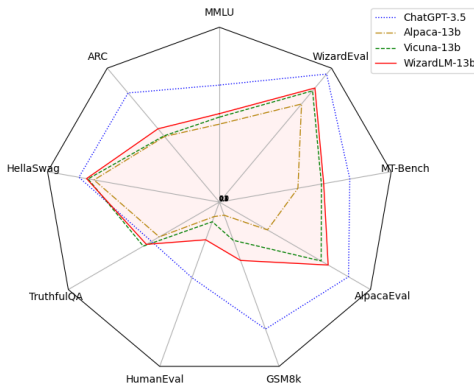


Figure 3: Automatic evaluations on nine LLM benchmarks.

Model	Avg.	MMLU	ARC	HellaSwag	TruthfulQA	HumanEval	GSM8k	AlpacaEval	MT-Bench	WizardEval
ChatGPT-3.5	76.15	70.0	85.2	85.5	47.0	48.1	80.8	89.37	7.94	100.0
Alpaca-13b	43.44	46.63	51.20	76.31	41.62	9.2	8.35	33.25	4.78	76.6
Vicuna-13b	54.60	50.84	51.71	79.94	52.68	12.5	24.34	70.43	6.21	86.9
Baize-13b	51.46	49.72	56.91	79.29	47.88	14.6	8.95	66.96	5.75	81.3
CAMEL-13b	51.29	49.74	55.63	79.25	47.42	17.7	7.13	64.84	5.78	82.1
Tulu-13b	52.46	53.19	53.92	80.66	43.84	21.3	36.50	45.34	5.76	79.8
WizardLM-13b	58.96	52.92	57.25	80.88	50.55	24.0	37.15	75.31	6.35	89.1

Table 1: Performance comparison of ChatGPT-3.5, open-source baselines, and WizardLM-13b.

As shown in Figure 3 and Table 1, compared with other same-sized open-sourced models, *WizardLM* has a remarkable performance advantage in most benchmarks. Especially in math, code, and GPT-4 evaluations, it achieves significant improvement over Alpaca, Vicuna, Baize, CAMEL, and Tulu.

⁵gpt-3.5-turbo from <https://oai.azure.com/portal>

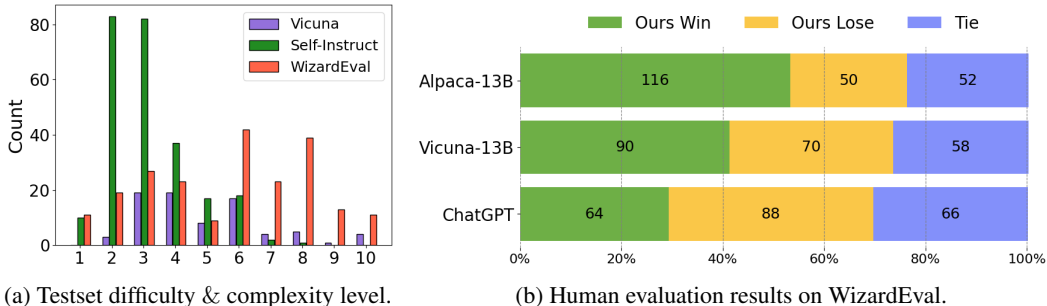


Figure 4: WizardEval difficulty and complexity level distribution, and the human evaluation results between WizardLM and baselines (ChatGPT-3.5, Alpaca, Vicuna) on WizardEval.

4.4 HUMAN EVALUATION

To evaluate *WizardLM*, we conduct human evaluation on our crafted testbed *WizardEval*, which includes 218 real-world human instructions from diverse sources such as online opensource projects (Github, ShareGPT), platforms (Twitter), and forums (Reddit, Discord). The data contains 29 skills and domains that represent the main requirements of humanity, such as Coding Generation, Math, Reasoning, Complex Formats, Writing, Extensive Disciplines, and so on. As shown in Figure 4a and Appendix Figure 6, we also analyse the difficulty and skills distribution of WizardEval respectively, which indicate that WizardEval is able to handle the evaluation on more complex and demanding scenarios than Self-Instruct and Vicuna testset.

We perform a blind pairwise comparison between *WizardLM*-13b and baselines. Specifically, we recruit 10 well-educated annotators. To each annotator, four responses from Alpaca-13b, Vicuna-13b, *WizardLM* and ChatGPT are presented, which are randomly shuffled to hide their sources. The annotators then judge which response is better following criterion (for detailed definition, please refer to Appendix K): (1) Relevance, (2) Knowledgeable, (3) Reasoning, (4) Calculation, and (5) Accuracy.

Then they should rank the four responses from 1 to 5 (1 means best), and allowing equal scores for comparable instances. To estimate the win rate, we compare the frequency of win, lost, and tie between each pair of models. As shown in Figure 4 (b). *WizardLM* achieved significantly better results than Alpaca and Vicuna, which demonstrates the effectiveness of *Evol-Instruct* method. All of the Kappa scores are greater than 0.6, which indicates the good agreement among the annotators.

4.5 ABLATION STUDY

Training with different data (seed, size), evol model, and base model size. In order to study the impact of different data seeds, Evol models, scale of evolved dataset, pre-trained models on our proposed method, we conducted the following experiments: a) Using 70k ShareGPT as the seed data to obtain WizardLM-13b (ShareGPT Seed); b) Using LLaMA-2-70B-Chat to replace ChatGPT as the evolutionary execution model to obtain WizardLM-13b (LLaMA-2-70B-Chat Evol); c) We train on larger size pre-trained models Llama-1 65B and Llama-2 70B to obtain WizardLM-65b and WizardLM-70b respectively; d) Using the complete 250k evolved data to obtain WizardLM-13b (250K); e) Using a completely different base from the LLaMA family, Mistral-7B, to obtain WizardLM-7b (Mistral); f) In order to compare more diverse instruction data, we choose Supernatural Instructions(Wang et al., 2022b) and randomly extract 70k data to train llama-13b to obtain LLaMA-13b (SNI). The full results are shown in the Table 2. To investigate the reason of why does WizardLM-13b (ShareGPT Seed) performs worse on GSM8k, we random sample 2000 instructions from ShareGPT and Alpaca data respectively, then use ChatGPT to judge (prompt please refer to Appendix G) whether an instruction is “math” related, we find that the ShareGPT only contains 4.3% math data, and Alpaca data contains 11.8% math data, thus we think that less math data results in worse GSM8k performance of WizardLM-13b (ShareGPT Seed).

The results indicate that (i) the ShareGPT is a better seed for evol-instruct than Alpaca, (ii) larger evolved data size can improve model capacity, and (iii) our proposed Evol-Instruct method is not dependent on ChatGPT, other strong open source model such as Llama-2 is also a good substitute for

Model	Avg.	MMLU	ARC	HellaSwag	TruthfulQA	HumanEval	GSM8k	AlpacaEval	MT-Bench	WizardEval
WizardLM-13b	58.96	52.92	57.25	80.88	50.55	24.0	37.15	75.31	6.35	89.1
WizardLM-13b (ShareGPT Seed)	61.87	50.92	60.24	81.39	54.56	25.0	31.46	86.32	6.76	99.3
WizardLM-13b (250K)	60.30	53.78	58.53	81.39	52.26	25.6	37.46	78.10	6.51	90.3
WizardLM-13b (LlaMA-2-70B-Chat Evol)	56.27	51.09	57.34	79.12	48.76	19.5	33.83	70.47	6.18	84.5
LlaMA-13b (SNI)	37.73	54.90	54.95	80.40	38.69	4.20	5.79	13.67	2.86	58.4
Alpaca-7b (Mistral)	52.87	56.34	55.38	79.49	43.92	19.2	32.05	54.26	5.47	80.5
WizardLM-7b (Mistral)	65.81	60.70	57.47	82.08	51.79	37.80	59.49	80.70	7.10	91.3
WizardLM-65b	69.40	62.09	65.83	85.48	52.19	36.5	66.39	87.50	7.12	97.5
WizardLM-70b	71.33	63.32	64.52	83.21	54.60	42.1	70.61	89.32	7.46	99.7

Table 2: WizardLM with different data seed, data size, evol model, and base model size.

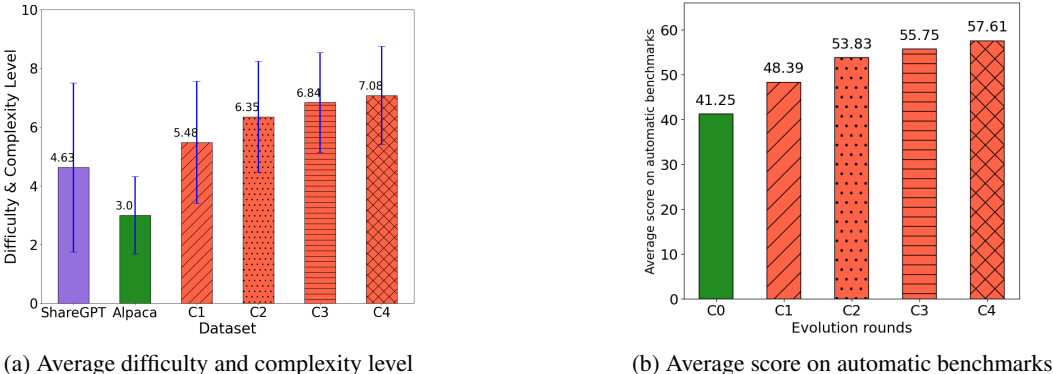


Figure 5: The difficulty level between ShareGPT, Alpaca, and our four epochs of evolved instruction.

ChatGPT, (iv) our evolved data also shows better finetune performance than Supernatural Instructions. Furthermore, the results on different pre-trained bases (e.g., Llama-1 65B, Llama-2, Mistral-7B) indicate that our Evol-Instruct can be widely applied to various pre-trained models.

Analysis of In-depth Evolving. The Figure 5a and 5b presents an ablation study investigating the impact of the number of data evolution rounds. To study the depth of the evolving process, we use ChatGPT to judge the difficulty level of instruction. The used prompt please refer to Appendix E.

Figure 5b shows the average scores (on nine automatic benchmarks in Section 4.3) of the models fine-tuned with the data from each evolution round. Each round of data from C0 to C4 is about 52k. From the trend of this figure, it can be seen that as the complexity of the training instruction data gradually increases, the performance of the fine-tuned models also improves synchronously. To investigate the correctness of the difficulty score by ChatGPT, we also use GPT-4 and human to measure the instructions difficulty, the detailed results in the Table 3 of Appendix I indicate the good agreement among the ChatGPT, GPT-4 and human annotators.

Analysis of In-breadth Evolving. We aims to examine the semantic breadth of instructions. We use t-SNE van der Maaten & Hinton (2008) and the k-means Hartigan & Wong (1979) algorithm to partition instructions BERT embeddings into 20 clusters. Figure 6 in Appendix F displays clusters, highlighting our method’s superior dispersion compared to ShareGPT and Alpaca, indicating greater topic diversity in our instructions.

5 CONCLUSIONS

This paper presented Evol-Instruct, an evolutionary algorithm that generates diverse and complex instruction data for LLM. Comprehensive experiments demonstrate that *WizardLM* significantly surpasses typical open-source LLMs such as Alpaca and Vicuna in a wide range of well-recognized benchmarks. Notably, *WizardLM* outperforms baselines by a substantial margin in terms of code, math, GPT-4 and human evaluations.

Limitations. This paper acknowledges the limitations of our automatic GPT-4 and human evaluation methods. This method poses challenges for scalability and reliability. Moreover, our test set may not represent all the scenarios or domains where LLM can be applied or compared with other methods.

REFERENCES

- Vamsi Aribandi, Yi Tay, Tal Schuster, Jinfeng Rao, Huaixiu Steven Zheng, Sanket Vaibhav Mehta, Honglei Zhuang, Vinh Q. Tran, Dara Bahri, Jianmo Ni, Jai Gupta, Kai Hui, Sebastian Ruder, and Donald Metzler. Ext5: Towards extreme multi-task scaling for transfer learning. In *International Conference on Learning Representations*, 2022. URL <https://openreview.net/forum?id=Vzh1BFUCiIX>.
- Keqin Bao, Jizhi Zhang, Yang Zhang, Wenjie Wang, Fuli Feng, and Xiangnan He. Tallrec: An effective and efficient tuning framework to align large language model with recommendation. *ArXiv*, abs/2305.00447, 2023.
- Edward Beeching, Clémentine Fourrier, Nathan Habib, Sheon Han, Nathan Lambert, Nazneen Rajani, Omar Sanseviero, Lewis Tunstall, and Thomas Wolf. Open llm leaderboard. https://huggingface.co/spaces/HuggingFaceH4/open_llm_leaderboard, 2023.
- Ning Bian, Pei Yu Liu, Xianpei Han, Hongyu Lin, Yaojie Lu, Ben He, and Le Sun. A drop of ink may make a million think: The spread of false information in large language models. *ArXiv*, abs/2305.04812, 2023.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, et al. Language models are few-shot learners. *Advances in neural information processing systems*, 33:1877–1901, 2020.
- Vivien A. Cabannes, Léon Bottou, Yann LeCun, and Randall Balestriero. Active self-supervised learning: A few low-cost relationships are all you need. *ArXiv*, abs/2303.15256, 2023.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Pondé de Oliveira Pinto, Jared Kaplan, Harrison Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Joshua Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. Evaluating large language models trained on code. *CoRR*, abs/2107.03374, 2021. URL <https://arxiv.org/abs/2107.03374>.
- Zhihong Chen, Feng Jiang, Junying Chen, Tiannan Wang, Fei Yu, Guiming Chen, Hongbo Zhang, Juhao Liang, Chen Zhang, Zhiyi Zhang, Jianquan Li, Xiang Wan, Benyou Wang, and Haizhou Li. Phoenix: Democratizing chatgpt across languages. *ArXiv*, abs/2304.10453, 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://vicuna.lmsys.org>.
- 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.
- Peter Clark, Isaac Cowhey, Oren Etzioni, Tushar Khot, Ashish Sabharwal, Carissa Schoenick, and Oyvind Tafjord. Think you have solved question answering? try arc, the ai2 reasoning challenge, 2018.
- Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, et al. Training verifiers to solve math word problems. *arXiv preprint arXiv:2110.14168*, 2021.
- Adrian de Wynter, Xun Wang, Alex Sokolov, Qilong Gu, and Si-Qing Chen. An evaluation on large language model outputs: Discourse and memorization. *ArXiv*, abs/2304.08637, 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>.
- Zhen Guo, Peiqi Wang, Yanwei Wang, and Shangdi Yu. Dr. llama: Improving small language models in domain-specific qa via generative data augmentation. 2023.
- J. A. Hartigan and M. A. Wong. A k-means clustering algorithm. *JSTOR: Applied Statistics*, 28(1): 100–108, 1979.
- Xingwei He, Zheng-Wen Lin, Yeyun Gong, Alex Jin, Hang Zhang, Chen Lin, Jian Jiao, Siu Ming Yiu, Nan Duan, and Weizhu Chen. Annollm: Making large language models to be better crowdsourced annotators. *ArXiv*, abs/2303.16854, 2023.
- 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.
- Zhiqiang Hu, Yihuai Lan, Lei Wang, Wanyu Xu, Ee-Peng Lim, Roy Ka-Wei Lee, Lidong Bing, and Soujanya Poria. Llm-adapters: An adapter family for parameter-efficient fine-tuning of large language models. *ArXiv*, abs/2304.01933, 2023.
- Rongjie Huang, Mingze Li, Dongchao Yang, Jiatong Shi, Xuankai Chang, Zhenhui Ye, Yuning Wu, Zhiqing Hong, Jia-Bin Huang, Jinglin Liu, Yixiang Ren, Zhou Zhao, and Shinji Watanabe. Audio-gpt: Understanding and generating speech, music, sound, and talking head. *ArXiv*, abs/2304.12995, 2023.
- Andreas Kopf, Yannic Kilcher, Dimitri von Rutte, Sotiris Anagnostidis, Zhi Rui Tam, Keith Stevens, Abdullah Barhoum, Nguyen Minh Duc, Oliver Stanley, Richard Nagyfi, ES Shahul, Sameer Suri, David Glushkov, Arnav Dantuluri, Andrew Maguire, Christoph Schuhmann, Huu Nguyen, and Alexander Mattick. Openassistant conversations - democratizing large language model alignment. *ArXiv*, abs/2304.07327, 2023.
- Guohao Li, Hasan Abed Al Kader Hammoud, Hani Itani, Dmitrii Khizbullin, and Bernard Ghanem. Camel: Communicative agents for "mind" exploration of large language model society, 2023a.
- Jia Li, Ge Li, Yongming Li, and Zhi Jin. Enabling programming thinking in large language models toward code generation. 2023b.
- 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, 2023c.
- Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods, 2022.
- Haotian Liu, Chunyuan Li, Qingyang Wu, and Yong Jae Lee. Visual instruction tuning. *ArXiv*, abs/2304.08485, 2023.
- 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, Xiubo Geng, Chongyang Tao, Jing Ma, Qingwei Lin, and Daxin Jiang. Augmented large language models with parametric knowledge guiding. *ArXiv*, abs/2305.04757, 2023.
- Huan Ma, Changqing Zhang, Yatao Bian, Lemao Liu, Zhirui Zhang, Peilin Zhao, Shu Zhang, H. Fu, Qinghua Hu, and Bing Wu. Fairness-guided few-shot prompting for large language models. *ArXiv*, abs/2303.13217, 2023.

- Potsawee Manakul, Adian Liusie, and Mark John Francis Gales. Selfcheckgpt: Zero-resource black-box hallucination detection for generative large language models. *ArXiv*, abs/2303.08896, 2023.
- Subhabrata Mukherjee, Arindam Mitra, Ganesh Jawahar, Sahaj Agarwal, Hamid Palangi, and Ahmed Awadallah. Orca: Progressive learning from complex explanation traces of gpt-4, 2023.
- OpenAI. Gpt-4 technical report, 2023.
- 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, 2022.
- Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21(140):1–67, 2020. URL <http://jmlr.org/papers/v21/20-074.html>.
- Victor Sanh, Albert Webson, Colin Raffel, Stephen Bach, Lintang Sutawika, Zaid Alyafeai, Antoine Chaffin, Arnaud Stiegler, Arun Raja, Manan Dey, M Saiful Bari, Canwen Xu, Urmish Thakker, Shanya Sharma Sharma, Eliza Szczechla, Taewoon Kim, Gunjan Chhablani, Nihal Nayak, Debajyoti Datta, Jonathan Chang, Mike Tian-Jian Jiang, Han Wang, Matteo Manica, Sheng Shen, Zheng Xin Yong, Harshit Pandey, Rachel Bawden, Thomas Wang, Trishala Neeraj, Jos Rozen, Abheesht Sharma, Andrea Santilli, Thibault Fevry, Jason Alan Fries, Ryan Teehan, Teven Le Scao, Stella Biderman, Leo Gao, Thomas Wolf, and Alexander M Rush. Multitask prompted training enables zero-shot task generalization. In *International Conference on Learning Representations*, 2022. URL <https://openreview.net/forum?id=9Vrb9D0WI4>.
- Zhiqing Sun, Yikang Shen, Qinlong Zhou, Hongxin Zhang, Zhenfang Chen, David D. Cox, Yiming Yang, and Chuang Gan. Principle-driven self-alignment of language models from scratch with minimal human supervision. *ArXiv*, abs/2305.03047, 2023.
- Ekaterina Svikhnushina and Pearl Pu. Approximating human evaluation of social chatbots with prompting. *ArXiv*, abs/2304.05253, 2023.
- 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, et al. Llama: Open and efficient foundation language models. *arXiv preprint arXiv:2302.13971*, 2023.
- Laurens van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of Machine Learning Research*, 9(86):2579–2605, 2008. URL <http://jmlr.org/papers/v9/vandermaaten08a.html>.
- 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*, 2022a.
- Yizhong Wang, Swaroop Mishra, Pegah Alipoormolabashi, Yeganeh Kordi, Amirreza Mirzaei, Anjana Arunkumar, Arjun Ashok, Arut Selvan Dhanasekaran, Atharva Naik, David Stap, et al. Super-naturalinstructions: Generalization via declarative instructions on 1600+ nlp tasks. *arXiv preprint arXiv:2204.07705*, 2022b.
- Yizhong Wang, Hamish Ivison, Pradeep Dasigi, Jack Hessel, Tushar Khot, Khyathi Raghavi Chandu, David Wadden, Kelsey MacMillan, Noah A. Smith, Iz Beltagy, and Hannaneh Hajishirzi. How far can camels go? exploring the state of instruction tuning on open resources, 2023.
- Yufei Wang, Jiayi Zheng, Can Xu, Xiubo Geng, Tao Shen, Chongyang Tao, and Daxin Jiang. Knowda: All-in-one knowledge mixture model for data augmentation in few-shot nlp. *arXiv preprint arXiv:2206.10265*, 2022c.

- Jason Wei, Maarten Bosma, Vincent Y Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M Dai, and Quoc V Le. Finetuned language models are zero-shot learners. *arXiv preprint arXiv:2109.01652*, 2021.
- Wen Xiao, Yujia Xie, Giuseppe Carenini, and Pengcheng He. Chatgpt-steered editing instructor for customization of abstractive summarization. *ArXiv*, abs/2305.02483, 2023.
- Canwen Xu, Daya Guo, Nan Duan, and Julian McAuley. Baize: An open-source chat model with parameter-efficient tuning on self-chat data, 2023.
- Hanwei Xu, Yujun Chen, Yulun Du, Nan Shao, Yanggang Wang, Haiyu Li, and Zhilin Yang. Zeroprompt: Scaling prompt-based pretraining to 1,000 tasks improves zero-shot generalization. *arXiv preprint arXiv:2201.06910*, 2022.
- Zheng Yuan, Hongyi Yuan, Chuanqi Tan, Wei Wang, Songfang Huang, and Feiran Huang. Rrhf: Rank responses to align language models with human feedback without tears. *ArXiv*, abs/2304.05302, 2023.
- Xiang Yue, Boshi Wang, Kai Zhang, Zi-Yuan Chen, Yu Su, and Huan Sun. Automatic evaluation of attribution by large language models. *ArXiv*, abs/2305.06311, 2023.
- Rowan Zellers, Ari Holtzman, Yonatan Bisk, Ali Farhadi, and Yejin Choi. Hellaswag: Can a machine really finish your sentence? In *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*, 2019.
- Shujian Zhang, Chengyue Gong, Lemeng Wu, Xingchao Liu, and Mi Zhou. Automl-gpt: Automatic machine learning with gpt. *ArXiv*, abs/2305.02499, 2023.
- Wayne Xin Zhao, Kun Zhou, Junyi Li, Tianyi Tang, Xiaolei Wang, Yupeng Hou, Yingqian Min, Beichen Zhang, Junjie Zhang, Zican Dong, Yifan Du, Chen Yang, Yushuo Chen, Z. Chen, Jinhao Jiang, Ruiyang Ren, Yifan Li, Xinyu Tang, Zikang Liu, Peiyu Liu, Jianyun Nie, and Ji rong Wen. A survey of large language models. *ArXiv*, abs/2303.18223, 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.
- Shan Zhong, Zhongzhan Huang, Wushao Wen, Jinghui Qin, and Liang Lin. Sur-adapter: Enhancing text-to-image pre-trained diffusion models with large language models. *ArXiv*, abs/2305.05189, 2023.
- Deyao Zhu, Jun Chen, Xiaoqian Shen, Xiang Li, and Mohamed Elhoseiny. Minigpt-4: Enhancing vision-language understanding with advanced large language models. *ArXiv*, abs/2304.10592, 2023.

A DEEPENING PROMPT

Example A.1: Prompt for Deepening of In-Depth Evolving

I want you act as a Prompt Rewriter.

Your objective is to rewrite a given prompt into a more complex version to make those famous AI systems (e.g., ChatGPT and GPT4) a bit harder to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

Your rewriting cannot omit the non-text parts such as the table and code in #Given Prompt#. Also, please do not omit the input in #Given Prompt#.

You SHOULD complicate the given prompt using the following method:

If #Given Prompt# contains inquiries about certain issues, the depth and breadth of the inquiry can be increased.

You should try your best not to make the #Rewritten Prompt# become verbose, #Rewritten Prompt# can only add 10 to 20 words into #Given Prompt#. '#Given Prompt#', '#Rewritten Prompt#', 'given prompt' and 'rewritten prompt' are not allowed to appear in #Rewritten Prompt#

#Given Prompt#:

{Here is instruction.}

#Rewritten Prompt#:

B CONCRETIZING PROMPT

Example B.1: Prompt for Concretizing of In-Depth Evolving

I want you act as a Prompt Rewriter.

Your objective is to rewrite a given prompt into a more complex version to make those famous AI systems (e.g., ChatGPT and GPT4) a bit harder to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

Your rewriting cannot omit the non-text parts such as the table and code in #Given Prompt#. Also, please do not omit the input in #Given Prompt#.

You SHOULD complicate the given prompt using the following method:

Please replace general concepts with more specific concepts.

You should try your best not to make the #Rewritten Prompt# become verbose, #Rewritten Prompt# can only add 10 to 20 words into #Given Prompt#. '#Given Prompt#', '#Rewritten Prompt#', 'given prompt' and 'rewritten prompt' are not allowed to appear in #Rewritten Prompt#

#Given Prompt#:

{Here is instruction.}

#Rewritten Prompt#:

C INCREASED REASONING STEPS PROMPT

Example C.1: Prompt for Increased Reasoning Steps of In-Depth Evolving

I want you act as a Prompt Rewriter.

Your objective is to rewrite a given prompt into a more complex version to make those famous AI systems (e.g., ChatGPT and GPT4) a bit harder to handle. But the rewritten prompt must be

reasonable and must be understood and responded by humans.

Your rewriting cannot omit the non-text parts such as the table and code in #Given Prompt#. Also, please do not omit the input in #Given Prompt#.

You SHOULD complicate the given prompt using the following method:

If #Given Prompt# can be solved with just a few simple thinking processes, you can rewrite it to explicitly request multiple-step reasoning.

You should try your best not to make the #Rewritten Prompt# become verbose, #Rewritten Prompt# can only add 10 to 20 words into #Given Prompt#. '#Given Prompt#', '#Rewritten Prompt#', 'given prompt' and 'rewritten prompt' are not allowed to appear in #Rewritten Prompt#

#Given Prompt#:

{Here is instruction.}

#Rewritten Prompt#:

D COMPLICATE INPUT PROMPT

Example D.1: Prompt for Complicate Input of Evolving

I want you act as a Prompt Rewriter. Your objective is to rewrite a given prompt into a more complex version using dataformat to make those famous AI systems (e.g., chatgpt and GPT4) more difficult to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

You must add [XML data] format text as input data in [Rewritten Prompt]

#Given Prompt#:

I'm using this php code to fetch the xml data

#Rewritten Prompt#: I have this xml and i want to get the xml data to auto populate HTML table, the codes works but it makes duplicate on the table content

Here is the xml data:

```
<root>
<stats>
<item>
<day>2017-11-01</day>
<impressions>2192</impressions>
<money>1.96790003</money>
</item>
<item>
<day>2017-11-02</day>
<impressions>2824</impressions>
<money>3.208500033</money>
</item>
<item>
<day>2017-11-03</day>
<impressions>3680</impressions>
<money>3.321799981</money>
</item>
</stats>
<total>
<impressions>8696</impressions>
<money>8.498200044</money>
```

```

</total>
<filter>
<dateFrom>2017-11-01</dateFrom>
<dateTo>2017-11-03</dateTo>
<groupBy>day</groupBy>
<format>xml</format>
</filter>
</root>

```

I'm using this php code to fetch the xml data but this code fetching from whole xml data which makes duplicate field table

```

<?php
\ $dom = new DOMDocument;

\ $dom -> load('http://example.com/' . \ $dateselected . '&dateTo
    =' . \ $dateselected2 . '&format=xml');

\ $day = \ $dom->getElementsByTagName('day');
\ \ $impressions = \ \ $dom->getElementsByTagName('impressions');

echo ( "<table>");

    foreach(\ \ $day as \ \ $node1) {
        foreach(\ \ $impressions as \ \ $node2) {

            echo '<tr>';
            echo "<td>". \ \ $node1 -> textContent . "<td>";
            echo "<td>". \ \ $node2 -> textContent . "<td>";
            echo "<td>". \ \ $node2 -> textContent *0.5/1000 . "<td>";
            echo '</tr>';

        }
    }
    echo( "</table>");
?>

```

Could anyone give a hint how I can fix this? thank you

####

Example D.2: Prompt for Complicate Input of Evolving

I want you act as a Prompt Rewriter. Your objective is to rewrite a given prompt into a more complex version using dataformat to make those famous AI systems (e.g., chatgpt and GPT4) more difficult to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

You must add [SQL database] format text as input data in [Rewritten Prompt]

#Given Prompt#:

achieve the SQL query result

#Rewritten Prompt# (MUST contain a specific SQL database as input):

There is a table messages that contains data as shown below:


```
Id Name Other_Columns
-----
```

```
1 A A_data_1
2 A A_data_2
3 A A_data_3
4 B B_data_1
5 B B_data_2
6 C C_data_1
```

I If I run a query `select * from messages group by name`, I will get the result as:

```
1 A A_data_1
4 B B_data_1
6 C C_data_1
```

What query will return the following result?

```
3 A A_data_3
5 B B_data_2
6 C C_data_1
```

That is, the last record in each group should be returned. At present, this is the query that I use:

```
SELECT
  *
FROM (SELECT
  *
FROM messages
ORDER BY id DESC) AS x
GROUP BY name
```

But this looks highly inefficient. Any other ways to achieve the same result?

```
####
```

Example D.3: Prompt for Complicate Input of Evolving

I want you act as a Prompt Rewriter. Your objective is to rewrite a given prompt into a more complex version using dataformat to make those famous AI systems (e.g., chatgpt and GPT4) more difficult to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

You must add [python code] format text as input data in [Rewritten Prompt]

#Given Prompt#:

Transformat python code

#Rewritten Prompt# (MUST contain a specific python code as input):

I have the following Python code:

```
cursor.execute("INSERT INTO table VALUES var1, var2, var3,")
```

where var1 is an integer, var2 and var3 are strings. How can I write the variable names without Python including them as part of the query text?

```
####
```

Example D.4: Prompt for Complicate Input of Evolving

I want you act as a Prompt Rewriter. Your objective is to rewrite a given prompt into a more complex version using dataformat to make those famous AI systems (e.g., chatgpt and GPT4) more difficult to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

You must add [HTML page] format text as input data in [Rewritten Prompt]

#Given Prompt#:

scroll through the whole HTML page

#Rewritten Prompt# (MUST contain a specific HTML page as input):

I want to be able to scroll through the whole page, but without the scrollbar being shown. In Google Chrome it's:

```
::-webkit-scrollbar {
  display: none;
}
```

But Mozilla Firefox and Internet Explorer don't seem to work like that.

I also tried this in CSS:

```
overflow: hidden;
```

That does hide the scrollbar, but I can't scroll any more. Is there a way I can remove the scrollbar while still being able to scroll the whole page?

With just CSS or HTML, please.
####

Example D.5: Prompt for Complicate Input of Evolving

I want you act as a Prompt Rewriter. Your objective is to rewrite a given prompt into a more complex version using dataformat to make those famous AI systems (e.g., chatgpt and GPT4) more difficult to handle. But the rewritten prompt must be reasonable and must be understood and responded by humans.

You must add [Shell cmd] format text as input data in [Rewritten Prompt]

#Given Prompt#:

Shell scp file

#Rewritten Prompt# (MUST contain a specific Shell cmd as input):

I'm trying to scp a file from a remote server to my local machine. Only port 80 is accessible. I tried:

```
scp -p 80 username@www.myserver.com:/root/file.txt .
```

but got this error: cp: 80: No such file or directory
How do I specify the port number in a scp command?

####

Example D.6: Prompt for Complicate Input of Evolving

I want you act as a Prompt Rewriter. Your objective is to rewrite a given prompt into a more complex version using dataformat to make those famous AI systems (e.g., chatgpt and GPT4) more difficult to handle. But the rewritten prompt must be reasonable and must be understood and

responded by humans.
 You must add [JSON data] format data as input data, add [JSON data] code as input code in [Rewritten Prompt]
 Rewrite prompt must be a question style instruction
#Given Prompt#:
 Given a JSON dataset of customer purchase history, how can we calculate the probability of a customer making a repeat purchase from the same store? Can we utilize the formula for conditional probability: $P(A|B) = P(A \cap B)/P(B)$ where A represents the event of a customer making a repeat purchase and B represents the event of a customer making a purchase from the same store again? Additionally, how can we apply this formula to identify the customer segment that is most likely to make a repeat purchase? Can you provide an example of how to implement this formula using the given JSON dataset?
 Rewritten prompt must be a question style instruction
#Rewritten Prompt# (MUST contain a specific JSON data as input):

E DIFFICULTY JUDGE PROMPT

Example E.1: Prompt for Judging the Difficulty of Instructions

We would like you to evaluate and rate the difficulty and complexity of the following question. You should give an overall score on a scale of 1 to 10, where a higher score indicates higher difficulty and complexity. You must just give a score without any other reasons.
Question:
 { Here is instruction. }
Score:

F EQUAL PROMPT

Example F.1: Prompt for Determining whether Two Instructions are Equal

Here are two Instructions to ChatGPT AI, do you think they are equal to each other, which meet the following requirements:
 1. They have same constraints and requirments.
 2. They have same depth and breadth of the inquiry.
 The First Prompt: {Here is first instruction.}
 The Second Prompt: {Here is second instruction.}
 Your Judgement (Just answer: Equal or Not Equal. No need to explain the reason.):

G MATH JUDGEMENT PROMPT

Example G.1: Prompt for judging whether an instruction is math related

Please judge whether the following question is a math problem, and only return True or False without providing any explanation.
 Question: {instruction}

H WIZARDEVAL ANALYSIS

We collected our *Evol-Instruct* testset that includes real-world human instructions from diverse sources such as online open-source projects, platforms, and forums. We analyzed the data and identified 29 distinct skills that represent the main requirements of humanity, such as Coding Generation & Debugging, Math, Reasoning, Complex Formats, Writing, Extensive Disciplines, and so on. Figure 6 illustrates the distribution of the instances and skills in our test set. Our test set consists of 218

instances, each of which is an instruction for a specific skill. We compared our test set with Vicuna’s test set, which is a benchmark dataset for evaluating instruction following models. We found that Vicuna’s test set only 80 instances and 9 skills and is much smaller and less diverse than ours. Figure 4a shows how the difficulty and complexity of the test data vary across different instances. Our test data has a more uniform distribution, meaning that it contains instructions with different levels of difficulty and complexity. On the other hand, Vicuna and Alpaca have a skewed distribution, meaning that they mostly contain instructions with low difficulty and complexity. This indicates that these two corpus are not able to handle the evaluation on more complex and demanding scenarios.

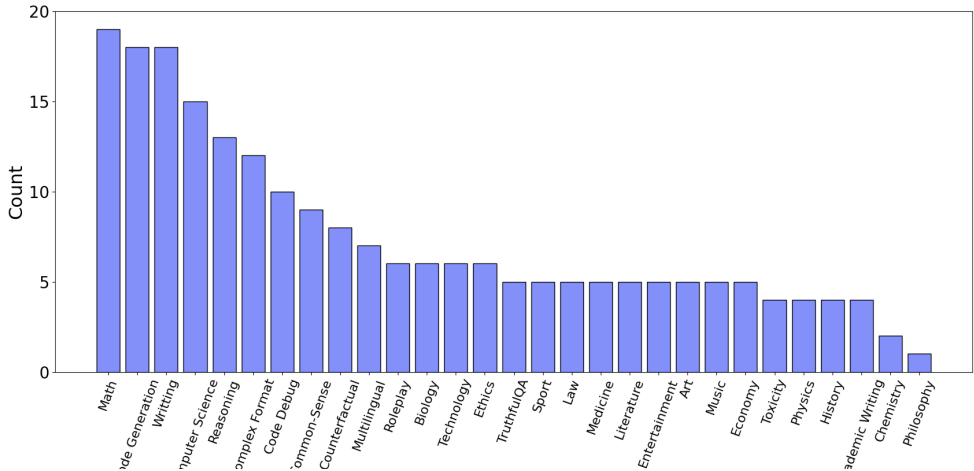


Figure 6: The skills distribution of *Evol-Instruct* testset.

I DIFFERENT DIFFICULTY ANNOTATORS

We just use the ChatGPT to post analyse the “difficult” distribution of the generated instructions, but we do not use this analysis results to guide the data generation or model training. In order to explore the ability of ChatGPT to perform difficulty analysis, we sample 600 instructions and use the more powerful GPT4 model and 5 well-educated human annotators together for difficulty assessment. The assessment results are in the Table 3. The results show that ChatGPT, GPT4, and manual annotation show a high degree of consistency in the trend of difficulty changes.

	ShareGPT	Alpaca	C1	C2	C3	C4
GPT-3.5	4.63	3.00	5.48	6.35	6.84	7.08
GPT-4	4.31	2.69	4.68	4.90	5.37	5.54
Human	4.55	3.15	5.51	5.86	6.49	6.82

Table 3: Use ChatGPT, GPT-4, human to measure the instruction difficulty.

To investigate the correctness of the difficulty score by ChatGPT, we add a new experiment to measure agreement of difficulty judge between ChatGPT and humans: We randomly select two instructions from the six datasets - Alpaca, ShareGPT, C1 to C4 - with equal probability each time, forming a pair. In total, we have selected 300 instruction pairs. Then, we ask ChatGPT and 5 well-educated human annotators to judge which one is more difficulty in one instruction pair, the Kappa score between humans is 0.68, and the Kappa between ChatGPT and human (majority voting) is 0.66, which indicates the good agreement among the ChatGPT and human annotators.

J CLUSTER SCATTER PLOT

In-breadth Evolving aims to enhance topic coverage, skill coverage, and overall dataset diversity. To examine (qualitative analysis) the breadth (diversity) of different dataset, we firstly use BERT to

encode each instruction and get its embedding with 768 dimensions, then use a dimension reduction algorithm named t-SNE to reduce embedding dimension to 2, finally we apply a clustering algorithm k-means to partition the instructions of each dataset into 20 clusters for an intuitive visualization. As shown in the Figure 7, the data points of our dataset are more dispersed than ShareGPT and Alpaca (Self-Instruct), which indicates the better topic diversity in our instructions.

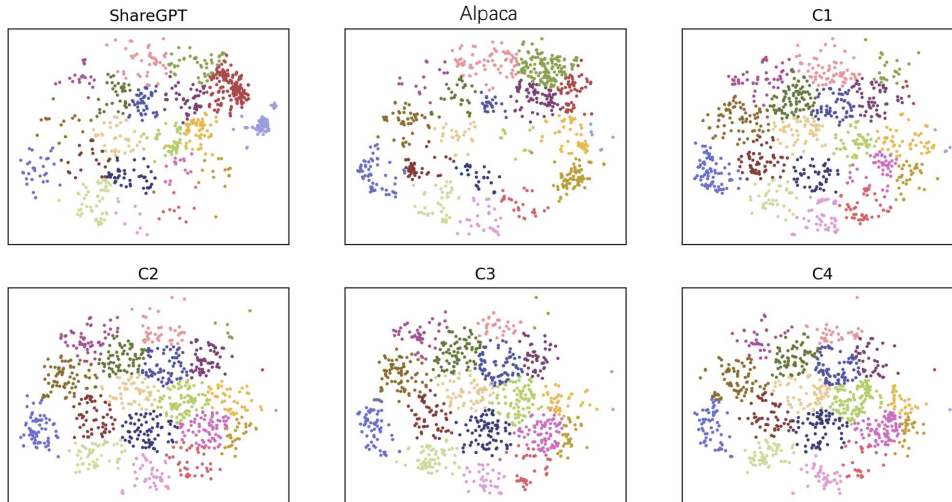


Figure 7: The cluster scatter plot between ShareGPT, Alpaca, and ours four rounds of instruction evolution from C1 to C4. The number of cluster centers is 20.

K HUMAN EVALUATION ASPECTS

The annotators then judge which response is better from five aspects:

- (1) Relevance: Assessing the model’s ability to correctly interpret the semantic meaning of the context and questions.
- (2) Knowledgeable: Whether the model can accurately use various and detailed knowledge for problem-solving.
- (3) Reasoning: Assessing the model’s ability to execute correct reasoning processes or devise valid reasoning concepts to solve problems.
- (4) Calculation: Evaluating whether the model can perform accurate mathematical computations of the provided formulas in the domains of math, biology, chemistry and physics.
- (5) Accuracy: Evaluating whether the model can perform correctly in the corresponding for a given instruction.

L PERFORMANCE DETAILS OF DIFFERENT CHECKPOINTS

In this paper, we train our model with 3 epochs and only reported the performance of the final checkpoint in the above “Section 4 Experiment” to align with previous works.

As shown in the following Table 4, we report the model checkpoints performance on different epochs (2.5, 2,75, 3). For 13B models, we can see that the best performance always appears on WizardLM-13b (ShareGPT Seed) for each benchmark except GSM8k. And for 65b/70b models, we also see that the WizardLM-70b is the best one on all the benchmarks. Therefore, we think this is mainly caused by the fluctuations on some benchmarks in model training.

Model	Epoch	Avg.	MMLU	ARC	HellaSwag	TruthfulQA	HumanEval	GSM8k	AlpacaEval	MT-Bench	WizardEval
WizardLM-13b	2.50	57.92	52.50	56.83	78.63	49.72	22.8	35.81	74.09	6.27	88.2
WizardLM-13b	2.75	58.24	50.64	58.33	80.25	49.80	23.4	35.66	73.62	6.40	88.5
WizardLM-13b	3.0	58.96	52.92	57.25	80.88	50.55	24.0	37.15	75.31	6.35	89.1
WizardLM-13b (ShareGPT Seed)	2.50	61.48	51.76	60.02	81.53	53.24	25.3	31.83	85.71	6.52	98.7
WizardLM-13b (ShareGPT Seed)	2.75	62.00	53.10	58.53	79.77	54.21	27.2	33.04	86.68	6.65	99.0
WizardLM-13b (ShareGPT Seed)	3.0	61.87	50.92	60.24	81.39	54.56	25.0	31.46	86.32	6.76	99.3
WizardLM-65b	2.50	68.12	60.50	63.24	84.11	50.55	35.8	66.01	86.49	7.06	95.8
WizardLM-65b	2.75	69.89	62.84	65.51	85.26	52.22	37.1	67.46	89.68	7.20	96.9
WizardLM-65b	3.0	69.40	62.09	65.83	85.48	52.19	36.5	66.39	87.50	7.12	97.5
WizardLM-70b	2.50	71.22	61.85	66.31	85.60	54.76	41.3	68.70	87.73	7.53	99.4
WizardLM-70b	2.75	71.08	63.44	64.89	84.06	53.21	42.4	69.55	89.09	7.38	99.3
WizardLM-70b	3.0	71.33	63.32	64.52	83.21	54.60	42.1	70.61	89.32	7.46	99.7

Table 4: Performance details of different checkpoints.