Neither Valid nor Reliable? Investigating the Use of LLMs as Judges

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Abstract

Evaluating natural language generation (NLG) systems remains a core challenge of natural language processing (NLP), further complicated by the rise of large language models (LLMs) that aims to be general-purpose. Recently, large language models as judges (LLJs) have emerged as a promising alternative to traditional metrics, but their validity remains underexplored. This position paper argues that the current enthusiasm around LLJs may be premature, as their adoption has outpaced rigorous scrutiny of their reliability and validity as evaluators. Drawing on measurement theory from the social sciences, we identify and critically assess four core assumptions underlying the use of LLJs: their ability to act as proxies for human judgment, their capabilities as evaluators, their scalability, and their cost-effectiveness. We examine how each of these assumptions may be challenged by the inherent limitations of LLMs, LLJs, or current practices in NLG evaluation. To ground our analysis, we explore three applications of LLJs: text summarization, data annotation, and safety alignment. Finally, we highlight the need for more responsible evaluation practices in LLJs evaluation, to ensure that their growing role in the field supports, rather than undermines, progress in NLG.

1 Introduction

Evaluating natural language generation (NLG) systems remains a significant challenge—particularly with the advent of "general-purpose" models—due to several factors, including the subjectivity of the task and the high cost of evaluation. The stakes of this challenge are high: metrics and benchmarks not only shape our understanding of model capabilities, but also influence which research space receives attention and funding, ultimately steering the broader trajectory of the field [75]. In this context, researchers have explored the use of large language models as judges (LLJs) as an humanlike and cost-effective evaluation metrics [55, 52]. This promising potential has sparked a surge of interest in the use of LLMs as evaluators, and thousands of related papers have appeared on academic research platforms, reflecting the rapid growth and attention the topic is receiving across the research community.

Despite their growing adoption, the *validity* of LLJs remains relatively underexplored [111, 36], with existing work focusing instead on their *reliability* by exploring their consistency over multiple evaluations or robustness to small stylistic changes in prompts [117, 61, 81, 104, 51]. *Validity* and *reliability* are key concepts from *measurement theory*—a social science framework used to inform evaluation practices [1]. In the ML context, researchers have advocated for applying this framework to improve and systematize existing evaluation practices [47, 102, 115]. Similarly, in this position paper, we leverage a measurement theory framework [47] to investigate the key underlying assumptions behind the widespread use of LLJs: (1) their ability to serve as proxies for human evaluators; (2) their capabilities as evaluators; (3) their potential for scalability; and (4) their cost-effectiveness.

For each of these assumptions, we highlight current limitations—whether inherent to LLMs, related to their use as evaluators, or stemming from existing practices in the NLG community—that may compromise their reliability and validity. While we offer a high-level perspective on the field, we also examine three popular LLJs applications, to ground our analysis in concrete examples: text summarization, data annotation, and safety alignment. We conclude by emphasizing the need for the community to establish robust standards for the responsible evaluation of NLG systems, as well as the importance of accounting for contextual factors during evaluation. These steps are crucial to unlocking the full potential of LLJs, which mark a significant shift in evaluation practices and open promising pathways toward broader, more comprehensive, and more realistic evaluation of LLMs.

To summarize, this position paper advocates for more rigorous evaluation practices for LLJs, highlighting that their rapid and widespread adoption may have occurred prematurely, without proper evaluation of their reliability and validity as evaluators.

2 Large Language Models as Judges

Early work on LLJs demonstrated their potential for NLG evaluation [103, 63, 50], sparking growing interest in the research community. Building on these early insights, the adoption of LLJs has quickly proliferated, establishing them as a common tool for evaluation and guidance in a variety of machine learning settings. Leveraging zero-shot or few-shot prompting, LLJs can evaluate outputs across various criteria—such as relevance, fluency, or safety— and can even generate explanations to justify their assessments or provide feedback.

Li et al. [55] formalize the evaluation process of LLJs as an evaluation function that takes various inputs. The evaluation function can be a single LLJ, multiple LLJs (usually referred to as Juries), or a LLJ with a human in the loop. This function takes as input: an *evaluation type*: pointwise (one item at the time), pairwise or listwise; an *evaluation criteria*: specific to the task at hand and refers to linguistic quality, content accuracy or task-specific metrics; an *evaluation item*; an *optional reference*: the evaluation can be reference-based or reference-free. This evaluation function can produce three outputs: the *evaluation result*: e.g, a score, ranking, label or qualitative assessment; the *explanation*: an explanation of the reasoning that led to the assessment; the *feedback*: suggestions to improve the input. This formalization accounts for the high variety of LLJ paradigms, we refer to Li et al. [55]'s work on the topic for a comprehensive survey on LLJs. Furthermore, while different types of LLJs may exhibit different biases, our analysis in this paper deliberately adopts a higher-level perspective. This enables us to provide a broader perspective on their use and introduction in the field, rather than limiting the discussion to biases tied to specific evaluation types.

Although early work on LLJs introduced them as an alternative to traditional NLG evaluation metrics [103, 63, 50], their use has since expanded to different applications. Li et al. [55] identify three main functionalities: (1) performance evaluation, (2) model enhancement, and (3) data construction. Performance evaluation refers to the conventional use of LLJs to assess model outputs or overall performance. Model enhancement captures the use of LLJs to improve models, either through reward modeling or by providing feedback throughout the training process. Lastly, data construction involves leveraging LLJs for tasks such as data annotation or data generation. In this work, we examine the use of LLJs along three use cases to ground our analysis, each corresponding to one of these functionalities: text summarization, safety alignment, and data annotation.

3 Measurement Theory

In this section, we briefly introduce measurement theory, which offers a conceptual framework to formalize and evaluate the validity and reliability of an evaluation [111]. Measurement theory has its roots in the quantitative social sciences, particularly in fields such as psychology, education, and political science. Scholars in these disciplines have long aimed to develop formal methods for validating theoretical—and often abstract—concepts. Adcock and Collier [1] outline a four-level framework to understand the connection between concepts and observations. At the most abstract level is the background concept, encompassing the full range of meanings a concept might have. This is followed by the systematized concept, which refers to the precise definition adopted by researchers for analytical purposes. The third level involves the measures, or the scoring procedures used to assess the concept. Finally, the fourth level consists of the scores, which are derived from applying

Table 1: Components of construct validity as described by Jacobs and Wallach [47]

Dimension	Description
Face Validity	The measurements obtained from the evaluation look plausible.
Content Validity	The operationalization captures all relevant aspects of the underlying construct.
Convergent Validity	The measurements obtained correlate with other measurements of the construct.
Discriminant Validity	The measurements variation suggests the operationalization captures other constructs.
Predictive Validity	The measurements are predictive of relevant observable properties related to the construct.
Hypothesis Validity	The measurements support known hypotheses about the construct.
Consequential Validity	The consequences of using the measurements obtained from an evaluation.

the measures. In this context, *conceptualization* refers to the process of refining a background concept into a systematized concept, while *operationalization* involves converting the systematized concept into specific indicators or procedures for generating scores.

According to Adcock and Collier [1], a measurement is considered *valid* when the resulting observations—or scores—accurately reflect the content of the systematized concept. Validity is often discussed in light of measurement error, which refers to the difference between the observed score and the systematized concept it aims to represent. Measurement errors can be either systematic or random. Systematic errors, associated to bias, pertain to issues of *validity*, whereas random errors, manifesting as inconsistent results across repeated applications of the same procedure, relate to *reliability* [1].

Building on these foundations, Jacobs and Wallach [47] introduce a framework for understanding fairness in computational systems with respect to *construct reliability* and *construct validity* [18]. Construct reliability is defined in terms of *test-retest reliability*, i.e. how stable the scores obtained from the measurement model are over time, while construct validity is understood as being both context-dependent [1] and gradational in nature [47] and decomposed into seven dimensions described in Table 1.

4 Investigating the Assumptions Behind the Use of LLMs As Judges

Whether in the conceptualization or operationalization of a construct, the process of measurement modeling inevitably involves underlying assumptions [47]. To inform our position, we conducted a high-level qualitative review of commonly cited works on LLJs, focusing on how researchers motivate their use and describe their applications. The goal was to surface frequently recurring themes, implicit assumptions, and shared framings that appear across papers. Although not exhaustive, this approach provides insight into the dominant narratives and foundational premises that shape current research directions. We first explored the literature on LLJs across various applications (text summarization, machine translation, alignment, etc.) to get a broader understanding of their use, before focusing more in-depth on three applications illustrating the different functionalities presented in Section 2. As we believe that assessing the validity and reliability of LLJs needs to be done in context.

In this section, we identify and examine four common assumptions motivating the use of LLJs in the field. For each assumption, we illustrate key challenges using concrete examples from existing literature. Table 2 presents example quotes for each of these assumptions while Figure 1 presents an overview of our findings.

4.1 Assumption 1: LLMs as a Proxy for Human Judgment

Traditionally, NLG evaluation has relied on human annotators to assess the quality of language model outputs. Consequently, a range of benchmarks has been developed for tasks such as summarization, data-to-text generation, and machine translation, incorporating "human judgment"—either in the form of a score or human-written reference outputs. However, recent advances in LLMs are beginning to shift this paradigm. In particular, progress in reinforcement learning from human feedback [76] has significantly enhanced LLMs' ability to produce human-like text, making it increasingly challenging to distinguish between human-written and LLM-generated content [17]. The ability of LLMs to generate human-like text and align with human preferences [76] has prompted researchers to investigate their potential as effective alternatives to humans in NLG evaluation.

Table 2: Example quotes illustrating the assumptions behind the use of LLMs judges from selected publications.

LLMs as a Proxy for Human Judgment

Zheng et al. [117]: To automate the evaluation, we explore the use of state-of-the-art LLMs, such as GPT-4, as a surrogate for humans.

Gilardi et al. [33]: It strongly suggests that ChatGPT may already be a superior approach compared to crowd annotations on platforms such as MTurk.

LLMs as Capable Evaluators

Chiang and Lee [14]: LLMs have demonstrated exceptional performance on unseen tasks when only the task instructions are provided.

Mohta et al. [70]: It also exhibits the unique capability to provide reasons for classification, a feature often absent in human-labeled data.

LLMs as Scalable Evaluators

Sun et al. [95]: However, acquiring high-quality human annotations, including consistent response demonstrations and in-distribution preferences, is costly and not scalable.

Mazeika et al. [68]: However, companies currently rely on manual red teaming, which suffers from poor scalability.

LLMs as Cost-Effective Evaluators

He et al. [39]: From a cost perspective, GPT-4 is also more affordable than hiring MTurk workers. Sun et al. [96]: [...] offering cost-effective and accessible alternatives.

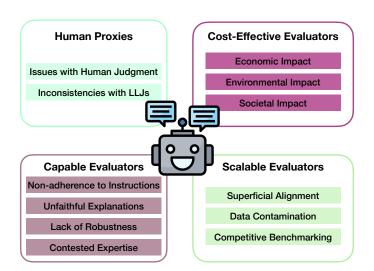


Figure 1: We look at the main assumptions made in the LLJs literature and identify potential pitfalls that can undermine the validity and reliability of LLMs as measurement models.

Early studies on LLJs [50, 14, 103, 63] have primarily validated their use through *convergent validity*. As shown in Table 1, this approach assumes that a metric is valid if it correlates with an existing, already validated metric for the same construct [47]. As a result, researchers have evaluated LLM-generated text using other LLJs, comparing their scores to human gold standards present in common NLG benchmarks (e.g., SummEval [27], RealSumm [8] or Topical-Chat [69]) using correlation metrics such as Pearson, Spearman, or Kendall's Tau. Demonstrating correlation between human ground-truth judgments and LLM-based evaluations has laid the groundwork for the field, driving their widespread adoption across various tasks and applications in academia and industry alike [52]. Although a body of work [63, 50] has shown a degree of correlation between LLM-based evaluations

and human judgment—indicating a form of *convergent validity*—we argue that existing shortcomings in NLG evaluation practices undermine the validity of LLJs as measurement models because the human judgments themselves might not be valid. In this section, we highlight how these shortcomings may undermine LLJs *convergent validity*.

Inconsistencies in Human Judgment Collection. As noted by Nenkova and Passonneau [74]: to show that an automatic method is a reasonable approximation of human judgments, one needs to demonstrate that these [human judgments] can be reliably elicited." However, prior work [120, 42] has revealed significant inconsistencies in how human judgments in NLG evaluation are being elicited and collected, casting doubt on their validity as a benchmark. Indeed, while human evaluation has long been considered the gold standard in NLG, there remains little agreement on what constitutes human judgment or how it should be collected. Howcroft et al. [42] examine twenty years of human evaluation practices in NLG and reveal a lack of shared practices within the community. They highlight significant inconsistencies in the definitions of evaluation criteria, when such definitions are provided at all, along with vague instructions for annotators (e.g., missing examples or clear rating scales) which lead to diverse interpretations of the evaluation task. Resulting in a clear mismatch between the evaluation criteria intended by researchers and how annotators actually understand them [17]. In addition, Zhou et al. [120] interview both academic and non-academic NLG practitioners about their evaluation practices, and reveal additional pitfalls in human evaluation practices, including ambiguity around the kind of expertise needed when involving human annotators, a conflation of quality criteria with their measurement, and the re-purposing of benchmarks created for other tasks. These issues have increasingly called into question the role of human judgment as the gold standard in NLG evaluation, sparking concerns about quality and reproducibility. This raises doubts about whether human judgments capture the intended aspects of evaluation.

Inconsistencies in LLJs Judgment Collection. Despite this uncertain foundation, the LLJs literature has adopted correlation with human judgment as the primary validation criterion of their use without critically investigating what aspects of the human judgment construct LLJs actually correlate with. Even this correlation is sometimes disputed—either because practitioners question whether LLJs actually correlate with human judgment as they notice great variability across tasks and benchmarks [51, 6], or because the methods used to compute the correlation are themselves contested [25]. For example, Elangovan et al. [25] show how human uncertainty in labeling affects the correlation scores produced by an LLJ. Specifically, under high human uncertainty—such as an improperly documented subjective annotation task—correlation between automatic metrics like LLJs may appear artificially inflated. Moreover, the literature on LLM judges seems to reproduce and even exacerbate many of the same issues found in previous NLG evaluation research—especially inconsistent conceptualization of evaluation criteria and ambiguous operationalization [43], not just across different benchmarks but also within individual benchmarks themselves. These inconsistencies in both human and LLM judgment collection practices raise important concerns about the validity of using LLMs as reliable proxies for human evaluation. Without standardized definitions, evaluation methods, and scoring scales, it becomes difficult to ensure that LLM-based assessments faithfully reflect human judgment.

Example: The SummEval Benchmark. The SummEval benchmark [27] has emerged as a key reference for validating the use of LLJs within the broader community given its pivotal role in NLG evaluation research. To better understand how LLJs judgements are collected and evaluated, we look at how different papers use this benchmark and notice various inconsistencies illustrated in Table 3. For example, while the original work provides the instructions given to annotators for the different evaluation criteria (relevance, consistency, fluency, coherence), work on LLJs do not always make use of these definitions. Across three different papers, only one uses the provided definition of fluency but also includes irrelevant information—confusing disfluency (which refers to a vocal communication disorder) with a lack of fluency in text. One paper does not provide any definition of fluency at all, while another introduces its own interpretation of the criterion. Additionally, although the human evaluation in the benchmark was conducted via relative comparisons by assessing five summaries simultaneously, studies using LLJs adopt either absolute or pairwise comparisons. They also employ varying rating scales (e.g., 1–3 or 1–100) instead of the benchmark's original 1–5 Likert scale.

Table 3: Instructions provided to LLM judges for evaluating the fluency criterion in SummEval [27]

Instructions	Scale	Process
Original instructions to annotators from Fabbri et al. [27]: This rating measures the quality of individual sentences, are they well-written and grammatically correct. Consider the quality of individual sentences.	Likert Scale (1-5)	Relative Comparison
The quality of the summary in terms of grammar, spelling, punctuation, word choice, and sentence structure. 1: Poor. The summary has many errors that make it hard to understand or sound unnatural. 2: Fair. The summary has some errors that affect the clarity or smoothness of the text, but the main points are still comprehensible. 3: Good. The summary has few or no errors and is easy to read and follow [63].	Likert Scale (1-3)	Absolute Comparison
Score the following news summarization given the corresponding news with respect to fluency with one to five stars, where one star means "disfluency" and five stars means "perfect fluency". Note that fluency measures the quality of individual sentences, are they well-written and grammatically correct. Consider the quality of individual sentences[103].	Likert Scale from 1-5 and from 1-100	Absolute Comparison
Which Summary is more fluent relative to the passage, Summary A or Summary B? or Provide a score between 1 and 10 that measures the summaries' fluency [65].	Binary Option or Scale 1-10	Pairwise Comparison or Absolute Comparison

4.2 Assumption 2: LLMs as Capable Evaluators

Another key assumption underlying the use of LLMs as judges is their high potential as evaluators. General-purposes LLMs have demonstrated impressive capabilities in in-context learning and instruction-following [105, 107, 106]—even surpassing human performance in certain tasks [5], suggesting that they could be used as evaluators without additional training. In this section, we explore how inherent limitations in LLMs' capabilities may affect their validity and reliability as evaluators across four key dimensions: instructions adherence, explainability, robustness, and expertise.

Instruction Adherence. While LLMs are widely recognized for their strong instruction-following capabilities [76], recent work has exposed notable limitations in these capabilities when applied to NLG evaluation. For instance, Hu et al. [43] show that LLMs frequently rely on their own interpretations of evaluation criteria, rather than following the instructions provided in the prompts, particularly across popular quality criteria used in the NLG literature. Moreover, LLMs often conflate distinct dimensions of evaluation, such as fluency and relevance, raising concerns about their *discriminant validity* as their operationalization of one criterion may inadvertently reflect aspects of another. Feuer et al. [28] corroborate these findings and further show that LLM judges exhibit strong implicit biases across quality criteria, assigning varying levels of importance to each and, as a result, scoring them inconsistently.

Explainability. A body of work has explored the effect of self-explanation on LLMs as evaluators, demonstrating that generating rationales through chain-of-thought reasoning can increase the correlation between model-generated scores and human judgments [15, 71, 48, 38], and improve transparency and interpretability of LLMs as judges. However, none of these studies examined the faithfulness of the generated explanations—either omitting any evaluation of the explanations altogether or focusing instead on aspects such as coherence [71], or the consistency and stability of the rationales provided [38]. As a result, they primarily assess the *face validity* of LLMs as judges, rather than rigorously validating their role as interpretable evaluation metrics. This is, in fact, one of the key challenges in LLM validation: their high *face validity*, as their outputs often appear coherent and plausible, even when they are wrong [90, 2].

Robustness. While the literature on LLJs has paid limited attention to their *construct validity* (§ 3), focusing primarly on *convergent validity* (§ 4.1) and *face validity* as seen above, it has, by contrast, extensively examined their *construct reliability*, particularly through assessments of *test-retest reliability*, given the known stochasticity of LLMs. For instance, [117, 56, 116, 54, 41, 61, 81, 104, 51, 112] examine position bias (also referred to as selection bias or order bias), showing that LLJs can favor responses based on their position in the response set [55]. Indeed, studies have demonstrated that LLJs are vulnerable to a broad spectrum of biases in their role as evaluators [52]. One prominent category includes cognitive biases [51]. For instance, saliency or verbosity bias describes the tendency

of LLMs to be swayed by the length of responses [117, 112]. Other biases include compassion-fade bias (favoring recognizable names over anonymized aliases), bandwagon-effect bias (favoring majority opinions), and attentional bias (giving too much attention to irrelevant details). We refer readers to Li et al. [55]'s survey for a more comprehensive discussion of the different documented biases in LLJs. Finally, a growing body of research [81, 118, 89, 57, 24] has demonstrated that LLJs are highly susceptible to superficial adversarial attacks and prompt manipulations. Raina et al. [81] show that it is possible to design universal attacks to inflate LLJs scores. Similarly, Li et al. [57] design a simple attack to inflate the scores obtained by diverse state-of-the-art LLJs. In the context of LLMs safety judges, Eiras et al. [24] show that they can lead a model to misclassify up to 100% of harmful generations as harmless through simple prompt variations. This lack of robustness to a multitude of biases and adversarial attacks undermines the *construct reliability* of LLJs, as small perturbations may lead to completely different evaluation results.

Expertise. A key argument in the literature supporting the use of LLJs is their strong performance on specific tasks. As Kocmi and Federmann [50] point out: "if the model can translate, it may be able to differentiate good from bad translations". Others may argue that comparison is easier than generation—even if both are probably correlated, and is therefore still valid for tasks for which LLJs are known to have inherent weaknesses, including math and reasoning [117], factuality [21] and safety [24]. However, we maintain that an LLM performance on a given task may impact its content validity as a judge for that same task.

Example: LLJs as Annotators. Because of LLMs ability to produce human-like text often indistinguishable from human-written text [17] and even perceived as higher quality [114, 91, 78], they are often seen as a great alternative for automated annotation, despite some researchers still disagreeing on their proficiency on the task [51, 72]. Interestingly, LLJs have been proposed as substitutes for humans in highly subjective and contested tasks, such as hate speech detection [44] and political affiliation classification [100]. The contested nature of these tasks makes it challenging to establish the content validity of LLJs as annotators. These constructs are highly subjective [40, 35], and relying on LLJs—who tend to yield higher inter-annotator agreement and present their own inherent biases—risks overlooking the valuable diversity found in human disagreement, which is especially important in these contexts. While disagreement is often treated as a marker of poor annotation quality, studies have shown it can instead provide important insights for subjective tasks [29, 49].

4.3 Assumption 3: LLMs as Scalable Evaluators

Another key assumption underlying the use of LLJs lies in their potential for scalability. Since scaling is widely recognized as a major driver of LLM performance [106], recent research has increasingly focused on scaling both datasets and model training. Within this context, LLJs have gained momentum, especially for alignment purposes. Considering the prohibitive cost of reinforcement learning from human feedback— which depends heavily on large amount of high quality human data [76], researchers have explored automated alternatives, leveraging LLJs for automatic red-teaming [79], self-improvement [5], self-alignment [96, 95], and human feedback generation [23], among other things. Most notably, LLJs have been widely used for safety at different steps of the mitigation pipeline: for generating harmless preferences, or annotating human preferences, for safety benchmarking, automatic red-teaming or as online guardrails for example [79, 5, 45, 68, 95]. For each of these tasks, researchers have been leveraging one or multiple LLJs through the safety pipeline. In this section, we show how these new safety pipelines can challenge the *discriminant validity* and *predictive validity* of LLJs.

Scaling Contamination. Beyond their "traditional" role in evaluation, LLJs are increasingly being used for model enhancement [55] (see Section 2). They can assume various roles throughout the training pipeline, including data generation and annotation, reward modeling, and verification [5, 95, 96]. While these applications have led to notable improvements in utility, the generalization of these performance gains remains to be rigorously validated, especially as such practices blur the boundary between training and testing. Considering that LLJs are mostly validated using publicly available benchmarks, this raises the issue of data contamination: several studies have shown evidence of memorization of popular benchmarks in various state-of-the-art LLMs [34, 83, 19, 22, 4]. Although the extent to which such contamination may inflate the performance of LLJs on popular benchmarks for NLG evaluation has yet to be thoroughly investigated, adjacents issues have been documented in

the literature. A growing body of research has demonstrated *self-enhancement bias* (also referred to as egocentric or narcissist bias) in LLJs, referring to their tendency to favor and inflate evaluation scores for responses generated by models from the same family [117, 64, 77]. Li et al. [53] further demonstrate that this bias can be exacerbated through the phenomenon of *preference leakage*, a specific form of contamination affecting LLJs. Preference leakage arises when LLMs used for data generation and evaluation in the training pipeline are closely related, which is typically the case in alignment settings, as practitioners use off-the-shelf models or previous versions of the same model as a judge. They show how this issue is especially prevalent in LLJs-based benchmarks, like AlpacaEval [23] and Arena-Hard [60], and that its severity increases with the degree of similarity between the models. Similarly, Li et al. [57] show that preference-based LLJs evaluation can be easily manipulated by adapting the responses of a model to align more closely with the judge. In cases where the evaluated model and the judge belong to the same model family, such adaptation may not even be necessary, as their preferences are already aligned.

Competitive Benchmarking. While the aforementioned biases raise important concerns about the use of LLJs for model alignment and benchmarking, even in the absence of such biases, incorporating LLJs inside the training pipeline remains questionable. The issue of competitive benchmarking has gained increasing attention in recent years [75], particularly in light of the rapid advancement of LLM capabilities and considering that in NLP, benchmarks are both testing instrument and testing material [87]. The emergence of various leaderboards and other LLJs powered evaluation framework has accentuated these concerns, as automatic evaluations are prone to negative feedback loop and inflated results. For example, Singh et al. [92] expose critical flaws in current evaluation practices that undermine the validity of one of the most widely used leaderboards for LLM evaluation: Chatbot Arena [16]. These flaws include unequal data access favoring proprietary providers such as Google and OpenAI, increased risks of overfitting to the benchmark, and the ability for participants to selectively disclose results or privately remove models from the platform. Numerous studies have demonstrated how easily evaluation frameworks can be manipulated [87, 10, 92], and we argue that automatizing the pipeline can only facilitate such practices as seen in [117, 64, 77, 53]. These biases and malpractices undermine the predictive validity of LLJs, as their scores are disproportionately affected by confounding factors unrelated to the task. This issue likely arises from overfitting to benchmarks and optimizing for specific metrics instead of the task itself, highlighting a gap between the intended construct (e.g., safety) and its operationalization (e.g., general framework for automated safety mitigation and evaluation).

Scaling Superficiality. Zhou et al. [119] introduced the Superficial Alignment Hypothesis, which suggests that LLMs acquire most of their knowledge and capabilities during pre-training, while alignment primarily affects the stylistic format of their outputs. This hypothesis is later supported by Lin et al. [62], who show that the most significant distribution shifts between base and aligned LLMs involve stylistic tokens. While such findings should have prompted critical reflection on the effectiveness of current safety mitigation practices—particularly in light of numerous documented failures in the literature [108] and encouraged greater investment in advancing safety research, they have inadvertently steered the field in a less constructive direction. Specifically, the perception that alignment is largely superficial has led to the belief that it can now be achieved at a lower cost [62], and that human feedback may no longer be necessary, paving the way for the adoption of LLJs as a realistic alternative.

Example: LLMs as Safety Judges. In an effort to prevent deployed models from producing harmful content, companies have released LLSJs as real-time safeguards. These judges act as guardrails, evaluating user inputs to determine whether they are appropriate for the base model to respond to. Examples of these models include Llama Guard [45, 97], ShielGamma [113], and Guardformer [73], among others [37, 66, 32, 68, 58]. LLSJs are typically responsible for classifying user inputs and model responses acording to predefined safety-taxonomies. While the exact criteria depend on each company's safety policies, they generally cover similar dimensions such as violence, hate speech, sexual content, weapons, illicit substances, suicide, and criminal activity. Eiras et al. [24] show that LLSJs are highly sensitive to distribution shift and adversarial attacks. Notably, they show how small modifications in outputs can lead LLMs safety judges to misclassify up to 100% of harmful generation as harmless. Similarly, Chen and Goldfarb-Tarrant [13] demonstrate that injecting artifacts into safety-related prompts can mislead LLSJs, revealing an over-reliance on surface-level statistical cues rather than a genuine understanding of safety. For instance, adding an apology to an unsafe

prompt may cause the model to wrongly classify it as harmless. This focus on stylistic markers over substantive safety concerns supports the superficial alignment hypothesis and echoes findings from prior work on the limitations of safety safeguards—such as exaggerated safety behaviors [84] and the ways in which such behaviors can reinforce existing societal biases [10]. Such tendencies call into question the *discriminant validity* of LLSJs, as their vulnerability to superficial interventions suggests a limited understanding of safety concepts, relying instead on loosely correlated proxies—such as a model's refusal to respond to a query.

4.4 Assumption 4: LLMs as Cost-Effective Evaluators

Another key assumption underlying the use of LLJs is their potential to serve as a more cost-effective alternative to human evaluation. Although LLM-based evaluation can incur higher costs in certain scenarios [28] such as LLJs-based benchmarks like Arena-Hard [60], it is generally more economical overall. Instead of relying on crowdworkers (e.g., via Amazon Mechanical Turk) or domain experts, practitioners can now leverage open- or closed-source LLMs for evaluation. While inference costs vary across models, this approach remains more affordable than human labor, particularly as the operational costs of LLMs continue to decrease [28].

The conversation around LLJs as a cheap, realistic, and scalable alternative echoes the introduction of Amazon Mechanical Turk (AMT) into the research sphere, as it was similarly praised for these qualities [9, 93]. Although the platform was initially introduced as a more diverse, scalable, and cost-effective alternative to traditional human evaluation methods, it has since come under scrutiny. For instance, Marshall et al. [67] highlight a decline in data quality on AMT over time, despite the implementation of numerous mitigation strategies aimed at enhancing the reliability of collected data—such as attention checks, reading comprehension tasks, and pre-screening workers based on specific criteria. Beyond this deterioration in quality, researchers have also raised significant ethical concerns about the platform and crowdwork more broadly, particularly emphasizing its exploitative nature, characterized by extremely low wages, lack of transparency, pronounced power asymmetries, and threats to workers' privacy [30, 80, 86].

The AMT example highlights the importance of considering more than just short-term financial costs when adopting new evaluation methods. While localized short-term economies might seem attractive, they can snowball into larger societal impacts once such practices become established in the field. Similarly, the adoption of LLJs often overlooks long-term implications and non-financial costs, factors that are largely ignored in the literature and rarely discussed in critical depth, despite being crucial to establishing the validity of the framework. Using LLMs as benchmarks not only influences perceived progress in the field but also shapes how research is conducted, how LLMs capabilities are understood, and how we interpret the very constructs these models are purported to measure. Moreover, while LLJs offer clear cost savings for researchers, it remains unclear who will ultimately bear the broader costs of their widespread adoption over time. Below, we examine how the non-financial impacts associated with LLJs may affect their *consequential validity* (see Table 1).

Economic Impact. Although early efforts to explore LLMs as an alternative to human annotators [33, 3] have been widely criticized in both the media [99, 109] and academic literature [39], researchers continue to pursue the use of LLJs as annotators [121, 100, 70, 121, 44, 39, 38], raising concerns about the future of crowdworkers—an already vulnerable population [80]—especially as many agree that ongoing advances in LLM research are likely to have disruptive effects on the labor market [98, 46]. While automation may appear as a more "ethical" alternative in certain contexts—such as content moderation, where workers are regularly exposed to traumatic material (e.g., child sexual abuse, bestiality, incest [110])—it is crucial to acknowledge that, despite their precarity, these jobs remain the primary source of income for many. Displacing workers does not resolve the underlying issues. Instead, efforts should focus on improving working conditions and developing alternatives that are grounded in the needs and lived realities of these workers ¹.

Environmental Impact. Although frequently overshadowed by the environmental costs of training[7, 59], the environmental impact of large language models during inference remains considerable—whether in terms of energy consumption [85], carbon emissions [26], or water usage [59]—and continues to grow as model sizes increase [20]. While there is a growing focus on

¹https://data-workers.org/

more efficient computational methods (e.g., model distillation, sparsification) [85], the LLJs literature continues to favor larger models, as they have been shown to produce more accurate evaluations, sometimes even leveraging "juries", i.e., ensembles of smaller LLMs [101], to improve performance. Few have investigated less resource-intensive alternatives, addressing a gap in the current discourse on evaluating LLJs.

Societal Impact. LLJs are not exempt from the well-documented societal biases present in large language models [88, 108, 31]—even if such biases have not yet been extensively studied in this context. NLG systems are known to reinforce social stereotypes and discriminatory patterns, and they are prone to producing hate speech, offensive content, and exclusionary language [108]. When used for evaluation, LLJs have the potential to exhibit fairness-related biases, potentially favoring responses associated with certain demographic groups over others. However, few studies have examined the potential of LLJs to reproduce existing discriminatory patterns [94, 112, 12]. Among these, Ye et al. [112] demonstrate that LLJs exhibit diversity bias, meaning their judgment shift in the presence of identity markers. While Chen et al. [12] show evidence of gender bias in LLJs. Given these findings, it is likely that LLJs reproduce societal biases. This highlights the need for further investigation before deploying them, particularly in high-stakes applications.

5 The Path Forward

In this section, we offer recommendations to support the responsible and effective integration of LLJs into evaluation practices.

First, despite the wide range of applications for LLJs, there has been little adaptation in how they are deployed or in how evaluations are designed across different tasks and domains—an oversight that can lead to harmful consequences. For instance, while using LLJs to scale red-teaming efforts can enhance the breadth of evaluation, applying the same approach within a safety mitigation pipeline can result in superficial safety behaviors. In such contexts, more targeted and domain-specific mitigation strategies can be more effective than a trial-and-error approach that does not account for the sociotechnical aspect of safety [11]. Evaluating the role of LLJs as evaluators necessitates a comprehensive approach that considers several critical dimensions, including the task at hand, the goal of the evaluation, and the type of LLJ being used, among other things.

Finally, although mitigating the biases of LLJs has become an active area of research [52], the field urgently requires improved evaluation practices. Recent controversies [82, 92] have exposed how tech companies manipulate existing evaluation frameworks, raising serious concerns about data contamination, competitive benchmarking, and overfitting among other things. Despite the importance of evaluation in ML development, there is a lack of rigorous shared practices among practitioners. While technical artifacts like benchmarks and metrics are commonly shared, methodologies and practices are not. [42, 120, 102] highlight that current practices in NLG evaluation lack standardization and systematization, and as demonstrated in this paper, the adoption of LLJs is no exception. LLJs not only reproduce and exacerbate existing issues, but also introduce new challenges for the community. We need to not only focus on mitigating the individual biases associated with LLJs but also consider how to improve NLG evaluation practices as a whole, and better train ML practitioners for such a complex task. It is perhaps time to move beyond a paradigm where we rely on interested companies to provide transparent and comprehensive evaluation of the products they aim to market, and instead work into putting in place proper mechanisms for transparent, valid and reliable evaluation.

6 Conclusion

In this work, we have explored how various pitfalls in NLG evaluation practices and the inherent limitations of LLMs can impact LLJs as evaluators. We argue that fully realizing the potential of LLJs depends on our ability to critically and systematically address these challenges. When properly implemented, LLJs offer a valuable opportunity to advance NLG evaluation—whether by enabling more realistic, interactive, and long-term evaluation pipelines that better reflect real-world usage, or by alleviating the burden of problematic annotation tasks involving harmful or traumatic content for example. Therefore, leveraging LLJs effectively will require a careful balance: improving efficiency without disregarding their broader societal impact.

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References

- [1] Robert Adcock and David Collier. Measurement Validity: A Shared Standard for Qualitative and Quantitative Research. *American Political Science Review*, 95(3):529-546, September 2001. ISSN 0003-0554, 1537-5943. doi: 10.1017/S0003055401003100. URL https://www.cambridge.org/core/journals/american-political-science-review/article/abs/measurement-validity-a-shared-standard-for-qualitative-and-quantitative-research/91C7A9800DB26A76EBBABC5889A50C8B#.
- [2] Chirag Agarwal, Sree Harsha Tanneru, and Himabindu Lakkaraju. Faithfulness vs. Plausibility: On the (Un)Reliability of Explanations from Large Language Models, March 2024. URL http://arxiv.org/abs/2402.04614. arXiv:2402.04614 [cs].
- [3] Meysam Alizadeh, Maël Kubli, Zeynab Samei, Shirin Dehghani, Juan Diego Bermeo, Maria Korobeynikova, and Fabrizio Gilardi. Open-Source Large Language Models Outperform Crowd Workers and Approach ChatGPT in Text-Annotation Tasks. *CoRR*, January 2023. URL https://openreview.net/forum?id=FboDJ1SGlp.
- [4] Norah Alzahrani, Hisham Alyahya, Yazeed Alnumay, Sultan AlRashed, Shaykhah Alsubaie, Yousef Almushayqih, Faisal Mirza, Nouf Alotaibi, Nora Al-Twairesh, Areeb Alowisheq, M Saiful Bari, and Haidar Khan. When Benchmarks are Targets: Revealing the Sensitivity of Large Language Model Leaderboards. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 13787–13805, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.744. URL https://aclanthology.org/2024.acl-long.744/.
- [5] Yuntao Bai, Saurav Kadavath, Sandipan Kundu, Amanda Askell, Jackson Kernion, Andy Jones, Anna Chen, Anna Goldie, Azalia Mirhoseini, Cameron McKinnon, Carol Chen, Catherine Olsson, Christopher Olah, Danny Hernandez, Dawn Drain, Deep Ganguli, Dustin Li, Eli Tran-Johnson, Ethan Perez, Jamie Kerr, Jared Mueller, Jeffrey Ladish, Joshua Landau, Kamal Ndousse, Kamile Lukosuite, Liane Lovitt, Michael Sellitto, Nelson Elhage, Nicholas Schiefer, Noemi Mercado, Nova DasSarma, Robert Lasenby, Robin Larson, Sam Ringer, Scott Johnston, Shauna Kravec, Sheer El Showk, Stanislav Fort, Tamera Lanham, Timothy Telleen-Lawton, Tom Conerly, Tom Henighan, Tristan Hume, Samuel R. Bowman, Zac Hatfield-Dodds, Ben Mann, Dario Amodei, Nicholas Joseph, Sam McCandlish, Tom Brown, and Jared Kaplan. Constitutional AI: Harmlessness from AI Feedback, December 2022. URL http://arxiv.org/abs/2212.08073. arXiv:2212.08073 [cs].
- [6] Anna Bavaresco, Raffaella Bernardi, Leonardo Bertolazzi, Desmond Elliott, Raquel Fernández, Albert Gatt, Esam Ghaleb, Mario Giulianelli, Michael Hanna, Alexander Koller, André F. T. Martins, Philipp Mondorf, Vera Neplenbroek, Sandro Pezzelle, Barbara Plank, David Schlangen, Alessandro Suglia, Aditya K. Surikuchi, Ece Takmaz, and Alberto Testoni. LLMs instead of Human Judges? A Large Scale Empirical Study across 20 NLP Evaluation Tasks. CoRR, January 2024. URL https://openreview.net/forum?id=zDoOyPlpLq.
- [7] Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big? In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '21, pages 610–623, New York, NY, USA, March 2021. Association for Computing Machinery. ISBN 978-1-4503-8309-7. doi: 10.1145/3442188.3445922. URL https://dl.acm.org/doi/10. 1145/3442188.3445922.
- [8] Manik Bhandari, Pranav Narayan Gour, Atabak Ashfaq, Pengfei Liu, and Graham Neubig. Re-evaluating Evaluation in Text Summarization. In Bonnie Webber, Trevor Cohn, Yulan He,

- and Yang Liu, editors, *Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pages 9347–9359, Online, November 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.emnlp-main.751. URL https://aclanthology.org/2020.emnlp-main.751/.
- [9] Michael Buhrmester, Tracy Kwang, and Samuel D. Gosling. Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data? Perspectives on Psychological Science: A Journal of the Association for Psychological Science, 6(1):3–5, January 2011. ISSN 1745-6916. doi: 10.1177/1745691610393980.
- [10] Khaoula Chehbouni, Megha Roshan, Emmanuel Ma, Futian Wei, Afaf Taik, Jackie Cheung, and Golnoosh Farnadi. From Representational Harms to Quality-of-Service Harms: A Case Study on Llama 2 Safety Safeguards. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, Findings of the Association for Computational Linguistics: ACL 2024, pages 15694–15710, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.927. URL https://aclanthology.org/2024.findings-acl.927/.
- [11] Khaoula Chehbouni, Jonathan Colaço Carr, Yash More, Jackie CK Cheung, and Golnoosh Farnadi. Beyond the Safety Bundle: Auditing the Helpful and Harmless Dataset. In Luis Chiruzzo, Alan Ritter, and Lu Wang, editors, *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 11895–11925, Albuquerque, New Mexico, April 2025. Association for Computational Linguistics. ISBN 9798891761896. URL https://aclanthology.org/2025.naacl-long.596/.
- [12] Guiming Hardy Chen, Shunian Chen, Ziche Liu, Feng Jiang, and Benyou Wang. Humans or LLMs as the Judge? A Study on Judgement Bias. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 8301–8327, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.474. URL https://aclanthology.org/2024.emnlp-main.474/.
- [13] Hongyu Chen and Seraphina Goldfarb-Tarrant. Safer or Luckier? LLMs as Safety Evaluators Are Not Robust to Artifacts, March 2025. URL http://arxiv.org/abs/2503.09347. arXiv:2503.09347 [cs].
- [14] Cheng-Han Chiang and Hung-yi Lee. Can Large Language Models Be an Alternative to Human Evaluations? In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki, editors, *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 15607–15631, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.870. URL https://aclanthology.org/2023.acl-long.870/.
- [15] Cheng-Han Chiang and Hung-yi Lee. A Closer Look into Using Large Language Models for Automatic Evaluation. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Findings of the Association for Computational Linguistics: EMNLP 2023*, pages 8928–8942, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.findings-emnlp.599. URL https://aclanthology.org/2023.findings-emnlp.599/.
- [16] Wei-Lin Chiang, Lianmin Zheng, Ying Sheng, Anastasios N. Angelopoulos, Tianle Li, Dacheng Li, Banghua Zhu, Hao Zhang, Michael I. Jordan, Joseph E. Gonzalez, and Ion Stoica. Chatbot arena: an open platform for evaluating LLMs by human preference. In *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *ICML*'24, pages 8359–8388, Vienna, Austria, 2024. JMLR.org.
- [17] Elizabeth Clark, Tal August, Sofia Serrano, Nikita Haduong, Suchin Gururangan, and Noah A. Smith. All That's 'Human' Is Not Gold: Evaluating Human Evaluation of Generated Text. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 7282–7296, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acllong.565. URL https://aclanthology.org/2021.acl-long.565/.

- [18] Lee J. Cronbach and Paul E. Meehl. Construct validity in psychological tests. *Psychological Bulletin*, 52(4):281–302, 1955. ISSN 1939-1455. doi: 10.1037/h0040957. Place: US Publisher: American Psychological Association.
- [19] Chunyuan Deng, Yilun Zhao, Xiangru Tang, Mark Gerstein, and Arman Cohan. Investigating Data Contamination in Modern Benchmarks for Large Language Models. In Kevin Duh, Helena Gomez, and Steven Bethard, editors, *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 8706–8719, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-long.482. URL https://aclanthology.org/2024.naacl-long.482/.
- [20] Radosvet Desislavov, Fernando Martínez-Plumed, and José Hernández-Orallo. Trends in AI inference energy consumption: Beyond the performance-vs-parameter laws of deep learning. *Sustainable Computing: Informatics and Systems*, 38:100857, April 2023. ISSN 2210-5379. doi: 10.1016/j.suscom.2023.100857. URL https://www.sciencedirect.com/science/article/pii/S2210537923000124.
- [21] Laurence Dierickx, Arjen van Dalen, Andreas L. Opdahl, and Carl-Gustav Lindén. Striking the Balance in Using LLMs for Fact-Checking: A Narrative Literature Review. In Mike Preuss, Agata Leszkiewicz, Jean-Christopher Boucher, Ofer Fridman, and Lucas Stampe, editors, *Disinformation in Open Online Media*, pages 1–15, Cham, 2024. Springer Nature Switzerland. ISBN 978-3-031-71210-4. doi: 10.1007/978-3-031-71210-4_1.
- [22] Yihong Dong, Xue Jiang, Huanyu Liu, Zhi Jin, Bin Gu, Mengfei Yang, and Ge Li. Generalization or Memorization: Data Contamination and Trustworthy Evaluation for Large Language Models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics: ACL 2024*, pages 12039–12050, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.716. URL https://aclanthology.org/2024.findings-acl.716/.
- [23] Yann Dubois, Chen Xuechen Li, Rohan Taori, Tianyi Zhang, Ishaan Gulrajani, Jimmy Ba, Carlos Guestrin, Percy S. Liang, and Tatsunori B. Hashimoto. AlpacaFarm: A Simulation Framework for Methods that Learn from Human Feedback. Advances in Neural Information Processing Systems, 36:30039-30069, December 2023. URL https://proceedings.neurips.cc/paper_files/paper/2023/hash/5fc47800ee5b30b8777fdd30abcaaf3b-Abstract-Conference.html.
- [24] Francisco Eiras, Eliott Zemour, Eric Lin, and Vaikkunth Mugunthan. Know Thy Judge: On the Robustness Meta-Evaluation of LLM Safety Judges, March 2025. URL http://arxiv.org/abs/2503.04474. arXiv:2503.04474 [cs].
- [25] Aparna Elangovan, Lei Xu, Jongwoo Ko, Mahsa Elyasi, Ling Liu, Sravan Babu Bodapati, and Dan Roth. Beyond correlation: The impact of human uncertainty in measuring the effectiveness of automatic evaluation and LLM-as-a-judge. October 2024. URL https://openreview.net/forum?id=E8gYIrbP00.
- [26] Brad Everman, Trevor Villwock, Dayuan Chen, Noe Soto, Oliver Zhang, and Ziliang Zong. Evaluating the Carbon Impact of Large Language Models at the Inference Stage. In 2023 IEEE International Performance, Computing, and Communications Conference (IPCCC), pages 150–157, November 2023. doi: 10.1109/IPCCC59175.2023.10253886. URL https://ieeexplore.ieee.org/abstract/document/10253886. ISSN: 2374-9628.
- [27] Alexander R. Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. SummEval: Re-evaluating Summarization Evaluation. *Transactions of the Association for Computational Linguistics*, 9:391–409, April 2021. ISSN 2307-387X. doi: 10.1162/tacl_a_00373. URL https://doi.org/10.1162/tacl_a_00373.
- [28] Benjamin Feuer, Micah Goldblum, Teresa Datta, Sanjana Nambiar, Raz Besaleli, Samuel Dooley, Max Cembalest, and John P. Dickerson. Style Outweighs Substance: Failure Modes of LLM Judges in Alignment Benchmarking. October 2024. URL https://openreview.net/forum?id=MzHNftnAM1.

- [29] Eve Fleisig, Rediet Abebe, and Dan Klein. When the Majority is Wrong: Modeling Annotator Disagreement for Subjective Tasks. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 6715–6726, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.415. URL https://aclanthology.org/2023.emnlp-main.415/.
- [30] Karen Fort, Gilles Adda, and Kevin Bretonnel Cohen. Amazon Mechanical Turk: Gold Mine or Coal Mine? *Computational Linguistics*, 37(2):413–420, April 2011. doi: 10.1162/COLI_a_00057. URL https://hal.science/hal-00569450. Publisher: Massachusetts Institute of Technology Press (MIT Press).
- [31] Isabel O. Gallegos, Ryan A. Rossi, Joe Barrow, Md Mehrab Tanjim, Sungchul Kim, Franck Dernoncourt, Tong Yu, Ruiyi Zhang, and Nesreen K. Ahmed. Bias and Fairness in Large Language Models: A Survey. *Computational Linguistics*, 50(3):1097–1179, September 2024. doi: 10.1162/coli_a_00524. URL https://aclanthology.org/2024.cl-3.8/. Place: Cambridge, MA Publisher: MIT Press.
- [32] Shaona Ghosh, Prasoon Varshney, Makesh Narsimhan Sreedhar, Aishwarya Padmakumar, Traian Rebedea, Jibin Rajan Varghese, and Christopher Parisien. AEGIS2.0: A Diverse AI Safety Dataset and Risks Taxonomy for Alignment of LLM Guardrails. In Luis Chiruzzo, Alan Ritter, and Lu Wang, editors, *Proceedings of the 2025 Conference of the Nations of the Americas Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 5992–6026, Albuquerque, New Mexico, April 2025. Association for Computational Linguistics. ISBN 9798891761896. URL https://aclanthology.org/2025.naacl-long.306/.
- [33] Fabrizio Gilardi, Meysam Alizadeh, and Maël Kubli. ChatGPT outperforms crowd workers for text-annotation tasks. *Proceedings of the National Academy of Sciences*, 120(30):e2305016120, July 2023. doi: 10.1073/pnas.2305016120. URL https://www.pnas.org/doi/abs/10.1073/pnas.2305016120. Company: National Academy of Sciences Distributor: National Academy of Sciences Institution: National Academy of Sciences Publisher: Proceedings of the National Academy of Sciences.
- [34] Shahriar Golchin and Mihai Surdeanu. Time Travel in LLMs: Tracing Data Contamination in Large Language Models. October 2023. URL https://openreview.net/forum?id=2Rwq6c3tvr.
- [35] Nitesh Goyal, Ian D. Kivlichan, Rachel Rosen, and Lucy Vasserman. Is Your Toxicity My Toxicity? Exploring the Impact of Rater Identity on Toxicity Annotation. *Proc. ACM Hum.-Comput. Interact.*, 6(CSCW2):363:1–363:28, November 2022. doi: 10.1145/3555088. URL https://dl.acm.org/doi/10.1145/3555088.
- [36] Luke Guerdan, Solon Barocas, Kenneth Holstein, Hanna Wallach, Zhiwei Steven Wu, and Alexandra Chouldechova. Validating LLM-as-a-Judge Systems in the Absence of Gold Labels, March 2025. URL https://arxiv.org/abs/2503.05965v2.
- [37] Seungju Han, Kavel Rao, Allyson Ettinger, Liwei Jiang, Bill Yuchen Lin, Nathan Lambert, Yejin Choi, and Nouha Dziri. WildGuard: Open One-Stop Moderation Tools for Safety Risks, Jailbreaks, and Refusals of LLMs, December 2024. URL http://arxiv.org/abs/2406.18495. arXiv:2406.18495 [cs].
- [38] Xingwei He, Zhenghao Lin, Yeyun Gong, A-Long Jin, Hang Zhang, Chen Lin, Jian Jiao, Siu Ming Yiu, Nan Duan, and Weizhu Chen. AnnoLLM: Making Large Language Models to Be Better Crowdsourced Annotators. In Yi Yang, Aida Davani, Avi Sil, and Anoop Kumar, editors, Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 6: Industry Track), pages 165–190, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-industry.15. URL https://aclanthology.org/2024.naacl-industry.15/.

- [39] Zeyu He, Chieh-Yang Huang, Chien-Kuang Cornelia Ding, Shaurya Rohatgi, and Ting-Hao Kenneth Huang. If in a Crowdsourced Data Annotation Pipeline, a GPT-4. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*, CHI '24, pages 1–25, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400703300. doi: 10.1145/3613904.3642834. URL https://dl.acm.org/doi/10.1145/3613904.3642834.
- [40] Danula Hettiachchi, Indigo Holcombe-James, Stephanie Livingstone, Anjalee de Silva, Matthew Lease, Flora D. Salim, and Mark Sanderson. How Crowd Worker Factors Influence Subjective Annotations: A Study of Tagging Misogynistic Hate Speech in Tweets. *Proceedings of the AAAI Conference on Human Computation and Crowdsourcing*, 11: 38–50, November 2023. ISSN 2769-1349. doi: 10.1609/hcomp.v11i1.27546. URL https://ojs.aaai.org/index.php/HCOMP/article/view/27546.
- [41] Yupeng Hou, Junjie Zhang, Zihan Lin, Hongyu Lu, Ruobing Xie, Julian McAuley, and Wayne Xin Zhao. Large Language Models are Zero-Shot Rankers for Recommender Systems. In *Advances in Information Retrieval: 46th European Conference on Information Retrieval, ECIR 2024, Glasgow, UK, March 24*–28, 2024, Proceedings, Part II, pages 364–381, Berlin, Heidelberg, March 2024. Springer-Verlag. ISBN 978-3-031-56059-0. doi: 10.1007/978-3-031-56060-6_24. URL https://doi.org/10.1007/978-3-031-56060-6_24.
- [42] David M. Howcroft, Anya Belz, Miruna-Adriana Clinciu, Dimitra Gkatzia, Sadid A. Hasan, Saad Mahamood, Simon Mille, Emiel van Miltenburg, Sashank Santhanam, and Verena Rieser. Twenty Years of Confusion in Human Evaluation: NLG Needs Evaluation Sheets and Standardised Definitions. In Brian Davis, Yvette Graham, John Kelleher, and Yaji Sripada, editors, *Proceedings of the 13th International Conference on Natural Language Generation*, pages 169–182, Dublin, Ireland, December 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.inlg-1.23. URL https://aclanthology.org/2020.inlg-1.23/.
- [43] Xinyu Hu, Mingqi Gao, Sen Hu, Yang Zhang, Yicheng Chen, Teng Xu, and Xiaojun Wan. Are LLM-based Evaluators Confusing NLG Quality Criteria? In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 9530–9570, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.516. URL https://aclanthology.org/2024.acl-long.516/.
- [44] Fan Huang, Haewoon Kwak, and Jisun An. Is ChatGPT better than Human Annotators? Potential and Limitations of ChatGPT in Explaining Implicit Hate Speech. In *Companion Proceedings of the ACM Web Conference 2023*, WWW '23 Companion, pages 294–297, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 978-1-4503-9419-2. doi: 10.1145/3543873.3587368. URL https://doi.org/10.1145/3543873.3587368.
- [45] Hakan Inan, Kartikeya Upasani, Jianfeng Chi, Rashi Rungta, Krithika Iyer, Yuning Mao, Michael Tontchev, Qing Hu, Brian Fuller, Davide Testuggine, and Madian Khabsa. Llama Guard: LLM-based Input-Output Safeguard for Human-AI Conversations, December 2023. URL http://arxiv.org/abs/2312.06674. arXiv:2312.06674 [cs].
- [46] Lilly Irani. Justice for "Data Janitors", January 2015. URL https://www.publicbooks.org/justice-for-data-janitors/.
- [47] Abigail Z. Jacobs and Hanna Wallach. Measurement and Fairness. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '21, pages 375–385, New York, NY, USA, March 2021. Association for Computing Machinery. ISBN 978-1-4503-8309-7. doi: 10.1145/3442188.3445901. URL https://dl.acm.org/doi/10.1145/3442188.3445901.
- [48] Pei Ke, Bosi Wen, Andrew Feng, Xiao Liu, Xuanyu Lei, Jiale Cheng, Shengyuan Wang, Aohan Zeng, Yuxiao Dong, Hongning Wang, Jie Tang, and Minlie Huang. CritiqueLLM: Towards an Informative Critique Generation Model for Evaluation of Large Language Model Generation. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 13034–13054, Bangkok, Thailand, August 2024. Association for Computational Linguistics.

- doi: 10.18653/v1/2024.acl-long.704. URL https://aclanthology.org/2024.acl-long. 704/.
- [49] Urja Khurana, Eric Nalisnick, Antske Fokkens, and Swabha Swayamdipta. Crowd-calibrator: Can annotator disagreement inform calibration in subjective tasks? In *First Conference on Language Modeling*, 2024. URL https://openreview.net/forum?id=VWWzO3ewMS.
- [50] Tom Kocmi and Christian Federmann. Large Language Models Are State-of-the-Art Evaluators of Translation Quality. In Mary Nurminen, Judith Brenner, Maarit Koponen, Sirkku Latomaa, Mikhail Mikhailov, Frederike Schierl, Tharindu Ranasinghe, Eva Vanmassenhove, Sergi Alvarez Vidal, Nora Aranberri, Mara Nunziatini, Carla Parra Escartín, Mikel Forcada, Maja Popovic, Carolina Scarton, and Helena Moniz, editors, *Proceedings of the 24th Annual Conference of the European Association for Machine Translation*, pages 193–203, Tampere, Finland, June 2023. European Association for Machine Translation. URL https://aclanthology.org/2023.eamt-1.19/.
- [51] Ryan Koo, Minhwa Lee, Vipul Raheja, Jong Inn Park, Zae Myung Kim, and Dongyeop Kang. Benchmarking Cognitive Biases in Large Language Models as Evaluators. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Findings of the Association for Computational Linguistics: ACL 2024*, pages 517–545, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.29. URL https://aclanthology.org/2024.findings-acl.29/.
- [52] Dawei Li, Bohan Jiang, Liangjie Huang, Alimohammad Beigi, Chengshuai Zhao, Zhen Tan, Amrita Bhattacharjee, Yuxuan Jiang, Canyu Chen, Tianhao Wu, Kai Shu, Lu Cheng, and Huan Liu. From Generation to Judgment: Opportunities and Challenges of LLM-as-a-judge, February 2025. URL http://arxiv.org/abs/2411.16594. arXiv:2411.16594 [cs].
- [53] Dawei Li, Renliang Sun, Yue Huang, Ming Zhong, Bohan Jiang, Jiawei Han, Xiangliang Zhang, Wei Wang, and Huan Liu. Preference Leakage: A Contamination Problem in LLM-as-a-judge, February 2025. URL http://arxiv.org/abs/2502.01534. arXiv:2502.01534 [cs].
- [54] Haitao Li, Junjie Chen, Qingyao Ai, Zhumin Chu, Yujia Zhou, Qian Dong, and Yiqun Liu. CalibraEval: Calibrating Prediction Distribution to Mitigate Selection Bias in LLMs-as-Judges, October 2024. URL http://arxiv.org/abs/2410.15393. arXiv:2410.15393 [cs].
- [55] Haitao Li, Qian Dong, Junjie Chen, Huixue Su, Yujia Zhou, Qingyao Ai, Ziyi Ye, and Yiqun Liu. LLMs-as-Judges: A Comprehensive Survey on LLM-based Evaluation Methods, December 2024. URL http://arxiv.org/abs/2412.05579. arXiv:2412.05579 [cs].
- [56] Junlong Li, Shichao Sun, Weizhe Yuan, Run-Ze Fan, Hai Zhao, and Pengfei Liu. Generative Judge for Evaluating Alignment. October 2023. URL https://openreview.net/forum?id=gtkFw6sZGS.
- [57] Junlong Li, Fan Zhou, Shichao Sun, Yikai Zhang, Hai Zhao, and Pengfei Liu. Dissecting Human and LLM Preferences. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1790–1811, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.99. URL https://aclanthology.org/2024.acl-long.99/.
- [58] Lijun Li, Bowen Dong, Ruohui Wang, Xuhao Hu, Wangmeng Zuo, Dahua Lin, Yu Qiao, and Jing Shao. SALAD-Bench: A Hierarchical and Comprehensive Safety Benchmark for Large Language Models. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, Findings of the Association for Computational Linguistics: ACL 2024, pages 3923–3954, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.235. URL https://aclanthology.org/2024.findings-acl.235/.
- [59] Pengfei Li, Jianyi Yang, Mohammad A. Islam, and Shaolei Ren. Making AI Less "Thirsty": Uncovering and Addressing the Secret Water Footprint of AI Models, March 2025. URL http://arxiv.org/abs/2304.03271. arXiv:2304.03271 [cs].

- [60] Tianle Li, Wei-Lin Chiang, Evan Frick, Lisa Dunlap, Tianhao Wu, Banghua Zhu, Joseph E. Gonzalez, and Ion Stoica. From Crowdsourced Data to High-Quality Benchmarks: Arena-Hard and BenchBuilder Pipeline, June 2024. URL http://arxiv.org/abs/2406.11939. arXiv:2406.11939 [cs] version: 1.
- [61] Zongjie Li, Chaozheng Wang, Pingchuan Ma, Daoyuan Wu, Shuai Wang, Cuiyun Gao, and Yang Liu. Split and Merge: Aligning Position Biases in LLM-based Evaluators. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 11084–11108, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024. emnlp-main.621. URL https://aclanthology.org/2024.emnlp-main.621/.
- [62] Bill Yuchen Lin, Abhilasha Ravichander, Ximing Lu, Nouha Dziri, Melanie Sclar, Khyathi Chandu, Chandra Bhagavatula, and Yejin Choi. The Unlocking Spell on Base LLMs: Rethinking Alignment via In-Context Learning. October 2023. URL https://openreview.net/forum?id=wxJ0eXwwda¬eId=YM3ghGUbjR.
- [63] Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. G-Eval: NLG Evaluation using Gpt-4 with Better Human Alignment. In Houda Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 2511–2522, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.153. URL https://aclanthology.org/2023.emnlp-main.153/.
- [64] Yiqi Liu, Nafise Moosavi, and Chenghua Lin. LLMs as Narcissistic Evaluators: When Ego Inflates Evaluation Scores. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, Findings of the Association for Computational Linguistics: ACL 2024, pages 12688– 12701, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-acl.753. URL https://aclanthology.org/2024.findingsacl.753/.
- [65] Adian Liusie, Potsawee Manakul, and Mark Gales. LLM Comparative Assessment: Zero-shot NLG Evaluation through Pairwise Comparisons using Large Language Models. In Yvette Graham and Matthew Purver, editors, *Proceedings of the 18th Conference of the European Chapter of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 139–151, St. Julian's, Malta, March 2024. Association for Computational Linguistics. URL https://aclanthology.org/2024.eacl-long.8/.
- [66] Blazej Manczak, Eliott Zemour, Eric Lin, and Vaikkunth Mugunthan. PrimeGuard: Safe and Helpful LLMs through Tuning-Free Routing, July 2024. URL http://arxiv.org/abs/2407.16318. arXiv:2407.16318 [cs].
- [67] Catherine C. Marshall, Partha S.R. Goguladinne, Mudit Maheshwari, Apoorva Sathe, and Frank M. Shipman. Who Broke Amazon Mechanical Turk? An Analysis of Crowdsourcing Data Quality over Time. In *Proceedings of the 15th ACM Web Science Conference 2023*, WebSci '23, pages 335–345, New York, NY, USA, 2023. Association for Computing Machinery. ISBN 9798400700897. doi: 10.1145/3578503.3583622. URL https://dl.acm.org/doi/10.1145/3578503.3583622.
- [68] Mantas Mazeika, Long Phan, Xuwang Yin, Andy Zou, Zifan Wang, Norman Mu, Elham Sakhaee, Nathaniel Li, Steven Basart, Bo Li, David Forsyth, and Dan Hendrycks. HarmBench: a standardized evaluation framework for automated red teaming and robust refusal. In *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *ICML*'24, pages 35181–35224, Vienna, Austria, 2024. JMLR.org.
- [69] Shikib Mehri and Maxine Eskenazi. USR: An Unsupervised and Reference Free Evaluation Metric for Dialog Generation. In Dan Jurafsky, Joyce Chai, Natalie Schluter, and Joel Tetreault, editors, *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 681–707, Online, July 2020. Association for Computational Linguistics. doi: 10.18653/v1/2020.acl-main.64. URL https://aclanthology.org/2020.acl-main.64/.

- [70] Jay Mohta, Kenan Ak, Yan Xu, and Mingwei Shen. Are large language models good annotators? In *Proceedings on*, pages 38–48. PMLR, April 2023. URL https://proceedings.mlr.press/v239/mohta23a.html. ISSN: 2640-3498.
- [71] Ben Naismith, Phoebe Mulcaire, and Jill Burstein. Automated evaluation of written discourse coherence using GPT-4. In Ekaterina Kochmar, Jill Burstein, Andrea Horbach, Ronja Laarmann-Quante, Nitin Madnani, Anaïs Tack, Victoria Yaneva, Zheng Yuan, and Torsten Zesch, editors, *Proceedings of the 18th Workshop on Innovative Use of NLP for Building Educational Applications (BEA 2023)*, pages 394–403, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.bea-1.32. URL https://aclanthology.org/2023.bea-1.32/.
- [72] Arbi Haza Nasution and Aytuğ Onan. ChatGPT Label: Comparing the Quality of Human-Generated and LLM-Generated Annotations in Low-Resource Language NLP Tasks. *IEEE Access*, 12:71876–71900, 2024. ISSN 2169-3536. doi: 10.1109/ACCESS.2024.3402809. URL https://ieeexplore.ieee.org/document/10534765.
- [73] James O' Neill, Santhosh Subramanian, Eric Lin, Abishek Satish, and Vaikkunth Mugunthan. GuardFormer: Guardrail Instruction Pretraining for Efficient SafeGuarding. October 2024. URL https://openreview.net/forum?id=vr31i9pzQk.
- [74] Ani Nenkova and Rebecca Passonneau. Evaluating Content Selection in Summarization: The Pyramid Method. In *Proceedings of the Human Language Technology Conference of the North American Chapter of the Association for Computational Linguistics: HLT-NAACL 2004*, pages 145–152, Boston, Massachusetts, USA, May 2004. Association for Computational Linguistics. URL https://aclanthology.org/N04-1019/.
- [75] Will Orr and Edward B. Kang. AI as a Sport: On the Competitive Epistemologies of Benchmarking. In *Proceedings of the 2024 ACM Conference on Fairness, Accountability, and Transparency*, FAccT '24, pages 1875–1884, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400704505. doi: 10.1145/3630106.3659012. URL https://dl.acm.org/doi/10.1145/3630106.3659012.
- [76] Long Ouyang, Jeff Wu, Xu Jiang, Diogo Almeida, Carroll L. Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, John Schulman, Jacob Hilton, Fraser Kelton, Luke Miller, Maddie Simens, Amanda Askell, Peter Welinder, Paul Christiano, Jan Leike, and Ryan Lowe. Training language models to follow instructions with human feedback, March 2022. URL http://arxiv.org/abs/2203.02155. arXiv:2203.02155 [cs].
- [77] Arjun Panickssery, Samuel R. Bowman, and Shi Feng. LLM Evaluators Recognize and Favor Their Own Generations. November 2024. URL https://openreview.net/forum?id=4NJBV6Wp0h.
- [78] Petr Parshakov, Iuliia Naidenova, Sofia Paklina, Nikita Matkin, and Cornel Nesseler. Users Favor LLM-Generated Content Until They Know It's AI, February 2025. URL http://arxiv.org/abs/2503.16458. arXiv:2503.16458 [cs].
- [79] Ethan Perez, Saffron Huang, Francis Song, Trevor Cai, Roman Ring, John Aslanides, Amelia Glaese, Nat McAleese, and Geoffrey Irving. Red Teaming Language Models with Language Models. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 3419–3448, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.225. URL https://aclanthology.org/2022.emnlp-main.225/.
- [80] Matthew Pittman, , and Kim Sheehan. Amazon's Mechanical Turk a Digital Sweatshop? Transparency and Accountability in Crowdsourced Online Research. *Journal of Media Ethics*, 31(4):260–262, October 2016. ISSN 2373-6992. doi: 10.1080/23736992.2016.1228811. URL https://doi.org/10.1080/23736992.2016.1228811. Publisher: Routledge _eprint: https://doi.org/10.1080/23736992.2016.1228811.

- [81] Vyas Raina, Adian Liusie, and Mark Gales. Is LLM-as-a-Judge Robust? Investigating Universal Adversarial Attacks on Zero-shot LLM Assessment. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen, editors, *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 7499–7517, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.emnlp-main.427. URL https://aclanthology.org/2024.emnlp-main.427/.
- [82] Tiernan Ray. Meta's Llama 4 'herd' controversy and AI contamination, explained, April 2025. URL https://www.zdnet.com/article/metas-llama-4-herd-controversy-and-ai-contamination-explained/.
- [83] Manley Roberts, Himanshu Thakur, Christine Herlihy, Colin White, and Samuel Dooley. To the Cutoff... and Beyond? A Longitudinal Perspective on LLM Data Contamination. October 2023. URL https://openreview.net/forum?id=m2NVG4Htxs.
- [84] Paul Röttger, Hannah Kirk, Bertie Vidgen, Giuseppe Attanasio, Federico Bianchi, and Dirk Hovy. XSTest: A Test Suite for Identifying Exaggerated Safety Behaviours in Large Language Models. In Kevin Duh, Helena Gomez, and Steven Bethard, editors, *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 5377–5400, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacllong.301. URL https://aclanthology.org/2024.naacl-long.301/.
- [85] Siddharth Samsi, Dan Zhao, Joseph McDonald, Baolin Li, Adam Michaleas, Michael Jones, William Bergeron, Jeremy Kepner, Devesh Tiwari, and Vijay Gadepally. From Words to Watts: Benchmarking the Energy Costs of Large Language Model Inference. In 2023 IEEE High Performance Extreme Computing Conference (HPEC), pages 1–9, September 2023. doi: 10.1109/HPEC58863.2023.10363447. URL https://ieeexplore.ieee.org/abstract/document/10363447. ISSN: 2643-1971.
- [86] Shruti Sannon and Dan Cosley. Privacy, Power, and Invisible Labor on Amazon Mechanical Turk. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems*, CHI '19, pages 1–12, New York, NY, USA, 2019. Association for Computing Machinery. ISBN 978-1-4503-5970-2. doi: 10.1145/3290605.3300512. URL https://dl.acm.org/doi/10.1145/3290605.3300512.
- [87] David Schlangen. Targeting the Benchmark: On Methodology in Current Natural Language Processing Research. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pages 670–674, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-short.85. URL https://aclanthology.org/2021.acl-short.85/.
- [88] Emily Sheng, Kai-Wei Chang, Prem Natarajan, and Nanyun Peng. Societal Biases in Language Generation: Progress and Challenges. In Chengqing Zong, Fei Xia, Wenjie Li, and Roberto Navigli, editors, Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers), pages 4275–4293, Online, August 2021. Association for Computational Linguistics. doi: 10.18653/v1/2021.acl-long.330. URL https://aclanthology.org/2021.acl-long.330/.
- [89] Jiawen Shi, Zenghui Yuan, Yinuo Liu, Yue Huang, Pan Zhou, Lichao Sun, and Neil Zhenqiang Gong. Optimization-based Prompt Injection Attack to LLM-as-a-Judge. In *Proceedings of* the 2024 on ACM SIGSAC Conference on Computer and Communications Security, CCS '24, pages 660–674, New York, NY, USA, 2024. Association for Computing Machinery. ISBN 9798400706363. doi: 10.1145/3658644.3690291. URL https://doi.org/10.1145/ 3658644.3690291.
- [90] Chenglei Si, Navita Goyal, Tongshuang Wu, Chen Zhao, Shi Feng, Hal Daumé Iii, and Jordan Boyd-Graber. Large Language Models Help Humans Verify Truthfulness Except When They Are Convincingly Wrong. In Kevin Duh, Helena Gomez, and Steven Bethard, editors,

- Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers), pages 1459–1474, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-long.81. URL https://aclanthology.org/2024.naacl-long.81/.
- [91] Gisele S. Silva, Rohan Khera, and Lee H. Schwamm. Reviewer Experience Detecting and Judging Human Versus Artificial Intelligence Content: The Stroke Journal Essay Contest. *Stroke*, 55(10):2573–2578, October 2024. ISSN 1524-4628. doi: 10.1161/STROKEAHA.124. 045012.
- [92] Shivalika Singh, Yiyang Nan, Alex Wang, Daniel D'Souza, Sayash Kapoor, Ahmet Üstün, Sanmi Koyejo, Yuntian Deng, Shayne Longpre, Noah Smith, Beyza Ermis, Marzieh Fadaee, and Sara Hooker. The Leaderboard Illusion, April 2025. URL http://arxiv.org/abs/2504.20879. arXiv:2504.20879 [cs].
- [93] Rion Snow, Brendan O'Connor, Daniel Jurafsky, and Andrew Ng. Cheap and Fast But is it Good? Evaluating Non-Expert Annotations for Natural Language Tasks. In Mirella Lapata and Hwee Tou Ng, editors, *Proceedings of the 2008 Conference on Empirical Methods in Natural Language Processing*, pages 254–263, Honolulu, Hawaii, October 2008. Association for Computational Linguistics. URL https://aclanthology.org/D08-1027/.
- [94] Tianxiang Sun, Junliang He, Xipeng Qiu, and Xuanjing Huang. BERTScore is Unfair: On Social Bias in Language Model-Based Metrics for Text Generation. In Yoav Goldberg, Zornitsa Kozareva, and Yue Zhang, editors, *Proceedings of the 2022 Conference on Empirical Methods in Natural Language Processing*, pages 3726–3739, Abu Dhabi, United Arab Emirates, December 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.emnlp-main.245. URL https://aclanthology.org/2022.emnlp-main.245/.
- [95] Zhiqing Sun, Yikang Shen, Hongxin Zhang, Qinhong Zhou, Zhenfang Chen, David Daniel Cox, Yiming Yang, and Chuang Gan. SALMON: Self-Alignment with Instructable Reward Models. October 2023. URL https://openreview.net/forum?id=xJbsmB8UMx¬eId=qeg84066Y6.
- [96] Zhiqing Sun, Yikang Shen, Qinhong Zhou, Hongxin Zhang, Zhenfang Chen, David Daniel Cox, Yiming Yang, and Chuang Gan. Principle-Driven Self-Alignment of Language Models from Scratch with Minimal Human Supervision. November 2023. URL https://openreview.net/forum?id=p40XRfBX96¬eId=Uzc2oM2otj.
- [97] Llama Team. Meta llama guard 2. https://github.com/meta-llama/PurpleLlama/blob/main/Llama-Guard2/MODEL_CARD.md, 2024.
- [98] Songül Tolan, Annarosa Pesole, Fernando Martínez-Plumed, Enrique Fernández-Macías, José Hernández-Orallo, and Emilia Gómez. Measuring the Occupational Impact of AI: Tasks, Cognitive Abilities and AI Benchmarks. *Journal of Artificial Intelligence Research*, 71:191–236, June 2021. ISSN 1076-9757. doi: 10.1613/jair.1.12647. URL https://jair.org/index.php/jair/article/view/12647.
- [99] Turkopticon. Beware the Hype: ChatGPT Didn't Replace Human Data Annotators, April 2023. URL https://techworkerscoalition.org/blog/2023/04/04/issue-5/.
- [100] Petter Törnberg. Large Language Models Outperform Expert Coders and Supervised Classifiers at Annotating Political Social Media Messages. Sage Journals, September 2024. doi: 10.1177/08944393241286471. URL https://journals.sagepub.com/doi/10.1177/08944393241286471. Publisher: SAGE PublicationsSage CA: Los Angeles, CA.
- [101] Pat Verga, Sebastian Hofstatter, Sophia Althammer, Yixuan Su, Aleksandra Piktus, Arkady Arkhangorodsky, Minjie Xu, Naomi White, and Patrick Lewis. Replacing Judges with Juries: Evaluating LLM Generations with a Panel of Diverse Models, May 2024. URL http://arxiv.org/abs/2404.18796. arXiv:2404.18796 [cs].

- [102] Hanna Wallach, Meera Desai, Nicholas Pangakis, A. Feder Cooper, Angelina Wang, Solon Barocas, Alexandra Chouldechova, Chad Atalla, Su Lin Blodgett, Emily Corvi, P. Alex Dow, Jean Garcia-Gathright, Alexandra Olteanu, Stefanie Reed, Emily Sheng, Dan Vann, Jennifer Wortman Vaughan, Matthew Vogel, Hannah Washington, and Abigail Z. Jacobs. Evaluating Generative AI Systems is a Social Science Measurement Challenge, November 2024. URL http://arxiv.org/abs/2411.10939. arXiv:2411.10939 [cs].
- [103] Jiaan Wang, Yunlong Liang, Fandong Meng, Zengkui Sun, Haoxiang Shi, Zhixu Li, Jinan Xu, Jianfeng Qu, and Jie Zhou. Is ChatGPT a Good NLG Evaluator? A Preliminary Study. In Yue Dong, Wen Xiao, Lu Wang, Fei Liu, and Giuseppe Carenini, editors, *Proceedings of the 4th New Frontiers in Summarization Workshop*, pages 1–11, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.newsum-1.1. URL https://aclanthology.org/2023.newsum-1.1/.
- [104] Peiyi Wang, Lei Li, Liang Chen, Zefan Cai, Dawei Zhu, Binghuai Lin, Yunbo Cao, Lingpeng Kong, Qi Liu, Tianyu Liu, and Zhifang Sui. Large Language Models are not Fair Evaluators. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar, editors, *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 9440–9450, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.511. URL https://aclanthology.org/2024.acl-long.511/.
- [105] Jason Wei, Maarten Bosma, Vincent Zhao, Kelvin Guu, Adams Wei Yu, Brian Lester, Nan Du, Andrew M. Dai, and Quoc V. Le. Finetuned Language Models are Zero-Shot Learners. October 2021. URL https://openreview.net/forum?id=gEZrGCozdqR.
- [106] Jason Wei, Yi Tay, Rishi Bommasani, Colin Raffel, Barret Zoph, Sebastian Borgeaud, Dani Yogatama, Maarten Bosma, Denny Zhou, Donald Metzler, Ed H. Chi, Tatsunori Hashimoto, Oriol Vinyals, Percy Liang, Jeff Dean, and William Fedus. Emergent Abilities of Large Language Models. *Transactions on Machine Learning Research*, June 2022. ISSN 2835-8856. URL https://openreview.net/forum?id=yzkSU5zdwD.
- [107] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Brian Ichter, Fei Xia, Ed H. Chi, Quoc V. Le, and Denny Zhou. Chain-of-thought prompting elicits reasoning in large language models. In *Proceedings of the 36th International Conference on Neural Information Processing Systems*, NIPS '22, pages 24824–24837, Red Hook, NY, USA, November 2022. Curran Associates Inc. ISBN 978-1-71387-108-8.
- [108] Laura Weidinger, View Profile, Jonathan Uesato, View Profile, Maribeth Rauh, View Profile, Conor Griffin, Search about this author, Po-Sen Huang, View Profile, John Mellor, View Profile, Amelia Glaese, View Profile, Myra Cheng, View Profile, Borja Balle, Search about this author, Atoosa Kasirzadeh, View Profile, Courtney Biles, Search about this author, Sasha Brown, View Profile, Zac Kenton, Search about this author, Will Hawkins, View Profile, Tom Stepleton, View Profile, Abeba Birhane, View Profile, Lisa Anne Hendricks, Search about this author, Laura Rimell, View Profile, William Isaac, Search about this author, Julia Haas, Search about this author, Sean Legassick, View Profile, Geoffrey Irving, Search about this author, Iason Gabriel, and View Profile. Taxonomy of Risks posed by Language Models. *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, pages 214–229, June 2022. ISSN 9781450393522. doi: 10.1145/3531146.3533088. URL https://dl.acm.org/doi/10.1145/3531146.3533088.
- [109] Chloe Xiang. ChatGPT Can Replace the Underpaid Workers Who Train AI, Researchers Say, March 2023. URL https://www.vice.com/en/article/chatgpt-can-replace-the-underpaid-workers-who-train-ai-researchers-say/.
- [110] Chloe Xiang. OpenAI Used Kenyan Workers Making \$2 an Hour to Filter Traumatic Content from ChatGPT, January 2023. URL https://www.vice.com/en/article/openai-used-kenyan-workers-making-dollar2-an-hour-to-filter-traumatic-content-from-chatgpt/.
- [111] Ziang Xiao, Susu Zhang, Vivian Lai, and Q. Vera Liao. Evaluating Evaluation Metrics: A Framework for Analyzing NLG Evaluation Metrics using Measurement Theory. In Houda

- Bouamor, Juan Pino, and Kalika Bali, editors, *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, pages 10967–10982, Singapore, December 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.emnlp-main.676. URL https://aclanthology.org/2023.emnlp-main.676/.
- [112] Jiayi Ye, Yanbo Wang, Yue Huang, Dongping Chen, Qihui Zhang, Nuno Moniz, Tian Gao, Werner Geyer, Chao Huang, Pin-Yu Chen, Nitesh V. Chawla, and Xiangliang Zhang. Justice or Prejudice? Quantifying Biases in LLM-as-a-Judge. October 2024. URL https://openreview.net/forum?id=3GTtZFiajM.
- [113] Wenjun Zeng, Yuchi Liu, Ryan Mullins, Ludovic Peran, Joe Fernandez, Hamza Harkous, Karthik Narasimhan, Drew Proud, Piyush Kumar, Bhaktipriya Radharapu, Olivia Sturman, and Oscar Wahltinez. ShieldGemma: Generative AI Content Moderation Based on Gemma, August 2024. URL http://arxiv.org/abs/2407.21772. arXiv:2407.21772 [cs].
- [114] Yunhao Zhang and Renée Gosline. Human favoritism, not AI aversion: People's perceptions (and bias) toward generative AI, human experts, and human—GAI collaboration in persuasive content generation. Judgment and Decision Making, 18:e41, January 2023. ISSN 1930-2975. doi: 10.1017/jdm.2023.37. URL https://www.cambridge.org/core/journals/judgment-and-decision-making/article/human-favoritism-not-ai-aversion-peoples-perceptions-and-biastoward-generative-ai-human-experts-and-humangai-collaboration-in-persuasive-content-generation/419C4BD9CE82673EAF1D8F6C350C4FA8.
- [115] Dora Zhao, Jerone T. A. Andrews, Orestis Papakyriakopoulos, and Alice Xiang. Position: measure dataset diversity, don't just claim it. In *Proceedings of the 41st International Conference on Machine Learning*, volume 235 of *ICML'24*, pages 60644–60673, Vienna, Austria, 2024. JMLR.org.
- [116] Chujie Zheng, Hao Zhou, Fandong Meng, Jie Zhou, and Minlie Huang. Large Language Models Are Not Robust Multiple Choice Selectors. October 2023. URL https://openreview.net/forum?id=shr9PXz7T0.
- [117] Lianmin Zheng, Wei-Lin Chiang, Ying Sheng, Siyuan Zhuang, Zhanghao Wu, Yonghao Zhuang, Zi Lin, Zhuohan Li, Dacheng Li, Eric P. Xing, Hao Zhang, Joseph E. Gonzalez, and Ion Stoica. Judging LLM-as-a-judge with MT-bench and Chatbot Arena. In *Proceedings of the 37th International Conference on Neural Information Processing Systems*, NIPS '23, pages 46595–46623, Red Hook, NY, USA, 2023. Curran Associates Inc.
- [118] Xiaosen Zheng, Tianyu Pang, Chao Du, Qian Liu, Jing Jiang, and Min Lin. Cheating Automatic LLM Benchmarks: Null Models Achieve High Win Rates. October 2024. URL https://openreview.net/forum?id=syThiTmWWm.
- [119] Chunting Zhou, Pengfei Liu, Puxin Xu, Srini Iyer, Jiao Sun, Yuning Mao, Xuezhe Ma, Avia Efrat, Ping Yu, Lili Yu, Susan Zhang, Gargi Ghosh, Mike Lewis, Luke Zettlemoyer, and Omer Levy. LIMA: Less Is More for Alignment. November 2023. URL https://openreview.net/forum?id=KBMOKmX2he.
- [120] Kaitlyn Zhou, Su Lin Blodgett, Adam Trischler, Hal Daumé III, Kaheer Suleman, and Alexandra Olteanu. Deconstructing NLG Evaluation: Evaluation Practices, Assumptions, and Their Implications. In Marine Carpuat, Marie-Catherine de Marneffe, and Ivan Vladimir Meza Ruiz, editors, *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 314–324, Seattle, United States, July 2022. Association for Computational Linguistics. doi: 10.18653/v1/2022.naacl-main.24. URL https://aclanthology.org/2022.naacl-main.24/.
- [121] Yiming Zhu, Peixian Zhang, Ehsan-Ul Haq, Pan Hui, and Gareth Tyson. Can ChatGPT Reproduce Human-Generated Labels? A Study of Social Computing Tasks, April 2023. URL http://arxiv.org/abs/2304.10145. arXiv:2304.10145 [cs].