A Survey on Evaluation of Large Language Models

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Abstract—Large language models (LLMs) are gaining increasing popularity in both academia and industry, owing to their unprecedented performance in various applications. As LLMs continue to play a vital role in both research and daily use, their evaluation becomes increasingly critical, not only at the task level, but also at the society level for better understanding of their potential risks. Over the past years, significant efforts have been made to examine LLMs from various perspectives. This paper presents a comprehensive review of these evaluation methods for LLMs, focusing on three key dimensions: what to evaluate, where to evaluate, and how to evaluate. Firstly, we provide an overview from the perspective of evaluation tasks, encompassing general natural language processing tasks, reasoning, medical usage, ethics, educations, natural and social sciences, agent applications, and other areas. Secondly, we answer the 'where' and 'how' questions by diving into the evaluation methods and benchmarks, which serve as crucial components in assessing performance of LLMs. Then, we summarize the success and failure cases of LLMs in different tasks. Finally, we shed light on several future challenges that lie ahead in LLMs evaluation. Our aim is to offer invaluable insights to researchers in the realm of LLMs evaluation, thereby aiding the development of more proficient LLMs. Our key point is that evaluation should be treated as an essential discipline to better assist the development of LLMs. We consistently maintain the related open-source materials at: https://github.com/MLGroupJLU/LLM-eval-survey.

Index Terms—Large language models, eval	ation, model assessment, benchmark
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1 Introduction

UNDERSTANDING the essence of intelligence and establishing whether a machine embodies it poses a compelling question for scientists. It is generally agreed upon that authentic intelligence equips us with reasoning capabilities, enables us to test hypotheses, and prepare for future eventualities (Khalfa, 1994). In particular, Artificial Intelligence (AI) researchers focus on the development of machine-based intelligence, as opposed to biologically based intellect (McCarthy, 2007). Proper measurement helps to understand intelligence. For instance, measures for general intelligence in human individuals often encompass IQ tests (Brody, 1999).

Within the scope of AI, the Turing Test (Turing, 2009), a widely recognized test for assessing intelligence by discerning if responses are of human or machine origin, has been a longstanding objective in AI evolution. It is generally

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believed among researchers that a computing machine that successfully passes the Turing Test can be regarded as intelligent. Consequently, when viewed from a wider lens, the chronicle of AI can be depicted as the timeline of creation and evaluation of intelligent models and algorithms. With each emergence of a novel AI model or algorithm, researchers invariably scrutinize its capabilities in real-world scenarios through evaluation using specific and challenging tasks. For instance, the Perceptron algorithm (Gallant et al., 1990), touted as an Artificial General Intelligence (AGI) approach in the 1950s, was later revealed as inadequate due to its inability to resolve the XOR problem. The subsequent rise and application of Support Vector Machines (SVMs) (Cortes and Vapnik, 1995) and deep learning (LeCun et al., 2015) have marked both progress and setbacks in the AI landscape. A significant takeaway from previous attempts is the paramount importance of AI evaluation, which serves as a critical tool to identify current system limitations and inform the design of more powerful models.

Recently, large language models (LLMs) has incited substantial interest across both academic and industrial domains (Bommasani et al., 2021; Wei et al., 2022a; Zhao et al., 2023a). As demonstrated by existing work (Bubeck et al., 2023), the great performance of LLMs has raised promise that they could be AGI in this era. LLMs posses the capabilities to solve diverse tasks, contrasting with prior models confined to solving specific tasks. Due to its great performance in handling different applications such as general natural language tasks and domain-specific ones, LLMs are increasingly used by individuals with critical information needs, such as students or patients.

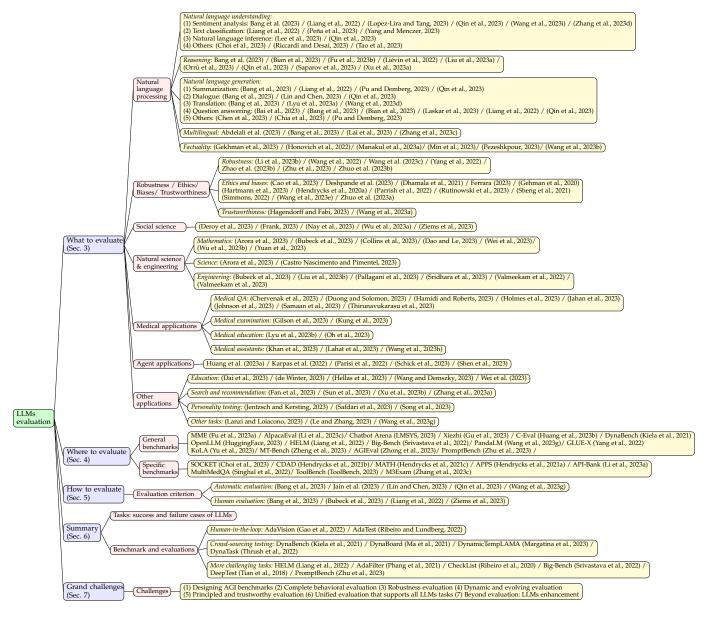


Fig. 1. Structure of this paper.

Evaluation is of paramount prominence to the success of LLMs due to several reasons. First, evaluating LLMs helps us better understand the strengths and weakness of LLMs. For instance, the PromptBench (Zhu et al., 2023) benchmark illustrates that current LLMs are sensitive to adversarial prompts, thus a careful prompt engineering is necessary for better performance. Second, better evaluations can provide a better guidance for human-LLMs interaction, which could inspire future interaction design and implementation. Third, the broad applicability of LLMs underscores the paramount importance of ensuring their safety and reliability, particularly in safety-sensitive sectors such as financial institutions and healthcare facilities. Finally, as LLMs are becoming larger with more emergent abilities, existing evaluation protocols may not be enough to evaluate their capabilities and potential risks. Therefore, we aim to call awareness of the community of the importance to LLMs evaluations by reviewing the current evaluation protocols

and most importantly, shed light on future research about designing new LLMs evaluation protocols.

With the introduction of ChatGPT (OpenAI, 2023a) and GPT-4 (OpenAI, 2023b), there have been a number of research efforts aiming at evaluating ChatGPT and other LLMs from different aspects (Fig. 2), encompassing a range of factors such as natural language tasks, reasoning, robustness, trustworthiness, medical applications, and ethical considerations. Despite these efforts, a comprehensive overview capturing the entire gamut of evaluations is still lacking. Furthermore, the ongoing evolution of LLMs has also presents novel aspects for evaluation, thereby challenging existing evaluation protocols and reinforcing the need for thorough, multifaceted evaluation techniques. While existing research such as (Bubeck et al., 2023) claimed that GPT-4 can be seen as sparks of AGI, others contest this claim due to the human-crafted nature of its evaluation approach.

This paper serves as the first comprehensive survey on

evaluation of large language models. As depicted in Fig. 1, we explore existing work in three dimensions: 1) What to evaluate, 2) Where to evaluate, and 3) How to evaluate. Specifically, "what to evaluate" encapsulates existing evaluation tasks for LLMs, "where to evaluate" involves selecting appropriate datasets and benchmarks for evaluation, while "how to evaluate" is concerned with the evaluation process given appropriate tasks and datasets. These three dimensions are integral to the evaluation of LLMs. We subsequently discuss potential future challenges in the realm of LLMs evaluation.

The contributions of this paper are as follows:

- We provide a comprehensive overview of LLMs evaluations from three aspects: what to evaluate, where to evaluate, and how to evaluate. Our categorization is general and encompasses the entire life cycle of LLMs evaluation.
- Regarding what to evaluate, we summarize existing tasks in various areas and obtain insightful conclusions on the success and failure case of LLMs (Sec. 6), providing experience for future research.
- 3) As for where to evaluate, we summarize evaluation metrics, datasets, and benchmarks to provide a profound understanding of current LLMs evaluations. In terms of how to evaluate, we explore current protocols and summarize novel evaluation approaches.
- 4) We further discuss future challenges in evaluating LLMs. We open-source and maintain the related materials of LLMs evaluation at https://github.com/ MLGroupJLU/LLM-eval-survey to foster a collaborative community for better evaluations.

The paper is organized as follows. In Sec. 2, we provide the basic information of LLMs and AI model evaluation. Then, Sec. 3 reviews existing work from the aspects of "what to evaluate". After that, Sec. 4 is the "where to evaluate" part, which summarizes existing datasets and benchmarks. Sec. 5 discusses how to perform the evaluation. In Sec. 6, we summarize the key findings of this paper. We discuss grand future challenges in Sec. 7 and Sec. 8 concludes the paper.

2 BACKGROUND

2.1 Large Language Models

Language models (LMs) (Devlin et al., 2018; Gao and Lin, 2004; Kombrink et al., 2011) are computational models that have the capability to understand and generate human language. LMs have the transformative ability to predict the likelihood of word sequences or generate new text based on a given input. N-gram models (Brown et al., 1992), the most common type of LM, estimate word probabilities based on the preceding context. However, LMs also face challenges, such as the issue of rare or unseen words, the problem of overfitting, and the difficulty in capturing complex linguistic phenomena. Researchers are continuously working on improving LM architectures and training methods to address these challenges.

Large Language Models (LLMs) (Chen et al., 2021; Kasneci et al., 2023; Zhao et al., 2023a) are advanced language models with massive parameter sizes and exceptional learning capabilities. The core module behind many LLMs such

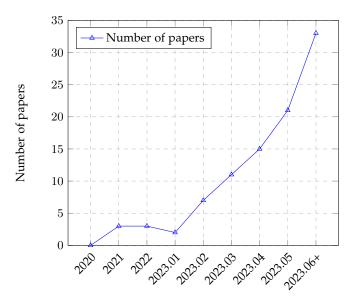


Fig. 2. Trend of LLMs evaluation papers over time (2020 - Jun. 2023, including Jul. 2023.).

as GPT-3 (Floridi and Chiriatti, 2020), InstructGPT (Ouyang et al., 2022), and GPT-4 (OpenAI, 2023b) is the self-attention module in Transformer (Vaswani et al., 2017) that serves as the fundamental building block for language modeling tasks. Transformers have revolutionized the field of NLP with their ability to handle sequential data efficiently, allowing for parallelization and capturing long-range dependencies in text. One key feature of LLMs is in-context learning (Brown et al., 2020), where the model is trained to generate text based on a given context or prompt. This enables LLMs to generate more coherent and contextually relevant responses, making them suitable for interactive and conversational applications. Reinforcement Learning from Human Feedback (RLHF) (Christiano et al., 2017; Ziegler et al., 2019) is another crucial aspect of LLMs. This technique involves fine-tuning the model using human-generated responses as rewards, allowing the model to learn from its mistakes and improve its performance over time.

In an autoregressive language model, such as GPT-3 (Floridi and Chiriatti, 2020) and PaLM (Chowdhery et al., 2022), given a context sequence X, the LM tasks aim to predict the next token y. The model is trained by maximizing the probability of the given token sequence conditioned on the context, i.e., $P(y|X) = P(y|x_1, x_2, ..., x_{t-1})$, where $x_1, x_2, ..., x_{t-1}$ are the tokens in the context sequence, and t is the current position. By using the chain rule, the conditional probability can be decomposed into a product of probabilities at each position:

$$P(y|X) = \prod_{t=1}^{T} P(y_t|x_1, x_2, ..., x_{t-1}),$$

where T is sequence length. In this way, the model predicts each token at each position in an autoregressive manner, generating a complete text sequence.

One common approach to interacting with LLMs is prompt engineering (Clavié et al., 2023; White et al., 2023; Zhou et al., 2022), where users design and provide specific

TABLE 1
Comparison of traditional ML, deep learning, and LLMs

Comparison	Traditional ML	DL	LLMs
Training Data Size Feature Engineering	Large Manual	Large Automatic	Very large Automatic
Model Complexity	Limited	Complex	Very Complex
Interpretability	Good	Poor	Poorer
Performance Hardware Requirements	Moderate Low	High High	Highest Very High

prompt texts to guide LLMs in generating desired responses or completing specific tasks. This is widely adopted in existing evaluation efforts. People can also engage in questionand-answer interactions (Jansson et al., 2021), where they pose questions to the model and receive answers, or engage in dialogue interactions, having natural language conversations with LLMs. In conclusion, LLMs, with their Transformer architecture, in-context learning, and RLHF capabilities, have revolutionized NLP and hold promise in various applications. TABLE 1 provides a brief comparison of traditional ML, deep learning, and LLMs.

2.2 Al Model Evaluation

AI model evaluation is an essential step in assessing the performance of a model. There are some standard model evaluation protocols, including K-fold cross-validation, Holdout validation, Leave One Out cross-validation (LOOCV), Bootstrap, and Reduced Set (Berrar, 2019; Kohavi et al., 1995). For instance, k-fold cross-validation divides the dataset into k parts, with one part used as a test set and the rest as training sets, which can reduce training data loss and obtain relatively more accurate model performance evaluation (Fushiki, 2011); Holdout validation divides the dataset into training and test sets, with a smaller calculation amount but potentially more significant bias; LOOCV is a unique K-fold cross-validation method where only one data point is used as the test set (Wong, 2015); Reduced Set trains the model with one dataset and tests it with the remaining data, which is computationally simple, but the applicability is limited. The appropriate evaluation method should be chosen according to the specific problem and data characteristics for more reliable performance indicators.

Fig. 3 illustrates the evaluation process of AI models, including LLMs. Some evaluation protocols may not be feasible to evaluate deep learning models due to the extensive training size. Thus, evaluation on a static validation set has long been the standard choice for deep learning models. For instance, computer vision models leverage static test sets such as ImageNet (Deng et al., 2009) and MS COCO (Lin et al., 2014) for evaluation. LLMs also use GLUE (Wang et al., 2018) or SuperGLUE (Wang et al., 2019) as the common test sets.

As LLMs are becoming more popular with even poorer interpretability, existing evaluation protocols may not be enough to evaluate the true capabilities of LLMs thoroughly. We will introduce recent evaluations of LLMs in Sec. 5.

3 What to Evaluate

What tasks should we evaluate LLMs to show their performance? On what tasks can we claim the strength and weak-



Fig. 3. The evaluation process of Al models.

ness of LLMs? In this section, we divide existing tasks into the following categories: natural language processing tasks, ethics and biases, medical applications, social sciences, natural science and engineering tasks, agent applications (using LLMs as agents), and others.¹

3.1 Natural Language Processing Tasks

The initial objective behind the development of language models, particularly large language models, was to enhance performance on natural language processing tasks, encompassing both understanding and generation. Consequently, the majority of evaluation research has been primarily focused on natural language tasks. TABLE 2 summarizes the evaluation aspects of existing research, and we mainly highlight their conclusions in the following.²

3.1.1 Natural language understanding

Natural language understanding represents a wide spectrum of tasks that aims to obtain a better understanding of the input sequence. We summarize recent efforts in LLMs evaluation from several aspects.

Sentiment analysis is a task that analyzes and interprets the text to determine the emotional inclination. It is typically a binary (positive and negative) or triple (positive, neutral, and negative) class classification problem. Evaluating sentiment analysis tasks is a popular direction. Liang et al. (2022); Zeng et al. (2022) showed that model performance was often high. ChatGPT's sentiment analysis prediction performance is superior to traditional sentiment analysis methods (Lopez-Lira and Tang, 2023) and comes close to that of GPT-3.5 (Qin et al., 2023). In fine-grained sentiment and emotion cause analysis, ChatGPT also exhibits exceptional performance (Wang et al., 2023i). In low-resource learning environments, LLMs exhibit significant advantages over small language models (Zhang et al., 2023d), but the ability of ChatGPT to understand low-resource languages is limited (Bang et al., 2023). In conclusion, LLMs have demonstrated commendable performance in sentiment analysis tasks. Future work should focus on enhancing their capability to understand emotions in under-resourced languages.

Text classification and sentiment analysis are related fields, text classification not only focuses on sentiment, but also includes the processing of all texts and tasks. Liang et al. (2022) showed that GLM-130B was the best-performed model, with an overall accuracy of 85.8% for miscellaneous text classification. Yang and Menczer (2023) found that ChatGPT can produce credibility ratings for a wide range of news outlets, and these ratings have a moderate correlation

- 1. Note that LLMs are evaluated in various tasks and the categorization in this paper is only one possible way for classification of these works. There are certainly other taxonomies.
- 2. Several NLP areas have intersections and thus our categorization of these areas is only one possible way to categorize.

TABLE 2

Summary of evaluation on **natural language processing** tasks: NLU (Natural Language Understanding, including SA (Sentiment Analysis), TC (Text Classification), NLI (Natural Language Inference) and other NLU tasks), Rng. (Reasoning), NLG (Natural Language Generation, including Summ. (Summarization), Dlg. (Dialogue), Tran (Translation), QA (Question Answering) and other NLG tasks), and Mul. (Multilingual tasks) (ordered by the name of the first author).

			NLU		Rng.			NLG			Mul.
Reference	SA	TC	NLI	Others	m.g.	Summ.	Dlg.	Tran.	QA	Others	
(Abdelali et al., 2023)											√
(Bian et al., 2023)					✓				\checkmark		
(Bang et al., 2023)	\checkmark				\checkmark	\checkmark	\checkmark	\checkmark	\checkmark		\checkmark
(Bai et al., 2023)									\checkmark		
(Chen et al., 2023)										\checkmark	
(Choi et al., 2023)				\checkmark							
(Chia et al., 2023)										\checkmark	
(Fu et al., 2023b)					\checkmark						
(Gekhman et al., 2023)						\checkmark					
(Honovich et al., 2022)			\checkmark			\checkmark	\checkmark			\checkmark	
(Lai et al., 2023)											\checkmark
(Laskar et al., 2023)	\checkmark		\checkmark		\checkmark	✓		\checkmark	\checkmark	\checkmark	\checkmark
(Lopez-Lira and Tang, 2023)	\checkmark										
(Liang et al., 2022)	\checkmark	\checkmark				✓			\checkmark		
(Lee et al., 2023)			\checkmark								
(Lin and Chen, 2023)							\checkmark				
(Liévin et al., 2022)					\checkmark						
(Liu et al., 2023a)					\checkmark						
(Lyu et al., 2023a)									\checkmark		
(Manakul et al., 2023a)									\checkmark	\checkmark	
(Min et al., 2023)										\checkmark	
(Orrù et al., 2023)					\checkmark						
(Peña et al., 2023)		\checkmark									
(Pu and Demberg, 2023)						✓				\checkmark	
(Pezeshkpour, 2023)										\checkmark	
(Qin et al., 2023)	\checkmark		\checkmark		\checkmark	✓	✓		\checkmark		
(Riccardi and Desai, 2023)				\checkmark							
(Saparov et al., 2023)					\checkmark						
(Tao et al., 2023)				\checkmark							
(Wang et al., 2023d)								\checkmark			
(Wang et al., 2023i)	\checkmark										
(Wang et al., 2023b)			\checkmark						\checkmark		
(Xu et al., 2023a)					✓						
(Yang and Menczer, 2023)		\checkmark									
(Zhang et al., 2023d)	\checkmark										
(Zhang et al., 2023c)											\checkmark

with those from human experts. Furthermore, ChatGPT achieves acceptable accuracy in a binary classification scenario (AUC=0.89). Peña et al. (2023) discussed the problem of topic classification for public affairs documents and showed that using an LLM backbone in combination with SVM classifiers is a useful strategy to conduct the multi-label topic classification task in the domain of public affairs with accuracies over 85%. Overall, LLMs perform well on text classification and can even handle text classification tasks in unconventional problem settings as well.

Natural language inference (NLI) is the task of determining whether the given "hypothesis" logically follows from the "premise". Qin et al. (2023) showed that ChatGPT outperforms GPT-3.5 for NLI tasks. They also found that ChatGPT excels in handling factual input that could be attributed to its RLHF training process in favoring human feedback. However, Lee et al. (2023) observed LLMs perform poorly in the scope of NLI and further fail in representing human disagreement, which indicates that LLMs still have a large room for improvement in this field.

Semantic understanding refers to the meaning or understanding of language and its associated concepts. It involves the interpretation and comprehension of words, phrases, sentences and the relationships between them. Semantic

processing goes beyond the surface level and focuses on understanding the underlying meaning and intent. Tao et al. (2023) comprehensively evaluated the event semantic processing abilities of LLMs covering understanding, reasoning, and prediction about the event semantics. Results indicated that LLMs possess an understanding of individual events, but their capacity to perceive the semantic similarity among events is constrained. In reasoning tasks, LLMs exhibit robust reasoning abilities in causal and intentional relations, yet their performance in other relation types is comparatively weaker. In prediction tasks, LLMs exhibit enhanced predictive capabilities for future events with increased contextual information. Riccardi and Desai (2023) explored the semantic proficiency of LLMs and showed that these models perform poorly in evaluating basic phrases. Furthermore, GPT-3.5 and Bard cannot distinguish between meaningful and nonsense phrases, consistently classifying highly nonsense phrases as meaningful. GPT-4 shows significant improvements, but its performance is still significantly lower than that of humans. In summary, the performance of LLMs in semantic understanding tasks is poor. In the future, we can start from this aspect and focus on improving its performance on this application.

In the field of social knowledge understanding, Choi

et al. (2023) evaluates how well models perform at learning and recognizing concepts of social knowledge and the results reveal that despite being much smaller in the number of parameters, finetuning supervised models such as BERT lead to much better performance than zero-shot models using state-of-the-art LLMs, such as GPT (Radford et al., 2018), GPT-J-6B (Wang and Komatsuzaki, 2021) and so on. This shows that supervised models significantly outperform zero-shot models and that more parameters do not guarantee more social knowledge in this setting.

3.1.2 Reasoning

From TABLE 2, it can be found that evaluating the reasoning ability of LLMs is a popular direction, and more and more articles focus on exploring its reasoning ability. The reasoning task is a very challenging task for an intelligent AI model. It requires the model not only to understand the given information, but also to reason and infer from the existing context in the absence of direct answers. At present, the evaluation of reasoning tasks can be roughly classified into mathematical reasoning, common sense reasoning, logical reasoning, professional field reasoning, etc.

ChatGPT exhibits a strong capability for arithmetic reasoning by outperforming GPT-3.5 in the majority of tasks (Qin et al., 2023). However, its proficiency in mathematical reasoning still requires improvement (Bang et al., 2023; Frieder et al., 2023; Zhuang et al., 2023). On symbolic reasoning tasks, ChatGPT is mostly worse than GPT-3.5, which may be because ChatGPT is prone to uncertain responses, leading to poor performance (Bang et al., 2023). Through the poor performance of LLMs on task variants of counterfactual conditions, Wu et al. (2023c) showed that the current LLMs had certain limitations in abstract reasoning ability. In logical reasoning, Liu et al. (2023a) indicated that ChatGPT and GPT-4 outperformed traditional fine-tuning methods on most logical reasoning benchmarks, demonstrating their superiority in logical reasoning. However, both models face challenges when handling new and out-of-distribution data. ChatGPT does not perform as well as other LLMs, including GPT-3.5 and BARD (Qin et al., 2023; Xu et al., 2023a). This is because ChatGPT is designed explicitly for chatting, so it does an excellent job of maintaining rationality. FLAN-T5, LLaMA, GPT-3.5, and PaLM perform well in general deductive reasoning tasks (Saparov et al., 2023). GPT-3.5 is not good at keep oriented for reasoning in the inductive setting (Xu et al., 2023a). For multi-step reasoning, Fu et al. (2023b) showed PaLM and Claude2 are the only two model families that achiving similar performance (but still worse than) the GPT model family. Moreover, LLaMA-65B is the most robust open-source LLMs to date, which performs closely to code-davinci-002. Some papers separately evaluate the performance of ChatGPT on some reasoning tasks: ChatGPT generally performs poorly on commonsense reasoning tasks, but relatively better than non-text semantic reasoning (Bang et al., 2023). Meanwhile, ChatGPT also lacks spatial reasoning ability, but exhibits better temporal reasoning. Finally, while the performance of ChatGPT is acceptable on causal and analogical reasoning, it performs poorly on multi-hop reasoning ability, which is similar to the weakness of other LLMs on complex reasoning (Ott et al., 2023). In professional domain reasoning tasks, zeroshot InstructGPT and Codex are capable of complex medical reasoning tasks, but still need to be further improved (Liévin et al., 2022). In terms of language insight issues, (Orrù et al., 2023) demonstrated the potential of ChatGPT for solving verbal insight problems, as ChatGPT's performance was comparable to that of human participants. It should be noted that most of the above conclusions are obtained for specific data sets. Overall, LLMs show great potential in reasoning and show a continuous improvement trend, but still face many challenges and limitations, requiring more in-depth research and optimization.

3.1.3 Natural language generation

Natural language generation (NLG) evaluates the capabilities of LLMs in generating specific texts, which consists of several tasks, including summarization, dialogue generation, machine translation, question answering, and other open-ended generation applications.

Summarization is a generation task that aims to learn a concise abstract for the given sentence. In this line of evaluation, Liang et al. (2022) showed that TNLG v2 (530B) (Smith et al., 2022) had the highest score for both scenarios, and OPT (175B) (Zhang et al., 2022) ranked second. It is disappointing that ChatGPT sometimes generates a longer summary than the input document (Bang et al., 2023). The fine-tuned Bart (Lewis et al., 2019) is still better than zero-shot ChatGPT. Specifically, ChatGPT has similar zeroshot performance to text-davinci-002 (Bang et al., 2023), but performs worse than GPT-3.5 (Qin et al., 2023). In controllable text summarization, Pu and Demberg (2023) showed that ChatGPT summaries are slightly more extractive (i.e., containing more content copied directly from the source) compared to human summaries. The above shows that LLMs, especially ChatGPT, have a general performance in summarizing tasks, but the summary and generalization ability still needs to be improved.

Evaluating the performance of LLMs on dialogue tasks is crucial to the development of dialogue systems and improving the human-computer interaction. Through such evaluation, the natural language processing ability, context understanding ability and generation ability of the model can be improved, so as to realize a more intelligent and more natural dialogue system. Both Claude and ChatGPT generally achieve better performance across all dimensions when compared to GPT-3.5 (Lin and Chen, 2023; Qin et al., 2023). When comparing the Claude and ChatGPT models, both models demonstrate competitive performance across different evaluation dimensions, with Claude slightly outperforming ChatGPT in specific configurations. Bang et al. (2023) test ChatGPT's for response generation in various dialogue settings: 1) Knowledge-Grounded Open-Domain Dialogue and 2) Task-Oriented Dialogue. The automatic evaluation results showed that the performance of ChatGPT is relatively low compared to GPT2 fine-tuned on the dataset for knowledge-grounded open-domain dialogue. In taskoriented dialogue, the performance of ChatGPT is acceptable, but it is prone to errors when the following problems occur: long-term multi-turn dependency, fundamental reasoning failure, and extrinsic hallucination.

While LLMs are not trained explicitly for translation tasks, it can indeed show strong performance. Wang et al.

(2023d) showed that ChatGPT and GPT-4 demonstrated superior performance compared to commercial machine translation (MT) systems in terms of human evaluation and outperformed most document-level NMT methods in terms of sacreBLEU. When comparing ChatGPT to traditional translation models during contrastive testing, it exhibits lower accuracy. On the other hand, GPT-4 showcases a robust capability in explaining discourse knowledge, despite the possibility of selecting incorrect translation candidates. The results in (Bang et al., 2023) suggested that ChatGPT could perform $X \to Eng$ translation well, but it still lacked the ability to perform Eng \rightarrow X translation. (Lyu et al., 2023a) explored several research directions in machine translation using LLMs. This work contributes to the advancement of MT research and underscores the potential of LLMs in enhancing translation capabilities. In summary, while LLMs perform satisfactorily in several translation tasks, there is still room for improvement, e.g., enhancing the translation capability from English to non-English languages.

Question answering is one of the key technologies in the field of human-computer interaction, and it has been widely used in application scenarios such as search engines, intelligent customer service, and intelligent question answering. Measuring the accuracy and efficiency of QA models will have important implications for these applications. Liang et al. (2022) showed that InstructGPT davinci v2 (175B) performed best in terms of accuracy, robustness, and fairness for the 9 question answering scenarios, among all the evaluated models. GPT-3.5 and ChatGPT achieve significant improvements over GPT-3 on the task of answering general knowledge questions. ChatGPT outperforms GPT-3.5 by over 2% in most domains (Bian et al., 2023; Qin et al., 2023). However, ChatGPT falls slightly behind GPT-3.5 on CommonsenseQA and Social IQA. This is because ChatGPT is likely to be cautious, refusing to give an answer when there is not enough information. Fine-tuned models, including Vicuna and ChatGPT, demonstrate near-perfect performance in terms of their scores, far outperforming models without supervised fine-tuning (Bai et al., 2023; Bang et al., 2023). Laskar et al. (2023) evaluated the effectiveness of ChatGPT on a range of academic datasets, including various tasks such as answering questions, summarizing text, generating code, reasoning with common sense, solving math problems, translating languages, detecting bias, and addressing ethical issues. Overall, LLMs performed flawlessly on QA tasks, and can further improve performance on social, event, and temporal commonsense knowledge in the future.

There are also other generation tasks. In the field of sentence style transfer, Pu and Demberg (2023) showed that ChatGPT outperformed the previous supervised SOTA model by training on the same subset for few-shot learning, as evident from the higher BLEU score. In terms of controlling the formality of sentence style, ChatGPT's performance still exhibits significant differences compared to human behavior. In writing tasks, Chia et al. (2023) found that LLMs perform consistently across writing-based tasks including informative, professional, argumentative, and creative writing categories, showing that their writing capabilities are general. In text generation quality, Chen et al. (2023) showed that ChatGPT was able to effectively evaluate text quality from various perspectives in the absence of reference texts

and outperformed most existing automated metrics. Using ChatGPT to generate numerical scores for text quality was considered the most reliable and effective method among various testing methods.

3.1.4 Multilingual tasks

Many LLMs are trained on mixed-language training data. While English is the predominant language, the combination of multilingual data indeed helps LLMs gain the ability to process inputs and generate responses in different languages, making them widely adopted and accepted across the globe. However, given the relatively recent emergence of this technology, LLMs are primarily evaluated on English data, while evaluating their multilingual performance is an important aspect that cannot be ignored. Several articles have provided comprehensive, open, and independent evaluations of LLMs performance on various NLP tasks in different non-English languages, offering appropriate perspectives for future research and applications.

Abdelali et al. (2023) evaluated the performance of Chat-GPT in standard Arabic NLP tasks and found that ChatGPT had lower performance compared to SOTA in the zero-shot setting for most tasks. Bang et al. (2023); Lai et al. (2023); Zhang et al. (2023c) used more languages on more datasets, covered more tasks, and conducted a more comprehensive evaluation of LLMs. The results showed LLMs (including BLOOM, Vicuna, Claude, ChatGPT, and GPT-4) performed worse for non-Latin languages as well as low-resource languages. Despite the languages being resource-rich, Bang et al. (2023) highlighted that ChatGPT faced a limitation in translating sentences written in non-Latin script languages. The aforementioned demonstrates that there are numerous challenges and ample opportunities for enhancement in multilingual tasks for LLMs. Future research should pay attention to multilingual balance, and strive to solve the problem of non-Latin languages and low-resource languages to better support users around the world. At the same time, attention should be paid to the impartiality and neutrality of the language to avoid the impact of the model's English bias or other biases on multilingual applications.

3.1.5 Factuality

Factuality in the context of LLMs refers to the extent to which the information or answers provided by the model align with real-world truths and verifiable facts. Factuality in LLMs significantly impacts a variety of tasks and downstream applications, such as question answering systems, information extraction, text summarization, dialogue systems, and automated fact-checking, where incorrect or inconsistent information could lead to substantial misunderstandings and misinterpretations. Evaluating factuality is of great importance in order to trust and efficiently use these models. This includes the ability of these models to maintain consistency with known facts, avoid generating misleading or false information (known as "factual hallucination"), and effectively learn and recall factual knowledge. A range of methodologies have been proposed to measure and improve the factuality of LLMs.

Wang et al. (2023b) evaluate the internal knowledge of large models, specifically InstructGPT (Ouyang et al., 2022), ChatGPT-3.5, GPT-4, and BingChat (Microsoft, 2023), by

having them directly answer Open Questions based on the Natural Questions (Kwiatkowski et al., 2019) and TriviaQA (Joshi et al., 2017) datasets. The evaluation is conducted through human assessment. The paper finds that while GPT-4 and BingChat can correctly answer over 80% of the questions, there is still a gap of more than 15% to achieve complete accuracy. Honovich et al. (2022) review existing factual consistency evaluation methods, pointing out the lack of a unified comparison and the limited reference value of related scores compared to binary labels. They transform existing fact consistency related tasks into binary labels, taking into account only if there's factual conflict with the input text, not considering external knowledge. The paper finds that fact evaluation methods based on Natural Language Inference (NLI) and Question Generation-Question Answering (QG-QA) perform best and can complement each other. Pezeshkpour (2023) propose a new metric based on information theory to measure whether a certain knowledge is included in LLMs. It uses uncertainty in knowledge to measure factualness, calculated by LLMs filling in prompts and examining the probability distribution of the answer. Two methods to inject knowledge are discussed: explicitly by including the knowledge in the prompt, and implicitly by fine-tuning the LLMs on the knowledge piece. The paper shows that this approach outperforms the traditional ranking methods metrics by over 30% in accuracy. Gekhman et al. (2023) improve the fact consistency evaluation method for summarization tasks. It proposes training student NLI models on summaries generated by multiple models and annotated by LLMs for fact consistency. This trained student model is then used for summarization fact consistency evaluation. Manakul et al. (2023a) operate on two hypotheses about how LLMs create factual or hallucinated responses. It proposes using three formulas (BERTScore (Zhang et al., 2019), MQAG (Manakul et al., 2023b), n-gram) to evaluate factuality, utilizing alternative LLMs to gather token probabilities for black-box language models. The study finds that merely computing sentence likelihood or entropy helps validate the factuality of responses. Min et al. (2023) break text generated by LLMs down into individual 'atomic' facts, which are then evaluated for their correctness. The FActScore is used to measure the performance of estimators through the calculation of F1 scores. The paper tests various estimators and reveals that current estimators are still some way off from effectively addressing the task. Lin et al. (2021) introduces the TruthfulQA dataset, designed to cause models to make mistakes. Several language models are tested in providing factual answers. The findings suggest that simply scaling up model sizes might not improve its truthfulness, and recommendations are provided for the training approach. This dataset is widely used in evaluating the factuality of LLMs (Kadavath et al., 2022; OpenAI, 2023b; Touvron et al., 2023; Wei et al., 2022b).

3.2 Robustness, Ethic, Bias, and Trustworthiness

The evaluation of LLMs encompasses the crucial aspects of robustness, ethics, biases, and trustworthiness. These factors have gained increasing importance in assessing the performance of LLMs comprehensively.

TABLE 3
Summary of LLMs evaluation on **robustness**, **ethics**, **biases**, **and trustworthiness** (ordered by the name of the first author).

Reference	Robustness	Ethics and Biases	Trustworthiness
(Cao et al., 2023)		✓	
(Dhamala et al., 2021)		✓	
(Deshpande et al., 2023)		✓	
(Ferrara, 2023)		✓	
(Gehman et al., 2020)		✓	
(Hartmann et al., 2023)		✓	
(Hendrycks et al., 2020a)		✓	
(Hagendorff and Fabi, 2023)			✓
(Li et al., 2023b)	✓		
(Parrish et al., 2022)		✓	
(Rutinowski et al., 2023)		✓	
(Sheng et al., 2021)		✓	
(Simmons, 2022)		✓	
(Wang et al., 2022)	✓		
Wang et al. (2023c)	✓		
(Wang et al., 2023a)	✓	✓	✓
(Wang et al., 2023e)		✓	
(Yang et al., 2022)	✓		
(Zhao et al., 2023b)	✓		
(Zhuo et al., 2023b)	✓		
(Zhu et al., 2023)	✓		
(Zhuo et al., 2023a)		✓	

3.2.1 Robustness

Robustness studies the stability of a system when facing unexpected inputs. Specifically, out-of-distribution (OOD) (Wang et al., 2022) and adversarial robustness are two popular research topics for robustness. Wang et al. (2023c) is an early work that evaluated ChatGPT and other LLMs from both the adversarial and OOD perspectives using existing benchmarks such as AdvGLUE (Wang et al., 2021), ANLI (Nie et al., 2019), and DDXPlus (Fansi Tchango et al., 2022) datasets. Zhuo et al. (2023b) evaluated the robustness of semantic parsing. Yang et al. (2022) evaluated OOD robustness by extending the GLUE (Wang et al., 2018) dataset. The results of this study emphasize the potential risks to the overall system security when manipulating visual input. For vision-language models, Zhao et al. (2023b) evaluated LLMs on visual input and transferred them to other visual-linguistic models, revealing the vulnerability of visual input. Li et al. (2023b) provides an overview of OOD evaluation for language models: adversarial robustness, domain generalization, and dataset biases. The authors compare and unify the three research lines, summarize the data-generating processes and evaluation protocols for each line, and highlight the challenges and opportunities for future work.

For adversarial robustness, Zhu et al. (2023) evaluated the robustness of LLMs to prompts by proposing a unified benchmark called PromptBench. They comprehensively evaluated adversarial text attacks at multiple levels (character, word, sentence, and semantics). The results showed that contemporary LLMs are vulnerable to adversarial prompts, highlighting the importance of the models' robustness when facing adversarial inputs. As for new adversarial datasets, Wang et al. (2023a) introduced the use of the AdvGLUE++ benchmark data for assessing adversarial robustness and implemented a new evaluation protocol to scrutinize machine ethics via jailbreaking system prompts.

3.2.2 Ethic and bias

LLMs have been found to internalize, spread, and potentially magnify harmful information existing in the crawled

training corpora, usually, toxic languages, like offensiveness, hate speech, and insults (Gehman et al., 2020), as well as social biases like stereotypes towards people with a particular demographic identity (e.g., gender, race, religion, occupation and ideology) (Sheng et al., 2021). More recently, Zhuo et al. (2023a) uses conventional testing sets and metrics (Dhamala et al., 2021; Gehman et al., 2020; Parrish et al., 2022) to perform a systematic evaluation of ChatGPT's toxicity and social bias, finding that it still exhibits noxious content to some extend. Taking a further step, Deshpande et al. (2023) introduced role-playing into the model and observed an increase in generated toxicity up to 6x. Furthermore, such role-playing also caused biased toxicity towards specific entities. Different from simply measuring social biases, Ferrara (2023) investigated the sources, underlying mechanisms and corresponding ethical consequences of these biases potentially produced by ChatGPT. Beyond social biases, LLMs have also been assessed by political tendency and personality traits (Hartmann et al., 2023; Rutinowski et al., 2023) based questionnaires like Political Compass Test and MBTI test, demonstrating a propensity for progressive views and an ENFJ personality type. In addition, LLMs like GPT-3 were found to have moral biases (Simmons, 2022) in terms of the Moral Foundation theory (Graham et al., 2013); The study conducted by (Hendrycks et al., 2020a) reveals that existing LMs have potential in ethical judgment, but still need improvement. Moreover, in the assessment of GPT-4 alignment, (Wang et al., 2023e) discovered a systematic bias. ChatGPT was also observed to exhibit somewhat bias on cultural values (Cao et al., 2023). Wang et al. (2023a) also incorporated an evaluation dataset specifically aimed at gauging stereotype bias, using both targeted and untargeted system prompts. All these ethical issues might elicit serious risks, impeding the deployment of LLMs and having a profound negative impact on society.

3.2.3 Trustworthiness

Some work focuses on other trustworthiness problems in addition to robustness and ethics.³ In their 2023 study, DecodingTrust, Wang et al. (2023a) offered a multifaceted exploration of trustworthiness vulnerabilities in the GPT models, especially GPT-3.5 and GPT-4. Their evaluation expanded beyond the typical trustworthiness concerns to include eight critical aspects: toxicity, stereotype bias, adversarial and out-of-distribution robustness, robustness to adversarial demonstrations, privacy, machine ethics, and fairness. DecodingTrust's investigation employs an array of newly constructed scenarios, tasks, and metrics. They revealed that while GPT-4 often showcases improved trustworthiness over GPT-3.5 in standard evaluations, it is simultaneously more susceptible to attacks.

In another study by Hagendorff and Fabi (2023), LLMs with enhanced cognitive abilities were evaluated. They found that these models can avoid common human intuitions and cognitive errors, demonstrating super-rational performance. By utilizing cognitive reflection tests and semantic illusion experiments, the researchers gained insights into the psychological aspects of LLMs. This method offers

3. The term 'trustworthiness' in this section refers to other work that contains more than robustness and ethics.

new perspectives for evaluating model biases and ethical issues that may not have been previously identified.

3.3 Social Science

Social science involves the study of human society and individual behavior, including economics, sociology, political science, law, and other disciplines. Evaluating the performance of LLMs in social science is important for academic research, policy formulation, and social problem-solving. Such evaluations can help improve the applicability and quality of models in the social sciences, increasing understanding of human societies and promoting social progress.

Wu et al. (2023a) evaluated the potential use of LLMs in addressing scaling and measurement issues in social science and found that LLMs could generate meaningful responses regarding political ideology and significantly improve text-as-data methods in social science.

In computational social science (CSS) tasks, Ziems et al. (2023) presented a comprehensive evaluation of LLMs on several CSS tasks. During classification tasks, LLMs exhibit the lowest absolute performance on event argument extraction, character tropes, implicit hate, and empathy classification, achieving accuracy below 40%. These tasks either involve complex structures (event arguments) or subjective expert taxonomies with semantics that differ from those learned during LLM pretraining. Conversely, LLMs achieve the best performance on misinformation, stance, and emotion classification. When it comes to generation tasks, LLMs often produce explanations that surpass the quality of gold references provided by crowdworkers. In summary, while LLMs can greatly enhance the traditional CSS research pipeline, they cannot completely replace it.

Some articles also evaluate LLMs on legal tasks. The zero-shot performance of LLMs is mediocre in legal case judgment summarization. LLMs have several problems, including incomplete sentences and words, meaningless sentences merge, and more serious errors such as inconsistent and hallucinated information (Deroy et al., 2023). The results show that further improvement is necessary for LLMs to be useful for case judgment summarization by legal experts. Nay et al. (2023) indicated that LLMs, particularly when combined with prompting enhancements and the correct legal texts, could perform better but not yet at expert tax lawyer levels.

Lastly, within the realm of psychology, (Frank, 2023) adopts an interdisciplinary approach and draws insights from developmental psychology and comparative psychology to explore alternative methods for evaluating the capabilities of large language models (LLMs). By integrating different perspectives, researchers can deepen their understanding of the essence of cognition and effectively leverage the potential of advanced technologies such as large language models, while mitigating potential risks.

In summary, although these models have shown excellent performance in various tasks, the existing models are primarily designed for single-task systems and lack sufficient expressive and interactive capabilities, which creates a gap between their capabilities and the practical clinical requirements. While these models bring hope for interactive medical systems, they still face challenges such as generat-

TABLE 4
Summary of evaluations on **natural science and engineering tasks**based on three aspects: Mathematics, Science and Engineering
(ordered by the name of the first author).

Reference	Mathematics	Science	Engineering
(Arora et al., 2023)	✓	✓	
(Bubeck et al., 2023)	✓		✓
(Castro Nascimento and Pimentel, 2023)		✓	
(Collins et al., 2023)	✓		
(Dao and Le, 2023)	✓		
(Liu et al., 2023b)			✓
(Pallagani et al., 2023)			✓
(Sridhara et al., 2023)			✓
(Valmeekam et al., 2022)			✓
(Valmeekam et al., 2023)			✓
(Wei et al., 2023)	✓		
(Wu et al., 2023b)	✓		
(Yuan et al., 2023)	✓		

ing erroneous outputs and illusions, making them currently unsuitable for direct application in real-world scenarios.

3.4 Natural Science and Engineering

Evaluating the performance of LLMs in natural science and engineering fields can help guide applications and development in scientific research, technology development, and engineering studies.

3.4.1 Mathematics

For fundamental mathematical problems, most large language models (LLMs) demonstrate proficiency in addition and subtraction, and possess some capability in multiplication. However, they face challenges when it comes to division, exponentiation, trigonometry functions, and logarithm functions. On the other hand, LLMs exhibit competence in handling decimal numbers, negative numbers, and irrational numbers (Yuan et al., 2023). In terms of performance, GPT-4 and ChatGPT outperform other models significantly, showcasing their superiority in solving mathematical tasks (Wei et al., 2023). These two models have a distinct advantage in dealing with large numbers (greater than 1e12) and complex, lengthy mathematical queries. GPT-4 outperforms ChatGPT by achieving a significant increase in accuracy of 10 percentage points and a reduction in relative error by 50%, due to its superior division and trigonometry abilities, proper understanding of irrational numbers, and consistent step-by-step calculation of long expressions. When confronted with complex and challenging mathematical problems, LLMs exhibit subpar performance. Specifically, GPT-3 demonstrates nearly random performance, while GPT-3.5 shows improvement, and GPT-4 performs the best (Arora et al., 2023). Despite the advancements made in the new models, it is important to note that the peak performance remains relatively low compared to that of experts and these models lack the capability to engage in mathematical research (Bubeck et al., 2023). The specific tasks of algebraic manipulation and calculation continue to pose challenges for GPTs (Bubeck et al., 2023; Collins et al., 2023). The primary reasons behind GPT-4's low performance in these tasks are errors in algebraic manipulation and difficulties in retrieving pertinent domain-specific concepts.

Wu et al. (2023b) evaluated the use of GPT-4 on difficult high school competition problems and GPT-4 reached 60%

accuracy on half of the categories. Intermediate algebra and precalculus can only be solved with a low accuracy rate of around 20%. ChatGPT is not good at answering questions on topics including derivatives and applications, Oxyz spatial calculus and spatial geometry (Dao and Le, 2023). Dao and Le (2023); Wei et al. (2023) showed that ChatGPT's performance worsens as task difficulty increases: it correctly answered 83% of the questions at the recognition level, 62% at the comprehension level, 27% at the application level, and only 10% at the highest cognitive complexity level. Given those problems at higher knowledge levels tend to be more complex, requiring in-depth understanding and problem-solving skills, such results are to be expected. These results suggest that LLMs' ability is easily affected by the complexity of problems. It has great implications for the design of optimized artificial intelligence systems for handling such challenging tasks.

3.4.2 General science

The application of LLMs in chemistry is still in its infancy. Castro Nascimento and Pimentel (2023) posed five simple tasks in different subareas of chemistry to evaluate ChatGPT's understanding of chemistry, with accuracy ranging from 25% to 100%. (Arora et al., 2023) showed that LLMs perform worse on physics problems than chemistry problems, probably because chemistry problems have lower inference complexity than physics problems in this setting. There are few evaluation studies of LLMs in general science, and the existing evaluation results show that the performance of LLMs in this field still needs to be improved.

3.4.3 Engineering

In the field of engineering, the task from easy to difficult can be arranged as code generation, software engineering, and commonsense planning. In code generation tasks, the smaller LLMs trained for the tasks are competitive in performance, and CODEGEN-16B is comparable in performance to ChatGPT using a larger parameter setting, reaching about a 78% match (Liu et al., 2023b). Despite facing challenges in mastering and comprehending certain fundamental concepts in programming languages, ChatGPT showcases a commendable level of coding level (Zhuang et al., 2023). Specifically, ChatGPT has developed superior skills in dynamic programming, greedy algorithm, and search, surpassing highly capable college students, but it struggle in data structure, tree, and graph theory. GPT-4 exhibits an advanced ability to write code based on provided instructions and comprehend existing code (Bubeck et al., 2023). Additionally, it can effectively reason about code execution, simulate the impact of instructions, articulate outcomes in natural language, and execute pseudocode.

In software engineering tasks, ChatGPT usually performs credibly and the response from it is detailed and often better than the human expert output or the SOTA output. However, in the case of a few other tasks like code vulnerability detection and information retrieval-based test prioritization, the current form of ChatGPT fails to deliver accurate answers, making it unsuitable for such tasks (Sridhara et al., 2023). In commonsense planning tasks, LLMs may not be good, even in simple planning tasks that humans are good at (Valmeekam et al., 2023, 2022). Pallagani

TABLE 5

Summary of evaluations on **medical applications** based on the four aspects: Med. Exam. (Medical Examination), Med. Ass. (Medical Assistants), Med. QA(Medical Questions and Answers) and Med. Edu.(Medical Education) (ordered by the name of the first author).

Reference	Med. Exam	Med. Ass.	Med. QA	Med. Edu.
(Chervenak et al., 2023)			√	
(Duong and Solomon, 2023)			✓	
(Gilson et al., 2023)	✓			
(Holmes et al., 2023)			✓	
(Hamidi and Roberts, 2023)			✓	
(Johnson et al., 2023)			✓	
(Jahan et al., 2023)			✓	
(Kung et al., 2023)	✓			
(Khan et al., 2023)		✓		
(Lahat et al., 2023)		✓		
(Lyu et al., 2023b)				✓
(Oh et al., 2023)				✓
(Samaan et al., 2023)			✓	
(Sharma et al., 2023)	✓			
(Thirunavukarasu et al., 2023)			✓	
(Wang et al., 2023h)		✓		

et al. (2023) demonstrated that the fine-tuned CodeT5 model performed best across all considered domains, with the least inference time. Moreover, it explored whether LLMs are capable of plan generalization and found that generalization capabilities seem limited. It turns out that LLMs can handle simple engineering tasks, but performs terribly on complex engineering tasks.

3.5 Medical Applications

The application of LLMs in the medical field has recently gained significant attention. In this section, we review existing efforts in applying LLMs to medical applications. Specifically, we categorized them into four aspects as shown in TABLE 5: medical QA, medical examination, medical assessment, and medical education.

3.5.1 Medical QA

TABLE 5 shows that in medical applications, most evaluations of LLMs are in medical question answering. The reason for this trend may be the widespread application and the need for accurate and reliable answers in the medical field. Due to the strong natural language processing and reasoning capabilities of LLMs, they have been widely used in medical QA systems to provide accurate and timely medical information.

Several studies have been conducted to evaluate the performance of ChatGPT in Medical QA, demonstrating its abilities in human respondents (Duong and Solomon, 2023), QA with bariatric surgery patients (Samaan et al., 2023), medical physicists (Holmes et al., 2023), biomedical applications (Jahan et al., 2023), and many other QA situations (Hamidi and Roberts, 2023; Johnson et al., 2023). As for the limitations, Thirunavukarasu et al. (2023) assess its performance in primary care and find that ChatGPT's average score in the student comprehensive assessment falls below the passing score, indicating room for improvement. Chervenak et al. (2023) highlight that while ChatGPT can generate responses similar to existing sources in fertilityrelated clinical prompts, its limitations in reliably citing sources and potential for fabricating information restrict its clinical utility.

3.5.2 Medical examination

Gilson et al. (2023); Kung et al. (2023); Sharma et al. (2023) evaluate the performance of LLMs in medical exam assessment to explore their potential applications in the USMLE ⁴.

In (Gilson et al., 2023), ChatGPT's performance in answering USMLE Step 1 and Step 2 exam questions was assessed using novel multiple-choice question sets. The results indicated that ChatGPT achieved varying accuracies across different datasets. However, the presence of out-ofcontext information was found to be lower compared to the correct answer in the NBME-Free-Step1 and NBME-Free-Step2 datasets. Kung et al. (2023) showed that ChatGPT achieved or approached the passing threshold in these exams with no tailored training. The model demonstrated high consistency and insight, indicating its potential to assist in medical education and clinical decision-making. ChatGPT can be used as a tool to answer medical questions, provide explanations, and support decision-making processes. This offers additional resources and support for medical students and clinicians in their educational and clinical practices. Sharma et al. (2023) indicate that answers generated by ChatGPT are more context-aware with better deductive reasoning abilities compared to Google search results.

3.5.3 Medical education

Several studies have evaluated the performance and feasibility of ChatGPT in the medical education field. In the study by Oh et al. (2023), ChatGPT, specifically GPT-3.5 and GPT-4 models, were evaluated in terms of their understanding of surgical clinical information and their potential impact on surgical education and training. The results indicate an overall accuracy of 46.8% for GPT-3.5 and 76.4% for GPT-4, demonstrating a significant performance difference between the two models. Notably, GPT-4 consistently performs well across different subspecialties, suggesting its capability to comprehend complex clinical information and enhance surgical education and training. Another study by Lyu et al. (2023b) explores the feasibility of utilizing ChatGPT in clinical education, particularly in translating radiology reports into easily understandable language. The findings demonstrate that ChatGPT effectively translates radiology reports into accessible language and provides general recommendations. Furthermore, the quality of ChatGPT has shown improvement compared to GPT-4. These findings suggest that employing large-scale language models in clinical education is feasible, although further efforts are needed to address limitations and unlock their full potential.

3.5.4 Medical assistants

In the field of medical assistance, LLMs demonstrate potential applications, including research on identifying gastrointestinal diseases Lahat et al. (2023), dementia diagnosis Wang et al. (2023h) and accelerating the evaluation of COVID-19 literature Khan et al. (2023). However, there are also limitations and challenges, such as lack of originality, high input requirements, resource constraints and uncertainty in answers.

3.6 Agent Applications

Instead of focusing solely on general language tasks, LLMs can be utilized as powerful tools in various domains. Equipping LLMs with external tools can greatly expand the capabilities of the model.

Huang et al. (2023a) introduce KOSMOS-1, which is capable of understanding general patterns, following instructions, and learning based on context. Karpas et al. (2022) emphasize that knowing when and how to use these external symbolic tools is crucial, and this knowledge is determined by the LLMs' capabilities, especially when these tools can reliably function. In addition, two other studies, Toolformer (Schick et al., 2023) and TALM (Parisi et al., 2022), explore the utilization of tools to enhance language models. Toolformer employs a training approach to determine the optimal usage of specific APIs and integrates the obtained results into subsequent token predictions. On the other hand, TALM combines indistinguishable tools with text-based methods to augment language models and employs an iterative technique known as "self-play," guided by minimal tool demonstrations. (Shen et al., 2023) propose the HuggingGPT framework, which leverages LLMs to connect various artificial intelligence models within the machine learning community (like Hugging Face), aiming to address artificial intelligence tasks.

3.7 Other Applications

In addition to the categories mentioned above, there have been evaluations of LLMs in various other domains, including education, search and recommendation, personality testing, and specific applications.

3.7.1 Education

LLMs have shown promise in revolutionizing the field of education. They have the potential to contribute significantly to several areas, such as assisting students in improving their writing skills, facilitating better comprehension of complex concepts, expediting the delivery of information, and providing personalized feedback to enhance student engagement. These applications aim to create more efficient and interactive learning experiences, offering students a wider range of educational opportunities. However, to fully harness the potential of LLMs in education, extensive research and ongoing refinement are necessary.

The evaluation of LLMs for **educational assistance** aims to investigate and assess their potential contributions to the field of education. Such evaluations can be conducted from various perspectives. According to Dai et al. (2023), ChatGPT demonstrates the ability to generate detailed, fluent, and coherent feedback that surpasses that of human teachers. It can accurately assess student assignments and provide feedback on task completion, thereby assisting in the development of student skills. However, as mentioned by Wang and Demszky (2023), ChatGPT's responses may lack novelty or insightful perspectives regarding teaching improvement. Additionally, the study conducted by Hellas et al. (2023) revealed that LLMs can successfully identify at least one actual problem in student code, although instances of misjudgment were also observed. In conclusion,

TABLE 6

Summary of evaluations on **other applications** based on the four aspects: Edu. (Education), Sea. & Rec. (Search and Recommendation), Pers. Test. (Personality Testing) and Specific applications (ordered by the name of the first author).

Reference	Edu.	Sea. & Rec.	Pers. Test.	Specific applications
(Dai et al., 2023)	√			
(de Winter, 2023)	✓			
(Hellas et al., 2023)	✓			
(Jentzsch and Kersting, 2023)			✓	
(Lanzi and Loiacono, 2023)				Game design
(Le and Zhang, 2023)				Log parsing
(Sun et al., 2023)		✓		0.
(Song et al., 2023)			✓	
(Safdari et al., 2023)			✓	
(Wang and Demszky, 2023)	✓			
(Wang et al., 2023g)				Model performance
(Xu et al., 2023b)		✓		•
(Zhang et al., 2023a)		✓		

the utilization of LLMs shows promise in addressing program logic issues, although challenges remain in achieving proficiency in output formatting. It is important to note that while these models can provide valuable insights, they may still generate errors similar to those made by students.

In **educational testing**, researchers aim to evaluate the application effectiveness of LLMs in educational assessments including automatic scoring, question generation, and learning guidance. de Winter (2023) showed that Chat-GPT achieved an average of 71.8% correctness, which is comparable to the average score of all participating students. Subsequently, the evaluation was conducted using GPT-4, and it achieved a score of 8.33. Furthermore, this evaluation showed the effectiveness of leveraging bootstrapping that combines randomness via the "temperature" parameter in diagnosing incorrect answers. Zhang et al. (2023b) claimed that GPT-3.5 can solve MIT math and EECS exams with GPT-4 achieving better performance. However, it turned out to be not fair since they accidentally input the correct answers to the prompts.

3.7.2 Search and recommendation

The assessment of LLMs in search and recommendation can be broadly categorized into two areas:

In the realm of **information retrieval**, Sun et al. (2023) investigate the effectiveness of generative ranking algorithms, such as ChatGPT and GPT-4, for information retrieval tasks. Experimental results demonstrate that guided ChatGPT and GPT-4 exhibit competitive performance on popular benchmark tests, even outperforming supervised methods. Additionally, the extraction of ChatGPT's ranking functionality into a specialized model shows superior performance when trained on 10K ChatGPT-generated data compared to training on 400K annotated MS MARCO data in the BEIR dataset (Thakur et al., 2021).

Moving to the domain of **recommendation systems** (Fan et al., 2023), LLMs play a crucial role by leveraging natural language processing capabilities to understand user preferences, item descriptions, and contextual information. Incorporating LLMs into recommendation pipelines enables systems to provide more accurate and personalized recommendations, thereby enhancing user experience and improving overall recommendation quality. Zhang et al. (2023a) highlight the potential risks of using ChatGPT for recommendations, as it has been found to produce unfair

recommendations. This underscores the importance of evaluating fairness when employing LLMs for recommendation purposes. Furthermore, Xu et al. (2023b) did a randomized online experiment to test the behavioral differences of users on information retrieval tasks via search engine and chatbot tools. Participants were divided into two groups: one using tools similar to ChatGPT and the other using tools similar to Google Search. The results show that the ChatGPT group spent less time on all tasks and the difference between these two groups are not significant.

3.7.3 Personality testing

Personality testing aims to measure individuals' personality traits and behavioral tendencies, and LLMs as powerful natural language processing models have been widely applied in such tasks. Research conducted by (Bodroza et al., 2023) investigated the personality features of using Davinci-003 as a chatbot and found variations in the consistency of its answers, despite exhibiting prosocial characteristics. However, there remains uncertainty regarding whether the chatbot's responses are driven by conscious self-reflection or algorithmic processes. Song et al. (2023) examined the manifestation of personality in language models and discovered that many models performed unreliably in self-assessment tests and exhibited inherent biases. Therefore, it is necessary to develop specific machine personality measurement tools to enhance reliability. These studies offer vital insights to better understand LLMs in personality testing. Safdari et al. (2023) proposed a comprehensive approach to conduct effective psychometric testing for the personality traits in the text generated by LLMs.

Jentzsch and Kersting (2023) discussed the challenges of incorporating humor into LLMs, particularly ChatGPT. They found that while ChatGPT demonstrates impressive capabilities in NLP tasks, it falls short in generating humorous responses. This study emphasizes the importance of humor in human communication and the difficulties that LLMs face in capturing the subtleties and context-dependent nature of humor. It discusses the limitations of current approaches and highlights the need for further research to develop more sophisticated models that can effectively understand and generate humor.

3.7.4 Specific applications

Furthermore, several studies have investigated the application and evaluation of large language models across diverse tasks, such as **game design** (Lanzi and Loiacono, 2023), **model performance assessment** (Wang et al., 2023g), and **log parsing** (Le and Zhang, 2023). Collectively, these findings enhance our comprehension of the practical implications associated with the utilization of large language models across diverse tasks. They shed light on the potential and limitations of these models, while providing valuable insights for performance improvement.

4 WHERE TO EVALUATE: DATASETS AND BENCH-MARKS

LLMs evaluation datasets are used to test and compare the performance of different language models on various tasks, as depicted in Sec. 3. These datasets, such as GLUE (Wang

et al., 2018) and SuperGLUE (Wang et al., 2019), aim to simulate real-world language processing scenarios and cover diverse tasks such as text classification, machine translation, reading comprehension, and dialogue generation. This section will not discuss any single dataset for language models, but benchmarks for LLMs.

As benchmarks for LLMs are evolving, we list 24 popular benchmarks in TABLE 7.⁵ Each benchmark focuses on different aspects and evaluation criteria, providing valuable contributions to their respective domains. For a better summarization, we divide these benchmarks into two categories: benchmarks for general language tasks and benchmarks for specific downstream tasks.

4.1 Benchmarks for General Tasks

LLMs are designed to solve a vast majority of tasks. To this end, existing benchmarks tend to evaluate the performance in different tasks.

Chatbot Arena (LMSYS, 2023) and MT-Bench (Zheng et al., 2023) are two significant benchmarks that contribute to the evaluation and advancement of chatbot models and LLMs in different contexts. Chatbot Arena is a pioneering evaluation benchmark that offers a distinctive and competitive platform to assess and compare the effectiveness of diverse chatbot models. Users can engage with anonymous models and express their preferences via voting. The platform gathers a significant volume of votes, facilitating the evaluation of models' performance in realistic scenarios. Chatbot Arena provides valuable insights into the strengths and limitations of chatbot models, thereby contributing to the progress of chatbot research and advancement.

MT-Bench is a dedicated benchmark for evaluating the performance of LLMs in multi-turn conversation scenarios. It provides a comprehensive set of questions specifically designed for assessing the capabilities of models in handling multi-turn dialogues. MT-Bench possesses several distinguishing features that differentiate it from conventional evaluation methodologies. Notably, it excels in simulating dialogue scenarios representative of real-world settings, thereby facilitating a more precise evaluation of a model's practical performance. Moreover, MT-Bench effectively overcomes the limitations in traditional evaluation approaches, particularly in gauging a model's competence in handling intricate multi-turn dialogue inquiries.

Instead of focusing on specific tasks and evaluation metrics, HELM (Liang et al., 2022) provides a comprehensive assessment of LLMs. It evaluates language models across various aspects such as language understanding, generation, coherence, context sensitivity, common-sense reasoning, and domain-specific knowledge. HELM aims to holistically evaluate the performance of language models across different tasks and domains. Furthermore, Xiezhi (Gu et al., 2023) provides a comprehensive suite for assessing the knowledge level of large-scale language models in different subject areas. The evaluation conducted through Xiezhi enables researchers to comprehend the notable limitations

5. Note that as the evaluation of LLMs is a hot research area, it is very likely that we cannot cover all benchmarks. We welcome suggestions and comments to make this list perfect.

TABLE 7
Summary of existing LLMs evaluation benchmarks (ordered by the name of the first author).

Benchmark	Focus	Domain	Evaluation Criteria
SOCKET (Choi et al., 2023)	Social knowledge	Specific downstream task	Social language understanding
MME (Fu et al., 2023a)	Multimodal LLMs	General language task	Ability of perception and cognition
Xiezhi (Gu et al., 2023)	Comprehensive domain knowledge	General language task	Overall performance across multiple benchmarks
CUAD (Hendrycks et al., 2021b)	Legal contract review	Specific downstream task	Legal contract understanding
MMLU (Hendrycks et al., 2020b)	Text models	General language task	Multitask accuracy
MATH (Hendrycks et al., 2021c)	Mathematical problem solving	Specific downstream task	Mathematical ability
APPS (Hendrycks et al., 2021a)	Coding challenge competence	Specific downstream task	Code generation ability
C-Eval (Huang et al., 2023b)	Chinese evaluation	General language task	52 Exams in a Chinese context
OpenLLM (HuggingFace, 2023)	Language model evaluation	General language task	Task-specific metrics, Leaderboard rankings
DynaBench (Kiela et al., 2021)	Dynamic evaluation	General language task	NLI, QA, Sentiment, Hate speech
Chatbot Arena (LMSYS, 2023)	Chat assistants	General language task	Crowdsourcing, Elo rating system
AlpacaEval (Li et al., 2023c)	Automated evaluation	General language task	Metrics, Robustness, Diversity
HELM (Liang et al., 2022)	Transparency of language models	General language task	Multi-metric
API-Bank (Li et al., 2023a)	Tool utilization capability of LLMs	Specific downstream task	API call, API retrieval, API planning
Big-Bench (Srivastava et al., 2022)	Capabilities and limitations of LMs	General language task	Model performance, Calibration
MultiMedQA (Singhal et al., 2022)	Medical QA	Specific downstream task	Model performance, Medical Knowledge, Reasoning ability
ToolBench (ToolBench, 2023)	Software tools	Specific downstream task	Execution success rate
PandaLM (Wang et al., 2023g)	Automatic evaluation	General language task	Winrate judged by PandaLM
GLUE-X (Yang et al., 2022)	OOD robustness for NLU tasks	General language task	OOD performance
KoLA (Yu et al., 2023)	Knowledge-oriented evaluation	General language task	Self-contrast metrics
AGIEval (Zhong et al., 2023)	Human-centered foundational models	General language task	General
PromptBench (Žhu et al., 2023)	Adversarial prompt resilience	General language task	Adversarial robustness
MT-Bench (Zheng et al., 2023)	Multi-turn conversation	General language task	Winrate judged by GPT-4
M3Exam (Zhang et al., 2023c)	Human exams	Specific downstream task	Task-specific metrics

inherent in these models and facilitates a deeper comprehension of their capabilities in diverse fields. Big-Bench (Srivastava et al., 2022) introduces a diverse collection of 204 challenging tasks contributed by 450 authors from 132 institutions. These tasks cover various domains such as math, childhood development, linguistics, biology, common-sense reasoning, social bias, physics, software development etc. The primary objective of Big-Bench is to evaluate tasks that go beyond the capabilities of existing language models. Moreover, MME (Fu et al., 2023a) serves as an extensive evaluative benchmark specifically designed for multimodal large language models (MLLM), aiming to assess their perceptual and cognitive aptitudes. MME employs meticulously crafted instruction-answer pairs alongside succinct instruction design, thereby guaranteeing equitable evaluation conditions.

KoLA (Yu et al., 2023), a Knowledge-Oriented LLMs Evaluation Benchmark, is specially designed to evaluate the language understanding and reasoning abilities of LLMs. It emphasizes the comprehension and utilization of semantic knowledge and inference. KoLA serves as a crucial platform for researchers to assess the depth of LLMs' understanding and reasoning, thereby propelling progress in language comprehension models. To allow for crowd-sourcing evaluations in language tasks, DynaBench (Kiela et al., 2021) was designed for conducting dynamic benchmark testing. It explores exciting new research directions, such as the impact of integration within a loop, characteristics of distributional shifts, exploring annotator efficiency, studying the influence of expert annotators, and enhancing model robustness against targeted adversarial attacks in interactive environments. Additionally, it contributes to advancing research on dynamic data collection and conducting cross-task analysis in the domain of general human-computer interaction.

The main goal of MMLU (Hendrycks et al., 2020b) was to develop a comprehensive test for evaluating the performance of text models in multi-task contexts. Additionally, AlpacaEval (Li et al., 2023c) stands as an automated evaluation benchmark, which places its focus on assessing

the performance of LLMs across various natural language processing tasks. It provides a range of metrics, robustness measures, and diversity evaluations to gauge the capabilities of LLMs. AlpacaEval has significantly contributed to advancing LLMs in diverse domains and promoting a deeper understanding of their performance. Furthermore, AGIEval, (Zhong et al., 2023), serves as a dedicated evaluation framework for assessing the performance of foundation models in the domain of human-centric standardized exams. Moreover, OpenLLM (HuggingFace, 2023) functions as an evaluation benchmark by offering a public competition platform for comparing and assessing different LLM models' performance on various tasks. It encourages researchers to submit their models and compete on different tasks, driving progress and competition in the field of LLM research.

As for tasks beyond standard performance, there are benchmarks designed for OOD, adversarial robustness, and fine-tuning. GLUE-X (Yang et al., 2022) is a novel attempt to create a unified benchmark aimed at evaluating the robustness of NLP models in OOD scenarios. This benchmark emphasizes the significance of robustness in NLP and provides insights into measuring and enhancing the robustness of models. PromptBench (Zhu et al., 2023) centers on the importance of prompt engineering in fine-tuning LLMs. It provides a standardized evaluation framework to compare different prompt engineering techniques and assess their impact on model performance. PromptBench facilitates the enhancement and optimization of fine-tuning methods for LLMs. To ensure impartial and equitable evaluation, PandaLM (Wang et al., 2023g) is introduced as a discriminative large-scale language model specifically designed to differentiate among multiple high-proficiency LLMs through training. In contrast to conventional evaluation datasets that predominantly emphasize objective correctness, PandaLM incorporates crucial subjective elements, including relative conciseness, clarity, adherence to instructions, comprehensiveness, and formality.

4.2 Benchmarks for Specific Downstream Tasks

Other than benchmarks for general tasks, there exist benchmarks specifically designed for certain downstream tasks.

MultiMedQA (Singhal et al., 2022) is a medical QA benchmark that focuses on medical examinations, medical research, and consumer healthcare questions. It consists of seven datasets related to medical QA, including six existing datasets and one new dataset. The goal of this benchmark is to evaluate the performance of LLMs in terms of clinical knowledge and QA abilities.

Other specific benchmarks include C-Eval (Huang et al., 2023b), which is the first extensive benchmark to assess the advanced knowledge and reasoning capabilities of foundation models in Chinese. M3Exam (Zhang et al., 2023c) provides a unique and comprehensive evaluation framework that incorporates multiple languages, modalities, and levels to test the general capabilities of LLMs in diverse contexts. SOCKET (Choi et al., 2023) serves as an NLP benchmark designed to evaluate the performance of LLMs in learning and recognizing social knowledge concepts. It consists of several tasks and case studies to assess the limitations of LLMs in social capabilities. MATH (Hendrycks et al., 2021c) concentrates on assessing reasoning and problemsolving proficiencies of AI models within the domain of mathematics. APPS (Hendrycks et al., 2021a) is a more comprehensive and rigorous benchmark for evaluating code generation, measuring the ability of language models to generate python code according to natural language specifications. CUAD (Hendrycks et al., 2021b) is an expertannotated, domain-specific legal contract review dataset that presents a challenging research benchmark and potential for enhancing deep learning models' performance in contract understanding tasks.

In addition to existing evaluation benchmarks, there is a research gap in assessing the effectiveness of utilizing tools for LLMs. To address this gap, the API-Bank benchmark (Li et al., 2023a) is introduced as the first benchmark explicitly designed for tool-augmented LLMs. It comprises a comprehensive Tool-Augmented LLM workflow, encompassing 53 commonly used API tools and 264 annotated dialogues, encompassing a total of 568 API calls. Furthermore, the ToolBench project (ToolBench, 2023) aims to empower the development of large language models that effectively leverage the capabilities of general-purpose tools. By providing a platform for creating optimized instruction datasets, the ToolBench project seeks to drive progress in language models and enhance their practical applications.

5 How to Evaluate

In this section, we introduce two common evaluation methods: automatic evaluation and human evaluation. In fact, the taxonomy of "how to evaluate" is also not definite. Our categorization is based on whether or not the evaluation criterion can be automatically computed. If it can be automatically calculated, we categorize it into *automatic* evaluation; otherwise, it falls into *human* evaluation.

5.1 Automatic Evaluation

Automated evaluation of LLMs is a common and perhaps the most popular evaluation method that usually uses standard metrics or indicators and evaluation tools to assess the performance of models, such as accuracy, BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), BERTScore (Zhang et al., 2019), to name a few. For instance, we can use BLEU score to quantify the similarity and quality between the model-generated text and the reference text in a machine translation task. In fact, most of the existing evaluation efforts adopt this evaluation protocol due to its subjectivity, automatic computing, and simplicity. Thus, most of the deterministic tasks, such as natural language understanding and math problems, often adopt this evaluation protocol.

Compared with human evaluation, automatic evaluation does not require human participation, which saves evaluation costs and takes less time. For example, both (Qin et al., 2023) and Bang et al. (2023) use automated evaluation methods to evaluate a large number of tasks. Recently, with the development of LLMs, some advanced automatic evaluation techniques are also designed to help evaluate. Lin and Chen (2023) proposed LLM-EVAL, a unified multidimensional automatic evaluation method for open-domain conversations with LLMs. PandaLM (Wang et al., 2023g) can achieve reproducible and automated language model assessment by training an LLM that serves as the "judge" to evaluate different models. Proposing a self-supervised evaluation framework, Jain et al. (2023) enabled a more efficient form of evaluating models in real-world deployment settings by eliminating the need for laborious labeling of new data.

Due to the large volume of automatic evaluation papers, we will not introduce them in detail. The principle of automatic evaluation is in fact the same as other AI model evaluation process: we just use some standard metrics to compute certain values under these metrics, which serves as indicators for model performance.

5.2 Human Evaluation

The increasingly strengthened capabilities of LLMs have certainly gone beyond standard evaluation metrics on general natural language tasks. Therefore, human evaluation becomes a natural choice in some non-standard cases where automatic evaluation is not suitable. For instance, in open generation tasks where embedded similarity metrics (such as BERTScore) are not enough, human evaluation is more reliable (Novikova et al., 2017). While some generation tasks can adopt certain automatic evaluation protocols, human evaluation in these tasks is more favorable as generation can always go better than standard answers.

Human evaluation of LLMs is a way to evaluate the quality and accuracy of model-generated results through human participation. Compared with automatic evaluation, manual evaluation is closer to the actual application scenario and can provide more comprehensive and accurate feedback. In the manual evaluation of LLMs, evaluators (such as experts, researchers, or ordinary users) are usually invited to evaluate the results generated by the model. For example, Ziems et al. (2023) used the annotations from experts for generation. By human evaluation, (Liang et al., 2022) performed human evaluation on summarization and disinformation scenarios on 6 models and Bang et al. (2023) evaluated analogical reasoning tasks. The seminal

TABLE 8 Summary of new LLMs evaluation protocols.

Method	References
Human-in-the-loop	AdaVision (Gao et al., 2022), AdaTest (Ribeiro and Lundberg, 2022)
Crowd-sourcing testing	DynaBench (Kiela et al., 2021), DynaBoard (Ma et al., 2021), DynamicTempLAMA (Margatina et al., 2023), DynaTask (Thrush et al., 2022)
More challenging tests	HÉLM (Liang et al., 2022), AdaFilter (Phang et al., 2021), CheckList (Ribeiro et al., 2020), Big-Bench (Srivastava et al., 2022), DeepTest (Tian et al., 2018)

evaluation work by Bubeck et al. (2023) did a series of human-crafted tests using GPT-4 and they found that GPT-4 performs close to or even exceeds human performance on multiple tasks. This evaluation requires human evaluators to actually test and compare the performance of the models, not just evaluate the models through automated evaluation metrics. Note that even human evaluations can have high variance and instability, which could be due to cultural and individual differences (Peng et al., 1997). In practical applications, these two evaluation methods are considered and weighed in combination with the actual situation.

6 SUMMARY

In this section, we summarize the key findings based on our review in sections 3, 4, and 5.

First of all, we would like to highlight that despite all the efforts spent on summarizing existing works on evaluation, there is *no* evidence to explicitly show that one certain evaluation protocol or benchmark is the most useful and successful, but with **different characteristics and focuses**. This also demonstrates that not a single model can perform best in all kinds of tasks. The purpose of this survey is to go beyond simply determining the "best" benchmark or evaluation protocol. By summarizing and analyzing existing efforts on LLMs evaluation, we may identify the current success and failure cases of LLMs, derive new trend for evaluation protocols, and most importantly, propose new challenges and opportunities for future research.

6.1 Task: Success and Failure Cases of LLMs

We now summarize the success and failure cases of LLMs in different tasks. Note that all the following conclusions are made based on existing evaluation efforts and the results are only dependent on specific datasets.

6.1.1 What can LLMs do well?

- LLMs demonstrate proficiency in generating text by producing fluent and precise linguistic expressions.
- LLMs obtain impressive performance in tasks involving language understanding, such as sentiment analysis, and text classification.
- LLMs exhibit robust contextual comprehension, enabling them to generate coherent responses that align with the given input.
- LLMs achieve satisfying performance across several natural language processing tasks, including machine translation, text generation, and question answering.

6.1.2 When can LLMs fail?

- LLMs may exhibit biases and inaccuracies during the generation process, resulting in the production of biased outputs.
- LLMs have limited abilities in comprehending complex logic and reasoning tasks, often experiencing confusion or making errors in intricate contexts.
- LLMs face constraints in handling extensive datasets and long-term memory, which can pose challenges in processing lengthy texts and tasks involving longterm dependencies.
- LLMs have limitations in incorporating real-time or dynamic information, making them less suitable for tasks that require up-to-date knowledge or rapid adaptation to changing contexts.
- LLMs is sensitive to prompts, especially adversarial prompts, which triggers new evaluations and algorithms to improve its robustness.
- In the domain of text summarization, it is observed that LLMs might demonstrate subpar performance on particular evaluation metrics, which can potentially be attributed to inherent limitations or inadequacies within those specific metrics.
- LLMs do not achieve satisfying performance in counterfactual tasks.

6.2 Benchmark and Evaluation Protocol

With the rapid development and widespread use of LLMs, the importance of evaluating them in practical applications and research has become crucial. This evaluation process should include not only task-level evaluation but also a deep understanding of the potential risks they pose from a societal perspective. In this section, we summarize existing benchmark and evaluation protocols in TABLE 8.

First, a shift from objective calculation to human-in-the-loop testing, allowing for greater human feedback during the evaluation process. AdaVision (Gao et al., 2022), an interactive process for testing vision models, enables users to label a small amount of data for model correctness, which helps users identify and fix coherent failure modes. In AdaTest (Ribeiro and Lundberg, 2022), the user filters test samples by only selecting high quality tests and organizing them into semantically related topics.

Second, a move from static to crowd-sourcing test sets is becoming more common. Tools like DynaBench (Kiela et al., 2021), DynaBoard (Ma et al., 2021), and DynaTask (Thrush et al., 2022) rely on crowdworkers to create and test hard samples. Additionally, DynamicTempLAMA (Margatina et al., 2023) allows for dynamically constructed time-related tests.

Third, a shift from a unified to a challenging setting in evaluating machine learning models. While unified settings

involve a test set with no preference for any specific task, challenging settings create test sets for specific tasks. Tools like DeepTest (Tian et al., 2018) use seeds to generate input transformations for testing, CheckList (Ribeiro et al., 2020) builds test sets based on templates, and AdaFilter (Phang et al., 2021) adversarially constructs tests. However, it is worth noting that AdaFilter may not be entirely fair as it relies on adversarial examples. HELM (Liang et al., 2022) evaluates LLMs from different aspects, while the Big-Bench (Srivastava et al., 2022) platform is used to design hard tasks for machine learning models to tackle. PromptBench (Zhu et al., 2023) aims to evaluate the adversarial robustness of LLMs by creating adversarial prompts, which is more challenging and the results demonstrated that current LLMs are not robust to adversarial prompts.

7 GRAND CHALLENGES AND OPPORTUNITIES FOR FUTURE RESEARCH

Evaluation as a new discipline: Our summarization inspires us to redesign a wide spectrum of aspects related to evaluation in the era of LLMs. In this section, we present several grand challenges. Our key point is that evaluation should be treated as an essential discipline to drive the success of LLMs and other AI models. Existing protocols are not enough to thoroughly evaluate the true capabilities of LLMs, which poses grand challenges and triggers new opportunities for future research on LLMs evaluation.

7.1 Designing AGI Benchmarks

As we discussed earlier, while all tasks can potentially serve as evaluation tools for LLMs, the question remains as to which can truly measure AGI capabilities. As we expect LLMs to demonstrate AGI abilities, a comprehensive understanding of the differences between human and AGI capacities becomes crucial in the creation of AGI benchmarks. The prevailing trend seems to conceptualize AGI as a superhuman entity, thereby utilizing cross-disciplinary knowledge from fields such as education, psychology, and social sciences to design innovative benchmarks. Nonetheless, there remains a plethora of unresolved issues. For instance, does it make sense to use human values as a starting point for test construction, or should alternative perspectives be considered? The process of developing suitable AGI benchmarks presents many open questions demanding further exploration.

7.2 Complete Behavioral Evaluation

An idea AGI evaluation should contain not only standard benchmarks on common tasks, but also evaluations on open tasks such as complete behavioral tests. By behavioral test, we mean that AGI models should also be evaluated in an open environment. For instance, by treating LLMs as the central controller, we can construct evaluations on a robot manipulated by LLMs to test its behaviors in real situations. By treating LLMs as a completely intelligent machine, the evaluations of its multi-modal dimensions should also be considered. In fact, complete behavioral evaluations are complementary to standard AGI benchmarks and they should work together for better testing.

7.3 Robustness Evaluation

Beyond general tasks, it is crucial for LLMs to maintain robustness against a wide variety of inputs in order to perform optimally for end-users, given their extensive integration into daily life. For instance, the same prompts but with different grammars and expressions could lead ChatGPT and other LLMs to generate diverse results, indicating that current LLMs are not robust to the inputs. While there are some prior work on robustness evaluation (Wang et al., 2023c; Zhu et al., 2023), there are much room for advancement, such as including more diverse evaluation sets, examining more evaluation aspects, and developing more efficient evaluations to generate robustness tasks. Concurrently, the concept and definition of robustness are constantly evolving. It is thus vital to consider updating the evaluation system to better align with emerging requirements related to ethics and bias.

7.4 Dynamic and Evolving Evaluation

Existing evaluation protocols for most AI tasks rely on static and public benchmarks, i.e., the evaluation datasets and protocols are often publicly available. While this facilitates rapid and convenient evaluation within the community, it is unable to accurately assess the evolving abilities of LLMs, given their rapid rate of development. The capabilities of LLMs may enhance over time which cannot be consistently evaluated by existing static benchmarks. On the other hand, as LLMs grow increasingly powerful with larger model sizes and training set sizes, static and public benchmarks are likely to be memorized by LLMs, resulting in potential training data contamination. Therefore, developing dynamic and evolving evaluation systems is the key to providing a fair evaluation of LLMs.

7.5 Principled and Trustworthy Evaluation

When introducing an evaluation system, it is crucial to ascertain its integrity and trustworthiness. Therefore, the necessity for trustworthy computing extends to the requirement for reliable evaluation systems as well. This poses a challenging research question that intertwines with measurement theory, probability, and numerous other domains. For instance, how can we ensure that dynamic testing truly generates out-of-distribution examples? There is a scarcity of research in this domain, and it is hoped that future work will aim to scrutinize not only the algorithms but the evaluation system itself.

7.6 Unified Evaluation that Supports All LLMs Tasks

There are many other research areas of LLMs and we need to develop evaluation systems that can support all kinds of tasks such as value alignment, safety, verification, interdisciplinary research, fine-tuning, and others. For instance, PandaLM (Wang et al., 2023g) is an evaluation system that assists LLMs fine-tuning by providing an opensource evaluation model, which can automatically assess the performance of fine-tuning. We expect that more evaluation systems are becoming more general and can be used as assistance in certain LLMs tasks.

7.7 Beyond Evaluation: LLMs Enhancement

Ultimately, evaluation is not the end goal but rather the starting point. Following the evaluation, there are undoubtedly conclusions to be drawn regarding performance, robustness, stability, and other factors. A proficient evaluation system should not only offer benchmark results but should also deliver an insightful analysis, recommendations, and guidance for future research and development. For instance, PromptBench (Zhu et al., 2023) provides not only robustness evaluation results on adversarial prompts but also a comprehensive analysis through attention visualization, elucidating how adversarial texts can result in erroneous responses. The system further offers a word frequency analysis to identify robust and non-robust words in the test sets, thus providing prompt engineering guidance for end users. Subsequent research can leverage these findings to enhance LLMs. Another example is that Wang et al. (2023f) first explored the performance of large vision-language models on imbalanced (long-tailed) tasks, which demonstrates the limitation of current large models. Then, they explored different methodologies to enhance the performance on these tasks. In summary, enhancement after evaluation helps to build better LLMs and much can be done in the future.

8 Conclusion

Evaluation carries profound significance, becoming imperative in the advancement of AI models, especially within the context of large language models. This paper presents the first survey to give an comprehensive overview of the evaluation on LLMs from three aspects: what to evaluate, how to evaluate, and where to evaluate. By encapsulating evaluation tasks, protocols, and benchmarks, our aim is to augment understanding of the current status of LLMs, elucidate their strengths and limitations, and furnish insights for future LLMs progression.

Our survey reveals that current LLMs exhibit certain limitations in numerous tasks, notably reasoning and robustness tasks. Concurrently, the need for contemporary evaluation systems to adapt and evolve remains evident, ensuring the accurate assessment of LLMs' inherent capabilities and limitations. We identify several grand challenges that future research should address, with the aspiration that LLMs can progressively enhance their service to humanity.

DISCLAIMER

The goal of this paper is mainly to summarize and discuss existing evaluation efforts on large language models. Results and conclusions in each paper are original contributions of their corresponding authors, particularly for potential issues in ethics and biases. This paper may discuss some side effects of LLMs and the only intention is to foster a better understanding of large language models.

Additionally, due to the evolution of LLMs especially online services such as Claude and ChatGPT, it is very likely that they become stronger and some of their limitations described in this paper are mitigated (and new limitations may arise). We encourage interested readers to take this survey as a reference for future research and conduct real experiments in current systems when performing evaluations.

Finally, the evaluation of LLMs is continuously developing, thus we may miss some new papers or benchmarks. We welcome all constructive feedback and suggestions to help make this survey better.

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