

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 and flexible 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 on LLM-as-a-Judge, offering a **formal definition** and a **detailed classification**, while focusing on addressing the core question: **How to built reliable LLM-as-a-Judge systems?** 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://awesome-lm-as-a-judge.github.io/>.

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* [61], *Introduction IV*, 5:179; *Critique of Pure Reason* [60], A132/B171.

Recently, Large Language Models (LLMs) have achieved remarkable success across numerous domains [179], ranging from technical fields [145, 191, 208] to the humanities [58, 101, 115, 214] and social sciences [49, 130, 165, 178]. Building on their success, the concept of using LLMs as evaluators—commonly referred to as "LLM-as-a-Judge" [210]—has gained significant attention, where LLMs are tasked with determining whether something falls within the scope of a given rule [60, 61]. 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

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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, finding a balance between comprehensive and scalable evaluation posed a persistent challenge. On the one hand, widely used subjective methods like expert-driven assessments [41, 129] integrate holistic reasoning and fine-grained contextual understanding, making them the gold standard in comprehensiveness. However, these approaches are costly, difficult to scale, and susceptible to inconsistency. On the other hand, objective assessment methods, such as automatic metrics offer strong scalability and consistency. For example, tools such as BLEU [110] or ROUGE [87] can rapidly evaluate machine-generated translations or summaries against reference texts without human intervention. However, these metrics, which heavily rely on surface-level lexical overlaps, often fail to capture deeper nuances, resulting in poor performance in tasks like story generation or instructional texts [124]. As a solution to this persistent dilemma, “LLM-as-a-Judge” has emerged as a promising idea to combine the strengths of the above two evaluation methods. Recent studies have shown that this idea can merge the scalability of automatic methods with the detailed, context-sensitive reasoning found in expert judgments [19, 81, 163, 210, 220]. Moreover, LLMs may become sufficiently flexible to handle multimodal inputs [18] under appropriate prompt learning or fine-tuning [64]. 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.

LLM-as-a-Judge holds significant potential as a scalable and adaptable evaluation framework compared to aforementioned two traditional methods [160]. However, the widespread application of this idea is hindered by two key challenges. The first challenge lies in the absence of a systematic review, which highlights the lack of formal definitions, fragmented understanding, and inconsistent usage practices in the relevant studies. As a result, researchers and practitioners struggle to fully understand and apply effectively. The second challenge involves addressing concerns about reliability [189], as merely employing LLM-as-a-Judge does not ensure accurate evaluations aligned with established standards. These challenges emphasize the need for a deeper assessment of the outputs generated by LLM-as-a-Judge, as well as 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. It offers a comprehensive overview of the field and explores 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 question: “*What is LLM-as-a-Judge?*” Next, we categorize existing methods and approaches, exploring “*How to use LLM-as-a-Judge?*”. Following this, to tackle the critical question: “*How to build reliable LLM-as-a-Judge systems?*”, 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 the second aspect, we examine the metrics, datasets, and methodologies used to evaluate LLM-as-a-Judge systems, highlighting potential sources of bias and methods for their mitigation. Building on this, we introduce a novel benchmark specifically designed for evaluating LLM-as-a-Judge systems. Additionally, we explore practical application scenarios and identify challenges unique to each context. Finally, we discuss future research directions, emphasizing key areas for improving reliability, scalability, and applicability.

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 the implementation of an LLM as a judge for specific scenarios, you can find answers in Quick

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

Practice (2.5). Strategies for enhancing and evaluating the reliability of LLM-as-a-Judge systems are discussed in Sections 3, 4, and 5, respectively. Notably, in Section 6, we discuss the synergy between LLM-as-a-Judge and o1-like reasoning enhancement, where dynamic feedback is used to optimize reasoning paths and significantly improve the model's ability to solve complex problems. Section 7 explores practical applications, while Sections 8 and 9 address challenges and outline future research directions. Finally, Section 10 presents our conclusions.

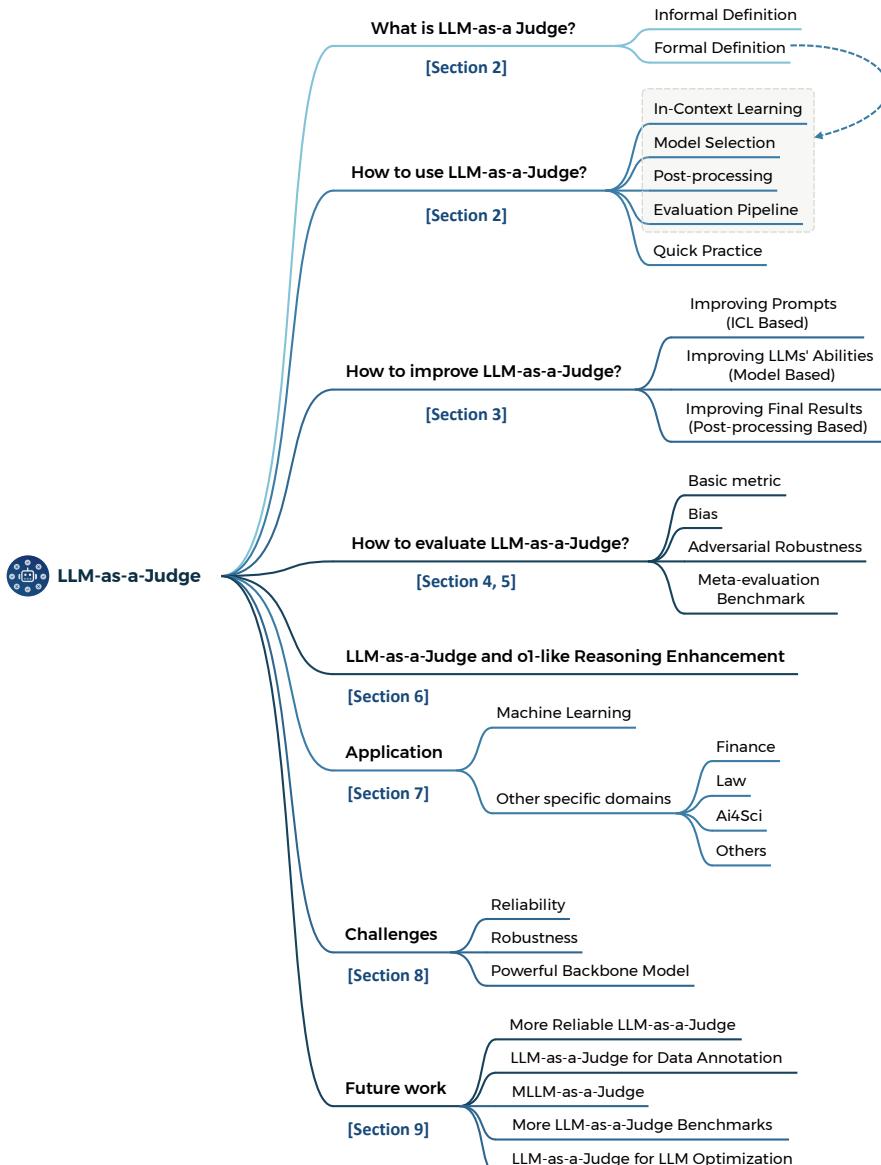


Fig. 1. The overall framework of this paper.

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2 BACKGROUND AND METHOD

The capacity of LLMs to emulate human reasoning and evaluate specific inputs against a set of predefined rules has paved the way for "LLM-as-a-Judge." Existing studies indicate that LLM's 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. As a result, adoption of LLM in evaluation has progressed rapidly in practice. Initially, the primary focus of LLMs was on language generation and comprehension. With advancements in training paradigms like Reinforcement Learning from Human Feedback (RLHF) [108], LLMs became increasingly 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 denotes 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** [31, 154], **Evaluators/Assessors** [82, 196], **Critics** [63, 112, 175], **Verifiers** [90, 131, 166], **Examiners** [9], **Reward/Ranking Models** [100, 139, 180, 193], 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:

$$\mathcal{E} \leftarrow \mathcal{P}_{\mathcal{LLM}}(x \oplus C)$$

- \mathcal{E} : The final evaluation obtained from the whole LLM-as-a-Judge process in the expected manner. It could be a score, a choice, a label 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 and then obtains 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 specified using In-Context Learning methods, which provide instructions and examples to guide the model's reasoning and judgment. This process involves two key aspects: input design and prompt design. 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 its position (e.g., at the beginning, middle, or end). For the prompt design, four different methods can be adopted, as illustrated in Figure 2. These methods include generating scores, solving true/false questions, conducting pairwise comparisons, and making multiple-choice selections. Further details will be presented in the following sections.

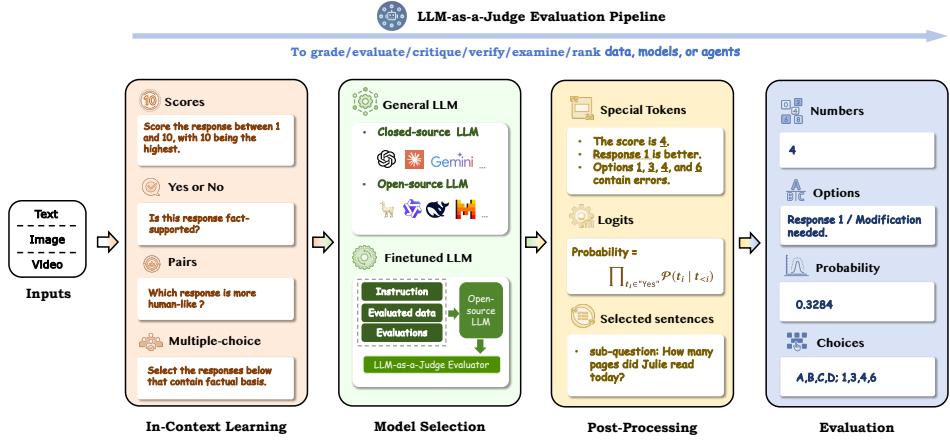
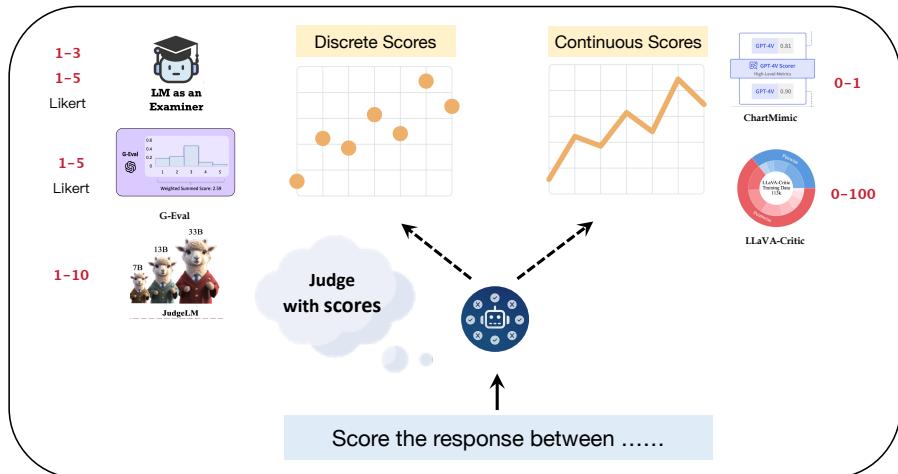


Fig. 2. LLM-as-a-Judge evaluation pipelines.

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 [59], or 1-10 [81, 220]. Alternatively, it can be continuous, ranging from 0 to 1 or 0 to 100 [175]. 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" [220]. A slightly more complex way is to provide more detailed scoring criteria. More complex scoring situations can be as *Language-Model-as-an-Examiner* [9], which use Likert scale scoring functions as an absolute evaluative measure, showed in Figure 4. 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

Fig. 3. The illustrations of method *generating scores* in ICL

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. 4. The template for Likert scale scoring from Gao et al. [41].

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—with no 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* [131], 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 [149], 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 [138], 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 5.

Is the sentence supported by the article? Answer "Yes" or "No".
Article: {Article}
Sentence: {Sentence}

Fig. 5. 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, shown in Figure 6. 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 [114]. As noted by [97], 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 [98, 210]. Furthermore, pairwise comparisons can be extended to more complex relation-based assessment frameworks, such as list-wise comparisons, using advanced ranking algorithms [97, 114], data filtering [193]. 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, as shown in Figure 9 (right). Evaluations typically involve determining the outcomes of win, tie, or loss for responses [163] 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."

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. 6. The template for pairwise comparison from Gao et al. [41]

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 7. However, this kind of prompt design is more rare than the first three.

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. 7. 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 [107] instead of human evaluators [210]. For instance, Li et al. [83] 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. [210] designed 80 multi-round 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 [163] constructs data based on Alpaca instructions and GPT-3.5 annotation, and then fine-tunes LLaMA-7B [151] as an evaluator model. JudgeLM [220] constructs data from diversified instruction sets and GPT-4 annotations, and fine-tunes Vicuna [152] as a scalable evaluator model. Auto-J [81] constructs evaluation data upon multiple scenarios to train a generative evaluator model, which can provide both evaluation and critical opinion. Prometheus [65] defines thousands of evaluation criteria and constructs 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 as shown in Figure 8. **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 [108]. 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 ensure accurate evaluations. The evaluation format should align with our In-Context Learning design and may involve procedures to enhance the reliability of extracted evaluations, which should be applied consistently. We focus on three main post-processing methods: extracting specific tokens, normalizing the output logits, and selecting sentences with high returns.

However, it is important to note that each method has significant limitations when evaluating objective questions. For example, in text response evaluation [189], 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 tightly linked to the prompt design used in 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 [149]: "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 Constrained decoding. Constrained decoding is a technique that enforces structured output from Large Language Models (LLMs) by restricting token generation according to predefined schemas, typically in formats like JSON. This approach uses a finite state machine (FSM) to compute valid next tokens at each decoding step, effectively masking the model's output probability distribution to ensure conformity with the desired schema. While this method guarantees syntactically valid outputs, it presents several challenges: it can distort the model's learned distribution and potentially degrade output quality, requires significant engineering implementation effort, and introduces computational overhead during inference.

Recent work has proposed various solutions to address these challenges. [12] introduce DOMINO, a decoding algorithm that preserves natural tokenization while enforcing constraints. Their system minimizes overhead through precomputation and speculative decoding, sometimes achieving faster performance than unconstrained decoding. [32] develop XGrammar, which accelerates grammar-constrained generation by separating tokens into those that can be pre-checked and those requiring runtime verification. By co-designing the grammar engine with LLM inference, they achieve up to 100x speedup over existing approaches. [212] present SGLang, combining a domain-specific language with an optimized runtime. Their system features efficient KV cache reuse and compressed finite state machines for faster decoding, demonstrating that thoughtful co-design of programming model and runtime can minimize constrained decoding overhead.

2.3.3 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 [47, 166, 224]. For example, the self-consistency and self-reflection scores [166] 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 auto-regressive 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 $\rho_j = \rho_{\text{SC},j} \cdot \rho_{\text{SR},j}$.

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

In addition, Self-evaluation [47] 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."

2.3.4 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 [47], builds a reasoning tree by iteratively considering the most promising reasoning steps (actions, sub-questions) by LLM-as-a-Judge.



Fig. 8. Four typical scenarios using LLM-as-a-Judge evaluation pipeline.

2.4 Evaluation Pipeline

After completing the three processes, we obtain the final evaluation \mathcal{E} . From input to output, these steps collectively constitute the LLM-as-a-Judge evaluation pipeline, as illustrated in Figure 2. This pipeline is commonly applied in four scenarios shown in Figure 8: LLM-as-a-Judge for models, LLM-as-a-Judge for data, LLM-as-a-Judge for agents, and LLM-as-a-Judge for reasoning or thinking.

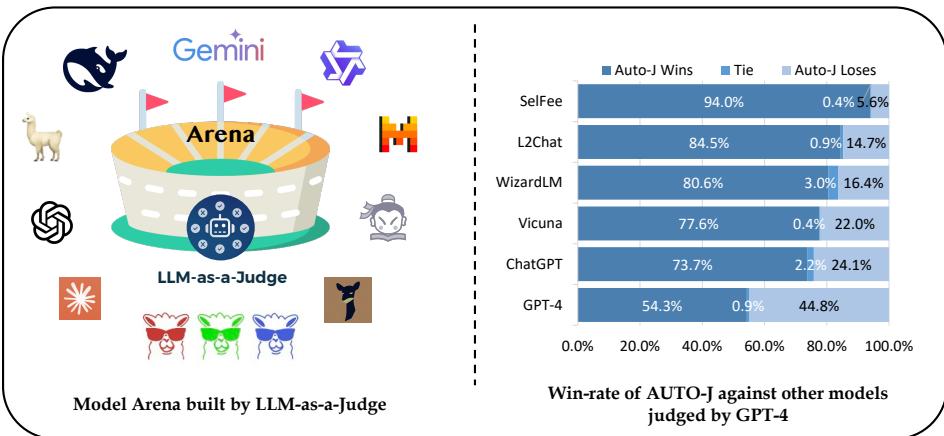


Fig. 9. The illustrations of the scenario *LLM-as-a-Judge for Models*. The example of "win-tie-lose" is from Li et al. [81]

2.4.1 LLM-as-a-Judge for Models. 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 [108, 210]. 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 [215], as shown in Figure 9.

With appropriate prompt design, the quality of evaluation and agreement to human judgment can be promising [35, 158, 205, 210]. 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 [187] collects generations, feedback, and revised generations from ChatGPT and fine-tunes LLaMA models to build a critique model. Shepherd [161] trains a model that can output critiques for single-response with the data of feedback from online communities and human annotation. PandaLM [163] trains a model to conduct pairwise comparison for LLM Instruction Tuning Optimization, and Zheng et al. [210] also fine-tune Vicuna [152] on a 20K pairwise comparison dataset to explore the potential of open-source models as a more cost-friendly proxy.

2.4.2 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 [146, 162]. After that, reinforcement learning techniques have been explored to align language models with human preferences [108, 120]. The most successful way is applying a RLHF framework [108] via training a reward model on human feedback and using PPO [125] 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, [31, 193] use general LLM (ChatGPT) to get better alignment with human preferences. The Aplaca prompts [146] 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 [93, 203] and principle-driven self-alignment [140].

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* [100] 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 iii) 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 [160] 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 [26, 84, 157]. 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 [139]. Benchmarks such as MLLM-as-a-Judge [18] 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.

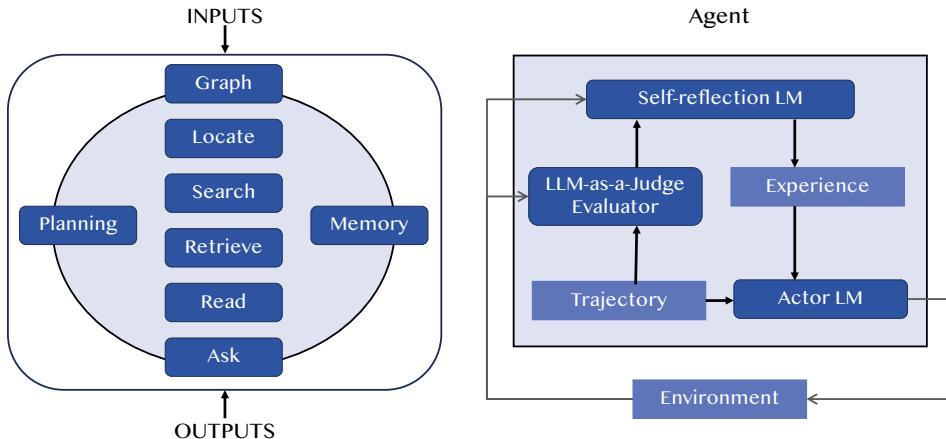


Fig. 10. LLM-as-a-Judge appears in two common forms in the agent. The left diagram is Agent-as-a-Judge, designing a complete agent to serve as an evaluator. The right diagram shows using LLM-as-a-Judge in the process of an Agent.

2.4.3 LLM-as-a-Judge for Agents. There are two ways to apply LLM-as-a-Judge for an agent. One is to evaluate the entire process of the intelligent agent [225], and the other is to evaluate it at a specific stage in the agent framework process [47, 131]. Both approaches are briefly illustrated in Figure 10. Using LLM as the brain of agent, an agentic system [225] 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 [131] can interact with the environment through language and receive feedback on actions through LLM to make decisions for the next action.

2.4.4 LLM-as-a-Judge for Reasoning/Thinking. Reasoning [52], defined as the cognitive process of applying logic, arguments, and evidence to draw conclusions, is central to intellectual tasks such as decision-making, problem-solving, and critical analysis. While reasoning is inherently more demanding and multifaceted than judging, it often depends on judgments to ensure logical coherence, refine intermediate steps, and achieve clarity in its outcomes. LLM-as-a-Judge, in this sense, becomes an integral tool for enhancing the reasoning capability of LLM.

The role of LLM-as-a-Judge in enhancing reasoning or thinking can be understood through two frameworks: scaling training time [40, 154] and scaling test time [132]. In the training phase, LLM-as-a-Judge frequently operates within reinforcement learning paradigms, where it functions as a reward model or evaluator for data or processes. This enables the creation of high-quality reasoning datasets through mechanisms such as step-by-step verification [86], Direct Preference Optimization(DPO) [117], and self-refinement [192]. Recently, several LLMs trained with reinforcement learning to exhibit advanced reasoning and thinking abilities have gained attention, such as o1², DeepSeek-R1³, gemini-thinking⁴, and QVQ⁵. In the test-time framework, LLM-as-a-Judge is crucial for evaluating and selecting the best reasoning paths. For example, in "Best-of-N" generation scenarios, where multiple reasoning outputs are produced, the judge determines the most accurate and coherent response. This dual role in both training and test phases demonstrates the indispensable nature of LLM-as-a-Judge in enhancing reasoning systems.

2.5 Quick Practice

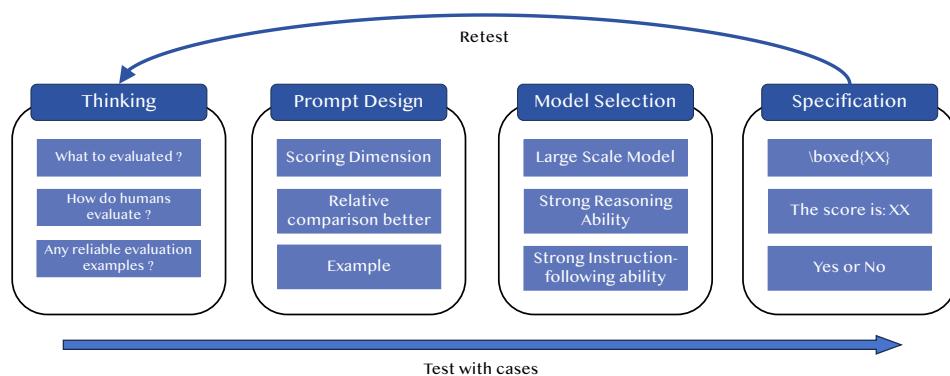


Fig. 11. Flowchart of Quick Practice

To effectively apply LLM-as-a-Judge design, it is recommended to find more effective configurations in the **testing cycle** for various scenarios. The success of using LLM-as-a-Judge also heavily depends on the implementation details, including the task complexity, the prompt design, the model selected, and the post-processing method. As shown in Figure 11, **The process of quick practice for LLM-as-a-Judge involves four main stages**. First is the thinking phase, in which users define the evaluation objectives by determining what needs to be evaluated, understanding typical human evaluation approaches, and identifying some reliable evaluation examples. Next is prompt design, detailed in Section 2.1, both wording and formats matter. 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").

²<https://openai.com/index/learning-to-reason-with-langs/>

³<https://api-docs.deepseek.com/news/news1120>

⁴<https://ai.google.dev/gemini-api/docs/thinking-mode>

⁵<https://huggingface.co/Qwen/QVQ-72B-Preview>

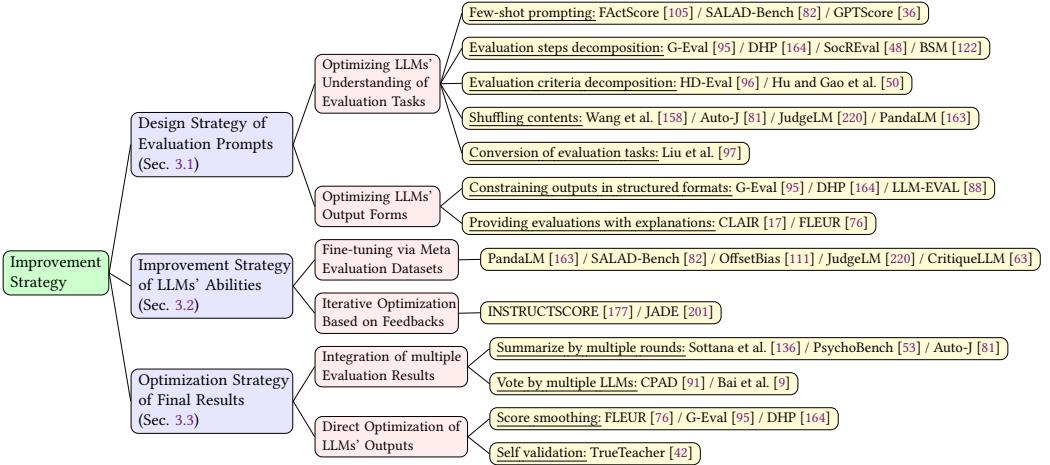


Fig. 12. Structure of Improvement Strategy.

The entire process includes iterative testing with cases and refinement through retesting thereby enhancing reliability. During development, it is essential to compare models or prompts and verify ongoing improvements.

3 IMPROVEMENT STRATEGY

When directly utilizing LLMs to conduct evaluation tasks—such as scoring, selection, pairwise comparison, or ranking—their inherent biases of LLMs like length bias, position bias, and concreteness bias[111] will undermine evaluation outcomes. Mitigating these inherent biases and improving the overall evaluation performance of LLMs remains a critical challenge for applying LLMs as evaluators. In this section, we introduce three improvement strategies to boost 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). As shown in Figure 12, our categorization is based on the formal definition of LLM-as-a-judge 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}_{LLM} and the post-processing \leftarrow to obtain the final results \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, enabling them to learn how to perform specified tasks from relevant examples or instructions in prompts, without requiring weight updates or retraining[15]. This suggests that the design strategy of evaluation prompts will significantly impact the effectiveness of LLM-as-a-judge. Therefore, optimizing the design of evaluation prompts, including better methods to help LLMs interpret the evaluation tasks and generate results, is the most direct and effective way to boost 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[15]. 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[105], SALAD-Bench[82], and GPTScore[36].

In addition to providing high-quality examples for LLMs, refining the evaluation task instructions is also an effective approach to optimize LLMs' understanding of evaluation tasks. Current methods for refining evaluation tasks mainly include 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[95] and DHP[164] use Chain-of-Thought(CoT)[168] to guide LLMs. SocREval[48] employs the Socratic method to meticulously design each step to enhance evaluation performance. Saha et al. propose Branch-Solve-Merge(BSM)[122], 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 finer-grained sub-criteria like Grammar, Engagingness, and Readability, and then generating overall scores based on these different dimensions. HD-Eval[96] iteratively aligns LLM evaluators with human preference via hierarchical criteria decomposition thereby addressing the potential bias in LLMs. Hu and Gao et al.[50] summarize and clearly define an explicit hierarchical classification system encompassing 11 criteria, addressing the issue of LLMs potentially confusing different evaluation standards. These refinements are 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.[158] 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[81] and JudgeLM[220] also enhance the evaluation consistency by shuffling the texts to be evaluated. In contrast to averaging scores, PandaLM[163] 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[118], some research works convert scoring tasks into pairwise comparison, thereby enhancing the reliability of evaluation results. Liu et al.[97] 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[95] and DHP framework[164] 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[88] further modifies this form-filling paradigm, efficiently outputs evaluation results in JSON format, and obtains 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[17] requires LLMs to output evaluation scores between 0-100 simultaneously with relevant reasons as explanations in JSON format, which enhances the rationality and interpretability of the scores. FLEUR[76] 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 are a reflection of their powerful general language understanding and generation abilities triggered by specific prompts. Methods for optimizing evaluation through prompt design—focused 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 GPT-4 encounter problems such as conceptual confusion[50], and smaller open-source LLMs have even more limitations in their evaluation capabilities. Consequently, refining the evaluation capabilities of LLMs, including how to fine-tune LLMs through meta-evaluation datasets and how to iteratively optimize models based on the 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[163] samples inputs and instructions from Alpaca 52K[146] and generates responses using GPT-3.5 to construct training data, while SALAD-Bench[82] builds its training data from a subset of LMSYS-Chat[211] and Toxicchat[89].

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[111] 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[220] enhances LLMs' evaluation capabilities by creating different types of training

data through paradigms like reference support and reference drop. CritiqueLLM[63] 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 gives them the ability to produce evaluations that are more aligned with human preferences. However, LLM-as-a-judge may still introduce biases during the evaluation process in practice, which can impact the overall evaluation quality. A natural improvement strategy is to iteratively optimize the model based on the 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[177]. To improve model performance and further benefit the final quality score calculation, this scoring framework collects failure modes of metric outputs, queries 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[201] 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 humans when optimizing evaluation capabilities based on this feedback, leading to better evaluation results. This feedback-based iterative optimization strategy addresses the problem of models' imperfect generalization and improves the evaluation capabilities through dynamic updates.

3.3 Optimization Strategy of Final Results

Through optimization based on in-context learning and the model' own capabilities, LLMs have become fairly reliable evaluators that 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.[136] reduces randomness in evaluations by averaging multiple scores of the same sample. Similarly, PsychoBench[53] takes the mean and standard deviation from ten

independent runs. Auto-J[81] 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 integrating the results is another effective method, which can reduce biases introduced by LLMs. For instance, CPAD[91] utilizes ChatGLM-6B[34], Ziya-13B[199], and ChatYuan-Large-v2[200] as evaluators to evaluate the contents and obtain the final results by voting. Bai et al.[9] 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 a 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 evaluation results based on the outputs of multiple rounds or LLMs, directly optimizing the output of a 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 LLM'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[76] 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.[169] and Madaan et al.[104], self-verification can be used to filter out the evaluation results without sufficient robustness. For example, TrueTeacher[42] 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 requires 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 [150], biases [37], and a lack of robustness [219]. 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).

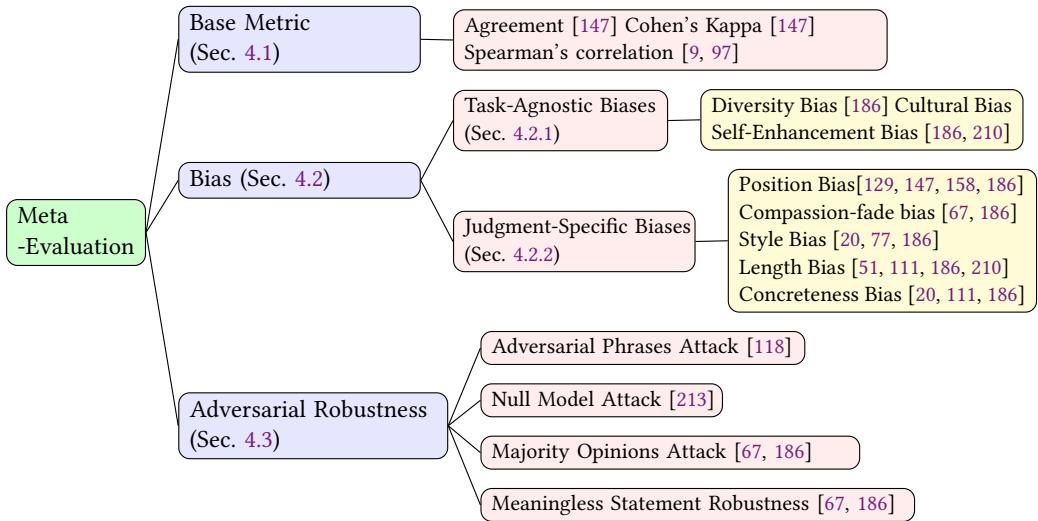


Fig. 13. Structure of Meta-Evaluation.

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 [147].

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

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 [147] and Spearman's correlation [9, 97] 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 [163, 220].

Datasets. Both of above metrics rely on the datasets with LLM-generated response and responding human judgments. Therefore, there is also a practical need to construct a comprehensive benchmark for the meta-evaluation. We list the existing benchmarks and their statistics in Table 1. MTBench [210] has only 80 human-crafted queries with their responding human annotation and LLMs' responses. FairEval [158] is constructed from the 80 queries from VicunaBench [152] with human annotated preference between ChatGPT and Vicuna responses. Chatbot Arena Conversations [210] is a larger collection of crowdsourced data (about 30k) with human annotated preference. Research [195] construct a benchmark to access the capability of LLM evaluator in evaluating whether a response is following the instruction. This dataset contains human-curated 419 pairs of outputs, one adhering to instructions while the other diverging, yet may possess deceptive qualities that mislead an LLM evaluator. Research [18] evaluate the capabilities of multi-modal LLMs in assisting evaluation tasks across various modalities and introduce MLLM-as-a-Judge, a comprehensive multi-modal benchmark. Recent advances also expand the scope of meta-evaluation benchmarks to specialized domains, including code assessment [209] and non-English language

tasks [133]. Furthermore, CALM [186] presents a systematic framework for bias quantification, featuring an automated perturbation mechanism to generate meta-evaluation data for examining 12 distinct types of potential biases in LLM evaluators.

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 assessment 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 [210]	2023	80	Pairwise	✓	✓	✓	3
Chatbot Arena [210]	2023	30k	Pairwise	✓	✓	✓	3
FairEval [158]	2023	80	Pairwise	✓	✓	✗	1
PandaLM [163]	2023	-	Pairwise	✓	✓	✗	0
LLMEval ² [205]	2023	2553	Pairwise	✓	✗	✗	0
Shepherd [161]	2023	1317	Score	✓	✗	✗	0
EvalBiasBench [111]	2023	80	Pairwise	✓	✓	✓	6
CALM [186]	2024	4356	Pairwise & Score	✗	✓	✓	12
JudgeBench [142]	2024	-	Pairwise	✓	✗	✗	0
MLLM-as-a-Judge [18]	2024	30k	Pairwise & Score	✓	✗	✗	0
CodeJudge [209]	2024	1860	Score	✓	✗	✗	0
KUDGE [133]	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 [27, 37, 141]. 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.

The meta-evaluation of LLM-as-a-judge introduces systematic biases that can be broadly categorized into two classes: **task-agnostic biases** inherent to LLMs across general applications, and **judgment-specific biases** unique to LLM-as-a-judge scenarios. This taxonomy aims to clarify their distinct characteristics and implications.

4.2.1 Task-Agnostic Biases. These biases manifest across diverse LLM applications, including open-domain QA, classification, and summarization. However, when arising in the LLM-as-a-judge, the biases are particularly critical due to their cascading effects on downstream tasks. When LLM-generated judgments serve as feedback for model training or data annotation, these biases risk being amplified and propagated. We present a few typical examples and recommend consulting comprehensive reviews on language model bias [38, 45] for a more thorough understanding.

Diversity Bias refers to bias against certain demographic groups [186], including certain genders [20], race, and sexual orientation [71]. In the context of LLM-as-a-judge scenarios, this bias may appear when evaluators give higher scores to responses that align with stereotypes of certain groups.

Cultural Bias. In general domains, cultural bias refers to situations where models might misinterpret expressions from different cultures or fail to recognize regional language variants [38]. In the context of LLM-as-a-judge, it indicates that evaluators might score expressions from unfamiliar cultures poorly.

Self-Enhancement Bias describe the phenomenon that LLM evaluators may prefer response generated by themselves [186, 210]. This bias has also been known as source bias in retrieval task [28] and open-domain question answering systems [141]. Considering the significant self-enhancement bias, as suggested in [186], 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.

4.2.2 Judgment-Specific Biases. Judgment-specific biases are either unique to the LLM-as-a-judge setting or have a significant impact on judgment tasks. A classic example is the "position bias", which has a more pronounced effect in the context of LLM-as-a-judge where the evaluator often need to compare pairwise responses. Different from task-agnostic biases, judgment-specific biases are more difficult to resolve naturally with the development of foundational large model capabilities and require targeted optimization for judgment tasks.

Position Bias is the tendency of LLM evaluators to favor responses in certain positions within the prompt [129, 147, 158, 186]. 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 [158]. To measure this bias, recent work [129] 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 [158] 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.

Compassion-fade bias describes the effect of the model names [67, 186]. This tendency occurs when we explicitly provide model names; for instance, evaluators may be inclined to give higher scores to results labeled as "gpt-4". This tendency underscores the necessity of anonymous evaluation.

Style Bias refers to the tendency towards certain text style. As revealed in [20], evaluator may also prefer visually appealing content, regardless of its actual validity, such as the text with emoji. Furthermore, LLM evaluators may favor response with certain emotional tones, such as cheerful, sad, angry, and fearful, which is defined as sentiment bias [77, 186].

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** [51, 111, 186, 210]. Length bias can be revealed by rephrasing one of the original response into a more verbose one [186, 210]. 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 [123] 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.

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** [111] or **citation bias** [20, 186].

The negative effects of concreteness bias arises from the neglect of the factual correctness of these details, thereby encouraging hallucination [1].

4.2.3 Challenges. 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* [111] was proposed as a test set to measure six types of bias. Other work [186] 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 [118] 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. Similarly, work by Lee et al. [75] introduced EMBER, a benchmark that revealed biases in when assessing outputs with epistemic markers, such as expressions of certainty or uncertainty. Furthermore, other work [213] 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 [67, 186] proposed to increase the evaluation score by adding the **majority opinions**, such as "90 Other research [67, 186] 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 [54, 118] 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 META-EVALUATION EXPERIMENT

In Section 3, we have introduced the improvement strategies adopted by researchers in existing LLM-as-a-judge works to improve the evaluation capabilities of LLM. Although numerous works have proposed meta-evaluation benchmarks to assess the performance of LLMs in evaluation tasks, as shown in Table 1, there is still a lack of meta-evaluation of whether these improvement strategies effectively optimize LLM evaluators and which dimensions of evaluation performance are being enhanced. Some improvement strategies may fail to improve the LLM evaluators' performance or mitigate biases in practical use, leading to computing waste.

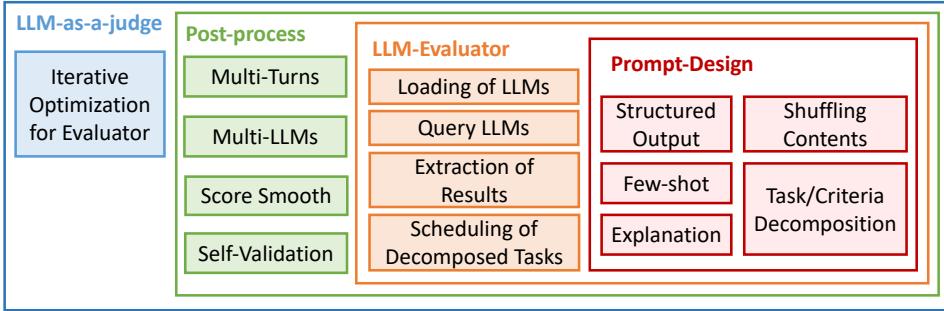


Fig. 14. LLM-as-a-Judge Meta-evaluation Pipeline and Tools

In this section, based on the benchmarks mentioned in Section 4, we designed a robust and scalable meta-evaluation tool as shown in Fig. 14, 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 metric to reflect the quality of automatic evaluation is the alignment with human evaluation. We use LLMEval² [205] 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 evaluation results. We use EVALBIASBENCH[111] to measure six types of biases in LLM-as-a-judge, 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 **Percentage Agreement Metric**[147] for evaluation, as shown in Section 4.1. For biases except for position bias, we use **Accuracy** for evaluation, which represents the proportion of samples where LLM-as-a-judge selects the correct candidate response annotated in EVALBIASBENCH.

For position bias, we use **Position Consistency** as the metric, which quantifies how frequently the LLM-as-a-judge selects the same response after swapping the position of candidate responses. Formally, given N samples $\{(q_i, r_{1i}, r_{2i})\}_{i=1}^N$, for each sample (q_i, r_{1i}, r_{2i}) , we queried the LLM-as-a-judge with two prompts $P(q_i, r_{1i}, r_{2i})$ and $P(q_i, r_{2i}, r_{1i})$, and obtained two corresponding evaluation results S_i^{r12} and S_i^{r21} . Each S_i is r_{1i} , r_{2i} or "TIE". Then we calculate the position consistency as follows:

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

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

LLMs	Alignment			Biases				
	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-4-turbo	61.54	80.31	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
gemini-2.0-thinking	60.75	76.84	94.12	89.29	50.00	100.00	83.33	100.00
o1-mini	60.16	76.73	91.18	89.29	53.85	95.83	75.00	95.83
o3-mini	61.66	74.63	82.35	92.86	73.08	95.83	87.50	91.67
deepseek r1	56.48	69.17	94.12	100.00	50.00	100.00	75.00	87.50

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

5.1.3 Target LLMs and Strategies. For LLMs, we selected six LLMs commonly used in the automatic evaluation, including closed-source LLMs GPT-4, GPT-3.5, and open-source LLMs Qwen2.5-7B, 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 straightforward and relatively common in many works. We adopt GPT-3.5 as the base evaluator for the meta-evaluation of these improvement strategies.

5.1.4 Model Configuration. For closed-source LLMs, we interact using OpenAI’s official APIs. 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 respectively⁶.

For open-source LLMs, we adopt Qwen2.5-7B-Instruct⁷, Meta-Llama-3-8B-Instruct⁸, Mistral-7B-Instruct-v0.3⁹, Mixtral-8×7B-Instruct-v0.1¹⁰, 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 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

⁶<https://platform.openai.com/docs/models>

⁷<https://huggingface.co/Qwen/Qwen2.5-7B-Instruct>

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

⁹<https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3>

¹⁰<https://huggingface.co/mistralai/Mixtral-8x7B-Instruct-v0.1>

LLMs	human=model1		human=model2		human=TIE	
	aligned / total	accuracy (%)	aligned / total	accuracy (%)	aligned / total	accuracy (%)
GPT-4-turbo	1418 / 2071	68.47	1438 / 2070	69.47	286 / 962	29.73
gemini-2.0-thinking	1354 / 2070	65.41	1621 / 2070	78.31	127 / 962	13.20
o1-mini	1444 / 2070	69.76	1401 / 2071	67.65	227 / 963	23.57
o3-mini	1448 / 2004	72.26	1206 / 2004	60.18	399 / 943	42.31
deepseek r1	1369 / 2071	66.10	1342 / 2071	64.80	173 / 964	17.95

Table 3. The evaluation results of each human label in LLMEval². Only valid responses are counted when calculating the accuracy, while samples that couldn't receive responses due to triggering Azure OpenAI's content management policy are excluded. So there are some differences in the total values of different models.

Improvement Strategies	Alignment			Biases				
	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 4. The meta-evaluation results for different strategies based on GPT-3.5-turbo. All the values are percentages.

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. 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 humans among different LLMs in the experiments, and all of them showed significant room for improvement.

5.2.2 Comparison with Different Strategies. Table 4 shows the effectiveness of different improvement strategies for enhancing the evaluation performance of GPT-3.5-turbo. The results reveal that not 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 8.1.

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 helps 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 Evaluation of Reasoning LLM-as-a-Judge. As discussed in Sections 2.4 and 2.5, judgment serves as the foundation for effective reasoning capabilities. In other words, models with stronger reasoning capabilities are generally better equipped to perform as reliable judges. To validate this assumption, we conducted evaluations on several reasoning LLMs including o1-mini, o3-mini, Gemini-thinking and Deepseek-R1. The results in Tables 2 and 3 provide key insights into the performance of reasoning-focused LLMs. While these models—gemini-2.0-thinking, o1-mini, o3-mini and deepseek r1—demonstrate **competitive alignment and accuracy** relative to the top-performing GPT-4-turbo, **their improvements in tasks requiring human alignment are not as pronounced as expected**.

GPT-4-turbo remains the benchmark for alignment, achieving the highest accuracy rates of 68.47. Among reasoning-enhanced models, gemini-2.0-thinking shows strong performance in the human= model2 scenario, achieving an accuracy of 78.27. These results indicate that reasoning-enhanced LLMs **provide meaningful advancements over baseline models but fall short of delivering consistent advantages in alignment-related tasks**, suggesting room for further optimization in this area.

5.2.4 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 8.

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 LLM-AS-A-JUDGE AND O1-LIKE REASONING ENHANCEMENT

When faced with a challenging problem, humans often spend considerable time and effort reflecting on various possibilities before arriving at a solution. In a similar fashion, o1, an advanced model developed by OpenAI, engages in a structured chain of thought to solve complex tasks. This process of deliberate reasoning allows o1 to continuously refine its approach [113], step by step,

as it navigates through difficult scenarios. **A key factor in enhancing o1's reasoning is the integration of LLM-as-a-Judge**, which evaluates the model's reasoning paths at each stage. As o1 works through a problem, the judge provides feedback that helps the model improve by pointing out inconsistencies, suggesting corrections, and identifying simpler ways to break down difficult tasks. By using the feedback from its own evaluations, much like a constitutional AI framework, o1 is able to adapt its reasoning strategies and enhance its performance. Through reinforcement learning, o1 fine-tunes its strategies, learning not only from its successes but also from its mistakes. The combination of LLM-as-a-Judge, reinforcement learning, and the feedback loop from constitutional evaluation allows o1 to dynamically adjust its reasoning, ensuring that the model continuously improves its ability to solve complex problems over time. This synergy between reasoning and judgment, combined with continuous feedback, drives o1's advanced problem-solving capabilities.

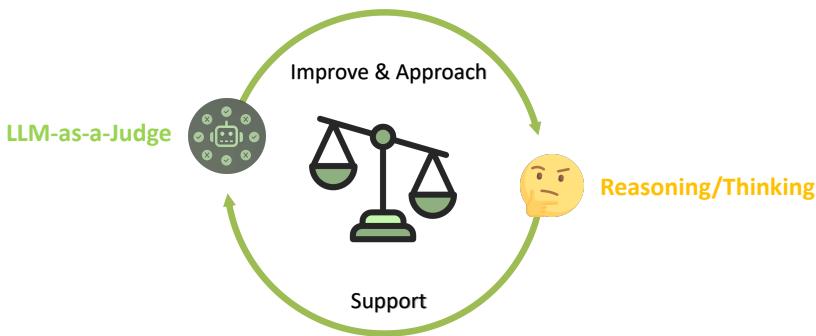


Fig. 15. The relationship of LLM-as-a-Judge and Reasoning/Thinking.

In this process, we can observe two ways in which LLM-as-a-Judge evaluates both Reasoning and Thinking. The first method involves evaluating the reasoning process during the training phase, where LLM-as-a-Judge provides feedback that is used to fine-tune the model through reinforcement learning, enhancing its reasoning ability. This feedback helps o1 refine its approach, identify errors, and break down complex tasks into more manageable components. The second method occurs during test time, where LLM-as-a-Judge dynamically evaluates the model's reasoning outputs, providing real-time feedback that further improves the model's performance. What both methods share is their ability to offer o1 continuous feedback, whether it is positive or negative, which drives a process of self-improvement. By incorporating this feedback into its reasoning process, o1 is able to iteratively adjust its approach and learn from its mistakes. This cycle of reflection and correction enhances the model's ability to think critically and solve increasingly complex problems. The synergy between the two evaluation strategies—during both training and testing—creates a powerful feedback loop that allows o1 to dynamically optimize its reasoning and thinking capabilities over time, leading to significant advancements in its problem-solving abilities.

Constitutional AI [7], which was used to build DeepSeek-R1 can be seen as a specific form of LLM-as-a-Judge, where the model uses its own evaluations, such as voting results, as feedback to guide its optimization. In this approach, o1 evaluates its reasoning through internal assessments, refining its decisions based on predefined principles. This self-generated feedback loop helps o1 correct errors and improve its performance over time, without needing external verification. By integrating LLM-as-a-Judge within the Constitutional AI framework, o1 continuously adjusts its reasoning strategies, leading to better problem-solving abilities through self-improvement and reinforcement learning.

Relationship Between LLM-as-a-Judge and Reasoning. Reasoning, as a cognitive process, involves applying logic and evidence to derive conclusions. It is central to intellectual tasks such as decision-making, problem-solving, and critical analysis. Reasoning requires evaluating multiple possibilities and determining the most logically sound and coherent path. In contrast, LLM-as-a-Judge refers to the use of LLMs to perform judgment tasks, such as evaluating, scoring, ranking, or selecting optimal answers based on generated outputs. This concept parallels a judge's role in ensuring fairness, accuracy, and coherence in competitive contexts. Although reasoning and judgment are separate concepts, they are closely connected. As shown in Figure 15, reasoning frequently relies on judgment to evaluate intermediate steps, improve logic, and guarantee clarity in its results. **When the process involves an infinite number of judgments, we can consider it as a process that approximates both reasoning and thinking.** At the same time, effective judgment relies on strong reasoning capabilities to evaluate options against a set of logical criteria, which we discussed in Section 2.5 and Section 5.2.3. Therefore, LLM-as-a-Judge not only evaluates outputs but also enhances the reasoning process by helping to identify the most coherent, accurate solutions.

7 APPLICATIONS

LLMs' abilities as evaluators have gained widespread recognition in specialized fields, especially in complex, qualitative areas like legal texts, mathematical reasoning, and scientific research [208]. This section reviews recent developments in LLM-as-a-judge applications across finance, law, science, and other industries, investigating how domain knowledge and LLM evaluators can further expand their impact in critical areas.

7.1 Machine Learning

7.1.1 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.

Text Generation Text generation tasks, such as dialog response generation, summarization, story creation, and creative writing, require content that is safe, accurate, and contextually relevant, though there isn't a single "correct" answer [6, 10]. Unlike traditional metrics-based evaluations, LLM-as-a-judge offers a nuanced, adaptable, and customized assessment. According to Zheng et al. [210], LLMs like GPT-4 can evaluate text generation comparably to humans. This method has been used to evaluate outputs from single models and to compare multiple models in competitive settings. For instance, Gao et al. [41] employ ChatGPT for human-like summarization evaluation, while Wu et al. [171] propose a comparison-based framework where LLMs act as judges to evaluate summarization quality.

Modern LLMs excel at generating detailed, long-form responses, but longer outputs increase the risk of hallucinations. To address this, Cheng et al. [22] and Zhang et al. [197] use GPT-4 to identify logically structured yet nonsensical statements. Additionally, Wang et al. [155] propose a critique-based system to evaluate hallucinations by selecting relevant evidence and providing detailed critiques. Beyond hallucinations, generating harmful or unsafe responses is a significant concern. To tackle this, Li et al. [82] introduce MD-Judge and MCQ-Judge for evaluating safety-related QA pairs, focusing on queries designed to provoke unsafe responses. However, an overly cautious approach can lead to excessive refusal responses, affecting user experience. To explore this, Xie et al. [173] conduct a meta-evaluation of various LLM-as-a-judge frameworks, assessing refusal tendencies in response to potentially unsafe queries. Additionally, Yu et al. [189] introduce an LLM-based answer extractor to accurately identify critical parts of answers in text generation,

and An et al. [2] propose L-Eval, a framework for standardized evaluation of long-context language models, followed by Bai et al. [8] who use LLM-as-a-judge to filter evaluation data for long-context LLMs.

Recent studies have also used LLM-as-a-judge to evaluate the general capabilities of generative models through debate-based frameworks. For example, Chan et al. [16] introduce a multi-agent debate framework to facilitate autonomous discussions and assess the quality of generated responses in tasks. Similarly, Moniri et al. [106] propose an automated debate framework to evaluate LLMs on domain knowledge, problem definition, and inconsistency recognition.

Reasoning Enhancing the reasoning capabilities of LLMs can overcome the limitations of scaling laws, unlocking their full potential. Effective reasoning is essential for tackling complex problems, making informed decisions, and delivering accurate, context-aware responses. Wei et al. [168] introduce Chain-of-Thought (CoT) prompting to facilitate step-by-step reasoning. More sophisticated cognitive structures [47, 183] have been proposed to further enhance reasoning, yet selecting a reliable reasoning path remains a significant challenge. LLM-as-a-judge has been employed to address this issue.

Some studies focus on sample-level reasoning path selection. Gao et al. [39] present a strategy evaluator for assessing candidate strategies. Kawabata and Sugawara [62] propose REPS (Rationale Enhancement through Pairwise Selection), which uses pairwise self-evaluation to select valid rationales. Lahoti et al. [72] demonstrate that LLMs can identify and enhance response diversity by aggregating multiple critiques. In multi-agent frameworks, Liang et al. [85] introduce multi-agent debating (MAD), where a judge LLM selects the most reasonable response. Similarly, Li et al. [78] utilize a judge LLM in layer-based multi-agent collaboration to improve response quality and efficiency.

For step-level reasoning path selection, LLMs act as process reward models (PRMs) to evaluate state scores. Creswell et al. [25] break down reasoning into Selection and Inference, using LLMs to judge potential reasoning traces. Xie et al. [174] propose the Kwai-STaR framework, transforming LLMs into state-transition reasoners for mathematical reasoning. Lightman et al. [86] train LLMs as PRMs for inference-time supervision and best-of-N sampling. Setlur et al. [126] introduce process advantage verifiers (PAVs) to generate rewards based on the likelihood of future correct responses. Advanced cognitive structures are also simulated; Hao et al. [47] use LLMs as a world model with Monte Carlo Tree Search (MCTS) for deliberate path selection. Besta et al. [11] model LLM outputs as graphs to evaluate coherence and logical reasoning. Additionally, critique-based LLM judges [4, 74, 185, 194] provide detailed feedback to enhance the reasoning process.

Yao et al. [184] pioneered the use of LLMs in an interleaved manner to generate reasoning traces and task-specific actions. Reasoning traces guide the model in updating action plans, while actions facilitate interaction with external sources. Building on this, Yang et al. [181] introduced Auto-GPT, which leverages LLM-as-a-judge to enhance tool usage accuracy. By integrating a variety of external tools, LLMs become more versatile, improving planning performance through judicious tool selection. Sha et al. [127] explored the potential of LLMs in decision-making for complex autonomous driving scenarios, requiring human-like commonsense reasoning. Zhou et al. [217] employed a self-discovery process where LLMs judge queries and select the most suitable reasoning structure for subsequent inference.

Retrieval The role of LLM-as-a-judge in retrieval encompasses both traditional document ranking and dynamic Retrieval-Augmented Generation (RAG) approaches. In traditional retrieval, LLMs enhance ranking accuracy through advanced prompting techniques, enabling effective document ordering with minimal labeled data. RAG frameworks leverage LLMs' ability to generate content guided by retrieved information, supporting applications requiring complex or evolving knowledge integration.

Recent studies have explored LLMs as judges for document ranking, aiming to boost precision and reduce reliance on extensive training data. Zhuang et al. [222] embed fine-grained relevance labels within LLM prompts, enabling models to distinguish subtle relevance variations for refined document ordering. Innovations in listwise ranking include Ma et al. [103]'s Listwise Reranker with a Large Language Model (LRL), which reorders document identifiers without task-specific training data. Zhuang et al. [223] introduce a Setwise prompting strategy for zero-shot ranking, enhancing efficiency without sacrificing performance. To address positional biases, Tang et al. [144] propose permutation self-consistency, averaging multiple list orders to yield order-independent rankings. Qin et al. [114] critique pointwise and listwise ranking prompts, proposing Pairwise Ranking Prompting (PRP) with medium-sized, open-source LLMs as a cost-efficient alternative to larger models.

Recent advancements in RAG have explored LLMs' capacity for self-evaluation and improvement without annotated datasets or parameter adjustments. Tang et al. [143] propose Self-Retrieval, consolidating information retrieval within a single LLM using natural language indexing, transforming retrieval into a document generation and self-assessment process. In question answering, LLMs are increasingly used as evaluative agents. Rackauckas et al. [116] introduce an LLM-based evaluation framework generating synthetic queries from user interactions and domain-specific documents, with LLMs evaluating retrieved documents and ranking RAG agent variants via RAGElo. Zhang et al. [198] study LLMs' ability to assess relevance versus utility in open-domain QA, demonstrating effective distinction and adaptability with counterfactual passages.

Domain-specific RAG systems reveal LLMs' potential to navigate complex queries by integrating specialized knowledge structures. Wang et al. [156] present BIORAG, enhancing vector retrieval with hierarchical knowledge structures and a self-aware evaluated retriever. Li et al. [79] introduce DALK, combining an LLM with a continuously evolving Alzheimer's Disease knowledge graph, using self-aware knowledge retrieval for noise filtering. Jeong et al. [55] propose Self-BioRAG, adapting RAG principles to biomedical applications Liu et al. [94], with LLMs selecting the best evidence for answer generation.

7.1.2 Social Intelligence. As LLM capabilities advance, machines are increasingly taking on tasks once deemed exclusive to humans, particularly in context-specific domains. A notable area is social intelligence, where models must navigate complex social scenarios involving cultural values, ethical principles, and social impacts. For instance, Xu et al. [176] assess the social intelligence of LLMs, noting that despite significant progress, these models still fall short compared to their academic problem-solving abilities. Similarly, Zhou et al. [218] introduce SOTPIA and SOTPIA-EVAL to simulate intricate social interactions among LLM agents and evaluate their social intelligence. In their study, GPT-4 serves as a stand-in for human judgment, assessing goal completion, financial management, and relationship preservation within these simulated interactions.

7.1.3 Multi-Modal . 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 [18]. 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 [172]. Furthermore, advancements in multi-modal and multi-agent systems have been reviewed, emphasizing collaboration mechanisms to improve rationality and minimize biases [56]. Xiong et al. [175] investigate the use of LLM-as-a-judge to assess the performance of multimodal models, offering both a final score and the rationale behind the evaluations to enhance transparency and consistency. Chen et al. [21] introduce the first benchmark for the automatic

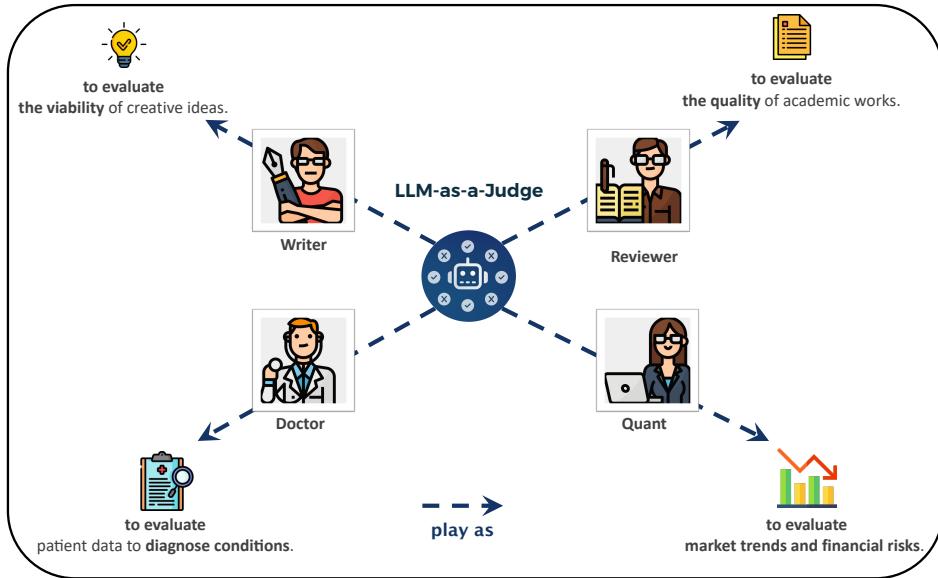


Fig. 16. Scenarios where the role that can be assisted by LLM-as-a-Judge is applied.

evaluation of LVLMs, focusing on self-driving corner cases. Their findings indicate that evaluations conducted by LLMs-as-judges align more closely with human preferences compared to those performed by LVLM-as-judges.

7.2 Other Specific Domains

7.2.1 Finance. LLMs have demonstrated significant potential in the finance domain, particularly in tasks such as forecasting, anomaly detection, and personalized text generation [207], 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 [14], while Yu et al. (2024) introduced FinCon, a multi-agent system that uses conceptual verbal reinforcement to improve financial decision-making [190]. The second area of research aims to provide benchmarks to evaluate and enhance the understanding of domain-specific knowledge by LLMs. These benchmarks include UCFE [182] based on user feedback, IndoCareer: a dataset of professional exam questions [68], and AI-generated domain-specific evaluation sets [119]. In quantitative investment, LLM-as-a-judge approaches have demonstrated value in refining and enhancing LLM-generated trading signals. [159] (Figure 17) proposes a two-layer architecture for generating self-improving trading signals. Their system employs a dual-LLM setup in the inner loop, where one LLM generates trading ideas while another serves as a judge to evaluate and refine them. The outer loop incorporates an additional LLM judge that provides comprehensive reviews based on quantitative metrics such as information coefficient and Sharpe ratio, ensuring trading signals meet rigorous performance standards.

Moreover, the concept of LLM-as-a-judge shows promising applications in credit scoring [5, 188] and Environmental, Social, and Governance (ESG) scoring [207]. This work remains in its early

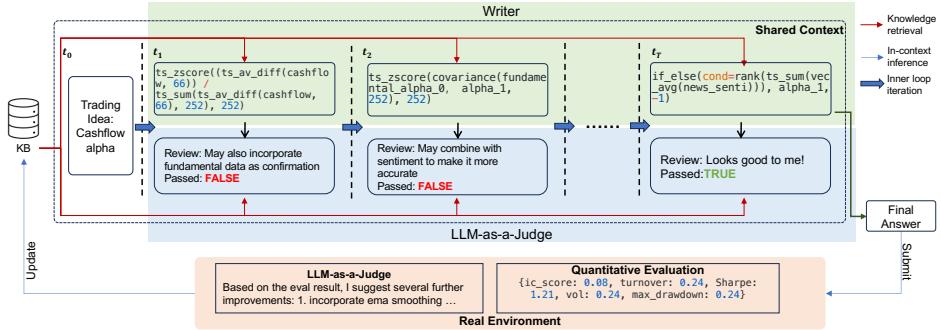


Fig. 17. Illustration of using dual-LLM iterative feedback loop for alpha generation in finance. Figure adapted from Wang et al. [159].

stages, necessitating further exploration to refine evaluation methods and expand applications in the finance domain.

7.2.2 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 instance, [102] employ general LLMs with few-shot expert prompts to effectively simulate annotation processes for legal fact relevance, demonstrating the potential of LLMs as automated judicial evaluators. 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 [23]. 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 [121].

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 [68] and LegalBench, a collaboratively built benchmark for assessing legal reasoning capabilities in LLMs across multiple domains and languages [44]. These benchmarks are often language-specific due to the unique legal structures and terminologies, such as LexEval for Chinese legal texts [80] and Eval-RAG for Korean [121]. Other benchmarks target specific attributes, such as ethics [202] and harmfulness [3].

7.2.3 AI for Science. LLMs have demonstrated notable potential in scientific fields Tang et al. [145], Zhao et al. [208], Zhou et al. [216], especially in areas like medical question-answering and mathematical reasoning, where they serve as evaluators to improve accuracy and consistency. In the medical field, 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 [13, 69]. 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 theorem-proving tasks [99]. For example, WizardMath was introduced by employing RL through step-by-step feedback to refine reasoning in mathematical tasks [100]. 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 [221]. 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 [99]. These methods highlight the value of combining RL, cooperative reasoning, and prompt engineering in improving LLMs' evaluative and reasoning skills across mathematical reasoning.

7.2.4 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 [70]. This approach offers a scalable solution for evaluation. In education, automated essay scoring and revising have been 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 [135]. 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 [66]. 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 [33]. 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 focus more on these areas, exploring how LLMs as judges can enhance assessment accuracy and consistency where traditional quantitative methods fall short.

8 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.

8.1 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 [170, 210] and

may not even provide reliable answers [24, 46]. As an alternative to humans, LLM evaluations are also found to have certain biases, and the annotation results require more evaluation [109], 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 [73] 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 [148]. 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.

8.2 Robustness

Despite LLM’s superior power, it is found prone to adversarial attacks [57, 128, 226], 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 [20]. 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 vulnerabilities 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.

8.3 Powerful Backbone 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.

9 FUTURE WORK

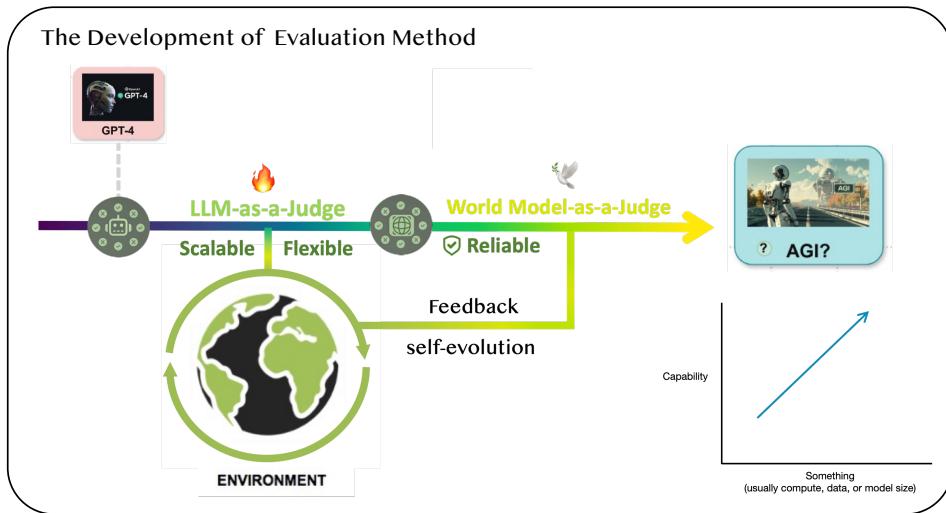


Fig. 18. The development process and future prospects of LLM-as-a-Judge.

In the AI era [179], LLM-as-a-Judge systems are increasingly demonstrating their potential to assist or even replace human judgment across a wide range of professional domains. Many roles inherently require the ability to evaluate, assess, or adjudicate complex scenarios, and LLMs, with their advanced data processing and pattern recognition capabilities, are well-suited to support or enhance these tasks. As shown in Figure 16, LLMs can serve as versatile evaluators in diverse fields [167]. For instance, writers can leverage LLMs to assess the viability and originality of creative ideas by analyzing narrative structures and market trends; doctors can use LLMs to diagnose conditions and predict outcomes by processing medical records and imaging data [145, 204, 214]; quantitative analysts can employ LLMs to forecast market movements and assess risks by identifying patterns in financial data; and judges can rely on LLMs to interpret laws and precedents, aiding in the adjudication of legal cases. While LLMs excel in scalable and flexible evaluation, they do have limitations. Future work should focus on addressing these limitations while exploring new applications and improving the reliability, fairness, and adaptability of LLM-as-a-Judge systems to ensure their alignment with societal values and professional standards.

As shown in Figure 18, the development of evaluation methodologies has evolved significantly with the advent of GPT-4, enabling more scalable and flexible approaches to LLM-as-a-Judge systems. These evaluation paradigms typically rely on interactions with the environment to obtain feedback, which forms the foundation for self-evolution signals. If we can establish **reliable LLM-as-a-Judge** in the future, and further enhance AI's intelligent performance as a *World Model*, using

World Model-as-a-Judge could make our simulations of the real world more realistic and widely reliable. AI can use this approach to achieve self-evolution, potentially enhancing the scaling of artificial general intelligence (AGI) by using LLM-as-a-Judge as crucial tools and capabilities.

9.1 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. Finally, 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.

9.2 LLM-as-a-Judge for Data Annotation

In contrast, LLM-as-a-judge is a general technique where you use LLM to approximate human labeling. When you ask an LLM to assess qualities like "faithfulness to source," "correctness," or "helpfulness," you define what these terms mean in the evaluation prompt and rely on the semantic relationships the LLM learned from training data. 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 [107], Gemini [43], and LLaMA-2 [153] 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 [206], ensure consistency across large volumes of data, and adapt through fine-tuning or prompting for specific domains [102, 134], 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 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.

9.3 MLLM-as-a-Judge

AI systems are evolving into highly versatile and multifunctional entities [29]. 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 [137]. 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-4o [107], Gemini [43], and LLaVA [92] 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, MLLM-as-a-Judge frameworks [18] are emerging for evaluating models. 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 multi-modal evaluators capable of reasoning and assessing complex content spanning text, audio, images, and video. While current multi-modal 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 multi-modal evaluator has the potential to not only advance AI research but also enable new applications in areas such as multi-modal content moderation and automated knowledge extraction.

9.4 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 [30] in scale and impact, the LLM-as-a-Judge field can achieve deeper insights and foster greater innovation.

9.5 LLM-as-a-Judge for LLM Optimization

LLM-as-a-Judge shows substantial promise for advancing LLM optimization. Recent studies [225] 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 [154], 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, multi-modal 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.

10 CONCLUSION

LLM-as-a-Judge has emerged as a promising paradigm for automated evaluation, offering scalability and adaptability that surpass traditional expert-driven or metric-based methods. By leveraging the reasoning capabilities of large language models, this framework excels in tasks such as text quality assessment, model evaluation, and automated data annotation. It is particularly valuable for large-scale, efficient, and adaptable evaluation. Its ability to process diverse content formats and integrate domain-specific knowledge makes it particularly well-suited for applications in education, peer review, and decision-making systems.

Despite these strengths, several challenges must be addressed to fully realize its potential. Ensuring reliability remains a key issue, because probabilistic outputs can introduce inconsistencies, overconfidence, and biases inherited from training data. Although techniques RLHF have improved alignment with human judgment, they do not eliminate all sources of subjectivity. Moreover, ensuring robustness is another critical concern. LLM-as-a-Judge can be susceptible to adversarial prompt manipulation and contextual framing biases, potentially causing unintended or unreliable evaluations. Finally, generalization across domains and modalities remains a significant hurdle, as current models struggle with evaluating multi-modal inputs, reasoning over structured data, and adapting to domain-specific evaluation standards.

To address these challenges, future research should focus on three key areas. First, improving reliability requires advancements in self-consistency mechanisms, uncertainty calibration, and bias mitigation techniques, ensuring that models provide stable and well-calibrated judgments. Second, enhancing robustness involves developing adversarial-resistant evaluation frameworks and refining prompt engineering methodologies, reducing sensitivity to context variations. Third, expanding generalization capabilities calls for advancing multi-modal reasoning, integrating structured knowledge representations, and refining domain-adaptive learning strategies, allowing models to handle diverse evaluation scenarios more effectively.

Ultimately, LLM-as-a-Judge is poised to become an integral component of next-generation evaluation systems, augmenting human expertise rather than replacing it. By addressing the challenges of reliability, robustness, and generalization, we can create more trustworthy, adaptive, and comprehensive evaluators, paving the way for their adoption across scientific research, education, industry, and beyond.

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