A Survey on LLM-as-a-Judge

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ABSTRACT

Accurate and consistent evaluation is crucial for decision-making across numerous fields, yet it remains a challenging task due to inherent subjectivity, variability, and scale. Large Language Models (LLMs) have achieved remarkable success across diverse domains, leading to the emergence of "LLM-as-a-Judge," where LLMs are employed as evaluators for complex tasks. With their ability to process diverse data types and provide scalable, cost-effective, and consistent assessments, LLMs present a compelling alternative to traditional expert-driven evaluations. However, ensuring the reliability of LLM-as-a-Judge systems remains a significant challenge that requires careful design and standardization. This paper provides a comprehensive survey of LLM-as-a-Judge, addressing the core question: How can reliable LLM-as-a-Judge systems be built? We explore strategies to enhance reliability, including improving consistency, mitigating biases, and adapting to diverse assessment scenarios. Additionally, we propose methodologies for evaluating the reliability of LLM-as-a-Judge systems, supported by a novel benchmark designed for this purpose. To advance the development and real-world deployment of LLM-as-a-Judge systems, we also discussed practical applications, challenges, and future directions. This survey serves as a foundational reference for researchers and practitioners in this rapidly evolving field. The associated resources can be accessed at https://github.com/IDEA-FinAI/LLM-as-a-Judge.

1 INTRODUCTION

Judgment is the faculty of thinking the particular as contained under the universal. It involves the capacity to subsume under rules, that is, to distinguish whether something falls under a given rule.

-- Kant, Critique of Judgment [40], Introduction IV, 5:179; Critique of Pure Reason [39], A132/B171.

Recently, Large Language Models (LLMs) have achieved remarkable success across numerous domains, ranging from technical fields to the humanities and social sciences. Building on their success, the concept of using LLMs as evaluators—commonly referred to as "LLM-as-a-Judge" [156]—has gained significant attention, where LLMs are tasked with determining whether something falls within the scope of a given rule. This growing interest stems from LLMs' ability to mimic human-like reasoning and thinking processes, enabling them to take on roles traditionally reserved for human experts while offering a cost-effective solution that can be effortlessly scaled to meet increasing evaluation demands. For instance, employing LLM-as-a-Judge in the academic peer-review¹ process can help handle the rapid increase in submissions while maintaining expert-level judgment.

Before the era of LLMs, achieving a balance between comprehensive and scalable evaluation had posed a persistent challenge. On the one hand, commonly used subjective methods like expert-driven assessments integrate holistic reasoning and nuanced contextual understanding, making

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¹https://blog.iclr.cc/2024/10/09/iclr2025-assisting-reviewers/

them the gold standard in comprehensiveness [25, 97]. However, these approaches are expensive, challenging to scale, and susceptible to inconsistency. On the other hand, objective assessment methods like automatic metrics offer strong scalability and consistency. For example, tools such as BLEU [84] or ROUGE [60] can quickly score machine-generated translations or summaries against reference texts without human intervention. Yet these metrics, which heavily rely on surface-level lexical overlaps, often fail to capture deeper nuances of meaning, coherence, or logical reasoning. As a result, they perform poorly when evaluating tasks like open-ended story generation or complex instructional texts [94]. With the rise of advanced LLM techniques, the "LLM-as-a-Judge" has emerged as a potential idea to combine the strengths of above two ways of evaluation. LLMs have been proven to merge the scalability of automatic methods with the nuanced, context-sensitive reasoning found in expert judgments [11, 55, 128, 156, 163]. Moreover, LLMs might become flexible enough to handle multimodal inputs citemIlm-as-a-judge under decent prompt learning or fine-tuning [42], which is a unique advantage compared with traditional methods. These advantages suggest that the LLM-as-a-Judge approach could serve as a novel and broadly applicable paradigm for addressing complex and open-ended evaluation problems.

While LLM-as-a-Judge holds significant potential as a scalable and adaptable evaluation framework compared to expert-driven human evaluations and traditional automated metrics [124], its adoption is hindered by two key challenges. The first challenge is *the absence of a systematic review*, which reflects the lack of formal definitions, fragmented understanding, and casual usage practices in the study of LLM-as-a-Judge. These gaps make it difficult for researchers and practitioners to fully understand LLM-as-a-Judge and apply it effectively. Building on this, the second challenge involves addressing ongoing concerns about reliability [141], as merely employing LLM-as-a-Judge does not guarantee evaluations that are both accurate and aligned with established standards. These challenges demand not only a deeper assessment of the outputs generated by LLM-as-a-Judge but also a crucial investigation into the question: *How to build reliable LLM-as-a-Judge systems?*

To address these challenges, this paper provides a systematic review of research on LLM-as-a-Judge, offering a comprehensive overview of the field while exploring strategies for building reliable LLM-as-a-Judge systems. We begin by defining LLM-as-a-Judge through both formal and informal definitions, answering the foundational query: 'What is LLM-as-a-Judge?' Next, we categorize existing methods and approaches for its use, exploring how LLM-as-a-Judge can be effectively implemented in practice. Following this, we tackle the critical question: How to build reliable LLM-as-a-Judge systems? To answer this, we explore two core aspects: (1) strategies to enhance the reliability of LLM-as-a-Judge systems and (2) methodologies for evaluating the reliability of these systems. For the first aspect, we review key strategies to optimize the performance of LLM-as-a-Judge for diverse evaluation tasks. For the second aspect, we examine the metrics, datasets, and methodologies used to evaluate the performance of LLM-as-a-Judge systems, highlighting potential sources of bias and methods for their mitigation. Building on this foundation, we propose a novel benchmark specifically designed for evaluating LLM-as-a-Judge systems. Additionally, we explore practical application scenarios, identify challenges unique to each context, and propose solutions to address these issues. Finally, we discuss future research directions, emphasizing key areas for improving the reliability, scalability, and applicability of LLM-as-a-Judge systems.

The rest of this survey is organized as Figure 1. Section 2 provides an overview of the LLM-as-a-Judge field, including its definitions and categorization of existing methods. For a quick guide on implementing an LLM-as-a-Judge for specific scenarios, you can find answers in Quick Practice (2.5). Strategies for enhancing and evaluating the reliability of LLM-as-a-Judge systems are discussed in Sections 3 and 4, respectively. Section 6 explores practical applications, while Sections 7 and 8 address challenges and outline future research directions. Finally, Section 9 presents our conclusions.

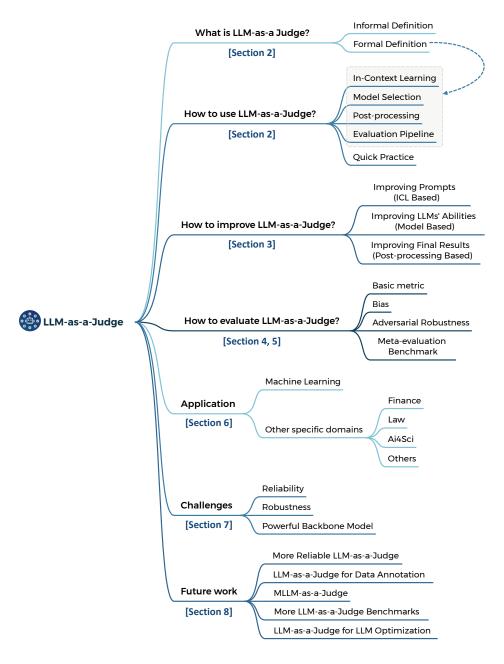


Fig. 1. The overall framework of this paper.

2 BACKGROUND AND METHOD

The ability of LLMs to mimic human reasoning and evaluate specific inputs against a set of predefined rules has paved the way for "LLM-as-a-Judge." Their scalability, adaptability, and cost-effectiveness make them well-suited for managing a growing number of evaluative tasks that were traditionally done by humans. These abilities are key in utilizing LLMs flexibly across various evaluation scenarios and objectives. The adoption of LLM-as-a-Judge has progressed rapidly. Initially, the primary focus of LLMs was on language generation and comprehension. With advancements in training paradigms like Reinforcement Learning from Human Feedback (RLHF) [80], LLMs became more aligned with human values and reasoning processes. This alignment has allowed LLMs to transition from generative tasks to evaluative roles. At its core, LLM-as-a-Judge refers to the use of LLMs to evaluate objects, actions, or decisions based on predefined rules, criteria, or preferences. It encompasses a broad spectrum of roles, including: **Graders** [119], **Evaluators/Assessors** [56, 145], **Critics** [41, 86, 135], **Verifiers** [63, 99, 130], **Examiners** [3], **Reward/Ranking Models** [74, 98, 106, 143], etc.

Currently, the definition of how to effectively use LLM-as-a-Judge for evaluation tasks is largely informal or vague, lacking clear and formal expression. Therefore, we will start with a formal definition of LLM-as-Evaluator as follows:

$$\mathcal{E} \leftarrow \mathcal{P}_{f,f,M}(x \oplus C)$$

- &: The final evaluation obtained from the whole LLM-as-a-Judge process in the expected manner. It could be a score, a choice, or a sentence, etc.
- $\mathcal{P}_{\mathcal{LLM}}$: The probability function defined by the corresponding LLM, and the generation is an auto-regressive process.
- x: The input data in any available types (text, image, video), which waiting to be evaluated.
- *C*: The context for the input *x*, which is often prompt template or combined with history information in dialogue.
- \oplus : The combination operator combines the input x with the context C, and this operation can vary depending on the context, such as being placed at the beginning, middle, or end.

The formulation of LLM-as-a-Judge reflects that LLM is a type of auto-regressive generative model, which generates subsequent content based on the context then obtain target evaluation from it. It illustrates how we utilize LLM for evaluation tasks, encompassing input design, model selection and training, as well as output post-processing. The basic approaches of implementing LLM-as-a-Judge can be classified according to the formulation: In-Context Learning, Model Selection, Post-processing Method and Evaluation Pipeline, which concluded in Figure 2. By following this pipeline, one can build a basic LLM-as-a-Judge for evaluation. A quick practice guide is available in section 2.5.

2.1 In-Context Learning

To apply LLM-as-a-Judge, evaluation tasks are typically defined using In-Context Learning methods, which provide instructions and examples to guide the model's reasoning and judgment. This process involves two key aspects: the design of prompt and input. For input design, it is important to consider the type of variables to be evaluated (such as text, image, or video), the manner of input (e.g., individually, in pairs, or in batches), and the position of the input (e.g., at the beginning, middle, or end). As for the prompt design, four different methods can be adopted, as illustrated in Figure 2. The four methods include generating scores, solving true/false questions, conducting pairwise comparisons, and making multiple-choice selections. Further details will be provided in the following sections.

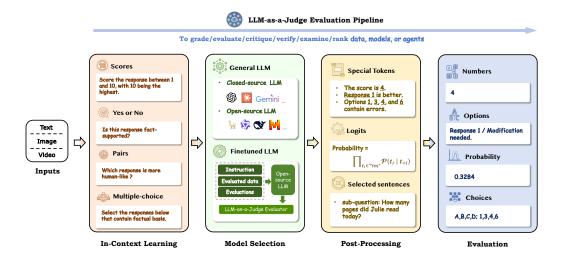


Fig. 2. LLM-as-a-Judge evaluation pipelines.

2.1.1 Generating scores. It is quite intuitive to represent an evaluation using a corresponding score. What requires more careful consideration, however, is the nature and range of the score used for evaluation. The score can be discrete, with common ranges like 1-3, 1-5 [38], or 1-10 [55, 163]. Alternatively, it can be continuous, ranging from 0 to 1 or 0 to 100 [135]. The simplest way to score is through the context, setting the range of scores and the main criteria for scoring. For example, "Please rate the helpfulness, relevance, accuracy, level of details of their responses. Each assistant receives an overall score on a scale of 1 to 10, where a higher score indicates better overall performance" [163]. A slightly more complex way is to provide more detailed scoring criteria. More complex scoring situations can be as Language-Model-as-an-Examiner [3], which use Likert scale scoring functions as an absolute evaluative measure showed in Figure 3. The evaluator assigns scores to a given response along predefined dimensions including accuracy, coherence, factuality and comprehensiveness. Each of these dimensions is scored on a scale of 1 to 3, ranging from worst to best. The evaluator is also asked to provide an overall score ranging from 1 to 5, based on the scores assigned to the previous 4 dimensions. This score serves as an indicator of the overall quality of the answer.

Evaluate the quality of summaries written for a news article. Rate each summary on four dimensions: {Dimension_1}, {Dimension_2}, {Dimension_3}, and {Dimension_4}. You should rate on a scale from 1 (worst) to 5 (best).

Article: {Article}
Summary: {Summary}

Fig. 3. The template for Likert scale scoring from Gao et al. [25].

2.1.2 **Solving Yes/No questions**. A Yes/No question requires a judgment on a given statement, focusing solely on its accuracy. This type of question is simple and direct, providing only two fixed responses—yes or no, true or false—without any additional comparisons or choices.

This type of evaluation is often utilized in intermediate processes, creating the conditions for a feedback loop. For example, it promotes a self-optimization cycle, as seen in *Reflexion* [99], which generates verbal self-reflections to provide valuable feedback for future attempts. In scenarios with sparse reward signals, such as a binary success status (success/fail), the self-reflection model uses the current trajectory and persistent memory to generate nuanced and specific feedback. Similarly, in self-improvement contexts [114], Yes/No questions can be employed to evaluate custom phrases, such as "Modification needed." and "No modification needed.", facilitating entry into the next cycle. Moreover, these evaluations are common for testing knowledge accuracy and assessing whether statements align with established facts [105], like "Given a question and the associated retrieved knowledge graph triples (entity, relation, entity), you are asked to answer whether it's sufficient for you to answer the question with these triples and your knowledge (Yes or No)." A detailed and specific example can be seen in the Figure 4.

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Is the sentence supported by the article? Answer "Yes" or "No".

Article: {Article}
Sentence: {Sentence}
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Fig. 4. The template for Yes/No evaluation for example.

2.1.3 **Conducting pairwise comparisons**. Pairwise comparison refers to comparing two options and selecting which one is superior or more aligned with a specific standard, showed in Figure 5. It involves making a decision between two options rather than judgement between 'yes' or 'no'. The comparison can be subjective or based on objective criteria. This evaluation is a relative evaluation. Pairwise comparison is often used for ranking multiple options or prioritizing them, where several comparisons are made between pairs to identify the better choice or establish a hierarchy.

Pairwise comparison is a well-established method that has significantly impacted a variety of fields [87]. As noted by [70], LLM and human evaluations are more aligned in the context of pairwise comparisons compared to score-based assessments. Numerous studies have demonstrated that pairwise comparative assessments outperform other judging methods in terms of positional consistency [71, 157]. Furthermore, pairwise comparisons can be extended to more complex relation-based assessment frameworks, such as list-wise comparisons, using advanced ranking algorithms [70, 87], data filtering [143]. In pairwise comparative assessments, LLM-as-a-Judge is prompted to select the response that better answers the question at hand. To accommodate the possibility of a tie, several option modes are introduced. The Two-Option mode requires judges to choose the better response from two given options. The Three-Option mode introduces an additional choice, allowing judges to indicate a tie if neither response is preferable. Evaluations typically involve determining the outcomes of win, tie, or loss for responses [128] through pairwise comparisons, with win rounds counted for each response. The Four-Option mode further expands the choices, allowing judges to classify responses as either a "both good tie" or a "both bad tie."

2.1.4 **Making multiple-choice selections**. Multiple-choice selections involve providing several options, not giving relative choices in pairwise comparison, nor making a yes/no judgment. The evaluator must choose the most appropriate or correct one. This method allows for a broader range of responses compared to true/false questions and can assess deeper understanding or preferences and an example is showed in Figure 6. However, this kind of prompt design is more rare than the first three.

```
Given a new article, which summary is better? Answer "Summary 0" or "Summary 1". You do not need to explain the reason.

Article: {Article}
Summary 0: {Summary_0}
Summary 1: {Summary_1}
```

Fig. 5. The template for pairwise comparison from Gao et al. [25]

```
You are given a summary and some semantic content units. For each semantic unit, choose those can be inferred from the summary, return their number.

Summary: {Summary}
Semantic content units:

1. {SCU_1}
2. {SCU_2}
......
n. {SCU_n}
```

Fig. 6. The template for multiple-choice for example.

2.2 Model Selection

- 2.2.1 **General LLM**. To automate evaluation by LLM-as-a-Judge, one effective approach is to employ advanced language models such as GPT-4 [78] instead of human evaluators [157]. For instance, Li et al. [58] created a test set with 805 questions and assessed the performance by comparing it to text-davinci-003 using GPT-4. Additionally, Zheng et al. [157] designed 80 multiround test questions across eight common areas and used GPT-4 to automatically score the model's responses. The accuracy of the GPT-4-based evaluator has been demonstrated to be high compared to professional human evaluators, showing superior consistency and stability in evaluations. At the same time, if the general LLM used has limitations in instruction-following or reasoning abilities, the effectiveness of the LLM-as-a-Judge method may be significantly affected.
- 2.2.2 Fine-tuned LLM. However, relying on external API for evaluation may introduce consideration about privacy leakage, and the opacity of API models also challenges the evaluation reproducibility. Therefore, subsequent studies recommend refining language models tailored for evaluations by emphasizing the use of pairwise comparisons or grading. For instance, PandaLM [128] constructs data based on Alpaca instructions and GPT-3.5 annotation, and then fine-tunes LLaMA-7B [116] as an evaluator model. JudgeLM [163] constructs data from diversified instruction sets and GPT-4 annotations, and fine-tunes Vicuna [117] as a scalable evaluator model. Auto-J [55] constructs evaluation data upon multiple scenarios to train a generative evaluator model, which can provide both evaluation and critical opinion. Prometheus [43] defines thousands of evaluation criteria and construct a feedback dataset based on GPT-4, and fine-tunes a fine-grained evaluator model.

The typical process for fine-tuning a judge model involves three main steps. **Step 1: Data Collection.** The training data generally consists of three components: instructions, the objects to be evaluated, and evaluations. Instructions are typically sourced from instruction datasets, while evaluations can come from either GPT-4 or human annotations. **Step 2-Prompt Design.** The

structure of the prompt template can vary based on the evaluation scheme, which already detailed in § 2.1. **Step 3: Model Fine-Tuning.** Using the designed prompts and collected data, the fine-tuning process for the evaluator model typically adheres to the instruction fine-tuning paradigm [81]. The model receives an instruction along with one or more responses to generate output that includes evaluation results and possibly explanations.

After fine-tuning, the evaluator model can be employed to evaluate the target object. While these fine-tuned models often demonstrate superior performance on self-designed test sets, they are identified several limitations in their evaluation capabilities, which detailed in Section 4.2. The current prompt and fine-tuning dataset designs often result in evaluation LLMs with poor generalization, making them difficult to compare with strong LLMs like GPT-4.

2.3 Post-processing Method

Post-processing refines the probability distributions generated by LLM-as-a-Judge to provide accurate evaluations. The evaluation format should align with our In-Context Learning design. Additionally, post-processing may involve procedures to enhance the reliability of extracted evaluations, closely linked to the In-Context Learning framework and consistently applied. There are three main methods of post-processing, which are extracting specific tokens, normalizing the output logits, and selecting sentences with high returns.

We will provide a detailed explanation of these methods. However, it is important to note that each method has significant limitations when evaluating objective questions. For example, in text response evaluation [141], failing to accurately extract the key answer token from the LLM's response can result in incorrect evaluation outcomes. These challenges in post-processing are deeply connected to the prompt design used in the earlier ICL stages and the selected model's ability to follow instructions reliably.

- 2.3.1 Extracting specific tokens. As showed in In-context Learning (Section 2.1), when the evaluation target take the form of a score, selecting specific options, or responding with Yes/No, applying rule-match to extract the corresponding token from the response generated during probability distribution iteration is common used. It is worth noting that Yes/No is a broad definition, including custom statements involving judgment. Considering a Yes/No question for evaluation in custom phrases [114]: "Modification needed." and "No modification needed." or a yes-no question "Does the above answer need to be further modified?". When the input sample is put through the template, it might have outputs such as "Modification needed.", "Conclusion: Modification needed." or "Yes". This variance in response formats is difficult to parse consistently. The corresponding post-processing with the response is necessary. Using rules to extract specific tokens for our designed prompts and input content, as well as the backbone model used for the evaluator, all have higher requirements as we discussed in Section 2.2. In contextual learning, if there is no clear indication of the output format for response, there may be various expressions of evaluation, which can be seen in Figure 2. For example, "Response 1 is better" and "The better one is response 1", which convey the same choice but differ in format leading to the difficulty of rule recognition. Simple solutions often involve providing clear instructions, such as "The last sentence should be started with 'The better response is'", or using a few-shot strategy. Also, the general model with insufficient instruction following capability may not be able to generate the evaluation format and content of the target according to the instruction, resulting in the post-processing extracted according to the rules not as smooth as expected.
- 2.3.2 **Normalizing the output logits**. LLM-as-a-Judge in the intermediate steps with Yes/No setting often normalize the output logits to obtain the evaluation in the form of a continuous decimal

between 0 and 1. This is also very common in agent methods and prompt-based optimization methods [30, 130, 166]. For example, the self-consistency and self-reflection scores [130] within one forward pass of $\mathcal{M}_{\text{Evaluator}}$, are effectively obtained by constructing a prompt $[(x \oplus C), \text{"Yes"}]$ and acquire the probability of each token conditioned on the previous tokens $P(t_i|t_{< i})$. The autoregressive feature is leveraged, thus aggregate the probability of the relevant tokens to compute the self-consistent score $\rho_{\text{Self-consistency}}$ and self-reflection score $\rho_{\text{Self-reflection}}$. The final score is produced by $\rho_j = \rho_{\text{SC},j} \cdot \rho_{\text{SR},j}$.

$$\underbrace{\overbrace{(x \oplus C)}^{\rho_{SC}} \xrightarrow{\rho_{SR}}}_{\text{"Yes"}} \Rightarrow \begin{cases} \rho_{SC} = \prod_{t_i \in \alpha} P(t_i | t_{< i}) \cdot \prod_{t_i \in \beta} P(t_i | t_{< i}) \\ \rho_{SR} = \prod_{t_i \in \text{"Yes"}} P(t_i | t_{< i}) \end{cases}$$

In addition, Self-evaluation [30] is also common using this method for LLM-as-a-Judge. It can be helpful to let the LLM evaluate itself by asking, "Is this reasoning step correct?" and then reward it based on the probability of the next word being "Yes."

2.3.3 **Selecting sentences**. In addition to selecting specific tokens and normalizing the output logits, the content extracted by LLM-as-a-Judge may also be a sentence or paragraph. As showed in Figure 2, agent for reasoning task [30], builds a reasoning tree by iteratively considering the most promising reasoning steps (actions, sub-questions) by LLM-as-a-Judge.

2.4 Evaluation Pipeline

After completing the three processes, we obtain the final evaluation. From input to output, these steps collectively form the LLM-as-a-Judge evaluation pipeline, as illustrated in Figure 2. This pipeline is commonly applied in three scenarios: LLM-as-a-Judge for LLMs, LLM-as-a-Judge for data, and LLM-as-a-Judge for agents.

2.4.1 LLM-as-a-Judge for model. It is universally known that the best way to evaluate LLMs is human judgment, but collecting human annotations can be costly, time-consuming, and laborious [81, 158]. Using strong LLMs (usually closed-source ones, e.g., GPT-4, Claude, ChatGPT) as an automated proxy for assessing LLMs has become a natural choice [161]. With appropriate prompt design, the quality of evaluation and agreement to human judgment can be promising [21, 123, 152, 158]. However, the cost concern still exists when calling the APIs of these proprietary models, especially when there is a frequent need for model validation on large-scale data. Moreover, closed-source LLM-as-a-Judge leads to low reproducibility due to potential changes in models behind the API. Some recent works have started to make attempts for open-source alternatives. SelFee [139] collects generations, feedback, and revised generations from ChatGPT and fine-tunes LLaMA models to build a critique model. Shepherd [125] trains a model that can output critiques for single-response with the data of feedback from online communities and human annotation. PandaLM [128] trains a model to conduct pairwise comparison for LLM Instruction Tuning Optimization, and Zheng et al. [158] also fine-tune Vicuna [117] on a 20K pairwise comparison dataset to explore the potential of open-source models as a more cost-friendly proxy.

Recent advancements in using Large Multimodal Models (LMMs) as evaluators have showcased their potential to perform complex judgment tasks in vision-language scenarios. Proprietary models like GPT-4V and GPT-40 have been pivotal in benchmarks such as detailed captioning and visual chats, utilizing both pointwise and pairwise evaluation methods [65, 73, 151]. Open-source alternatives have emerged, with Prometheus-Vision [51] being the first vision-language model specifically trained to act as an evaluator for user-designed scoring criteria. While Prometheus-Vision introduced the concept of open-source evaluators with a focus on specialized tasks, it remains

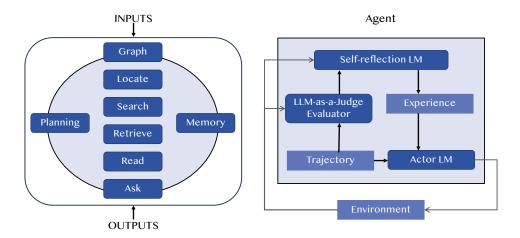


Fig. 7. LLM-as-a-Judge appears in two common forms in the agent. The left diagram is Agent-as-a-Juge, designing a complete agent to serve as an evaluator. The right diagram shows using LLM-as-a-Judge in the process of an Agent.

limited to predefined criteria. In contrast, LLaVA-Critic [135], another open-source innovation, expands the scope by serving as a generalist evaluator. Trained on diverse and detailed datasets, LLaVA-Critic provides robust scoring and preference learning, closely aligning with human and proprietary evaluations. These models mark significant progress in democratizing and enhancing multimodal evaluation tools.

LLM-as-a-Judge for data. Data annotation generally refers to the labeling or generating of raw data with relevant information, which could be used for improving the efficacy of machine learning models. The process, however, is labor-intensive and costly. The emergence of LLMs presents an unprecedented opportunity to automate the complicated process of data annotation by LLM-as-a-Judge. Most of the data need to be evaluated by LLM-as-a-Judge is generated by models, or large-scale crawled data. Language models first conduct supervised fine-tuning to imitate how to align with human instructions [111, 127]. After that, reinforcement learning techniques have been explored to align language models with human preferences [82, 90]. The most successful way is applying a RLHF framework [82] via training a reward model on human feedback and using PPO [95] to obtain the policy model for language generation. However, in practices, the PPO training paradigm is complex in coding and hyper-parameter tuning while it needs four models that are hard for training. This motivates us to explore simpler and more straightforward methods to align language models with human preferences. This involves how to use LLM-as-a-Judge to evaluate whether different responses are aligned with human preferences. For example, [18, 143] use general LLM (ChatGPT) to get better alignment with human preferences. The Aplaca prompts [111] is used as sampling queries to different models generate responses. And these data was evaluated by LLM-as-a-Judge to obtain human preference scores (reward score) to train a new language model. Other works would like to use Supervised Fine-Tuning (SFT) model itself as evaluator, like generating better-aligned datasets for SFT including hindsight-modified prompts [67, 150] and principle-driven self-alignment [108].

In addition, the lack of domain-specific model training data is a common phenomenon. In order to obtain annotated high-quality data, it is also very common to use LLM-as-a-Judge for the generation and evaluation of domain data. *WizardMath* [74] would use its Instruction Reward Model (IRM) as

Evaluator, aiming to judge the quality of the evolved instructions on three aspects: i) Definition, ii) Precision, and iti) Integrity. To produce the ranking list training data of IRM, for each instruction, ChatGPT and Wizard-E are used to generate 2-4 evolved instructions respectively. Then we leverage Wizard-E to rank the quality of those 4-8 instructions.

However, solely relying on LLM-as-a-Judge for data annotation poses challenges, particularly as the value of annotated data diminishes with the rapid improvement of model performance. To address this, approaches like Self-Taught Evaluator [124] offer a promising alternative by eliminating the need for human annotations. This method leverages synthetic training data, starting with unlabeled instructions and generating contrasting outputs from models. These outputs are then used to train an LLM-as-a-Judge to produce reasoning traces and final judgments. With each iteration, the evaluator improves by learning from its refined predictions, creating a cycle of continuous self-enhancement. This iterative approach not only keeps annotations relevant but also ensures that evaluators evolve alongside advancing models.

Recent research on evaluating multimodal data focuses on addressing vision-language misalignments in Multimodal Large Language Models (MLLMs), which often cause hallucinations—outputs inconsistent with visual or contextual evidence [15, 59, 121]. Techniques like Reinforcement Learning from Human Feedback (RLHF) and Factually Augmented RLHF have been employed to improve model alignment by incorporating structured ground-truth data and image captions, enhancing hallucination detection [107]. Benchmarks such as MLLM-as-a-Judge [9] assess these models using tasks like scoring, pair comparison, and batch ranking, revealing limitations in alignment with human preferences. Persistent issues include biases (e.g., position, verbosity) and hallucinations, with even advanced models like GPT-4V displaying challenges. While pair comparison tasks align better with human judgment, scoring and batch ranking require significant improvements for reliable deployment. These findings emphasize the need for innovative frameworks and datasets to refine MLLM evaluation and alignment.

2.4.3 **LLM-as-a-Judge for agent**. There are two ways to apply LLM-as-a-Judge for an agent. One is to evaluate the entire process of the intelligent agent [167], and the other is to evaluate it at a specific stage in the agent framework process [30, 99]. Both approaches are briefly illustrated in Figure 7. Using LLM as the brain of agent, an agentic system [167] could evaluate like a human, it would reduce the need for human involvement and eliminate the trade-off between thoroughness and effort. In addition, the agent [99] can interact with the environment through language and receive feedback on actions through LLM to make decisions for the next action.

2.5 Quick Practice

To effectively apply LLM-as-a-Judge design, it is more recommended to find more effective settings in the testing cycle for different scenarios. The process of quick practice for LLM-as-a-Judge involves four main stages. First, thinking, where users define the evaluation objectives by determining what needs to be evaluated, understanding how humans typically perform such evaluations, and identifying some reliable evaluation examples. Next is prompt design, detailed in Section 2.1. The most efficient and generally effective approach involves specifying scoring dimensions, emphasizing relative comparisons for improved assessments, and creating effective examples to guide the LLM. The third stage, model selection (Section 2.2), focuses on choosing a large-scale model with strong reasoning and instruction-following abilities to ensure reliable evaluations. Finally, standardizing the evaluation process ensures that the outputs are structured (Section 2.3). This can be achieved by using specific formats like \boxed{XX}, numerical scores, or binary responses (e.g., "Yes" or "No"). The entire process includes iterative testing with cases and refinement through retesting to enhance reliability.

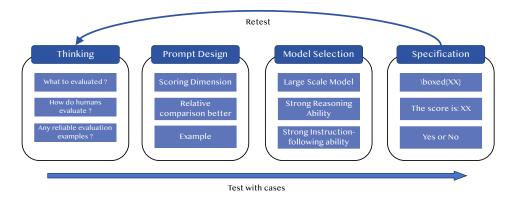


Fig. 8. Flowchart of Quick Practice

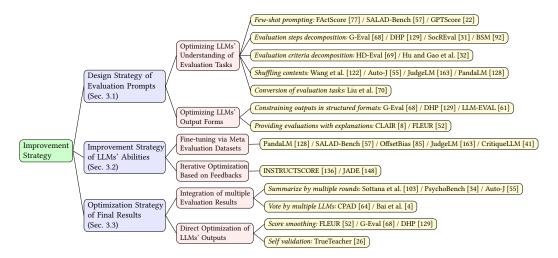


Fig. 9. Structure of Improvement Strategy.

3 IMPROVEMENT STRATEGY

When directly utilizing LLMs to conduct evaluation tasks such as scoring, selection, pairwise comparison or ranking, the inherent biases of LLMs like length bias, positional bias and concreteness bias[85] will lead to poor evaluation results. Addressing these inherent biases and improving the overall evaluation performance of LLMs is a critical challenge for applying LLMs as evaluators. In this section, we introduce three improvement strategy aimed at enhancing the evaluation performance of LLM-as-a-judge: design strategy of evaluation prompts (in-context learning based), improvement strategy of LLMs' evaluation capabilities (model based), and optimization strategy of final evaluation results (post-processing based). Our categorization is based on the formal definition of LLM-as-Evaluator in Section 2, focusing on enhancing the evaluation effectiveness by targeting three key phases of the process: the context C, the abilities of LLMs themselves $\mathcal{P}_{\mathcal{LLM}}$ and the

post processing \leftarrow to obtain the final results $\ensuremath{\mathcal{E}}$

3.1 Design Strategy of Evaluation Prompts

An evaluation prompt is an input to LLM evaluators, which is used to guide the LLMs to complete the required evaluation tasks. LLMs possess in-context learning ability to learn how to perform specified tasks through relevant examples or instructions provided in prompts without requiring weight updates or retraining[7]. It indicates that the design strategy of evaluation prompts will significantly impact the effectiveness of LLM-as-a-judge. Therefore, how to optimize the design of evaluation prompts, including better methods to help LLMs understand the evaluation tasks and produce evaluation results, is the most direct and effective way to improve the evaluation performance of LLM-as-a-judge.

3.1.1 **Optimizing LLMs' Understanding of Evaluation Tasks**. In optimization methods of prompting LLMs to better understand evaluation tasks, one of the most commonly used and effective approaches is few-shot prompting[7]. By incorporating several high-quality evaluation examples into the evaluation prompts, LLM evaluators can effectively grasp the objectives, general processes and rough evaluation criteria of evaluation tasks. Many research works employ this prompt paradigm for evaluation, such as FActScore[77], SALAD-Bench[57] and GPTScore[22].

In addition to providing hight-quality examples for LLMs to inference, refining the evaluation task instructions is also an effective approach to optimize LLMs' understanding of evaluation tasks. Current methods for refining evaluation tasks mainly including the decomposition of evaluation steps and criteria: (a) Decomposition of Evaluation Steps entails breaking down the entire evaluation tasks into smaller steps, providing detailed definitions and constraints for each small step in prompts, thereby guiding LLMs comprehensively through the whole evaluation pipeline. For instance, G-Eval[68] and DHP[129] use Chain-of-Thought(CoT)[131] to provide guidance for LLMs. SocREval[31] employs the Socratic method to meticulously design each step to enhance evaluation performance. Saha et al. proposes Branch-Solve-Merge(BSM)[92], which divides evaluation tasks into multiple parallel sub-tasks for separate evaluation and final merge. (b) Decomposition of Evaluation Criteria involves breaking down coarse evaluation criteria like Fluency into finergrained sub-criteria like Grammar, Engagingness and Readability, and then generating overall scores based on these difference dimensions. HD-Eval[69] iteratively aligns LLM evaluators with human preference via hierarchical criteria decomposition and thereby addressing the potential bias in LLMs. Hu and Gao et al.[32] summarize and clearly define an explicit hierarchical classification system encompassing 11 criteria, addressing the issue of LLMs potentially confusing different evaluation standards. These refinements specific to enable LLMs to understand the details of evaluation tasks more deeply, thereby aligning evaluation results more closely with human evaluation requirements and preferences.

Furthermore, the evaluation capabilities can be optimized based on specific shortcomings of LLMs in prompts. For instance, to address specific biases like position bias which is common in pairwise evaluations, several research efforts have optimized prompts design by randomly swapping contents to be evaluated. Wang et al.[122] analyzed and validated the impact of position bias on LLM-as-a-judge, and proposed a calibration framework to mitigate this bias by swapping the contents and averaging the scores. Auto-J[55] and JudgeLM[163] also enhance the evaluation consistency by shuffling the texts to be evaluated. In contrast to averaging scores, PandaLM[128] annotates the conflicting evaluation results after swapping as "Tie" to address the position bias.

To address the challenge of LLMs' absolute scoring being less robust than relative comparing[88], some research works convert scoring tasks into pairwise comparison, thereby enhancing the reliability of evaluation results. Liu et al.[70] transform the scoring evaluation to ranking evaluation and introduce Pairwise-Preference Search (PARIS), which employs LLMs to conduct pairwise

comparisons locally and efficiently ranks candidate texts globally, making evaluation results more aligned with human preferences.

In summary, the design of prompts for better understanding evaluation tasks is a core method for optimizing LLMs' in-contextual learning abilities. By refining evaluation task instructions and criteria in prompts or few-shot prompting with high-quality examples, the details of evaluation prompts can be enriched and the understanding of LLMs on evaluation tasks can be directly or indirectly enhanced. Additionally, targeted adjustments to prompts can address potential biases of LLMs such as position bias.

3.1.2 **Optimizing LLMs' Output Forms.** Directly requiring LLM evaluators to output evaluation results poses robustness problems. The response text may unexpectedly vary due to the inherent generative randomness of LLMs, such as outputting text like "low relevance" while asked to measure it with discrete scores, which hinders the automated and accurate extraction of evaluation results from LLMs' output. An effective method to enhance the robustness of output forms is to constrain LLMs' output in structured formats within prompts. G-Eval[68] and DHP framework[129] perform evaluation tasks with a form-filling paradigm, constraining outputs with formats like "X: Y", where X represents the dimension or metric to be evaluated and Y denotes an identifiable output form like scores or specific tokens. LLM-EVAL[61] further codifies this form-filling paradigm, efficiently output evaluation results in JSON dictionary format and obtain multidimensional scores, leveraging LLMs' high understanding and generation capabilities of code-like textural formats.

Apart from challenges in robustness, directly outputting evaluation results by LLMs also suffer from the lack of interpretability. The meaning of evaluation results from LLM evaluators is difficult to align consistently with instructions and metrics provided in prompts. To address the challenges, CLAIR[8] requires LLMs to output evaluation scores between 0-100 simultaneously with relevant reasons as explanations in JSON format, which enhancing the rationality and interpretability of the scores. FLEUR[52] utilizes LLaVA to first provide quality scores for image captions and subsequently asks with "Why? Tell me the reason." for explanations with the images, captions and scores as inputs, offering a stepwise approach to provide interpretable scores.

In general, by constraining or guiding the output process and format of LLM evaluators within prompts, the robustness and rationality of evaluation results can be effectively improved through structured outputs. This also facilitates the automated post-processing of evaluation results in subsequent steps, thereby enhancing the overall stability of the evaluation pipeline.

3.2 Improvement Strategy of LLMs' Abilities

The evaluation capabilities of LLMs is a reflection of their powerful general language understanding and generation abilities triggered by specific prompts. Methods for optimizing evaluation through prompt design, which focuses on LLMs' in-contextual learning capabilities, require LLMs to fully comprehend the meaning of prompts and consistently follow the relevant evaluation instructions. However, even state-of-the-art LLMs like GPT4 face issues such as conceptual confusion[32], and smaller open-source LLMs which are easier to deploy as evaluators have even more limitations in their evaluation capabilities. Therefore, how to improve the evaluation capabilities of LLMs, including how to fine-tune LLMs through meta evaluation datasets and how to iteratively optimizing models based on feedback of evaluation results, is significant for improving the fundamental evaluation performance of LLM-as-a-judge.

3.2.1 **Fine-tuning via Meta Evaluation Datasets**. A straightforward approach to enhancing the evaluation capabilities of LLMs is to fine-tune them via meta evaluation datasets specifically constructed for evaluation tasks, which helps improve the LLMs' understanding of specific evaluation prompts, boosts the evaluation performance, or addresses potential biases. The most critical

step in this optimization strategy is the collection and construction of training data. A common method involves sampling evaluation questions from publicly available datasets, modifying them with certain templates, and supplementing the dataset with evaluation responses generated either manually or by powerful LLMs like GPT4. For instance, PandaLM[128] samples inputs and instructions from Alpaca 52K[111] and generate responses using GPT-3.5 to construct training data, while SALAD-Bench[57] builds its training data from a subset of LMSYS-Chat[159] and Toxicchat[62].

To better align with the requirements of evaluation tasks, many research works further transform inputs and instructions sampled from public datasets to construct more targeted training data. OffsetBias[85] aims to reduce biases of LLMs by using GPT4 to generate off-topic versions of the original inputs and then having GPT-3.5 respond to the new inputs to produce bad responses. By pairing good and bad responses as training data to fine-tune the LLMs as evaluators, the biases in LLMs are significantly reduced, including length bias, concreteness bias, knowledge bias and so on. JudgeLM[163] enhances LLMs' evaluation capabilities by creating different types of training data through paradigms like reference support and reference drop. CritiqueLLM[41] proposes a multi-path prompting approach, combining pointwise-to-pairwise and referenced-to-reference-free prompting strategies to restructure referenced pointwise grading data into four types, which helps create Eval-Instruct to fine-tune LLMs, addressing shortcomings in pointwise grading and pairwise comparison.

In summary, constructing meta evaluation training data targeted at specific evaluation tasks and fine-tuning LLMs can directly adjust the model's internal parameterized knowledge and language abilities. This is the most straightforward method to improve the evaluation performance of LLM evaluators and address potential biases.

3.2.2 Iterative Optimization Based on Feedback of Evaluation Results. Fine-tuning LLMs on meta evaluation datasets give them the ability to produce evaluations which are more aligned with human preferences. However, LLM-as-a-judge may still introduce biases during evaluation process in practice, which can impact the overall evaluation quality. A natural improvement strategy is to iteratively optimize the model based on feedback of evaluation results, which mainly comes from stronger models or directly from human evaluators' correction of the evaluation results.

A typical example is INSTRUCTSCORE[136]. To improve model performance and further benefit the final quality score calculation, this score framework collects failure modes of metric outputs, query GPT-4 on each failure mode to gather automatic feedback, and finally selects explanations most aligned with human preferences to iteratively fine-tune the LLaMA model. Unlike INSTRUCTSCORE which directly optimizes the model, the LLM evaluator in JADE[148] relies on human judges to correct LLMs' evaluation results and updates the most frequently corrected samples into the example sets for few-shot prompting. JADE utilizes this relatively low-cost method to achieve iterative updates of the evaluation capabilities.

Since the feedback is more closely aligned with human preferences, LLM evaluators can dynamically align with human when optimizing evaluation capabilities based on this feedback, leading to better evaluation results. This feedback-based iterative optimization strategy address the problem of models' imperfect generalization and improve the evaluation capabilities through dynamic updates.

3.3 Optimization Strategy of Final Results

Through the optimization based on in-context learning and the model' own capabilities, LLMs have become fairly reliable evaluators which are capable of understanding evaluation task requirements and providing rational evaluation results. However, the inherent generation randomness within

the black box of LLMs still introduces significant instability to the entire evaluation pipeline, affecting the overall evaluation quality. Therefore, optimization strategies during the post-processing stage from LLM evaluators' outputs to final evaluation results are necessary. In this survey, these optimization strategies are categorized into three types: integration of multiple evaluation results, direct optimization of LLMs' outputs, and conversion of evaluation tasks from pointwise evaluation to pairwise comparison.

3.3.1 Integration of Multiple Evaluation Results. Integrating multiple evaluation results for the same content to obtain the final result is a common strategy in various experiments and engineering pipelines, which can reduce the impacts of accidental factors and random errors. The most basic optimization strategy is to perform multiple runs of evaluation on the same content with different hyper-parameters and settings, and then summarize these results. For example the work of Sottana et al.[103] reduces randomness in evaluations by averaging multiple scores of the same sample. Similarly, PsychoBench[34] takes the mean and standard deviation from ten independent runs. Auto-J[55] further amplifies the differences between evaluation rounds, which combine critiques with and without scenario criteria to obtain the final results.

In addition to integrating results from multiple rounds of evaluation, using multiple LLM evaluators to assess the contents simultaneously and the integrating the results is another effective method, which can reduce biases introduced by LLMs. For instance, CPAD[64] utilizes ChatGLM-6B[20], Ziya-13B[146] and ChatYuan-Large-v2[147] as evaluators to evaluate the contents and obtain the final results by voting. Bai et al.[4] propose a novel evaluation method called decentralized peer review of LLMs, which utilizes LLMs that generate contents to evaluate each other's generated contents and eventually integrate the results.

In summary, forming the final evaluation results by combining multiple rounds of evaluations or multiple LLM evaluators can reduce the random effects caused by accidental factors in a single round and reduce the potential biases of single LLM evaluator. This strategy significantly enhances the stability and reliability of the evaluation results.

3.3.2 **Direct Optimization of LLMs' Outputs**. Different from obtaining evaluations results based on the outputs of multiple rounds or LLMs, directly optimizing the output of single LLM evaluator involves further processing the evaluation output to make it more reliable, especially when dealing with scoring outputs from LLM evaluators. Due to the inherent randomness in LLMs' generation, the scores may not fully reflect the LLMs' complete view of the evaluation criteria. Therefore, to obtain more reliable evaluation results, it is necessary to optimize the LLMs's score outputs. An effective optimization strategy is to combine the implicit logits which capture the LLMs' randomness with the explicit output scores. For example, FLEUR[52] proposes a score smoothing strategy. For scores generated by LLaVA, the probability of the token corresponding to each digit l (0 $\leq l$ \leq 9) would be used as the weight to smooth the explicit scores and calculate the final evaluation scores.

However, methods like score smoothing, which combine implicit logits and explicit outputs require the LLMs to be open-source, or to provide interfaces that allow access to token probabilities, which brings some limitations. Inspired by the work of Weng et al.[132] and Madaan et al.[76], self-verification can be used to filter out the evaluation results without sufficient robustness. For example, TrueTeacher[26] applies self-verification in its evaluation of distilled data by asking the LLM evaluator for its certainty about the evaluation results after providing them, and retaining only those results that pass self-verification. Self-verification is suitable for all LLMs and require no complex computing and processing.

In summary, compared to integrating multiple evaluation results, directly optimizing the LLMs' outputs to obtain the final results is faster and more low-cost, although the effectiveness still

needs further validation. However, these two approaches are not mutually exclusive. Performing integration after direct optimization of LLMs' output may lead to more stable evaluation results.

4 EVALUATION OF LLM EVALUATORS

Despite their impressive performance, LLMs exhibit several notable shortcomings, such as hallucinations [115], biases [23], and a lack of robustness [162]. When LLMs are employed as evaluators, these inherent issues can lead to suboptimal evaluation outcomes. Therefore, it is crucial to accurately and comprehensively assess the quality of LLM-as-a-judge and identify potential vulnerabilities. This section will review existing work on the evaluation of LLM-as-a-judge, focusing on three key areas: base metric (Section 4.1), bias (Section 4.2), and robustness (Section 4.3).

4.1 Basic Metric

The main objective of LLM-as-a-judge is to achieve alignment with human judges. Numerous studies approach this by considering the LLM evaluator as a virtual annotator and evaluating the extent of its agreement with human annotators. The percentage agreement metric represents the proportion of samples on which LLM and human annotators agree [112].

$$\text{Agreement} = \frac{\sum_{i \in \mathcal{D}} \mathbf{I}(\mathbf{S}_{\text{llm}} = \mathbf{S}_{\text{human}})}{\|\mathcal{D}\|}$$

where \mathcal{D} is the dataset, S_{llm} and S_{human} is the evaluation result of LLM evaluator and human judge respectively, which can be in the form of both score or rank. Additionally, widely used correlation metrics such as Cohen's Kappa [112] and Spearman's correlation [4, 70] are also employed to access agreement. Other works treat the LLM-as-a-judge task as a classification problem, where human annotations serve as the labels, and compute precision, recall, and F1 scores to evaluate the performance [128, 164].

Both of above metrics rely on the datasets with LLM-generated response and responding human judgements. Therefore, there is also a practical need to construct a comprehensive benchmark for the meta-evaluation. In [158], MTBench and Chatbot Arena Conversations are proposed. The former has only 80 human-crafted queries, each with several LLMs' responses and expert-level human annotation on pairwise comparison; the latter is a large collection of crowdsourced data, with more than 30K queries from real-world users and their vote on pairs of responses from different LLMs. FairEval [123] is based on the 80 queries from VicunaBench [117] with human annotated labels between ChatGPT and Vicuna responses. PandaLM [128] constructs a test set comprising 999 pairwise samples, with queries from 252 user-oriented instructions in [126]. LLMEval² [152] is much larger than the previous two, with 2,553 samples compiled from multiple data sources with human-annotated preferences. Shepherd [125] collects 352 samples from multiple sources for its critique model as a test set to evaluate the quality of the critiques. In [144], a meta-evaluation benchmark was created to evaluate the effectiveness of LLM evaluators in recognizing instruction-following outputs, focusing on only a part of the LLM-as-a-Judge pipeline.

More recent works propose benchmark for code [155], multi-modal [9] and non-English [100] tasks. Table 1 shows the benchmarks and their statistics.

Current meta-evaluation primarily focuses on LLM-as-a-judge for models, while there is a lack of sufficient meta-evaluation when these LLM evaluators are used for automatically annotating large-scale datasets (Section 2.4.2). We advocate for more rigorous accessment of the alignment between LLM-as-a-judge and human judgment when they are employed for large-scale data annotation. Additionally, it is also crucial to assess the potential bias and robustness, which will be discussed in the following sections.

Benchmark	Release Year	Size	Annotation Format	Evaluation Dimension				
				Agreement	Position Bias	Length Bias	Bias Types	
MTBench [158]	2023	80	Pairwise	/	1	/	3	
Chatbot Arena [158]	2023	30k	Pairwise	1	/	✓	3	
FairEval [123]	2023	80	Pairwise	1	/	×	1	
PandaLM [128]	2023	-	Pairwise	1	/	×	0	
LLMEval ² [152]	2023	2553	Pairwise	1	×	×	0	
Shepherd [125]	2023	1317	Score	1	×	×	0	
EvalBiasBench [85]	2023	80	Pairwise	1	/	✓	6	
CALM [138]	2024	4356	Pairwise & Score	×	/	✓	12	
JudgeBench [110]	2024	-	Pairwise	1	X	×	0	
MLLM-as-a-Judge [9]	2024	30k	Pairwise & Score	1	×	×	0	
CodeJudge [155]	2024	1860	Score	1	×	×	0	
KUDGE [100]	2024	3324	Pairwise & Score	✓	×	×	0	

Table 1. Benchmark for meta-evaluation of LLM-judge.

4.2 Bias

Previous reviews have highlighted that large language models exhibit various types of biases across various tasks [16, 24, 109]. These internal biases of LLMs may also affect LLM-as-a-judge, leading to unfair evaluation outcomes and subsequently impacting the development of LLMs. Therefore, it is crucial to understand the types of biases that LLM evaluators might possess and to systematically assess these biases. In this section, we systematically review various types of biases in the LLM-as-a-judge context, including their definitions, relevant metrics, and datasets that can be used for evaluation.

Position Bias is the tendency of LLM evaluators to favor responses in certain positions within the prompt [97, 112, 122, 138]. This bias may have detrimental effects, as Vicuna-13B could outperform ChatGPT when evaluated by ChatGPT, simply by positioning the response of Vicuna-13B in the second place [122]. To measure this bias, recent work [97] proposed two metrics: **Position Consistency**, which quantifies how frequently a judge model selects the same response after changing their positions, and **Preference Fairness**, which measures the extent to which judge models favor response in certain positions. The study [122] also introduced a metric **Conflict Rate** to measure the percent of disagreement after change the position of two candidate responses. Their analytical experiments reveal that the degree of positional bias fluctuates depending on the disparity in response quality and the preferred position varies with different LLMs. For instance, GPT-4 tends to favor the first position, while ChatGPT shows a preference for the second position.

Length Bias refers to the tendency to favor responses of a particular length, such as a preference for more verbose responses which is also known as verbosity bias [33, 85, 138, 158]. Length bias can be revealed by rephrasing one of the original response into a more verbose one [138, 158]. Even though these expansions do not introduce new information, there is still concern regarding changes to the original response in terms of perplexity, fluency, or style. Alternatively, previous study [93] investigated this bias by comparing multiple sampled responses and revealed a statistical tendency towards longer answers. However, ensuring the comparable quality of multiple samples remains a challenging problem.

Self-Enhancement Bias describe the phenomenon that LLM evaluators may prefer response generated by themselves [138, 158]. Considering the significant self-enhancement bias, as suggested in [138], we should avoid using the same model as the evaluator. This is only a stopgap, as we may not use the optimal evaluator when evaluating the most advanced LLMs.

Other Bias. Diversity Bias refers to bias against certain demographic groups [138], including certain genders [12], race, and sexual orientation [49]. As revealed in [12], evaluators' tendency toward visually appealing content, regardless of its actual validity, such as the text with emoji. Concreteness bias reflects that LLM evaluators favor responses with specific details, including citation of authoritative sources, numerical values and complex terminologies, which is called authority bias [85] or citation bias [12, 138]. Furthermore, LLM evaluators may favor response with certain emotional tones, such as cheerful, sad, angry, and fearful, which is defined as seyiment bias [53, 138].

To advance the development of LLM-as-a-Judge systems, future efforts should address two key challenges: (i) *Need for Systematic Benchmark*. Due to the diversity of biases, it is crucial to propose a systematic benchmark to evaluate the extent of various biases. As shown in Table 1, *EVALBIASBENCH* [85] was proposed as a test set to measure six types of bias. Other work [138] is dedicated to proposing a unified bias testing process, including automated perturbation and a unified metric. They constructed a bias quantification framework *CALM*, which covers 12 types of bias. Despite these efforts, there is still no systematic benchmark and dataset that includes all types of biases. (ii) *Challenges of Controlled Study*. When conducting an investigation into a certain type of bias, it is challenging to isolate the specific direction of interest from other biases and quality-related characteristics. For instance, in the case of position bias, lengthening the response could potentially alter the style, fluency, and coherence, or even introduce new biases such as self-enhancement bias. Additionally, the tendency for GPT-4 to favor its own responses over those of GPT-3.5 can be interpreted as either self-enhancement bias or a proper tendency towards higher quality text. Therefore, it is essential for analytical work to carefully control for these variances.

4.3 Adversarial Robustness

Adversarial robustness refers to the ability of a model to withstand deliberate attempts to manipulate the scores through carefully crafted inputs. Unlike bias evaluations (Section 4.2) which mainly focus on naturally occurring samples, adversarial robustness involves samples intentionally crafted to manipulate scoring, such as inserting phrases that artificially enhance scores. Robustness is crucial because insufficient robustness allows trivial manipulations to deceive the evaluators and to undermine the evaluation of text quality. Ensuring robust evaluators is essential for maintaining accurate and reliable assessments, particularly in high-stakes applications.

Research [88] constructed a surrogate model from the black-box LLM-evaluator and the learn a **adversarial attack phrases** based on it. The evaluation score can be drastically inflated by universally inserting the learned attack phrases without improving the text quality. Furthermore, other work [160] demonstrated that even a "**null model**" that outputs a constant response irrelevant to input instructions can achieve high win rates for various LLM-as-a-judge methods. Several recent works [45, 138] proposed to increase the evaluation score by adding the **majority opinions**, such as "90% believe this is better". Other researches [45, 138] evaluated robustness against **meaningless statement** in the System Prompt, e.g., ""Assistant A loves eating pasta". These works revealed that LLM-as-a-judge are still insufficiently robust against interference irrelevant to text quality. Defensive measures like the perplexity score [35, 88] can only detect limited types of adversarial examples. Therefore, constructing more robust LLM-as-a-judge is a crucial research direction for the future.

5 EFFECTIVENESS EXPERIMENTS

In Section 3, We have introduced improvement strategies adopted by researchers in existing LLM-as-a-judge works to improve the evaluation capabilities of LLMs. Although numerous works have proposed meta-evaluation benchmarks to assess the performance of LLMs in evaluation tasks, as

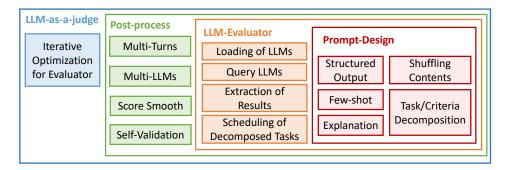


Fig. 10. LLM-as-a-Judge Meta-evaluation Pipeline and Tools

shown in Table 1, there is still a lack of meta-evaluation on whether these improvement strategies effectively optimize the LLM evaluators and which dimensions of evaluation performance are being enhanced. It is possible that some improvement strategies fail to enhance the LLM evaluators' performance or mitigate biases in practical use, leading to computing waste. In this section, based on benchmarks mentioned in Section 4, we designed a robust and scalable meta-evaluation pipeline and tools as shown in Fig 10, and conducted a simple meta-evaluation experiment on the improvement strategies summarized in Section 3, examining their effectiveness from the perspectives of biases and agreement with human evaluation.

5.1 Experiment Settings

5.1.1 Evaluation Dimensions and Benchmarks. The most direct meta-evaluation metric for reflecting the quality of automatic evaluation is the alignment with human evaluation. We use LLMEval² [152] to assess the alignment of LLM-as-a-judge with human evaluations. LLMEval² is the largest and most diverse evaluation benchmark for LLM-as-a-judge to date, with 2,553 samples compiled from multiple data sources with human-annotated preferences. Each sample consists of a question, a pair of candidate responses, and a human label indicating the preferred response.

Bias is also a crucial dimension for assessing the quality of LLM-as-a-judge's evaluation results. We use *EVALBIASBENCH*[85] to measure six types of biases in LLMs, including length bias, concreteness bias, empty reference bias, content continuation bias, nested instruction bias, and familiar knowledge bias. *EVALBIASBENCH* consists of 80 samples, each containing a question, a pair of candidate responses, and a label indicating the correct response without bias influence. In addition to the six types of biases, we also evaluated position bias. The meta-evaluation samples for position bias are the paired samples constructed by swapping the position of candidate responses within prompts in samples of LLMEval² and *EVALBIASBENCH*.

5.1.2 Evaluation Metrics. For the alignment with human evaluation, we use the **Percentage Agreement Metric** for evaluation[112], as shown in Section 4.1. For biases, we use the **Accuracy** for evaluation, which represents the proportion of samples on which LLMs select the correct candidate response annotated in EVALBIASBENCH.

For position bias, we use **Position Consistency** as a metric, which quantifies how frequently a judge model selects the same response after changing their positions. Formally, given N samples $\{(q_i, r1_i, r2_i)\}_{i=1}^N$, for each sample $(q_i, r1_i, r2_i)$, we query the LLM evaluator with two prompts $P(q_i, r1_i, r2_i)$ and $P(q_i, r2_i, r1_i)$, and obtain corresponding two evaluation results S_i^{r12} and S_i^{r21} .

	Alignment	Biases						
LLMs	with	Position	Length	Concre-	Empty	Content	Nested	Familiar
ELIVIS	Human			teness	Reference	Continuation	Instruction	Knowledge
	(n=5106)	(n=2633)	(n=34)	(n=28)	(n=26)	(n=24)	(n=24)	(n=24)
GPT-4-turbo	61.57	80.49	91.18	89.29	65.38	95.83	70.83	100.0
GPT-3.5-turbo	54.72	68.78	20.59	64.29	23.08	91.67	58.33	54.17
Qwen2.5-7B-Instruct	56.54	63.50	64.71	71.43	69.23	91.67	45.83	83.33
LLaMA3-8B-Instruct	50.72	38.85	20.59	57.14	65.38	75.00	45.83	54.17
Mistral-7B-Instruct-v0.3	55.42	59.78	26.47	67.86	53.85	66.67	37.50	41.67
Mixtral-8×7B-Instruct-v0.1	56.29	59.06	50.00	78.57	42.31	83.33	29.17	83.33

Table 2. The meta-evaluation results for different LLMs. All the values are percentages.

Each S_i is $r1_i$, $r2_i$ or "TIE". Then we calculate the position consistency as follows:

Position Consistency =
$$\frac{\sum_{i=1}^{N} \mathbb{I}(S_i^{r12} = S_i^{r21})}{N}$$

where $\mathbb{I}(\cdot)$ is the indicator function.

5.1.3 Target LLMs and Strategies. For LLMs, we selected three LLMs commonly used in automatic evaluation as evaluators, including closed-source LLMs GPT-4, GPT-3.5, and open-source LLMs Owen2.5-7B, LLaMA3-8B, Mistral-7B, and Mixtral-8×7B.

For improvement strategies, we selected *Providing Evaluations with Explanations, Self Validation, Summarize by Multiple Rounds*, and *Vote by Multiple LLMs*, since these strategies are all very straightforward and relatively uniform in many works. We adopt GPT-3.5 as the base evaluator when conducting meta-evaluation for these improvement strategies.

5.1.4 Model Configuration. For the closed-source LLMs, we use the official API provided by OpenAI to interact with LLMs. The model versions we selected are GPT-4-turbo and GPT-3.5-turbo, specifically referencing gpt-4-turbo-2024-04-09 and gpt-3.5-turbo-0125 respectively².

For the open-source LLM, we adopt Qwen2.5-7B-Instruct³, Meta-Llama-3-8B-Instruct⁴, Mistral-7B-Instruct-v0.3⁵, Mixtral-8×7B-Instruct-v0.1⁶, deployed on an Ubuntu machine equipped with a 40GB NVIDIA A100 GPU.

To stabilize the evaluation results of LLMs, we set the hyper-parameter *temperature* to 0 to reduce the impact of randomness in LLMs' output. For *Summarize by Multiple Rounds*, we conduct 5 rounds for each sample, and verify the effects of three different processing methods for results of multiple rounds: *majority voting*(- majority@5), *taking the mean score*(- mean@5), and *taking the best score*(- best@5). For *Vote by Multiple LLMs*, we conduct experiments on two settings, each involving three LLMs. Setting 1 consists of GPT-4-turbo, GPT-3.5-turbo, and LLaMA3-8B-Instruct, while setting 2 consists of GPT-4-turbo, GPT-3.5-turbo, and Qwen2.5-7B-Instruct.

5.2 Experiment Results and Analysis

5.2.1 Comparison with Different LLMs. The experiment results on different LLMs are shown in Table 2. Comparing the evaluation performance of different LLMs, we found GPT-4 outperformed other LLMs with a large margin across all meta-evaluation dimensions and showed fewer biases. Therefore, when conditions allow, using GPT-4 as an automated evaluator may obtain more

 $^{^2} https://platform.openai.com/docs/models \\$

 $^{^3} https://hugging face.co/Qwen/Qwen2.5-7B-Instruct\\$

⁴https://huggingface.co/meta-llama/Meta-Llama-3-8B-Instruct

⁵https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3

⁶https://huggingface.co/mistralai/Mixtral-8x7B-Instruct-v0.1

	Alignment		Biases						
Improvement Strategies	with Human (n=5106)	Position (n=2633)	Length (n=34)	Concreteness (n=28)	Empty Reference (n=26)	Content Continuation (n=24)	Nested Instruction (n=24)	Familiar Knowledge (n=24)	
GPT-3.5-turbo									
- base	54.72	68.78	20.59	64.29	23.08	91.67	58.33	54.17	
- w∕ explanation	52.47	48.97	35.29	60.71	38.46	91.67	41.67	50.00	
- w/ self-validation	54.86	69.31	23.53	60.71	23.08	91.67	41.67	50.00	
- w/ multi rounds									
- majority@5	54.68	70 11	26.47	67.86	23.08	95.83	54.17	50.00	
- mean@5	54.72	69.58	11.76	57.14	26.92	87.50	50.00	50.00	
- best-of-5	51.95	58.72	5.88	42.86	19.23	87.50	37.50	45.83	
multi LLMs (set 1)	57.66	32.28	26.47	64.28	46.15	87.50	66.67	62.50	
multi LLMs (set 2)	58.19	70.98	64.71	71.43	69.23	91.67	45.83	83.33	

Table 3. The meta-evaluation results for different strategies based on GPT-3.5-turbo. All the values are percentages.

objective and less biased evaluation results. For open-source LLMs, we found that Qwen2.5-7B-Instruct showed exceptional evaluation capabilities, outperforming other open-source LLMs in the experiments. Moreover, it surpassed GPT-3.5-turbo in most dimensions except for Position Bias and Nested Instruction Bias, indicating that it can be a promising choice as an open source LLM-as-a-Judge, with the potential to serve as a robust base model for specialized evaluators in specific scenarios.

Additionally, we observed that, apart from Concreteness Bias and Content Continuation Bias, the performance of LLMs except GPT-4-turbo was generally poor, particularly in the Length Bias. And even GPT-4-turbo experienced substantial performance degradation in Empty Reference Bias and Nested Instruction Bias. While Position Bias can be mitigated by swapping the positions of the evaluation contents, addressing other biases may require researchers to explore more effective evaluation strategies. Meanwhile, we also observed that there was not much difference in alignment with human among different LLMs in the experiments, and all of them showed significant room for improvement.

5.2.2 Comparison with Different Strategies. Table 3 shows the effectiveness of different improvement strategies for enhancing the evaluation performance of GPT-3.5-turbo. The results reveals that no all evaluation strategies effectively improve LLM-as-a-judge's evaluation outcomes. Providing with Explanation (w/ explanation) provides interpretability by offering reasons alongside evaluation scores or selections, which aids in logical backtracking during human review. However, in terms of evaluation performance and bias mitigation, it generally has a negative impact. This performance decline is speculated to be caused by deeper biases introduced by self-explanation. Self Validation (w/ self-validation) shows minimal effectiveness, likely due to the LLMs' overconfidence, which may limit its re-evaluation efforts during self-validation. We will further discuss this limitation in Section 7.1.

Summarize by Multiple Rounds with majority voting (w/ majority@5) is a strategy with clear benefits, showing improvements across multiple dimensions. It suggests that taking the majority voting results from repeated evaluations help reduce the impact of randomness in LLMs, thereby addressing bias issues. However, Summarize by Multiple Rounds with taking mean score (w/ mean@5) or with taking best score (w/ best-of-5) did not improve the evaluation performance and even had some adverse effects. Compared to w/ majority@5, which selects the major result from multiple rounds, w/ mean@5 might include results with biases in the mean score calculation, and similarly w/ best-of-5 could potentially select overly high scores influenced by biases. Therefore, the latter two strategies do not effectively mitigate the impact of biases on automated evaluation.

The evaluation results of *Vote by Multiple LLMs* (multi LLMs *set 1* and *set 2*) are closely related to the LLM selection. Comparing *set 1* and *set 2*, where LLaMA3-8B-Instruct was replaced by Qwen2.5-7B-Instruct in *set 2*, it revealed significant differences in performance across various dimensions. In *set 1*, the poor performance of GPT-3.5-turbo and LLaMA3-8B-Instruct in the Length Bias negatively impacted the overall performance, whereas in *set 2*, the performance in this dimension was better, which was aligned with Qwen2.5-7B-Instruct. Similar trends were observed in dimensions like Position Bias, Familiar Knowledge Bias, and so on. This suggests that when multiple LLMs are adopted for joint evaluation, the differences between their evaluation performances must be carefully considered.

5.2.3 Summary. Due to the inherent capabilities and potential risks of LLMs, common improvement strategies for LLM-as-a-judge are not fully effective in improving the evaluation performance or mitigating biases. The limitations and challenges will be further discussed in Section 7.

Based on the current experimental analysis, an empirical strategy for pairwise comparison evaluation tasks is **to select more powerful LLMs and to adopt two evaluation strategies: one is swapping the positions of the evaluation contents, the other is taking the majority voting results from multiple rounds of evaluation**, which can effectively mitigate biases. As for improving the alignment with humans, further exploration is still needed.

6 APPLICATION

LLMs' ability as evaluators has gained widespread recognition in specialized fields, especially in complex, qualitative areas like legal texts, mathematical reasoning, and scientific research. This section reviews recent developments in LLM-as-a-judge applications across finance, law, science, and other industries, investigating how domain knowledge and LLM evaluator can further expand their impact in critical areas.

6.1 Machine Learning

6.1.1 NLP. LLMs have been successfully employed as evaluators in several NLP tasks, including sentiment analysis, machine translation, and text summarization. In sentiment analysis, numerous biases influencing LLM-based judgments have been identified, prompting the creation of automated frameworks to systematically quantify these biases. Despite progress, issues like self-preference and verbosity biases continue to exist [138]. For translation, studies have shown that the effectiveness of LLM evaluators depends heavily on their English training, creating limitations in assessing cultural and factual accuracy in non-English contexts [100]. In text summarization, comprehensive guides have been developed to assist in evaluating LLM-generated content, stressing the importance of new metrics to better capture semantic qualities and minimize hallucinations [120].

6.1.2 Multi-Modal AI Applications. In the field of multi-modal AI, benchmarks have been created to assess LLM-based systems that function across text and vision modalities. These benchmarks have enabled the evaluation of tasks such as image captioning and mathematical reasoning, where LLMs aligned with human preferences in pairwise comparisons but performed poorly in scoring and batch ranking [9]. For Chinese multi-modal alignment, benchmarks have identified challenges in coherence and reasoning, leading to the proposal of a calibrated evaluation model that achieves greater consistency than existing systems [134]. Furthermore, advancements in multi-modal and multi-agent systems have been reviewed, emphasizing collaboration mechanisms to improve rationality and minimize biases [36].

6.2 Other specific domains

6.2.1 Finance. LLMs have demonstrated significant potential in the finance domain, particularly in tasks such as forecasting, anomaly detection, and personalized text generation [154], thereby driving an increasing demand for LLM evaluators.

In the context of LLM-as-a-judge applications within finance, expert knowledge is crucial for domain-specific evaluations. Current research can be divided into two areas: one focuses on designing LLM-based evaluators that leverage expert knowledge for specific tasks. For instance, Brief et al. (2024) conducted a case study on multi-task fine-tuning in finance to enhance LLM performance [6], while Yu et al. (2024) introduced FinCon, a multi-agent system that uses conceptual verbal reinforcement to improve financial decision-making [142]. The second area of research aims to provide benchmarks to evaluate and enhance LLMs' understanding of domain-specific knowledge. These benchmarks include user-feedback-based UCFE [137], IndoCareer—a dataset of professional exam questions [46], and AI-generated domain-specific evaluation sets [89].

Additionally, the concept of LLM-as-a-judge shows promising applications in credit scoring [2, 140] and Environmental, Social, and Governance (ESG) scoring [154]. This work remains in its early stages, necessitating further exploration to refine evaluation methods and expand applications in the finance domain.

6.2.2 Law. LLMs have shown growing capabilities in providing professional advice in specialized fields such as legal consultation, particularly excelling in tasks like text summarization and legal reasoning. However, compared to other fields, the legal sector is more concerned about potential biases and factual inaccuracies within LLMs. Similar to the finance domain, existing research in law can be divided into two main categories.

The first category focuses on developing LLM evaluators specifically for legal applications by addressing professional limitations or designing evaluators themselves. For example, Cheong et al. (2024) propose a four-dimensional framework for constructing responsible LLMs for legal advice, emphasizing (a) user attributes and behaviors, (b) the nature of queries, (c) AI capabilities, and (d) social impacts [13]. Ryu et al. (2023) developed Eval-RAG, a retrieval-augmented generator (RAG)-based evaluator that assesses the validity of LLM-generated legal texts. Testing on a Korean legal question-answering task, they found that combining Eval-RAG with traditional LLM evaluation methods aligns more closely with human expert evaluations [91].

The second category of research involves creating benchmarks for evaluating LLM applicability in legal scenarios. Examples include multi-domain evaluation sets, such as the IndoCareer dataset for professional exams in Indonesia [46] and LegalBench, a collaboratively built benchmark for assessing legal reasoning capabilities in LLMs across multiple domains and languages [28]. These benchmarks are often language-specific like LexEval for Chinese legal texts [54] and Eval-RAG for Korean [91]. Other benchmarks target specific attributes, such as ethics [149] and harmfulness [1].

6.2.3 Al for Science. LLMs have demonstrated notable potential in scientific fields, especially in areas like medical question-answering and mathematical reasoning, where they serve as evaluators to improve accuracy and consistency. In medical applications, studies by Brake et al. (2024) and Krolik et al. (2024) showed that models like LLaMA2 can assess clinical notes and Q&A responses with a level of accuracy approaching that of human experts [5, 47]. This approach leverages prompt engineering to embed expert knowledge, enabling LLMs to handle complex, nuanced information, which provides a reliable first-line assessment that lessens the load on human experts.

In mathematical reasoning, reinforcement learning (RL) and cooperative reasoning methods further enhance LLM's capability as an evaluator, especially for theory-proofing works [72]. For example, WizardMath was introduced by employing RL through step-by-step feedback to refine

reasoning in mathematical tasks [75]. Zhu et al. (2023) proposed a Cooperative Reasoning (CoRe) framework that combines generation and verification to mimic human-like dual-process reasoning, enhancing the model's problem-solving accuracy [165]. Additionally, Lu et al. (2023) developed MathVista, a benchmark for evaluating mathematical reasoning in visual contexts, which assesses LLMs like GPT-4V on tasks involving mathematical reasoning with visual components [72]. These methods highlight the value of combining RL, cooperative reasoning, and prompt engineering in improving LLMs' evaluative and reasoning skills across mathematical reasoning.

6.2.4 Others. LLMs have also been employed as evaluators to enhance efficiency and consistency across various fields. In software engineering, a method was proposed for using LLMs to evaluate bug report summarizations, demonstrating high accuracy in assessing correctness and completeness, even surpassing human evaluators who experienced fatigue [48]. This approach offers a scalable solution for evaluation. In education, automated essay scoring and revising were explored using open-source LLMs, achieving performance comparable to traditional deep-learning models. Techniques such as few-shot learning and prompt tuning improved scoring accuracy, while revisions effectively enhanced essay quality without compromising original meaning [102]. In content moderation, an LLM-based approach was developed to identify rule violations on platforms like Reddit, achieving high true-negative rates but encountering challenges with complex rule interpretation, emphasizing the necessity of human oversight for nuanced cases [44]. In behavioral sciences, the LLM-as-a-Judge framework was evaluated for assessing user preferences based on personas, revealing limitations in reliability and consistency due to oversimplified personas, but improved significantly through verbal uncertainty estimation, achieving high agreement with human evaluations for high-certainty cases [19]. These applications of LLMs as evaluators highlight their growing potential in diverse sectors, emphasizing the need for integrating domain-specific knowledge and refining methodologies.

Moreover, LLMs as evaluators demonstrate significant advantages in qualitative assessments that are difficult to quantify, such as evaluating service quality, analyzing user experience feedback, and assessing creative content like art or literature reviews. LLMs' capability to understand and generate nuanced language makes them well-suited for subjective evaluation tasks traditionally requiring human judgment. Future research will increasingly focus on these areas, exploring how LLMs as judges can enhance assessment accuracy and consistency where traditional quantitative methods fall short.

7 CHALLENGES

In this chapter, we explore the key challenges that arise when utilizing LLMs for evaluation tasks, particularly in the context of LLM-as-a-Judge. Despite their growing capabilities, LLMs still face significant issues related to reliability, robustness, and their backbone models' limitations. Understanding these challenges is crucial for advancing the use of LLMs in a fair, consistent, and reliable manner. We address these concerns under three main themes: reliability, robustness, and the need for more powerful backbone models.

7.1 Reliability

Evaluating the reliability of LLMs when used as judges reveals several pressing challenges. Both human and LLM judges exhibit biases, which raises concerns regarding the consistency and fairness of their evaluations. Specifically, human judges are also found to have inherent bias [133, 156] and may not even provide reliable answers [14, 29]. As an alternative to humans, LLM evaluations are also found to have certain biases, and the annotation results require more evaluation [83], as we discussed in § 4. The bias of LLM-as-a-judge is more due to the fact that LLM is a probabilistic

model, as we have defined in § 4. Moreover, Reinforcement Learning with Human Feedback (RLHF) improves LLM performance by aligning them with human preferences. However, ensuring models trained with RLHF [50] produce robust and consistent outputs remains an ongoing challenge.

In this section, to better understand reliability, we discuss the reliability issues that arise from biases, overconfidence, and challenges in generalization.

Overconfidence. Instruction-tuned LLMs have been demonstrated to possess the issue of overconfidence, which means they tend to offer overly favorable scores when evaluating their own responses [113]. The overconfidence is also highly likely to exist in the scenario of LLM-as-a-judge, which is also engaged in evaluating the responses generated by LLMs. Consequently, when LLM-as-a-judge is utilized with the latest LLMs, which are typically instruction-tuned, the existence and impact of overconfidence need to be meticulously examined.

Fairness and Generalization. Another significant aspect of reliability is fairness and generalization. Evaluations by LLM-as-a-judge can exhibit considerable inconsistency depending on the context. This is why prompt-based methods are often used to improve LLM-as-a-judge performance. However, challenges related to fairness and generalization may arise due to the sensitivity of prompt engineering.

For example, the order of the examples in the context can significantly affect the model's output, leading to unfair evaluations if the examples are poorly arranged. Moreover, LLMs struggle to handle long context windows effectively, often showing degraded performance or prioritizing later examples in the sequence. These issues raise concerns about fairness and generalization in LLM-based evaluations.

7.2 Robustness

Despite LLM's superior power, it is found prone to adversarial attacks [37, 96, 168], under which LLMs can be induced to generate harmful content. While existing works on LLM attacks mainly focus on NLG tasks, more attacks on LLM-as-a-judge are relatively under-explored [12]. This means that we will face some robustness challenges when using LLM-as-a-Judge, and these risks are unknown.

Addressing these robustness challenges requires a deeper understanding of the specific vulner-abilities associated with LLM-as-a-Judge tasks. Unlike traditional adversarial attacks on natural language generation (NLG), where the goal is often to mislead the model into generating harmful or incorrect outputs, attacks on LLM-as-a-Judge aim to exploit biases, inconsistencies, or loopholes in the model's decision-making processes. For instance, subtle manipulations in input phrasing or context framing could potentially lead to significant deviations in judgments, raising concerns about reliability in high-stakes applications.

Currently, we have some methods to defend against such attacks to maintain robustness. These approaches mainly involve post-processing techniques, such as response filtering and consistency checks, which are essential for improving evaluation quality. However, these techniques still face significant challenges. One major issue is self-consistency, as LLMs often produce inconsistent outputs when evaluating the same input multiple times. Another challenge is random scoring, where the model assigns arbitrary or overly positive scores that fail to accurately reflect the true quality of the generated outputs. Such limitations undermine the reliability and robustness of these defense mechanisms.

7.3 Powerful Backone Model

Although LLMs show superior performance in text-based evaluation, the field lacks robust multi-modal models to effectively serve as reliable judges for multi-modal content. Current multi-modal

LLMs, such as GPT-4 Vision, still struggle with complex reasoning across different modalities. This limitation poses a challenge to achieving reliable evaluations on multi-modal assessment tasks. Even in many cases, our LLM cannot complete high-quality evaluation content due to insufficient powerful instruction-following ability and reasoning ability for evaluating text content.

8 FUTURE WORK

The rapid advancements in LLMs open new avenues for innovation while posing significant challenges for their application in critical domains. This section outlines potential directions to enhance the reliability and versatility of LLMs, focusing on their role as evaluators, annotators, and multi-modal evaluators to address pressing needs in research and industry.

8.1 More Reliable LLM-as-a-Judge

As highlighted in our Formulation (§ 2) and Strategy (§ 3), LLMs are probabilistic models that require extensive research and optimization to enhance their reliability as judges. Although current methods have improved the reliability of LLM-as-a-Judge, many challenges, including adaptability and robustness, remain unresolved. To enable probabilistic models to deliver evaluations closely aligned with real-world scenarios, future research should prioritize refining and implementing LLM-as-a-Judge across the evaluation pipeline.

There is considerable potential for improving reliability in various aspects, including In-Context Learning, model selection, post-processing techniques, and the overall evaluation framework for LLM-as-a-Judge. These efforts should prioritize not only enhancing the reliability of assessments but also developing methodologies to systematically evaluate and validate the robustness of these assessments. Furthermore, the establishment of comprehensive evaluation benchmarks and interpretable analytical tools will be crucial for assessing and improving the reliability of LLM evaluators.

inally, the uncertain and evolving nature of robustness risks underscores the necessity of proactive mitigation strategies. These strategies should include the development of adversarial training techniques tailored to judgment tasks, the integration of robust uncertainty quantification methods, and the implementation of human-in-the-loop systems to oversee critical decisions. By addressing these challenges, we can build more resilient and dependable systems capable of maintaining high levels of reliability even under adversarial conditions.

8.2 LLM-as-a-Judge for Data Annotation

Despite its wide applications, data annotation poses significant challenges for current machine learning models due to the complexity, subjectivity, and diversity of data. This process requires domain expertise and is resource-intensive, particularly when manually labeling large datasets. Advanced LLMs such as GPT-4 [78], Gemini [27], and LLaMA-2 [118] offer a promising opportunity to revolutionize data annotation. LLMs serve as more than just tools but play a crucial role in improving the effectiveness and precision of data annotation. Their ability to automate annotation tasks [153], ensure consistency across large volumes of data, and adapt through fine-tuning or prompting for specific domains [101], significantly mitigates the challenges encountered with traditional annotation methods, setting a new standard for what is achievable in the realm of NLP.

Whether in the field of scientific research or industry, we are all still suffering from insufficient target data and domain-specific data, or situations where the data quality is not high enough. Assuming that LLM-as-a-judge can achieve stable performance and be fair and reliable, we can use LLM to annotate data in scenarios where data is insufficient to expand the data. In scenarios with low data quality, we can assess the data quality through LLM, and label the quality tags to achieve the goal of selecting high-quality data. Currently, we have not been able to experimentally

rely solely on LLM for a reliable evaluation of various different scenarios of data; most of the time, we still rely on human annotation to ensure professionalism and reliability. LLM-as-a-judge often needs to learn from human annotations in order to perform certain labeling tasks.

8.3 MLLM-as-a-Judge

AI systems are evolving into highly versatile and multifunctional entities. Traditionally, specialized models were required for distinct language processing tasks, such as sentiment analysis, syntactic parsing, and dialogue modeling. However, large language models (LLMs) have demonstrated competence across these tasks using a single set of weights [104]. Similarly, advancements are being made toward unified systems capable of processing multiple data modalities. Instead of employing distinct architectures for processing text, audio, and images, recent models like GPT-40 [79], Gemini [27], and LLaVA [66] integrate these capabilities within a single framework. These developments highlight a growing trend toward unification in the structure and functionality of AI systems, which extends to the emerging paradigm of LLM-as-a-Judge.

Currently, the emergence of MLLM-as-a-Judge frameworks [10] for evaluating models can be observed. However, research exploring how MLLM-as-a-Judge could be applied to the evaluation of data or agents remains limited. Beyond model evaluation, MLLM-as-a-Judge, much like LLM-as-a-Judge, is envisioned to have the capability to assess or annotate data, function as a Reward Model, or serve as a Verifier within intermediate reasoning processes. These expanded roles would allow MLLM-as-a-Judge to contribute more broadly to the AI pipeline.

The future of evaluation lies in developing robust multimodal evaluators capable of reasoning about and assessing complex content spanning text, audio, images, and video. While current multimodal LLMs exhibit promising capabilities, they often lack the reasoning depth and reliability of their text-based counterparts. Future research must address these limitations, with a focus on enhancing reasoning capabilities, improving reliability, and enabling seamless integration across modalities. A practical multimodal evaluator has the potential to not only advance AI research but also enable new applications in areas such as multimodal content moderation and automated knowledge extraction.

8.4 More LLM-as-a-Judge Benchmarks

The development of more comprehensive and diverse benchmarks is also critical for advancing the reliability and applicability of LLM-as-a-Judge systems. Future efforts could focus on creating high-quality, large-scale datasets that encompass a wide range of scenarios, including domain-specific applications, multi-modal content, and real-world complexities. Additionally, benchmarks should integrate more detailed and fine-grained evaluation metrics. These improvements will not only provide a more holistic understanding of LLM performance but also guide the development of methodologies to enhance their capabilities. By establishing rigorous standards and datasets akin to ImageNet [17] in scale and impact, the LLM-as-a-Judge field can achieve deeper insights and foster greater innovation.

8.5 LLM-as-a-Judge for LLM Optimization

LLM-as-a-Judge shows substantial promise for advancing LLM optimization. Recent studies [167] have begun incorporating LLM-as-a-Judge into multi-agent frameworks to guide inter-agent interactions, thereby improving overall decision-making efficiency and quality. In addition, LLM-as-a-Judge has been employed in Reinforced Fine-Tuning (ReFT) pipelines [119], functioning as a crucial scoring module for evaluating the reasoning processes of models. By flexibly adapting to diverse content formats and domains, LLM-as-a-Judge offers a robust and efficient evaluation mechanism for a wide range of optimization tasks.

Despite these encouraging developments, current research efforts are still in their infancy. Future work should focus on broadening the application domains and strategies for implementing LLM-as-a-Judge, especially in complex, multimodal scenarios. Furthermore, a systematic assessment of its reliability and generalization capabilities will be critical for fully realizing the potential of LLM-as-a-Judge in enhancing model performance and robustness.

9 CONCLUSION

LLM-as-a-Judge represents an LLM-based paradigm for evaluation, offering a compelling alternative to traditional methods that rely either on human experts or quantitative assessments. By leveraging the powerful capabilities of LLMs, this framework excels in scoring, rating, and evaluating tasks with exceptional scalability, adaptability, and precision. These qualities align directly with the growing demand for efficient and robust evaluation systems across diverse fields.

However, fully realizing the potential of LLM-as-a-Judge requires addressing significant challenges, particularly those concerning reliability. The evaluation process must account for factors such as consistency, bias mitigation, and contextual adaptability, ensuring that the system operates under well-defined rules while delivering human-aligned and objective results. Each stage of development—from dataset curation and model fine-tuning to evaluation protocol standardization—demands careful consideration to uphold reliability. Simply deploying LLM-as-a-Judge does not guarantee outcomes that are both accurate and aligned with evaluation needs. Building reliable systems requires systematic efforts to evaluate and refine its outputs, while addressing gaps in definitions, practices, and research.

This survey has provided a comprehensive review of the LLM-as-a-Judge landscape, offering insights into its current state and practical strategies for improvement. By addressing these challenges through robust methodologies and innovative benchmarks, LLM-as-a-Judge can evolve into a highly reliable and practical tool for diverse applications. Ultimately, while the current capabilities of LLMs are impressive, their effectiveness as evaluators depends on thoughtful design and systematic refinement. We hope this work serves as a foundation for further research, guiding the development of more reliable LLM-as-a-Judge systems and facilitating their widespread deployment across academic, industrial, and societal domains.

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