From Generation to Judgment: Opportunities and Challenges of LLM-as-a-judge

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Abstract

Automatic model assessment has long been a critical challenge. Traditional methods, usually matching-based or small model-based, often fall short in open-ended and dynamic scenarios. Recent advancements in Large Language Models (LLMs) inspire the "LLM-as-a-judge" paradigm, where LLMs are leveraged to perform scoring, ranking, or selection for various machine learning evaluation scenarios. This paper presents a comprehensive survey of LLM-based judgment and assessment, offering an in-depth overview to review this evolving field. We first provide the definition from both input and output perspectives. Then we introduce a systematic taxonomy to explore LLM-as-a-judge along three dimensions: *what* to judge, *how* to judge, and *how* to benchmark. Finally, we also highlight key challenges and promising future directions for this emerging area. We have released and will maintain a paper list about **LLM-as-a-judge** at: https://anonymous.4open.science/r/Awesome-LLM-as-a-judge-266D.

1 Introduction

Automatic model assessment and evaluation have long been essential yet challenging tasks in machine learning (ML) and natural language processing (NLP) (Sai et al., 2022; Chang et al., 2024). Traditional static metrics like BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004) measure quality by calculating lexical overlap between output and reference texts. While computationally efficient, these metrics perform poorly in dynamic and open-ended scenarios (Liu et al., 2016; Reiter, 2018). With the rise of deep learning, small language model-based metrics like BERTScore (Zhang et al., 2020) and BARTScore (Yuan et al., 2021) have emerged. However, these metrics still face challenges in capturing nuanced attributes like fairness (Sun et al., 2022) and helpfulness (Zhu et al., 2024a).

Recently, the advancements of large language models (LLMs) such as GPT-4 (Achiam et al., 2023) and o1 (Jaech et al., 2024), have led to striking improvements in various applications, leveraging substantial prior knowledge in vast training corpora. This progress has motivated researchers to propose the concept of "LLM-as-a-judge" (Zheng et al., 2023; Wang et al., 2023c; Liu et al., 2023b; Chiang and Lee, 2023b), where LLMs are used to assess the candidate outputs by assigning scores, producing rankings, or selecting the best options, based on various input formats (e.g., point- and pair-wise), given context and instruction. The strong capability of LLMs combined with well-designed assessment pipelines (Li et al., 2023b; Bai et al., 2023a) leads to fine-grained and human-like judgment for various evaluation applications, addressing the previous limitations.

Beyond evaluation, LLMs-as-a-judge has been adopted across the lifecycle for next generations of LLM developments and applications. LLMs-as-a-judge is often used as a scalable way to provide supervisions for key development steps like alignment (Lee et al., 2023), retrieval (Li et al., 2024c), and reasoning (Liang et al., 2023). LLM-as-a-judge also empowers LLMs with a series of advanced capabilities such as self-evolution (Sun et al., 2024), active retrieval (Li et al., 2024c), and decision-making (Yang et al., 2023), driving their elevations from generative models to intelligent agents (Zhuge et al., 2024). However, as the field develops rapidly, challenges like bias and vulnerability (Koo et al., 2023; Park et al., 2024; Fu et al., 2024; Huang et al., 2024a) are emerging. Therefore, a systematic review of both techniques and limitations is crucial for facilitating this field.

This survey delves into the details of LLM-as-a-judge, aiming to provide a systematic overview of LLM-based judgment systems. We start by formally defining LLM-as-a-judge with its diverse input and output formats (Section 2). Next, we

propose an in-depth and comprehensive taxonomy to address the three key questions (Section 3, 4 5):

- **Attribute: What to judge?** We outline six subtle attributes that are uniquely assessed by LLM-as-a-judge, including helpfulness, safety & security, reliability, relevance, logical, and overall quality.
- **Methodology: How to judge?** We explore ten tuning and prompting methods for LLM-as-a-judge, including manual labeling, synthetic feedback, supervised fine-tuning, preference learning, swapping operation, rule augmentation, multi-agent collaboration, demonstration, multi-turn interaction, and comparison acceleration.
- **Benchmark: How to evaluate LLM-as-a-judge?** We categorize existing benchmarks for LLM-as-a-judge into four types: for general performance, bias quantification, challenging tasks, and domain-specific performance.

Finally, we discuss challenges and potential future directions for LLM-as-a-judge in Section 6.

Differences from Existing Surveys. Existing concurrent surveys investigate LLM for the evaluation of natural language generation (NLG) (Gao et al., 2024; Li et al., 2024n; Gu et al., 2024). However, LLM-as-a-judge has been applied across a broader range of scenarios beyond evaluation, as we discussed, necessitating a systematic survey to categorize and summarize its various applications.

2 Preliminary

In this section, we provide a detailed definition of LLM-as-a-judge, discussing the various input and output formats as shown in Figure 1.

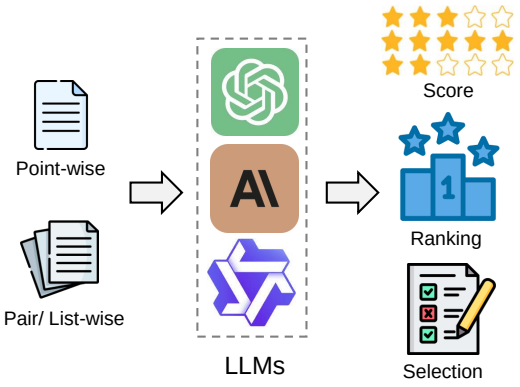

Figure 1: Overview of I/O formats of LLM-as-a-judge.

2.1 Input

Given a judge LLM J, the assessment process can be formulated as: $R = J(C_1, ...C_n)$. Here C_i is the i_{th} candidate to be judged and R is the judging result. We categorize two input formats based on the different candidate numbers n.

Point-Wise: When $n = 1$, it becomes a point-wise judgment where the LLMs judges will solely focus on one candidate sample (Gao et al., 2023).

Pair/ List-Wise: When $n \geq 2$, it becomes a pair-wise ($n = 2$) or list-wise ($n > 2$) judgment where multiple candidate samples are provided together for the LLM judges to compare and make a comprehensive assessment (Zheng et al., 2023).

2.2 Output

In this section, we discuss three kinds of output of the judgment based on the different formats of R.

Score: When each candidate sample is assigned a continuous or discrete score: $R = \{C_1 : S_1, ..., C_n : S_n\}$, it becomes a score-based judgment. This is the most widely adopted protocol, leveraging LLMs to generate scores for quantitative comparisons (Li et al., 2024a) or attribute detection (Xie et al., 2024a).

Ranking: In ranking-based judgment, the output is a ranking of each candidate sample, represented as $R = \{C_i > ... > C_j\}$. This comparative approach is useful in scenarios where establishing a rank order among candidates is required (Li et al., 2023b; Liu et al., 2024b).

Selection: In selection-based judgment, the output involves selecting one or more optimal candidates, represented as $R = \{C_i, ..., C_j\} > \{C_1, ...C_n\}$. This method is particularly crucial in decision-making (Yao et al., 2023a) or content-filtering (Li et al., 2024c) contexts.

3 Attribute

In this section, we categorize current research in LLM-as-a-judge from attribute perspectives. Figure 2 gives an overview summarization of what aspects can be assessed by the LLM judges.

3.1 Helpfulness

Helpfulness is a critical criterion to measure the utility and informativeness of a generated response. Due to the high cost of manually assessing helpfulness in training data, recent studies have explored leveraging LLMs to label helpfulness and to generate or filter alignment data (Bai et al., 2022; Lee et al., 2023; Guo et al., 2024; Zhang et al., 2025d). Beyond alignment tuning, helpfulness assessment using LLM-as-a-judge also plays a vital role in au-

Figure 2: Overview of different judging aspects.

tomatic model evaluation (Zheng et al., 2023; Lin et al., 2023; Li et al., 2024e; Zhang et al., 2025a).

3.2 Safety & Security

Safety and security are essential to ensure that models do not generate harmful content or respond inappropriately to malicious inputs. Current studies have validated that LLMs can be effectively used for model safety assessment, either as off-the-shelf models guided by policy instructions (Bai et al., 2022; Phute et al., 2023; Li et al.; Ye et al., 2024b; Wang et al., 2024l; Eiras et al., 2025; Chen and Goldfarb-Tarrant, 2025; Rodriguez et al., 2025; Hengle et al., 2025), or as lightweight models fine-tuned on safety-specific datasets (Inan et al., 2023; Zhang et al., 2024f; Xie et al., 2024a). Besides, LLM-as-a-judge has been widely adopted to detect and purify adversarial and toxic prompts designed with malicious intent (Cantini et al., 2025; Mu et al., 2025; Armstrong et al., 2025).

3.3 Reliability

Reliability is a crucial attribute for LLMs, enabling them to generate faithful content while presenting uncertainty or acknowledging missing knowledge about certain topics. Regarding sentence-level faithfulness assessment, existing researches leverage LLM-as-a-judge to either instruct the powerful LLMs (e.g., GPT-4) directly (Cheng et al., 2023; Gekhman et al., 2023; Luo et al., 2024a; Hsu et al., 2024) or train specific reliability judges (Wang et al., 2024a). Several works adopt LLM judges for long-form and fine-grained faithfulness evaluation (Tan et al., 2024a; Bai et al., 2024; Wu et al., 2025), using external retrieval bases (Min et al., 2023; Cao et al., 2025b; Loru et al., 2025) or search engines (Wei et al., 2024b). Jing et al. (2024); Pu et al. (2025) further expand this assessment to the multimodal area. Besides evaluation, there are also many works that adopt LLM-as-a-judge to improve the reliability of the generated content, either by external verifiers (Xie et al., 2024b) or synthetic alignment datasets (Zhang et al., 2024g; Wen et al., 2024). For uncertainty judgment, Xu et al. (2024d) propose SaySelf, a training framework that teaches LLMs to express more fine-grained confidence estimates with self-consistency prompting and group-based calibration training.

3.4 Relevance

Relevance assessment with LLM-as-a-judge has been explored and validated to be a more refined and effective manner across various tasks (Chiang and Lee, 2023a; Arabzadeh and Clarke, 2025a). In conversation evaluation, both Lin and Chen (2023a) and Abbasiantaeb et al. (2024) propose to replace expensive human annotation with LLM judgment in relevance assessment. In retrieval-augmented generation (RAG) scenarios, there are also many works that utilize LLMs to determine which demonstrations (Li and Qiu, 2023) or documents (Li et al., 2024c) are most relevant for solving the current problem. Recently, LLM-as-a-judge has also been used in multimodal applications for cross-modality relevance judgment (Lee et al., 2024b; Chen et al., 2024g; Yang and Lin, 2024; Chen et al., 2024a; Lu et al., 2024b; Luo et al., 2024b; Lin et al., 2025). Additionally, LLM-as-a-judge has also been explored in many traditional retrieval applications for relevance assessment (Zhao et al., 2023a; Alaofi et al., 2024; Dietz et al., 2025; Arabzadeh and Clarke, 2025b; Balog et al., 2025), such as search (Thomas et al., 2024; Sebastian and Hoppe, 2025), retrieval (Ma et al., 2024; Dey et al., 2025), recommendation (Hou et al., 2024; Zhang et al., 2024h).

3.5 Logic

In agentic LLMs, assessing the logical correctness of candidate actions or steps is crucial for LLMs' planning, reasoning and decision-making, which further releases their great potential at inference-time. While some works leverage metrics or external tools for this feasibility assessment (Huang et al., 2023a; Yuan et al.), many others leverage LLMs' feedback as the signal (Lightman et al.; Kawabata and Sugawara, 2024) to perform planning and searching in complex reasoning spaces (Hao et al., 2023; Yao et al., 2023a; Besta et al., 2024). In multi-agent collaboration systems,

both Liang et al. (2023) and Li et al. (2024b) propose to leverage the judge LLM to select the most feasible solutions among multiple candidates' responses. Besides, other works adopt LLM judges to perform logical assessment in API selection (Zhao et al., 2024b), tool using (Yang et al., 2023) and LLM routing (Ong et al., 2024).

3.6 Overall Quality

As previously mentioned, LLM-as-a-judge can be employed to perform multi-aspect and fine-grained assessments. However, in many cases, a general assessment is still required to represent the candidates' overall quality. One straightforward approach to obtain this overall score is based on the aspect-specific scores, either by averaging them (Lin et al., 2023) or referring them to generate an overall judgment (Yu et al., 2024c). Moreover, in many traditional NLP tasks (Lu et al., 2024a; Jiang et al., 2024; Ho et al., 2025; Shibata and Miyamura, 2025; Kartáč et al., 2025) like summarization (Gao et al., 2023; Jain et al., 2023a; Chen et al., 2023; Kumar et al., 2024a; Qi et al., 2025; Barnes et al., 2025; Altemeyer et al., 2025; Jeong et al., 2025; Calderon et al., 2025) and machine translation (Kocmi and Federmann, 2023; Huang et al., 2024b; Piergentili et al., 2025; Wang et al., 2025d), the evaluation dimensions are less diverse compared to more open-ended, long-form generation tasks. As a result, LLM-as-a-judge is often prompted directly to produce an overall judgment in these tasks.

4 Methodology

In this section, we present commonly adopted methods and tricks to improve LLMs' judging capabilities, splitting them into tuning (Section 4.1) and prompting strategies (Section 4.2).

4.1 Tuning

To enhance the judging capabilities of a general LLM, various tuning techniques have been employed in different studies. In this section, we discuss these tuning approaches for LLM-as-a-judge from two perspectives: data sources (Section 4.1.1) and training techniques (Section 4.1.2).

4.1.1 Data Source

Manually-labeled Data: To train a LLM judge with human-like criteria, one intuitive method is to collect manually-labeled judgments. Previous works have leveraged and integrated existing sources annotated by humans, including instruction tuning datasets (Lee et al., 2024a; Wang et al., 2024k) and traditional NLP datasets (Vu et al., 2024), for tuning LLM judges. Other works collect manually-labeled datasets with fine-grained judgment feedback. These fine-grained feedbacks can be rationales behind judgment results (Xu et al., 2023a), multi-aspect judgment formats (Liu et al., 2024a) and fine-grained judgment labels (Yue et al., 2023), all of which facilitate the LLM judges to produce more detailed and context-rich judging results. Notably, Ke et al. (2024) first prompt GPT-4 to generate judgment and then manually verify and revise the outputs to ensure high-quality annotations.

Synthetic Feedback: While manually labeled feedback is high-quality and accurately reflects human judgment preferences, it is limited in both scale and coverage. To address it, researchers have also explored synthetic feedback as a data source for LLM judges' tuning. Some rely on the LLM judges themselves to generate the synthetic feedback. It involves instructing the LLM to self-evaluate and improve its judgments (Wu et al., 2024a), or by generating corrupted instructions and corresponding responses as negative samples for Directed Preference Optimization (DPO) training (Wang et al., 2024h). Besides, other powerful and stronger LLMs are also introduced for feedback synthesis. For example, GPT-4 has been widely leveraged to synthesize judging evidence (Wang et al., 2024a), erroneous responses (Park et al., 2024), rationale and feedback (Li et al., 2024e; Kim et al., 2024b; Xiong et al., 2024), and judgment labels (Zhu et al., 2023; Xie et al., 2024a).

4.1.2 Tuning Techniques

Supervised Fine-tuning: Supervised fine-tuning (SFT) is the most widely used approach for training LLM judges (Hu et al., 2025a), enabling them to learn from pairwise (Li et al., 2024e; Wang et al., 2023b; Zhu et al., 2023; Wang et al., 2024k; Pombal et al., 2025b; Salinas et al., 2025) or pointwise (Wang et al., 2023b; Yue et al., 2023; Xie et al., 2024a; Lee et al., 2024a; Chiang et al., 2025) judgment data. Among many tricks applied in SFT, multi-task training and weight merging are introduced to enhance the robustness and generalization of LLM judges (Kim et al., 2024b; Vu et al., 2024; Saad-Falcon et al., 2024b). Other works try to enrich the original training set with augmented

or self-generated samples. Ke et al. (2024) augment pairwise training data by swapping the order of two generated texts and exchanging the corresponding content in critiques. Xu et al. (2023a) further fine-tune their INSTRUCTSCORE model on self-generated outputs to align diagnostic reports better with human judgment. Additionally, Liu et al. (2024a) propose a two-stage SFT process: an initial phase of vanilla instruction tuning for evaluation diversity, followed by additional tuning with auxiliary aspects to enrich the model's evaluative depth.

Preference Learning: Preference learning is closely tied to judgment and evaluation tasks, particularly those involving comparison and ranking. Rather than directly adopt or augment preference learning datasets for SFT, several studies apply preference learning techniques to enhance LLMs' judging capabilities. One straightforward way is to treat the off-topic responses as inferior samples and apply DPO (Wang et al., 2024a; Yu et al., 2025; Rad et al., 2025). Besides, Wu et al. (2024a) propose meta-rewarding, which leverages the policy LLMs to judge the quality of their own judgment and produce pairwise signals for enhancing the LLMs' judging capability. This concept is also adopted by Wang et al. (2024h), who propose self-taught evaluators that use corrupted instructions to generate suboptimal responses as inferior examples for preference learning. Moreover, Hu et al. (2024b) introduce rating-guided DPO, in which the rating difference between two responses is considered in preferences modeling.

4.2 Prompting

Designing appropriate prompting strategies and pipelines at the inference stage could improve judgment accuracy and mitigate bias. We summarize existing prompting strategies for LLM-as-a-judge into six categories (see Figure 3).

4.2.1 Swapping Operation

Previous studies have demonstrated that LLM-based judges are sensitive to the positions of candidates, and the ranking results of candidate responses can be easily manipulated by merely altering their order in the context (Wang et al., 2023d). To mitigate this positional bias and establish a more fair LLM judging system, (Zheng et al., 2023) propose a swapping operation, which involves invoking the judge LLM twice, swapping the order of the two candidates in each instance. If the two results are inconsistent, it is labeled a "tie", indicating that the LLM is unable to confidently distinguish the quality of the candidates. This swapping operation technique has also been widely adopted in pairwise feedback synthesis to produce more accurate reward signals (Lee et al., 2023; Sun et al., 2024; Lee et al., 2024a).

4.2.2 Rule Augmentation

Rule-augmented prompting involves embedding a set of principles, references, and evaluation rubrics directly within the prompt for LLM judges. This approach is commonly employed in LLM-based evaluations, where LLM judges are guided to assess specific aspects (Lahoti et al., 2023; Li et al., 2024e; Bai et al., 2023a; Yu et al., 2024c; Qian et al., 2024; Dong et al., 2024; Wei et al., 2025; Xie et al., 2025b) and provided with detailed rubrics and criteria (Gao et al., 2023; Kim et al.; Wang et al., 2024g; Murugadoss et al., 2024; Li et al., 2024l,h; Hu et al., 2024a; Liu et al., 2024d; Li et al., 2025b; Fan et al., 2025) to ensure accurate judgments. Following this concept, studies in alignment (Bai et al., 2022; Lee et al., 2023, 2024a; Guo et al., 2024; Sun et al., 2024; Beigi et al., 2024) enhance this principle-driven prompting by incorporating more detailed explanations for each aspect of the principle or rubric. Apart from these human-written rules, some works (Liu et al., 2024c; Zhang et al., 2024f; Xu et al., 2025b; Wen et al., 2025; Zhou et al., 2024a) embed the self-generated or automaticaly-searched scoring criteria and principles as a part of their instruction.

4.2.3 Multi-agent Collaboration

Accessing results from a single LLM judge may not be reliable due to inherent biases in LLMs (Wang et al., 2023d; Liusie et al., 2024; Ohi et al., 2024). To address this limitation, Li et al. (2023b); Chen et al. (2024c); Ning et al. (2024) introduce the Peer Rank (PR) algorithm, which produces the final ranking based on each LLM judge's output. Building on this, several architectures and techniques for multi-agent LLMs emerge, including mixture-of-agent (Zhang et al., 2023; Xu et al., 2023b; Beigi et al., 2024; Cao et al., 2025a), role play (Wu et al., 2023; Li et al., 2024m; Patel et al., 2024), debating (Chan et al., 2023; Zhang et al., 2024e; Bandi and Harrasse, 2024; Kenton et al., 2024), voting & aggregation (Zhu et al., 2024c; Verga et al., 2024; Li et al., 2025c; Guerdan et al.,

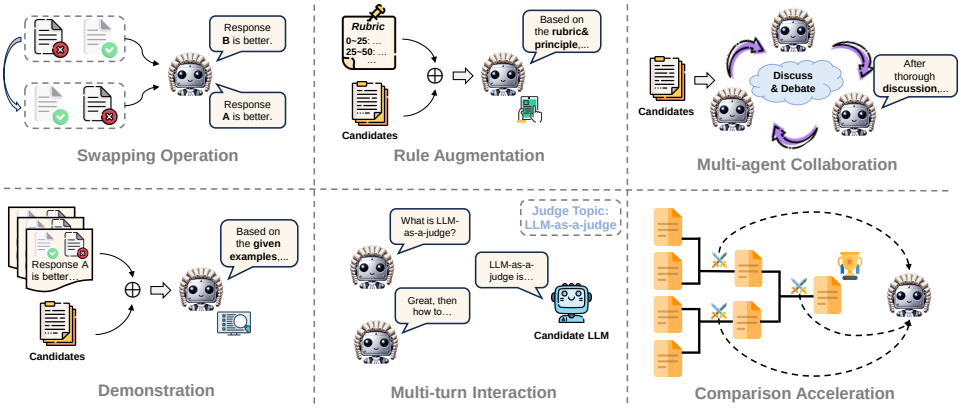

Figure 3: Overview of prompting strategies for LLM-as-a-judge.

2025; Rahmani et al., 2024) and cascaded selection Jung et al. (2024); Badshah and Sajjad (2025). Additionally, others apply multi-agent collaboration for alignment data synthesis, leveraging multiple LLM judges to refine responses (Arif et al., 2024) or provide more accurate feedback (Li et al., 2024i).

4.2.4 Demonstration

In-context samples or demonstrations (Brown et al., 2020; Dong et al., 2023; Agarwal et al.) provide concrete examples for LLMs to follow and have been shown to be a crucial factor in the success of in-context learning for LLMs. Several studies have introduced human assessment results as demonstrations for LLMs-as-judges, aiming to help LLMs learn evaluation standards from a few illustrative examples (Jain et al., 2023b; Kotonya et al., 2023). To improve the robustness of LLM evaluations, Hasanbeig et al. (2023) propose ALLURE, an approach that iteratively incorporates demonstrations of significant deviations to enhance the evaluator's robustness. Additionally, Song et al. (2024b) borrow the insights from many-shot in-context learning and apply it in LLM-as-a-judge applications.

4.2.5 Multi-turn Interaction

A single response may not provide enough information for an LLM judge to thoroughly and fairly assess each candidate. To address this limitation, multi-turn interactions are proposed to offer a more comprehensive evaluation. Typically, the process begins with an initial query or topic, followed by dynamically interacting between the LLM judge and candidate models (Bai et al., 2023b; Yu et al., 2024c; Pombal et al., 2025a). Besides, some approaches facilitate debates among candidates in a multi-round manner, allowing their true knowledge and performance to be fully revealed and evaluated (Zhao et al., 2024c; Moniri et al., 2024).

4.2.6 Comparison Acceleration

Among various input formats in LLM-as-a-judge, pair-wise comparison is the most common approach for model comparison in evaluation or producing pair-wise feedback for training. However, when multiple candidates need to be ranked, this method can be quite time-consuming (Zhai et al., 2024). To mitigate the computational overhead, Zhai et al. (2024) propose a ranked pairing method in which all candidates are compared against an intermediate baseline response. In addition, Lee et al. (2024a); Liu et al. (2025d) utilize a tournament-based approach (Liu et al., 2023a; Zhao et al., 2023b) for rejection sampling during inference to speed up the pair-wise comparison.

5 Benchmark: Judging LLM-as-a-judge

We categorize benchmarks for evaluating LLMs-as-judges into four groups: general performance (Section 5.1), bias quantification (Section 5.2), challenging task performance (Section 5.3), and domain-specific performance (Section 5.4).

5.1 General Performance

Benchmarks focusing on general performance aim to evaluate the overall competence of LLMs in various tasks. One direct way to benchmark LLM judges' performance is to calculate the alignment between LLM prediction and the manual judgment result, using various metrics like Cohen's kappa, Discernment Score, and normalized accuracy (Li et al., 2023a; Tan et al., 2024b; Wang et al., 2024j; Lambert et al., 2024; Penfever et al., 2024; Qu

et al., 2025; Xu et al., 2025a; Chang et al., 2025; Hu et al., 2025b; Calderon et al., 2025; Elangovan et al., 2024; Schroeder and Wood-Doughty, 2024; Gera et al., 2024). Moreover, several studies build LLM leaderboards using LLM-as-a-judge and assess their validity by comparing model rankings with those from established benchmarks and leaderboards, such as Chatbot Arena (Zheng et al., 2023)) (Zheng et al., 2023; Dubois et al., 2024; Li et al., 2024k; Zhao et al., 2024c; Chi et al., 2025).

5.2 Bias Quantification

Quantifying and mitigating bias in LLM judgments is critical to ensuring fairness and reliability (Xie et al., 2025a). Typical benchmarks include EvalBiasBench (Park et al., 2024) and CALM (Ye et al., 2024a), focus explicitly on quantifying biases, including those emerging from alignment and robustness under adversarial conditions. Besides, Shi et al. (2024) adopt metrics such as position bias and percent agreement in question-answering tasks. Recently, (Tripathi et al., 2025) examine the influence of protocol choice (pairwise and pointwise) on the bias degree of LLM judges.

5.3 Challenging Task Performance

Benchmarks designed for difficult tasks push the boundaries of LLM evaluation. For example, Arena-Hard (Li et al., 2024k) and JudgeBench (Tan et al., 2024b) select harder questions based on LLMs' performance for conversational QA and various reasoning tasks, respectively. CALM (Ye et al., 2024a) explores alignment and challenging scenarios, using metrics like separability and agreement to evaluate performance in manually identified hard datasets.

5.4 Domain-Specific Performance

Domain-specific benchmarks provide task-focused evaluations to assess LLMs' effectiveness in specialized contexts. Concretely, Raju et al. (2024) measure separability and agreement across tasks in specific domains such as coding, medical, finance, law and mathematics. CodeJudge-Eval (Zhao et al., 2024a) specifically evaluates LLMs for judging code generation with execution-focused metrics such as accuracy and F1 score. This idea has also been adopted by several following works in code summarization and generation evaluation (Wu et al., 2024b; Yang et al., 2024; Tong and Zhang, 2024). Besides, there are also domain-specific benchmarks focusing on LLMs' assessing capabilities in multimodal (Chen et al., 2024a), multilingual (Son et al., 2024b,a), instruction following (Murugadoss et al., 2024) and LLM agent (Lù et al., 2025).

6 Challenges & Future Works

6.1 Bias & Vulnerability

The use of LLMs-as-a-judge inherently introduces significant challenges related to bias and vulnerability, which significantly compromise fairness and reliability when LLMs are deployed for diverse judging tasks. Among the various types of bias, some are consistent across all LLM judges, for example, a tendency to prefer longer (Koo et al., 2023; Dubois et al., 2024; Domhan and Zhu, 2025; Yuan et al., 2024a), authoritative-looking (Stephan et al., 2024; Chen et al., 2024b) and well-formatted (Chen et al., 2024b) responses. In addition, other biases stem from individual judges' own preferences or knowledge, such as egocentric bias (Liu et al., 2023c; Wataoka et al., 2024; Panickssery et al., 2024; Chen et al., 2025c) and preference leakage (Li et al., 2025a; Goel et al., 2025; Naseh and Mireshghallah, 2025). LLM judges are also susceptible to adversarial manipulations. Techniques like prompt injection attacks (Shi et al., 2024; BENCHMARK; Banerjee et al., 2024; Tong et al., 2025) and adversarial phrases (Liusie et al., 2023; Raina et al., 2024; Doddapaneni et al., 2024) can drastically influence LLMs' judgment, thus raising concerns about the reliability of LLM judges in high-stakes scenarios (Shi et al., 2024; Raina et al., 2024).

Future Direction. Existing studies have already explored approaches, such as providing more detailed evaluation principles (Zheng et al., 2023; Zhu et al., 2023; Liusie et al., 2023; Krumdick et al., 2025) and eliminating spurious features through calibration (Li et al., 2024d; Raina et al., 2024; Zhou et al., 2024b; Liu et al., 2024c; Chen et al., 2025a; Wang et al., 2025c; van den Burg et al., 2025), to mitigate LLM judges' bias. Future work could focus more on analyzing and understanding the **root causes** of these biases. For example, why would LLMs prefer their own generation (Panickssery et al., 2024)?

6.2 Scaling Judgment at Inference Time.

Motivated by recent inference-time scaling (ITS) studies in LLMs (Snell et al., 2024; Zhang et al.,

2025b), several works have begun to explore how to scale LLMs' judgment capabilities at inference time (Saha et al., 2025; Liu et al., 2025e; Zhou et al., 2025). By expanding the reasoning process in judgment tasks and incorporating advanced behaviors such as reflection and exploration, both the accuracy and fairness (Chen et al., 2025c; Wang et al., 2025a) of judge LLMs have seen significant improvements. A straightforward approach to scaling judge LLMs is to employ Large Reasoning Models (LRMs) that generate judgments via long CoT reasoning (Chen et al., 2025b). Additionally, traditional sampling and search strategies, such as self-consistency, best-of-N, and Monte Carlo Tree Search (MCTS), have been used to more thoroughly explore the space of possible judgment trajectories (Wang et al., 2025f; Kalra and Tang, 2025). Other methods leverage golden labels as supervision, applying rule-based reinforcement learning (Chen et al., 2025b; Liu et al., 2025e; Whitehouse et al., 2025; Chen et al., 2025d; Shi and Jin, 2025), DPO (Saha et al., 2025) or distillation (Zhao et al., 2025) to train LLMs to serve as more effective judges.

Future Directions. While LLM-as-a-judge approaches benefit from ITS techniques, it is also important to recognize the associated challenges. These include efficiency bottlenecks (Sui et al., 2025), performance degradation from overthinking (Chen et al., 2024e), and increased vulnerability of long CoTs to adversarial attack (Jiang et al., 2025). Future research could investigate these limitations and develop mitigation strategies, paving the way for more efficient, accurate, and robust judge LLMs enhanced by ITS.

6.3 Dynamic & Complex Judging Strategy

Compared with earlier static and straightforward approaches that directly prompt LLMs for judgment (Zheng et al., 2023), more dynamic and complex judgment pipelines have been proposed recently to address various limitations, improving the robustness and effectiveness of LLM-as-a-judge. One approach is to follow the concept of "**LLM-as-a-examiner**", where the system dynamically and interactively generates both questions and judgments based on the candidate LLMs' performance (Yu et al., 2024c; Bai et al., 2023a; Pombal et al., 2025a; Dammu et al., 2025; Khalili and Smyth, 2025; Wang et al., 2024i; Kim et al., 2024a; Zhang et al., 2025e). Other works focus on making judgments based on multiple candidate LLMs' **battling and debating** (Moniri et al., 2024; Zhao et al., 2024c). Additionally, building complex judgment agents is another popular research area (Li et al., 2023b; Chan et al., 2023; Zhuge et al., 2024), which typically involves multi-agent collaboration with well-designed planning systems.

Future Direction. One promising direction for future research is to equip LLMs with human-like and agentic judgment capabilities (Yuan et al., 2024a; Liang et al., 2024b; Li et al., 2024o; Saha et al., 2024; Zhang et al., 2024b; Wang et al., 2025e; Song et al., 2025), such as anchoring, comparing, and meta-judgment. Another intriguing avenue would be to develop an **adaptive difficulty assessment system** (Hu, 2024; Patel et al., 2025), dynamically adjusting problems' difficulties based on candidates' performance.

6.4 Human-LLMs Co-judgement

As mentioned earlier, the biases and vulnerabilities in LLM-as-a-judge can be addressed through human-in-the-loop for further intervention and proofreading. However, only a few studies have focused on this direction (Wang et al., 2023d; Faggioli et al., 2023; Pradeep et al., 2025).

Future Direction. As **data selection** (Xie et al., 2023; Albalak et al., 2024) becomes an increasingly popular research area for improving the efficiency of LLMs' training and inference, it also holds the potential for enhancing LLMs-based evaluation. LLM-as-a-judge can draw insights from data selection to enable judge LLMs to serve as a critical sample selector, choosing a small subset of samples based on specific criteria (e.g., difficulty) for human annotators to conduct evaluation.

Due to the space limitation, we put the application of LLM-as-a-judge, paper collection for our taxonomy, tuning techniques and benchmark for LLM-as-a-judge in Appendix A, B, C and D.

7 Conclusion

This survey explores the intricacies of LLM-as-a-judge. We begin by categorizing existing LLM-based judgment methods based on input and output formats. Then, we propose a comprehensive taxonomy for LLM-as-a-judge, encompassing judging attributes, methodologies and benchmarks. After this, a detailed and thoughtful analysis of current challenges and future directions of LLM-as-a-judge is proposed, aiming to provide more resources and insights for future works in this emerging area.

Limitations

This work aims to provide a comprehensive survey of the LLM-as-a-judge paradigm. Due to space constraints, we focus on three core aspects in the main paper: judging attributes, methods, and benchmarks. Applications of LLM-as-a-judge and a detailed list of related papers are included in the appendix. Additionally, as discussed in Section 6.1, LLM-as-a-judge carries inherent limitations and biases. The substantial computational resources required for deploying LLMs may also pose challenges in resource-constrained scenarios.

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A Application

We introduce four applications (see Figure 4) which LLM-as-a-judge can be applied: evaluation (Section A.1), alignment (Section A.2), retrieval (Section A.3), and reasoning (Section A.4).

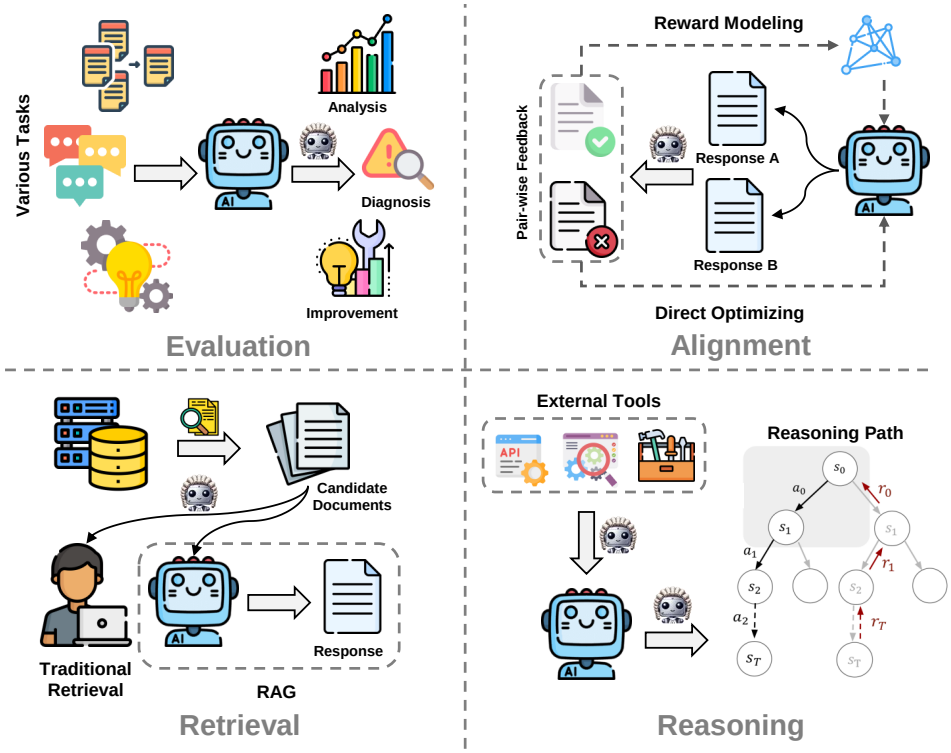

Figure 4: Overview of application and scenario for LLM-as-a-judge.

A.1 Evaluation

LLM-as-a-judge is first proposed for evaluation. It enables human-like evaluations rather than overlap-based matching (Post, 2018; Lin and Chen, 2023b). We discuss how LLM-as-a-judge has been utilized to evaluate open-ended generation (Section A.1.1), reasoning (Section A.1.2), and emerging NLP tasks (Section A.1.3).

A.1.1 Open-ended Generation Tasks

Open-ended generation includes tasks like dialog response, text summarization, and creative writing, where outputs must be safe, accurate, and contextually relevant with multiple "correct" answers (Badshah and Sajjad, 2024; Kumar et al., 2024b; Zeng et al.; Song et al., 2024a; Jones et al., 2024). Unlike traditional metrics, LLM-as-a-judge enables nuanced and adaptable evaluation (Zheng et al., 2023). This approach has been used for single-model evaluations and competitive comparisons (Gao et al., 2023; Wu et al., 2023). While LLMs-as-judges demonstrate human-like judgments, longer outputs risk hallucinations (Wang et al., 2024a; Cheng et al., 2023). Another concern is biased and unsafe judgements (Yu et al., 2024a; Li et al., 2024g; Ye et al., 2024a), though excessive caution may cause overly refusal (Xie et al., 2024a). To address these, researchers have proposed conversational frameworks like self-reflection (Ji et al., 2023) and debating (Moniri et al., 2024).

A.1.2 Reasoning Tasks

The reasoning abilities of LLMs can be assessed through their intermediate thinking processes and final answers (He et al., 2023; Parmar et al., 2024; Mondorf and Plank, 2024). For mathematical reasoning, Xia et al. (2024) introduce a framework using judge LLMs to assess the quality of reasoning steps. Similarly, for temporal reasoning, Fatemi et al. (2024) create synthetic datasets to evaluate models' ability to reason about event sequences, causality, and dependencies. To distinguish genuine reasoning ability from pattern

memorization, Wang et al. (2023a) propose a human-in-the-loop framework where LLMs and users adopt opposing positions to reach correct decisions. Nan et al. (2024) develop a multi-agent framework simulating peer review, leveraging LLMs-as-judges to collaboratively assess reasoning capabilities in data-driven tasks.

A.1.3 Emerging Tasks

LLM-as-a-judge is also applied to tasks once exclusive to humans, particularly in context-specific areas. A prominent task is in social intelligence, where models are presented with complex social scenarios requiring the understanding of cultural values, ethical principles, and potential social impacts (Xu et al., 2024a; Zhou et al., 2023). Research has also extended to evaluating Large Multimodal Models (LMMs) and Large Vision-Language Models (LVLMs) (Zhu et al., 2024b). For example, Xiong et al. (2024) use LMM-as-a-judge to provide transparent evaluations with rationales, while Chen et al. (2024d) propose a benchmark for LVLMs in self-driving scenarios, showing that LLM-based evaluations align better with human preferences than LVLM-based ones. Recently, we have seen more customized utilization of LLM-as-a-judge to evaluate emerging tasks such as code understanding and generation (Zhao et al., 2024a; Zhuo, 2024; Tseng et al., 2024; Wu et al., 2024c; He et al., 2025; Yu et al.; Wang et al., 2025b; Prasad et al., 2025; Liu et al., 2025b; Chi et al., 2025), legal knowledge (Fei et al., 2023), game development (Isaza-Giraldo et al., 2024), nature science (Bi et al., 2023; Chuang et al., 2025; Kim et al., 2025), manufacture engineering (Liu et al., 2025a), healthcare conversations (Wang et al., 2024m; Zhang et al., 2024a; Zhou et al., 2024c), debating judgment (Liang et al., 2024a), RAG (Dhole et al., 2024; Saad-Falcon et al., 2024a; Jin et al., 2024; Liu et al., 2025c; Seo et al., 2025), biomedical application (Brake and Schaaf, 2024; Zheng et al., 2025; Zhang et al., 2024i), paper review (Zhou et al., 2024e; Wang et al., 2024c; Zhu et al., 2025; Kirtani et al., 2025), novelty & creativity evaluation (Olson et al., 2024; Feng et al., 2025; Sawicki et al., 2025), and human-computer interaction (Li et al., 2024j).

A.2 Alignment

Alignment tuning is a vital technique to align LLMs with human preferences and values (Wei et al., 2022a; Ouyang et al., 2022; Rafailov et al., 2023). In this section, we discuss the use of larger LLMs as judges (Section A.2.1) and self-judging (Section A.2.2) for alignment.

A.2.1 Larger Models as Judges

Recently, alignment tuning leverages feedback from larger LLMs to guide smaller models. Bai et al. (2022) first propose to train reward models with synthetic preferences from pre-trained LLMs. Following this, there are also some works explore online learning (Guo et al., 2024) and direct preference optimization (Lee et al., 2023) with larger models as judges. To prevent reward hacking, Sun et al. (2024) develop an instructable reward model enabling real-time human interventions for alignment. Moreover, multi-agent collaborations employ diverse workflows and LLM debates to improve judgments in alignment tuning (Arif et al., 2024; Sengupta et al., 2024; Li et al., 2024i). For code alignment, Weyssow et al. (2024) create CodeUltraFeedback, a dataset using LLM judges to align smaller code models. Wang et al. (2024f) introduce BPO, employing GPT-4 as a judge to augment pairwise feedback.

A.2.2 Self-Judging

Self-judging utilizes LLMs' own preference signals for self-improvement. Some focus on directly judging the preference ranking with the policy LLMs. Yuan et al. (2024c); Zhang et al. (2025c) first introduce self-rewarding, where LLMs judge their outputs to construct pairwise data. Following works adopt various methods to improve the judging capabilities, including meta-rewarding (Wu et al., 2024a), Judge-Augmented Supervised Fine-Tuning (JSFT) (Lee et al., 2024a) and self-evaluation (Zhang et al., 2024g). To guarantee the quality of synthetic pairwise data, Pace et al. (2024) introduce West-of-N approach while Tong et al. (2024) apply self-filtering to produce high-quality synthetic data pairs for reasoning tasks. To reduce computational overhead, Zhai et al. (2024) propose ranked pairing for self-preferring models. Liu et al. (2024e) introduce meta-ranking, enabling smaller LLMs to act as judges and combining this method with Kahneman-Tversky optimization for post-SFT alignment. Besides pairwise data, (Liang et al., 2024c) and (Yasunaga et al., 2024) leverage LLM-as-a-judge to filter synthetic instruction tuning

data. Other works adopt self-assessment and self-judgment in specific domains, such as robotics (Zeng et al., 2024; Yi et al., 2024) and multimodal (Ahn et al., 2024).

A.3 Retrieval

In traditional retrieval, LLM-as-a-judge ranks documents by relevance with minimal labeled data (Section A.3.1). LLM judges can also enhance the RAG system by dynamically integrating retrieved knowledge into the final response (Section A.3.2).

A.3.1 Traditional Retrieval

LLMs enhance document ranking by employing methods like permutation-based ranking (Sun et al., 2023), fine-grained relevance labeling (Zhuang et al., 2024a), and listwise reranking without task-specific training (Ma et al., 2023). Moreover, Setwise (Zhuang et al., 2024b) and Pairwise Ranking Prompting (PRP) (Qin et al., 2024) offer a cost-efficient alternative for complex tasks. Tang et al. (2024b) introduce a permutation self-consistency technique that averages across multiple orders to obtain order-independent rankings. Domain-specific knowledge retrieval with LLM-as-a-judge includes legal information, recommender systems and searching (Ma et al., 2024; Hou et al., 2024; Thomas et al., 2023).

A.3.2 Retrieval-Augmented Generation (RAG)

Li and Qiu (2023) propose the Memory-of-Thought (MoT) framework, where LLMs store and recall reasoning to enhance response relevance. Tang et al. (2024a) introduce Self-Retrieval, an architecture integrating retrieval into document generation, enabling end-to-end IR within a single LLM. Similarly, Asai et al. (2024) develop SELF-RAG, combining retrieval with self-reflection to enhance response quality. In the domain of Q&A, Rackauckas et al. (2024) present an LLM-based evaluation framework using synthetic queries to judge RAG agent performance. Zhang et al. (2024c) study LLMs' ability to assess relevance versus utility. In the biomedical area, several studies explore the usage of LLM-as-a-judge for active and dynamic retrival (Wang et al., 2024b) or retrieved knowledge filtering (Jeong et al., 2024; Li et al., 2024c).

A.4 Reasoning

Reasoning is a critical aspect of LLMs because it directly affects their ability to solve complex problems. Recently, many studies leverage LLM-as-a-judge in reasoning path selection (Section A.4.1) and external source utilization (Section A.4.2).

A.4.1 Reasoning Path Selection

While many complex reasonng and cognition structures emerges for LLMs reasoning (Yao et al., 2023a; Hao et al., 2023), one crucial challenge is how to select a reasonable and reliable reasoning path or trajectory for LLMs to reason. To achieve this, LLM-as-a-judge has been introduced. Some works adopt the reasoner LLMs to perform self-assessment, alternatively excuting reasoning and judging steps to achieve the best result (Lahoti et al., 2023; Creswell et al., 2023; Xie et al., 2024c; Kawabata and Sugawara, 2024) or perform sample-level selection among a group of candidates (Musolesi, 2024). Additionally, there are also many work train LLM-based verifiers, leveraging the judge LLM as the process reward model (PRM) to evaluate each state (Lightman et al., 2023; Setlur et al., 2024; Zhang et al., 2024d; Ye et al., 2025). Besides, there are also studies train critique-based LLM judges (Xu et al., 2024c; Ankner et al., 2024; Yu et al., 2024b; Wang et al., 2024e; Lan et al.; Xie et al., 2024b) which provide fine-grained verbal feedback to boost the reasoning process.

A.4.2 Reasoning with External Source

Selecting appropriate external source to use is essential in the success of agentic LLM systems (Xi et al., 2023; Wang et al., 2024d). Auto-GPT (Yang et al., 2023) is the first to benchmark LLMs' performance in real-world decision-making scenarios. Following them, many other works adopt LLM-as-a-judge in various external tool selection applications, including autonomous driving (Sha et al., 2023), reasoning structure selection (Zhou et al., 2024d) and multi-modal area (Zhao et al., 2024b). In addition to selecting among external tools or APIs, LLM-as-a-judge has also been widely adopted as a controller in multi-agent

systems, to selectively activate agents for a given problem (Ong et al., 2024) or to assess and manage message flow among a group of agents (Liang et al., 2023; Li et al., 2024b).

B Taxonomy

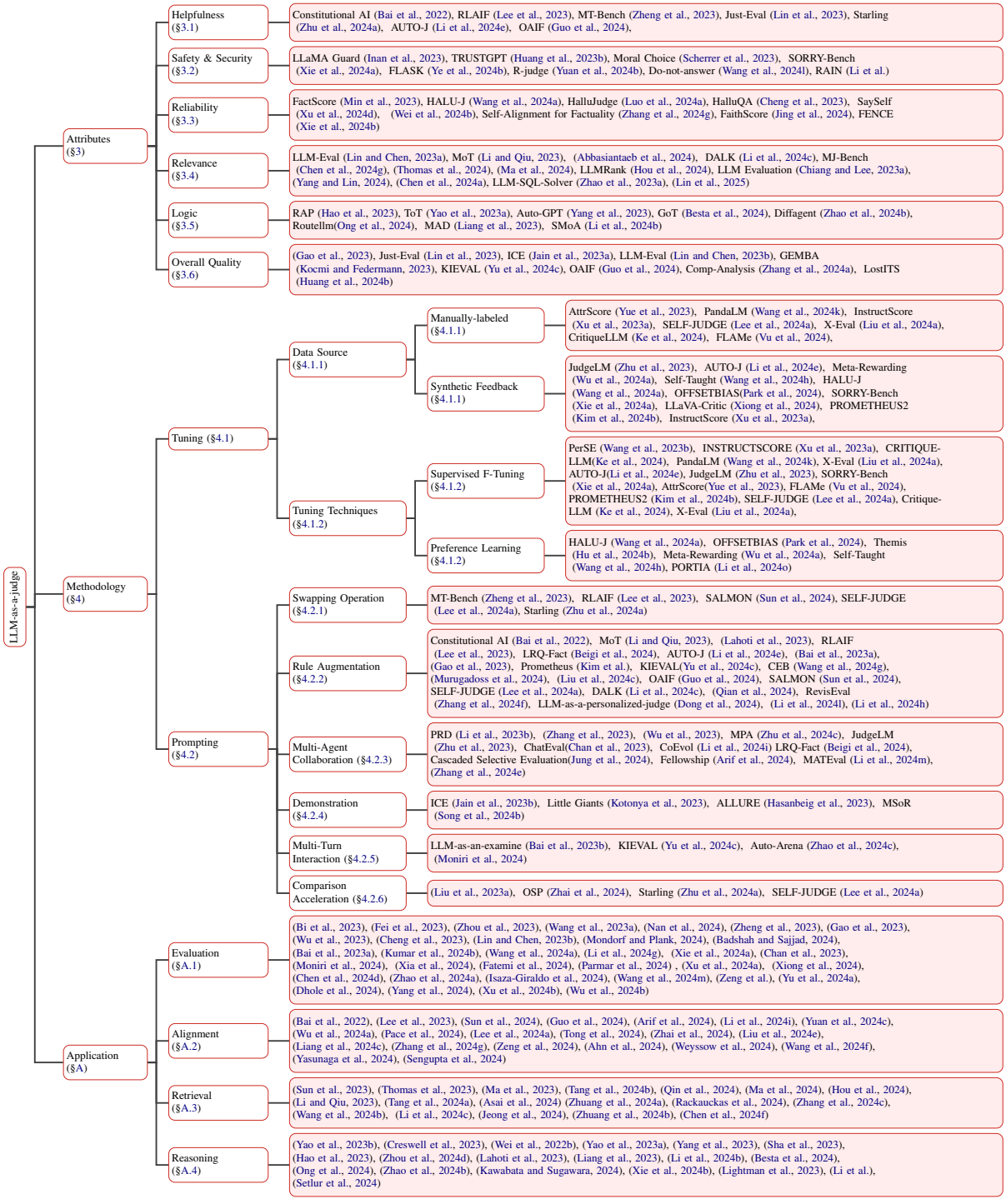

Figure 5: Taxonomy of research in LLM-as-a-judge that consists of judging attribution, methodology and application.

C Tuning Methods

Method	Data				Tuning Method		Base LLM
	Source	Annotator	Type	Scale	Technique	Trick	
AttrScore (Yue et al., 2023)	Manual	Human	QA, NLI, Fact-Checking, Summarization	63.8K	SFT	-	Multiple LLMs
PandaLM (Wang et al., 2024k)	Manual	Human	Instruction Following	300K	SFT	-	Multiple LLMs
AUTO-J (Li et al., 2024e)	Synthetic	GPT-4	Real-world Scenarios	4K	SFT	-	LLaMA-2
JudgeLM (Zhu et al., 2023)	Synthetic	GPT-4	Instruction Following	100K	SFT	-	Vicuna
Self-Judge (Lee et al., 2024a)	Manual	Human	Preference Learning	65/57K	SFT	JSFT	LLaMA-2
X-EVAL (Liu et al., 2024a)	Manual	Human	Dialogue, Summarization, Data-to-Text	55K	SFT	Two-Stage Instruction Tuning	Flan-T5
FLAMe (Vu et al., 2024)	Manual	Human	Various Tasks	5M+	SFT	Multi-task Training	PaLM-2
InstructScore (Xu et al., 2023a)	Manual& Synthetic	Human& GPT-4	Various Tasks	20K	SFT	Meta-Feedback	LLaMA
CritiqueLLM (Ke et al., 2024)	Manual	Human	Instruction Following, real-world scenarios	5K	SFT	Prompt Simplify, Swapping Augmentation	ChatGLM3
Meta-Rewarding (Wu et al., 2024a)	Synthetic	LLaMA-3	Preference Learning	20K	Preference Learning	Meta-Rewarding	LLaMA-3
Self-Taught Evaluator (Wang et al., 2024h)	Synthetic	Mixtral	Various Tasks	20K	Preference Learning	Self-Taught	LLaMA-3
HALU-J (Wang et al., 2024a)	Synthetic	GPT-4o	Fact Extraction	2.6K	Preference Learning	DPO	Mistral
OffsetBias (Park et al., 2024)	Synthetic	GPT-4, Claude3	Preference Learning	8.5K	SFT	Debiasing Augmentation	LLaMA-3
SorryBench (Xie et al., 2024a)	Synthetic	GPT-4	Safety	2.7K	SFT	-	Multiple LLMs
LLaVA-Critic (Xiong et al., 2024)	Synthetic	GPT-4o	Preference Learning	113K	Preference Learning	DPO	LLaVA-v.1.5
PROMETHEUS2 (Kim et al., 2024b)	Synthetic	GPT-4	Preference Learning	300K	SFT	Joint Training, Weight Merging	Mistral
Themis (Hu et al., 2024b)	Manual & Synthetic	Human & GPT-4	Various Tasks	67K	Preference Learning	Multi-perspective Consistency Verification, Rating-oriented DPO	LLaMA-3

Table 1: Overview of tuning methods in LLM-as-a-judge.

D Benchmark

E AI Assistants In Writing

We acknowledge the use of ChatGPT-4o in paper polishing, but not in any direct paper writing or relevant work collections.

Method	Data Type	Scale	Reference	Metrics	Purpose
MT-Bench (Zheng et al., 2023)	Multi-turn Conversation	80	Human Expert	Consistency, Bias, Error	General Performance, Position/Verbosity/Self-enhancement Bias
Chatbot Arena (Zheng et al., 2023)	Single-turn Conversation	30K	User	Consistency, Bias, Error	General Performance, Position/Verbosity/Self-enhancement Bias
CodeJudge-Eval (Zhao et al., 2024a)	Code	457	Execution System	Accuracy, F1	General Performance
JudgeBench (Tan et al., 2024b)	Various Tasks	70K	Human	Cohen's kappa, Correlation	General Performance
SOS-BENCH (Penfever et al., 2024)	Various Tasks	152K	Human	Normalized Accuracy	General Performance
LLM-judge-eval (Wei et al., 2024a)	Summarization, Alignment	1K	Human	Accuracy, Flipping Noise, Position Bias, Length Bias	General Performance
DHP (Wang et al., 2024j)	Various Tasks	400	Human	Discernment Score	General Performance
EvalBiasBench (Park et al., 2024)	Alignment	80	Human	Accuracy	Various Bias
Raju et al. (2024)	Various Tasks	1.5K	Human	Separability, Agreement, BrierScore	Domain-specific Performance
MLLM-as-a-judge (Chen et al., 2024a)	Various Tasks	30K	Human	Human Agreement, Analysis Grading, Hallucination Detection	Multimodal
MM-EVAL (Son et al., 2024b)	Various Tasks	5K	Human	Accuracy	Multilingual
KUDGE (Son et al., 2024a)	Question Answering	3.3K	Human & GPT-4o	Accuracy, Correlation	Non-English & Challenging
Murugadoss et al. (2024)	Various Tasks	-	Human	Correlation	Evaluation Instruction Following
Thakur et al. (2024)	Question Answering	400	Human	Scott's π, Percent Agreement	Vulnerability
Rewardbench (Lambert et al., 2024)	Various Tasks	20K	Human & LLMs	Accuracy	General Performance
Arena-Hard Auto (Li et al., 2024k)	Alignment	500	GPT-4-Turbo	Separability, Agreement	Challenging
R-Judge (Yuan et al., 2024b)	Multi-turn Interaction	569	Human	F1, Recall, Spec, Effect	Safety
Shi et al. (2024)	Alignment	100K	Human	Repetition Stability, Position Consistency, Preference Fairness	Position Bias
CALM (Ye et al., 2024a)	Various Tasks	14K	Human	Robustness/Consistency Rate, 0riginal/ Hacked Accuracy	Bias Quantification
VL-RewardBench (Li et al., 2024f)	Various Tasks	1.2K	Human & LLMs	Overall Accuracy, Macro Average Accuracy	Multimodal

Table 2: Overview of various benchmarks and datasets for LLM-as-a-judge.