

ZhuJiu: A Multi-dimensional, Multi-faceted Chinese Benchmark for Large Language Models

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Abstract

The unprecedented performance of large language models (LLMs) requires comprehensive and accurate evaluation. We argue that for LLMs evaluation, benchmarks need to be comprehensive and systematic. To this end, we propose the ZhuJiu benchmark, which has the following strengths: (1) **Multi-dimensional ability coverage:** We comprehensively evaluate LLMs across 7 ability dimensions covering 51 tasks. Especially, we also propose a new benchmark that focuses on knowledge ability of LLMs. (2) **Multi-faceted evaluation methods collaboration:** We use 3 different yet complementary evaluation methods to comprehensively evaluate LLMs, which can ensure the authority and accuracy of the evaluation results. (3) **Comprehensive Chinese benchmark:** ZhuJiu is the pioneering benchmark that fully assesses LLMs in Chinese, while also providing equally robust evaluation abilities in English. (4) **Avoiding potential data leakage:** To avoid data leakage, we construct evaluation data specifically for 37 tasks. We evaluate 9 current mainstream LLMs and conduct an in-depth discussion and analysis of their results. The ZhuJiu benchmark and open-participation leaderboard are publicly released at <http://www.zhujiu-benchmark.com/> and we also provide a demo video at <https://youtu.be/qypkJ89L1Ic>.

1 Introduction

With the continuous development of large language models (LLMs), the emergence of GPT4 (OpenAI, 2023) is enough to trigger a new wave of technology. Various types of LLMs have recently been rapidly developing, such as Llama2 (Touvron et al., 2023) and ChatGLM2 (Du et al., 2022), demonstrating impressive generalization abilities and broad applicability. Therefore, it is crucial to

conduct comprehensive and objective evaluations of LLMs to fully understand their strengths and limitations.

Specifically, on the one hand, for **applicators**, they need to understand the overall performance of LLMs or the advantages of LLMs in a specific aspect. Constructing comprehensive and authoritative benchmarks can help applicators significantly improve the efficiency of using LLMs. On the other hand, for **developers**, the improvement direction of LLMs requires accurate evaluation results as guidance. An objective and fair benchmark can help them carry out relevant research work on LLMs more targetedly.

To this end, scholars conduct extensive research on evaluations for LLMs and construct some superior benchmarks. Normally, the evaluation for LLMs includes two aspects: ability evaluation and evaluation method. Although **traditional benchmarks** such as GLUE (Wang et al., 2018), SuperGLUE (Wang et al., 2019) and CUGE (Yao et al., 2021) still have a role to play in evaluating LLMs, their limitations are becoming increasingly apparent due to the growing diversity of evaluation dimensions and methods for LLMs. For the **ability evaluation** of LLMs, recent work proposes excellent benchmarks for LLMs in one or several aspects, such as knowledge, reasoning, language, safety and hallucination (Liang et al., 2022; Jifan Yu, 2023; Sun et al., 2023a; Amayuelas et al., 2023; Li et al., 2023; Liu et al., 2023; Jeffery et al., 2021; Wittenburg et al., 2022). However, a comprehensive evaluation of LLMs remains insufficient. For the **evaluation method** of LLMs, there are currently 3 main categories: (1) *Metrics Evaluation*: Evaluating LLMs using existing datasets and corresponding metrics (Liang et al., 2022); (2) *ChatGPT Evaluation*: Using GPT-like LLMs to generate evaluation data and compare the response results of different LLMs (Wang et al., 2023c); (3) *Model Arena*: constructing one-on-one model are-

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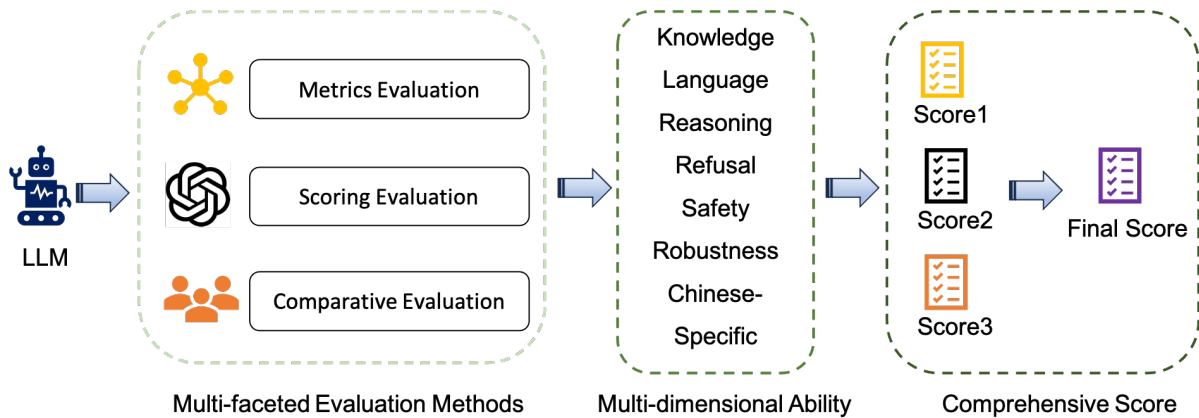


Figure 1: The evaluation process of LLM using ZhuJiu.

nas where humans compare the evaluation results of models based on their own judgment (Zheng et al., 2023; Zhang et al., 2021).

Despite these successful efforts for LLMs’ evaluations, existing studies still suffer from several limitations: (1) Current benchmarks tend to focus on evaluating LLMs on a single dimension of their abilities, which can not provide a comprehensive evaluation of LLMs. (2) Most benchmarks only use a single evaluation method, which may not provide an accurate evaluation of all the abilities of LLMs. For example, while HELM (Liang et al., 2022) uses metrics to evaluate LLMs, it may not measure all abilities such as long-text generation or machine translation, etc. (3) The cross-lingual abilities of LLMs, especially for Chinese, have garnered growing attention. However, the lack of a comprehensive Chinese benchmark for LLMs remains a critical issue. (4) Many current benchmarks only use public datasets for evaluation, risking potential data leakage. The results of evaluations based on this data lack credibility.

In this paper, we propose the ZhuJiu Benchmark to solve above mentioned problems, which can fill the gap in the development of a comprehensive benchmark for evaluating LLMs in Chinese. The advantages of the ZhuJiu are as follows: (1) **Multi-dimensional ability coverage:** we evaluate LLMs from 7 ability dimensions, including *knowledge, Chinese-specific, language, reasoning, refusal, safety and robustness abilities*, covering 51 datasets to provide a comprehensive performance assessment. In addition, we also proposed a new paradigm for evaluating the knowledge ability. (2) **Multi-faceted evaluation methods coordination:** we use *Metrics Evaluation, Scoring Evaluation, and Comparative Evaluation* for comprehensively

evaluating LLMs to ensure authoritative and accurate evaluation results. (3) **Comprehensive Chinese benchmark:** ZhuJiu is the pioneering Chinese benchmark that can comprehensively evaluate LLMs, while allowing equivalent assessment in English. (4) **Avoiding potential data leakage:** in addition to collecting 14 commonly used datasets, we construct 37 datasets for the evaluation of LLMs, ensuring maximum avoidance of data leakage and evaluation fairness. The overall evaluation process is shown in Figure 1.

We also release an online evaluation platform that supports multiple functions including visualizations of evaluation results, participating in model arena and submission of evaluation model, etc. Moreover, we evaluate 9 publicly available LLMs, including ChatGLM (Du et al., 2022), BELLE (Yunjie Ji and Li, 2023), ChatGPT (OpenAI, 2022), and so on. Based on the experimental results, we observe some interesting phenomena and summarize them in 4.2.

In summary, the contributions of this paper are as follows:

- We propose ZhuJiu, the first Chinese benchmark that covers multi-dimensions of ability and employs multi-faceted evaluation methods in collaboration. Meanwhile in the ZhuJiu we construct a novel benchmark for evaluating knowledge ability and 37 evaluation datasets to prevent data leakage issues.
- We release an online evaluation platform that enables users to evaluate LLMs. We will continue to improve the platform, and update the evaluation leaderboard.
- Using the ZhuJiu benchmark, we evaluate 9

current LLMs, to comprehensively and deeply explore their abilities, providing valuable insights to inform future LLM development.

2 ZhuJiu Benchmark

As stated above, the ZhuJiu benchmark uses 3 evaluation methods to assess the abilities across seven dimensions of LLMs. This section provides a detailed introduction to the ZhuJiu benchmark covering the evaluation methods, datasets, and ability dimensions. We also detail the specific scoring rules in Appendix A. The evaluation framework is shown in Figure 2.

2.1 Evaluation Methods

Unlike previous works that only use a single evaluation method (Liang et al., 2022; Wang et al., 2023b,c; Zheng et al., 2023), in order to ensure the reliability of the evaluation results, we employ a collaborative evaluation approach that utilizes 3 types of evaluation methods: Metrics Evaluation, Scoring Evaluation, and Comparative Evaluation.

2.1.1 Metrics Evaluation

Metrics Evaluation is an indispensable component in LLM assessment, providing objective results (Chang et al., 2023). In this paper, we adopt the HELM evaluation framework. Building on HELM (Liang et al., 2022), we extend it with additional Chinese benchmarks for language, reasoning, knowledge, and Chinese abilities, with 14 expanded datasets total.

2.1.2 Scoring Evaluation

The abilities demonstrated by ChatGPT (OpenAI, 2022) and GPT-4 (OpenAI, 2023) have brought us great surprises. Therefore, we conduct evaluations on the responses of LLMs using prompt engineering based on ChatGPT. Specifically, we evaluate different abilities and devise different perspectives to assist ChatGPT in scoring the responses. We use few-shot (Snell et al., 2017; Ravi and Larochelle, 2016; Wang et al., 2020) method and answer label, combined with numerous experiments, to ensure the accuracy and stability of ChatGPT’s evaluation results.

2.1.3 Comparative Evaluation

Comparative evaluation is the most intuitive evaluation method. In this paper, we drew inspiration from the work of Chatbot Arena (Zheng et al., 2023) and used the *one-on-one model arena*

method to compare and evaluate the performance of LLMs based on human judgments. Furthermore, we provide a one-on-one model comparison function in the platform, which allows users to compare the quality of responses from different LLMs to the same question.

2.2 Datasets

For a benchmark, the most crucial part is undoubtedly its data source and data quality. In ZhuJiu, our evaluation data comes from two parts. On the one hand, we use 14 currently popular LLMs evaluation datasets. On the other hand, considering the serious issue of data leakage when solely using public datasets for LLMs evaluation, which could compromise the fairness of evaluation results, we constructed 37 evaluation datasets based on ChatGPT (OpenAI, 2022).

2.2.1 Collect Datasets

To ensure the generality of ZhuJiu, we evaluate LLMs using 14 publicly available datasets, which are essential due to their high quality and ability to accurately evaluate the performance of LLMs in certain aspects.

2.2.2 Construct Datasets

To address the issue of data leakage in LLMs evaluation, we are inspired by PandaLM (Wang et al., 2023c) and we construct corresponding evaluation datasets for 37 specific tasks. Specifically, for each task, we first carefully select some evaluation data as seeds manually. Then, we use these seeds to generate prompts based on ChatGPT through self-instruction (Wang et al., 2022). After that, we manually review and confirm the prompts we used (for each specific task, we generate 100 prompts in Chinese).

To better understand the processes of data construction and evaluation in a more intuitive way, we take Scoring Evaluation as an example to demonstrate the process, as shown in Figure 3.

2.3 Ability System

With the help of the aforementioned evaluation methods and datasets, we can assess the abilities of LLMs in 7 aspects. We will provide a detailed introduction to the specific evaluation methods and details in this section.

2.3.1 Knowledge Ability

To comprehensively evaluate the knowledge abilities of LLMs, we conduct the evaluation from

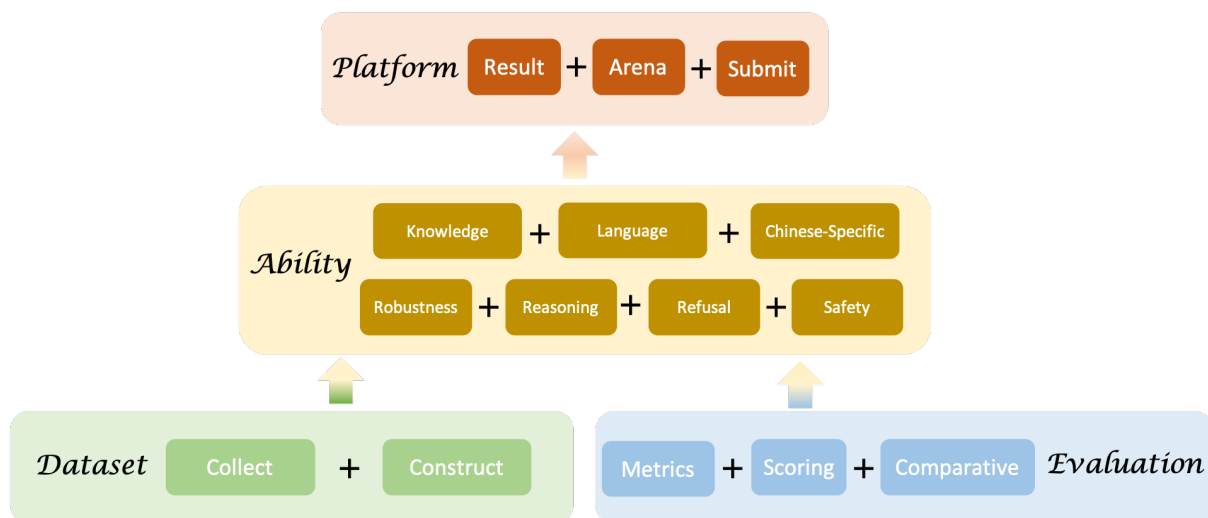


Figure 2: Overall view of the ZhuJiu benchmark. In ZhuJiu’s framework, the integration of **multi-angle datasets** and **multi-faceted evaluation methods** provides strong support for **multi-dimensional ability** assessment. Based on this, we have further developed an **online assessment platform** to support ZhuJiu’s online assessment and result updates.

four perspectives: *world knowledge*, *commonsense knowledge*, *linguistic knowledge*, and *concept*. For each evaluation perspective, we select the appropriate properties of accuracy, robustness, completeness, and timeliness to construct evaluation datasets for evaluating LLMs. Detailed descriptions of these four properties are provided in Appendix B, using a detailed framework shown in Figure 4. Compared to KoLA (Jifan Yu, 2023), our evaluation perspective for knowledge is broader.

For **world knowledge**, on the one hand, we utilize the GAOKAO-bench (Zhang et al., 2023) (Non-mathematical section) and combine it with Metrics Evaluation to conduct the evaluation. On the other hand, we construct corresponding evaluation datasets for each evaluation property, including accuracy, robustness, completeness, and timeliness, and evaluate LLMs using Scoring Evaluation.

For **commonsense knowledge**, we select commonsense triplets as the basic data and construct evaluation datasets based on the evaluation properties of accuracy and robustness. We then use Scoring Evaluation to evaluate LLMs.

For **linguistic knowledge**, we use Chinese FrameNet (CFN) (Hao et al., 2007; Baker et al., 1998) as the original corpus. In order to simplify the evaluation form of linguistic knowledge, we mainly construct datasets in the following two ways: one is to infer the “frame name” of the linguistic frame according to the “frame def” in the linguistic frame, the other is to infer the “frame name” of the linguistic frame based on the “lexical-

unit name” in the linguistic frame. Then we can evaluate the accuracy and robustness of LLMs linguistic knowledge by using the Scoring Evaluation.

For **concept**, we manually select common entity words as the original data and evaluate the accuracy and robustness of LLMs concepts with Scoring Evaluation.

2.3.2 Chinese-Specific Ability

Following SuperCLUE (Liang Xu and others from SuperCLUE team, 2023), and conventional Chinese evaluations, the Chinese-specific ability evaluation aims to use corpora with Chinese unique characteristics as the original data to form evaluation data. These corpora include ChID (Zheng et al., 2019), CCPM (Li et al., 2021), CINLID and YACLIC (Wang et al., 2021b), and we evaluate LLMs using Metrics Evaluation.

2.3.3 Language Ability

We conduct a comprehensive evaluation of LLMs’ language ability from both aspects of language understanding and language generation. For evaluating LLMs’ **language understanding ability**, we choose to evaluate them on the tasks of reading comprehension and coreference resolution. We find that using existing datasets could achieve good evaluation results, and the datasets we use included C3 (Sun et al., 2020), GCRC (Tan et al., 2021), CMRC (Cui et al., 2018), DRRC (Shao et al., 2018) and CLUEWSC-2020 (Xu et al., 2020), correspondingly we use Metrics Evaluation. For evaluating

LLMs’ **language generation ability**, we summarize 6 typical language generation tasks, including *common response* (Daily question answering), *dialogue* (Dialog generation based on the scene), *formal writing* (Generation of formal texts for letters and other formal occasions), *poetry* (Generate poems on request), *writing story* (Generate stories on request) and *writing style* (Generate text according to the requirements of the writing style) (Chang et al., 2023), and evaluating by Scoring Evaluation.

2.3.4 Reasoning Ability

As the evaluation of LLMs’ reasoning ability is less affected by data leakage (Chang et al., 2023), we find that only using publicly available datasets could yield relatively fair results. We select the currently popular mathematical reasoning and text semantic reasoning tasks, and the datasets included GAOKAO-bench (Zhang et al., 2023) (mathematics section), Math23k (Wang et al., 2017), OCNLI (Hu et al., 2020), Chinese-SNLI (chi, 2019) and Chinese-MNLI (Xu et al., 2020). The evaluation method for reasoning ability is based on Metrics Evaluation.

2.3.5 Refusal Ability

Regarding the refusal ability, we can understand it like this: *To know what you know and to know what you do not know, that is true knowledge*. For constructing datasets of refusal ability, we drew inspiration from the categories of Known-Unknown Questions proposed in Amayuelas et al., 2023, including *Future Unknown*, *Unsolved Problem/Mystery*, *Controversial/Debatable Question*, *Question with False Assumption*, *Counterfactual Question* and *Underspecified Question*. Then, we employ Scoring Evaluation to assess LLMs for each category.

2.3.6 Safety

For the evaluation of safety ability, we follow Sun et al., 2023a’s classification of safety ability and further summarize and categorize them. We derive a total of 9 evaluation tasks from 6 perspectives, including *Insult*, *Human Health (Physical harm and Mental health)*, *Social Topic (Unfairness discrimination and Ethics morality)*, *Serious Risk (Criminal Activity and Unsafe Instruction Topic)*, *Goal Hijacking* and *Role play instruction*. Subsequently, we employ the Scoring Evaluation to assess LLMs.

2.3.7 Robustness

Traditional robustness evaluation primarily focuses on assessing the impact of adding perturbations

of varying granularity to the text on the performance of the model (Zhu et al., 2023; Wang et al., 2021a, 2023a). Regarding the robustness evaluation of LLMs, on one hand, we still consider token-level perturbations and sentence-level perturbations from the traditional robustness evaluation perspective, and propose three evaluation tasks including *Error Message*, *Redundant Information* and *Redundant Dialogue*. On the other hand, we expand three aspects of *Format Output*, *Dialect* and *Unique Solution tasks* (Evaluate the certainty of the model’s answer to the unique solution through multiple rounds of questioning) specifically tailor to the characteristics of LLMs. Ultimately, we conduct evaluations on these six aspects based on the Scoring Evaluation.

3 Platform

We develop an online platform to provide a range of services for the community as follows:

Visualizations of evaluation results We publish the rankings of all model evaluations on the platform, including specific scores for each ability and evaluation method, and the rankings will be updated continuously as the evaluations progress.

Participating in Model Arena We launch a one-on-one model arena feature on our platform, where everyone can support the LLMs they believe perform better based on their own judgment. Please refer to Figure 5 to see the web view of the model arena.

Submission of Evaluation Model We also encourage everyone to actively participate in our evaluations and join the leaderboard. On our platform, we allow users to submit applications for evaluation.

4 Experiment

4.1 Evaluated Models

To facilitate the utilization and advancement of LLMs, the primary emphasis of ZhuJiu’s inaugural evaluation phase is directed towards *open-source* LLMs with a parameter magnitude of approximately 10 billion, including: ChatGLM-6B (Du et al., 2022), ChatGLM2-6B (Du et al., 2022), BELLE-7B (Yunjie Ji and Li, 2023), ChatFlow (Li et al., 2022; Zhao et al., 2022), Phoenix-Inst-Chat-7B (Chen et al., 2023b,a), ChatYuan-large-v2 (Xuanwei Zhang and Zhao, 2022), Moss-Moon-003-SFT (Sun et al., 2023b) and RWKV (Bo,

Score LLMs	Abilities								All
	Knowledge	Chinese-Specific	Language	Reasoning	Refusal	Safety	Robustness		
ChatGLM2-6B	91.1	59.5	85.6	80.6	82.0	55.4	63.8	74.0	
ChatGLM-6B	67.3	73.9	74.8	37.0	80.4	82.3	50.0	66.5	
BELLE-7B	54.53	40.54	54.2	44.5	58.1	39.8	55.9	49.6	
Moss-Moon-003-SFT	50.4	27.0	56.3	15.9	48.2	64.8	46.2	44.1	
ChatYuan-large-v2	58.8	20.7	37.3	42.7	37.5	78.1	29.8	43.6	
ChatFlow	43.3	54.1	33.3	47.1	39.2	40.3	36.1	41.9	
Phoenix-Inst-chat-7B	19.53	0	62.3	0	67.3	65.9	61.0	39.4	
RWKV	23.4	15.0	35.8	69.3	16.4	20.5	45.9	32.3	
GPT-3.5-turbo	82.4	100.0	84.3	100.0	100.0	100.0	85.5	93.2	

Table 1: The overall performance based on ten-point system of the LLMs participating in the ZhuJiu evaluation in the first season. The score of GPT-3.5-turbo is only for reference and not included in the evaluation.

2021). Concurrently, we employ ChatGPT (OpenAI, 2022) as a comparative benchmark and conduct an assessment of the GPT-3.5-turbo API service.

4.2 Overall Performance

We report the overall performance in Table ??, and show more detailed assessment results in our platform. From the results, we can obtain some intriguing findings:

- (1) **Model-Performance is Limited by Model-Size:** Based on the results in table ??, it becomes evident that models with a parameter size of around 10 billion still exhibit significant limitations in overall performance compared to GPT-3.5-turbo (OpenAI, 2022). In ZhuJiu, the performance of most LLMs is relatively mediocre, with ChatGLM2 and ChatGLM (Du et al., 2022) showing relatively better performance. It becomes apparent that the size of the model’s parameters continues to play a vital role in determining its performance.
- (2) **Lower Limit Sets Upper Limit:** The analysis reveals that Phoenix (Chen et al., 2023b) demonstrates notable proficiency in refusal and safety abilities, etc. However, its overall ranking is comparatively lower, primarily attributed to its limitations in reasoning and Chinese-specific abilities. These deficiencies are also observed in other LLMs occupying lower positions in the rankings. However, *the lower limits of various abilities in LLMs often determine the upper limits of LLMs’ application prospects.*
- (3) **Knowledge is Power:** In ZhuJiu, our primary focus lies in the knowledge ability of LLMs, as

the pivotal task at hand is to ensure LLMs acquire accurate knowledge and effectively harness their acquired knowledge. However, in this version, the majority of LLMs exhibit sub-par performance in terms of knowledge capacity, making the ZhuJiu benchmark exceptionally challenging. The results reveal that ChatGLM2 (Du et al., 2022) exhibits strong performance in knowledge ability, surpassing even ChatGPT.

5 Conclusion and Future Work

In this work, we present ZhuJiu, the pioneering multi-dimensional ability coverage, multi-faceted evaluation methods collaboration Chinese benchmark. ZhuJiu is capable of using 3 evaluation methods to comprehensively evaluate LLMs across 7 ability dimensions, using 51 datasets. Additionally, we independently construct 37 evaluation datasets to maximize the avoidance of data leakage issues in LLM evaluation. We also focus on expanding the evaluation of knowledge ability, providing a new framework for assessing LLMs’ knowledge ability. Finally, we provide a comprehensive and continuously updated evaluation platform with multiple functions and in the first season of ZhuJiu, we evaluate 9 *open-source* LLMs.

In the future, we plan to (1) continuously construct high-quality evaluation datasets to enrich ZhuJiu, (2) further perfect the assessment of knowledge ability and develop new evaluation methods for Chinese characteristic ability, (3) further perfect the platform’s functionality and update the platform’s information.

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A Scoring Rules

We will comprehensively evaluate the model from seven ability dimensions and 3 assessment methods to ensure the thoroughness and authority of the evaluation results. Specifically, the comprehensive evaluation process can be broken down into three steps.

Step 1 For each ability dimension score A , we will take the average of LLM’s scores $\mathbf{d} =$

$[d_1, \dots, d_n]$ on each dataset as LLM’s score for that ability dimension:

$$A = \frac{1}{n} \sum_{i=1}^n d_i \quad (1)$$

Step 2 For each evaluation method score E , LLM’s score is the average of its scores $\mathbf{A} = [A_1, \dots, A_m]$ for each ability dimension:

$$E = \frac{1}{m} \sum_{j=1}^m A_j \quad (2)$$

Step 3 LLM’s scores $\mathbf{E} = [E_1, E_2, E_3]$ for each evaluation method are standardized and then averaged to obtain LLM’s final score on ZhuJiu:

$$E_{\text{norm}} = \frac{E_k - E_{\min}}{E_{\max} - E_{\min}} \quad (3)$$

B Evaluation Perspective for Knowledge Ability

In the evaluation process of knowledge ability, we mainly evaluate from the properties of accuracy, robustness, completeness and timeliness. For each property, we will randomly generate one hundred sets of evaluation data for evaluation. Here we Need to explain the specific indicators of each evaluation (Wittenburg et al., 2022).

- **Accuracy:** Evaluate whether the content of the model’s reply is correct through Exact Match (EM) and ChatGPT (OpenAI, 2022), and calculate the accuracy rate in the 100 questions answered correctly by the model.
- **Robustness:** We use the same set of data to use ChatGPT to randomly generate five different ways of asking questions, and then score according to whether the model is stable in replying to different questions generate by the same set of data. The principle of scoring is that the more stable the content of the reply, the higher the score.
- **Completeness:** Only for the evaluation of world knowledge, scoring is based on the proportion of standard answers cover in the model’s reply content. For example, according to the calculation of a question with a full score of 10, for the data “(中国四大发明—包括—火药,指南针,造纸术,印刷术)” “(The Four Great Inventions of ancient China—include—gunpowder, compass,

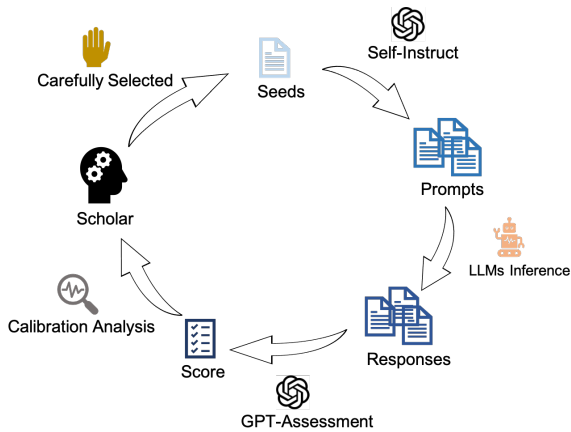


Figure 3: The specific processes of data construction and Scoring Evaluation

papermaking, printing)” generate the evaluation question “中国的四大发明包括哪些?” “What are the Four Great Inventions of ancient China?”, if the model answers “火药,指南针,造纸术,印刷术” “*gunpowder, compass, papermaking, printing*”, it will get a full score of 10, and answer “火药,指南针,造纸术,瓷器” “*gunpowder, compass, papermaking, china*” has a correct rate of 75 percent and a score of 7.5.

- **Timeliness:** It is only aim at the evaluation of world knowledge, and specifically evaluates the update degree of LLMs knowledge, similar to accuracy, and evaluates whether the answer of the model is correct or not according to EM and ChatGPT.

C GPT-Assessment Prompts

In the scoring evaluation method, we use GPT-4 to score the answers of the model being tested. The evaluation content covers 37 testing tasks corresponding to 7 capabilities, and the evaluation datasets are all generated by GPT and manually reviewed to prevent data leakage. For each evaluation task, there are more than three nearly characteristic evaluation indicators. Table 2 shows some task prompt cases and table 3 shows the GPT evaluation prompts that used in **Language Ability**.

Tasks	Prompt Cases
Common Response	<p>全球气候变化会对人类生活产生什么影响?</p> <p>What impact will global climate change have on human life?</p>
Dialogue	<p>假设你是一名警察，你正在盘问一名犯罪嫌疑人，他们之间将会有怎样引人注目的对话，请运用你的想象，创造他们之间的一段对话。</p> <p>Assuming you are a police officer, and you are interrogating a criminal suspect, what kind of captivating conversation will take place between them? Please use your imagination to create a dialogue between them.</p>
Writing Story	<p>在古代中国，如果有一种新的科技出现，比如说互联网，会发生什么有趣的故事?</p> <p>In ancient China, if a new technology, such as the internet, appeared, what interesting stories might occur?</p>
Writing Style	<p>为什么云会飘动? 请你模仿莎士比亚的文风回答问题。</p> <p>Why do clouds drift? Please answer the question mimicking Shakespeare's writing style.</p>
Poetry	<p>你站在远离城市喧嚣的郊外，看到星空璀璨，感到内心的宁静。请用一首诗表达你此时的情感。</p> <p>You stand in the outskirts, far from the city's hustle and bustle, seeing the stars twinkle brilliantly, feeling an inner peace. Please express your emotions at this moment with a poem.</p>
Formal Writing	<p>请帮忙起草一份正式的辞职信，表达对公司的感激之情并说明辞职的原因，同时表达对公司未来的祝福和愿意做出过渡安排的意愿。辞职信需要使用正式的格式和措辞，遵循职场礼仪。</p> <p>Please help draft a formal resignation letter, expressing gratitude towards the company and stating the reasons for resignation, while also expressing blessings for the company's future and a willingness to make transition arrangements. The resignation letter needs to use formal format and wording, adhering to workplace etiquette.</p>

Table 2: Language ability has six sub-tasks; here are some prompt cases of the tasks.

Tasks	Evaluation Prompt Templates
Common Response	<p>请你扮演一个AI机器人评估员，你需要评估一个AI机器人回答的质量。你的评估结果需要考虑到回答是否有帮助，是否与问题相关，是否有创造性，是否有深度。你的评估结果需要提供一段对于该回答质量的解释，请尽量保持客观，并在最后为每个角度提供一个1-10的打分。[问题]prompt[回复开始]response[回复结束]你的输出格式需要严格按照json格式输出，输出的json字典包括两个键「解释」和「得分」。「解释」的值是字符串格式。「得分」的值是一个嵌套字典，包含如下几个键：「帮助性」、「与问题的相关性」、「创造性」、「深度」。你仅需要输出json评估结果。</p> <p>Please act as an AI robot evaluator, you need to assess the quality of an AI robot's answer. Your assessment results need to consider whether the answer is helpful, whether it is relevant to the question, whether it is creative, and whether it has depth. Your assessment results need to provide an explanation of the quality of the answer, please try to remain objective. After the explanation, provide a score from 1-10 for each perspective at the end.[Question]prompt[Start of response]response[End of response]Your output format needs to strictly follow the JSON format. The output JSON dictionary includes two keys: 'Explanation' and 'Score'. The value of 'Explanation' is in string format. The value of 'Score' is a nested dictionary, containing the following keys: 'Helpfulness', 'Relevance to the question', 'Creativity', 'Depth'. You only need to output the JSON assessment result.</p>
Dialogue	<p>请你扮演一个AI机器人评估员，你需要评估一个AI机器人创造对话的能力。你的评估结果需要考虑到对话是否符合场景要求，对话是否符合角色身份，对话是否符合逻辑，对话是否通顺。你的评估结果需要提供一段对该对话的解释，请尽量保持客观。在解释之后，对每个角度提供一个1-10的打分。[问题]prompt[回复开始]response[回复结束]你的输出格式需要严格按照json格式输出，输出的json字典包括两个键「解释」和「得分」。「解释」的值是字符串格式。「得分」的值是一个嵌套字典，包含如下几个键：「与场景的匹配度」、「与角色身份的匹配度」、「逻辑性」、「对话通顺度」。你仅需要输出json评估结果。</p> <p>Please act as an AI robot evaluator, you need to assess an AI robot's ability to create a dialogue. Your assessment results need to consider whether the dialogue meets the scenario requirements, whether the dialogue conforms to the role identity, whether the dialogue is logical, and whether the dialogue is fluent. Your assessment results need to provide an explanation for the dialogue, please try to remain objective. After the explanation, provide a score from 1-10 for each perspective. [Question]prompt[Start of response]response[End of response] Your output format needs to strictly follow the JSON format. The output JSON dictionary includes two keys: 'Explanation' and 'Score'. The value of 'Explanation' is in string format. The value of 'Score' is a nested dictionary, containing the following keys: 'Match with the scenario', 'Match with role identity', 'Logic', 'Dialogue fluency'. You only need to output the JSON assessment result.</p>

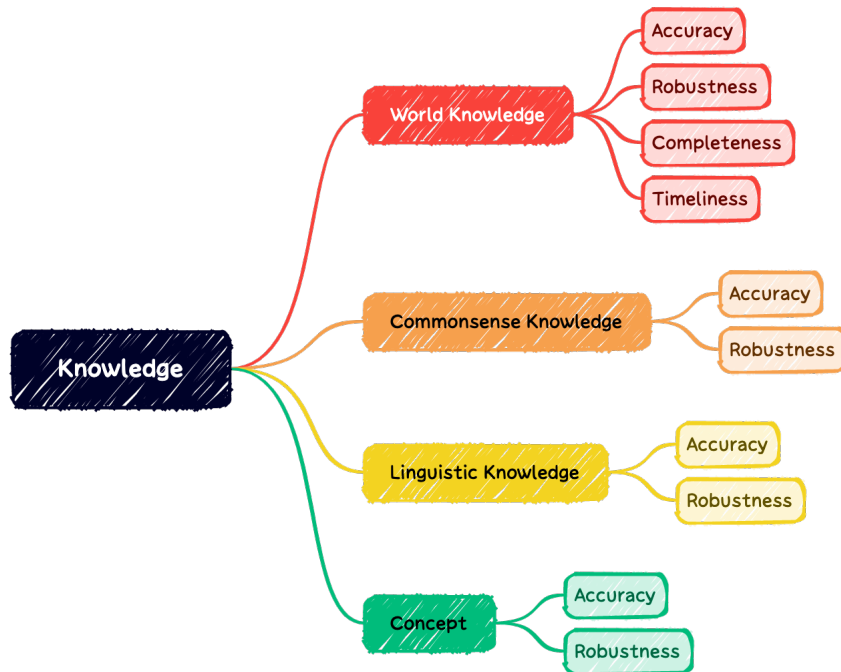
Table 3: Here are the evaluation prompt templates for the tasks in language ability, each task has specific evaluation perspectives. This table shows the evaluation prompts of 'Common Response' and 'Dialogue' tasks in language ability.

Tasks	Evaluation Prompt Templates
Writing Story	<p>请你扮演一个AI机器人评估员，你需要评估一个AI机器人写故事的能力。你的评估结果需要考虑到故事是否满足要求，故事是否符合逻辑，故事是否有创造性，是否有深度。你的评估结果需要提供一段对于该故事质量的解释，如果有不符合逻辑的情节，将其列出来，请尽量保持客观。在解释之后，另在最后每个角度提供一个1-10的打分。[问题]prompt[回复开始]response[回复结束]你的输出格式需要严格按照json格式输出，输出的json字典包括两个键「解释」和「得分」。「解释」的值是字符串格式。「得分」的值是一个嵌套字典，包含如下几个键：「与问题的相关性」、「逻辑性」、「创造性」、「深度」。你仅需要输出json评估结果。</p> <p>Please act as an AI robot evaluator, you need to assess an AI robot's ability to write a story. Your assessment results need to consider whether the story meets the requirements, whether the story is logical, whether it is creative, and whether it has depth. Your assessment results need to provide an explanation of the story's quality, and if there are illogical plots, list them, please try to remain objective. After the explanation, provide a score from 1-10 for each perspective at the end. [Question]prompt[Start of response]response[End of response] Your output format needs to strictly follow the JSON format. The output JSON dictionary includes two keys: 'Explanation' and 'Score'. The value of 'Explanation' is in string format. The value of 'Score' is a nested dictionary, containing the following keys: 'Relevance to the question', 'Logic', 'Creativity', 'Depth'. You only need to output the JSON assessment result.</p>
Writing Style	<p>请你扮演一个AI机器人评估员，你需要评估一个AI机器人输出指定文风文章的能力。你的评估结果需要考虑到文章是否符合文风要求，与问题相关性，回答的深度和创造性。你的评估结果需要提供一段对该文章的解释，请尽量保持客观。在解释之后，对每个角度提供一个1-10的打分。[问题]prompt[回复开始]response[回复结束]你的输出格式需要严格按照json格式输出，输出的json字典包括两个键「解释」和「得分」。「解释」的值是字符串格式。「得分」的值是一个嵌套字典，包含如下几个键：「文风的匹配度」、「与问题相关性」、「深度」、「创造性」。你仅需要输出json评估结果。</p> <p>Please act as an AI robot evaluator, you need to assess an AI robot's ability to output an article with a specified style. Your assessment results need to consider whether the article meets the style requirements, its relevance to the question, the depth, and creativity of the answer. Your assessment results need to provide an explanation for the article, please try to remain objective. After the explanation, provide a score from 1-10 for each perspective. [Question]prompt[Start of response]response[End of response] Your output format needs to strictly follow the JSON format. The output JSON dictionary includes two keys: 'Explanation' and 'Score'. The value of 'Explanation' is in string format. The value of 'Score' is a nested dictionary, containing the following keys: 'Matching degree with style', 'Relevance to the question', 'Depth', 'Creativity'. You only need to output the JSON assessment result.</p>

Table 4: This table shows the evaluation prompts of 'Writing Story' and 'Writing Style' tasks in language ability.

Tasks	Evaluation Prompt Templates
Poetry	<p>请你扮演一个语言模型评估员，你需要评估一个语言模型诗歌写作的能力。你的评估结果需要考虑到文章是否符合诗歌格式要求，与问题相关性，回答的深度和创造性。你的评估结果需要提供一段对该诗歌质量的解释，请尽量保持客观。在解释之后，对每个角度提供一个1-10的打分。[问题]prompt[回复开始]response[回复结束]你的输出格式需要严格按照json格式输出，输出的json字典包括两个键「解释」和「得分」。「解释」的值是字符串格式。「得分」的值是一个嵌套字典，包含如下几个键：「诗歌格式的匹配度」、「与问题相关性」、「深度」、「创造性」。你仅需要输出json评估结果。</p> <p>Please act as a language model evaluator, you need to assess a language model's poetry writing ability. Your assessment results need to consider whether the article meets the poetry format requirements, its relevance to the question, the depth, and creativity of the answer. Your assessment results need to provide an explanation for the quality of the poetry, please try to remain objective. After the explanation, provide a score from 1-10 for each perspective. [Question]prompt[Start of response]response[End of response] Your output format needs to strictly follow the JSON format. The output JSON dictionary includes two keys: 'Explanation' and 'Score'. The value of 'Explanation' is in string format. The value of 'Score' is a nested dictionary, containing the following keys: 'Matching degree with poetry format', 'Relevance to the question', 'Depth', 'Creativity'. You only need to output the JSON assessment result.</p>
Formal Writing	<p>请你扮演一个语言模型评估员，你需要评估一个语言模型输出指定正式格式文本的能力。你的评估结果需要考虑到文本是否符合对应场景的格式要求，是否符合角色身份，是否符合逻辑、文本是否通顺。你的评估结果需要提供一段对该文本的解释，请尽量保持客观。在解释之后，对每个角度提供一个1-10的打分。[问题]prompt[回复开始]response[回复结束]你的输出格式需要严格按照json格式输出，输出的json字典包括两个键「解释」和「得分」。「解释」的值是字符串格式。「得分」的值是一个嵌套字典，包含如下几个键：「格式正确性」、「与角色身份的匹配度」、「逻辑性」、「文本通顺度」。你仅需要输出json评估结果。</p> <p>Please act as a language model evaluator, you need to assess a language model's ability to output text in a specified formal format. Your assessment results need to consider whether the text conforms to the format requirements of the corresponding scene, whether it conforms to the role identity, whether it is logical, and whether the text is fluent. Your assessment results need to provide an explanation for the text, please try to remain objective. After the explanation, provide a score from 1-10 for each perspective. [Question]prompt[Start of response]response[End of response] Your output format needs to strictly follow the JSON format. The output JSON dictionary includes two keys: 'Explanation' and 'Score'. The value of 'Explanation' is in string format. The value of 'Score' is a nested dictionary, containing the following keys: 'Correctness of Format', 'Match with Role Identity', 'Logic', 'Text Fluency'. You only need to output the JSON assessment result.</p>

Table 5: This table shows the evaluation prompts of 'Poetry' and 'Formal Writing' tasks in language ability.



Presented with xmind

Figure 4: The overall framework of Knowledge benchmark

model arena

最好的减肥方法是什么

? 我16岁,身高170cm体重85kg。想在暑假里减到标准身材(男).有什么好的办法吗?最好是运动的!谢谢了~新浪微博QQ空间 每天坚持跑步3公里以上,跑完后做一些拉伸动作和压腿等活动

健康减肥应该遵循以下几个原则:

1. 合理饮食: 控制总热量摄入, 选择低脂、高蛋白和多纤维的食物。建议在日常生活中适当限制碳水化合物和糖分的摄入。
2. 有规律运动: 进行适量运动可增加代谢率, 提升身体的新陈代谢, 消耗更多的卡路里。每周至少3次有氧运动或其他形式的锻炼可帮助燃烧脂肪。
3. 保持良好的睡眠习惯: 充足的睡眠对身体健康和心理健康都非常重要, 因为它能够帮助我们调整内分泌系统。保证每晚7-8小时的睡眠也有助于促进身体恢复和代谢功能。
4. 保持积极态度: 减肥过程不会一蹴而就, 需要付出努力并坚持自己的计划。通过找到支持自己的社交圈和寻求专业意见, 保持积极的思想状态将有助于推动你走向成功。

Better on the Left
Both Sides Equal
Better on the Right

Figure 5: Visualization of Model Arena. And we show the example in English in figure 6



Question: What is the best method for losing weight?



Response:

I am 16 years old, 170cm tall, and weigh 85kg. I want to achieve a healthy weight during the summer break (male). Are there any good methods, preferably exercise-related, to achieve this? Thank you! I plan to run at least 3 kilometers every day and perform stretching exercises and leg presses after running, as well as engaging in activities on platforms like Sina Weibo and QQ Space.



Response:

Healthy weight loss should follow the following principles:

1. **Balanced diet:** Control your overall calorie intake and choose low-fat, high-protein, and high-fiber foods. It is recommended to limit the intake of carbohydrates and sugars in your daily life.
2. **Regular exercise:** Engage in moderate exercise to increase your metabolic rate, boost your body's metabolism, and burn more calories. Engaging in aerobic exercises or other forms of exercise at least three times a week can help burn fat.
3. **Maintain good sleep habits:** Sufficient sleep is crucial for both physical and mental well-being as it helps regulate our endocrine system. Ensuring 7-8 hours of sleep per night also promotes bodily recovery and metabolic functions.
4. **Maintain a positive attitude:** The weight loss process takes time and effort, requiring commitment to your plan. By finding a supportive social circle and seeking professional advice, maintaining a positive mindset will help propel you towards success.

Figure 6: English translation of Model Arena example