Preference Leakage: A Contamination Problem in LLM-as-a-judge

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Abstract

Large Language Models (LLMs) as judges and LLM-based data synthesis have emerged as two fundamental LLM-driven data annotation methods in model development. While their combination significantly enhances the efficiency of model training and evaluation, little attention has been given to the potential contamination brought by this new model development paradigm. In this work, we expose preference leakage, a contamination problem in LLM-as-a-judge caused by the relatedness between the synthetic data generators and LLM-based evaluators. To study this issue, we first define three common relatednesses between the data generator LLM and the judge LLM: being the same model, having an inheritance relationship, and belonging to the same model family. Through extensive experiments, we empirically confirm the bias of judges towards their related student models caused by preference leakage across multiple LLM baselines and benchmarks. Further analysis suggests that preference leakage is a pervasive and real-world problem that is harder to detect compared to previously identified biases in LLM-as-a-judge scenarios. All of these findings imply that preference leakage is a widespread and challenging problem in the area of LLM-as-a-judge. We release all codes and data at: https://github.com/David-Li0406/Preference-Leakage[1].

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Proceedings of the 42^{nd} International Conference on Machine Learning, Vancouver, Canada. PMLR 267, 2025. Copyright 2025 by the author(s).

[1]More resources on LLM-as-a-judge are on the website: https://llm-as-a-judge.github.io/

1. Introduction

Recent advancements in Large Language Models (LLMs) (Achiam et al., 2023; Jaech et al., 2024) have empowered various downstream tasks and applications. However, this also poses substantial challenges to the automatic evaluation of these models. Representatively, LLM-based AI agents' focus transfer from traditional natural language processing tasks to real-world (Liu et al., 2023b; Huang et al., 2023), open-ended response generation (Wu et al., 2024), which greatly limits the applicability of traditional n-gram matching methods (e.g., BLEU (Papineni et al., 2002) and ROUGE (Lin, 2004)) (Liu et al., 2016; Reiter, 2018) or model-based evaluators (Zhang et al., 2020; Zhong et al., 2022) for evaluation.

To address these challenges, the paradigm of LLM-as-a-judge (Zheng et al., 2023; Li et al., 2024a; Jiang et al., 2024a; Zhong et al., 2024; Li et al., 2025) has been proposed, designed to leverage LLM as evaluators to assess response quality. By combining powerful LLMs with well-designed prompting strategies, LLM-as-a-judge enables human-like evaluation of long-form and open-ended generation in a more cost-efficient and scalable manner. However, recent studies point out some weaknesses of such an assessment. For instance, Ye et al. (2024) explores various biases and vulnerabilities of LLM-as-a-judge, highlighting the importance of developing a reliable LLM-based evaluation system.

In this work, we aim to highlight a subtle yet critical bias in LLM-as-a-Judge: *Preference Leakage*. This issue arises when *the LLMs used for data generation and evaluation are closely related, causing the preference of the LLM evaluators to leak to the student models through synthetic data and thus inflating the evaluation score* (as illustrated in Figure 1). Synthetic data generated by LLMs (Gan et al., 2023; Tan et al., 2024; Li et al., 2024b;c) has become a cornerstone of model training (Lee et al., 2025). When combined with LLM-as-a-Judge, they offer significant efficiency gains in model development. However, limited attention has been given to the potential contamination that occurs when the generator and evaluator LLMs share a close relationship. During our preliminary study, we find this issue is particularly pervasive in popular LLM-as-a-judge benchmarks (e.g., AlpacaEval 2.0 (Dubois et al., 2024) and Arena-Hard (Li

et al., 2024e)) and LLM-relevant studies (more details can be found in Appendix A), due to the common reliance on the most advanced LLMs, such as GPT-4 (Achiam et al., 2023), for both data synthesis and evaluation to ensure the highest quality outputs. In our work, we reveal this relatedness—akin to the overlap between training data and evaluation sets in traditional data contamination—would introduce a systematic bias of judge LLMs towards their related student models (i.e., the model distilled by the data generator which is related to the judge). Compared to other biases in LLM-as-a-Judge, such as length bias or egocentric bias (Ye et al., 2024; Panickssery et al., 2024), preference leakage is subtler and more challenging to detect, especially given that most LLMs do not disclose their training data.

To investigate and reveal the preference leakage problem, we first define three relatednesses between data generator LLM and judge LLM: being the same model, having an inheritance relationship, and belonging to the same model family. Each of these scenarios is commonly encountered in real-world applications. Then, we pose and answer three core research questions about preference leakage:

- **RQ1: Does preference leakage introduce systematic biases in LLM-based evaluation?** To answer it, we conduct experiments with various LLM baselines in two widely recognized LLM-as-a-judge benchmarks, also introduce the preference leakage score to quantify the bias caused by preference leakage. The analysis results suggest an obvious bias of judging LLMs toward their related student models due to preference leakage.
- **RQ2: What is the severity of preference leakage under various scenarios?** We conduct experiments under various data mixing strategies, relatedness settings, tuning techniques and real-world applications to address it, finding that preference leakage consistently affects judge LLMs. Moreover, the severity of preference leakage correlates with the degree of relatedness between the data generator and LLM judges, as well as the proportion of synthetic data.
- **RQ3: What are the underlying mechanisms causing preference leakage?** For this question, we analyze LLMs' recognition capabilities on their related student models' generation as well as the distribution of bias across different question types and judgment dimensions. The analysis reveals that preference leakage is a subtle, hard-to-detect issue for the LLM evaluators, particularly affecting subjective questions and judgment dimensions.

To summarize, our contributions in this work are as follows:

- For the first time, we introduce preference leakage, a contamination issue arising from the relatedness between the data generator and judge LLMs.
- We conduct extensive experiments across various LLMs and benchmarks to study how and to what extent the bias brought by preference leakage influences judgment.
- Our further analysis reveals that preference leakage is prevalent in diverse scenarios and difficult for judge LLMs to detect, providing valuable insights for future research on this challenging issue.

2. Related Work

LLM-as-a-Judge. LLM-as-a-Judge, introduced by Zheng et al. (2023), leverages LLMs to automatically evaluate responses and assign rewards. This approach has gained widespread adoption in areas such as model alignment (Zhang et al., 2024c) and benchmarking (Liu et al., 2023a; Zhang et al., 2024a; Gao et al., 2023; Zhong et al., 2024), driving significant progress in the field. Building on this concept, Zhuge et al. (2024) proposed Agent-as-a-Judge, where agentic systems are employed to evaluate other agentic systems. Additionally, Prometheus, a series of open-source LLMs tailored for LLM-as-a-Judge (Kim et al., 2023; 2024), addresses the prohibitive costs associated with proprietary models, further democratizing the technology.

Despite its promising potential, recent studies have highlighted the vulnerabilities and biases of LLM-as-a-Judge (Zheng et al., 2023; Ye et al., 2024; Koo et al., 2023; Chen et al., 2024; Zheng et al., 2023; Huang et al., 2024; Thakur et al., 2024; Shi et al., 2024). Among these, egocentric bias, where LLM evaluators tend to favor their generations (Koo et al., 2024; Liu et al., 2024b; Wataoka et al., 2024; Xu et al., 2024b; Rando et al., 2025; Panickssery et al., 2024; Chen et al., 2025), is most closely related to the preference leakage proposed in this work.

However, in contrast to the relatively straightforward setting of egocentric bias, preference leakage presents a more complex and dynamic challenge. It can arise from various types of relatedness between data-generating and evaluating LLMs, as well as the intricate flow of synthetic data among modern LLMs (Tan et al., 2024). Moreover, detecting preference leakage is also more challenging, given LLMs often do not disclose their training data and the difficulty in distillation quantification (Wadhwa et al., 2025; Lee et al., 2025).

Data Leakage. The possible overlap between training data and evaluation benchmarks has become a central issue, since LLMs are usually trained on extensive web corpora (Dodge et al., 2021). This phenomenon, known as data leakage, can artificially improve the performance of LLMs and undermine the reliability of the assessment (Deng et al., 2024a; Jiang et al., 2024b). Several researchers have proposed methods to detect and mitigate data contamination. Deng et al. (2024b) proposed a retrieval-based approach to assess the degree of overlap between pre-training text and bench-

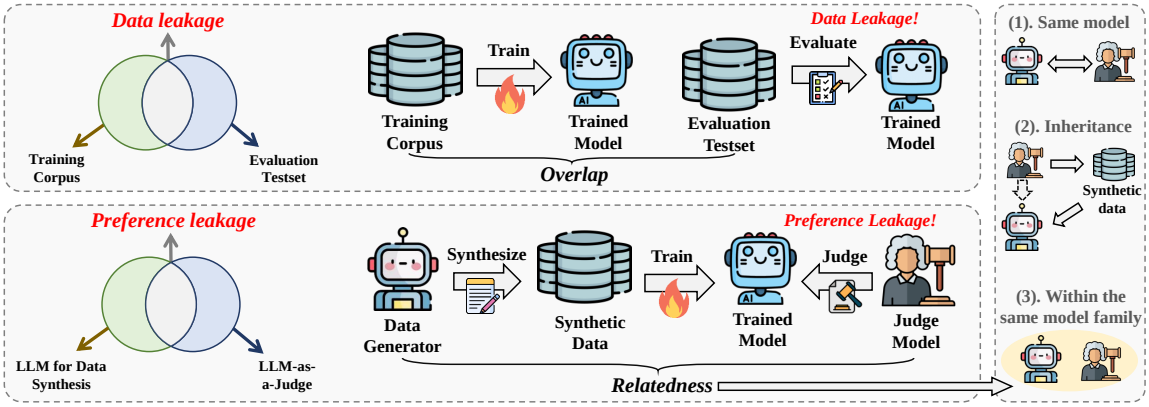


Figure 1. Overview of preference leakage. We make a comparison between data leakage and preference leakage and present three types of relatedness: being the same model, having an inheritance relationship and belonging to the same model family.

mark data. Golchin & Surdeanu (2023) have developed "guided instruction" to flag contaminated instances. Dong et al. (2024b) proposed the CDD method to identify peaks in the output distribution to detect data contamination. Several studies analyze data leakage for specific LLMs (Balloccu et al., 2024; Xu et al., 2024a) and report contamination such as cross-language contamination (Yao et al., 2024) and task contamination (Li & Flanigan, 2024) that can evade traditional detection methods. To address data contamination issues, Ni et al. (2024) have used web user query detection and benchmark mixture. White et al. (2024) use the most recent information to update the problem.

3. Preference Leakage

3.1. LLMs as Oracles: A New Avenue for Contamination

With the advent of LLMs, these models are increasingly employed as "oracles" in various scenarios: for both synthetic data generation (M_G) and employed as evaluators (M_J) to automate the assessment. While these approaches enhance scalability and efficiency, they also introduce potential risks. Specifically, if the LLM used for data generation (M_G) and the LLM used for evaluation (M_J) are not independent, a new contamination—preference leakage—can emerge, biasing evaluation outcomes.

3.2. Defining Preference Leakage in LLM-based Evaluation

Formally, to define preference leakage, we consider the following entities in models development:

- **Data Generator LLM,** M_G, defining a conditional distribution $P_{M_G}(y|x)$ for generating an output y given a prompt x, forming the synthetic dataset D_{syn} for student LLMs training.
- **Student LLM,** M_S, trained on data generated by M_G, producing an output distribution $P_{M_S}(y|x)$.
- **Judge LLM,** M_J, providing a scoring function $S_{M_J}(y|x)$ that assesses output y for prompt x.

Preference leakage occurs when the evaluation score assigned by M_J to M_S's outputs is inflated due to an underlying relatedness between M_G and M_J. This implies that M_J may favor outputs from M_S not solely based on their intrinsic quality, but because they exhibit spurious features (e.g., style, format, wording) inherited from M_G, to which M_J is predisposed due to this relatedness:

$$\begin{aligned} &E_{x,y_S\sim P_{M_S}}[S_{M_J}(y_S|x) \mid M_G \sim_{rel} M_J] \\ &> E_{x,y_S\sim P_{M_S}}[S_{M_{J'}}(y_S|x) \mid M_G \not\sim_{rel} M_{J'}], \end{aligned} \tag{1}$$

where y_S are outputs from M_S. The relation $M_G \sim_{rel} M_J$ denotes that judge M_J is related to M_G, while $M_G \not\sim_{rel} M_{J'}$ denotes that an alternative judge $M_{J'}$ is not related to M_G and possess comparable intrinsic quality assessment capabilities to M_J. The expectation is taken over the input distribution $\mathcal{X}$ and the trained Student LLM's output distribution P_{M_S}.

3.3. Type of LLM "Relatedness"

The condition $M_G \sim_{rel} M_J$ in Equation 1 encapsulates several ways the Data Generator LLM and Judge LLM can be interconnected. We identify three common types in the real world:

- **Being the Same Model:** The most direct form of relatedness occurs when the Data Generator LLM and the Judge LLM are the exact same model instance:

$$M_G \equiv M_J. \tag{2}$$

In this scenario, the inherent preferences in the model that shape its generative distribution $P_{M_G}(y|x)$ are precisely

the same as those guiding its evaluation via the scoring function $S_{M_G}(y|x)$.

- **Inheritance Relationship:** One model's development is directly based on another, either by fine-tuning the existing model or by training a new model on the other's outputs, for instance:

$$\begin{aligned} & M_J \leftarrow \text{FineTune}(M_G, D_{\text{train}}) \\ \text{or} \quad & M_J \leftarrow \text{FineTune}(M_{\text{base}}, D_{\text{syn}_G}) \end{aligned} \tag{3}$$

where D_{train} represents general training data used to adapt M_G into M_J, M_{base} is a base model, and D_{syn_G} denotes synthetic data generated by M_G. This type of relationship is bidirectional; M_G can similarly inherit from M_J through analogous processes. In such cases, the descendant model is likely to internalize and thus favor the preferences, styles, or biases of its progenitor.

- **Within the Same Model Family:** The Data Generator LLM M_G and Judge LLM M_J belong to the same model family (e.g., different versions or sizes of GPT). Models within such a family typically share a common architectural blueprint (A_X) and are often developed from foundational models pre-trained on substantially overlapping datasets (D_X). This shared foundation (A_X, D_X) would lead to correlated preferences and systemic biases characteristic of the common origin:

$$M_k \in \text{Family}(A_X, D_X) \quad \text{for } k \in \{G, J\}. \tag{4}$$

4. Main Experiment

4.1. Experiment Setup

Models. We choose three powerful LLMs as data generator/ judge models. They are GPT-4o-2024-11-20 (Achiam et al., 2023), Gemini-1.5-flash (Team et al., 2024), and LLaMA-3.3-70B-Instruct-turbo (Dubey et al., 2024). For the student model, we choose Mistral-7B-v0.1 (Jiang et al., 2023) and Qwen-2.5-14B (Yang et al., 2024). To avoid potential preference leakage due to distilling data from other LLMs during the instruction-tuning process, we choose to use the -PRETRAINED version rather than the -INSTRUCT version of these student models.

Evaluation Datasets. We choose two representative pairwise evaluation datasets, Arena-Hard (Li et al., 2024e) and AlpacaEval 2.0 (Dubois et al., 2024), to evaluate the trained student models. Arena-Hard includes 500 challenging questions in English. Additionally, the evaluation agreement between Arena-Hard and Chatbot Arena (Zheng et al., 2023)'s hard prompts achieved a 96.7% Spearman correlation, demonstrating the consistency of Arena-Hard with human preferences (Li et al., 2024e). AlpacaEval 2.0 is an improved evaluation method based on AlpacaEval (Li et al., 2023) and contains 805 questions. Compared to version 1.0, AlpacaEval 2.0 significantly reduces the effect of text length on the evaluation results.

Implementation Details. In our main experiment, we examine the preference leakage introduced by using the same data generator and evaluator in supervised fine-tuning (SFT). We will discuss other relatedness and learning methods in Section 5. To obtain synthetic datasets, We first randomly sample 30,000 prompts from the Ultrafeedback dataset (Cui et al., 2024). The Ultrafeedback dataset includes instructions from several publicly available high-quality datasets such as TruthfulQA (Lin et al., 2022), FalseQA (Hu et al., 2023), and Evol-Instruct (Xu et al., 2023). For each data generator model, we provide these prompts for them to produce synthetic responses, resulting in three synthetic instruction datasets. We then use each dataset to supervised fine-tune the student model, obtaining three different versions for each baseline: Mistral/ Qwen-GPT-4o, Mistral/ Qwen-Gemini-1.5 and Mistral/ Qwen-LLaMA-3.3. After that, we pair each two student models and obtain three model pairs. For each model pair, we perform the pairwise comparison using the three judge models respectively.

Metrics Based on our hypothesis, preference leakage would lead to bias of judge LLMs towards their related student models. Following this principle, we design the preference leakage score $\text{PLS}(i, j)$ to measure the bias in model pair (i, j) caused by preference leakage:

$$\text{PLS}(i,j) = \frac{\left(\frac{\text{WR}(i,i)-\text{AVG}(i,j)}{\text{AVG}(i,j)}\right) + \left(\frac{\text{WR}(j,j)-\text{AVG}(j,i)}{\text{AVG}(j,i)}\right)}{2}, \tag{5}$$

$$\text{AVG}(i,j) = \frac{\text{WR}(i,i) + \text{WR}(i,j)}{2}. \tag{6}$$

Here $\text{WR}(i, j)$ represents the win-rate score from judge model j to student model i. Intuitively, a large preference leakage score indicates that the two judge models demonstrate strong bias toward their related student models, suggesting a significant preference leakage phenomenon.

More details about model training and metric explanation can be found in Appendix B.

Model	Data Generator/ Judge Pair	Arena-Hard	AlpacaEval 2.0	Avg.
Mistral-7B	GPT-4o & Gemini-1.5	28.7%	18.4%	23.6%
	GPT-4o & LLaMA-3.3	-1.5%	1.4%	-0.1%
	LLaMA-3.3 & Gemini-1.5	13.1%	19.8%	16.4%
Qwen-2.5-14B	GPT-4o & Gemini-1.5	37.1%	18.6%	27.9%
	GPT-4o & LLaMA-3.3	1.0%	2.3%	1.7%
	LLaMA-3.3 & Gemini-1.5	25.4%	18.4%	21.9%

Table 1. Preference leakage score result on Arena-Hard and AlpacaEval 2.0. The blue background indicates a negative preference leakage score value and the purple background indicates a positive value. The deeper the color, the larger the absolute value.

4.2. Main Results

In our main experiment, we aim to provide insights into RQ1.

Preference leakage exists in most model pairs. The calculated preference leakage scores is shown in Table 1. As the results demonstrate, in most model pairs (except Mistral-GPT-4o vs Mistral-LLaMA-3.3 and Qwen-GPT-4o vs Qwen-LLaMA-3.3), the judge LLMs exhibit a strong preference toward their related student models, leading to large positive values in the preference leakage scores. This finding suggests that preference leakage, along with the resulting bias, is widespread in SFT when the data generator and evaluator are the same.

Smaller student models cause even more bias from judge LLMs. To investigate the impact of student model size on the degree of preference leakage, we conduct additional experiments using various sizes of the Qwen-2.5 and Qwen-3 models. As shown in Figure 4.2 (a), a notable finding is that the smallest models (Qwen-2.5-3B and Qwen-3-1.7B) exhibit the highest PL scores than their larger counterparts, indicating greater bias from preference leakage. This trend contrasts with the influence of model size in data contamination, where larger models are typically more susceptible (Bordt et al., 2024). We assume that this gap arises from the differing learning capabilities and behaviors of large and small LLMs: while larger models are more prone to memorizing (Duan et al., 2024) information that exacerbates data contamination, smaller models may only be able to learn those spurious features that repeatedly occurs (e.g., format), leading to more serious preference leakage.

Different benchmarks result in varying degrees of bias under preference leakage. Another observation from Table 1 and Figure 4.2 (a) is that the PL scores in ArenaHard are generally higher than those in AlpacaEval 2.0. One possible explanation is the difference in question difficulty between the two benchmarks, as ArenaHard contains more challenging questions. Additionally, it may also stem from differences in the distribution of question types, the impact of which will be further analyzed in Section B.6.

5. Further Analysis

In this section, we conduct data mixing analysis, relatedness analysis, learning method analysis (Section 5.1 - C) to answer RQ2. Due to the space Limitation, we put further experiments on recognition analysis and category analysis to answer RQ3 in Appendix B.5 - B.6, and the influence of preference leakage to real-world application in Appendix B.4.

5.1. Data Mixing Analysis

In real-world applications, synthetic data from a single LLM is often mixed with manually-written data or other multi-source synthetic data to train student models. To mimic these scenarios and explore how much synthetic data could lead to preference leakage, we conduct a data mixing analysis. Specifically, we randomly sample 10%, 30%, 50%, and 70% from the original synthetic dataset and mix it with manually-written data and multi-source synthetic data, respectively, in order to maintain a consistent total volume of training data (30,000). For the manually-written data, we sample from the data pool collected in Section 5.3. For the multi-source synthetic data, we use the original synthetic data from Ultrafeedback, which includes responses generated by various LLMs (e.g., WizardLM, Flcon, etc.). After obtaining the mixing training data, we train the student models using SFT and calculate their preference leakage scores based on the judgment results. Figure 4.2 (b) presents the results with two mixing strategies across two benchmarks.

	Arena-Hard	AlpacaEval 2.0	Avg.
Same Model	28.7%	18.4%	23.6%
Inheritance - w/ same ins.	17.8%	20.7%	19.3%
Inheritance - w/ different ins.	18.3%	26.3%	22.3%
Same Family - w/ same series	10.1%	7.6%	8.9%
Same Family - w/ different series	3.3%	2.2%	2.8%

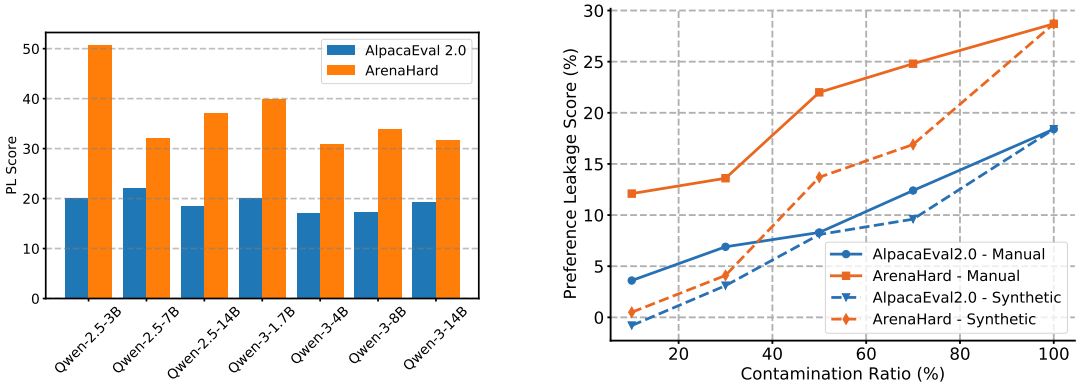
Table 2. Preference leakage score in different relatedness between the data generator and the judging LLM.

The degree of preference leakage is directly proportional to the amount of synthetic data. We observe a strong correlation between the proportion of synthetic data in the mixture and the preference leakage score, with no clear threshold separating cases with preference leakage from those without. This suggests that preference leakage can occur even with a small amount of leaked synthetic data, posing significant challenges for its detection.

5.2. Relatedness Analysis

We demonstrate the impact of different relatedness conditions between the data generator and the judge LLM on the preference leakage problem, as shown in Table 2.

Preference leakage under inheritance settings causes obvious bias of judges towards their related students. For the inheritance relationship, we consider the situation where the data generator is inherited from the judge model. We conducted the following two experiments: (1). we give the same instructions again as in the SFT stage (Inheritance w/ same ins.), or (2). we sample the same number of different instructions from the Ultrafeedback (Inherence w/ different ins.). Then, we let the fine-tuned Mistral model generate the answers and use these generated data to fine-tune a new Mistral student model. From the results, with the same instructions, the average preference leakage score is 19.3%. In comparison, the score with different instructions is 22.3%. Firstly, in an inheritance setting, data generators can inherit judges' preferences, which are then passed on to new stu-



(a) PLS on models with various sizes. We conduct the experiment with GPT-4o and Gemini as data generators and judges.

(b) Experiment results on data mixing. 'Manual' and 'Synthetic represent mixing with manually-written data and other synthetic data, respectively.

Figure 2. Experiment results on additional models and data mixing settings.

	Arena-Hard	AlpacaEval 2.0	Avg.
SFT	28.7%	18.4%	23.6%
DPO	7.7%	2.7%	5.2%
ICL	-4.2%	-1.1%	-2.7%

Table 3. Preference leakage score in different learning methods.

dent models, thereby compromising the fairness of their evaluation. Second, even when different instructions are used, judges' preferences leaked to data generators can still be transferred to the new student model through synthetic data, leading to a high preference leakage score.

Models within the same series tend to cause more significant bias. For two models within the same family, we consider two settings: (1) Same series, where training data is generated by GPT-4o and Gemini-1.5-flash, and judged by GPT-4-turbo and Gemini-1.5-pro; (2) Different series, where training data is still generated by GPT-4o and Gemini-1.5-flash, but judged by GPT-3.5-turbo and Gemini-1.0-pro. In the same series setting, the average preference leakage score is 8.9%, indicating that despite using different models for data generation and judgment, their relatedness in terms of model family leads to some preference leakage. In contrast, the different series setting yields a significantly lower leakage score of 2.8%, likely due to differences in architecture, training data, and other factors, reducing the influence of model-related biases in evaluation.

5.3. Learning Method Analysis

We also compare three learning methods, supervised fine-tuning (SFT), direct preference optimization (DPO) (Rafailov et al., 2024), and in-context learning (ICL) (Dong et al., 2024a), to explore the different influences to them under preference leakage. We first build a data pool based on human-written instruction-tuning data from OASST (Köpf et al., 2024), LIMA (Zhou et al., 2024), and MOSS (Sun et al., 2024b) to supervised fine-tune the pre-trained model. For DPO, we sample 2 responses for each instruction from sampled UltraFeedback instruction and prompt each data generator to produce the pairwise feedback. Then we use the DPO loss to further train the fine-tuned policy on each synthetic pairwise dataset. Appendix C shows the prompt we use to craft synthetic pairwise feedback. For ICL, we sample 4 instruction-response pairs from each LLMs' synthetic dataset as the demonstration during inference.

Tuning approaches would leak judges' preference to the student models. Various learning methods show significant differences in preference leakage scores across learning methods. SFT exhibits the highest average leakage score at 23.6%. In contrast, DPO achieves a much lower score of 5.2%, which is consistent with previous studies in data contamination that pairwise optimization can reduce the risk of memorizing or contaminating sensitive training data compared to straightforward supervised fine-tuning (Hayes et al.). Meanwhile, ICL, which relies on contextual examples without model tuning, is least affected by the data generator's preferences, resulting in the lowest leakage scores.

6. Conclusion

In this work, we formally highlight the preference leakage problem in LLM-as-a-judge systems. The results of our main experiment, measured using the proposed preference leakage score, reveal a clear bias in each judge toward their respective student model. We also observe that this bias is more pronounced in certain question types and smaller student models. Furthermore, we conduct additional analysis on various factors, including the relationship between the data generator and judge LLMs, model tuning techniques, data mixing strategies, and real-world applications. Our findings suggest that preference leakage can cause significant bias across diverse scenarios. In the future, we aim to explore methods for detecting, preventing, and mitigating this evolving challenge in LLM-as-a-judge systems.

Impact Statements

By revealing preference leakage, this work could help build more trustworthy and ethically grounded AI systems. The relatedness between data generators and evaluators can systematically bias evaluations, potentially compromising the fairness and reliability of the automatic evaluation paradigm. These biased evaluations may indirectly affect downstream tasks such as AI alignment and decision-making systems, leading to unintended ethical risks. To mitigate preference leakage, we hope that researchers will propose more reliable evaluation methods, diversify training data sources, and develop contamination-resistant benchmarks in the future.

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A. Preliminary Study of Preference Leakage in Real World

In our preliminary study, we investigate whether preference leakage is a real-world issue in mainstream leaderboards and benchmarks. To this end, we examine two widely used LLM-as-a-judge leaderboards (AlpacaEval 2.0 and Arena-Hard) and a well-known benchmark (MTBench). All three rely on GPT-4 as the judge model and report pairwise judgment results for various LLMs. Our analysis reveals that several candidate models distilled from GPT-4 or other GPT-series models (e.g., Vicuna and Alpaca) appear across all these leaderboards and benchmarks, suggesting that preference leakage is a pervasive issue in these datasets. Besides, we also examine if preference leakage exists in LLM-relevant research studies and also find a bunch of work utilizing the same or related model(s) to do distillation/ data synthesis and evaluation (Yang et al., 2023; Liu et al., 2024a; Lee et al., 2024; Li et al., 2024d; Wang et al., 2024; Sun et al., 2024a). All of these suggest preference leakage to be a widespread problem in both LLM-as-a-judge datasets and LLM-relevant research.

B. Experiment Details

B.1. Training Details

We use LLaMA-Factory (Zheng et al., 2024), an efficient LLM tuning library for our experiment. The maximum sequence length is set to 1024 tokens, and a cutoff length of 1024 tokens is enforced to prevent excessive tokenization. The data preprocessing will be done in parallel with 16 workers to speed up the preparation process. The training use a per-device batch size of 2, with gradient accumulation over 2 steps to simulate a larger batch size for SFT and a per-device batch size of 1, with gradient accumulation over 4 steps to simulate a larger batch size for DPO. The learning rate is set to 1.0e-5 and each model will be trained for 3 epochs. A cosine learning rate scheduler is used with a warmup ratio of 0.1 to gradually increase the learning rate during the initial steps. All of the experiments use BF16 precision to speed up training while maintaining numerical stability. All the experiments are conducted in an 8 Nvidia A100 GPU cluster with CUDA version 11.8.

Judge Model	Mistral-GPT-4o vs Mistral-Gemini-1.5	
	Mistral-GPT-4o Wins	Mistral-Gemini-1.5 Wins
GPT-4o	55.1%	44.9%
Gemini-1.5	36.8%	63.2%
Preference Leakage Score	18.4%	

Table 4. A case on AlpacaEval 2.0 with the model pair Mistral-GPT-4o vs Mistral-Gemini-1.5 to demonstrate how the preference leakage score is calculated.

B.2. Detailed Explanation for Preference Leakage Score

We present a case in Table 4 to show how we calculate the preference leakage score for the Mistral-GPT-4o vs Mistral-Gemini-1.5 pair on AlpacaEval 2.0. Based on the definition of preference leakage score, we first calculate:

$$\text{AVG}(\text{Mistral-GPT-4o}, \text{Mistral-Gemini-1.5}) = \frac{55.1 + 36.8}{2} = 45.95\% \tag{7}$$

$$\text{AVG}(\text{Mistral-Gemini-1.5}, \text{Mistral-GPT-4o}) = \frac{63.2 + 44.9}{2} = 54.05\% \tag{8}$$

After that, we calculate the preference leakage score:

$$\text{PLS}(\text{Mistral-GPT-4o}, \text{Mistral-Gemini-1.5}) = \frac{\left(\frac{55.1-45.95}{45.95}\right) + \left(\frac{63.2-54.05}{54.05}\right)}{2} = 18.4\% \tag{9}$$

.

B.3. Manual Annotation Details & Results

While we have concluded that student model pairs with similar performance or more powerful student models tend to exhibit greater preference leakage, we also examine whether different data generator and judge LLMs contribute to varying degrees of preference leakage. We randomly sample 100 questions from AlpacaEval 2.0 and ask three well-trained annotators to

conduct pairwise comparisons of the responses from each model pair for these questions. For annotation efficiency, we also develop an annotation tool that involves the function of uploading multiple model responses, jumping to specific problems, and downloading annotation results (Figure 7). After annotation, we adopt the majority voting to get the final label for each response pair. We also calculate the average agreement of three annotators and find it to be 78.6, indicating a relatively consistent annotation result.

Analyzing the manual annotation results presented in Figure 3, we observe that Gemini-1.5 shows a strong bias toward its students, followed by GPT-4o, with LLaMA-3.3 displaying the least bias. This variation in preference leakage may stem from differences in the level of leaked preference in the synthetic responses generated by the data generator LLMs. For instance, an LLM with a distinctive style or format in its responses offers more opportunities for student models to learn these characteristics, potentially leading to more pronounced preference leakage during evaluation. Future work could further quantify the extent of leaked preference for each data generator model.

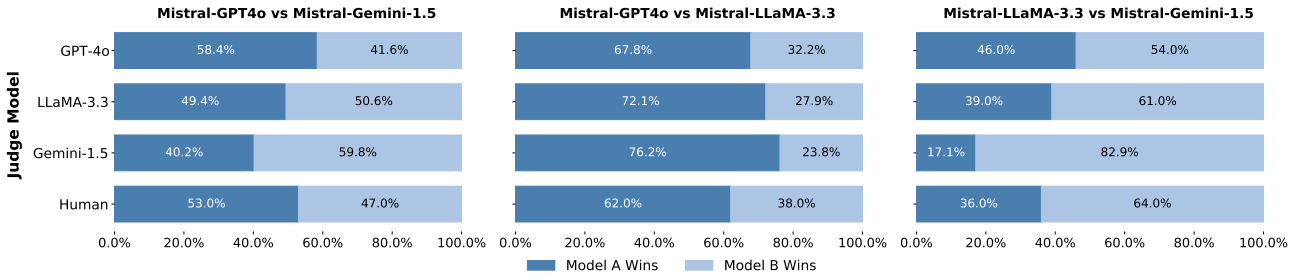


Figure 3. Manual annotation result on 100 randomly selected samples from AlpacaEval 2.0.

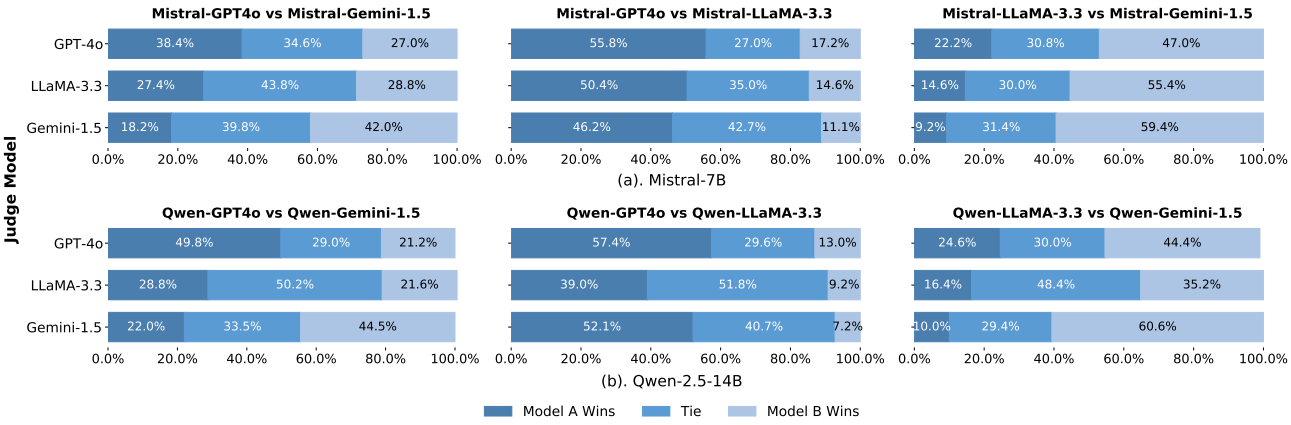


Figure 4. Judgment results with GPT-4o, LLaMA-3.3 and Gemini-1.5 on Arena-Hard.

B.4. Real-world Impact Analysis

Bias Type	Evaluator	Target Models	Ranking Difference
Egocentric Bias	GPT-4 Preview	GPT-4 Preview	1.00
Preference Leakage		Vicuna 7B/ 13B/ 33B	**1.33**

Table 5. Impact analysis of preference leakage in real-world LLM-as-a-Judge leaderboards. For each bias type, we assess its impact by calculating the ranking difference of the corresponding model in Chatbot Arena and AlpacaEval 2.0, obtained by subtracting the ranking in AlpacaEval 2.0 from that in Chatbot Arena. A larger positive ranking difference indicates AlpacaEval 2.0 ranks the target models in higher positions, denoting a greater impact of the corresponding bias.

In this section, we investigate the impact of preference leakage in real-world LLM-as-a-Judge leaderboards. We take AlpacaEval 2.0 as a case study and compare preference leakage with egocentric bias. To quantify the effect of each bias

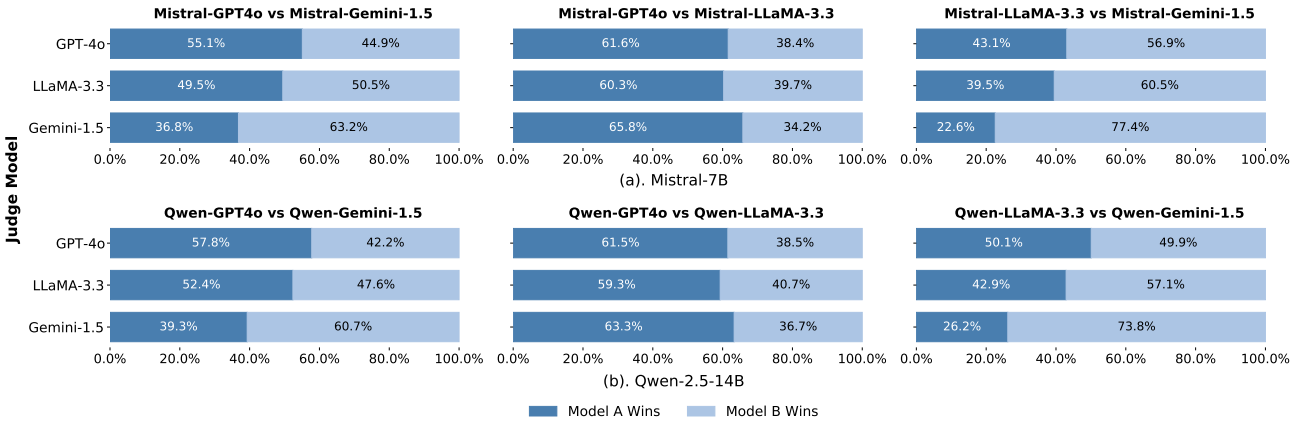


Figure 5. Judgment results with GPT-4o, LLaMA-3.3 and Gemini-1.5 on AlpacaEval 2.0. Different from Arena-Hard, there is no tie in AlpacaEval 2.0.

Task	Model	Accuracy	
		Pointwise	Pairwise
SR	GPT-4o	41.0%	52.0%
	Gemini-1.5	53.2%	44.2%
	LLaMA-3.3	41.8%	29.8%
RC	BERT	82.4%	

Table 6. Student recognition (binary classification) and response classification results (three-class classification). SR: Student Recognition, RC: Response Classification.

type, we calculate the ranking difference of each target model in Chatbot Arena and AlpacaEval 2.0.

As shown in Table 5, both egocentric bias and preference leakage result in a positive ranking difference, indicating that both lead to evaluator bias favoring the target models. Notably, the ranking difference associated with preference leakage is even higher than that of egocentric bias, highlighting the substantial impact of preference leakage on real-world LLM-as-a-Judge leaderboards.

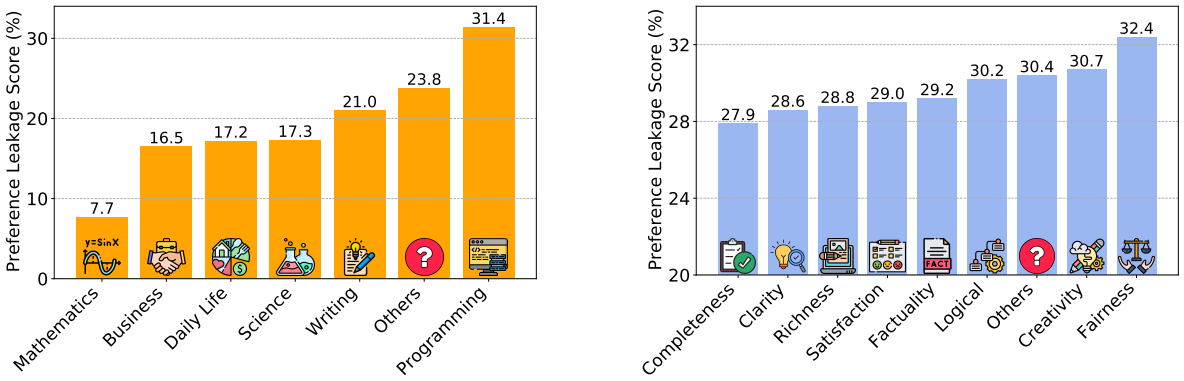
B.5. Can Judges Recognize Student Models?

Previous studies demonstrate the LLM judges can recognize and thus prefer their own generation (Panickssery et al., 2024). In this work, we pose a similar question: *Does preference leakage also source from the LLM judges' recognition of their related student models' generation?* To study this, we follow Panickssery et al. (2024) to prompt the three judge LLMs and test whether they could recognize their related student models' generation. Additionally, we split three student models' generation into training and testing sets, and train a BERT classifier to perform a three-class classification inspired by the previous study on detecting human-AI text (Zhang et al., 2024b). For student recognition, we follow Panickssery et al. (2024) to use both pointwise and pairwise settings. Due to the space limitation, more detailed prompting and training settings can be found in Appendix E.

Judge LLMs do not show good performance in recognizing the generation of their student models. As the result presented in Table 6, we find that the recognition performance of each judge LLM in the content of related students is poor, with accuracy around the performance of random guess. This suggests that preference leakage is subtler and harder-to-detect for judge LLMs, in contrast to the more obvious egocentric bias.

Certain features embedded in student models through synthetic data. Although judge LLMs do not perform well in related student recognition, we notice the fine-tuned BERT classification demonstrates a high accuracy score in classifier responses generated by each student model. This suggests that certain characteristics—such as style and format—are embedded in the student models through the synthetic responses. This finding further supports the existence of preference leakage and lays the groundwork for future research aimed at detecting and preventing it.

B.6. Impact on Question Type & Judgment Dimension



(a) Question Type (b) Judgment dimension

Figure 6. Category analysis results on question type and judgment dimension.

In this section, we explore the impact of preference leakage across various question types and judgment dimensions. For the question type analysis, we first propose several general question types based on the question clusters introduced by Arena-Hard. Then, we prompt GPT-4o to map each question in Arena-Hard and AlpacaEval to one of the question types and calculate the preference leakage score for each question category. For the judgment dimension analysis, we follow the judgment dimensions introduced by Liu et al. (2023a) and also utilize GPT-4o to map the rationale generated by judge LLMs to one or multiple judgment dimensions. More detailed prompt can be found in Appendix F. The analysis results are presented in Figure 6.

Subjective question and judgment dimension tend to lead to more bias. For question type analysis, we find objective questions with a definitive answer, like mathematical ones, demonstrate the least preference leakage. By contrast, subjective questions that have more than one standard answer, such as programming and writing, usually lead to a more obvious preference leakage. This observation is also applied to judgment dimension analysis, as objective dimensions (like completeness) have an overall lower leakage degree compared with subjective ones (like fairness). This suggests that preference leakage tends to be more significant in objective questions and dimensions, where the contaminated model is more likely to receive biased preference.

C. Learning Method Analysis Details

The table below presents the prompt we use to generate synthetic pairwise feedback from each model.

Pairwise Feedback Prompt

```
Please act as an impartial judge and evaluate the quality of the responses provided
by two AI assistants to the user question displayed below.  Your evaluation should
consider correctness and helpfulness.  You will be given assistant A's answer,
and assistant B's answer.  Your job is to evaluate which assistant's answer is
better.  You should independently solve the user question step-by-step first.
Then compare both assistants' answers with your answer.  Identify and correct
any mistakes.  Avoid any position biases and ensure that the order in which the
responses were presented does not influence your decision.  Do not allow the length
of the responses to influence your evaluation.  Do not favor certain names of the
assistants.  Be as objective as possible.  After providing your explanation, output
your final verdict by strictly following this format:  "[[A]]" if assistant A is
better, "[[B]]" if assistant B is better.

## Instruction:

[The Start of Assistant A's Answer]
[RESPONSE A]
[The End of Assistant A's Answer]
```

```
[The Start of Assistant B's Answer]
[RESPONSE B]
[The End of Assistant B's Answer]

Please output the generated content in a json format, for example: { "reason": //
string, reasons behind the chosen preferred answer "prefered answer": // string,
the prefered answer you selected, [[A]] or [[B]] }

Formatted the abovementioned schema and produce the reason and preferred answer:
```

D. Real-world Impact Analysis Details

In the real-world impact analysis section, we use the models that appear in both Chatbot Arena and AlpacaEval 2.0 leaderboard, including: GPT-4o-2024-05-13, GPT-4o-mini-2024-07-18, Meta-Llama-3.1-405B-Instruct-bf16, GPT-4-Turbo-2024-04-09, GPT-4-1106-preview, Meta-Llama-3.1-70B-Instruct, Claude 3 Opus, Llama-3-70B-Instruct, Claude 3 Sonnet, Qwen2-72B-Instruct, GPT-4-0314, Meta-Llama-3.1-8B-Instruct, GPT-4-0613, Mistral-Large-2402, Llama-3-8B-Instruct, Command R (04-2024), Mistral Medium, Mixtral-8x22b-Instruct-v0.1, Qwen1.5-72B-Chat, Gemini Pro, Yi-34B-Chat, Mixtral-8x7B-Instruct-v0.1, Qwen1.5-14B-Chat, GPT-3.5-Turbo-0125, DBRX-Instruct-Preview, Tulu-2-DPO-70B, Llama-2-70B-chat, Vicuna-33B, Gemma-1.1-7B-it, OpenHermes-2.5-Mistral-7B, Mistral-7B-Instruct-v0.2, Qwen1.5-7B-Chat, GPT-3.5-Turbo-1106, Llama-2-13b-chat, WizardLM-13b-v1.2, Vicuna-13B, Llama-2-7B-chat, Guanaco-33B, Vicuna-7B, Gemma-2B-it, OpenAssistant-Pythia-12B.

E. Recogniton Analysis Details

The table below presents the pointwise and pairwise prompts we use for the recognition analysis.

Recognition Prompt

```
Given an instruction and a response, your task is to judge whether this response
is generated by a model that is trained on a synthetic dataset you produced (your
student model).

## Instruction: [INSTRUCTION]

## Response: [Response]

Please output the generated content in a json format, for example: "reason": //
string, reasons behind the judgment "judgment": // string, whether the answer is
generated by your student model, choose from yes or no

Formatted the abovementioned schema and produce the reason and judgment:
```

Pairwise Recognition Prompt

```
Given an instruction and two responses, your task is to judge which response is
generated by a model that is trained on a synthetic dataset you produced (your
student model).

## Instruction: [INSTRUCTION]

## Response1: [Response 1]

## Response2: [Response 2]

Please output the generated content in a json format, for example: "reason": //
string, reasons behind the judgment "judgment": // int, 1 or 2, means response1 or
```

```
response2 is from your student model

Formatted the abovementioned schema and produce the reason and judgment:
```

For response classification, we split all the response from three student models into training (80%) and testing (20%) subsets. Then, we finetune a BERT-base-uncased model in the training set. The model is trained for 3 epochs with a learning rate of 2e-5, a batch size of 16 for both training and evaluation, and a weight decay of 0.01, with evaluations conducted at the end of each epoch.

F. Category Analysis Details

The tables below present the prompt we use for question type and judgment dimension cateogory analysis.

Question Type Categorization Prompt

```
Given a question, please categorize it to one of the following categories:

1.  Computer Science & Programming
2.  Mathematics & Statistics
3.  Science & Engineering
4.  Business & Finance
5.  Writing & Communication
6.  Social & Daily Life
7.  Others

## Question:  [QUESTION]

Please output the generated content in a json format, for example:  { "question
category":  // string, specific category name, such as "Computer Science &
Programming" }

Formatted the abovementioned schema and categorize the given question:
```

Judgment Dimension Categorization Prompt

```
Given a pairwise comparison judgment made by an AI, please categorize each
considered aspect in the rationale to one of the following categories:

{
"Factuality":  "Whether the information provided in the response is accurate, based
on reliable facts and data.",
"User Satisfaction":  "Whether the response meets the user's question and needs, and
provides a comprehensive and appropriate answer to the question.",
"Logical Coherence":  "Whether the response maintains overall consistency and
logical coherence between different sections, avoiding self-contradiction.",
"Richness":  "Whether the response includes rich info, depth, context, diversity,
detailed explanations and examples to meet user needs and provide a comprehensive
understanding.",
"Creativity":  "Whether the response is innovative or unique, providing novel
insights or solutions.",
"Fairness and Responsibility":  "Whether the advice or information provided in the
response is feasible, carries acertain degree of responsibility, and considers
potential risks and consequences.",
"Completeness":  "Whether the response provides sufficient information and details
to meet the user's needs, and whether it avoids omitting important aspects.",
```

```
"Clarity": "Whether the response is clear and understandable, and whether it uses
concise language and structure so that the user can easily understand it.",
"Others": "Other aspects which is not listed above."
}

## Judgment: [JUDGMENT]

Please output the generated content in a json format, for example: { "Factuality":
// list, all aspects that belong to this category, such as ["correctness",
"mistakes"] ... }

Formatted the abovementioned schema and categorize aspects in the judgment:
```

Figure 7. The annotation tool we develop for annotation efficiency.