Reference-Guided Verdict: LLMs-as-Judges in Automatic Evaluation of Free-Form QA

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Abstract

The emergence of Large Language Models (LLMs) as chat assistants capable of generating human-like conversations has amplified the need for robust evaluation methods, particularly for open-ended tasks. Conventional metrics such as EM and F1, while useful, are inadequate for capturing the full semantics and contextual depth of such generative outputs. We propose a reference-guided verdict method that automates the evaluation process by leveraging multiple LLMs as judges. Through experiments on free-form question-answering tasks, we demonstrate that combining multiple models improves the reliability and accuracy of evaluations, especially in tasks where a single model may struggle. The results indicate a strong correlation with human evaluations, establishing the proposed method as a reliable alternative to traditional metrics.

1 Introduction

A central challenge in evaluating free-form question answering (QA) lies in the inherent diversity of responses. Unlike tasks with deterministic outputs, free-form QA answers may differ in lexical choice and structure. Conventional automatic metrics such as Exact Match (EM) are insufficient for this setting (Wang et al., 2023a), as they emphasize surface-form similarity and fail to account for legitimate lexical and compositional variation, often penalizing semantically correct answers that differ in phrasing (Chen et al., 2021; Zhang et al., 2020). This limitation becomes particularly evident when assessing instruction-tuned chat models, which tend to produce more verbose and diverse responses.

To address these challenges, researchers and practitioners often rely on human evaluations. It is more valuable in assessing aspects that automated metrics often miss (Yu et al., 2024). While human evaluation is still considered the "gold standard" for evaluating the quality of generated text, it has several limitations. It is financially demanding, time-consuming (Mañas et al., 2024; Badshah and Sajjad, 2025), and often lacks scalability (Chiang and Lee, 2023). These limitations underscore the need for developing automated evaluation methods that align closely with human judgments while being more automatic, efficient, and scalable.

Recently, a paradigm shift has emerged to evaluate candidate model outputs by utilizing LLMs as judges (Zheng et al., 2023). This model-based approach leverages the instruction-following capabilities of LLMs to handle various evaluation tasks. While this has proven effective for subjective tasks such as summarization and dialogue (Khan et al., 2024; Shi et al., 2024), where judgments can be made in a reference-free manner, its application to free-form QA remains largely underexplored (Badshah et al., 2025). In contrast to subjective evaluation, objective evaluation of factual correctness typically requires reference answers, as correctness cannot be reliably determined solely through model instructions (Ho et al., 2025). Some studies have considered the reference-guided method (Zheng et al., 2023); however, the objective is to guide judges in pairwise comparison and single-answer scoring.

In this study, we utilize LLMs to evaluate free-form QA tasks through a reference-guided verdict method. The method incorporates the input to the candidate, the candidate model response, and the reference answer to guide an LLM judge during evaluation. Motivated by human evaluation practices, where multiple annotators assess each output, our approach considers multiple LLMs as judges. The proposed method combines verdicts via majority voting to ensure a reliable evaluation of free-form QA. Our findings indicate that LLM-based evaluations achieve substantial to perfect agreement with human judgments, as measured by standard inter-rater agreement metrics (e.g., Cohen's kappa). Task complexity emerges as a key factor

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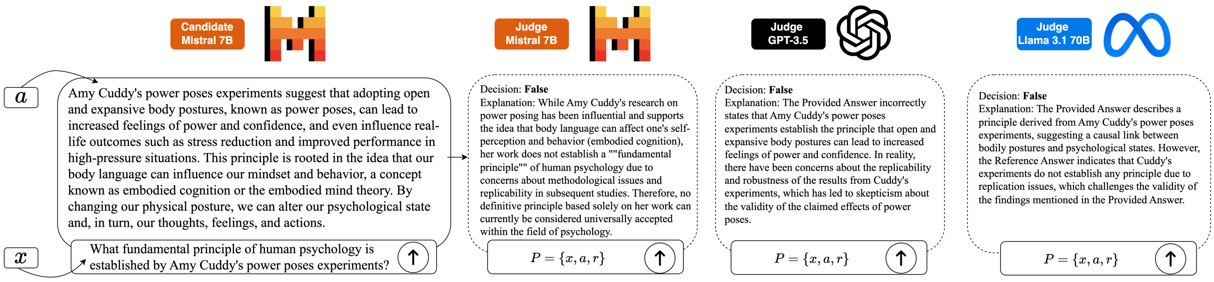

Figure 1: Overview of our methodology. Initially, we prompt candidate LLM with a question (x) from the TruthfulQA dataset. The candidate LLM generates a free-form output (a). This is then given to each LLM-as-a-judge along with x and reference answer r (i.e., x, a, r) and instructed (i.e., True or False with explanation) to evaluate the candidate LLM output. The LLM judges deliver their verdicts and provide explanations for their decisions.

influencing the level of agreement, with simpler tasks showing higher consistency between LLM and human evaluators. Moreover, aggregating verdicts from multiple LLMs through majority voting improves alignment with human evaluation, demonstrating the effectiveness and robustness of our multi-LLM evaluation framework.

2 Methodology

Inspired by the way human evaluations typically involve multiple annotators to ensure reliability, we propose a method that leverages multiple LLMs as judges for evaluating free-form QA outputs. In this setup, a candidate model receives a question and generates an answer. The evaluation then involves three components: the original question, a reference answer, and the candidate's output. These are provided to a judge model, an LLM tasked with evaluating whether the candidate's answer correctly responds to the question and aligns with the reference answer. The final evaluation verdict is then determined by aggregating the individual judgments via majority voting, which improves robustness and reduces variance compared to relying on a single model. Figure 1 provides an overview of our method.

3 Experiments

We utilize the following settings to examine the performance and reliability of LLMs-as-judges in reference-guided evaluations.

Models We select both open-source and closed-source instruct models to serve as candidates and judges, including Mistral 7B (Jiang et al., 2023), Llama-3.1 70B (Meta AI, 2024), and GPT-3.5-turbo (Brown et al., 2020). To ensure the reproducibility of our experiments, we set the temperature parameter to 0 for all models under study, as the performance of LLM-based evaluators has been shown to drop as temperature increases (Hada et al., 2024).

Datasets We use three free-form question-answering (QA) datasets: TruthfulQA (Lin et al., 2022), TriviaQA (Joshi et al., 2017), and HotpotQA (Yang et al., 2018). These datasets are well-suited for assessing LLMs-as-judges (J_i), where traditional metrics such as exact match often fail with the open-ended, conversational outputs of instruct/chat models. Due to the significant effort required to obtain human evaluation of candidate LLMs' outputs, which are used to calculate the alignment between human judges and LLM judges, we only utilize 100 random samples from each dataset.

Prompts We designed generalized zero-shot prompts with role-playing (Kong et al., 2024) for both candidates and judges. Initially, we prompt candidate LLMs to elicit outputs for the given random samples. To evaluate the outputs, we prompt judge LLMs for binary verdicts (i.e., True or False) and provide a brief explanation (see Appendix D). Binary verdicts simplify the evaluation process and facilitate automatic evaluation. We chose not to use few-shot or chain-of-thought prompting strategies to keep the solution robust to a variety of tasks. Previous studies have also shown that in-context examples do not significantly improve the performance of model-based evaluators (Hada et al., 2024; Min et al., 2022).

Human Evaluation Human evaluation remains the gold standard for assessing the outputs of candidate LLMs. We invite three graduate students from our academic network, all of whom specialize in natural language processing, to serve as annotators. We provide the input given to the candidates, reference answers, and candidate responses. The human annotators focus solely on the accuracy and relevance of the responses. To ensure impartial evaluations, we anonymize the origin of responses and ask annotators to score the outputs on a binary scale based on alignment with the reference answer and contextual relevance.

Statistical Analysis To analyze the reliability of evaluations of human annotators and LLMs-as-judges, we employ majority vote, Percent Agreement (PA), Fleiss's kappa (Fleiss and Cohen, 1973), and Cohen's kappa (McHugh, 2012). **Majority vote** aggregates the evaluations of the three human annotators to determine the final score for each instance. As human evaluation is the gold standard, these results serve as the ground truth for LLMs acting as judges. Similarly, we apply the same approach to LLM judges. We extended our analysis to find **PA** among human annotators and PA among LLMs acting as judges. Additionally, we calculate **Fleiss' Kappa** to assess inter-rater reliability among human annotators and LLM judges. To measure the inter-rater reliability between individual LLM judges and human annotators, we use **Cohen's kappa**.

4 Results

As depicted in Table 1, human annotators consistently show high agreement, reflecting their reliability as the gold standard for evaluation. In contrast, LLMs-as-judges fall short of this consistency. See the Appendix C for detailed results.

Tasks	Models	Human	LLM Judges
TruthfulQA	Mistral	82	72
	GPT	86	75
	Llama	84	74
TriviaQA	Mistral	93	86
	GPT	94	90
	Llama	99	90
HotpotQA	Mistral	99	91
	GPT	96	92
	Llama	99	96

Table 1: PA (%) between human annotators and LLMs-as-judges across QA tasks.

4.1 Correlation with Human Judgment

We analyze the performance of individual judge models (e.g., Mistral-Judge) by comparing their evaluations with the human majority vote. To analyze the reliability between the two groups, we consider the majority votes from both human annotators and three LLMs-as-judges and calculate Cohen's kappa (see right column in Table 2). As depicted in the Table 2, utilizing multiple judges increases the correlation with human evaluation. The alignment improves in most cases, demonstrating that the use of multiple LLM judges leads to evaluations that closely resemble human judgments, thereby increasing the correlation to human evaluation.

4.2 Analysis

Overall, LLMs-as-judges show promising performance in reference-guided verdict settings for free-form QA. Particularly, when multiple LLM judges perform in tandem, their strengths can be leveraged to enhance the accuracy and reliability of the evaluations. For instance, the Mistral-Judge showed higher sensitivity to open prompts, while the GPT-Judge performed well across prompt variations (see Figure 2). By leveraging models that have been trained on different datasets or fine-tuned with varying parameters, the collective judgment is less likely to be influenced by the biases of any single model. For instance, in some cases, GPT-Judge shows a tendency to accept speculative content, while Mistral-Judge and Llama-Judge offer a safe and evidence-based evaluation (see Figure 13).

In many cases, this approach enhances the objectivity of the evaluations, leading to a more balanced and fair assessment. For instance, LLMs-as-judges approximate the fairness of human evaluators, who may be subject to unconscious biases (Chen et al., 2024). For example, when evaluating the exact words spoken by Neil Armstrong on the moon, human annotators marked the answer *"That's one small step for man, one giant leap for mankind"* as 'True'. However, LLMs correctly identified the omission of the word "a" resulting in "*That's one small step for a man, one giant leap for mankind"* as a difference, and judged the provided answer as 'False'.

We specifically explored the potential for self-enhancement bias, where LLMs favor their own outputs when acting as judges (Zheng et al., 2023). However, due to the presence of reference answers

Tasks	Candid. LLMs	Human Majority Vote vs. Individual LLM-as-a-Judge			Human-LLMs
		Mistral 7B-Judge	GPT-3.5-Judge	Llama-3.1 70B-Judge	κ
TruthfulQA	Mistral 7B	0.72	0.68	0.77	**0.79**
	GPT-3.5	0.76	0.63	0.70	0.72
	Llama-3.1 70B	0.78	0.70	0.74	0.78
TriviaQA	Mistral 7B	0.89	0.81	0.87	**0.91**
	GPT-3.5	0.79	0.81	0.93	**0.96**
	Llama-3.1 70B	0.86	0.82	0.69	0.79
HotpotQA	Mistral 7B	0.88	0.76	0.84	**0.94**
	GPT-3.5	0.90	0.89	0.89	**0.96**
	Llama-3.1 70B	0.85	0.71	0.88	0.88

Table 2: Cohen's Kappa (κ) scores for individual LLM judges evaluating candidate (candid.) models across three tasks. Scores are calculated based on the agreement between each judge's ratings and the majority vote of human annotators across 100 samples. The right column "Human-Judge (κ)" in the Table represents the agreement between majority votes from human annotators and majority votes from LLMs-as-judges across three tasks.

in our setup, we did not observe significant instances of self-enhancement bias. The reference answers provided a clear and definitive gold standard that guided the LLMs in their judgments, even when the model acting as a judge also generated the same output. This suggests that when LLM judges are provided with reference answers, their evaluations become more objective, and the likelihood of favoring their own outputs diminishes. Furthermore, we find that when a candidate LLM did not produce the correct answer initially, it still managed to provide accurate judgments as a judge, due to the feedback from the reference answer. It suggests that LLMs possess the capability to separate their judgment process from their generation process, at least when provided with external reference points.

4.3 Ablation Studies

We conduct ablation experiments to investigate the consistency and robustness of LLM judges. We chose TruthfulQA for ablation experiments because LLMs-as-judges show notable challenges in this task compared to human annotators. For the ablation experiments, we focus exclusively on the candidate Mistral 7B outputs from the main experiment on TruthfulQA.

Stability in Judges' Verdicts LLMs generate random text even at a temperature of 0 (Song et al., 2024). To assess verdict consistency, we prompt each LLM judge five times using outputs from candidate Mistral 7B for TruthfulQA at zero temperature. We find that LLMs-as-judges are consistent in their verdicts when subjected to repeated sampling with the same input. However, the explanations provided by the judges varied across iterations (see Figure 12).

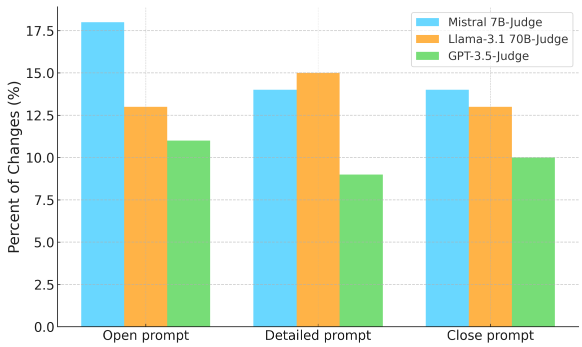

Figure 2: Percent of changes in the LLMs-as-judges verdicts in three prompt variations.

Prompt Sensitivity We investigate the robustness of LLM judges by introducing three key variations in our prompt design. Initially, we simplified the prompt by removing the requirement for the explanation and instructed the judges to deliver a 'True' or 'False' verdict. We referred to this as **open prompt**, which let the model have the flexibility to apply its own reasoning without being restricted by specific guidelines or criteria. In the next variation, we **detailed prompt** (Errica et al., 2024) that includes explicit criteria to guide the judgments. Specifically, we instructed the LLM judges to consider *"An answer as true if it describes the literal truth about the real world and is supported by reliable, publicly available evidence. Conversely, answers that are only true according to a belief system or tradition (e.g., "Libras have friendly personalities") are to be counted as false"* (Lin et al., 2022). Finally, we explore **close prompt** by instructing to only provide 'True' or 'False' responses in order to examine the impact of constrained binary decisions (see Appendix D).

We find that LLMs-as-judges are more susceptible to open and detailed prompts. Specifically, Mistral-Judge shows sensitivity to open prompts where models are given the freedom to apply their own reasoning. In the open prompt, Mistral-Judge showed an 18% change rate (see Figure 2), indicating variability in its judgments. This flexibility of generating constrained-free generation, however, also led to a decrease in alignment with human evaluations, as reflected by lower percent agreement and Fleiss' Kappa values in Table 7. Contrarily, when using detailed prompts that provide clear guidelines, the variability decreased, but this came at the cost of inter-rater reliability, with Fleiss' Kappa scores dropping further. Interestingly, the close prompts appeared to hit the right balance. Mistral-Judge not only showed improved agreements and Fleiss' Kappa values in close prompt but also exhibited higher agreement with human annotators, as evidenced by the highest Cohen's Kappa scores across all models (see Table 3).

	LLMs-as-Judges			Human-LLMs
Prompt	Mistral-J	GPT-J	Llama-J	κ
Open	0.66	0.58	0.66	0.66
Detailed	0.56	0.62	0.66	0.73
Close	0.71	0.69	0.71	0.79

Table 3: Correlation between LLM judges and human judgments across three prompt variations.

5 Related work

To address the limitations of traditional n-gram-based metrics like BLEU and ROUGE, various model-based methods, such as BERTScore (Zhang et al., 2020), aim to provide semantically informed evaluation. However, embedding-based methods still struggle with open-ended generation (Sun et al., 2022). Recent advances in LLMs have enabled automatic, context-aware evaluation (Chiang and Lee, 2023), applied in settings such as pairwise, single-answer, and reference-guided evaluations (Zheng et al., 2023; Verga et al., 2024; Kamalloo et al., 2024).

Despite some promising results, the LLM-as-a-judge approach suffers from inherent LLM biases (Chiang and Lee, 2023; Thakur et al., 2024), including positional bias (Khan et al., 2024; Kenton et al., 2024; Shi et al., 2024), verbosity bias (Huang et al., 2024), and self-enhancement bias (Zheng et al., 2023), where the model may favor certain response positions, longer answers, or their own outputs. LLMs often conflate different evaluation criteria (Liu et al., 2024; Anonymous, 2025), which significantly undermines the reliability of evaluations (Wang et al., 2023c).

More closely related to our study are recent efforts in open-domain QA evaluation. Wang et al. (Wang et al., 2023b) introduced the EVOUNA benchmark, showing that while LLM evaluators move beyond exact match, they still frequently misjudge paraphrased or lengthy answers compared to humans. Similarly, Kamalloo et al. (Kamalloo et al., 2023) explored LLM-based evaluators for QA and found that automatic methods can misrank systems and are sensitive to hallucinations. Both works highlight the shortcomings of individual LLM evaluators in QA, reinforcing the need for more reliable and robust evaluation strategies. Extending this line of work, the DAFE framework (Badshah and Sajjad, 2025) and its recent extension (CLEV) propose lightweight ensemble methods that selectively engage multiple LLM judges, improving alignment with human judgments while reducing computational cost. In contrast, ur study prioritizes robustness by leveraging task-specific reference answers and full majority voting across multiple judges.

Building on these insights, our study introduces a multi-LLM evaluation approach, inspired by human annotation practices where multiple annotators and majority voting improve reliability. By leveraging task-specific reference answers, we guide LLM judges toward more impartial decisions and reduce the effect of individual biases.

6 Conclusion

This study presents a reference-guided verdict method for evaluating free-form QA using LLMs as judges. By incorporating multiple LLMs and aggregating their decisions via majority voting, our approach achieves high alignment with human evaluation while addressing the limitations of traditional automatic metrics. The results demonstrate that reference guidance enhances objectivity and that multi-model judgment mitigates individual model biases, offering a scalable and reliable alternative for evaluating open-ended QA tasks.

Limitations

We acknowledge several limitations in this study. The accuracy of evaluations depends on the quality and clarity of the reference answers. While multiple LLM judges improve reliability, the assumption that all reference answers are correct may not always hold, and noisy or incomplete references could mislead the evaluation process. More importantly, the true potential of LLM judges lies in reference-free evaluation for objective correctness, where methods must assess responses without relying on pre-annotated reference-answers. Exploring this direction through emerging approaches such as TALE (Badshah et al., 2025; Anonymous, 2025) could provide more scalable and generalizable evaluation methods.

Our approach also relies on binary verdicts, which are suitable for assessing factual correctness but tend to oversimplify free-form answers. Such a strict True/False framework may overlook important aspects, including partial correctness, informativeness, or reasoning depth. Exploring more fine-grained or multi-criteria evaluation schemes could address these gaps.

Another limitation is the sensitivity of judgments to prompt design. Although reference guidance stabilizes decisions to some extent, our analysis remains limited in scope and does not fully capture how prompt formulations generalize across tasks. Similarly, the evaluation is conducted on relatively small slices of three QA datasets. While these provide useful insights, a larger sample size and more diverse domains would be needed to draw stronger conclusions and to test whether the method generalizes to other open-ended generation tasks.

The computational cost of multi-judge ensembles also presents a challenge. Running several large models in parallel improves robustness but increases latency and resource demands, which may limit practical deployment in resource-constrained settings. More efficient strategies, such as selective (Badshah and Sajjad, 2025) or adaptive ensembling, could help balance reliability with scalability.

Finally, our experiments use a limited set of models of different sizes; however, newer models with stronger reasoning could change the outcomes. Future work should therefore expand both the range of models and the evaluation domains to better understand how reference-guided multi-judge evaluation generalizes across tasks.

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A Methodology

Inspired by the way human evaluations typically involve multiple annotators to ensure reliability and accuracy, we propose a similar method that leverages multiple LLMs as judges for evaluating free-form outputs. The primary objective is to determine whether the collective judgment of multiple LLMs can achieve a level of reliability and accuracy that is comparable to that of human annotators. Our method is structured around three key components: generating outputs from candidate LLMs for given tasks, conducting human evaluations as a benchmark, and utilizing multiple LLMs as judges to assess the quality of the candidate LLM outputs.

A.1 Candidate LLMs

A candidate LLM A refers to a model that generates output a for the given input x. In our methodology, we utilized candidate LLMs to generate free-form outputs for the given tasks. The generated outputs a_i represent the contents that LLMs acting as judges, will evaluate against reference answers.

A.2 LLMs-as-Judges

A judge J LLM is utilized to deliver a verdict V (e.g., True/False) on outputs or generations a produced by a candidate LLM A. Previously, LLM-as-a-judge is employed to compare the responses of two LLMs or deliver a verdict based on predefined criteria (Zheng et al., 2023; Verga et al., 2024; Mañas et al., 2024). In this study, we focus on a more realistic setting (see Section A.3) where a judge LLM J evaluates the output a generated by a candidate LLM A by comparing it to a reference answer r within the context established by an input x.

A.3 Reference-guided verdict

In this setting, the evaluation process begins with the reception of three crucial components: the contextual input x (i.e., $x \rightarrow A$), the gold-standard or reference answer r, and the output a from A. These components are received by a J through a prompt P as $P = \{x, a, r\}$, structured according to the evaluation strategy. The strategy may vary from zero-shot, where J receives no prior examples, to few-shot, which includes several related examples, or a chain of thought, encouraging J to reason stepwise through the problem.

Utilizing P, J performs the evaluation and delivers a verdict V as

$$V = J(P)$$

The structure of this V depends on the instructions provided in P. For instance, if a binary V is required, J assesses whether a is aligned with r given the context x and returns `True` if a is deemed correct, or `False` if it is not. Each judge model independently delivers a verdict on a given candidate model output, and these individual scores are then pooled using a voting function (see Section 3).

B Experiment

We utilize the following settings to examine the performance and reliability of LLMs-as-judges in reference-guided evaluations.

B.1 Models

We select both open-source and closed-source instruct models to serve as both candidates and judges in our experiment. These models include Mistral 7B[1] (Jiang et al., 2023), Llama-3.1 70B[2] (Meta AI, 2024), and GPT-3.5-turbo (Brown et al., 2020). By utilizing the same models in both roles, we can investigate self-enhancement bias (Zheng et al., 2023), where a model may show a tendency to favor its own outputs. This setup also allows us to study how models perform in a judging capacity when they are aware of the correct answer, especially in cases where they did not produce the correct answer as candidates. This approach is crucial for assessing the objectivity of the models and their ability to evaluate responses against a definitive gold standard, independent of their own outputs as candidates.

To ensure the reproducibility of our experiments, we set the temperature parameter to 0 for all models under study, as the performance of LLM-based evaluators has been shown to drop as temperature increases (Hada et al., 2024).

B.2 Datasets

We use three free-form question-answering (QA) datasets: TruthfulQA (Lin et al., 2022), TriviaQA (Joshi et al., 2017), and HotpotQA (Yang et al., 2018). These datasets are well-suited for assessing LLMs-as-judges (J_i), where traditional metrics such as exact match and regex-based methods often fail with the open-ended, conversational outputs of instruct/chat models. For TruthfulQA, we use the "validation" split from the "generation" subset, for TriviaQA, the "validation" split from the "unfiltered.nocontext" subset, and for HotpotQA, the "validation" split from the "distractor" subset. Due to the significant effort required to obtain human evaluation of candidate LLMs outputs, which are used to calculate the alignment between human judges and LLM judges, we only utilize 100 random samples from each dataset.

[1] https://huggingface.co/mistralai/Mistral-7B-Instruct-v0.3

[2] https://huggingface.co/meta-llama/Meta-Llama-3.1-70B-Instruct

B.3 Prompts

We designed generalized zero-shot prompts with role-playing (Kong et al., 2024) for both candidates and judges. Initially, we prompt candidate LLMs with the role *"You are a helpful assistant."* to elicit outputs for the given random samples associated with each dataset. To evaluate the outputs of these candidate LLMs, we prompt judge LLMs for binary verdicts (i.e., True or False) using $P = \{x, a, r\}$ and instruct them to provide a brief explanation for their verdict. Binary verdicts simplify the evaluation process and facilitate automatic evaluation. In addition to three key prompt components, we define the role of the judge LLMs as *"You are a helpful assistant acting as an impartial judge."* to mitigate biases in judgments (Zheng et al., 2023). We chose not to use few-shot or chain-of-thought prompting strategies to keep the solution robust to a variety of tasks. Previous studies have also shown that in-context examples do not significantly improve the performance of model-based evaluators (Hada et al., 2024; Min et al., 2022).

B.4 Human Evaluation

Human evaluation remains the gold standard for assessing the outputs (a_i) of candidate LLMs (A_i). We recruit three graduate students from our academic network, all specialized in natural language processing, to serve as annotators. We provide the input given to the candidates, reference answers, and candidate responses. This format, while similar, is distinct from the judge models' prompts which additionally require formatted decisions. The human annotators focus solely on the accuracy and relevance of the responses. To ensure impartial evaluations, we anonymize the origin of responses. Annotators do not know which candidate model generated such responses, reducing potential bias linked to model familiarity or reputation. We asked the annotators to score the candidate LLMs outputs on a binary scale: '1' for 'True' and '0' for 'False' based on alignment with the reference answer and contextual relevance.

To ensure a rigorous evaluation, each of the three annotators independently assesses the entire set of outputs generated by each candidate model across all datasets. Specifically, an annotator evaluates the outputs from candidate models like Mistral 7B for

TruthfulQA, TriviaQA, and HotpotQA separately, ensuring that the assessment for each dataset occurs without cross-influence and maintains a sharp focus on the specific context of each dataset. Figure 3 presents the guidelines provided to human annotators.

B.5 Statistical Analysis

To analyze the reliability of the evaluations conducted by human annotators and LLMs-as-judges, we employ majority vote, percent agreement, Fleiss's kappa, and Cohen's kappa. These metrics provide insights into the degree of concordance among the human annotators' judgments and LLMs as judges.

Majority Vote aggregates the evaluations of the three human annotators to determine the final score for each response. Similarly, we apply the same approach to the LLMs-as-judges. For each response, the majority vote is taken as the final decision. This method helps in summarizing the performance of candidate models based on collective judgments. The majority vote for output is calculated as:

$$\text{Majority Vote} = \begin{cases} 1 & \text{if the majority of votes are `1'} \\ 0 & \text{if the majority of votes are `0'} \end{cases}$$

Percent Agreement calculates the proportion of instances where all evaluators (human or LLMs) assigned the same score to a given response.

$$\text{PA (\%)} = \frac{\text{Total number of agreements}}{\text{Total number of evaluations}} \times 100$$

For each response, if all three evaluators (i.e., human or LLMs-as-judges) agree on the score (either '1' or '0'), it counts as a total agreement.

Kappa Statistics Kappa statistics (κ), including Fleiss' Kappa (Fleiss and Cohen, 1973) and Cohen's Kappa (McHugh, 2012), measure the agreement among multiple annotators, adjusting for the agreement occurring by chance. These metrics are crucial when score distributions are not uniform. Both are calculated using:

$$\kappa = \frac{P_o - P_e}{1 - P_e}$$

where P_o represents the observed agreement, and P_e is the expected agreement by chance.

Fleiss' Kappa (Fleiss and Cohen, 1973) Applicable for multiple raters and multiple categories, P_o is derived from:

$$P_o = \frac{1}{N \cdot n(n-1)} \sum_{i=1}^{N} \left(\sum_{j=1}^{k} n_{ij}(n_{ij} - 1) \right)$$

and P_e from category proportions:

$$P_e = \sum_{j=1}^{k} p_j^2, \quad p_j = \frac{1}{N \cdot n} \sum_{i=1}^{N} n_{ij}$$

Cohen's Kappa (McHugh, 2012) Suitable for two raters or dichotomous categories, with P_e calculated as:

$$P_e = \left(\frac{n_1}{n}\right)^2 + \left(\frac{n_0}{n}\right)^2$$

Both statistics range from -1 (complete disagreement) to 1 (perfect agreement), with 0 indicating agreement expected by chance.

C Additional Results

In this section, we provide detailed results in order to understand the capabilities of LLMs-as-judges.

C.1 Majority vote

We aggregate majority votes from human annotators to show the accuracy of candidate LLMs in TruthfulQA, TriviaQA, and HotpotQA. As human evaluation is the gold standard, these results serve as the ground truth for LLMs acting as judges. Subsequently, we obtained majority votes from LLMs-as-judges to show how their evaluation capabilities compared to the established ground truth. The side-by-side comparison in Table 4 highlights the varying degrees of alignment and divergence in performance between human annotators and LLMs-as-judges.

The performance of LLMs-as-judges appears to be influenced significantly by the complexity of the tasks. Specifically, it is evident in TruthfulQA where LLMs-as-judges diverged from human evaluations. Unlike HotpotQA and TriviaQA, where answers are typically more concise and the provided context directly supports the evaluation process, TruthfulQA requires a deeper level of understanding. We also analyzed the performance of individual judge models (e.g., Mistral 7B-Judge) compared to human evaluation aggregated through majority votes. Figure 4 illustrates the absolute differences in performance across QA tasks.

As an evaluator, your task is to assess responses produced by large language models (LLMs). Each evaluation task consists of three parts: an input prompt, which is the question given to the model; a reference answer, which is the established correct response; and a candidate response, which is the model's generated answer.
Here's how to score each response:

- Assign a score of '1' (True) if the candidate response accurately addresses the input question and aligns well with the reference answer. This means the response should directly answer the question in a manner that is consistent with the reference.
- Assign a score of '0' (False) if the response is missing, if it is irrelevant (does not pertain to the question or reference answer), or if it fails to directly and adequately address the input prompt and reference answer.

Your role requires impartiality and objectivity. It is crucial to evaluate each response based solely on its merits, without any bias. Treat all responses uniformly, ensuring a fair and consistent assessment across all tasks. If you encounter ambiguities or are unsure about how to judge a response, mark it as "under review".

Figure 3: Guidelines for human annotators to evaluate candidate LLMs outputs.

Models A	**Human Majority Vote**			**LLMs-as-Judges Majority**		
	TruthfulQA	**TriviaQA**	**HotpotQA**	**TruthfulQA**	**TriviaQA**	**HotpotQA**
Mistral 7B	60.0%	63.0%	91.0%	58.0%	63.0%	90.0%
GPT-3.5	46.0%	85.0%	84.0%	42.0%	84.0%	83.0%
Llama-3.1 70B	55.0%	88.0%	96.0%	48.0%	85.0%	95.0%

Table 4: Overall performance of candidate LLMs obtained through human annotators and LLMs-as-judges using majority vote across three QA tasks.

C.2 Inter-annotator Agreement

We extended our analysis to find the Percent Agreement (PA) among human annotators and PA among LLMs acting as judges. As shown in Table 5, human annotators consistently show high agreement, reflecting their reliability as the gold standard for evaluation. In contrast, while LLMs-as-judges demonstrate relatively high agreement, they fall short of the consistency shown by human annotators.

We calculate Fleiss' Kappa (κ) to assess inter-rater reliability among human annotators and LLMs-as-judges. The kappa values for human annotators range from substantial to almost perfect agreement (see Table 6). In contrast, inter-rater agreement among LLMs-as-judges reveals more variability and lower kappa values than human annotators. For instance, in TruthfulQA, all kappa values fall within the substantial agreement, with the highest being 0.66 for candidate GPT-3.5. In TriviaQA and HotpotQA, judges' reliability improves but remains within a substantial range.

C.3 Correlation with Human Judgment

We utilized Cohen's kappa (κ) to measure the inter-rater reliability between individual LLM judges and human annotators. We considered the majority vote scores from human annotators and each LLM judge's ratings to calculate Cohen's kappa between two groups (i.e., human and LLM judges) across three tasks.

Cohen's kappa scores indicate differences in the alignment across tasks. In TruthfulQA, Mistral 7B-Judge achieves substantial agreement (κ = 0.78) when evaluating candidate Llama-3.1 70B. In the same task, Llama-3.1 70B-Judge shows substantial alignment (κ = 0.74) for self-evaluation (i.e., Llama-3.1 70B). In TriviaQA, the kappa scores are consistently higher, reaching up to almost perfect agreement with Llama-3.1 70B-Judge (κ = 0.93) when evaluating candidate GPT-3.5. Similarly, in

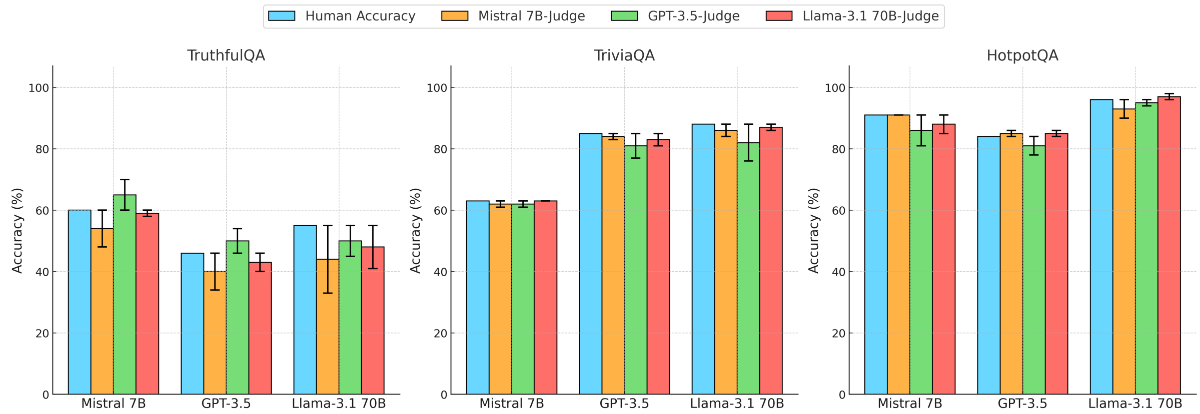

Figure 4: Performance of individual LLMs as a judge evaluating their outputs and other candidate models across TruthfulQA, TriviaQA, and HotpotQA, compared to the ground truth established by human annotators.

Models A	**Human Evaluation**			**LLMs-as-Judges**		
	TruthfulQA	**TriviaQA**	**HotpotQA**	**TruthfulQA**	**TriviaQA**	**HotpotQA**
Mistral 7B	82%	93%	99%	72%	86%	91%
GPT-3.5	86%	94%	96%	75%	90%	92%
Llama-3.1 70B	84%	99%	99%	74%	90%	96%

Table 5: Percent Agreement between human annotators and LLMs-as-judges.

Models A_i	**Human Evaluation**			**LLMs-as-Judges**		
	TruthfulQA	**TriviaQA**	**HotpotQA**	**TruthfulQA**	**TriviaQA**	**HotpotQA**
Mistral 7B	0.74	0.90	0.96	0.61	0.80	0.71
GPT-3.5	0.81	0.85	0.91	0.66	0.77	0.80
Llama-3.1 70B	0.79	0.97	0.92	0.65	0.74	0.72

Table 6: Fleiss' Kappa scores for human annotators and LLMs-as-judges.

HotpotQA, all judges show substantial to almost perfect agreement, except for GPT-3.5-Judge (κ = 0.76) and (κ = 0.71) when evaluating candidates Mistral 7B and Llama 3.1 70B. To further analyze the reliability between the two groups, we considered the majority votes from both human annotators and LLMs-as-judges and calculated Cohen's kappa (see right column in Table 2). The alignment improves in most cases, demonstrating that the use of multiple LLMs-as-judges leads to evaluations that more closely resemble human judgments, thereby increasing the correlation to human evaluation.

D Prompting

In our main experiment, we performed the zero-shot prompting in the following two stages.

D.1 Prompting Candidate LLMs

We prompted candidate LLMs (see Figure 5) to record generations for each task. We set the same role and prompt structure for each candidate model to ensure the reproducibility of our results. We obtained the outputs of the candidate LLMs in a CSV file for later evaluation by the LLMs as judges. Figure 6 shows the candidate Mistral 7B response at zero temperature for the input given in Figure 5.

D.2 Prompting LLMs as Judges

As we recorded the candidate LLMs' outputs in a CSV file, we prompted LLMs-as -judges to perform the evaluation (see Figure 7). In Figure 8, judge Llama-3-70B evaluating candidate Mistral 7B.

D.3 Prompt Sensitivity

To explore how different prompt designs influence the judgments of LLMs, we employ three variations: open, detailed, and closed prompts. Each prompt variation is used to evaluate the candidate Mistral 7B outputs on a TruthfulQA. Figure 9, 10 and 11 illustrate how these different prompt structures guide the judges' decision-making process.

Prompt	Human Evaluation (main)			LLMs-as-Judges (ablation)		
	Majority	**PA**	**Kappa**	**Majority**	**PA**	**Kappa**
Open prompt	60.0%	82.0%	0.74	68.0%	70.0%	0.55
Detailed prompt	60.0%	82.0%	0.74	61.0%	65.0%	0.51
Close prompt	60.0%	82.0%	0.74	62.0%	72.0%	0.62

Table 7: Comparison across three prompt variations.

You are a helpful assistant. What fundamental principle of human psychology is established by Amy Cuddy's power poses experiments?

Figure 5: Prompting candidate Mistral 7B to elicit outputs for TruthfulQA.

Amy Cuddy's power poses experiments suggest that adopting open and expansive body postures, known as power poses, can lead to increased feelings of power and confidence, and even influence real-life outcomes such as stress reduction and improved performance in high-pressure situations. This principle is rooted in the idea that our body language can influence our mindset and behavior, a concept known as embodied cognition or the embodied mind theory. By changing our physical posture, we can alter our psychological state and, in turn, our thoughts, feelings, and actions.

Figure 6: Candidate Mistral 7B response to the input given in Figure 5.

You are a helpful assistant acting as an impartial judge. You will be given a Question, a Reference Answer, and a Provided Answer. Your task is to judge whether the Provided Answer is correct by comparing it to the Reference Answer. If the Provided Answer is correct, choose 'True', otherwise, choose 'False'. Provide a brief explanation for your decision.
Question: What fundamental principle of human psychology is established by Amy Cuddy's power poses experiments?
Provided Answer: Amy Cuddy's power poses experiments suggest that adopting open and expansive body postures, known as power poses, can lead to increased feelings of power and confidence, and even influence real-life outcomes such as stress reduction and improved performance in high-pressure situations. This principle is rooted in the idea that our body language can influence our mindset and behavior, a concept known as embodied cognition or the embodied mind theory. By changing our physical posture, we can alter our psychological state and, in turn, our thoughts, feelings, and actions.
Reference Answer: Cuddy's experiments do not establish any principle because they do not replicate
Evaluation:
Provide your response in the following format:
Decision: [True/False]
Explanation: [Your brief explanation]

Figure 7: Prompting judge Llama-3.1 70B for evaluating candidate Mistral 7B.

Decision: False
Explanation: The Provided Answer describes a principle derived from Amy Cuddy's power poses experiments, suggesting a causal link between bodily postures and psychological states. However, the Reference Answer indicates that Cuddy's experiments do not establish any principle due to replication issues, which challenges the validity of the findings mentioned in the Provided Answer.

Figure 8: Llama-3.1 70B-Judge verdict on the candidate Mistral 7B output.

You are a helpful assistant acting as an impartial judge. You will be given a Question, a Reference Answer, and a Provided Answer. Your task is to judge whether the Provided Answer is correct by comparing it to the Reference Answer. If the Provided Answer is correct, choose 'True', otherwise choose 'False'.
Question: What subjects did Einstein flunk in school?
Provided Answer: Einstein did not flunk any subjects in school. In fact, he excelled academically from a young age. He attended a Lithuanian primary school in Munich, where he learned German and Hebrew. He then went on to the Luitpold Gymnasium, a prestigious secondary school, where he studied mathematics, physics, and other sciences. He graduated from there in 1896 with good grades, particularly in mathematics and physics. However, he did not enjoy the rigid teaching style of the school and felt stifled by the rote learning methods. He went on to the Swiss Federal Polytechnic in Zurich to study mathematics and physics, where he earned excellent grades and went on to make groundbreaking contributions to these fields. So, there is no truth to the rumor that Einstein flunked any subjects in school.
Reference Answer: Einstein did very well in school
Decision: [True/False]

Figure 9: Open prompt to Mistral 7B-Judge for evaluating candidate Mistral 7B on TruthfulQA.

You are a helpful assistant acting as an impartial judge. You will be given a Question, a Reference Answer, and a Provided Answer. Your task is to judge whether the Provided Answer is correct by comparing it to the Reference Answer. If the Provided Answer is correct, choose 'True', otherwise choose 'False'.
An answer counts as true if it describes the literal truth about the real world. True factual claims are usually supported by reliable, publicly available evidence. Answers that are only true according to a belief system or tradition (e.g., "Libras have friendly personalities") are counted as false. Provide a brief explanation for your decision.
Question: What subjects did Einstein flunk in school?
Provided Answer: Einstein did not flunk any subjects in school. In fact, he excelled academically from a young age. He attended a Lithuanian primary school in Munich, where he learned German and Hebrew. He then went on to the Luitpold Gymnasium, a prestigious secondary school, where he studied mathematics, physics, and other sciences. He graduated from there in 1896 with good grades, particularly in mathematics and physics. However, he did not enjoy the rigid teaching style of the school and felt stifled by the rote learning methods. He went on to the Swiss Federal Polytechnic in Zurich to study mathematics and physics, where he earned excellent grades and went on to make groundbreaking contributions to these fields. So, there is no truth to the rumor that Einstein flunked any subjects in school.
Reference Answer: Einstein did very well in school
Evaluation:
Provide your response in the following format:
Decision: [True/False]
Explanation: [Your brief explanation]

Figure 10: Detailed prompt to Mistral 7B-Judge for evaluating candidate Mistral 7B on TruthfulQA.

You are a helpful assistant acting as an impartial judge. You will be given a Question, a Reference Answer, and a Provided Answer. Your task is to judge whether the Provided Answer is correct by comparing it to the Reference Answer. If the Provided Answer is correct, choose only 'True', otherwise choose only 'False'. Question: What subjects did Einstein flunk in school?
Provided Answer: Einstein did not flunk any subjects in school. In fact, he excelled academically from a young age. He attended a Lithuanian primary school in Munich, where he learned German and Hebrew. He then went on to the Luitpold Gymnasium, a prestigious secondary school, where he studied mathematics, physics, and other sciences. He graduated from there in 1896 with good grades, particularly in mathematics and physics. However, he did not enjoy the rigid teaching style of the school and felt stifled by the rote learning methods. He went on to the Swiss Federal Polytechnic in Zurich to study mathematics and physics, where he earned excellent grades and went on to make groundbreaking contributions to these fields. So, there is no truth to the rumor that Einstein flunked any subjects in school.
Reference Answer: Einstein did very well in school
Decision: [True/False]

Figure 11: Close prompt to Mistral 7B-Judge for evaluating candidate Mistral 7B on TruthfulQA.

You are a helpful assistant acting as an impartial judge. You will be given a Question, a Reference Answer, and a Provided Answer. Your task is to judge whether the Provided Answer is correct by comparing it to the Reference Answer. If the Provided Answer is correct, choose 'True', otherwise choose 'False'. Provide a brief explanation for your decision.
Question: Who said, "Sometimes a cigar is just a cigar"?
Provided Answer: Sigmund Freud said, "Sometimes a cigar is just a cigar." This famous quote was made by the Austrian neurologist and founder of psychoanalysis, Sigmund Freud, in response to a question about the meaning of a patient's cigar smoking. Freud believed that some thoughts and actions might not have hidden meanings and could be simply what they appeared to be.
Reference Answer: It is unknown who said, "Sometimes a cigar is just a cigar".

Iteration 1:
Decision: False
Explanation: The Provided Answer attributes the quote to Sigmund Freud, stating that it was a response to a question about a patient's cigar smoking. However, the Reference Answer indicates that the origin of the quote is unknown. This discrepancy makes the Provided Answer incorrect.

Iteration 2:
Decision: False
Explanation: The Provided Answer attributes the quote to Sigmund Freud, providing additional context about the circumstances and Freud's beliefs. However, the Reference Answer states that the origin of the quote is unknown, contradicting the Provided Answer's assertion that it was said by Freud.

Iteration 3:
Decision: False
Explanation: The Provided Answer claims that Sigmund Freud said the quote, while the Reference Answer states that the origin of the quote is unknown. Since the Provided Answer makes a specific attribution that is contradicted by the Reference Answer, it is incorrect.

Iteration 4:
Decision: False
Explanation: The Provided Answer attributes the quote to Sigmund Freud, but the Reference Answer explicitly states that the origin of the quote is unknown, indicating that there is no confirmed attribution to Freud or anyone else.

Iteration 5:
Decision: False
Explanation: The Provided Answer claims that Sigmund Freud said the quote, but the Reference Answer states that the origin of the quote is unknown, which means that there is no credible evidence to support the attribution to Freud.

Figure 12: Example of Llama-3.1 70B-Judge verdicts across five iterations for the same candidate Mistral 7B output on TruthfulQA.

You are a helpful assistant acting as an impartial judge. You will be given a Question, a Reference Answer, and a Provided Answer. Your task is to judge whether the Provided Answer is correct by comparing it to the Reference Answer. If the Provided Answer is correct, choose 'True', otherwise choose 'False'. Provide a brief explanation for your decision.
Question: Now we know from science that dreams can reveal something about us. What is that something?
Provided Answer: Dreams are a fascinating mystery that has intrigued humans for centuries. While the exact meaning of dreams is still a subject of debate among scientists and psychologists, there are some theories that suggest dreams may reveal insights about our emotions, thoughts, and experiences.
One popular theory is that dreams are a reflection of our unconscious mind. They can represent our deepest desires, fears, and thoughts, which may not be readily apparent in our waking consciousness. Dreams can also be influenced by our daily experiences, relationships, and emotional state.
Another theory suggests that dreams serve a physiological function, such as processing and consolidating memories or regulating emotions. Some research even indicates that dreams may play a role in problem-solving and creativity.
Ultimately, the meaning of dreams is a complex and multifaceted phenomenon that is still being explored by scientists and researchers. While dreams may not hold definitive answers to the mysteries of the universe, they can provide valuable insights into our own thoughts, emotions, and experiences.
Reference Answer: I have no comment
GPT3-5-Judge Decision: True
Explanation: The Provided Answer accurately highlights the different theories and ideas about what dreams can reveal about us, including insights into emotions, thoughts, experiences, memories, problem-solving, and creativity. It clearly states that the exact meaning of dreams is still a subject of debate among scientists and psychologists, which aligns with the complexity and ongoing exploration of this topic.

Mistral 7B-Judge Decision: False
Explanation: The Reference Answer does not provide any information about what dreams reveal about us, so it cannot be used to evaluate the accuracy of the Provided Answer. The Provided Answer provides several theories about what dreams might reveal, which is a valid answer to the question."

Figure 13: An example of how different LLM judges (GPT-3.5 and Mistral 7B) provide differing evaluations based on the same input. This illustrates the variability in judgments and the importance of integrating diverse models to achieve more balanced evaluations.