Leveraging Large Language Models for NLG Evaluation: Advances and Challenges

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Abstract

In the rapidly evolving domain of Natural Language Generation (NLG) evaluation, introducing Large Language Models (LLMs) has opened new avenues for assessing generated content quality, e.g., coherence, creativity, and context relevance. This paper aims to provide a thorough overview of leveraging LLMs for NLG evaluation, a burgeoning area that lacks a systematic analysis. We propose a coherent taxonomy for organizing existing LLM-based evaluation metrics, offering a structured framework to understand and compare these methods. Our detailed exploration includes critically assessing various LLM-based methodologies, as well as comparing their strengths and limitations in evaluating NLG outputs. By discussing unresolved challenges, including bias, robustness, domain-specificity, and unified evaluation, this paper seeks to offer insights to researchers and advocate for fairer and more advanced NLG evaluation techniques.

1 Introduction

Natural Language Generation (NLG) stands at the forefront of modern AI-driven communication, with recent advancements in large language models (LLMs) revolutionizing the capabilities of NLG systems (Ouyang et al., 2022; OpenAI, 2023). These models, powered by deep learning techniques and vast amounts of training data, exhibit excellent proficiency in generating text across a wide range of applications. As NLG technology continues its rapid evolution, it becomes increasingly imperative to establish robust evaluation methodologies that can reliably gauge the quality of the generated content.

Traditional NLG evaluation metrics, such as BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) and TER (Snover et al., 2006), primarily focus on surface-level text differences and often fall short



Figure 1: Illustration of LLMs for NLG evaluation. The dashed line means that the references and sources are optional based on the scenarios.

in assessing semantic aspects (Freitag et al., 2020). This limitation has been noted to hinder research progress and can lead to misleading research conclusions. Additionally, other methods that employ neural embeddings to calculate the score (Liu et al., 2016; Sellam et al., 2020; Zhang et al., 2020), despite assessing aspects like semantic equivalence and fluency, are inflexible and limited in scope (Freitag et al., 2021a). Additionally, these traditional methods tend to have low alignment with human judgement (Liu et al., 2023c) and lack interpretability for the score (Xu et al., 2023). These drawbacks underscore the need for more nuanced and comprehensive evaluation methods in the NLG field.

The emergent abilities of LLMs present a promising avenue for the LLM-based NLG evaluation, such as Chain-of-Thought (CoT) (Wei et al., 2022b), zero-shot instruction following (Wei et al., 2022a), better alignment with human preference (Ouyang et al., 2022), etc. These attributes position LLMs as potent tools for evaluating NLG outputs, offering a more sophisticated and better human-aligned assessment compared to traditional methods (Liu et al., 2023c; Kocmi and Federmann, 2023; Fu et al., 2023). For instance, LLMs could generate reasonable explanations to support the ultimate score (Xu et al., 2023), and the reinforcement learning with human feedback (RLHF) could align

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LLMs' preference with human better (Ouyang et al., 2022; Zheng et al., 2023). As in Figure 1, the key strategy in these approaches involves instructing LLMs with prompts to evaluate generated texts from various aspects, either with references and sources or not. However, the wide array of LLM-based NLG evaluation methods, addressing different tasks and goals, lack a unified overview.

Given the burgeoning volume of work in the realm of LLMs for NLG evaluation, a synthesized summary is urgently needed to navigate the complexities and diverse methodologies within this space. This survey aims to provide a comprehensive overview of this promising domain, presenting a coherent taxonomy for organizing existing works. We meticulously delineate pivotal studies and their methodologies, and delve into an analytical discussion of the various strengths, limitations, and distinctive attributes of these approaches. Furthermore, we navigate through the yet-to-be-resolved challenges and the open-ended questions within this field, thereby charting potential avenues for future scholarly exploration. This comprehensive exploration aims to spark readers with an in-depth understanding of the nuances and evolving dynamics of LLM-based approaches in NLG evaluation.

Organization of this paper: We present the first comprehensive survey of recent advancements in leveraging LLMs for NLG evaluation. Initially, we establish a formal framework for NLG evaluation and propose a taxonomy to categorize relevant works (Section 2). Subsequently, we delve into and elaborate on these works in detail (Section 3). Furthermore, we conduct a systematic review of various meta-evaluation benchmarks that assess the efficacy of LLM-based evaluators (Section 4). Additionally, we provide a thorough comparison of LLM-based evaluators with traditional evaluators in terms of performance, efficiency and qualitative qualitative analysis (Section 5). In recognition of the rapid evolution of this field, we identify and discuss several potential open problems that may guide future research (Section 6). To conclude, we advocate for the advancement of this field through the development of more impartial, robust, expert and unified LLM-based evaluators.

2 Formalization and Taxonomy

In this section, we first briefly formalize LLMbased NLG Evaluation tasks. The objective of NLG evaluation is to assess the candidate generations of a model across various dimensions, such as fluency, consistency, etc. Recent advancements in LLMs have significantly enhanced their capabilities in context comprehension and the generation of reasonable responses. Notably, contemporary research has begun to reframe NLG evaluation as a series of instruction-following tasks, leveraging powerful capabilities of LLMs (Zhang et al., 2020; Fu et al., 2023). To maintain generality, we formalize the existing evaluation framework for texts generated by models as follows:

$$E = f(h, s, r). \tag{1}$$

Here, h represents the hypothesis text (i.e. candidate generation to be evaluated), and f denotes the evaluation function, which can be instantiated by LLMs. The variable s denotes the input source of the generation. This source might include the source text or any supporting documents that provide background or framing for the generated content. For instance, in machine translation tasks, c could be the sentence in the source language. Lastly, r refers to a set of ground truth references that serve as a benchmark for evaluation. These references are crucial in tasks like text summarization, where the quality of the generated summary is assessed by an annotated reference summary.

In this paper, we classify works in NLG evaluation along three primary dimensions: *evaluation task*, *evaluation references* and *evaluation function*. These dimensions provide a comprehensive framework for categorizing and understanding different approaches within this domain.

Evaluation Task \mathcal{T} : NLG encompasses a diverse range of tasks, such as Machine Translation (MT) (Farhad et al., 2021; Bapna et al., 2019), Text Summarization (TS) (Liu and Liu, 2021; Zhang et al., 2023a), Dialogue Generation (DG) (Tao et al., 2018; Kann et al., 2022), Story Generation (SG) (Yang et al., 2022; Fan et al., 2018), Image Caption (IC) (Tewel et al., 2022; Zhou et al., 2022), Data-to-Text generation (D2T) (Lin et al., 2023; Jing et al., 2023) and General Generation (GE) (Wang et al., 2023g; Zheng et al., 2023), each with its unique evaluation requirements and challenges. The specific nature of each task determines the target evaluation aspects and scenarios. For instance, in text summarization, the focus may be on relevance to the source content, while in dialogue generation, the coherence of the response is



Figure 2: Illustration of NLG evaluation functions: (a) generative-based and (b) matching-based methods.

crucial. Given these varied objectives, our taxonomy also extends to the lens of task-specific evaluation. This categorization enables us to understand how different evaluation methods perform across a spectrum of NLG tasks, thus offering insights into the strengths and limitations of existing evaluation paradigms in distinct task contexts.

Evaluation References r : According to whether the references are available, we divide the evaluation scenarios into reference-based and referencefree scenarios. In reference-based evaluation, the generated text h is compared against a set of ground truth references r. This approach is particularly prevalent in tasks where the quality of the generated text can be objectively measured against established standards. The comparison metrics might focus on aspects like accuracy, relevance, coherence, and the degree of similarity to the references. Typical applications include text summarization, where the generated summaries are evaluated against reference summaries, and machine translation, where the translations are compared with standard translations. The reference-free approach, in contrast, does not rely on any external references for evaluation. This method evaluates the generated text h based on the intrinsic qualities or its alignment with the provided source context s. Evaluation in this context may focus on aspects such as fluency, originality, relevance to the context, etc.

Evaluation Function f: Evaluation function could be matching-based or generative-based on the basis of different ways of utilizing LLMs. As shown in Figure 2, *matching-based methods* measure the semantic equivalence between the reference and hypothesis or measure the proper degree between the source text and hypothesis. Several works measure the semantic equivalence between the reference and hypothesis by using token-level matching functions in distributed representation space (Zhang et al., 2020; Zhao et al., 2019) or discrete string space (Lin, 2004; Papineni et al., 2002). Others focus on sequence-level, such as (Sellam et al., 2020; Rei et al., 2020). In contrast, *generative-based methods* include methods where LLMs are employed to generate evaluation metrics directly. These methods leverage the generative capabilities of LLMs to assess the quality of generated text by designing instructions.

Scope of this paper: Recent matching-based methods are based on a neural encoder to calculate a score-specific aspect of evaluation. However, these methods often face challenges such as limited interpretability, lower correlation with human judgments, and a restricted range of evaluated aspects (Xu et al., 2023; Fu et al., 2023). Fortunately, the emerging capabilities of LLMs open up a wealth of possibilities for NLG evaluation. This includes improved interpretability through CoT, higher customization via instruction-following capabilities, and better alignment with human evaluations through RLHF (Xu et al., 2023; Zheng et al., Given the abundance of recent surveys 2023). primarily focusing on matching-based evaluation methods (refer to (Celikyilmaz et al., 2020; Sai et al., 2022; Goyal et al., 2023) for comprehensive summaries), our paper is dedicated to exploring more burgeoning generative-based methods. Figure 3 presents our taxonomy of generative-based evaluation. We classify relevant works into two main categories: prompt-based and tuning-based evaluation, depending on whether the LLM is tuned. Further, we divide these methods into subcategories: score-based, probability-based, likert-style, pairwise comparison, ensemble, and advanced evaluation protocols, each distinguished by their evaluation form. These categories will be detailed in Section 3.



Figure 3: Taxonomy of research in NLG evaluation with large language models.

3 Generative Evaluation

Amidst the rapid evolution of LLMs, a burgeoning body of research has directed its focus toward leveraging these models as evaluators for NLG tasks. This attention is particularly rooted in the highcapacity generative abilities of LLMs, leading to the emergence of works employing them to produce quality evaluations of NLG text-a paradigm we refer to as generative evaluation. This category, broadly classified into prompt-based evaluation and tuning-based evaluation, hinges on whether the parameters of LLM evaluators require fine-tuning. Prompt-based evaluation typically involves prompting robust base LLMs to assess generated text through meticulous prompt engineering. On the other hand, tuning-based evaluation relies on open-source LLMs that are specifically calibrated for NLG evaluation. Both approaches cater to diverse evaluation protocols for measuring the quality of the generated text.

Current methods consider different scoring pro-

tocols to judge the quality of generated hypothesis text. Some endeavors deploy LLM evaluators to yield continuous scalar scores that represent the quality of individual generated texts-termed as **1** score-based evaluation. Others calculate the generation probability of generated texts based on prompts, sources, or reference texts (optional) as the evaluation metric, denoted as 2 probabilitybased evaluation. Further diversifying the landscape, certain works transform NLG evaluation into a classification task by categorizing text quality into multiple levels using likert scales. In this scenario, LLM evaluators assess the quality of generated text by assigning it to a specific quality level—referred to as ③ *likert-style evaluation*. Meanwhile, **4** pairwise comparison methods involve using LLM evaluators to compare the quality of pairs of generated texts. Additionally, 6 ensemble evaluation methods utilize multiple LLM evaluators with different LLMs or prompts, orchestrating communication among evaluators to yield

Prompt Type	Prompt	Output							
Score-based	Given the source document: []								
	Given the model-generated text: []	Scores: 2							
	Please score the quality of the generated text from 1 (worst) to 5 (best)								
Likert-style	Given the source document: []								
	Given the model-generated text: []	Yes							
	Is the generated text consistent with the source document? (Answer Yes or No)								
Pairwise	Given the source document: []								
	Given the model-generated text 1: []								
	And given the model-generated text 2: []								
	Please answer which text is better-generated and more consistent.								

Table 1: Illustration of different types of prompts.

final evaluation results. Finally, some recent studies explore ③ *advanced evaluation methods* (that consider fine-grained criteria or combine the capabilities of chain-of-thought or in-context leaning) with the goal of attaining more comprehensive and nuanced evaluation results.

This section delves into a detailed exploration of these two overarching categories of evaluation methods, each accompanied by their respective evaluation protocols. Table 2 provides a comprehensive overview of current prompt-based and tuning-based evaluation methods. The table delineates their respective adaptation tasks, backbone models, scoring protocols, and evaluated aspects for clarity and reference.

3.1 Prompt-based Evaluation

Prompt-based text evaluation stands at the forefront of advancements in NLG, particularly leveraging the capabilities of LLMs. In this method, the evaluation process is intricately woven into the crafting of prompts - specialized cues designed to guide LLMs in assessing the quality and coherence of generated text. More recently, the Eval4NLP workshop held a shared task on prompting LLMs as explainable metrics (Leiter et al., 2023). Typically, a prompt template serves as a structured framework that encompasses instructions, aspects, criteria, and desired output formats, providing a systematic guide for evaluating generated text. These templates empower researchers and practitioners to articulate precise evaluation requirements, ensuring consistency and reproducibility in the assessment process. By harnessing the prowess of LLMs, prompt-based evaluation not only provides a comprehensive understanding of NLG system performance but also offers a nuanced approach to extracting valuable insights.

Score Evaluation. An intuitive and widely employed protocol for utilizing LLM evaluators in text

evaluation involves prompting these evaluators to generate a continuous score that reflects the quality of the generated text. A concrete example of such a prompt is illustrated in the first row of Table 1. Pioneering this method, GEMBA (Kocmi and Federmann, 2023) proposed the use of LLM evaluators to assign quality scores, ranging from 0 to 100, to generate translations both with and without a reference. GEMBA demonstrates the efficacy of employing GPT-3.5 or larger LLMs for translation quality evaluation, showcasing their capabilities with simple zero-shot prompts. Building on this foundation, Lin and Chen (2023) have extended score evaluation methods to broader NLG evaluation domains, aiming to enhance the alignment between LLM evaluators and manual annotators.

Liu et al. (2023e) tailored LLM evaluators to assess the quality of closed-end response generation, characterized by unique and correct semantic references. Their innovative approach involves prompting LLMs evaluators to generate explanatory judgments for the generated responses, subsequently extracting numerical quality scores. Similarly, Wang et al. (2023b) proposed a unified prompt applicable across various NLG evaluation tasks, which directly generates quality scores for the produced texts across different evaluation aspects, both with and without reference. Additionally, Jain et al. (2023) employed LLM evaluators with in-context examples to evaluate summarization tasks, generating numeric strings that effectively capture the quality of summarization outputs. These diverse applications underscore the versatility and adaptability of score-based evaluation methods when harnessing LLM evaluators for comprehensive NLG assessments.

Probability-based evaluation. Recognizing that the quality of the generated text is often correlated with the ease of generation by LLMs based on source or reference text, some studies adopt a

Metric	M	ГTS	DO	G IC	D2	TSC	GE	E REF	F LLMs	Protocol	Aspects
						Pro	mpt-	basea	l Evaluation		
BARTScore (Yuan et al., 2021)	\checkmark	\checkmark	*	*	√	*	*	\checkmark	BART	Prob	CON/COH/REL/FLU/ INF/COV/ADE
GPTScore (Fu et al., 2023)	√	√	√		~	*	*		GPT3	Prob	CON/COH/REL/FLU/COV/ACC MQM/INF/FAC/INT/ENG/NAT
G-EVAL (Liu et al., 2023c)	*	√	√		*	*	*		ChatGPT/GPT-4	Advanced	CON/COH/REL/FLU /NAT/ENG/GRO
Embed Llama (Dreano et al., 2023)	~	*	*		*	*	*		LlaMA-2	Score	NONE
ICE (Jain et al., 2023)	*	\checkmark	*		*	*	*		GPT-3	Score	CON/COH/REL/FLU
GEMBA (Kocmi and Federmann, 2023)	\checkmark	*	*		*	*	*		ChatGPT	Score/Like	rt NONE
LLM_eval (Chiang and Lee, 2023)	*	*	*		*	\checkmark	*		ChatGPT	Likert	GRAM/COH/REL/LIK
FairEval (Wang et al., 2023c)	*	*	*		*	*	\checkmark		ChatGPT/GPT-4	Pairwise	NONE
AuPEL (Wang et al., 2023e)	*	*	*		*	*	\checkmark		PaLM-2	Pairwise	PER/QUA/REL
DRPE (Wu et al., 2023a)	*	\checkmark	*	*	*	*	*	\checkmark	GPT-3	Ensemble	CON/COH/REL/FLU/INT/USE
ChatEval (Chan et al., 2023)	*	*	\checkmark		*	*	\checkmark		ChatGPT/GPT-4	Ensemble	NAT/COH/ENG/GRO
WideDeep (Zhang et al., 2023b)	*	*	*		*	*	\checkmark		ChatGPT	Ensemble	COH/REL/HARM/ACC
PRD (Li et al., 2023c)	*	*	*		*	*	√		GPT-4/GPT-3.5 Vicuna/Claude/Bard	Ensemble	INF/COH
FACTSCORE (Min et al., 2023)		*					 \		ChatGPT	Advanced	FAC
EAprompt (Lu et al., 2023)	\checkmark	*	*		*	*	*		ChatGPT/text-davinci-003	Advanced	NONE
AUTOCALIBRATE (Liu et al., 2023f)	*	\checkmark	*		*	*	*		GPT-4	Likert	CON/COH/REL/FLU/INF/NAT
ALLURE (Hasanbeig et al., 2023)	*	\checkmark	*		*	*	\checkmark		GPT-4	Advanced	CON/COH/FLU/REL
						Tun	ing-	based	Evaluation		
PRISM (Thompson and Post, 2020)	\checkmark	*	*	*	*	*	*	\checkmark	Transformer	Prob	NONE
T5Score (Qin et al., 2022)	\checkmark	\checkmark	*	*	*	*	*	\checkmark	T5	Prob	NONE
TrueTeacher (Gekhman et al., 2023)	*	\checkmark	*		*	*	*		T5	Likert	CON
Attscore (Yue et al., 2023)	*	*	*		*	*	~		Roberta/T5/GPT2 LLaMA/Vicuna	Likert	CON
X-EVAL (Liu et al., 2023a)	*	√	√		√	*	*		FLAN-T5-large	Likert	DEP/LIK/UND/FLE/INF/INQ INT/SPE/COR/SEM/COH/ENG NAT/GRO/CON/REL/FLU
AUTO-J (Li et al., 2023a)	*	*	*		*	*	*		LLaMA	Likert/Pairv	ACC/CLA/FEA/CRE/THO wise STR/LAY/COM/INF
PERSE (Wang et al., 2023a)	*	*	*	*	*	~	*	· ✓	LLaMA	Likert/Pairv	wiseINT/ADA/SUR/CHA/END
PandaLM (Wang et al., 2023f)	*	*	*		*	*	\checkmark		LLaMA	Pairwise	CLA/COM/FOR/ADH
TIGERScore (Jiang et al., 2023)	\checkmark	\checkmark	*		\checkmark	\checkmark	\checkmark		LLaMA	Advanced	COH/INF/ACC/COM
INSTRUCTSCORE (Xu et al., 2023)	\checkmark	*	*	*	*	*	*	\checkmark	LLaMA	Advanced	NONE
Prometheus (Kim et al., 2023a)	*	*	*		*	*	\checkmark		LLaMA-2	Likert/Pairv	wise NONE
CritiqueLLM (Ke et al., 2023)	*	*	*		*	*	\checkmark		ChatGLM	Likert	NONE

Table 2: Automatic metrics proposed (\checkmark) and adopted (*) for various NLG tasks. **REF** indicate the method is source context-free. **MT**: Machine Translation, **TS**: Text Summarization, **DG**: Dialogue Generation, **IC**: Image Captioning, **D2T**: Data-to-Text, **SG**: Story Generation, **GE**: General Generation. We adopted the evaluation aspects for different tasks from Fu et al. (2023). Specifically, for each evaluation aspect, *CON*: consistency, *COH*: coherence, *REL*: relevance, *FLU*: fluency, *INF*: informativeness, *COV*: semantic coverage, *ADE*: adequacy, *NAT*: naturalness, *ENG*: engagement, *GRO*: groundness, *GRAM*: grammaticality, *LIK*: likability, *PER*: personalization, *QUA*: quality, *INT*: interest, *USE*: usefulness, *HARM*: harmlessness, *ACC*: accuracy, *FAC*: factuality, *ADA*: adaptability, *SUR*: surprise, *CHA*: character, *END*: ending, *FEA*: feasibility, *CRE*: creativity, *THO*: thoroughness, *STR*: structure, *LAY*: layout, *CLA*: clarity, *COM*: comprehensiveness, *SPE*: specificity, *COR*: correctness, *SEM*: semantic appropriateness. *NONE* means that the method does not specify any aspects and gives an overall evaluation. The detailed explanation of most evaluation aspect can be found in Fu et al. (2023).

unique perspective by framing the evaluation task as a conditional generation task. In this context, the generative likelihood of the produced text is calculated, serving as the score indicative of text quality, as illustrated in the second row of Table 1. Yuan et al. (2021) first leveraged BART (Lewis et al., 2019) as an evaluator to compute the probability of the generated text based on source or reference text across diverse evaluation aspects in machine translation, text summarization, and data-to-text tasks. Expanding on this methodology, Fu et al. (2023) devised prompts that encompass task descriptions and definitions of evaluation aspects, utilized to instruct an LLM-based evaluator to calculate the generation probability of generated text. In contrast to the conventional use of generation probability as a quality score, Jia et al. (2023) calculated the three probability changes as the reference-free metric to evaluate the faithfulness of the generated summary. These changes include the transition from generating a summary with the source document to directly generating a summary, altering the position of the source and summary, and the shift from generating a summary with the source document to generating a summary with a specific piece of a prefix.

Likert-Style Evaluation. Inspired by the human annotation process, several studies employ LLM evaluators to assess the quality levels of generated texts, where these evaluators produce ratings or quality labels based on a likert-style scale (Bai et al., 2023; Gao et al., 2023; Gilardi et al., 2023; Huang et al., 2023; Zhao et al., 2023; Wu et al., 2023b; Luo et al., 2023; Zheng et al., 2023; Zhuo, 2023; Sottana et al., 2023; Skopek et al., 2023). A representative likert-style prompt is depicted in the third line of Table 1. For instance, Chiang and Lee (2023) provided LLM evaluators with the same evaluation instructions as human annotators, prompting them to rate the quality of generated texts using a 5-point likert scale. Meanwhile, Gao et al. (2023) instructed ChatGPT to rate modelgenerated summarizations across multiple evaluation aspects, such as relevance, faithfulness, fluency, and coherence, using a scale ranging from 1 (worst) to 5 (best) based on the provided source document. In a similar vein, Ostheimer et al. (2023) designed multiple prompts, each guiding the LLM evaluator to assess a specific evaluation aspect of a text style transfer task. By comparing the transferred text with the source text, the LLM evaluator generates a discrete scale ranging from 1 to 5 to represent the quality of the transferred text. This approach exemplifies the adaptability of likert-style prompts in capturing diverse dimensions of text quality through LLM evaluations.

Yue et al. (2023) proposed to utilize LLM evaluator to evaluate the attribution capabilities of the generative models which judges if the generated statement is thoroughly supported by the referenced source. This work designs three categories of quality labels, including attributable, extrapolatory, and contradictory, and prompts the LLM evaluator with explicit instructions that include definitions of labels. Liu et al. (2023f) utilized LLMs to draft, filter, and refine comprehensive evaluation criteria as score instructions, which achieves more consistent evaluation results with human annotators when evaluating text summarization, data-to-text generation and hallucination tasks.

Pairwise Evaluation. Compared with utilizing LLM evaluators to individually evaluate the quality of generated texts through numerical scores or likert-style rating, another way of using LLM for evaluation is to explicitly compare with other generated text and decide which one is superior (Bai et al., 2023; Ji et al., 2023). A representative prompt is shown in the last row of Table 1. Wang et al. (2023c) utilized LLM evaluator to obtain evaluation result of two model-generated responses for one given query. This method proposes multiple evidence and balanced position calibration, and seeks assistance from human annotators when the quality of two texts is close to avoid the impact of the order of response pairs in the prompt on evaluation results. Wang et al. (2023e) introduced a reference-free personalized text generation evaluation framework that prompts LLM evaluator to perform pairwise comparisons between the generated text pairs in three essential aspects: personalization, quality, and relevance of the generated text through providing a detailed explanation of its judgment.

Ensemble Evaluation. As the actual evaluation process often involves collaborative evaluation by multiple human annotators, some works utilize multiple LLM evaluators with different base models or prompts and allow them to evaluate the quality of generated text from different perspectives, as shown in Figure 5. Wu et al. (2023a) set multiple roles for the LLM to evaluate the quality of the generated summary by comparing it with the reference one on both subjective and objective dimensions. This work generates dynamic role profiles according to input texts and synthesizes the results of multiple roles as the final evaluation result. Li et al. (2023c) utilized multiple LLM evaluators to conduct a pairwise evaluation for the model-generated responses by performing multiple rounds of discussions on the comparison results to reach a mutual agreement on the pairwise scoring. Similarly, Zhang et al. (2023b) proposed to set up LLM evaluators as multiple-layer neural network structures. The bottom evaluators obtain the evaluation result of model-generated responses from a specific evaluation perspective. The upper evaluators receive all evaluation information from the previous layer and discuss it with each other to obtain a more comprehensive evaluation result. Besides, Chan et al.



Figure 4: A example of fine-grained evaluation inspired by Jiang et al. (2023).

(2023) designed diverse communication strategies with various role prompts during collaborative discussions to evaluate pairwise generated responses.

Advanced Evaluation. Some recent works investigate advanced evaluation techniques aimed at achieving more thorough and nuanced assessment outcomes by leveraging chain-of-thought, incontext learning capabilities, fine-grained analysis, etc. A representative fine-grained evaluation method is shown in Figure 4. Liu et al. (2023c) utilized LLMs with chain-of-thought (CoT) prompting and a form-filling paradigm to evaluate the quality of generated texts across various NLG tasks. Min et al. (2023) proposed a find-grained evaluation schema that first extracts a series of atomic facts from the LLM-generated long text, and then utilizes LLM evaluator to validate each atomic fact with the given knowledge source. Lu et al. (2023) proposed a new prompting method called Error Analysis Prompting (EAPrompt) that combines CoT to prompt the LLM evaluator to analyze different types of pre-defined errors (e.g., major and minor errors) in the generated translation based on the given source text and reference translation, and then measures the quality of a generated translation with the previous error analysis. To enhance and improve the robustness of LLM-based evaluators, Hasanbeig et al. (2023) proposed ALLURE, a systematic protocol for auditing and improving LLMbased evaluation with iterative in-context-learning. Considering that the evaluation with a single or few references may not accurately reflect the quality of the model's hypotheses, Tang et al. (2023) leveraged LLMs to paraphrase a single reference into multiple high-quality ones in diverse expressions, which enhances various evaluation methods on MT, TS, and caption tasks. To further task advantages



Figure 5: A example of ensemble evaluation inspired by Li et al. (2023c).

of the in-context learning capability of LLMs, Liu et al. (2023f) proposed AUTOCALIBRATE to automatically align and calibrate an LLM-based evaluator through incorporating the mined and calibrated rubrics into scoring instructions.

3.2 Tuning-based Evaluation

Recently, researchers increasingly turn their attention towards fine-tuning open-source language models (e.g., LLaMA), in lieu of traditional closedbased LLMs (e.g., ChatGPT and GPT-4). This shift is propelled by a thorough exploration of key perspectives, including the expenses associated with API calls, the robustness of prompting, and the pivotal consideration of domain adaptability.

In contrast to closed-based models that invariably demand expensive API calls for each evaluation instance, the fine-tuning of smaller opensource LLMs provides a cost-effective alternative. This approach empowers researchers to evaluate their models on specific tasks without incurring the financial burden associated with extensive API usage. Additionally, the process of prompting LLMs for NLG evaluation requires meticulous crafting of prompts, with variations potentially resulting in significant differences in outcomes. Furthermore, the consideration of domain adaptability underscores the evolving landscape of NLG evaluation. Finetuning open-source LLMs affords researchers the flexibility to tailor models to diverse domains, transcending the limitations imposed by closed-based models confined to specific niches.

Typically, tuning-based methods construct evaluation data manually (Zheng et al., 2023) or with the assistance of advanced LLMs (e.g., GPT-4) (Xu et al., 2024), followed by performing supervised tuning. Similar to prompting-based evaluation, tuning-based methods can also be categorized into various types based on their scoring protocol, such as *likert-style evaluation*, *probability-based evaluation* and *pairwise evaluation*. In addition, based on the output explanations in supervised fine-tuning, these methods can be further divided into *holistic evaluation* or *error-oriented evaluation*. We will begin by introducing various types of scoring protocols and subsequently provide a summary of two output explanations in the final advance evaluation.

Likert-Style Evaluation. Some works tune LLMs to provide quality ratings or labels for generated texts. Gekhman et al. (2023) employed FLAN-PaLM 540B (Chung et al., 2022) to annotate the quality of real model-generated summaries and utilized these annotated data as training data to tune a light-weight LLM (e.g., T5-11B) as a factual consistency summary evaluator, which predicts "1" if the summary demonstrates factual consistency and "0" otherwise. Yue et al. (2023) reused and repurposed the existing fact-checking, NLI, and summarization tasks datasets and obtained simulated data from open-domain QA datasets to tune lightweight LLMs for attribution evaluation, which generates attributable, extrapolatory or contradictory labels for the generated answer with given query and reference documents. Li et al. (2023a) created a dataset containing multiple scenarios and used GPT-4 (OpenAI, 2023) to generate evaluation judgments for each scenario as supervision signals to tune LLaMA as a generative evaluator, which can output overall quality rating for individual LLM-generated response in various scenarios. Wang et al. (2023a) repurposed existing datasets with proper anonymization and new personalized labels to tune LLaMA2 (Touvron et al., 2023) as a personalized story evaluation model which provides personalized evaluation for generated texts through outputting a grade in [1, 10] and detailed reviews. Kim et al. (2023a) prompted GPT-4 to construct training data, including reference answers and crafted diverse customized score rubrics, and used them to tune LLaMA to evaluate modelgenerated responses of given instruction, which is generalized to realistic user demands. Ke et al. (2023) instructed GPT-4 to collect referenced and reference-free training data with dialogue-based prompting, utilized to tune LLMs for evaluating the alignment of model-generated texts with human instructions through generating scores and explanations. (Liu et al., 2023a) constructed a referencefree instruction-tuning dataset tailored for multiaspect evaluation across summarization, dialogue and data-to-text tasks. Considering that there is an internal correlation between the evaluation aspects, this work tuned with auxiliary aspects additionally on diverse evaluation task forms. During inference, this work combined auxiliary and target aspects and predicted either the "Yes" or "No" label to judge whether the generated text satisfied the target aspect and compute the evaluation score.

Probability-based Evaluation. Some works train generative LLMs to calculate the generation probability of generated texts to evaluate text quality. For example, Thompson and Post (2020) trained a transformer as a multilingual reference-to-candidate paraphraser to obtain the generated probability of model-generated translation based on their reference texts. Qin et al. (2022) tuned the T5 model in the generative and discriminative fashion, and used the probability of generating a text as the quality score.

Pairwise Evaluation. There are also some works tuning LLMs for comparison between generated text pairs. Wang et al. (2023f) collected response pairs from LLMs and asked GPT-3.5 to generate output judgments, utilized which to tune LLaMA-7B to evaluate a pair of model-generated responses with the given query, accompanied by a concise description of the evaluation procedure. Zheng et al. (2023) performed fine-tuning on Vicuna using a human votes dataset from Chatbot Arena to pairwise evaluate two answers with the given query.

Advanced Evaluation. Nearly all tuning-based evaluators are trained to emulate evaluate behavior (the score or explanations) produced by strong closed models like GPT-4 or ChatGPT. In the context of supervised fine-tuning, the majority of studies gravitate towards holistic evaluation (Li et al., 2023a; Wang et al., 2023f,a; Kim et al., 2023a), which involves a comprehensive assessment of the generated content, providing an overarching explanation for the assigned score. It takes into account a diverse range of factors, including coherence, relevance, and fluency, to offer a holistic understanding of the quality of the hypothesis text. Besides, some studies explore error-oriented evaluation which focused on examining and explaining the specific errors in the hypothesis text, offering insights into why a particular score is derived. This category delves into the fine-grained aspects of generated content to identify and justify evaluation outcomes. For instance, Yue et al. (2023) first defined different types of attribution errors, and then explored prompting LLMs or fine-tuning smaller LLMs on simulated and repurposed data from related tasks such as question answering (QA), fact-checking, natural language inference (NLI), and summarization. Xu et al. (2023) utilized GPT-4 to construct fine-grained analysis data to tune LLaMA to generate error analysis for generated text compared with reference text, after which this work utilized real model-generated response-reference pairs to refine and self-train evaluator. Furthermore, Jiang et al. (2023) sampled data from diverse text generation datasets, including summarization, translation and data2text, whose system outputs included real-world system output and GPT-4 synthesis, and prompted GPT-4 to curate error analysis to tune LLaMA for fine-grained evaluation.

4 Benchmarks and Tasks

LLM-based evaluators have found application across various NLG tasks. Simultaneously, a multitude of existing and recently introduced metaevaluation benchmarks serve the purpose of validating the efficacy of these evaluators. These benchmarks incorporate human annotations gauging the quality of generated text, and evaluating the degree of concurrence between automatic evaluators and human preferences. Categorized based on the tasks involved, these benchmarks can be classified into single-scenario examples, such as machine translation and summarization, as well as multiscenario benchmarks. This section will provide an overview of these NLG tasks and their associated meta-evaluation benchmarks.

Machine Translation (MT). MT task is centered around converting a sentence or document from a source language into a target language while preserving the same semantic meaning. The Annual WMT Metrics Shared tasks (Mathur et al., 2020; Freitag et al., 2021b, 2022) annually introduce a set of benchmarks encompassing model-generated translations, source text, reference text, and human judgment across multiple languages, such as English to German, English to Russian, among others. These benchmarks provide a valuable resource for evaluating the correlation between automatic evaluators and human judgment. Simultaneously, Freitag et al. (2021a) curated and annotated outputs from 10 translated systems for both English-to-German and Chinese-to-English translation pairs

in the WMT 2020 news translation task (Barrault et al., 2020). Employing professionals and crowd workers as annotators, they assigned scalar ratings on a 7-point scale to each translation, utilizing multi-dimensional quality metrics scoring.

Text Summarizing (TS). TS involves generating a concise and coherent summary of a given piece of text while capturing its essential meaning. There are many meta-evaluation benchmarks are proposed (Grusky et al., 2018; Gliwa et al., 2019; Bhandari et al., 2020; Wang et al., 2020b; Pagnoni et al., 2021; Laban et al., 2022; Skopek et al., 2023). One of the widely used benchmarks is SummEval (Fabbri et al., 2021b). This benchmark includes summaries generated by 16 models from 100 source news articles randomly sampled from the CNN/DailyMail test set (Hermann et al., 2015), and each summary underwent annotation by five separate crowd-sourced workers and three independent experts on a Likert scale from 1 to 5 along four dimensions: coherence, consistency, fluency and relevance. In addition, Shen and Wan (2023) presented a meta-evaluation benchmark for opinion summarization tasks, including human judgments and outputs from 14 opinion summarization models over four dimensions: aspect relevance, selfcoherence, sentiment consistency and readability, where opinion summarization task focuses on extracting opinions from a large number of reviews.

Dialogue Generation (DG). DG task aims to generate human-like responses in the context of a conversation, including open-domain and taskoriented dialogue generation tasks. The modelgenerated dialogue should be natural and interesting, while also being consistent with the context. Mehri and Eskenazi (2020b) performed human annotations across two open-domain dialog corpora Topical-Chat (Gopalakrishnan et al., 2019) and PersonaChat (Zhang et al., 2018). For each dataset, 60 dialogue contexts are sampled with six responses per context for Topical-Chat and five responses for PersonaChat, where each response is generated from dialogue systems and human outputs. Each response is scored from 6 dimensions including naturalness, coherence, engagingness, groundedness, understandability and overall quality. Mehri and Eskenazi (2020a) sampled and annotated a subset from a set of conversations between a human and another human or two open-domain dialog systems (Adiwardana et al., 2020). Turn-level and

dialog-level human judgment are performed, respectively, for each sampled conversation on eighteen dialog quality dimensions.

Image Caption (IC). The task involves generating textual descriptions or captions for images. Meta-evaluation benchmarks of image caption contain human annotations for image-textual pairs (Aditya et al., 2015; Vedantam et al., 2015). For example, the commonly used Flickr 8k dataset (Hodosh et al., 2013) collects two sets of human annotations. One set includes 17K expert judgments annotation, which asks human experts to rate the image-caption pairs with scores ranging from 1 to 4, and another set includes 145K binary quality judgments gathered from CrowdFlower for each image-caption pair, which decide whether a caption describes the corresponding image or not. Considering some NLG evaluators can only handle textual modal information, some meta-evaluation benchmarks also include a reference caption for each image. Cui et al. (2018) collected human judgments for twelve submission entries from the 2015 COCO Captioning Challenge on the COCO validation set (Vinyals et al., 2016), where each system generates one caption for each image, and each image has five reference captions.

Data-to-Text (D2T). D2T task involves generating fluent and factual human-readable text from structured data. Mairesse et al. (2010) proposed BAGEL, which contains 202 samples about restaurants in Cambridge, where each sample includes structured information context with corresponding generated texts, references and human judgments. Wen et al. (2015) further proposed SFRES and SFHOT, which contain 581 samples of restaurants and 398 samples of hotels in San Francisco, respectively. The human judgments in these benchmarks focus on informativeness, naturalness and overall quality of generated texts. WebNLG+ Shared Tasks (Castro Ferreira et al., 2020) also publish WebNLG dataset annually, which contains Wikipedia triples with corresponding humanannotated texts.

Story Generation (SG). The task involves creating coherent and contextually relevant narratives or stories with the given beginning of a story or writing requirement. Most meta-evaluation benchmarks of story generation always contain stories and corresponding manually annotated judgment scores (Guan et al., 2021; Chen et al., 2022). Be-

sides, Wang et al. (2023a) created two personalized story evaluation benchmarks denoted as Per-MPST and Per-DOC to evaluate the quality of generated stories with a given evaluator persona. This work repurposes existing datasets (Kar et al., 2018; Yang et al., 2023b) through anonymizing and summarizing. Both them view multiple reviews by the same reviewer as an implicit persona preference and provide personalized human judgements for each generated story.

General Generation (GE). As LLMs have been increasingly used in general NLG tasks, such as math, reason, dialogue and open-ended QA, etc., LLM evaluators have proposed to effectively evaluate the quality of the model-generated texts across multiple scenario (Kim et al., 2023a; Ke et al., 2023). Accordingly, there are many multi-scenario meta-evaluation benchmarks are proposed (Wang et al., 2023c; Zheng et al., 2023; Wang et al., 2023d; Yue et al., 2023). Typically, Zhang et al. (2023b) sampled 2,553 evaluation samples, including instructions and model-generated response pairs with corresponding human-annotated preference labels from multiple task datasets such as dialogue, opendomain QA, and programming. Further, Zeng et al. (2023) proposed a benchmark that includes 419 evaluation samples and can be categorized into two parts: NATURAL and ADVERSARIAL sets. The former collects and filters instances from existing human-preference benchmarks to ensure that each instance has an objective preference. The latter includes the adversarial instances created by authors that go against instruction but have good superficial qualities and are challenging for evaluators. Liu et al. (2023b) sampled 400 evaluation instances, including Chinese queries, corresponding references and model-generated answers from ALIGNBENCH across extensive task categories, such as open-ended questions, writing ability, logical reasoning, etc. Then the authors assigned human annotators to judge ratings for each instance to verify the agreement of LLM-based evaluators with human judging.

5 Comparison with Traditional Evaluators

Qualitative Comparison Traditional evaluation metrics (e.g., BLEU (Papineni et al., 2002) and ROUGE) focus on exacting n-gram matches, which penalizes semantically correct but lexically different hypotheses. These methods are simple and fast

Metrics	Sup		S	ummEv	al		Topical-Chat					WMT22		
witting	Sup	СОН	CON	FLU	REL	Avg	NAT	COH	ENG	GRO	Avg	En-De	En-Ru	Zh-Eu
					Tradit	ional M	etrics (W	ord Ove	rlap)					
ROUGE-1		0.167	0.160	0.115	0.326	0.192	0.158	0.206	0.319	0.264	0.233	-	-	-
ROUGE-2		0.184	0.187	0.159	0.290	0.205	0.168	0.247	0.337	0.311	0.266	-	-	-
ROUGE-L		0.128	0.115	0.105	0.311	0.165	0.145	0.205	0.306	0.293	0.237	-	-	-
BLEU		-	-	-	-	-	0.175	0.235	0.316	0.310	0.259	0.169	0.140	0.145
						BERT	-based M	letrics						
BERTScore		0.284	0.110	0.193	0.312	0.225	0.209	0.233	0.335	0.317	0.273	0.232	0.192	0.316
BLEURT	\checkmark	-	-	-	-	-	-	-	-	-	-	0.344	0.359	0.361
BARTScore	\checkmark	0.448	0.382	0.356	0.356	0.385	-0.053	-0.079	-0.084	-0.197	-0.103	-	-	0.220
UniTE	\checkmark	-	-	-	-	-	-	-	-	-	-	0.369	0.378	0.357
UniEval	\checkmark	0.575	0.446	0.449	0.426	0.474	0.450	0.616	0.615	0.590	0.568	-	-	-
						LLM-	based M	etrics						
GPTScore		0.434	0.449	0.403	0.381	0.417	-	-	-	-	-	-	-	0.187
CHATGPT(DA)		0.451	0.432	0.380	0.439	0.425	0.474	0.527	0.599	0.576	0.544	0.306	0.332	0.371
G-Eval		0.582	0.507	0.455	0.547	0.514	0.607	0.590	0.605	0.536	0.590	-	-	-
Embed Llama		-	-	-	-	-	-	-	-	-	-	0.400	0.227	0.217
X-Eval	\checkmark	0.530	0.428	0.461	0.500	0.480	0.478	0.622	0.593	0.728	0.605	-	-	-

Table 3: Performance of traditional and LLM-based metrics on Text Summarizing (SummEval), Dialogue Generation (Topical-Chat) and Machine Translation (WMT22) tasks. We demonstrate the sample-level Spearman correlations on SummEval and Topical-Chat benchmarks and the segment-level Kendall-Tau correlations on WMT22 benchmarks respectively. **Sup** indicates the metric is supervised. The specific representation of the evaluation aspects (COH/CON/FLU/REL/NAT/ENG/GRO) is shown in Table 2.

but not robust to paraphrasing. BERTScore (Zhang et al., 2020) measures quality through semantic similarity based on BERT contextual embeddings, effectively handling paraphrases and synonyms. However, such matching-based evaluators depend on the quality of the pre-trained embeddings, may struggle with very fine-grained semantic distinctions, and neglect the overall semantics of the hypotheses and references. Additionally, neither metric accounts for fluency or readability during evaluation and both still rely on reference texts.

In contrast, LLMs have a strong capability for language understanding and generation, which supports evaluating quality without needing references. They can adapt to various domains and languages, making them suitable for a wide range of NLG tasks without requiring task-specific feature engineering. LLMs also provide more nuanced evaluation criteria beyond traditional metrics, such as semantic coherence, fluency and possible explanations. However, LLM-based methods are computationally more intensive due to their vast architectures. Additionally, prompting LLMs for NLG evaluation requires careful crafting of prompts. Variations in these prompts can lead to substantial differences in evaluation outcomes, as indicated in (Gao et al., 2023). Section 6 summarizes more open problems of LLM-based metrics.

Performance Comparison Table 3 summarizes the performance of both traditional word-overlap metrics, BERT-based metrics and recent LLMbased metrics on representative benchmarks such as SummEval, WMT, and Topical-Chat. We can easy to observe that the latter two metrics generally perform better than word-overlap metrics. Despite not being fine-tuned, the most competitive LLMbased methods (e.g., G-Eval for summarization and CHATGPT(DA) for machine translation) generally achieve a higher correlation with all traditional metrics, whether for unsupervised or fine-tuned methods. These results reveal the strong capability of LLMs in language understanding, contextual analysis, coherence checking, and fluency assessment of generated text. Among the three tasks, the performance gap between LLM-based evaluators and traditional evaluators is not significant in the machine translation task. This phenomenon might be due to the limitations of LLM-based models in cross-lingual understanding. Additionally, according to the results of last row in the table, we can observe that the performance of different LLM-based metrics varies significantly, which implies their sensitivity to prompt crafting. In contrast, traditional unsupervised methods like ROUGE, BLEU, and BERTScore are more robust, although their overall performance is relatively worse.

Methods	Backbone	TS	DG
BLEU	-	<u>977.31</u>	2344.16
ROUGE	-	446.36	2379.24
BERTScore	BERT	37.64	42.37
ChatGPT(DA)	ChatGPT	1.94	1.87
G-Eval	GPT-4	1.51	1.40
TIGERScore	Llama	2.67	3.72

Table 4: Efficiency Comparison. We report the average number of texts evaluated per second for different metrics.

Efficiency Comparison Table 4 presents the average number of texts evaluated per second for different metrics in the SummEval (TS task) and Topical-chat (DG task) benchmarks. This comparison highlights the efficiency differences between traditional metrics and LLM-based metrics. Our tests were conducted on an NVIDIA A40 GPU. The results show that efficiency generally correlates with model size and traditional word-overlap metrics (e.g., BLEU and ROUGE) are significantly faster than other metrics. Specifically, LLM-based evaluators are about 200 to 400 times slower than traditional word-overlap metrics. However, their efficiency can be improved with advanced LM inference tools such as vLLM¹. While LLM-based evaluators are suitable for offline evaluation, they may not be feasible for online evaluation.

6 Challenges and Open Problems

This paper provides a comprehensive review of recent natural language generation evaluations based on LLMs, encompassing both prompt-based and tuning-based evaluation approaches. Despite significant efforts and notable achievements across various text generation benchmarks, several challenges in the field persist.

Bias of LLM-based Evaluators. The use of LLMs as evaluators inherently cast the text evaluation as a generation task. Consequently, when LLMs are employed in this evaluator role, they may carry over biases intrinsic to their function as generators. These biases may include social biases, such as stereotypes related to specific demographic identities (e.g., race, gender, religion, culture, and ideology) (Sheng et al., 2021). In addition to these general biases, LLMs-as-evaluators are subject to specific biases unique to their evaluative role. These include order bias, where preference

is given to options based on their sequence (Zheng et al., 2023; Wang et al., 2023c; Koo et al., 2023); egocentric bias, where a tendency exists to favor texts generated by the same LLM (Liu et al., 2023d; Koo et al., 2023); and length bias, which leads to a preference for longer or shorter texts (Zheng et al., 2023; Koo et al., 2023). Therefore, in leveraging LLMs for evaluation purposes, it is crucial to calibrate both the inherent biases of LLMs as well as those biases specific to their function as evaluators. This dual consideration is essential for the effective and fair use of LLMs in NLG evaluation tasks.

Robustness of LLM-based Evaluators. Most LLMs-based evaluation methods rely heavily on prompt engineering. However, the process of prompting LLMs for NLG evaluation demands careful and meticulous crafting of prompts. The variations in these prompts can potentially lead to substantial differences in the outcomes of the evaluation process. Some works have investigated the robustness of LLM-based evaluators by constructing adversarial datasets. These datasets are designed to test the evaluators' resilience by introducing false or off-topic information, thereby examining the impact of such distortions on their evaluative accuracy. Their findings shed light on the significant room for improvement in the robustness of LLM-based evaluators. For instance, Liu et al. (2023e) developed two adversarial meta-evaluation datasets for dialogue generation with adversarial instances inconsistent with gold references. Koo et al. (2023) introduced a benchmark containing two adversarial aspects: Distraction and Bandwagon Effect, which involve appending irrelevant information or fabricated statistics, such as a misleading majority preference, to the initial instructions. The results suggest a general lack of robustness in many LLMs under such adversarial conditions. The robustness of LLM-based evaluators emerges as a critical area of exploration, underscoring the need for further research to enhance their robustness in the face of challenging or misleading inputs.

Which came first, the chicken or the egg? LLM-based evaluators frequently utilize GPT-4 (Liu et al., 2023c; Xu et al., 2023; Zheng et al., 2023), owing to its status as one of the most advanced LLM (OpenAI, 2023). However, relying on GPT-4 for evaluation might lead to biased or skewed results, especially when evaluating outputs generated by itself or an equally powerful

¹ https://github.com/vllm-project/vllm

model (Bai et al., 2023; Zheng et al., 2023). The impartiality of such evaluations is questionable if the evaluator (LLM-as-evaluator) possesses capabilities comparable to the model being evaluated (LLM-as-generator). This is compounded by the egocentric bias of LLMs, including GPT-4, to exhibit biases like favoring their own generated responses (Bai et al., 2023). This scenario mirrors the chicken-and-egg dilemma: an LLM-based evaluator relies on a more powerful LLM, yet the development of a more powerful LLM depends on having a robust evaluator. To address this dilemma, a broader spectrum of evaluation methods is necessary, involving various benchmark (Srivastava et al., 2022; Liang et al., 2022), evaluation criteria (Sellam et al., 2020), and human feedback (Xu et al., 2023; Ouyang et al., 2022) to ensure more balanced and comprehensive assessments.

Domain-Specific Evaluation. LLMs have been prevalent across various domains, such as law (Cui et al., 2023a), medicine (Singhal et al., 2023), finance (Yang et al., 2023a), etc. However, most LLMs employed as evaluators are designed for general domains and are not specifically tailored to any particular field. This lack of specialization poses significant challenges. On one hand, these LLMs often lack the requisite domain-specific knowledge, making it difficult for them to accurately assess the correctness of content within specialized fields. On the other hand, the evaluation prompts need to be meticulously designed for different domains. This may involve tailoring the aspects of evaluation relevant to each field. For example, while evaluating legal documents, aspects such as legal accuracy and adherence to the judicial system are crucial (Cui et al., 2023b), which differ significantly from the aspects relevant in medical or financial texts. Therefore, to enhance the efficacy of LLMs as evaluators in specialized domains, there's a pressing need to develop models that are not only domain-aware but also equipped with the capability to evaluate based on domain-specific criteria.

Unified Evaluation. LLMs have been expanded w.r.t their broad capabilities beyond traditional single-task focuses, encompassing complex instructions like coding and open-ended real-world requirements (OpenAI, 2023; Significant Gravitas). Consequently, there is an increasing demand for more comprehensive and flexible evaluation methods. However, traditional evaluation methods and

most current LLM-based evaluators are limited to constrained tasks and evaluation aspects (cf. Table 2). Some promising attempts have been made in this direction. For instance, MT-Bench (Zheng et al., 2023) uses GPT-4 as an evaluator across multiple domains for multi-turn questions. Yet, this is too confined to a few evaluation aspects and limits dialogue to two turns only. Another model, Auto-J (Li et al., 2023b), approaches from a data construction perspective, training a 13B LLM on user queries and GPT-4 generated responses across a wide range of real-world scenarios. It accommodates diverse evaluation protocols and has been validated in 58 different scenarios, even outperforming many proprietary LLMs. In light of increasingly complex user queries, we advocate that developing a more unified and contemporaneous evaluation protocol is a promising direction. Additionally, constructing high-quality, comprehensive datasets to train unified models holds great potential. Such advancements could significantly contribute to more effective and universal evaluations of LLMs.

7 Conclusion

In this paper, we have meticulously surveyed the role of LLMs in the evaluation of NLG. Our comprehensive taxonomy classifies works along three primary dimensions: evaluation function, evaluation references and evaluation task. This framework enabled us to systematically categorize and understand LLM-based evaluation methodologies. We delved into various LLM-based approaches, scrutinizing their strengths and comparing their differences. Additionally, we summarized prevalent meta-evaluation benchmarks for NLG evaluation. Throughout our study, we highlighted both the advancements and the prevailing challenges in this rapidly evolving field. While LLMs offer groundbreaking potential in evaluating NLG outputs, there still remain unresolved issues that require attention, including bias, robustness, the integration of hybrid evaluation methods, and the need for domainspecific and unified evaluation within LLM-based evaluators. We anticipate that addressing these challenges will pave the way for more general, effective, and reliable NLG evaluation techniques. Such advancements would contribute significantly to the progression of both NLG evaluation and the broader application of LLMs.

References

- Somak Aditya, Yezhou Yang, Chitta Baral, Cornelia Fermuller, and Yiannis Aloimonos. 2015. From images to sentences through scene description graphs using commonsense reasoning and knowledge. *arXiv* preprint arXiv:1511.03292.
- Daniel Adiwardana, Minh-Thang Luong, David R So, Jamie Hall, Noah Fiedel, Romal Thoppilan, Zi Yang, Apoorv Kulshreshtha, Gaurav Nemade, Yifeng Lu, et al. 2020. Towards a human-like open-domain chatbot. arXiv preprint arXiv:2001.09977.
- Yushi Bai, Jiahao Ying, Yixin Cao, Xin Lv, Yuze He, Xiaozhi Wang, Jifan Yu, Kaisheng Zeng, Yijia Xiao, Haozhe Lyu, et al. 2023. Benchmarking foundation models with language-model-as-an-examiner. arXiv preprint arXiv:2306.04181.
- Ankur Bapna, Naveen Arivazhagan, and Orhan Firat. 2019. Simple, scalable adaptation for neural machine translation. *arXiv preprint arXiv:1909.08478*.
- Loïc Barrault, Magdalena Biesialska, Ondřej Bojar, Marta R. Costa-jussà, Christian Federmann, Yvette Graham, Roman Grundkiewicz, Barry Haddow, Matthias Huck, Eric Joanis, Tom Kocmi, Philipp Koehn, Chi-kiu Lo, Nikola Ljubešić, Christof Monz, Makoto Morishita, Masaaki Nagata, Toshiaki Nakazawa, Santanu Pal, Matt Post, and Marcos Zampieri. 2020. Findings of the 2020 conference on machine translation (WMT20). In *Proceedings of the Fifth Conference on Machine Translation*, pages 1–55, Online. Association for Computational Linguistics.
- Manik Bhandari, Pranav Narayan Gour, Atabak Ashfaq, Pengfei Liu, and Graham Neubig. 2020. Reevaluating evaluation in text summarization. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9347–9359, Online. Association for Computational Linguistics.
- Thiago Castro Ferreira, Claire Gardent, Nikolai Ilinykh, Chris van der Lee, Simon Mille, Diego Moussallem, and Anastasia Shimorina. 2020. The 2020 bilingual, bi-directional WebNLG+ shared task: Overview and evaluation results (WebNLG+ 2020). In Proceedings of the 3rd International Workshop on Natural Language Generation from the Semantic Web (WebNLG+), pages 55–76, Dublin, Ireland (Virtual). Association for Computational Linguistics.
- Asli Celikyilmaz, Elizabeth Clark, and Jianfeng Gao. 2020. Evaluation of text generation: A survey. *arXiv* preprint arXiv:2006.14799.
- Chi-Min Chan, Weize Chen, Yusheng Su, Jianxuan Yu, Wei Xue, Shanghang Zhang, Jie Fu, and Zhiyuan Liu. 2023. Chateval: Towards better llm-based evaluators through multi-agent debate. *arXiv preprint arXiv:2308.07201*.

- Hong Chen, Duc Vo, Hiroya Takamura, Yusuke Miyao, and Hideki Nakayama. 2022. StoryER: Automatic story evaluation via ranking, rating and reasoning. In Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing, pages 1739–1753, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.
- Yi Chen, Rui Wang, Haiyun Jiang, Shuming Shi, and Ruifeng Xu. 2023. Exploring the use of large language models for reference-free text quality evaluation: A preliminary empirical study. *arXiv preprint arXiv:2304.00723*.
- Cheng-Han Chiang and Hung-yi Lee. 2023. Can large language models be an alternative to human evaluations? In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 15607–15631, Toronto, Canada. Association for Computational Linguistics.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Yunxuan Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*.
- Jiaxi Cui, Zongjian Li, Yang Yan, Bohua Chen, and Li Yuan. 2023a. Chatlaw: Open-source legal large language model with integrated external knowledge bases. *arXiv preprint arXiv:2306.16092*.
- Junyun Cui, Xiaoyu Shen, and Shaochun Wen. 2023b. A survey on legal judgment prediction: Datasets, metrics, models and challenges. *IEEE Access*.
- Yin Cui, Guandao Yang, Andreas Veit, Xun Huang, and Serge Belongie. 2018. Learning to evaluate image captioning. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5804–5812.
- Sören Dreano, Derek Molloy, and Noel Murphy. 2023. Embed_Llama: Using LLM embeddings for the metrics shared task. In *Proceedings of the Eighth Conference on Machine Translation*, pages 738–745, Singapore. Association for Computational Linguistics.
- Alexander R. Fabbri, Wojciech Kryściński, Bryan Mc-Cann, Caiming Xiong, Richard Socher, and Dragomir Radev. 2021a. SummEval: Re-evaluating summarization evaluation. *Transactions of the Association* for Computational Linguistics, 9:391–409.
- Alexander R. Fabbri, Wojciech Kryściński, Bryan Mc-Cann, Caiming Xiong, Richard Socher, and Dragomir Radev. 2021b. SummEval: Re-evaluating summarization evaluation. *Transactions of the Association* for Computational Linguistics, 9:391–409.
- Angela Fan, Mike Lewis, and Yann Dauphin. 2018. Hierarchical neural story generation. In Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 889–898, Melbourne, Australia. Association for Computational Linguistics.

- Akhbardeh Farhad, Arkhangorodsky Arkady, Biesialska Magdalena, Bojar Ondřej, Chatterjee Rajen, Chaudhary Vishrav, Marta R Costa-jussa, España-Bonet Cristina, Fan Angela, Federmann Christian, et al. 2021. Findings of the 2021 conference on machine translation (wmt21). In *Proceedings of the Sixth Conference on Machine Translation*, pages 1–88. Association for Computational Linguistics.
- Markus Freitag, George Foster, David Grangier, Viresh Ratnakar, Qijun Tan, and Wolfgang Macherey. 2021a. Experts, errors, and context: A large-scale study of human evaluation for machine translation. *Transactions of the Association for Computational Linguistics*, 9:1460–1474.
- Markus Freitag, David Grangier, and Isaac Caswell. 2020. BLEU might be guilty but references are not innocent. In *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 61–71, Online. Association for Computational Linguistics.
- Markus Freitag, Ricardo Rei, Nitika Mathur, Chi-kiu Lo, Craig Stewart, Eleftherios Avramidis, Tom Kocmi, George Foster, Alon Lavie, and André F. T. Martins. 2022. Results of WMT22 metrics shared task: Stop using BLEU – neural metrics are better and more robust. In *Proceedings of the Seventh Conference* on Machine Translation (WMT), pages 46–68, Abu Dhabi, United Arab Emirates (Hybrid). Association for Computational Linguistics.
- Markus Freitag, Ricardo Rei, Nitika Mathur, Chi-kiu Lo, Craig Stewart, George Foster, Alon Lavie, and Ondřej Bojar. 2021b. Results of the WMT21 metrics shared task: Evaluating metrics with expert-based human evaluations on TED and news domain. In *Proceedings of the Sixth Conference on Machine Translation*, pages 733–774, Online. Association for Computational Linguistics.
- Jinlan Fu, See-Kiong Ng, Zhengbao Jiang, and Pengfei Liu. 2023. Gptscore: Evaluate as you desire. arXiv preprint arXiv:2302.04166.
- Mingqi Gao, Jie Ruan, Renliang Sun, Xunjian Yin, Shiping Yang, and Xiaojun Wan. 2023. Human-like summarization evaluation with chatgpt. *arXiv preprint arXiv:2304.02554*.
- Zorik Gekhman, Jonathan Herzig, Roee Aharoni, Chen Elkind, and Idan Szpektor. 2023. Trueteacher: Learning factual consistency evaluation with large language models. *arXiv preprint arXiv:2305.11171*.
- Fabrizio Gilardi, Meysam Alizadeh, and Maël Kubli. 2023. Chatgpt outperforms crowd-workers for textannotation tasks. arXiv preprint arXiv:2303.15056.
- Bogdan Gliwa, Iwona Mochol, Maciej Biesek, and Aleksander Wawer. 2019. Samsum corpus: A humanannotated dialogue dataset for abstractive summarization. *arXiv preprint arXiv:1911.12237*.

- Karthik Gopalakrishnan, Behnam Hedayatnia, Qinlang Chen, Anna Gottardi, Sanjeev Kwatra, Anu Venkatesh, Raefer Gabriel, and Dilek Z. Hakkani-Tür. 2019. Topical-chat: Towards knowledge-grounded open-domain conversations. ArXiv, abs/2308.11995.
- Rupali Goyal, Parteek Kumar, and VP Singh. 2023. A systematic survey on automated text generation tools and techniques: application, evaluation, and challenges. *Multimedia Tools and Applications*, pages 1–56.
- Max Grusky, Mor Naaman, and Yoav Artzi. 2018. Newsroom: A dataset of 1.3 million summaries with diverse extractive strategies. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 708–719, New Orleans, Louisiana. Association for Computational Linguistics.
- Jian Guan, Zhexin Zhang, Zhuoer Feng, Zitao Liu, Wenbiao Ding, Xiaoxi Mao, Changjie Fan, and Minlie Huang. 2021. OpenMEVA: A benchmark for evaluating open-ended story generation metrics. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 6394–6407, Online. Association for Computational Linguistics.
- Hosein Hasanbeig, Hiteshi Sharma, Leo Betthauser, Felipe Vieira Frujeri, and Ida Momennejad. 2023. Allure: A systematic protocol for auditing and improving llm-based evaluation of text using iterative incontext-learning. *arXiv preprint arXiv:2309.13701*.
- Karl Moritz Hermann, Tomas Kocisky, Edward Grefenstette, Lasse Espeholt, Will Kay, Mustafa Suleyman, and Phil Blunsom. 2015. Teaching machines to read and comprehend. *Advances in neural information processing systems*, 28.
- Micah Hodosh, Peter Young, and Julia Hockenmaier. 2013. Framing image description as a ranking task: Data, models and evaluation metrics. *Journal of Artificial Intelligence Research*, 47:853–899.
- Fan Huang, Haewoon Kwak, and Jisun An. 2023. Is chatgpt better than human annotators? potential and limitations of chatgpt in explaining implicit hate speech. *arXiv preprint arXiv:2302.07736*.
- Sameer Jain, Vaishakh Keshava, Swarnashree Mysore Sathyendra, Patrick Fernandes, Pengfei Liu, Graham Neubig, and Chunting Zhou. 2023. Multidimensional evaluation of text summarization with incontext learning. arXiv preprint arXiv:2306.01200.
- Yunjie Ji, Yan Gong, Yiping Peng, Chao Ni, Peiyan Sun, Dongyu Pan, Baochang Ma, and Xiangang Li. 2023. Exploring chatgpt's ability to rank content: A preliminary study on consistency with human preferences. arXiv preprint arXiv:2303.07610.

- Qi Jia, Siyu Ren, Yizhu Liu, and Kenny Q Zhu. 2023. Zero-shot faithfulness evaluation for text summarization with foundation language model. *arXiv preprint arXiv:2310.11648*.
- Dongfu Jiang, Yishan Li, Ge Zhang, Wenhao Huang, Bill Yuchen Lin, and Wenhu Chen. 2023. Tigerscore: Towards building explainable metric for all text generation tasks. *arXiv preprint arXiv:2310.00752*.
- Liqiang Jing, Xuemeng Song, Xuming Lin, Zhongzhou Zhao, Wei Zhou, and Liqiang Nie. 2023. Stylized data-to-text generation: A case study in the e-commerce domain. ACM Transactions on Information Systems.
- Katharina Kann, Abteen Ebrahimi, Joewie Koh, Shiran Dudy, and Alessandro Roncone. 2022. Open-domain dialogue generation: What we can do, cannot do, and should do next. In *Proceedings of the 4th Workshop* on NLP for Conversational AI, pages 148–165.
- Sudipta Kar, Suraj Maharjan, A. Pastor López-Monroy, and Thamar Solorio. 2018. MPST: A corpus of movie plot synopses with tags. In Proceedings of the Eleventh International Conference on Language Resources and Evaluation (LREC 2018), Miyazaki, Japan. European Language Resources Association (ELRA).
- Pei Ke, Bosi Wen, Zhuoer Feng, Xiao Liu, Xuanyu Lei, Jiale Cheng, Shengyuan Wang, Aohan Zeng, Yuxiao Dong, Hongning Wang, et al. 2023. Critiquellm: Scaling llm-as-critic for effective and explainable evaluation of large language model generation. *arXiv preprint arXiv:2311.18702*.
- Seungone Kim, Jamin Shin, Yejin Cho, Joel Jang, Shayne Longpre, Hwaran Lee, Sangdoo Yun, Seongjin Shin, Sungdong Kim, James Thorne, et al. 2023a. Prometheus: Inducing fine-grained evaluation capability in language models. *arXiv preprint arXiv:2310.08491*.
- Tae Soo Kim, Yoonjoo Lee, Jamin Shin, Young-Ho Kim, and Juho Kim. 2023b. Evallm: Interactive evaluation of large language model prompts on user-defined criteria. *arXiv preprint arXiv:2309.13633*.
- Tom Kocmi and Christian Federmann. 2023. Large language models are state-of-the-art evaluators of translation quality. In *Proceedings of the 24th Annual Conference of the European Association for Machine Translation*, pages 193–203, Tampere, Finland. European Association for Machine Translation.
- Ryan Koo, Minhwa Lee, Vipul Raheja, Jong Inn Park, Zae Myung Kim, and Dongyeop Kang. 2023. Benchmarking cognitive biases in large language models as evaluators. *arXiv preprint arXiv:2309.17012*.
- Philippe Laban, Tobias Schnabel, Paul N. Bennett, and Marti A. Hearst. 2022. SummaC: Re-visiting NLIbased models for inconsistency detection in summarization. *Transactions of the Association for Computational Linguistics*, 10:163–177.

- Christoph Leiter, Juri Opitz, Daniel Deutsch, Yang Gao, Rotem Dror, and Steffen Eger. 2023. The eval4nlp 2023 shared task on prompting large language models as explainable metrics. *arXiv preprint arXiv:2310.19792*.
- Mike Lewis, Yinhan Liu, Naman Goyal, Marjan Ghazvininejad, Abdelrahman Mohamed, Omer Levy, Ves Stoyanov, and Luke Zettlemoyer. 2019. Bart: Denoising sequence-to-sequence pre-training for natural language generation, translation, and comprehension. *arXiv preprint arXiv:1910.13461*.
- Junlong Li, Shichao Sun, Weizhe Yuan, Run-Ze Fan, Hai Zhao, and Pengfei Liu. 2023a. Generative judge for evaluating alignment. *arXiv preprint arXiv:2310.05470*.
- Junlong Li, Shichao Sun, Weizhe Yuan, Run-Ze Fan, Hai Zhao, and Pengfei Liu. 2023b. Generative judge for evaluating alignment. *CoRR*, abs/2310.05470.
- Ruosen Li, Teerth Patel, and Xinya Du. 2023c. Prd: Peer rank and discussion improve large language model based evaluations. *arXiv preprint arXiv:2307.02762*.
- Xuechen Li, Tianyi Zhang, Yann Dubois, Rohan Taori, Ishaan Gulrajani, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. 2023d. Alpacaeval: An automatic evaluator of instruction-following models. https://github.com/tatsu-lab/alpaca_eval.
- Percy Liang, Rishi Bommasani, Tony Lee, Dimitris Tsipras, Dilara Soylu, Michihiro Yasunaga, Yian Zhang, Deepak Narayanan, Yuhuai Wu, Ananya Kumar, et al. 2022. Holistic evaluation of language models. *arXiv preprint arXiv:2211.09110*.
- Chin-Yew Lin. 2004. ROUGE: A package for automatic evaluation of summaries. In *Text Summarization Branches Out*, pages 74–81, Barcelona, Spain. Association for Computational Linguistics.
- Yen-Ting Lin and Yun-Nung Chen. 2023. Llm-eval: Unified multi-dimensional automatic evaluation for open-domain conversations with large language models. arXiv preprint arXiv:2305.13711.
- Yupian Lin, Tong Ruan, Jingping Liu, and Haofen Wang. 2023. A survey on neural data-to-text generation. *IEEE Transactions on Knowledge and Data Engineering*.
- Chia-Wei Liu, Ryan Lowe, Iulian V Serban, Michael Noseworthy, Laurent Charlin, and Joelle Pineau. 2016. How not to evaluate your dialogue system: An empirical study of unsupervised evaluation metrics for dialogue response generation. arXiv preprint arXiv:1603.08023.
- Minqian Liu, Ying Shen, Zhiyang Xu, Yixin Cao, Eunah Cho, Vaibhav Kumar, Reza Ghanadan, and Lifu Huang. 2023a. X-eval: Generalizable multi-aspect text evaluation via augmented instruction tuning with auxiliary evaluation aspects. *arXiv preprint arXiv:2311.08788*.

- Xiao Liu, Xuanyu Lei, Shengyuan Wang, Yue Huang, Zhuoer Feng, Bosi Wen, Jiale Cheng, Pei Ke, Yifan Xu, Weng Lam Tam, et al. 2023b. Alignbench: Benchmarking chinese alignment of large language models. *arXiv preprint arXiv:2311.18743*.
- Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. 2023c. Gpteval: Nlg evaluation using gpt-4 with better human alignment. *arXiv preprint arXiv:2303.16634*.
- Yiqi Liu, Nafise Sadat Moosavi, and Chenghua Lin. 2023d. Llms as narcissistic evaluators: When ego inflates evaluation scores. *arXiv preprint arXiv:2311.09766*.
- Yixin Liu and Pengfei Liu. 2021. SimCLS: A simple framework for contrastive learning of abstractive summarization. In Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 1065–1072, Online. Association for Computational Linguistics.
- Yongkang Liu, Shi Feng, Daling Wang, Yifei Zhang, and Hinrich Schütze. 2023e. Evaluate what you can't evaluate: Unassessable generated responses quality. *arXiv preprint arXiv:2305.14658*.
- Yuxuan Liu, Tianchi Yang, Shaohan Huang, Zihan Zhang, Haizhen Huang, Furu Wei, Weiwei Deng, Feng Sun, and Qi Zhang. 2023f. Calibrating llmbased evaluator. arXiv preprint arXiv:2309.13308.
- Qingyu Lu, Baopu Qiu, Liang Ding, Liping Xie, and Dacheng Tao. 2023. Error analysis prompting enables human-like translation evaluation in large language models: A case study on chatgpt. *arXiv preprint arXiv:2303.13809*.
- Zheheng Luo, Qianqian Xie, and Sophia Ananiadou. 2023. Chatgpt as a factual inconsistency evaluator for abstractive text summarization. *arXiv preprint arXiv:2303.15621*.
- François Mairesse, Milica Gašić, Filip Jurčíček, Simon Keizer, Blaise Thomson, Kai Yu, and Steve Young. 2010. Phrase-based statistical language generation using graphical models and active learning. In Proceedings of the 48th Annual Meeting of the Association for Computational Linguistics, pages 1552– 1561, Uppsala, Sweden. Association for Computational Linguistics.
- Nitika Mathur, Johnny Wei, Markus Freitag, Qingsong Ma, and Ondřej Bojar. 2020. Results of the WMT20 metrics shared task. In *Proceedings of the Fifth Conference on Machine Translation*, pages 688–725, Online. Association for Computational Linguistics.
- Shikib Mehri and Maxine Eskenazi. 2020a. Unsupervised evaluation of interactive dialog with DialoGPT. In Proceedings of the 21th Annual Meeting of the Special Interest Group on Discourse and Dialogue, pages 225–235, 1st virtual meeting. Association for Computational Linguistics.

- Shikib Mehri and Maxine Eskenazi. 2020b. USR: An unsupervised and reference free evaluation metric for dialog generation. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 681–707, Online. Association for Computational Linguistics.
- Sewon Min, Kalpesh Krishna, Xinxi Lyu, Mike Lewis, Wen-tau Yih, Pang Wei Koh, Mohit Iyyer, Luke Zettlemoyer, and Hannaneh Hajishirzi. 2023. Factscore: Fine-grained atomic evaluation of factual precision in long form text generation. *arXiv preprint arXiv:2305.14251*.
- OpenAI. 2023. Gpt-4 technical report.
- Phil Ostheimer, Mayank Nagda, Marius Kloft, and Sophie Fellenz. 2023. Text style transfer evaluation using large language models. *arXiv preprint arXiv:2308.13577*.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in Neural Information Processing Systems*, 35:27730–27744.
- Artidoro Pagnoni, Vidhisha Balachandran, and Yulia Tsvetkov. 2021. Understanding factuality in abstractive summarization with FRANK: A benchmark for factuality metrics. In Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, pages 4812–4829, Online. Association for Computational Linguistics.
- Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics, pages 311–318, Philadelphia, Pennsylvania, USA. Association for Computational Linguistics.
- Yiwei Qin, Weizhe Yuan, Graham Neubig, and Pengfei Liu. 2022. T5score: Discriminative fine-tuning of generative evaluation metrics.
- Ricardo Rei, Craig Stewart, Ana C Farinha, and Alon Lavie. 2020. COMET: A neural framework for MT evaluation. In *Proceedings of the 2020 Conference* on Empirical Methods in Natural Language Processing (EMNLP), pages 2685–2702, Online. Association for Computational Linguistics.
- Ananya B Sai, Akash Kumar Mohankumar, and Mitesh M Khapra. 2022. A survey of evaluation metrics used for nlg systems. ACM Computing Surveys (CSUR), 55(2):1–39.
- Thibault Sellam, Dipanjan Das, and Ankur Parikh. 2020. BLEURT: Learning robust metrics for text generation. In Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pages 7881–7892, Online. Association for Computational Linguistics.

- Yuchen Shen and Xiaojun Wan. 2023. Opinsummeval: Revisiting automated evaluation for opinion summarization. *arXiv preprint arXiv:2310.18122*.
- Emily Sheng, Kai-Wei Chang, Prem Natarajan, and Nanyun Peng. 2021. Societal biases in language generation: Progress and challenges. In *Proceedings* of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 4275–4293.

Significant Gravitas. AutoGPT.

- Karan Singhal, Shekoofeh Azizi, Tao Tu, S Sara Mahdavi, Jason Wei, Hyung Won Chung, Nathan Scales, Ajay Tanwani, Heather Cole-Lewis, Stephen Pfohl, et al. 2023. Large language models encode clinical knowledge. *Nature*, 620(7972):172–180.
- Ondrej Skopek, Rahul Aralikatte, Sian Gooding, and Victor Carbune. 2023. Towards better evaluation of instruction-following: A case-study in summarization. *arXiv preprint arXiv:2310.08394*.
- Matthew Snover, Bonnie Dorr, Richard Schwartz, Linnea Micciulla, and John Makhoul. 2006. A study of translation edit rate with targeted human annotation. In *Proceedings of the 7th Conference of the Association for Machine Translation in the Americas: Technical Papers*, pages 223–231.
- Andrea Sottana, Bin Liang, Kai Zou, and Zheng Yuan. 2023. Evaluation metrics in the era of gpt-4: Reliably evaluating large language models on sequence to sequence tasks. arXiv preprint arXiv:2310.13800.
- Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. 2022. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *arXiv preprint arXiv:2206.04615*.
- Tianyi Tang, Hongyuan Lu, Yuchen Eleanor Jiang, Haoyang Huang, Dongdong Zhang, Wayne Xin Zhao, and Furu Wei. 2023. Not all metrics are guilty: Improving nlg evaluation with llm paraphrasing. *arXiv preprint arXiv:2305.15067*.
- Chongyang Tao, Lili Mou, Dongyan Zhao, and Rui Yan. 2018. Ruber: An unsupervised method for automatic evaluation of open-domain dialog systems. In *Proceedings of the AAAI conference on artificial intelligence*, volume 32.
- Yoad Tewel, Yoav Shalev, Idan Schwartz, and Lior Wolf. 2022. Zerocap: Zero-shot image-to-text generation for visual-semantic arithmetic. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 17918–17928.
- Brian Thompson and Matt Post. 2020. Automatic machine translation evaluation in many languages via zero-shot paraphrasing. In *Proceedings of the 2020*

Conference on Empirical Methods in Natural Language Processing (EMNLP), pages 90–121, Online. Association for Computational Linguistics.

- Hugo Touvron, Louis Martin, Kevin Stone, Peter Albert, Amjad Almahairi, Yasmine Babaei, Nikolay Bashlykov, Soumya Batra, Prajjwal Bhargava, Shruti Bhosale, et al. 2023. Llama 2: Open foundation and fine-tuned chat models. *arXiv preprint arXiv:2307.09288*.
- Ramakrishna Vedantam, C Lawrence Zitnick, and Devi Parikh. 2015. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 4566–4575.
- Oriol Vinyals, Alexander Toshev, Samy Bengio, and Dumitru Erhan. 2016. Show and tell: Lessons learned from the 2015 mscoco image captioning challenge. *IEEE transactions on pattern analysis and machine intelligence*, 39(4):652–663.
- Alex Wang, Kyunghyun Cho, and Mike Lewis. 2020a. Asking and answering questions to evaluate the factual consistency of summaries. In *Proceedings of the* 58th Annual Meeting of the Association for Computational Linguistics, pages 5008–5020, Online. Association for Computational Linguistics.
- Alex Wang, Kyunghyun Cho, and Mike Lewis. 2020b. Asking and answering questions to evaluate the factual consistency of summaries. In *Proceedings of the* 58th Annual Meeting of the Association for Computational Linguistics, pages 5008–5020, Online. Association for Computational Linguistics.
- Danqing Wang, Kevin Yang, Hanlin Zhu, Xiaomeng Yang, Andrew Cohen, Lei Li, and Yuandong Tian. 2023a. Learning personalized story evaluation. *arXiv preprint arXiv:2310.03304*.
- Jiaan Wang, Yunlong Liang, Fandong Meng, Haoxiang Shi, Zhixu Li, Jinan Xu, Jianfeng Qu, and Jie Zhou. 2023b. Is chatgpt a good nlg evaluator? a preliminary study. arXiv preprint arXiv:2303.04048.
- Peiyi Wang, Lei Li, Liang Chen, Dawei Zhu, Binghuai Lin, Yunbo Cao, Qi Liu, Tianyu Liu, and Zhifang Sui. 2023c. Large language models are not fair evaluators. *arXiv preprint arXiv:2305.17926*.
- Tianlu Wang, Ping Yu, Xiaoqing Ellen Tan, Sean O'Brien, Ramakanth Pasunuru, Jane Dwivedi-Yu, Olga Golovneva, Luke Zettlemoyer, Maryam Fazel-Zarandi, and Asli Celikyilmaz. 2023d. Shepherd: A critic for language model generation. *arXiv preprint arXiv:2308.04592*.
- Yaqing Wang, Jiepu Jiang, Mingyang Zhang, Cheng Li, Yi Liang, Qiaozhu Mei, and Michael Bendersky. 2023e. Automated evaluation of personalized text generation using large language models. *arXiv preprint arXiv:2310.11593*.

- Yidong Wang, Zhuohao Yu, Zhengran Zeng, Linyi Yang, Cunxiang Wang, Hao Chen, Chaoya Jiang, Rui Xie, Jindong Wang, Xing Xie, et al. 2023f. Pandalm: An automatic evaluation benchmark for Ilm instruction tuning optimization. *arXiv preprint arXiv:2306.05087*.
- Yizhong Wang, Yeganeh Kordi, Swaroop Mishra, Alisa Liu, Noah A. Smith, Daniel Khashabi, and Hannaneh Hajishirzi. 2023g. Self-instruct: Aligning language models with self-generated instructions. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 13484–13508, Toronto, Canada. Association for Computational Linguistics.
- Jason Wei, Maarten Bosma, Vincent Y. Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. 2022a. Finetuned language models are zero-shot learners. In *The Tenth International Conference on Learning Representations, ICLR 2022, Virtual Event, April 25-29, 2022.* OpenReview.net.
- Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. 2022b. Chain-of-thought prompting elicits reasoning in large language models. *Advances in Neural Information Processing Systems*, 35:24824–24837.
- Tsung-Hsien Wen, Milica Gašić, Nikola Mrkšić, Pei-Hao Su, David Vandyke, and Steve Young. 2015. Semantically conditioned LSTM-based natural language generation for spoken dialogue systems. In *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*, pages 1711–1721, Lisbon, Portugal. Association for Computational Linguistics.
- Ning Wu, Ming Gong, Linjun Shou, Shining Liang, and Daxin Jiang. 2023a. Large language models are diverse role-players for summarization evaluation. *arXiv preprint arXiv:2303.15078*.
- Yunshu Wu, Hayate Iso, Pouya Pezeshkpour, Nikita Bhutani, and Estevam Hruschka. 2023b. Less is more for long document summary evaluation by llms. *arXiv preprint arXiv:2309.07382.*
- Wenda Xu, Danqing Wang, Liangming Pan, Zhenqiao Song, Markus Freitag, William Yang Wang, and Lei Li. 2023. Instructscore: Towards explainable text generation evaluation with automatic feedback. *arXiv preprint arXiv:2305.14282.*
- Xiaohan Xu, Ming Li, Chongyang Tao, Tao Shen, Reynold Cheng, Jinyang Li, Can Xu, Dacheng Tao, and Tianyi Zhou. 2024. A survey on knowledge distillation of large language models. *arXiv preprint arXiv:2402.13116*.
- Hongyang Yang, Xiao-Yang Liu, and Christina Dan Wang. 2023a. Fingpt: Open-source financial large language models. arXiv preprint arXiv:2306.06031.

- Kevin Yang, Dan Klein, Nanyun Peng, and Yuandong Tian. 2023b. DOC: Improving long story coherence with detailed outline control. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 3378–3465, Toronto, Canada. Association for Computational Linguistics.
- Kevin Yang, Yuandong Tian, Nanyun Peng, and Dan Klein. 2022. Re3: Generating longer stories with recursive reprompting and revision. *arXiv preprint arXiv:2210.06774*.
- Weizhe Yuan, Graham Neubig, and Pengfei Liu. 2021. Bartscore: Evaluating generated text as text generation. In Advances in Neural Information Processing Systems 34: Annual Conference on Neural Information Processing Systems 2021, NeurIPS 2021, December 6-14, 2021, virtual, pages 27263–27277.
- Xiang Yue, Boshi Wang, Kai Zhang, Ziru Chen, Yu Su, and Huan Sun. 2023. Automatic evaluation of attribution by large language models. *arXiv preprint arXiv:2305.06311*.
- Zhiyuan Zeng, Jiatong Yu, Tianyu Gao, Yu Meng, Tanya Goyal, and Danqi Chen. 2023. Evaluating large language models at evaluating instruction following. *arXiv preprint arXiv:2310.07641*.
- Haopeng Zhang, Xiao Liu, and Jiawei Zhang. 2023a. Summit: Iterative text summarization via chatgpt. arXiv preprint arXiv:2305.14835.
- Saizheng Zhang, Emily Dinan, Jack Urbanek, Arthur Szlam, Douwe Kiela, and Jason Weston. 2018. Personalizing dialogue agents: I have a dog, do you have pets too? *arXiv preprint arXiv:1801.07243*.
- Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with BERT. In 8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020. OpenReview.net.
- Xinghua Zhang, Bowen Yu, Haiyang Yu, Yangyu Lv, Tingwen Liu, Fei Huang, Hongbo Xu, and Yongbin Li. 2023b. Wider and deeper llm networks are fairer llm evaluators. *arXiv preprint arXiv:2308.01862*.
- Wei Zhao, Maxime Peyrard, Fei Liu, Yang Gao, Christian M. Meyer, and Steffen Eger. 2019. MoverScore: Text generation evaluating with contextualized embeddings and earth mover distance. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), pages 563–578, Hong Kong, China. Association for Computational Linguistics.
- Yilun Zhao, Haowei Zhang, Shengyun Si, Linyong Nan, Xiangru Tang, and Arman Cohan. 2023. Investigating table-to-text generation capabilities of llms in real-world information seeking scenarios.

- Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric Xing, et al. 2023. Judging llm-as-a-judge with mt-bench and chatbot arena. *arXiv preprint arXiv:2306.05685*.
- Yufan Zhou, Ruiyi Zhang, Changyou Chen, Chunyuan Li, Chris Tensmeyer, Tong Yu, Jiuxiang Gu, Jinhui Xu, and Tong Sun. 2022. Towards language-free training for text-to-image generation. In *Proceedings* of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 17907–17917.
- Terry Yue Zhuo. 2023. Large language models are state-of-the-art evaluators of code generation. *arXiv* preprint arXiv:2304.14317.