FAC^{2}E: Better Understanding Large Language Model Capabilities by Dissociating Language and Cognition

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Abstract

Large language models (LLMs) are primarily evaluated by overall performance on various text understanding and generation *tasks*. However, such a paradigm fails to comprehensively differentiate the fine-grained language and cognitive *skills*, rendering the lack of sufficient interpretation to LLMs' *capabilities*. In this paper, we present **FAC^{2}E**, a framework for **F**ine-gr**A**ined and **C**ognition-grounded LLMs' **C**apability **E**valuation. Specifically, we formulate LLMs' evaluation in a multi-dimensional and explainable manner by dissociating the language-related capabilities and the cognition-related ones. Besides, through extracting the intermediate reasoning from LLMs, we further break down the process of applying a specific capability into three sub-steps: recalling relevant knowledge, utilizing knowledge, and solving problems. Finally, FAC^{2}E evaluates each sub-step of each fine-grained capability, providing a **two**-faceted diagnosis for LLMs. Utilizing FAC^{2}E, we identify a common shortfall in knowledge utilization among models and propose a straightforward, knowledge-enhanced method to mitigate this issue. Our results not only showcase promising performance enhancements but also highlight a direction for future LLM advancements.

1 Introduction

Large language models (LLMs) (Brown et al., 2020), especially instruction-tuned LLMs (Ouyang et al., 2022; Bai et al., 2022; Touvron et al., 2023b; Chiang et al., 2023) revolutionized natural language processing and have surpassed human performance on tasks that require nontrivial reasoning (Guo et al., 2023; Malinka et al., 2023), while showing great potential in applications from conversational assistants (OpenAI, 2022; Achiam et al., 2023) to expertise problem-solving (Nori et al., 2023; Zhou et al., 2023; Suzgun and Kalai, 2024). However, despite the impressive performance, LLMs also show poor robustness on complex tasks (Ullman, 2023) and significantly inconsistent evaluation results under different settings, such as binary preference (Xu et al., 2023) and automatic metrics (Gudibande et al., 2023). Therefore, it is crucial to attain an overarching understanding of the capabilities and limitations of LLMs.

To address this challenge, most prior studies have assessed the performance of LLMs on different tasks based on independent benchmarks from various dimensions (Liang et al., 2022; Srivastava et al., 2023; Gao et al., 2023), such as knowledge (Hendrycks et al., 2020) and reasoning (Zellers et al., 2019). Recently, motivated by building LLM-based AI assistants, some studies propose highly curated benchmarks with instance-level fine-grained annotations, such as difficulty and required skills (Mialon et al., 2023; Ye et al., 2023), for holistic evaluation of LLMs.

However, the existing studies overlook a crucial distinction between *language* and *cognition* (Monti et al., 2012; Blank et al., 2014), rendering the insufficient understanding of a model's true capabilities and effectiveness in tasks. For instance, in the context of generative question answering, a model adept at extracting information but struggling to form a coherent understanding may exhibit similar overall performance to another model with profound cognitive insights but difficulties in articulating accurate responses. We argue that a multi-dimensional and interpretable understanding of LLMs' capabilities can not only accurately unveil their inherent limitations, but also help us to better identify why one model outperforms the other and how the different capabilities correlate. Additionally, such insights allow us to provide tailored guidance to improve training efficiency or facilitate more advanced model development.

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Capability	Description	Skill Example	
LINGUISTIC KNOWLEDGE	Encoding grammatical concepts support linguistic operations regarding word meanings and their combinatorial processing.	Grammaticality: Semantics:	agreements, licensing, long-distance dependencies, and garden-path effects. synonymy, antonymy, and hypernymy.
FORMAL KNOWLEDGE	Conducting word-based formal reasoning through understanding shallow semantics.	Mechanism: Skill:	deductive, inductive, and analogical. numeric, logic, and manipulation.
WORLD MODELING	Understanding text based on given context and associating it with world knowledge.	Remember: Understand:	factual knowledge, context, and commensense. narrative structure and discourse comprehension.
SOCIAL MODELING	Infering mental state behind text and intended meaning beyond literal content.	Pragmatics: Theory-of-mind	polite deceits, irony, maxims of conversation, metaphor, indirect speech, and humor. unexpected content and unexpected transfer tasks.

Table 1: Formulation of cognition-grounded LLMs' capabilities. See Section 2.1 for details.

In this paper, we propose FAC^{2}E, a fine-grained capability evaluation framework for LLMs. Specifically, FAC^{2}E dissociates the language-related and cognition-related capabilities of LLMs and organizing them into four distinct axes: LINGUISTIC KNOWLEDGE, FORMAL KNOWLEDGE, WORLD MODELING, and SOCIAL MODELING. This categorization is grounded in neuroscience evidence manifesting that language processing and cognitive processes, like memory and reasoning, operate differently in the brain. Drawing from this insight, we adapt a range of existing benchmarks into a unified question-answering format. We then develop specific instructions for each capability, allowing FAC^{2}E to evaluate LLMs through a method known as few-shot instruction-following.

Furthermore, we break down the application of a specific capability into three sub-steps: knowledge recall, knowledge utilization, and problem-solving, by iteratively drawing out the model's intermediate reasoning. After evaluating each sub-step, FAC^{2}E can reveal the quality of knowledge encoded in the model, and effectiveness in applying relevant knowledge to solve practical problems, offering a more comprehensive evaluation than a single performance metric could.

Our findings reveal a notable gap in capabilities between open-source and proprietary models, especially for cognition-related capabilities. Additionally, we found that many models have difficulties in applying knowledge effectively. To address this, we suggest a knowledge-enhance remedy by incorporating relevant knowledge text as additional input. Experimental results show that it can help the backbone model achieve about 90% performance compared to its instruction-tuned counterparts.

2 Methodology

In this section, we introduce FAC^{2}E framework, designed for fine-grained and cognition-grounded LLMs' capability evaluation. Specifically, we first define the taxonomy for LLMs' capabilities based on the distinction between language and cognition, which is drawn upon insights from neuroscience (Fedorenko and Varley, 2016; Mahowald et al., 2023). Based on this, we transform a variety of existing benchmarks into the unified question-answering format, design capability-specific instruction, and frame FAC^{2}E via few-shot instruction-following. Furthermore, we break down the evaluation process for each capability into a three-step reasoning approach. This involves identifying the knowledge pertinent to the input, examining how the model applies this knowledge in practical contexts, and assessing the effectiveness of its problem-solving. By evaluating each of these steps, FAC^{2}E provides a comprehensive overview of the model's performance, offering a more nuanced understanding of LLMs' intrinsic capabilities.

2.1 Formulation of LLMs' Capabilities

Human language processing has been investigated for a long time in cognitive science and neuroscience, which robustly attribute language and reasoning to different brain areas, namely "language network" and "multi-demand network" (Duncan, 2010; Scott et al., 2017). The former is sensitive to linguistic regularities and formal operations, and damage to the language network leads to linguistic deficits. The latter responds actively to a broader range of cognitively demanding processes, such as reasoning and memory. Motivated by this separated relationship, we define the LLMs' capabilities as a 4-dimensional schema as shown in Table 1. We then proceed to explain each capability and underline the specific skills they encompass.

LINGUISTIC KNOWLEDGE. For LLMs to effectively generate language, they must first grasp text at a basic linguistic level, which includes understanding both grammaticality and semantics. Grammaticality encompasses the rules that govern language structure, spanning from the sounds (phono-

logical) and words (lexical) to the arrangement of words in phrases and sentences. To capture this grammatical structure as comprehensively as possible, especially given the challenges conventional models face in benchmarks like BLiMP (Warstadt et al., 2020), we focus on four key skills: agreement (anaphor and subject-verb relationships), licensing (negative polarity items and reflexive pronouns), managing long-distance dependencies (filler-gap constructions and cleft sentences), and navigating garden-path sentences, which can mislead readers' initial interpretations. Semantics, on the other hand, while more closely related to high-level cognitive understanding, within the context of LINGUISTIC KNOWLEDGE, pertains to the meanings of individual words or lexical semantics. This aspect is distinct from general conceptual knowledge, which falls under other dimensions of LLM capabilities, highlighting the meaning-related understanding, such as synonymy, antonymy, and hypernymy.

FORMAL KNOWLEDGE. Beyond encoding linguistic structures and word meanings, an essential aspect of language capability involves understanding formal operations among words, or word-based reasoning. This means LLMs should be capable of recognizing relationships between words and deducing missing elements in a given pattern, such as completing analogies (*e.g.* "*man:woman :: king:_*"). FAC^{2}E includes three types of reasoning mechanisms—deductive, inductive, and analogical reasoning—between words (Bang et al., 2023). It also includes three categories of symbol-based formal skills: numeric (dealing with numbers), logic (applying logical operations), and manipulation (altering the inputs in a rule-based manner). An example task is concatenating the last letters of a word list ("*think, machine, learning*" → "*keg*").

WORLD MODELING. To step towards cognitive capabilities, well-grounded comprehension of factual and commonsense knowledge is required. Precisely, we decompose this capability into two primary mechanisms: *remember* and *understand*, respectively modeling the retrieval-based and comprehension-based capability (Sugawara et al., 2020; Wang et al., 2022a). Considering the versatility of knowledge sources, we instantiate the *remember* sub-capability as recalling factual knowledge (open-ended facts), reading comprehension (facts in context), and applying commonsense reasoning. Based on the multiple granularities of text comprehension and hierarchy of input text, we characterize the *understand* sub-capability as two skills: understanding narrative or event structure (paragraph-level), and discourse comprehension (document-level).

SOCIAL MODELING. The utility of human language lies in not only the understanding of the text itself but also the social context and mental states underlying communication, *i.e.* serving as a medium for information exchange between individuals. As suggested by research of cognitive science (Adolphs, 2009), the human brain has dedicated machinery, namely "theory of mind network", for processing social information and understanding somebody's mental state. Besides, since there are a lot of phenomena about non-literal language comprehension in daily life, such as jokes, sarcasm, and indirect speech, successful LLMs should be capable of applying social inference skills to attain the intended meaning beyond the literal content. In this paper, we incorporate two kinds of social modeling into FAC^{2}E, encompassing pragmatics and theory of mind (ToM) reasoning. Pragmatics is evaluated by six kinds of dialogue, including polite deceits, irony, maxims of conversation, metaphor, indirect speech, and humor, while ToM is based on the "unexpected tasks" devised by Kosinski (2023).

2.2 FAC^{2}E

Based on the formulation of LLMs' capabilities, we collect input and output pairs from various benchmarks and modify collected instances, yielding a unified question-answering (QA) format. After that, following the widely adopted few-shot in-context learning (ICL) (Brown et al., 2020), we devise capability-specific instruction and frame FAC^{2}E via instruction following (Ouyang et al., 2022). We further leverage chain-of-thought (CoT) (Wei et al., 2022a,b) style prompting to elicit two intermediate reasoning steps from the model, namely *crystallized* step and *fluid* step. The terms "*crystallized*" and "*fluid*" are borrowed from Cattel's theory (Cattell, 1963), a foundational building block of cognitive science about the source of intelligence. Cattel's theory delineates that crystallized intelligence is semantic knowledge from past experiences, fluid intelligence is the ability to navigate novel situations, and problem-solving uses both. Therefore, we add two intermediate steps to operationalize the two kinds of mechanisms, and aim to measure how well the model recalls and applies knowledge. Last, we compare the intermediate results with the reference answers to score the reasoning sub-steps, hence providing an assessment of

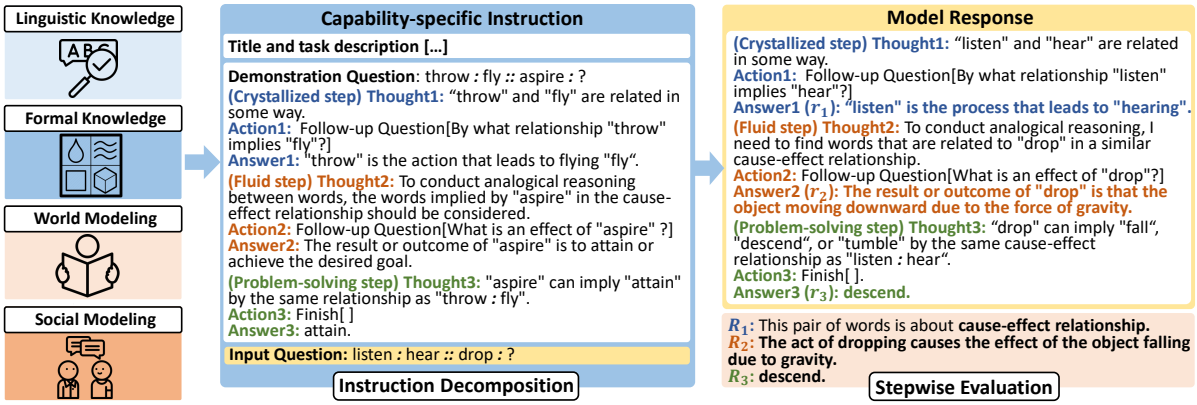

Figure 1: Illustration of FAC^{2}E pipeline. The input question is decomposed into two intermediate follow-up questions, which are used to help the model talk with itself to elicit reasoning sub-steps. FAC^{2}E evaluates each sub-step to reveal crystallized performance, fluid performance, and corresponding problem-solving performance. The content in the round parentheses is purely illustrative and is not part of the model input. The instruction has been omitted here for clarity. Please refer to Appendix B for full version example.

the crystallized performance and fluid performance as well as problem-solving performance.

As depicted in Figure 1, the pipeline FAC^{2}E can be divided into three steps, including capability-specific instruction design, instruction decomposition, and stepwise evaluation. Specifically, we devise natural instruction for each capability-related task. Borrowing the widely used template schema of instruction-following (Wang et al., 2022b; Mishra et al., 2022), the capability-specific instruction $\mathcal{I}_c$ is comprised of three parts: title, task description and few-shot demonstrations. Precisely, the title defines a given QA task in high-level natural language and highlights the associated skills, while the task description not only presents a complete clarification of how an input text is expected to be mapped to final output, but also define the output of reasoning sub-steps through instruction decomposition. After that, following the given task description, a few in-context demonstrations are provided to better steer the response generation. At last, we collect the response results for each reasoning sub-steps, denoted as $\{r_i\}_{i=1}^3$, and respectively evaluate them with the reference answer, denoted as $\{R_i\}_{i=1}^3$, which are directly extracted or manually constructed from corresponding benchmarks. Formally, the procedure can be represented as:

$$\{r_i\}_{i=1}^3 = \mathcal{M}(\mathcal{I}_c) \quad (1)$$

$$s_i = \text{Criterion}_i(r_i, R_i) \quad (2)$$

where $\mathcal{M}$ denotes the examined LLM, while Criterion_i and s_i represent the employed automatic metric and corresponding score, respectively.

Instruction decomposition. Motivated by building explainable evaluation methods for machine reading comprehension (MRC) (Ray Choudhury et al., 2022), which extracts relevant text spans and validates reasoning path, we propose to evaluate intermediate steps when LLMs apply a specific capability to solve practical problems. Specifically, we decompose the capability-specific instruction and add two intermediate steps, including crystallized and fluid steps. In practice, we leverage CoT-like iterative prompting strategy to elicit the intermediate reasoning from the model. Differing from the standard CoT that outputs a continuous rationale before the final answer, we first decompose the given question as follow-up sub-questions. After that, these sub-questions are used to help the model talk with itself to respectively discover (i) what knowledge this question is about, (ii) how to apply relevant knowledge to the given instance, and (iii) the final answer. In other words, FAC^{2}E convert the CoT continuous rationale into easily parseable multi-step rationales, which externalizes reasoning of the model (Shwartz et al., 2020; Zhou et al., 2022b) and enables the evaluation of crystallized performance and fluid performance. Formally, as depicted in the demonstrations of Figure 1, we expect that the the model outputs as: [Thought], [Action], [Answer] , where [Thought] can reason about the current situation, [Action] can be either (1) [Follow-up Question], which returns a sub-question, or (2) [Finish], and [Answer] is extracted as the reasoning result of a sub-step.

Stepwise evaluation. Given the reasoning results of three sub-steps, *i.e.* $\{r_i\}_{i=1}^3$, we engage automatic metrics as the criterion to evaluate them. Specifically, r_1 and r_2 are free-form rationales for intermediate reasoning steps. Considering

Capability	Benchmark	QA type
Agreements	BLiMP (Warstadt et al., 2020)	M
Licensing	Marvin and Linzen (2018)	M
Long-distance dependency	Wilcox et al. (2019)	M
Garden-path effects	Futrell et al. (2018)	M
Lexical semantics	Petersen and Potts (2023)	M
Deductive	Bang et al. (2023)	M
Inductive	Bang et al. (2023)	M
Analogical	Webb et al. (2023)	G
Numeric	MAWPS (Koncel-Kedziorski et al., 2016)	G
Logic	Tian et al. (2021)	G
Manipulatation	Wei et al. (2022b)	G
Factual Knowledge	LAMA (Petroni et al., 2019)	G
Reading Comprehension	Dua et al. (2019)	M
Commonsense	Talmor et al. (2019)	M
Discourse	Wang et al. (2023c)	G
Narrative	Xu et al. (2022)	G
Pragmatics	Hu et al. (2023)	M
Theory of mind	Ullman (2023)	G

Table 2: Breakdown statistics on source benchmarks and re-formulation types of the evaluation data employed by FAC^{2}E, where "G" and "M" stand for generative QA and multiple-choice QA, respectively.

the diversity of rationale generation, we resort to BARTScore-Recall (Yuan et al., 2021), one of the most superior metrics for natural language generation to evaluate the quality of generated rationale automatically. BARTScore-Recall gauges how many semantic content units from reference texts are covered by the generated candidates, and will not penalize the redundant and instance-specific information in the model response. For the last response r_3, since it is expected to be the final answer for the given question, it is evaluated by the BARTScore-Recall (Yuan et al., 2021) or accuracy for generative QA re-formulation and multiple choice QA re-formulation, respectively.

3 Experiments

Evaluation data construction. As summarized in Table 2, we collect a total of 17 English benchmarks and modify the corresponding input-output pairs into a unified QA format, *i.e.* generative QA or multiple-choice QA. The reference answers of the benchmarks are directly used as the final answer R_3, while the reference rationales (R_1 and R_2) for the intermediate reasoning steps are constructed manually. Specifically, on the one hand, R_1, *i.e.* the reference rationale for the first reasoning step is based on the metadata analysis about subset division of the employed benchmarks. For example, when we evaluate the grammaticality regarding negative polarity item (NPI) licensing, we manually write "The word '*any*', in their most common uses, are negative polarity items: they can only be used in an appropriate syntactic-semantic environment—to a first approximation, in the scope of negation." as the reference rationale R_1 for the whole "*any*"-based NPI licensing subset, other subset will substitute the "*any*" with corresponding licensing contexts or trigger words, such as "*ever*" and "*even*". On the other hand, R_2, *i.e.* the reference rationale for the second reasoning step is built on the instance-wise annotations of human evaluation publicly released by the authors of corresponding benchmarks, which annotates necessary explanations as well as final answer R_3 for a given question. Although this will leave few benchmarks available and lead to a limited number of evaluation data, it provides relatively reliable references and especially enables re-producible evaluation.

Model	Model size	Pre-training	Fine-tuning
T5	11B	1.0T tokens	✗
Flan-T5	11B	as above	IT
Flan-Alpaca	11B	as above	IT
LLaMA	7B	1.4T tokens	✗
Alpaca	7B	as above	IT
Vicuna	7B	as above	IT
TÜLU 1	7B,13B,30B,65B	as above	IT
LLaMA 2	7B	2T tokens	✗
LLaMA 2-Chat	7B	as above	IT+RLHF
GPT-3.5	175B	-	IT+RLHF
InstructGPT	175B	-	IT+RLHF
Bard	137B	-	IT+RLHF

Table 3: Statistics of examined LLMs, including model size, pre-training data scale, and fine-tuning techniques indicating whether the model is built with instruction tuning (IT) and reinforcement learning with human feedback (RLHF) or not.

Examined models. As summarized in Table 3, the examined LLMs can be categorized into publicly available open-source models and proprietary ones whose responses are provided through private APIs. On the one hand, open-source models include three backbone models, *i.e.* T5 (Raffel et al., 2020), LLaMA (Touvron et al., 2023a) and LLaMA 2 (Touvron et al., 2023b), which are pre-trained on large scale corpus and not applied to any fine-tuning. Initialized with T5, Flan-T5 (Longpre et al., 2023) and Flan-Alpaca (Chia et al., 2023) are instruction-tuned on Flan V2 (Longpre et al., 2023) and Alpaca (Taori et al., 2023), respectively. Built on LLaMA, Alpaca (Taori et al., 2023) and Vicuna (Chiang et al., 2023) are instruction-tuned with responses generated by GPT-3.5, while TÜLU 1 (Wang et al., 2023d) are instruction-tuned with a mixture of both manually curated and distilled dataset. Based on LLaMA 2, LLaMA 2-Chat (Touvron et al., 2023b) is firstly instruction-tuned with high-quality collected annotations, and then aligned with human preferences for the chat use case. Besides, to per-

Model	Linguistic Knowledge			Formal Knowledge			World Modeling			Social Modeling		
	s_1	s_2	s_3	s_1	s_2	s_3	s_1	s_2	s_3	s_1	s_2	s_3
T5	83.99	26.39	47.39	77.97	28.10	33.26	74.61	24.74	26.53	66.79	18.31	19.16
Flan-T5	84.96	42.50	64.12	80.10	35.22	42.58	74.82	36.13	34.64	67.73	27.23	21.27
Flan-Alpaca	85.25	39.41	60.15	79.88	34.99	41.72	75.54	37.42	36.57	68.38	28.74	23.82
LLaMA	85.34	31.36	53.77	80.02	31.18	40.04	75.57	27.46	30.47	67.54	20.14	20.75
Alpaca	86.02	45.78	68.39	82.03	38.10	53.85	77.30	41.91	49.42	69.93	29.61	32.96
Vicuna	85.23	47.45	72.66	84.35	40.10	57.07	75.33	43.38	44.37	65.68	26.87	30.63
TÜLU 1	84.14	45.84	70.72	82.32	39.29	51.21	75.90	43.30	40.80	69.73	26.77	27.02
LLaMA 2	83.19	34.56	57.89	82.19	34.18	46.15	77.48	34.84	40.92	68.22	24.74	24.20
LLaMA 2-Chat	87.04	48.95	74.46	84.05	43.21	57.13	78.43	46.09	44.46	71.06	28.89	29.59
GPT-3.5	87.91	53.91	82.72	85.93	45.20	70.47	81.53	53.18	67.68	77.23	36.34	40.56
InstructGPT	88.52	55.50	85.19	85.12	44.18	67.48	80.34	51.78	65.16	74.17	39.90	45.95
Bard	87.74	52.37	86.16	86.97	46.08	71.62	79.30	49.09	61.31	78.64	38.27	42.53

Table 4: Quantitative results in terms of four capability dimensions. As stated in Section 2.2, s_1, s_2, and s_3 refer to crystallized performance, fluid performance, and problem-solving performance, respectively. The shade of the red and blue text highlight the orders of s_3 in open-source and proprietary models, respectively.

form a fair comparison w.r.t instruction-tuning dataset, we also evaluate LLaMA checkpoints fine-tuned on other datasets, such as Flan V2 (Longpre et al., 2023) (human-written), Alpaca (model-generated) (Taori et al., 2023), ShareGPT [1] (user prompt with model response). On the other hand, proprietary models consist of OpenAI's GPT-3.5 (`gpt-3.5-turbo`) (OpenAI, 2022), OpenAI's InstructGPT (`gpt-3.5-turbo-instruct`) (Ouyang et al., 2022) and Google's Bard (Google, 2023). *Please refer to Appendix A for checkpoint details.*

3.1 Main results

The difference in problem-solving performance between open-source and proprietary models is significantly greater than the difference in their crystallized performance. On the one hand, in terms of problem-solving performance (s_3), as shown in Table 4, open-source models usually underperform the proprietary ones across various capabilities, especially cognition-related ones, such as world modeling and social modeling. For example, one of the most competitive open-source model Alpaca achieves a 49.42 accuracy in the world modeling dimension, while GPT-3.5 produces a performance of 67.68, excelling Alpaca by a substantial margin (around 36%). A similar conclusion can also be drawn from the other dimensions, such as the best problem-solving performance of proprietary models exceeds that of open-source models by about 16%, 25%, and 40% in linguistic knowledge, formal knowledge, and social modeling, respectively. On the other hand, in terms of crystallized performance (s_1), there is a rather smaller gap between open-source and proprietary models compared to problem-solving accuracy. For example, the maximal difference of

[1] https://sharegpt.com/

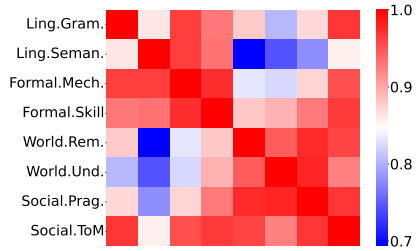

Figure 2: Pairwise correlation of problem-solving performance (s_1) among different capabilities. Please refer to Table 1 for full label names.

s_1 in the world modeling among all the examined models is about 9%, *i.e.* GPT-3.5's 81.53 vs. T5's 74.61, while their difference of s_3 is GPT-3.5's 67.68 vs. T5's 26.53. This kind of inconsistency between s_1 and s_3 can also be observed in other capability dimensions, potentially showing that either pre-training or supervised fine-tuning of LLMs can encode sufficient knowledge into the model, but the final task performance does not just depend on the amount or quality of knowledge.

Language-related capabilities show a relatively weak correlation with cognitive capabilities. Figure 2 presents the correlation results between different capabilities. Despite all showing strong correlations (Pearson's $r > 0.7$ (Krippendorff, 2004)), both the language-related and cognition-related capabilities exhibit stronger intra-dimension correlation (*e.g.* world modeling vs.social modeling) when compared to inter-dimension correlation (*e.g.* world modeling vs. formal knowledge). This indicates that excellence in language processing does not necessarily equate to a similar level of cognitive capability. This result can also be observed from Table 4. For example, the model LLaMA 2-Chat achieves better results in terms of problem-solving performance of linguistics knowledge than Alpaca, *i.e.* LLaMA

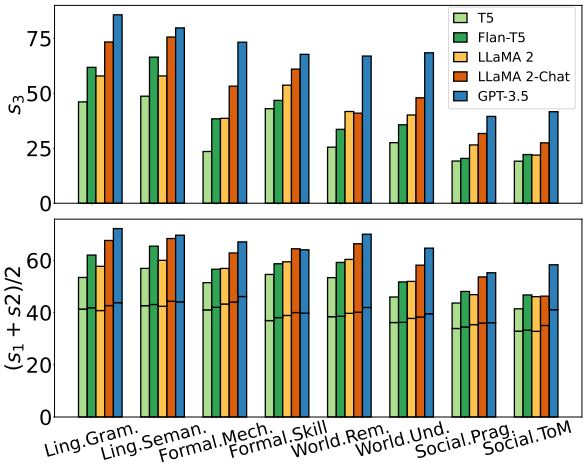

Figure 3: Bar diagram illustrating the relationship between problem-solving performance (s_3) and intermediate performance ($(s_1+s_2)/2$). Each bar of intermediate performance is divided into two stacked segments, the *lower* one denotes s_1, while the *upper* one denotes s_2.

2-Chat's 74.46 vs. Alpaca's 68.39, but it fails to surpass Alpaca in world modeling (44.46 vs. 49.42) and social modeling (29.59 vs. 32.96). This pattern also applies to other models, such as Bard vs. InstructGPT, further demonstrating the reasonability of disassociating language-related capabilities and cognition-related ones to better evaluate LLMs.

A possible reason behind it could be that dedicated structures of the model or subsets of parameters are highly correlated with language, whereas others serve as cognition, and they are optimized at different training stages and function as different mechanisms during inference, which has been verified by recent studies on knowledge locating and editing of LLMs. For example, Zhao et al. (2023) and Chen et al. (2023) respectively found core linguistic regions and language-independent knowledge neurons in LLMs, and Dai et al. (2022); Meng et al. (2022) proposed to explicitly edit knowledge neurons to improve performance, potentially providing a feasible approach to strengthening LLMs capability without fine-tuning, *i.e.* editing their parameters or architectures directly.

The crystallized step impacts problem-solving more than the fluid step. Figure 3 illustrates the relationship between problem-solving performance (s_3) and sum of crystallized (s_1) and fluid (s_2) performance. Both s_1 and s_2 make a difference to the final s_3, showing that problem-solving not only depends on the amount or quality of stored knowledge but also is reflective of the effectiveness of knowledge utilization. For example, LLaMA 2 underperforms LLaMA 2-Chat in terms of s_3

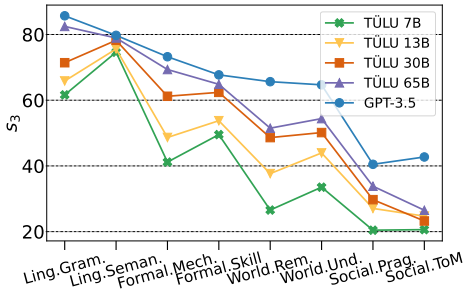

Figure 4: Problem-solving performance of instruction-tuned LLaMA with different model sizes.

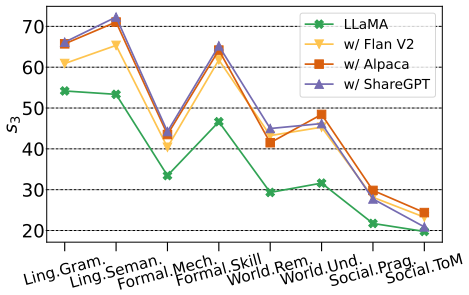

Figure 5: Problem-solving performance of LLaMA on different instruction-tuning datasets.

across various capabilities. When taking a closer look at the intermediate results, we can observe that both the models do well in crystallized step, but LLaMA 2 shows an worse result in fluid step, leading the worse problem-solving performance than LLaMA 2-Chat. Besides, all of the open-source models exhibit relatively poor fluid performance w.r.t. GPT-3.5, especially those that are pre-trained but not instruction-tuned, such as T5 and LLaMA 2. This implies a solution to improve problem-solving performance, *i.e.* boosting the efficacy of knowledge utilization. Section 3.2 devise a knowledge-enhanced method to demonstrate this solution.

Both the model size and the quality of fine-tuning dataset affect the capabilities of LLMs. Firstly, backbone models play a critical role in building superior models. For example, as shown in Table 4, fine-tuned on the same dataset, LLaMA-based Alpaca performs better than T5-based Flan-Alpaca, and the larger scale proprietary models show a greater advantage over other open-source models. In addition, scaling open-source models does improve both language and cognitive capability. As shown in Figure 4, problem-solving performance across various capabilities increases as the model size increases, and TÜLU-65B achieves the best performance. In particular, the level of formal knowledge of TÜLU-65B are close to that of GPT-3.5. Last, but not least, there is no significant performance difference among various open-source

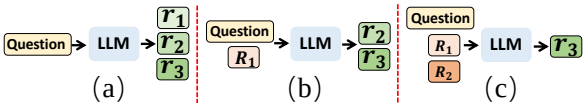

Figure 6: Comparisons between knowledge-enhanced baselines (b) $\mathcal{M}$+R_1 and (c) $\mathcal{M}$+R_1+R_2 and original setting (a).

instruction-tuning datasets whether it is comprised of human-written instruction or not. As illustrated in Figure 5, there is not a single best instruction tuning dataset across all tasks, indicating different datasets bring different benefits to LLMs' capabilities. This finding is consistent with the recent success of a mixture of instruction-tuning datasets or expert LLMs (Jiang et al., 2024; Xia et al., 2024).

3.2 Boosting LLMs with Injected Knowledge

Based on the above analysis showcasing the limitations of the crystallized performance of existing LLMs, as illustrated in Figure 6, we propose to a knowledge-enhanced approach. Specifically, for each given instance with question and answer, the first baseline, denoted as $\mathcal{M}$+R_1, append the first reference rationale, *i.e.* R_1, to the input question with string concatenation. Then the augmented input is fed into the model with the same instruction as the examined model. Note that we also remove the first triplet of ⟨ `[thought]`, `[action]`, `[answer]` ⟩ in the input demonstrations for the $\mathcal{M}$+R_1 baseline because we have provided the corresponding reference rationale. As a comparison, following a similar procedure, we also construct another baseline by incorporating both R_1 and R_2 into the model, denoted as $\mathcal{M}$+R_1+R_2.

Taking LLaMA 2, performing moderately in Table 4, as the backbone model, the multifaceted results are summarized in Figure 7. We can observe that explicit injected rationales both R_1 and R_2 can substantially improve the problem-solving performance, and R_2 results in more improvements than R_1. Specifically, R_1 contributes slightly to language-related capabilities, such as linguistic semantics and formal skills, while R_2 brings about significant improvements to cognition-related ones, especially social modeling. Overall, the knowledge-enhanced LLaMA 2 baseline can achieve approximately 90% performance compared to the corresponding instruction-tuned variant.

4 Related Works

Evaluation of LLMs. LLMs are initially assessed on various understanding (Wang et al., 2018, 2019)

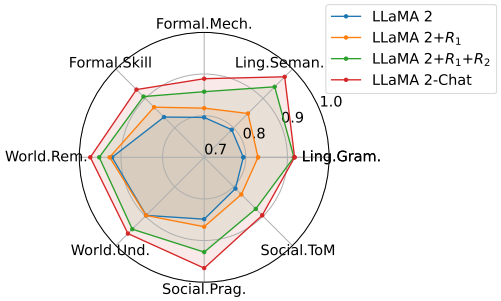

Figure 7: A 8-dimensional capability map of LLaMA 2 model when augmented with different knowledge text. The score is re-scaled through max-min normalization among each capability for clarity.

and generation tasks (Pilault et al., 2020; Thompson and Post, 2020). With the increasing emphasis on the trustworthiness of models, dedicated benchmarks are proposed to evaluate robustness (Yang et al., 2022; Wang et al., 2023b), hallucination (Li et al., 2023), bias (Zhong et al., 2023), and generalizability (Wang et al., 2023a). In a more unified form, recent-emerged works aim to evaluate LLMs on holistic benchmark (Mialon et al., 2023; Rein et al., 2023). Chia et al. (2023) conduct evaluation from problem-solving, writing, and human alignments, while Ye et al. (2023) annotates a single instance with a set of skills, including logical thinking, background knowledge, problem handling, and user alignment. Although they provide fine-grained analysis of LLMs' capability, they quantify each capability only using the performance metric, hence suffering from issues of interpretability.

Cognition-inspired intelligence evaluation. How to define and evaluate intelligence is widely investigated by both cognitive science and AI benchmark design (Cattell, 1963; Rogers et al., 2023). Taking MRC as the target, Chollet (2019) describes intelligence as skill-acquisition efficiency, while Sugawara et al. (2020) and Ray Choudhury et al. (2022) respectively propose to benchmark MRC based on reasoning skills and steps a system would be "reading slowly". As for the evaluation of LLMs, Mahowald et al. (2023) summarize lots of neuroscience evidence for dissociating language and thought, largely motivating the design of FAC^{2}E.

5 Conclusion

We present FAC^{2}E, defining a fine-grained capability evaluation framework for LLMs by dissociating language and cognition. FAC^{2}E decomposes each capability into sub-steps to assess performance of knowledge recalling and utilization as well as

problem-solving. FAC^{2}E reveals the inherent limitations of existing LLMs in knowledge utilization and provides a knowledge-enhanced remedy for it. Empirical results demonstrate its effectiveness.

Limitations

Our work proposes a fine-grained and cognition-grounded capability evaluation framework for LLMs, namely FAC^{2}E, which is based on the dissociated relationship of language and cognition, and evaluating the intermediate reasoning steps of LLMs. The limitations are two-fold, including data quality and domain generalizability.

On the other hand, motivated by a variety of empirical evidence from both neuroscience and probing experiments of LLMs, we formulate FAC^{2}E as four capability dimensions, then re-formulate instances from multiple existing benchmarks and conduct stepwise evaluation. Although we try to ensure that the employed datasets are as consistent and targeted with the defined dimensions as possible, the kind of evaluation data construction might not reflect the required skills accurately. For example, an instance can cover more than one language or cognition capabilities As discussed in Section 3.1, different capabilities are correlated to each other to some extent, Besides, the reference rationales, *i.e.* the gold standard of the intermediate reasoning step, are based on the human annotations from original benchmarks, leading to the inconsistency of reference answers and a limited number of available data, which might bias the evaluation results. One remedy to these incidental issues could be building a new holistic benchmark with fine-grained annotations following our proposed schema. We regard it as our future work and deem designing a new annotation specification a promising direction.

On the other hand, our FAC^{2}E only examined LLMs on general domains and English input, ignoring the domain-specific and multilingual application. In particular, the reasoning process of LLMs may expose social bias encoded in these models, such as race and gender (Lucy and Bamman, 2021). Therefore, additional evaluation protocols considering potential risks to user safety are left for our future work.

Ethics Statement

We introduce FAC^{2}E, a fine-grained and cognition-grounded capability evaluation framework for LLMs, and conduct evaluation experiments on publicly available datasets which are widely used in related research. Although LLMs have the potential to cause harm at the individual and societal levels (Gonen and Goldberg, 2019), our FAC^{2}E aims to provide a deep understanding of the capabilities and limitations of LLMs, potentially making the risks from the LLMs more predictable.

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A Implementation Details

All of the examined open-source models are based on HuggingFace Transformers package (Wolf et al., 2020). Their model cards, *i.e.* checkpoints consist of:

- T5 (t5-11b),
- Flan-T5 (google/flan-t5-xxl),
- Flan-Alpaca (declare-lab/flan-alpaca-xxl),
- LLaMA [2],
- Alpaca and LLaMA on Alpaca (allenai/open-instruct-stanford-alpaca-13b),
- Vicuna (lmsys/vicuna-7b-v1.1),
- TÜLU 1 (allenai/tulu-7b, allenai/tulu-13b, allenai/tulu-30b, allenai/tulu-65b),
- LLaMA on Flan V2 (allenai/open-instruct-flan-v2-13b),
- LLaMA on ShareGPT (allenai/open-instruct-sharegpt-13b),
- LLaMA 2 (meta-llama/Llama-2-7b-hf),
- LLaMA 2-Chat (meta-llama/Llama-2-7b-chat-hf)

For the response generation of each target model, as suggested by Wei et al. (2022b); Zhou et al. (2022a), we employ 4-shot instruction-following settings, *i.e.* 4 in-context demonstrations in the input prompt, set the temperature to 0.7 and set the max length of generated sequences as 1024. For automatic metrics, we leverage the official implementation of BARTScore (Yuan et al., 2021).

After collecting instances from various benchmarks as summarized in Table 2, we remove those instances where the input length is longer than 2048, maximal context length during training except T5, Flan-T5, and Flan-Alpaca,

We conduct evaluation experiments on 2 A100 GPUs and report the average results of a total of ten runs for each model on each benchmark. For the capabilities involving multiple benchmarks, the overall score are calculated as the arithmetic mean of crystallized performance (s_1), fluid performance (s_2), or problem-solving performance (s_3).

[2] https://huggingface.co/docs/transformers/main/en/model_doc/llama

B Instruction Design

See Figure 8 and Figure 9 for full version example of capability-specific instruction when evaluating the analogical reasoning and grammaticality.

Instruction: Solve a question-answering task by conducting analogical reasoning between words.
Given three words, i.e. A, B, and C in a format of A:B::C:?, which means that A implies B by some relationship, reason with this relationship and predict a word D such that C implies D by the same relationship. In other words, A:B is a reference pair in some relationship, complete the pair of C:D in the same relationship as A:B.
Please solve the task by interleaving Thought, Action, and Answer steps. Thought can reason about the current situation, and Action can be the following two types:
(1) Follow-up Question[question], which returns a sub-question with a single answer that helps solve the original question.
(2) Finish[], which means no more sub-questions. The final answer should be generated in the following line.
[Demonstration Question]: throw:fly::aspire:?
[Thought 1]: "throw" and "fly" are related in some way.
[Action 1]: Follow-up Question[By what relationship "throw" implies "fly"?]
[Answer 1]: "throw" is the action that leads to flying "fly".
[Thought 2]: To conduct analogical reasoning between words, the words implied by "aspire" in the cause-effect relationship should be considered.
[Action 2]: Follow-up Question[What is an effect of "aspire"?]
[Answer 2]: The result or outcome of "aspire" is to attain or achieve the desired goal.
[Thought 3]: "aspire" can imply "attain" by the same relationship as "throw:fly".
[Action 3]: Finish[]
[Answer 3]: attain.
[More Demonstration Questions] [...]
[Input Question]: listen:hear::drop:?

Figure 8: Full version example of the capability-specific instruction.

Instruction: Solve a question-answering task judging which one of the minimal pairs is acceptable and grammatical. The minimal pairs consist of two sentences that differ by a few words, one of them is grammatical, but another is ungrammatical.
Please solve the task by interleaving Thought, Action, and Answer steps. Thought can reason about the current situation, and Action can be the following two types:
(1) Follow-up Question[question], which returns a sub-question with a single answer that helps solve the original question.
(2) Finish[], which means no more sub-questions. The final answer should be generated in the following line.
[Demonstration Question]: Which sentence of the following two sentences is grammatical?
FirstSentence[No author that no senators liked has had any success.]
SecondSentence[The author that no senators liked has had any success.]
[Thought 1]: Both of the two sentences use the word "any". in their most common uses, they can only be used in an appropriate syntactic-semantic-environment.
[Action 1]: Follow-up Question[In what syntactic-semantic-environment can the word "any" be used?]
[Answer 1]: To a first approximation, they can be only in the scope of negation.
[Thought 2]: If a sentence does not contain a negation structure to match the word "any", it will be ungrammatical.
[Action 2]: Follow-up Question[Which sentence does not contain a negation structure?]
[Answer 2]: SecondSentence. Although it contains a negation structure of "no senators" in the subordinate clause, it does not contain a negation structure in the main clause to match the word "any" in the main clause.
[Thought 3]: The SecondSentence of minimal pairs lacks a negation structure, so it is ungrammatical.
[Action 3]: Finish[]
[Answer 3]: FirstSentence is grammatical and SecondSentnce is ungrammatical.
[More Demonstration Questions] [...]
[Input Question]:

Figure 9: Full version example of the capability-specific instruction.