Analyzing Uncertainty of LLM-as-a-Judge: Interval Evaluations with Conformal Prediction

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Abstract

LLM-as-a-judge has become a promising paradigm for using large language models (LLMs) to evaluate natural language generation (NLG), but the uncertainty of its evaluation remains underexplored. This lack of reliability may limit its deployment in many applications. This work presents the first framework to analyze the uncertainty by offering a prediction interval of LLM-based scoring via conformal prediction. Conformal prediction constructs continuous prediction intervals from a single evaluation run, and we design an ordinal boundary adjustment for discrete rating tasks. We also suggest a midpoint-based score within the interval as a low-bias alternative to raw model score and weighted average. We perform extensive experiments and analysis, which show that conformal prediction can provide valid prediction interval with coverage guarantees. We also explore the usefulness of interval midpoint and judge reprompting for better judgment.[1]

1 Introduction

Large language models (LLMs) have become powerful automatic evaluators for natural language generation (NLG) tasks, known as LLM-as-a-judge. Its consistency with human judgments results in strong performance with respect to metrics like ROUGE (Lin, 2004), BLEU (Papineni et al., 2002), and BERTScore (Zhang et al., 2020). Besides, LLM judges can flexibly adapt to diverse evaluation criteria and provide scalable, cost-effective assessments compared to expert annotation (Gao et al., 2024; Gu et al., 2025). These advantages make the LLM-as-a-judge useful in various scenarios, such as clinical radiology (Chaves et al., 2024), rumor detection (Hong et al., 2025), cyberattack detection (Yong et al., 2025) and wildlife trafficking identification (Barbosa et al., 2025).

However, a single evaluation from a LLM judge might be biased (Wu and Aji, 2023; Li et al., 2024c) and uncertain due to inherent randomness (Schroeder and Wood-Doughty, 2024), thus undermining its reliability in scenarios like healthcare (Chung et al., 2025) and finance (Kamble et al., 2025). Though a LLM judge can express its confidence with well-designed prompt or via finetuning (Xu et al., 2024a; Liu et al., 2024; Taubenfeld et al., 2025), it may still suffer from overconfidence (Xiong et al., 2024) or dishonesty (Li et al., 2024e). We ask: *How can a LLM judge provide reliable evaluation given the user request?*

Conformal prediction (Vovk et al., 2005) is a promising way to quantify the uncertainty of an LLM judge (Ye et al., 2024). It outputs a prediction interval (or set for classification) to a model output with three key advantages. First, conformal prediction is a distribution-free uncertainty quantification method, which is suitable for black-box models like LLMs due to unknown input data distribution for most (if not all) LLMs. Second, it can provide post-hoc uncertainty quantification using only a calibration step based on LLM outputs. Third, the prediction interval given by conformal prediction enjoys statistically guaranteed coverage, i.e., how likely the ground truth falls within the interval, as long as the data is exchangeable.

In this paper, we comprehensively evaluate nine[2] conformal prediction methods in quantifying the uncertainty of a LLM judge in rating-based evaluation tasks, each of which constructs a prediction interval for a rating output by the LLM judge. For each conformal prediction method, we evaluate its efficiency (i.e., average width of prediction intervals) and coverage (i.e., the probability that ground truths fall within prediction intervals). Furthermore, to adapt to the ordinal and discrete nature in organic rating-based evaluation, we propose boundary adjustment that adjusts the endpoints of prediction

[1] Our code and data are available at https://github.com/BruceSheng1202/Analyzing-Uncertainty-of-LLM-as-a-Judge.

[2] Seven regression-type and two ordinal-type methods.

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interval to be aligned with the rating scales. We prove that the boundary adjustment yields an interval suitable to the ordinal setting with provable non-decreasing coverage. From our comprehensive analysis, we demonstrate that the quality of prediction interval attributes to design choices of the LLM judge (e.g., which LLM to use as the judge, which prompting strategy for evaluation) as well as the size of calibration data during calibration. Finally, we show that the midpoint of the prediction interval provides better estimate to the ground truth to further assist better decision-making, while reprompting the LLM judge with prediction interval might not improve the judgement. Our analysis advocate for a shift from direct scoring to uncertainty-aware evaluations, offering references for more reliable evaluation and better decision-making.

In summary, our contributions are

- To our knowledge, we are the first to analyze the uncertainty of LLM-as-a-judge using conformal prediction in rating-based evaluation.
- We design boundary adjustment to improve the efficiency empirically without compromising the coverage. The interval midpoints suggest better alignment to human evaluation.
- We analyze factors affecting the interval quality, including the LLM-as-a-judge framework itself, the choice of LLM in the framework, and the size of calibration in conformal prediction, and offer practical insights or recommended choices.

2 Related Work

Uncertainty Quantification for LLM-as-a-Judge. Uncertainty quantification for LLM-as-a-judge is an important yet less explored area. Wagner et al. (2024) prompt the judge to justify each rating option as if it were correct and then construct a confusion matrix from token-level probabilities of these assessments to derive confidence scores. Xie et al. (2025) use token probabilities to estimate the confidence of judgments, and demonstrate that such measures exhibit bias and instability through extensive experiments. Similar conclusions are also found when applying other two common paradigms: (1) prompting LLMs to self-report confidence (Yona et al., 2024; Xu et al., 2024a), which can suffer from overconfidence (Xiong et al., 2024) or dishonesty (Li et al., 2024e), and (2) consistency-based approaches that rely on multiple generations (Tian et al., 2023; Xiong et al., 2024), which, like the confusion matrix-based method, are computationally expensive. To our best knowledge, Jung et al. (2024) is the most relevant work to us, which applies conformalized risk control (Angelopoulos et al., 2022b) to ensure agreement with human preferences in pairwise response comparison (Zhou et al., 2024; Li et al., 2024b,d; Zhang et al., 2025; van den Burg et al., 2025). In contrast, we focus on using conformal prediction to quantify uncertainty in rating tasks instead of pairwise preference modeling.

Conformal Prediction for LLMs. Conformal prediction (Vovk et al., 2005) has drawn interest for uncertainty quantification in LLMs (Ye et al., 2024; Campos et al., 2024a) due to its distribution-free and post-hoc nature with provable statistical guarantee. Owing to these advantages, recent works primarily apply conformal prediction to classification tasks, such as multiple-choice question answering (Kumar et al., 2023; Zhang et al., 2024; Su et al., 2024; Vishwakarma et al., 2025) and response selection for factual consistency (Quach et al., 2024; Mohri and Hashimoto, 2024; Wang et al., 2024; Kladny et al., 2025). These studies typically focus on ensuring that the correct answer is included in a unordered prediction set. Different from these works, we focus on providing prediction intervals that reflect the variability in LLM judgments in rating tasks, which has ordinal preference.

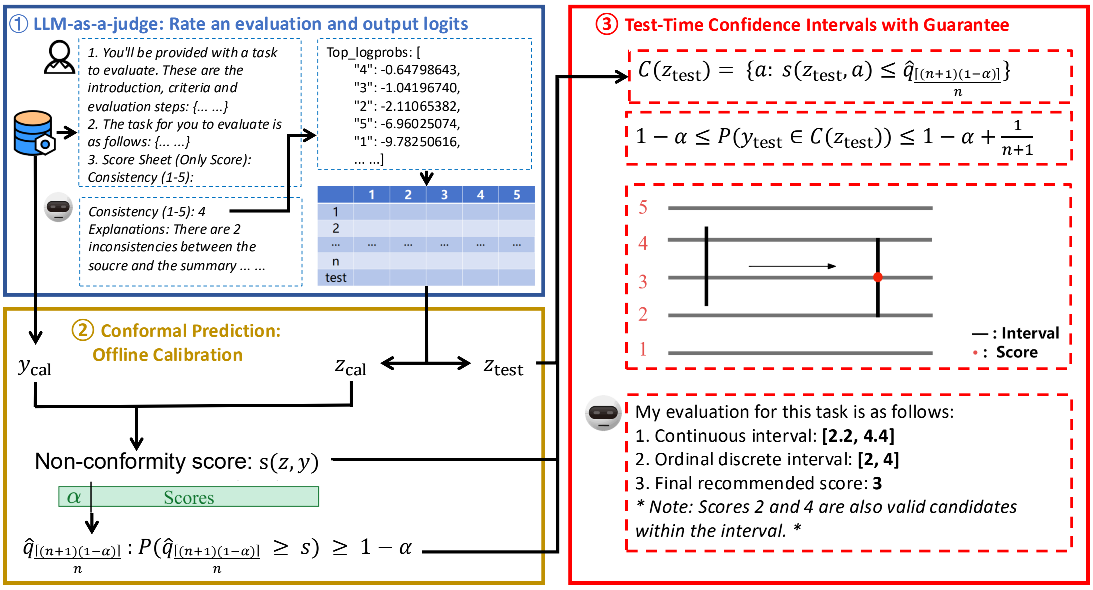
3 Analyzing Uncertainty of LLM Judges

3.1 Preliminaries

LLM-as-a-Judge. LLMs have been widely adopted as evaluators to score NLG tasks recently, known as LLM-as-a-judge. It commonly yields a predicted score y_0 on a Likert scale (Nemoto and Beglar, 2014). Following G-Eval (Liu et al., 2023), given a prompt p and a generated text x to be evaluated, an LLM judge M is expected to produce a response

$$M(p, x) = (z, y_0), \tag{1}$$

where z is the token logits, and y_0 is a scalar score in a predefined scale, indicating the quality of generated text given by LLM judge. For rating-based evaluations, we extract the logits of certain tokens (e.g., 1, 2, 3, 4, 5 if in a Likert scale) at the position of the rating token only. There are also other evaluation paradigms that a rating judge can help


① LLM-as-a-judge: Rate an evaluation and output logits
② Conformal Prediction: Offline Calibration
③ Test-Time Confidence Intervals with Guarantee
1
2
3
4
5
1
2
...
n
test
y_{cal}
z_{cal}
z_{test}
Non-conformity score: $s(z, y)$
α
Scores
$\hat{q}_{\frac{\lceil (n+1)(1-\alpha) \rceil}{n}} : P(\hat{q}_{\frac{\lceil (n+1)(1-\alpha) \rceil}{n}} \geq s) \geq 1-\alpha$
$C(z_{\text{test}}) = \{a\text{: } s(z_{\text{test}}, a) \leq \hat{q}_{\frac{\lceil (n+1)(1-\alpha) \rceil}{n}}\}$
$1-\alpha \leq P(y_{\text{test}} \in C(z_{\text{test}})) \leq 1-\alpha+\frac{1}{n+1}$
5
4
3
2
1
— : Interval
• : Score

1. You'll be provided with a task to evaluate. These are the introduction, criteria and evaluation steps: {... ...}
2. The task for you to evaluate is as follows: {... ...}
3. Score Sheet (Only Score): Consistency (1-5):

Consistency (1-5): 4
Explanations: There are 2 inconsistencies between the soucre and the summary ... ...

```
Top_logprobs: [
    "4": -0.64798643,
    "3": -1.04196740,
    "2": -2.11065382,
    "5": -6.96025074,
    "1": -9.78250616,
    ... ...]
```

My evaluation for this task is as follows:
1. Continuous interval: **[2.2, 4.4]**
2. Ordinal discrete interval: **[2, 4]**
3. Final recommended score: **3**
** Note: Scores 2 and 4 are also valid candidates within the interval. **

Figure 1: Overview of quantifying the uncertainty in rating-based evaluation. We apply conformal prediction to construct the prediction interval and set the width of the prediction interval as the uncertainty.

with (Gu et al., 2025), such as pairwise comparison or ranking, in which candidate outputs are first scored by the LLM judge and then compared or ordered based on those scores (Wang et al., 2025; Wei et al., 2025).

Conformal Prediction. Conformal prediction (Vovk et al., 2005) is a model-agnostic uncertainty quantification method. It constructs a prediction interval (or a prediction set for classification) with coverage guarantee, i.e., how likely the ground truth will fall within the prediction interval/set. Two notable advantages of conformal prediction are its post-hoc nature, i.e., free of training or prompting the judge model, and distribution-free nature, i.e., without requiring knowledge about underlying data distribution. In our work, we adopt split conformal prediction (Vovk et al., 2005), which quantifies the uncertainty with a held-out calibration set. A non-conformity score function $s(z, y)$ is computed for each point in the calibration set, to measure how "unusual" a prediction $\hat{y}$ is to a ground truth y. For regression tasks, the non-conformity score is often defined as

$$s(z, y) = |\hat{y} - y|. \qquad (2)$$

where $\hat{y} = f(z)$ is a score predicted from the input z using a function f. Then, given a user-desired miscoverage rate α, the $\frac{\lceil (n+1)(1-\alpha) \rceil}{n}$-quantile $\hat{q}$ of these scores can be used to construct the prediction interval $\mathcal{C}(z_{\text{test}}, \hat{y}_{\text{test}})$ for the prediction $\hat{y}_{\text{test}}$ of any test point z_{test} as

$$\mathcal{C}(z_{\text{test}}, \hat{y}_{\text{test}}) = [\hat{y}_{\text{test}} - \hat{q},\ \hat{y}_{\text{test}} + \hat{q}], \qquad (3)$$

or equivalently

$$\mathcal{C}(z_{\text{test}}, \hat{y}_{\text{test}}) = \{a : s(z_{\text{test}}, a) \leq \hat{q}\}. \qquad (4)$$

Statistically, it is proven that such a prediction interval enjoys the following coverage guarantee (Angelopoulos and Bates, 2022)

$$1-\alpha \leq \mathbb{P}(y_{\text{test}} \in \mathcal{C}(z_{\text{test}}, \hat{y}_{\text{test}})) \leq 1-\alpha+\frac{1}{n+1}, \qquad (5)$$

as long as the calibration set and test set are exchangeable, i.e., the joint distribution remain the same after any permutations on these two sets.

3.2 From Logits to Intervals

In this paper, we focus on quantifying the uncertainty of LLM-as-a-judge using conformal prediction in discrete rating-based evaluations (e.g., in Likert scale). An overview of the workflow is presented in Figure 1.

Extract Logits as Feature. Our framework mainly targets for uncertainty estimation in a discrete, Likert-scale (1 – 5) rating-based evaluation. An example of such rating-based evaluation is given in Figure 1. Specifically, an LLM judge, prompted with a chain-of-thought (CoT) instruction that specifies an output format, generates a response containing its rating. Prompts that we used are listed in Appendix A.13)

To obtain the $\frac{\lceil (n+1)(1-\alpha) \rceil}{n}$-quantile of the non-conformity scores of the ratings, we extract the token logits corresponding to Likert-scale scores as features for quantile estimation. However, LLMs may not always respond in a fixed format, making extraction of the rating token logit challenging. Thus, we resort to a rule-based strategy to locate the rating token at the most frequent position of the rating. After locating the rating token (e.g., 4 in Figure 1), we extract the log probabilities of all potential rating tokens (e.g., 1 – 5). Additionally, to ensure semantic consistency, we aggregate the probabilities of tokens with equivalent meanings (e.g., “two” vs. 2). As a result, we obtain a K-dimensional feature vector z representing the logits associated with each candidate rating token in $\{1, 2, \ldots, K\}$[3] as the input for conformal prediction (z, y). Here we assume the logits for each prompt-text sample to be exchangeable, following prior works (Kumar et al., 2023; Su et al., 2024; Quach et al., 2024).

Prediction Interval Estimation. To date, there has been a variety of conformal prediction methods (Angelopoulos and Bates, 2022; Fontana et al., 2023; Campos et al., 2024b). In our analysis, we choose a diverse set of nine conformal prediction methods that construct prediction interval rather than prediction set. Moreover, we observe that token logits exhibit strong heteroscedasticity (see more analysis in Appendix A.2). Thus, we include conformalized quantile regression (CQR) (Romano et al., 2019) and its variants, including asymmetric CQR, CHR (Sesia and Romano, 2021) that uses histogram-based quantile estimator, LVD (Lin et al., 2021) that uses kernel regression based quantile estimator, two boosted conformal prediction methods (Xie et al., 2024) (i.e., Boosted CQR and Boosted LCP) and R2CCP (Guha et al., 2024). Other than the regression-based approaches, rating-based evaluation can also be viewed as a ordinal classification task due to the ordinal nature of ratings. Thus, we also consider two conformal prediction methods designed for ordinal classification, namely Ordinal APS (Lu et al., 2022) and Ordinal Risk Control (Xu et al., 2024b). More details about these methods, including non-conformity score computation, interval construction and implementation details, are discussed in Appendix A.3. Note that, for ordinal classification-based conformal prediction methods, we view the token probabilities (i.e., token logits followed by a softmax operation) as a proxy of classification probabilities that classify the prompt and texts to be evaluated into the corresponding rating label. Consequently, we use token probabilities as input. However, token probabilities are well known to have multicollinearity, which makes them unsuitable for regression-based approaches. Thus, we only use token probabilities as the input for ordinal classification-based approaches, while use token logits directly for regression-based approaches.

3.3 Boundary Adjustment

Due to the ordinal and discrete nature of ratings, a continuous interval whose upper and lower bounds are continuous numeric values might not have exact meaning. Thus, we further apply a boundary adjustment strategy to transform the continuous interval to an ordinal interval whose upper and lower bounds align with the potential rating labels.

Specifically, boundary adjustment is essentially redefining the non-conformity score function as

$$s'(z, y) = s(z, y') = \begin{cases} s(z, \lceil y \rceil) & \text{if } y \leq \lfloor \hat{y} \rfloor, \\ s(z, y) & \text{otherwise,} \\ s(z, \lfloor y \rfloor) & \text{if } y \geq \lceil \hat{y} \rceil. \end{cases} \tag{6}$$

Because all potential labels y' are integers in rating evaluation, this new function ensures that the scores are consistent on calibration set. However, when constructing the prediction interval , it will transform the interval $\mathcal{C}(z_{\text{test}})$ in Equation (4) to

$$\{a : s'(z_{\text{test}}, a) \leq \hat{q}\} = [l, u] \rightarrow [l', u'] , \tag{7}$$

where $l' = \lceil l \rceil$ and $u' = \lfloor u \rfloor$.

We shrink the boundaries to integer labels closest to the original continuous-valued boundaries by cutting excessive areas, because the excessive areas cover no potential labels. Thus, this shrinking adjustment will have no influence to its coverage. On the other hand, we can also expand an interval to mitigate the marginal miscoverage of the ground-truth labels or limited calibration size. For example, assuming the interval $[2.2, 3.9]$ only covers one possible rating 3 but can be expanded to $[2, 4]$, a miscoverage can be avoided if the ground truth is either 2 or 4.

[3] We use $K = 5$ for the standard Likert scale or GPA-like settings, but K can be adapted to other granularities (e.g., 10) depending on the scale.

Theorem 1 shows the non-decreasing coverage after boundary adjustment. We defer its proof to Appendix A.1.

Theorem 1 (Non-decreasing Coverage After Boundary Adjustment)**.** *Based on coverage guarantee in Equation* (5)*, we transform the nonconformity score function* $s(z, y)$ *by Equation* (6) *and adjust an continuous interval by Equation* (7)*. Then, if the adjustment is performed by shrinking (i.e.,* $l' = \lceil l \rceil$*,* $u' = \lfloor u \rfloor$*, and* $\mathcal{C}'(z_{\text{test}}) = [l', u']$*), the coverage preserves:*

$$\mathbb{P}\left(Y_{\text{test}} \in \mathcal{C}'\left(z_{\text{test}}\right)\right) \geq 1 - \alpha. \tag{8}$$

If at least one boundary is expanded (i.e., $l' = \lfloor l \rfloor$ *or* $u' = \lceil u \rceil$*), the coverage increases:*

$$\mathbb{P}\left(Y_{\text{test}} \in \mathcal{C}'(z_{\text{test}})\right) > 1 - \alpha. \tag{9}$$

Though we assume all ratings are integers in Equation (6), ratings with discrete granularities can all be applicable. For example, GPA-scale scores can be mapped to a 1–13 Likert scale by linear transformation (e.g. $1.33 \times 3 - 2$). Then a boundary adjustment from $[4.6, 4.9]$ to $[4.67, 5]$ is equivalent to rounding $[11.8, 12.7]$ to $[12, 13]$.

3.4 Midpoints as Calibrated Scores

To make better use of the prediction interval for decision making, we seek to obtain a more accurate estimate of ground truth from the interval. One simple and intuitive way is to use the midpoint of the prediction interval as an alternative estimate. Due to the unknown distribution of the ground truth rating in a prediction interval, selecting the midpoint has several benefits. If the distribution can be naively assumed to be uniform or at least symmetric, the midpoint would be the best linear unbiased estimator of the true label. Even if biased, the midpoint is still the minimum-variance estimator of the ground truth rating given the interval. More intuitively, midpoint is a score evaluated in a shorter interval (i.e., the prediction interval) rather than the entire range of rating, thus should be more accurate than the primitive score given by the LLM judge.

4 Experiments

4.1 Experimental Setting

Datasets. We run experiments on evaluation benchmarks in text summarization, dialogue summarization and reasoning. For summarization, we use SummEval (Fabbri et al., 2021) (1,600 samples) and DialSumm (Gao and Wan, 2022) (1,400 samples), each annotated by three human raters using Likert-scale scores across four dimensions (i.e., consistency, coherence, fluency, relevance). The average of the three ratings is used as the ground-truth label on GPA scale. For reasoning, we use the annotations of overall quality on Likert scale for CosmosQA (Li et al., 2023), DROP (Dua et al., 2019), e-SNLI (Camburu et al., 2018) and GSM8K (Cobbe et al., 2021) in ROSCOE (Golovneva et al., 2023), each with around 200 samples on Likert scale.

LLM-based Evaluation. We primarily adopt G-Eval (Liu et al., 2023) as our judge framework with a chain-of-thought (CoT) prompt. For reasoning tasks, we additionally use SocREval (He et al., 2024). We provide the prompts used for experiments in Appendix A.13. Evaluations are mainly conducted using GPT-4o mini (2024-07-18), DeepSeek-R1-Distill-Qwen-32B (DeepSeek-AI et al., 2025) and Qwen2.5-72B-Instruct (Qwen et al., 2025) as LLM judges, all of which provide token-level logits. Though we choose these LLMs mainly due to budget constraints and limitations on computing resources, all selected LLMs are widely used and show strong performance in both summarization and reasoning tasks. In Appendix A.5, we provide more detailed justifications on the judge model selection and the comparison between GPT-4o mini and its larger variant GPT-4o in text summarization.

Conformal Prediction Methods. In our experiments, we compare seven regression-based conformal prediction methods and two ordinal classification-based methods. For regression-based approaches, we use CQR (Romano et al., 2019), Asymmetric CQR (Sesia and Candès, 2019), CHR (Sesia and Romano, 2021), LVD (Lin et al., 2021), and two boosted methods (Xie et al., 2024) namely Boosted CQR and Boosted LCP; for ordinal classification-based methods, we consider Ordinal APS (Lu et al., 2022) and Ordinal Risk Control (Xu et al., 2024b). Ordinal classification-based methods are only evaluated after boundary adjustment. More introduction of each method is provided in Appendix A.3. For each method, we split of dataset into 50% calibration set and 50% test set with 30 random seeds (1 – 30) and report the mean of interval width and coverage rate.

Table 1: Interval width and coverage on SummEval evaluated by G-Eval and ROSCOE evaluated by SocREval before boundary adjustment. We mark coverage $< 85\%$ with gray text, coverage between 85% – 90% with underline and coverage with the smallest interval width $\geq 90\%$ in **bold**.

Method	SummEval Evaluated with G-Eval				ROSCOE Evaluated with SocREval			
	Consistency	Coherence	Fluency	Relevance	CosmosQA	DROP	e-SNLI	GSM8K
GPT-4o mini								
CQR	1.15 / 94.16%	**2.87 / 93.15%**	1.44 / 92.92%	**2.09 / 90.92%**	**3.53 / 95.27%**	**3.82/96.70%**	3.04 / 96.62%	**3.53 / 95.67%**
Asym CQR	1.25 / 94.97%	2.91 / 93.76%	1.60 / 93.75%	2.13 / 91.42%	3.90 / 98.71%	3.91 / 98.60%	**2.87/ 96.67%**	3.89 / 98.80%
CHR	0.67 / 88.99%	2.41 / 82.96%	0.94 / 88.86%	1.74 / 82.62%	2.54 / 73.06%	1.86 / 68.92%	1.36 / 72.24%	1.98 / 78.67%
LVD	1.01 / 92.35%	2.73 / 89.76%	**1.11 / 90.59%**	2.02 / 89.55%	3.10 / 83.95%	2.49 / 83.05%	2.17 / 86.18%	3.08 / 89.57%
Boosted CQR	1.01 / 87.75%	2.73 / 87.80%	1.54 / 88.68%	2.00 / 87.42%	3.15 / 80.07%	2.63 / 78.57%	1.82 / 80.26%	3.08 / 82.50%
Boosted LCP	0.76 / 89.22%	2.67 / 87.34%	0.92 / 89.18%	1.91 / 87.19%	3.60 / 83.91%	2.92 / 85.40%	1.88 / 81.23%	3.36 / 85.93%
R2CCP	**0.69 / 90.88%**	2.62 / 89.63%	0.92 / 89.36%	1.97 / 89.70%	2.96 / 85.85%	2.43 / 84.73%	1.75 / 84.02%	2.15 / 85.07%
DeepSeek-R1-Distill-Qwen-32B								
CQR	1.16 / 93.88%	2.67 / 92.50%	1.31 / 93.01%	2.13 / 91.05%	**3.48 / 96.70%**	**3.83 / 96.35%**	2.97 / 96.36%	3.46 / 95.60%
Asym CQR	1.30 / 95.13%	2.72 / 92.86%	1.49 / 94.52%	2.21 / 92.06%	3.84 / 99.08%	3.95 / 99.27%	2.86 / 96.05%	3.85 / 98.43%
CHR	0.82 / 91.17%	2.23 / 87.07%	0.90 / 89.24%	1.87 / 86.38%	2.66 / 76.50%	1.95 / 78.06%	1.38 / 71.97%	2.01 / 81.60%
LVD	0.97 / 92.93%	2.43 / 91.10%	1.00 / 91.10%	**2.04 / 90.14%**	3.25 / 88.10%	2.62 / 88.06%	**2.24 / 90.96%**	**3.02/90.63%**
Boosted CQR	1.10 / 89.30%	2.36 / 88.98%	1.16 / 89.46%	2.00 / 88.98%	3.17 / 82.72%	2.47 / 81.11%	1.79 / 80.96%	2.94 / 79.83%
Boosted LCP	0.77 / 89.20%	2.32 / 86.70%	0.93 / 89.10%	1.91 / 86.89%	3.48 / 81.60%	2.79 / 85.46%	1.84 / 80.61%	3.43 / 85.23%
R2CCP	**0.69 / 90.44%**	**2.30 / 90.12%**	**0.89 / 90.09%**	2.00 / 89.84%	2.94 / 86.97%	2.29 / 86.35%	1.85 / 87.87%	1.88 / 85.33%
Qwen2.5-72B-Instruct								
CQR	0.98 / 93.10%	2.73 / 92.25%	1.44 / 93.73%	2.11 / 91.30%	**3.37 / 94.80%**	3.79 / 97.02%	3.01 / 97.37%	3.35 / 95.33%
Asym CQR	1.11 / 94.47%	2.80 / 93.13%	1.63 / 94.79%	2.17 / 92.21%	3.86 / 99.01%	3.89 / 98.67%	**2.77 / 96.84%**	3.87 / 98.97%
CHR	0.61 / 89.04%	2.14 / 80.93%	0.98 / 88.93%	1.61 / 79.61%	2.44 / 72.65%	2.08 / 75.87%	1.22 / 69.69%	1.81 / 77.50%
LVD	0.85 / 92.82%	2.55 / 90.49%	1.09 / 90.94%	1.94 / 89.27%	3.05 / 84.29%	**2.67 / 90.57%**	1.91 / 85.96%	**2.83/ 90.13%**
Boosted CQR	0.80 / 88.28%	2.46 / 87.82%	1.24 / 89.22%	1.88 / 87.17%	3.05 / 79.08%	2.56 / 81.17%	1.51 / 77.11%	2.81 / 80.67%
Boosted LCP	0.67 / 88.81%	2.43 / 86.92%	0.94 / 89.26%	1.86 / 87.51%	3.46 / 80.41%	2.81 / 85.75%	1.74 / 77.50%	3.38 / 86.23%
R2CCP	**0.61 / 90.73%**	2.44 / 89.54%	**0.95 / 90.18%**	**1.98 / 90.45%**	2.90 / 85.34%	2.39 / 86.25%	1.59 / 84.50%	2.00 / 86.73%

4.2 Continuous Intervals Indicate Uncertainty

Table 1 presents the interval width and coverage rate for each conformal prediction methods on SummEval evaluated by G-Eval and on ROSCOE evaluted SocREval. Additional results on DialSumm are presented in Table 12. From these results, most conformal predictors consistently output prediction intervals with coverage close to the 90% in summarization tasks, indicating that LLM judges are confident when evaluating summarization tasks, especially on fluency. However, most methods fail to achieve 90% (or close to 90%) coverage rate in reasoning tasks, and the interval widths are high in a few cases where 90% coverage is achieved. One possible reason is that ROSCOE has much fewer samples, resulting in poor calibration.

4.3 All Coverages Improve after Adjustment

Table 2 presents the interval width and coverage rate for each conformal prediction methods on SummEval evaluated by G-Eval and on ROSCOE evaluted SocREval. Additional results on DialSumm are presented in Table 13. From these results, we observe that all coverage rates are improved after boundary adjustment. In most settings, prediction intervals after boundary adjustment are close to or above the desired 90% coverage rate across all datasets and judge frameworks. The effectiveness of boundary adjustment is brought by the fact that continuous intervals before boundary adjustment is sensitive to the variability of quantile estimation during calibration in conformal prediction.

Moreover, improvements to coverage brought by boundary adjustment are empirically robust across different datasets, conformal prediction methods, LLM judges and judge frameworks. For example, coverage rates are consistently higher than 90% in SummEval and DialSumm, where coverage rates before boundary adjustment are in the range of 83%˘88%. A even more significant example is LVD, which, when applied to e-SNLI using Qwen2.5-72B-Instruct under SocREval, shows an increase from 85.96% to 95.53%.

4.4 Recommended Choice from Reliable LLM-as-a-Judge

Our experiments show that DeepSeek-R1-Distill-Qwen-32B provides the most consistent coverage (surpassing Qwen2.5-72B-Instruct and GPT-4o mini), while Qwen2.5-72B-Instruct typically yields the narrowest intervals. Under the G-Eval framework, we observe higher coverage (at the cost of slightly wider intervals) than SocREval. Regard-

Table 2: Interval width and coverage on SummEval evaluated by G-Eval and ROSCOE evaluated by SocREval after boundary adjustment. We mark coverage $< 85\%$ with gray text, coverage between 85% – 90% with underline and coverage $\geq 90\%$ with the smallest interval width in **bold**.

Method	**SummEval Evaluated with G-Eval**				**ROSCOE Evaluated with SocREval**			
	Consistency	**Coherence**	**Fluency**	**Relevance**	**CosmosQA**	**DROP**	**e-SNLI**	**GSM8K**
GPT-4o mini								
CQR	1.15 / 95.45%	2.87 / 94.94%	1.44 / 93.80%	2.09 / 93.56%	3.53 / 95.34%	3.82 / 97.05%	3.04 / 96.89%	3.53 / 95.67%
Asym CQR	1.25 / 96.02%	2.90 / 95.41%	1.60 / 94.57%	2.14 / 94.14%	3.90 / 98.84%	3.91 / 98.73%	2.87 / 96.89%	3.89 / 98.80%
CHR	0.70 / 91.79%	2.41 / 87.78%	0.94 / 90.60%	1.74 / 88.10%	2.56 / 82.45%	1.87 / 78.86%	1.34 / 83.46%	1.94 / 83.23%
LVD	1.01 / 94.11%	2.73 / 93.72%	1.12 / 92.70%	2.03 / 93.82%	**3.13 / 91.53%**	**2.52 / 90.22%**	2.17 / 94.82%	**3.09/93.37%**
Boosted CQR	0.99 / 92.81%	2.73 / 93.02%	1.54 / 94.38%	2.00 / 92.93%	3.20 / 93.40%	2.63 / 89.65%	1.82 / 92.15%	3.09 / 91.17%
Boosted LCP	0.74 / 91.90%	2.68 / 93.53%	**0.90 / 90.88%**	**1.91 / 92.70%**	3.60 / 95.48%	3.01 / 91.27%	1.90 / 91.80%	3.26 / 92.17%
R2CCP	**0.68 / 92.15%**	**2.62 / 92.81%**	0.91 / 90.99%	1.97 / 93.38%	2.93 / 89.46%	2.41 / 89.21%	**1.71 / 90.11%**	2.09 / 86.93%
OrdinalAPS	2.28 / 71.48%	1.88 / 64.84%	1.78 / 13.65%	2.36 / 87.94%	0.73 / 47.52%	0.83 / 55.08%	0.72 / 52.76%	0.58 / 73.90%
OrdinalRC	2.41 / 75.19%	2.02 / 67.38%	1.93 / 14.58%	2.51 / 90.30%	0.82 / 49.46%	0.91 / 57.11%	0.80 / 54.61%	0.60 / 74.43%
DeepSeek-R1-Distill-Qwen-32B								
CQR	1.15 / 95.02%	2.67 / 94.34%	1.32 / 94.44%	2.13 / 93.67%	3.48 / 96.80%	3.82 / 96.54%	2.99 / 96.80%	3.46 / 95.63%
Asym CQR	1.31 / 95.99%	2.72 / 94.83%	1.49 / 95.57%	2.21 / 94.53%	3.84 / 99.08%	3.95 / 99.27%	2.88 / 96.45%	3.84 / 98.47%
CHR	0.87 / 93.96%	**2.23 / 91.42%**	0.91 / 91.98%	**1.87 / 90.84%**	2.69 / 86.80%	1.97 / 85.90%	1.39 / 85.96%	2.01 / 86.60%
LVD	0.97 / 95.01%	2.44 / 94.58%	1.00 / 93.21%	2.04 / 94.12%	3.28 / 95.27%	2.67 / 93.75%	2.24 / 96.36%	3.03 / 94.40%
Boosted CQR	1.08 / 93.55%	2.37 / 93.96%	1.15 / 93.48%	2.01 / 93.72%	3.20 / 95.71%	**2.52 / 93.30%**	**1.79 / 93.25%**	2.94 / 92.23%
Boosted LCP	0.76 / 92.03%	2.32 / 92.37%	0.93 / 91.34%	1.92 / 92.81%	3.46 / 95.95%	2.80 / 91.94%	1.87 / 92.89%	3.36 / 93.63%
R2CCP	**0.68 / 91.57%**	2.30 / 93.22%	**0.89 / 91.80%**	1.99 / 92.96%	**2.91 / 90.58%**	2.25 / 89.97%	**1.80 / 92.35%**	1.82 / 86.93%
OrdinalAPS	2.51 / 90.06%	2.52 / 90.64	3.76 / 91.08%	2.13 / 89.98%	1.32 / 60.00%	1.26 / 78.22%	1.46 / 87.85%	1.50 / 85.67%
OrdinalRC	2.54 / 90.11%	2.56 / 91.18%	3.73 / 89.53%	2.14 / 90.07%	1.44 / 62.35%	1.33 / 78.22%	1.52 / 88.33%	1.55 / 86.07%
Qwen2.5-72B-Instruct								
CQR	0.98 / 94.35%	2.72 / 94.18%	1.45 / 94.79%	2.10 / 94.02%	3.36 / 95.07%	3.79 / 97.08%	3.01 / 97.68%	3.34 / 95.33%
Asym CQR	1.10 / 95.47%	2.79 / 94.70%	1.64 / 95.63%	2.17 / 94.85%	3.85 / 99.18%	3.89 / 98.67%	2.77 / 97.06%	3.87 / 98.97%
CHR	0.66 / 92.21%	2.14 / 86.10%	0.98 / 91.16%	1.61 / 85.78%	2.49 / 82.14%	2.05 / 82.89%	1.18 / 84.56%	1.79 / 85.27%
LVD	0.85 / 95.11%	2.56 / 94.05%	1.09 / 93.45%	1.95 / 93.86%	**3.07 / 92.01%**	2.67 / 93.87%	1.91 / 95.53%	2.87 / 93.43%
Boosted CQR	0.81 / 92.36%	2.47 / 93.06%	1.25 / 93.66%	1.88 / 92.81%	3.10 / 94.01%	2.56 / 90.79%	**1.49 / 92.11%**	2.82 / 92.03%
Boosted LCP	0.65 / 91.26%	2.44 / 92.26%	0.93 / 91.20%	**1.86 / 92.57%**	3.40 / 94.90%	2.84 / 92.41%	1.79 / 91.84%	3.33 / 92.90%
R2CCP	**0.59 / 91.83%**	**2.43 / 92.78%**	**0.95 / 92.12%**	1.98 / 93.72%	2.88 / 89.29%	**2.34 / 90.00%**	1.55 / 90.20%	1.96 / 88.57%
OrdinalAPS	2.86 / 90.18%	3.01 / 90.59%	3.05 / 45.43%	2.75 / 90.29%	0.71 / 55.99%	0.25 / 56.83%	0.67 / 77.68%	0.46 / 70.87%
OrdinalRC	2.85 / 90.00%	2.96 / 89.35%	3.21 / 53.31%	2.75 / 90.14%	0.75 / 57.28%	0.29 / 56.83%	0.80 / 79.74%	0.49 / 71.37%

ing the choice of conformal prediction methods, R2CCP strikes the best balance between coverage and width; Boosted LCP performs comparably but less efficiently; And LVD delivers very tight intervals without sacrificing coverage. In practice, our experiments suggest that DeepSeek-R1-Distill-Qwen-32B + G-Eval + LVD might be the best option for potentially high-stake applications, whereas Qwen2.5-72B-Instruct + R2CCP + SocREval could yield the most efficient prediction interval after boundary adjustment.

4.5 Midpoints Reduce Bias

Here we evaluate whether the midpoint of a prediction interval could better represent human preference. Since R2CCP is considered the best conformal prediction method that balances coverage and efficiency (i.e., interval width), we evaluate two midpoints computation: midpoint of R2CCP interval before boundary adjustment (Con R2CCP) and midpoint of R2CCP interval after boundary adjustment (Dis R2CCP). We compare these two midpoints with two baselines: the raw score output by LLM judge and the weighted average of token probabilities, both of which are used in G-Eval.

Our comparison results are shown in Table 3 and Table 16. From the table, we can see that, in addition to achieving comparable or slightly better correlation with respect to ground truth, midpoint estimates achieve substantially lower mean squared error (MSE) and mean absolute error (MAE). For example, the midpoints from Con R2CCP on fluency of SummEval evaluated by GPT-4o mini reduce 88.7% of MSE, from 3.907 to 0.443 (Table 3). Moreover, MAE between midpoints and true ratings are consistently lower than 0.5, which shows that midpoint is a less biased estimate of human preference. Empirically, though weighted average could achieve a comparable correlation, it often fall outside of the prediction interval due to model bias, while midpoints are on average closer to ground truth. More results on DialSumm (Table 16) and on multimodal text-to-image consistency (Table 20) yield similar observation that midpoint is consistently a more accurate alternative.

Table 3: Interval midpoints vs. Raw Score vs. Weighted Average (Avg.). Con R2CCP refers to midpoint of R2CCP interval before boundary adjustment, and Dis R2CCP refers to midpoint of R2CCP interval after boundary adjustment. Mean squared error (MSE), mean absolute error (MAE), mean Spearman's ρ and mean Kendall's τ are calculated over 30 experiments. **Bold** indicates better performance than both baselines; Gray indicates worse performance than both baselines; Otherwise we mark the results underlined.

Method	Coherence				Consistency				Fluency				Relevance			
	MSE	**MAE**	ρ	τ	**MSE**	**MAE**	ρ	τ	**MSE**	**MAE**	ρ	τ	**MSE**	**MAE**	ρ	τ
GPT-4o mini																
Raw Score	1.729	1.055	0.446	0.373	1.674	1.073	0.480	0.437	3.907	1.977	0.219	0.197	1.009	0.786	0.512	0.427
Weighted Avg.	1.643	1.037	0.514	0.379	1.548	1.066	0.478	0.383	3.412	1.733	0.319	0.250	0.865	0.737	0.567	0.419
Con R2CCP	**0.791**	**0.716**	0.512	0.373	**0.510**	**0.432**	0.455	0.371	**0.442**	**0.491**	**0.330**	**0.261**	**0.418**	**0.509**	0.546	0.403
Dis R2CCP	**0.794**	**0.715**	0.508	**0.386**	**0.512**	**0.428**	**0.506**	**0.468**	**0.443**	**0.488**	**0.336**	**0.300**	**0.423**	**0.509**	0.540	0.423
DeepSeek-R1-Distill-Qwen-32B																
Raw Score	1.010	0.775	0.549	0.457	1.229	0.770	0.467	0.425	2.843	1.549	0.387	0.355	0.763	0.682	0.520	0.437
Weighted Avg.	0.869	0.734	0.599	0.447	1.439	1.065	0.468	0.375	2.783	1.564	0.420	0.332	0.646	0.632	0.565	0.419
Con R2CCP	**0.599**	**0.619**	**0.663**	**0.492**	**0.564**	**0.446**	0.445	0.361	**0.373**	**0.455**	0.391	0.311	**0.431**	**0.513**	0.555	0.412
Dis R2CCP	**0.602**	**0.619**	**0.661**	**0.508**	**0.566**	**0.441**	0.462	0.423	**0.375**	**0.454**	0.393	0.351	**0.434**	**0.512**	0.548	0.431
Qwen2.5-72B-Instruct																
Raw Score	1.432	0.981	0.426	0.358	2.068	1.237	0.458	0.416	4.476	1.958	0.310	0.281	1.188	0.903	0.498	0.420
Weighted Avg.	1.282	0.932	0.539	0.395	1.847	1.213	0.483	0.387	4.236	1.928	0.363	0.285	1.091	0.885	0.555	0.412
Con R2CCP	**0.675**	**0.659**	**0.603**	**0.444**	**0.469**	**0.396**	0.465	0.378	**0.414**	**0.486**	0.340	0.269	**0.407**	**0.502**	**0.571**	**0.425**
Dis R2CCP	**0.678**	**0.659**	**0.600**	**0.456**	**0.469**	**0.387**	**0.538**	**0.498**	**0.416**	**0.485**	0.342	**0.306**	**0.411**	**0.501**	**0.566**	**0.444**

5 Analysis

5.1 Proper Calibration Improves Coverage

Given the limited sample size in ROSCOE and the results shown in Table 1, we explore the relationship between the size of calibration set and the coverage. We construct a continuous prediction interval before boundary adjustment using R2CCP under four calibration regimes – 25%, 50%, 75%, and 100% of the calibration set. Figure 2 shows the coverage with varying calibration set size. From the figure, it is clear that the mean coverage increases and the error bar shrinks as calibration set size increases. These results highlight the importance of a sufficiently large calibration set to ensure a stable coverage rate.

5.2 Why Boundary Adjustment is Effective

We analyze why boundary adjustment could consistently improve coverage empirically in all settings. In Figure 3, we plot the ground truth value (green if falling within prediction interval or red if falling outside) and the prediction interval (gray vertical line). From the figure, we can see that there are several ground-truth scores that fall outside of the interval are very close to the endpoints. Thus, a slight expansion to the discrete rating value would suffice to cover the ground truth. This demonstrates that a relatively small expansion of the prediction interval can lead to a substantial gain in calibration, successfully achieving the 90% coverage.

5.3 Reprompt and Regrade with Intervals

In addition to use midpoint as an alternative judgment, we explore whether reprompting the LLM judge with information about the prediction interval could improve the judgment. We reprompt the LLM judge with the best interval among 30 runs on ROSCOE (R2CCP + DeepSeek-R1-Distill-Qwen-32B) (Table 19). Our investigation shows that: (1) if the initial ratings fall within the prediction interval, reprompting could strengthen the judge confidence in initial ratings (Figures 9, 10 and 11); (2) If the initial ratings fall outside of the prediction interval, the judge might resist in changing to another rating that falls within the interval (Figures 12 and 13). After deeper analysis, we found the main cause is that the model is not allowed to output intermediate scores (e.g., 4.33, 4.67), and it thinks moving to the next integer (e.g., from 4 to 5) is unreasonable. If given the option to output intermediate score, it often changes its rating to the nearest bound of the prediction interval (see an example in Figure 16). For example, with initial score being 4 and interval being [4.33, 5.00], the judge typically raises its rating from 4 to 4.33.

6 Discussion

In this work, we provide the first analysis of uncertainty in LLM-as-a-judge using conformal prediction based on the output logits in a single evaluation run. Our analysis aims to construct prediction intervals that achieve or approximate 90% coverage

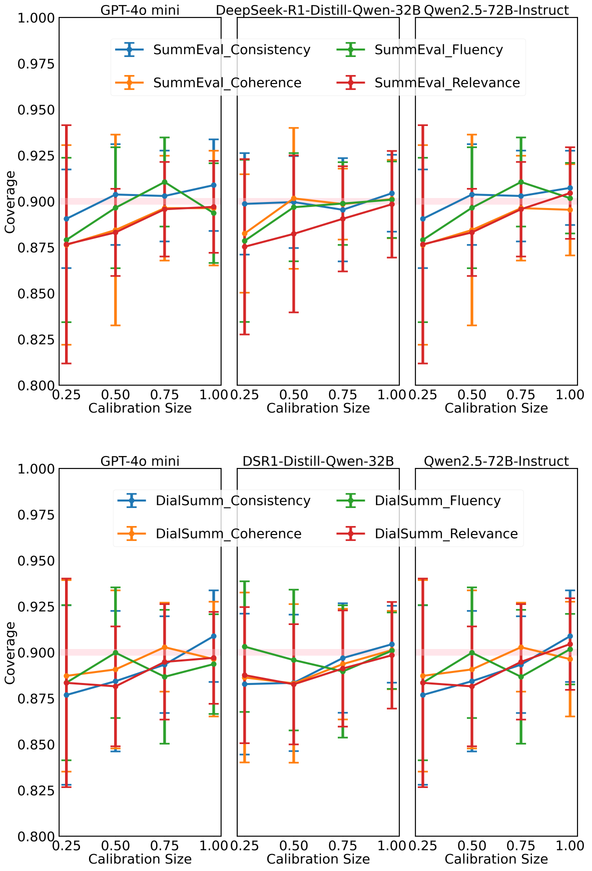


Figure 2: Coverage vs. calibration set size. Mean coverage rates increase to 90% and error bars shrinks, as calibration set increases.

rate, and includes nine conformal prediction methods, three LLM evaluators, two evaluation frameworks (i.e., G-Eval, SocREval) and two tasks (summarization and reasoning). Moreover, we design an intuitive yet theoretically grounded boundary adjustment technique that transforms continuous intervals to discrete rating scales, yielding improvements in coverage. Finally, we explore the use of interval midpoints as calibrated scores, to understand how prediction interval could help within the LLM-as-a-judge paradigm. Experimental results demonstrate that this strategy matches or slightly surpasses baselines on correlation metrics while significantly outperforming direct scoring on error metrics, thereby achieving higher accuracy.

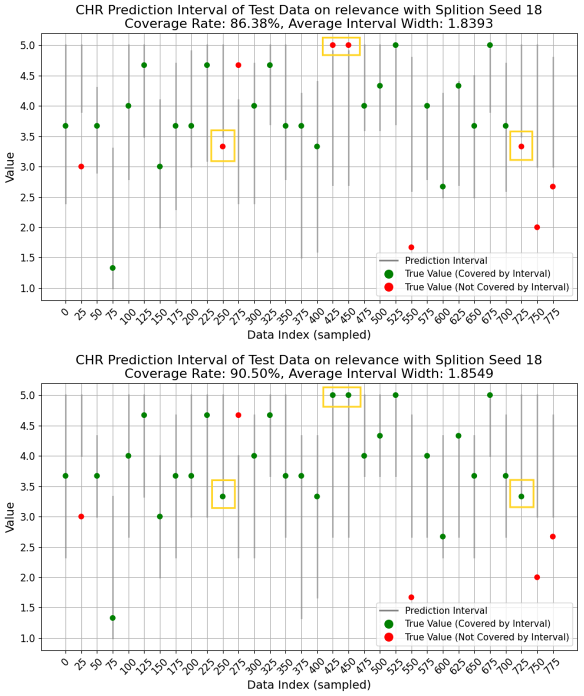


Figure 3: Red points mean the labels lying outside the intervals, which could turn green (inside) if the interval just extend to nearest labels (e.g. 3.33 and 5). After applying boundary adjustment, the coverage in this instance improves from 86.38% to 90.50%, while the average width increases slightly to 1.8549.

We believe this work take a step towards reliable LLM-as-a-judge. Our goal is to provide reference to help user determine when they can trust the judgment through uncertainty given by the width of prediction interval and sheds lights on the necessity of reliable LLM-as-a-judge. On the one hand, a wide prediction interval serves as a warning signal of unreliability with the LLM judge provided score, which might benefit in high-risk environments where uncertainty-induced errors must be minimized, such as in medical diagnosis (Lu et al., 2022; Tan et al., 2024). On the other hand, a narrow prediction interval suggests a higher degree of certainty in the score, thereby reducing the need for manual review in automated evaluation, such as in essay scoring (Song et al., 2024). We believe our framework might be helpful in example selection to avoid the model collapse when trained on LLM-generated data via active learning (Shumailov et al., 2024) or to help with reinforcement learning with a reliable AI feedback.

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Limitations

The main limitation of this work lies in the coverage of tasks that LLMs are used to judge. We primarily analyze summarization and reasoning for natural language generation through rating-based evaluations such as SummEval, DialSumm and ROSCOE. We acknowledge that there could be many other tasks that we have yet to explore, including but not limited to machine translation, multimodal generation, etc.

Ethical Considerations

Our work analyzes how reliable LLM-as-a-judge is in rating-based evaluation using conformal prediction. Though conformal prediction can quantify uncertainty with statistical guarantee, it may impose certain ethical considerations.

First, our framework, as well as other conformal prediction methods, relies on high-quality human annotations for calibration. If these annotations contain subjective or biased judgments, the resulting calibrated prediction intervals may reflect such subjective opinion or biases, which might further distort the evaluations. For example, a LLM judge could reduce workload in essay scoring (Song et al., 2024) with calibration from teacher evaluations. But biased annotations may systematically underrate certain linguistic styles, leading to unfairly low score and wide prediction intervals for essays with these linguistic styles. Second, our interval estimates are nonparametric and should not be interpreted as classical confidence intervals in statistics. The midpoint is a heuristic and convenient choice, but not a statistical mean or mode, and does not imply symmetric or continuous uncertainty. Misinterpreting this could result in misleading conclusions.

References

Anastasios Angelopoulos, Stephen Bates, Jitendra Malik, and Michael I. Jordan. 2022a. Uncertainty sets for image classifiers using conformal prediction.

Anastasios N. Angelopoulos and Stephen Bates. 2022. A gentle introduction to conformal prediction and distribution-free uncertainty quantification.

Anastasios N. Angelopoulos, Stephen Bates, Emmanuel J. Candès, Michael I. Jordan, and Lihua Lei. 2022b. Learn then test: Calibrating predictive algorithms to achieve risk control.

Shuai Bai, Keqin Chen, Xuejing Liu, Jialin Wang, Wenbin Ge, Sibo Song, Kai Dang, Peng Wang, Shijie Wang, Jun Tang, Humen Zhong, Yuanzhi Zhu, Mingkun Yang, Zhaohai Li, Jianqiang Wan, Pengfei Wang, Wei Ding, Zheren Fu, Yiheng Xu, Jiabo Ye, Xi Zhang, Tianbao Xie, Zesen Cheng, Hang Zhang, Zhibo Yang, Haiyang Xu, and Junyang Lin. 2025. Qwen2.5-vl technical report.

Juliana Barbosa, Ulhas Gondhali, Gohar A. Petrossian, Kinshuk Sharma, Sunandan Chakraborty, Jennifer Jacquet, and Juliana Freire. 2025. A cost-effective llm-based approach to identify wildlife trafficking in online marketplaces.

T. S. Breusch and A. R. Pagan. 1979. A simple test for heteroscedasticity and random coefficient variation. *Econometrica*, 47(5):1287–1294.

Oana-Maria Camburu, Tim Rocktäschel, Thomas Lukasiewicz, and Phil Blunsom. 2018. e-snli: Natural language inference with natural language explanations. In *Advances in Neural Information Processing Systems*, volume 31. Curran Associates, Inc.

Margarida M Campos, António Farinhas, Chrysoula Zerva, Mário AT Figueiredo, and André FT Martins. 2024a. Conformal prediction for natural language processing: A survey. *arXiv preprint arXiv:2405.01976*.

Margarida M. Campos, António Farinhas, Chrysoula Zerva, Mário A. T. Figueiredo, and André F. T. Martins. 2024b. Conformal prediction for natural language processing: A survey.

Juan Manuel Zambrano Chaves, Shih-Cheng Huang, Yanbo Xu, Hanwen Xu, Naoto Usuyama, Sheng Zhang, Fei Wang, Yujia Xie, Mahmoud Khademi, Ziyi Yang, Hany Hassan Awadalla, Julia Gong, Houdong Hu, Jianwei Yang, Chunyuan Li, Jianfeng Gao, Yu Gu, Cliff Wong, Mu-Hsin Wei, Tristan Naumann, Muhao Chen, Matthew P. Lungren, Serena Yeung-Levy, Curtis P. Langlotz, Sheng Wang, and Hoifung Poon. 2024. A clinically accessible small multimodal radiology model and evaluation metric for chest x-ray findings. *Nature communications*, 16 1:3108.

Philip Chung, Akshay Swaminathan, Alex J. Goodell, Yeasul Kim, S. Momsen Reincke, Lichy Han, Ben Deverett, Mohammad Amin Sadeghi, Abdel-Badih Ariss, Marc Ghanem, David Seong, Andrew A. Lee, Caitlin E. Coombes, Brad Bradshaw, Mahir A. Sufian, Hyo Jung Hong, Teresa P. Nguyen, Mohammad R. Rasouli, Komal Kamra, Mark A. Burbridge, James C. McAvoy, Roya Saffary, Stephen P. Ma, Dev Dash, James Xie, Ellen Y. Wang, Clifford A. Schmiesing, Nigam Shah, and Nima Aghaeepour. 2025. Verifact: Verifying facts in llm-generated clinical text with electronic health records.

Karl Cobbe, Vineet Kosaraju, Mohammad Bavarian, Mark Chen, Heewoo Jun, Lukasz Kaiser, Matthias Plappert, Jerry Tworek, Jacob Hilton, Reiichiro Nakano, Christopher Hesse, and John Schulman. 2021. Training verifiers to solve math word problems.

DeepSeek-AI, Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, Xiaokang Zhang, Xingkai Yu, Yu Wu, Z. F. Wu, Zhibin Gou, Zhihong Shao, Zhuoshu Li, Ziyi Gao, Aixin Liu, Bing Xue, Bingxuan Wang, Bochao Wu, Bei Feng, Chengda Lu, Chenggang Zhao, Chengqi Deng, Chenyu Zhang, Chong Ruan, Damai Dai, Deli Chen, Dongjie Ji, Erhang Li, Fangyun Lin, Fucong Dai, Fuli Luo, Guangbo Hao, Guanting Chen, Guowei Li, H. Zhang, Han Bao, Hanwei Xu, Haocheng Wang, Honghui Ding, Huajian Xin, Huazuo Gao, Hui Qu, Hui Li, Jianzhong Guo, Jiashi Li, Jiawei Wang, Jingchang Chen, Jingyang Yuan, Junjie Qiu, Junlong Li, J. L. Cai, Jiaqi Ni, Jian Liang, Jin Chen, Kai Dong, Kai Hu, Kaige Gao, Kang Guan, Kexin Huang, Kuai Yu, Lean Wang, Lecong Zhang, Liang Zhao, Litong Wang, Liyue Zhang, Lei Xu, Leyi Xia, Mingchuan Zhang, Minghua Zhang, Minghui Tang, Meng Li, Miaojun Wang, Mingming Li, Ning Tian, Panpan Huang, Peng Zhang, Qiancheng Wang, Qinyu Chen, Qiushi Du, Ruiqi Ge, Ruisong Zhang, Ruizhe Pan, Runji Wang, R. J. Chen, R. L. Jin, Ruyi Chen, Shanghao Lu, Shangyan Zhou, Shanhuang Chen, Shengfeng Ye, Shiyu Wang, Shuiping Yu, Shunfeng Zhou, Shuting Pan, S. S. Li, Shuang Zhou, Shaoqing Wu, Shengfeng Ye, Tao Yun, Tian Pei, Tianyu Sun, T. Wang, Wangding Zeng, Wanjia Zhao, Wen Liu, Wenfeng Liang, Wenjun Gao, Wenqin Yu, Wentao Zhang, W. L. Xiao, Wei An, Xiaodong Liu, Xiaohan Wang, Xiaokang Chen, Xiaotao Nie, Xin Cheng, Xin Liu, Xin Xie, Xingchao Liu, Xinyu Yang, Xinyuan Li, Xuecheng Su, Xuheng Lin, X. Q. Li, Xiangyue Jin, Xiaojin Shen, Xiaosha Chen, Xiaowen Sun, Xiaoxiang Wang, Xinnan Song, Xinyi Zhou, Xianzu Wang, Xinxia Shan, Y. K. Li, Y. Q. Wang, Y. X. Wei, Yang Zhang, Yanhong Xu, Yao Li, Yao Zhao, Yaofeng Sun, Yaohui Wang, Yi Yu, Yichao Zhang, Yifan Shi, Yiliang Xiong, Ying He, Yishi Piao, Yisong Wang, Yixuan Tan, Yiyang Ma, Yiyuan Liu, Yongqiang Guo, Yuan Ou, Yuduan Wang, Yue Gong, Yuheng Zou, Yujia He, Yunfan Xiong, Yuxiang Luo, Yuxiang You, Yuxuan Liu, Yuyang Zhou, Y. X. Zhu, Yanhong Xu, Yanping Huang, Yaohui Li, Yi Zheng, Yuchen Zhu, Yunxian Ma, Ying Tang, Yukun Zha, Yuting Yan, Z. Z. Ren, Zehui Ren, Zhangli Sha, Zhe Fu, Zhean Xu, Zhenda Xie, Zhengyan Zhang, Zhewen Hao, Zhicheng Ma, Zhigang Yan, Zhiyu Wu, Zihui Gu, Zijia Zhu, Zijun Liu, Zilin Li, Ziwei Xie, Ziyang Song, Zizheng Pan, Zhen Huang, Zhipeng Xu, Zhongyu Zhang, and Zhen Zhang. 2025. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning.

Dheeru Dua, Yizhong Wang, Pradeep Dasigi, Gabriel Stanovsky, Sameer Singh, and Matt Gardner. 2019. Drop: A reading comprehension benchmark requiring discrete reasoning over paragraphs.

Alexander R. Fabbri, Wojciech Kryściński, Bryan McCann, Caiming Xiong, Richard Socher, and Dragomir Radev. 2021. Summeval: Re-evaluating summarization evaluation.

Matteo Fontana, Gianluca Zeni, and Simone Vantini. 2023. Conformal prediction: A unified review of theory and new challenges. *Bernoulli*, 29(1).

Mingqi Gao, Xinyu Hu, Jie Ruan, Xiao Pu, and Xiaojun Wan. 2024. Llm-based nlg evaluation: Current status and challenges.

Mingqi Gao and Xiaojun Wan. 2022. DialSummEval: Revisiting summarization evaluation for dialogues. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 5693–5709, Seattle, United States. Association for Computational Linguistics.

Olga Golovneva, Moya Chen, Spencer Poff, Martin Corredor, Luke Zettlemoyer, Maryam Fazel-Zarandi, and Asli Celikyilmaz. 2023. Roscoe: A suite of metrics for scoring step-by-step reasoning.

Jiawei Gu, Xuhui Jiang, Zhichao Shi, Hexiang Tan, Xuehao Zhai, Chengjin Xu, Wei Li, Yinghan Shen, Shengjie Ma, Honghao Liu, Saizhuo Wang, Kun Zhang, Yuanzhuo Wang, Wen Gao, Lionel Ni, and Jian Guo. 2025. A survey on llm-as-a-judge.

Leying Guan. 2022. Localized conformal prediction: A generalized inference framework for conformal prediction.

Etash Kumar Guha, Shlok Natarajan, Thomas Möllenhoff, Mohammad Emtiyaz Khan, and Eugene Ndiaye. 2024. Conformal prediction via regression-as-classification. In *The Twelfth International Conference on Learning Representations*.

Hangfeng He, Hongming Zhang, and Dan Roth. 2024. Socreval: Large language models with the socratic method for reference-free reasoning evaluation.

Rongpei Hong, Jian Lang, Jin Xu, Zhangtao Cheng, Ting Zhong, and Fan Zhou. 2025. Following clues, approaching the truth: Explainable micro-video rumor detection via chain-of-thought reasoning. In *THE WEB CONFERENCE 2025*.

Jaehun Jung, Faeze Brahman, and Yejin Choi. 2024. Trust or escalate: Llm judges with provable guarantees for human agreement.

Kiran Kamble, Melisa Russak, Dmytro Mozolevskyi, Muayad Ali, Mateusz Russak, and Waseem AlShikh. 2025. Expect the unexpected: Failsafe long context qa for finance.

Klaus-Rudolf Kladny, Bernhard Schölkopf, and Michael Muehlebach. 2025. Conformal generative modeling with improved sample efficiency through sequential greedy filtering.

Bhawesh Kumar, Charlie Lu, Gauri Gupta, Anil Palepu, David Bellamy, Ramesh Raskar, and Andrew Beam. 2023. Conformal prediction with large language models for multi-choice question answering.

Baiqi Li, Zhiqiu Lin, Deepak Pathak, Jiayao Li, Yixin Fei, Kewen Wu, Tiffany Ling, Xide Xia, Pengchuan Zhang, Graham Neubig, and Deva Ramanan. 2024a. Genai-bench: Evaluating and improving compositional text-to-visual generation.

Haitao Li, Junjie Chen, Qingyao Ai, Zhumin Chu, Yujia Zhou, Qian Dong, and Yiqun Liu. 2024b. Calibraeval: Calibrating prediction distribution to mitigate selection bias in llms-as-judges.

Haitao Li, Qian Dong, Junjie Chen, Huixue Su, Yujia Zhou, Qingyao Ai, Ziyi Ye, and Yiqun Liu. 2024c. Llms-as-judges: A comprehensive survey on llm-based evaluation methods.

Minzhi Li, Zhengyuan Liu, Shumin Deng, Shafiq Joty, Nancy F. Chen, and Min-Yen Kan. 2024d. Dna-eval: Enhancing large language model evaluation through decomposition and aggregation.

Shiyang Li, Jianshu Chen, and Dian Yu. 2023. Teaching pretrained models with commonsense reasoning: A preliminary kb-based approach.

Siheng Li, Cheng Yang, Taiqiang Wu, Chufan Shi, Yuji Zhang, Xinyu Zhu, Zesen Cheng, Deng Cai, Mo Yu, Lemao Liu, Jie Zhou, Yujiu Yang, Ngai Wong, Xixin Wu, and Wai Lam. 2024e. A survey on the honesty of large language models.

Chin-Yew Lin. 2004. Rouge: A package for automatic evaluation of summaries. In *Annual Meeting of the Association for Computational Linguistics*.

Zhen Lin, Shubhendu Trivedi, and Jimeng Sun. 2021. Locally valid and discriminative prediction intervals for deep learning models. In *Advances in Neural Information Processing Systems*, volume 34, pages 8378–8391. Curran Associates, Inc.

Shudong Liu, Zhaocong Li, Xuebo Liu, Runzhe Zhan, Derek F. Wong, Lidia S. Chao, and Min Zhang. 2024. Can LLMs learn uncertainty on their own? expressing uncertainty effectively in a self-training manner. In *Proceedings of the 2024 Conference on Empirical Methods in Natural Language Processing*, pages 21635–21645, Miami, Florida, USA. Association for Computational Linguistics.

Yang Liu, Dan Iter, Yichong Xu, Shuohang Wang, Ruochen Xu, and Chenguang Zhu. 2023. G-eval: Nlg evaluation using gpt-4 with better human alignment. *arXiv preprint arXiv:2303.16634*.

Charles Lu, Anastasios N. Angelopoulos, and Stuart Pomerantz. 2022. Improving trustworthiness of ai disease severity rating in medical imaging with ordinal conformal prediction sets.

Christopher Mohri and Tatsunori Hashimoto. 2024. Language models with conformal factuality guarantees.

Tomoko Nemoto and David Beglar. 2014. Likert-scale questionnaires. In *JALT 2013 conference proceedings*, pages 1–8.

Kishore Papineni, Salim Roukos, Todd Ward, and Wei-Jing Zhu. 2002. Bleu: a method for automatic evaluation of machine translation. In *Annual Meeting of the Association for Computational Linguistics*.

Victor Quach, Adam Fisch, Tal Schuster, Adam Yala, Jae Ho Sohn, Tommi S. Jaakkola, and Regina Barzilay. 2024. Conformal language modeling.

Qwen, :, An Yang, Baosong Yang, Beichen Zhang, Binyuan Hui, Bo Zheng, Bowen Yu, Chengyuan Li, Dayiheng Liu, Fei Huang, Haoran Wei, Huan Lin, Jian Yang, Jianhong Tu, Jianwei Zhang, Jianxin Yang, Jiaxi Yang, Jingren Zhou, Junyang Lin, Kai Dang, Keming Lu, Keqin Bao, Kexin Yang, Le Yu, Mei Li, Mingfeng Xue, Pei Zhang, Qin Zhu, Rui Men, Runji Lin, Tianhao Li, Tianyi Tang, Tingyu Xia, Xingzhang Ren, Xuancheng Ren, Yang Fan, Yang Su, Yichang Zhang, Yu Wan, Yuqiong Liu, Zeyu Cui, Zhenru Zhang, and Zihan Qiu. 2025. Qwen2.5 technical report.

Yaniv Romano, Evan Patterson, and Emmanuel Candes. 2019. Conformalized quantile regression. *Advances in neural information processing systems*, 32.

Yaniv Romano, Matteo Sesia, and Emmanuel J. Candès. 2020. Classification with valid and adaptive coverage.

Kayla Schroeder and Zach Wood-Doughty. 2024. Can you trust llm judgments? reliability of llm-as-a-judge.

Matteo Sesia and Emmanuel J. Candès. 2019. A comparison of some conformal quantile regression methods. *Stat*, 9.

Matteo Sesia and Yaniv Romano. 2021. Conformal prediction using conditional histograms.

Ilia Shumailov, Zakhar Shumaylov, Yiren Zhao, Nicolas Papernot, Ross Anderson, and Yarin Gal. 2024. Ai models collapse when trained on recursively generated data. *Nature*, 631(8022):755–759.

Yishen Song, Qianta Zhu, Huaibo Wang, and Qinhua Zheng. 2024. Automated essay scoring and revising based on open-source large language models. *IEEE Transactions on Learning Technologies*, 17:1880–1890.

Jiayuan Su, Jing Luo, Hongwei Wang, and Lu Cheng. 2024. Api is enough: Conformal prediction for large language models without logit-access.

Ting Fang Tan, Kabilan Elangovan, Liyuan Jin, Yao Jie, Li Yong, Joshua Lim, Stanley Poh, Wei Yan Ng, Daniel Lim, Yuhe Ke, Nan Liu, and Daniel Shu Wei Ting. 2024. Fine-tuning large language model (llm) artificial intelligence chatbots in ophthalmology and llm-based evaluation using gpt-4.

Vianney Taquet, Vincent Blot, Thomas Morzadec, Louis Lacombe, and Nicolas Brunel. 2022. Mapie: an open-source library for distribution-free uncertainty quantification.

Amir Taubenfeld, Tom Sheffer, Eran Ofek, Amir Feder, Ariel Goldstein, Zorik Gekhman, and Gal Yona. 2025. Confidence improves self-consistency in llms.

Katherine Tian, Eric Mitchell, Allan Zhou, Archit Sharma, Rafael Rafailov, Huaxiu Yao, Chelsea Finn, and Christopher D. Manning. 2023. Just ask for calibration: Strategies for eliciting calibrated confidence scores from language models fine-tuned with human feedback.

Gerrit J. J. van den Burg, Gen Suzuki, Wei Liu, and Murat Sensoy. 2025. Aligning black-box language models with human judgments.

Harit Vishwakarma, Alan Mishler, Thomas Cook, Niccolo Dalmasso, Natraj Raman, and Sumitra Ganesh. 2025. Prune 'n predict: Optimizing LLM decision-making with conformal prediction. In *ICLR Workshop: Quantify Uncertainty and Hallucination in Foundation Models: The Next Frontier in Reliable AI*.

Vladimir Vovk, Alexander Gammerman, and Glenn Shafer. 2005. *Algorithmic learning in a random world*, volume 29. Springer.

Nico Wagner, Michael Desmond, Rahul Nair, Zahra Ashktorab, Elizabeth M. Daly, Qian Pan, Martín Santillán Cooper, James M. Johnson, and Werner Geyer. 2024. Black-box uncertainty quantification method for llm-as-a-judge.

Victor Wang, Michael J. Q. Zhang, and Eunsol Choi. 2025. Improving llm-as-a-judge inference with the judgment distribution.

Zhiyuan Wang, Jinhao Duan, Lu Cheng, Yue Zhang, Qingni Wang, Xiaoshuang Shi, Kaidi Xu, Hengtao Shen, and Xiaofeng Zhu. 2024. Conu: Conformal uncertainty in large language models with correctness coverage guarantees.

Tianjun Wei, Wei Wen, Ruizhi Qiao, Xing Sun, and Jianghong Ma. 2025. Rocketeval: Efficient automated llm evaluation via grading checklist.

Halbert White. 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica*, 48(4):817–838.

Minghao Wu and Alham Fikri Aji. 2023. Style over substance: Evaluation biases for large language models.

Qiujie Xie, Qingqiu Li, Zhuohao Yu, Yuejie Zhang, Yue Zhang, and Linyi Yang. 2025. An empirical analysis of uncertainty in large language model evaluations.

Ran Xie, Rina Foygel Barber, and Emmanuel J. Candès. 2024. Boosted conformal prediction intervals.

Miao Xiong, Zhiyuan Hu, Xinyang Lu, Yifei Li, Jie Fu, Junxian He, and Bryan Hooi. 2024. Can llms express their uncertainty? an empirical evaluation of confidence elicitation in llms.

Tianyang Xu, Shujin Wu, Shizhe Diao, Xiaoze Liu, Xingyao Wang, Yangyi Chen, and Jing Gao. 2024a. Sayself: Teaching llms to express confidence with self-reflective rationales.

Yunpeng Xu, Wenge Guo, and Zhi Wei. 2024b. Conformal risk control for ordinal classification.

Fanghua Ye, Mingming Yang, Jianhui Pang, Longyue Wang, Derek F. Wong, Emine Yilmaz, Shuming Shi, and Zhaopeng Tu. 2024. Benchmarking llms via uncertainty quantification.

Gal Yona, Roee Aharoni, and Mor Geva. 2024. Can large language models faithfully express their intrinsic uncertainty in words?

Javier Yong, Haokai Ma, Yunshan Ma, Anis Yusof, Zhenkai Liang, and Ee-Chien Chang. 2025. Attackseqbench: Benchmarking large language models' understanding of sequential patterns in cyber attacks.

Soroush H. Zargarbashi, Mohammad Sadegh Akhondzadeh, and Aleksandar Bojchevski. 2025. One sample is enough to make conformal prediction robust.

Mozhi Zhang, Mianqiu Huang, Rundong Shi, Linsen Guo, Chong Peng, Peng Yan, Yaqian Zhou, and Xipeng Qiu. 2024. Calibrating the confidence of large language models by eliciting fidelity.

Qiyuan Zhang, Yufei Wang, Yuxin Jiang, Liangyou Li, Chuhan Wu, Yasheng Wang, Xin Jiang, Lifeng Shang, Ruiming Tang, Fuyuan Lyu, and Chen Ma. 2025. Crowd comparative reasoning: Unlocking comprehensive evaluations for llm-as-a-judge.

Tianyi Zhang, Varsha Kishore, Felix Wu, Kilian Q. Weinberger, and Yoav Artzi. 2020. Bertscore: Evaluating text generation with bert.

Han Zhou, Xingchen Wan, Yinhong Liu, Nigel Collier, Ivan Vulić, and Anna Korhonen. 2024. Fairer preferences elicit improved human-aligned large language model judgments.

A Appendix

A.1 Proof of Theorem 1

Proof. By the standard split conformal prediction procedure with the nonconformity score $s(z, y) = |\hat{y} - y|$, the prediction set

$$\mathcal{C}(z_{\text{test}}) = \{a \in \mathbb{R} : s(x_{\text{test}}, z) \leq \hat{q}_{1-\alpha}\} \tag{10}$$

satisfies $\mathbb{P}(Y_{\text{test}} \in \mathcal{C}(z_{\text{test}})) \geq 1 - \alpha$.

In our discrete setting, every potential label is an element of a predetermined ordered set (e.g., $\{1, 2, 3, 4, 5\}$). The adjusted score $s'(z, y)$ is defined such that for each y,

$$s'(z, y) = s(z, y') \tag{11}$$

where y' is the label closest to y.

In regions where the original interval $\mathcal{C}(z_{\text{test}}) = [l, u]$ already contains some label, the shrinking adjustment leads to

$$s'(z_{\text{test}}, l) = s(z_{\text{test}}, \lceil l \rceil) \leq \hat{q}_{1-\alpha} \tag{12}$$

or

$$s'(z_{\text{test}}, u) = s(z_{\text{test}}, \lfloor u \rfloor) \leq \hat{q}_{1-\alpha}. \tag{13}$$

Thus, every label that was originally covered (i.e., satisfying $s(z_{\text{test}}, y) \leq \hat{q}$) remains covered. Thus, the coverage remains unchanged.

Now suppose that an expansion to the interval is performed. We have

$$s'(z_{\text{test}}, l) \leq \hat{q}_{1-\alpha} \leq s'(z_{\text{test}}, \lfloor l \rfloor) \leq \hat{q}_{1-\alpha_0} \tag{14}$$

or

$$s'(z_{\text{test}}, u) \leq \hat{q}_{1-\alpha} \leq s'(z_{\text{test}}, \lceil u \rceil) \leq \hat{q}_{1-\alpha_0} \tag{15}$$

where $0 \leq \alpha_0 < \alpha$.

In this case, for any $a \notin \mathcal{C}(z_{\text{test}})$, it is possible that $z \in \mathcal{C}'(z_{\text{test}})$ if z is either $\lfloor l \rfloor$ or $\lceil u \rceil$. As a consequence, if the original interval barely missed covering the label, the expansion guarantees that these outcomes are now covered.

Hence, we have

$$\{Y_{\text{test}} \in \mathcal{C}(z_{\text{test}})\} \subseteq \{Y_{\text{test}} \in \mathcal{C}'(z_{\text{test}})\} \tag{16}$$

which implies

$$\mathbb{P}(Y_{\text{test}} \in \mathcal{C}'(z_{\text{test}})) \geq \mathbb{P}(Y_{\text{test}} \in \mathcal{C}(z_{\text{test}})) \geq 1 - \alpha. \tag{17}$$

Moreover, we have

$$\begin{aligned} &\mathbb{P}(Y_{\text{test}} \in \mathcal{C}'(z_{\text{test}})) - \mathbb{P}(Y_{\text{test}} \in \mathcal{C}(z_{\text{test}})) \\ &= \mathbb{P}(q_{1-\alpha} \leq s'(z_{\text{test}}, \lfloor l \rfloor \text{ or } \lceil u \rceil) \leq q_{1-\alpha_0}) \\ &= (1 - \alpha_0) - (1 - \alpha) = \alpha - \alpha_0 > 0. \end{aligned} \tag{18}$$

Thus

$$\mathbb{P}(Y_{\text{test}} \in \mathcal{C}'(z_{\text{test}})) > 1 - \alpha \tag{19}$$

which completes the proof. □

A.2 Hypothesis Testing of Heteroscedasticity

Heteroscedasticity indicates a non-constant residual variance across all observation, which could cause deviation in terms of coverage rates and interval widths for regression-based conformal prediction. It further motivates several conformal prediction methods, including CQR (Romano et al., 2019), LCP (Guan, 2022), and R2CCP (Guha et al., 2024). Here, we perform two classic tests for heteroscedasticity in our datasets: the Breusch–Pagan test and the White test.

Breusch–Pagan Test. The Breusch–Pagan (BP) test (Breusch and Pagan, 1979) regresses the squared ordinary least square residuals $\hat{e}_i^2$ on the original covariates $Z_i \in R^k$ of the i-th observation. Formally, it tests

$$H_0 : \text{Var}(\varepsilon_i) = \sigma^2 \text{ vs. } H_1 : \text{Var}(\varepsilon_i) = \sigma^2 h(Z_i), \tag{20}$$

where $h(\cdot)$ is an unknown positive-valued function to capture how the variance might change with Z_i. Note that we do not need to estimate h since it is only used to define heteroscedasticity in alternative hypothesis. The BP test uses it to infer the simplified Langrange Multiplier (LM) test statistic as

$$\text{LM}_{\text{BP}} = n \cdot R^2_{\hat{e}^2 \sim Z} \dot{\sim} \chi^2_k, \quad m = \dim(Z_i) \tag{21}$$

from the auxiliary regression $\hat{e}^2 = \delta 0 + Z_i'\delta + v_i$, where n is the sample size. A small p-value indicates rejection of homoscedasticity.

White Test. The White test (White, 1980) extends BP by including not only Z but also their squares and cross products, so the variance function *h(·)* is not required. Let $Z_i = (Z_{i1}, \dots, Z_{ik})'$ and define

$$V_i = (Z_i', Z_{i1}^2, \dots, Z_{ik}^2, Z_{i1}Z_{i2}, \dots, Z_{i(k-1)}Z_{ik})'. \tag{22}$$

Then under null hypotheses,

$$\text{LM}_{\text{White}} = n \cdot R^2_{\hat{e}^2 \sim V} \dot{\sim} \chi^2_m, \quad m = \dim(V_i). \tag{23}$$

Table 4: Breusch-Pagan (BP) and White tests detect pervasive heteroscedasticity in SummEval and DialSumm: both tests yield highly significant p-values (p < 1e-12) across all four metrics and all evaluators. By contrast, in ROSCOE by G-Eval only DROP, e-SNLI and GSM8k exhibit significant heteroscedasticity (p < 0.05) while CosmosQA remains homoscedastic; in ROSCOE by SocREval heteroscedasticity is confined to DROP for DeepSeek-R1-Qwen-32B (DSR1-Qwen-32B) and GPT-4o mini and to CosmosQA and e-SNLI for Qwen2.5-72B-Instruct (Qwen2.5-72B).

SummEval by G-Eval																	
Evaluator	**Test**	**Consistency**				**Coherence**				**Fluency**				**Relevance**			
		LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value
GPT-4o mini	BP	372.121	3.02e-78	96.615	4.52e-89	147.034	5.71e-30	32.261	2.07e-31	144.954	1.58e-29	31.759	6.35e-31	102.860	1.32e-20	21.903	2.85e-21
	White	446.359	4.68e-82	30.547	2.61e-97	204.285	1.60e-32	11.556	4.96e-35	187.021	4.08e-29	10.450	3.71e-31	132.282	1.45e-18	7.116	1.85e-19
DSR1-Qwen-32B	BP	332.234	1.17e-69	83.545	4.44e-78	64.602	1.36e-12	13.414	7.81e-13	209.266	2.95e-43	47.970	2.46e-46	78.494	1.73e-15	16.447	7.41e-16
	White	406.728	8.21e-74	26.910	4.32e-86	142.666	1.58e-20	7.729	1.33e-21	242.606	3.52e-40	14.111	6.53e-44	92.448	2.76e-11	4.841	1.19e-11
Qwen2.5-72B	BP	351.775	7.26e-74	89.844	2.03e-83	82.248	2.84e-16	17.276	1.11e-16	227.917	2.99e-47	52.956	5.94e-51	83.830	1.32e-16	17.627	4.96e-17
	White	407.695	5.17e-74	26.996	2.33e-86	142.134	1.99e-20	7.697	1.71e-21	245.423	9.55e-41	14.304	1.40e-44	100.688	9.49e-13	5.302	3.34e-13
DialSumm by G-Eval																	
Evaluator	**Test**	**Consistency**				**Coherence**				**Fluency**				**Relevance**			
		LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value
GPT-4o-mini	BP	70.220	9.22e-14	14.723	4.30e-14	199.050	4.54e-41	46.209	2.85e-44	250.633	4.02e-52	60.796	2.06e-57	87.825	1.92e-17	18.664	5.49e-18
	White	96.250	5.87e-12	5.091	2.01e-12	238.533	2.32e-39	14.160	1.56e-43	271.824	4.40e-46	16.613	9.80e-52	170.231	7.82e-26	9.548	9.86e-28
DSR1-Qwen-32B	BP	100.158	4.90e-20	21.483	9.27e-21	126.174	1.54e-25	27.616	9.87e-27	169.680	8.54e-35	38.451	4.63e-37	177.728	1.64e-36	40.540	5.12e-39
	White	169.039	1.33e-25	9.468	1.83e-27	196.532	5.45e-31	11.260	1.21e-33	225.735	8.54e-37	13.255	1.83e-40	250.758	8.03e-42	15.045	1.65e-46
Qwen2.5-72B	BP	88.782	1.21e-17	18.877	3.37e-18	209.551	2.57e-43	49.076	6.76e-47	199.737	3.23e-41	46.395	1.92e-44	125.827	1.83e-25	27.532	1.19e-26
	White	123.892	5.40e-17	6.694	7.13e-18	228.974	1.92e-37	13.482	3.09e-41	235.628	8.89e-39	13.953	7.83e-43	175.737	6.61e-27	9.897	6.01e-29
ROSCOE by G-Eval																	
Evaluator	**Test**	**CosmosQA**				**DROP**				**e-SNLI**				**GSM8k**			
		LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value
GPT-4o-mini	BP	5.839	0.3222	1.167	0.3270	11.334	0.0451	2.328	0.0440	26.074	0.0001	6.053	0.0000	7.586	0.1806	1.530	0.1822
	White	17.194	0.6404	0.841	0.6609	23.456	0.2669	1.188	0.2681	35.174	0.0192	1.974	0.0124	26.151	0.1609	1.346	0.1556
DSR1-Qwen-32B	BP	8.042	0.1539	1.626	0.1550	20.313	0.0011	4.369	0.0008	24.209	0.0002	5.537	0.0001	15.828	0.0074	3.335	0.0065
	White	17.670	0.6092	0.867	0.6290	40.833	0.0039	2.281	0.0022	58.598	0.0000	4.122	0.0000	33.872	0.0270	1.825	0.0210
Qwen2.5-72B	BP	7.883	0.1628	1.592	0.1641	22.042	0.0005	4.785	0.0004	22.554	0.0004	5.092	0.0002	27.782	0.0000	6.259	0.0000
	White	25.904	0.1690	1.333	0.1640	31.326	0.0510	1.657	0.0438	49.770	0.0002	3.196	0.0000	56.739	0.0000	3.545	0.0000
ROSCOE by SocREval																	
Evaluator	**Test**	**CosmosQA**				**DROP**				**e-SNLI**				**GSM8k**			
		LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value	LM Stat.	p-value	F Stat.	p-value
GPT-4o-mini	BP	7.256	0.20231	1.461	0.20457	4.016	0.54705	0.796	0.55399	7.637	0.17742	1.545	0.17954	3.577	0.61180	0.707	0.61918
	White	20.130	0.26762	1.199	0.26973	37.301	0.01077	2.041	0.00732	12.766	0.75172	0.722	0.77546	11.661	0.82022	0.663	0.83626
DSR1-Qwen-32B	BP	5.659	0.34085	1.130	0.34606	29.404	0.00002	6.643	0.00001	6.994	0.22105	1.409	0.22457	4.244	0.51487	0.841	0.52199
	White	13.283	0.86492	0.636	0.88162	38.105	0.00860	2.095	0.00561	18.955	0.52477	0.933	0.54694	8.983	0.98311	0.421	0.98678
Qwen2.5-72B	BP	13.470	0.01935	2.805	0.01810	8.464	0.13245	1.714	0.13293	16.545	0.00545	3.569	0.00450	2.321	0.80313	0.456	0.80886
	White	34.356	0.00755	2.227	0.00499	22.780	0.19917	1.291	0.19706	29.926	0.03818	1.813	0.02981	12.387	0.77613	0.707	0.79345

Results. We report p-values for both BP Test and White Test in Table 4. From the table, we have the following observations: First, for SummEval and DialSumm by G-Eval, all four metrics and all models exhibit highly significant heteroskedasticity ($p < 10^{-12}$); Second, regarding ROSCOE by G-Eval, CosmosQA remains homoscedastic, whereas DROP, e-SNLI and GSM8k show $p < 0.05$; Third, regarding ROSCOE by SocREval, heteroscedasticity is confined to DROP for DSR1-Qwen-32B and GPT-4o mini and to CosmosQA and e-SNLI for Qwen2.5-72B.

A.3 Compared Conformal Prediction Methods

We test a total of seven regression-based conformal prediction (CP) methods to generate continuous prediction intervals (e.g., $[3.2, 4.1]$), as well as two ordinal classification-based CP methods to produce ordered discrete intervals (e.g., $[3, 4]$). Here we provide a detailed discussion of these approaches, including the motivation behind our choice to focus on regression and ordinal formulations rather than methods based on risk control. We further elaborate on how each method computes non-conformity scores and constructs predictive intervals accordingly.

Why Not Classification-based Methods. Prior works primarily apply conformal prediction to classification-style tasks, which produces non-ordered prediction set, e.g. $\{A, C\}$ in multiple choice question answering. Admittedly, the rating scale $\{1, 2, 3, 4, 5\}$ can be cast as a multiple-choice problem. However, it is hard to interpret a prediction set such as $\{1, 5\}$ (i.e., a set with both the lowest and highest scores to be both plausible but nothing in between). Moreover, Wang et al. (2025) show that the judgment distributions from LLMs can be irregular or even bimodal, making such fragmented prediction sets not only difficult to interpret, but also problematic for downstream decision-making. In contrast, regression-based and ordinal conformal predictors generate ordered prediction intervals, offering a more coherent and interpretable descriptions of score variability. These intervals not only shows inclusion, but also a range of plausible scores, which could be crucial in high-stakes applications such as medical diagnosis. For example, if an LLM judge assigns a rating of 3 (i.e., "neutral"), a prediction set like $\{1, 5\}$ could be confusing as it shows the condition can be either very mild or very severe. However, a prediction interval such as $[3, 5]$ would be more intuitive to medical experts and patients.

Continuous Conformal Prediction Methods. We present a brief description of each continuous conformal prediction method used in our experiments, including the definition of non-conformity score, procedure to construct prediction interval, and hyperparameter settings.

- *Conformalized Quantile Regression (CQR) (Romano et al., 2019).* CQR calibrates the prediction interval using a conditional quantile regression instead of conditional mean regression in naive conformal prediction. The non-conformity scores of the i-th calibration data in CQR is defined as

$$s_i = \max\left\{\hat{q}_{\alpha/2}\left(z_i\right) - y_i,\ y_i - \hat{q}_{1-\alpha/2}\left(z_i\right)\right\} \tag{24}$$

  where $\hat{q}_\tau$ is the τ–quantile regression estimator. The quantile regression estimator is obtained by optimizing the pinball loss. To construct the prediction interval, we compute $s_i, \forall\ i$ on the calibration set and let $Q_{1-\alpha}$ be the $(1-\alpha)$-quantile of $\{s_i | \forall\ i \in \text{calibration set}\}$. Then for any test data z_test, we obtain its prediction interval by

$$\left[\hat{q}_{\alpha/2}\left(z_{test}\right) - Q_{1-\alpha},\ \hat{q}_{1-\alpha/2}\left(z_{test}\right) + Q_{1-\alpha}\right]. \tag{25}$$

  In our experiments, we implement CQR using the `MapieQuantileRegressor` from the `mapie` package (Taquet et al., 2022). We use gradient boosting regressor as the base quantile regression estimator.

- *Asymmetric CQR (CQR) (Sesia and Candès, 2019).* It is an asymmetric variant of CQR. In asymmetric CQR, we define two non-conformity scores s_i^ℓ and s_i^u for the i-th data in the calibration set. These two scores are defined as

$$s_i^\ell = \hat{q}_\alpha\left(z_i\right) - y_i, \quad s_i^u = y_i - \hat{q}_{1-\alpha}\left(z_i\right) \tag{26}$$

  Then, let Q_ℓ and Q_u be the $(1-\alpha)$-quantiles of $\left\{s_i^\ell | \forall\ i \in \text{calibration set}\right\}$ and $\{s_i^u | \forall\ i \in \text{calibration set}\}$, respectively. we construct the interval by

$$\left[\hat{q}_\alpha\left(z_\text{test}\right) - Q_\ell,\ \hat{q}_{1-\alpha}\left(z_\text{test}\right) + Q_u\right] \tag{27}$$

  In our experiments, we also implement asymmetric CQR using the `MapieQuantileRegressor` from the `mapie` package with the same quantile regressor as CQR.

- *Conditional Histogram Regression (CHR) (Sesia and Romano, 2021).* CHR aims to predict a shortest interval that expected to meet the confidence level by estimating a histogram of conditional probability. It partitions the range of label into J bins and try to merge them into a valid interval, which is similar to ordinal predictors. To be specific, it firstly runs a model (e.g., quantile regression) to estimate the conditional probability $\mathbb{P}(Y \in \text{bin}_j \mid Z = z)$, $\forall\ j$ on each bin to form a probability histogram. Then for any given confidence level $1-\alpha_t = \frac{t}{T}$ for $t \in \{0, 1, ..., T\}$, it constructs the shortest continuous interval $\mathcal{C}_t$ containing J_t bins and satisfying

$$\Sigma_{j=1}^{J_t}\mathbb{P}(y_i \in \text{bin}_j \mid z_i) \geq 1 - \alpha_t, \tag{28}$$

  where t is an index representing the confidence level. For each confidence level $1-\alpha_t$, CHR constructs a series of nested intervals $\{\mathcal{C}_t\}_{t=0}^T$, where $\mathcal{C}_0 \subseteq \mathcal{C}_1 \subseteq ... \subseteq \mathcal{C}_T$ and $\mathcal{C}_T$ is the interval that cover the real label with 100% confidence. Then for each data point z_i we can calculate a score as

$$s_i = \min\{t : y_i \in \mathcal{C}_t(z_i)\}, \tag{29}$$

  which is the smallest index to contain y_i. Then a quantile $\hat{q}$ is estimated to construct the interval for the test point z_test as

$$\mathcal{C}(z_\text{test}) = \mathcal{C}_{\hat{q}}(z_\text{test}) \in \{\mathcal{C}_t(z_\text{test})\}_{t=0}^T. \tag{30}$$

- *Locally Valid and Discriminative (LVD) (Lin et al., 2021).* LVD follows the naive split conformal prediction with the same non-conformity score calculation (Equation 2) and interval construction (Equation 3). It then uses similarity to determine $\hat{q}$. Specifically, it first compute the similarity $K_f\left(z_i, z_\text{test}\right)$ between the test point z_test and any i-th calibration point z_i using a learned kernel function K_f, and then normalizes the similarities into a weight

$$w_i(z_\text{test}) \propto K_f\left(z_i, z_\text{test}\right). \tag{31}$$

Then points closer to z_{test} would have higher weights to estimate the quantile for a test point z_{test}. Mathematically, the quantile for a test point z_{test} can be estimated by

$$\hat{q}(z_{\text{test}}) = \inf\{s \geq 0 : \Sigma_{i=1}^{n} w_i \mathbb{1}\{s_i \leq s\} \geq 1-\alpha\} \tag{32}$$

Finally, the prediction interval is given by:

$$[\hat{y}_{\text{test}} - \hat{q}(z_{\text{test}}),\ \hat{y}_{\text{test}} + \hat{q}(z_{\text{test}})]\,. \tag{33}$$

- *Boosted Conformal Prediction (Xie et al., 2024).* Boosted conformal prediction is a post-hoc method that applies gradient boosting on top of classic conformal prediction methods such as CQR (Romano et al., 2019) and LCP (Guan, 2022). The boosted non-conformity score for i-th calibration data z_i is defined as

  $$s_i^T = s_i^0 - g_T(z_i), \tag{34}$$

  where s_i^0 is the baseline conformity score, and $g_T(z_i)$ is a correction that given by a gradient boosting model after T rounds. The loss function is designed to minimize interval width while guarantee the coverage. Following this paradigm, we analyze two variants: Boosted CQR which uses LCP as the conformal prediction method and Boosted LCP which uses LCP as the conformal prediction method.

- *R2CCP (Regression-to-Classification Conformal Prediction) (Guha et al., 2024).* R2CCP is similar to CHR that splits the whole prediction range ($[1, 5]$ in Likert scale) into bins and calculate conditional distribution $\mathbb{P}(Y \in \text{bin}_j \mid Z = z), \forall\, j$. But it predicts the bins that the true label might falls into by a softmax-output neural network and combines the predicted bins into an interval. To be specific, it predicts the probability of each bin and runs a linear interpolation between adjacent bin midpoints. Thus, for each calibration point z_i, we have a probability density function $\hat{f}_{z_i}()$ on the prediction range. Then we calculate the a score

  $$s_i = \hat{f}_{z_i}(y_i), \tag{35}$$

  which is the probability density at the real label y_i, on the calibration set. Then a $\hat{q}$ is calculated to infer a prediction set

  $$\mathcal{C}(z_{\text{test}}) = \{a : \hat{f}_{z_{\text{test}}}(a) \geq \hat{q}\} \tag{36}$$

  for a test point z_{test}, which implies the coverage guarantee. However, such a set may consist of multiple disjoint intervals. For the sake of explanability and to ensure fairness when comparing with other methods, we merge the disjoint intervals into a single one. For example, {[1, 1.35], [2.02, 3.1]} is merged into [1,3.1]. This procedure often leads to wider prediction intervals for R2CCP. Nevertheless, our experiments demonstrate that it remains the best predictor in terms of coverage, interval width, and computational cost.

Ordinal Conformal Prediction Methods. Ordinal conformal prediction methods is naturally suited for rating-based tasks. It generate intervals using the probabilities of ordinal labels (e.g., different ratings), which can be derived from judgment logits after softmax. We present two ordinal conformal prediction methods below.

- *Ordinal Adaptiive Prediction Set (OrdinalAPS) (Lu et al., 2022).* Ordinal APS is the ordinal version of Adaptive Prediction Set (APS) (Romano et al., 2020; Angelopoulos et al., 2022a). Its non-conformity score equals to 1 if the true label falls within in the interval and 0 otherwise

  $$s_i = \mathbb{1}_{y_i \in \mathcal{C}(z_i)}. \tag{37}$$

  The empirical quantile $\hat{q}$ is defined as $\frac{\lceil (n+1)(1-\alpha) \rceil}{n}$-quantile of non-conformity scores in calibration set. Then for a test point z_{test}, OrdinalAPS begins from the label with highest probability and then extend the prediction set in both directions until the accumulated probability mass reaches $\hat{q}$. Then the prediction interval can be transformed from the prediction set by solving the following problem

  $$\underset{(l,u)\in\mathcal{Y}^2,\, l\leq u}{\operatorname{argmin}} \left\{u - l : \Sigma_{j=l}^{u} \hat{f}(j|z_{\text{test}}) \geq \hat{q}\right\} \tag{38}$$

  where l and u denote the lower bound and upper bound, respectively, and $\hat{f}(j)$ is the probability of j in classification.

- *Ordinal Risk Control (OrdinalRC) (Xu et al., 2024b).* Ordinal Risk Control is similar to OrdinalAPS that they both start from the label with highest probability and then expand the set in both directions until a threshold is met. Specifically, OrdinalRC designs two types of risk: weight-based risk and divergence-based risk. In our analysis, we select the weight-based risk since predictions with another risk often only output a single score. Regarding interval construction with weight-based risk, similar to OrdinalAPS, $C(z_{\text{test}})$ can be obtained by solving the following optimization problem

$$\underset{(l,u)\in\mathcal{Y}^2, l\leq u}{\operatorname{argmin}} \left\{ u - l : \Sigma_{j=l}^{u} h\left(j\right) \hat{f}(j|z_{\text{test}}) \geq \hat{q} \right\}, \tag{39}$$

where $h(j)$ is a weight specifically assigned to label j and $\hat{q}$ here is a weight-adjusted counterpart compared to the quantile in OrdinalAPS.

A detailed hyperparameter settings for each aforementioned conformal prediction methods are listed in Table 5.

A.4 Running Time and Memory Cost

Table 6 shows the runtime and memory analysis of each method. Boosted CQR and Boosted LCP are having higher cost potentially due to boosting. For LVD, the main reason for higher cost might be due to computing the kernel matrix for hundreds of iterations to quantify pairwise similarities.

A.5 LLM Judge Selection and Prompt Sensitivity

In our experiments, we choose GPT-4o mini as a budget-friendly evaluator. In Table 7, we compare GPT-4o mini vs. its larger variant GPT-4o on five rephrased G-Eval chain-of-thought (CoT) prompts. We use R2CCP to construct prediction interval without boundary adjustment. Our preliminary results show that they tend to produce prediction interval with similar interval width and coverage rate. We can also observe that interval width and coverage are similar across all rephrases, which shows that GPT-4o mini, though a budget-friendly model, is insensitive to prompt variants.

Regarding the selection of Qwen2.5-72B-Instruct and DeepSeek-R1-Distill-Qwen-32B, we choose them because they are all widely used open-source models with strong performance and could also fit with our GPU limitations. Besides, we specifically choose DeepSeek-R1-Distill-Qwen-32B to investigate how reasoning models would impact the LLM-based evaluation and interval quality in both summarization and reasoning tasks.

A.6 On Exchangeability, Randomness, and Distribution Shift of Logits

We discuss the feasibility of using logits as input for conformal prediction.

In conformal prediction, a basic assumption is the exchangeability of data, which means that the joint distribution of test set and calibration set should remain invariant to any permutation. In our work, we assume logits from different (prompt and evaluation task) pair to satisfy exchangeability. The main intuition is that different pairs should not interfere with each other in evaluations.

There could also be randomness in LLM-as-a-judge. Temperature is commonly used to control such randomness in LLM decoding. However, we could view such randomness as adding a noise to the logits when temperature is 0. Then Zargarbashi et al. (2025) show that coverage could still be theoretically guaranteed. In Table 8, we show the interval width and coverage given by R2CCP when temperature is set to 0 and 1, respectively. From the table, we could see that the interval width could slightly increase when temperature is 1, which means that more randomness might introduce higher uncertainty. Besides, we show in Table 9 that, even in the case where the model gives different raw score to the same prompt, the prediction intervals remain close to each other, which demonstrate the reliability of using conformal prediction to quantify uncertainty. In our main results, we set temperture to 1 for GPT-4o mini and set temperature to 0 for Qwen2.5-72B-Instruct and DeepSeek-R1-Distill-Qwen-32B.

Note that our paper does not focus on distribution shift, which remains an open question in conformal prediction. To better understand the impact of distribution shift, we use SummEval and DialSumm to calibrate each other, since they share common dimensions. Table 10 presents the results under such distribution shift. From the table, we observe that, even though most settings fail to achieve 90% coverage, boundary adjustment could still help improve the coverage with a large margin. Besides, by digging deeper, we find that the coverage is often higher when the calibrated labels are roughly balanced or not too skewed.

A.7 Human-based Baseline in Summarization Tasks

In our experiments, we also consider a human-based baseline method. Following naive split con-

Table 5: Detailed hyperparameter settings for each conformal prediction method.

Method	Hyperparameter
CQR	MAPIE, gradient boosting regressor with quantile loss
Asymmetric CQR	Same as CQR
CHR	QNet estimator, batch_size=32, hidden_dim=256, lr=5e-4, epoch=1000
LVD	DNN_model, readout_layer = pretrain_general(seed=0, quiet=True, model_setting=0), kernel_model = KernelMLKR(d=10, seed=0, n_iters=500, norm=True, lr=1e-3)
Boosted LCP	len_local_boost: n_rounds_cv=500, learning_rate=0.02, store=True, verbose=False
Boosted CQR	len_cqr_boost: same with Boosted LCP
R2CCP	Default setting in original implementation but max_epochs=100
OrdinalAPS	Default setting in original implementation
OrdinalRC	Default setting in original implementation with WeightedCRPredictor

Table 6: Running time and memory cost of each conformal prediction method.

Method	Time Mean (s)	Time Std. (s)	Memory Mean (MB)	Memory Std. (MB)
CQR	0.83	0.03	0.35	0.00
Asymmetric CQR	0.82	0.03	0.35	0.00
CHR	9.54	0.25	0.62	0.01
LVD	93.67	2.82	0.55	0.01
Boosted CQR	91.43	3.24	0.89	0.05
Boosted LCP	87.27	2.57	2.05	0.01
R2CCP	9.25	0.53	1.35	0.00
OrdinalAPS	0.01	0.00	0.20	0.00
OrdinalRC	0.03	0.00	0.19	0.00

formal prediction (Equations (2) and (3)), we compute the non-conformity score as

$$s(y_{\text{random}}, y) = |y_{\text{random}} - y|, \tag{40}$$

where y_{random} is an annotation randomly chosen from three annotations while the ground truth y is their average. And then we estimate the quantile $\hat{q}$ to construct confidence interval by

$$[y_{\text{random}} - \hat{q},\ y_{\text{random}} + \hat{q}]. \tag{41}$$

A conformal prediction method is considered better than human performance if it achieves shorter intervals with a comparable or better coverage rate. From Table 11, we can see that R2CCP could consistently matches or outperforms the human baselines for both SummEval and DialSumm.

Adding more samples leads to varying effects on correlation across dimensions. For coherence and fluency, the impact is minimal or slightly negative. In contrast, consistency and relevance benefit, particularly under the quantile method. Among evaluation methods, quantile performs best in relevance, while stratified excels in other three dimensions.

A.8 Additional Results on Continuous Intervals Before Boundary Adjustment

Table 12 presents additional experiment results for DialSumm and ROSCOE evaluated with G-Eval before boundary adjustment. From the table, Boosted CQR and Boosted LCP consistently fail to achieve 90% coverage rate on the DialSumm dataset. In contrast, R2CCP maintains coverage in the 89%–91% range while yielding the narrowest intervals among methods with comparable performance, thus offering an optimal trade-off between coverage and efficiency. LVD achieves slightly higher coverage but at the cost of wider intervals, making it suitable for scenarios that prioritize coverage over interval compactness. Though CQR and Asymmetric CQR guarantee 90 % coverage, their interval widths are much larger than other methods (width $>$ 3 on ROSCOE). In terms of LLM judge, DeepSeek-R1-Distill-Qwen-32B achieve slightly higher average coverage rates, and those generated by Qwen2.5-72B-Instruct are generally shorter with lower coverage.

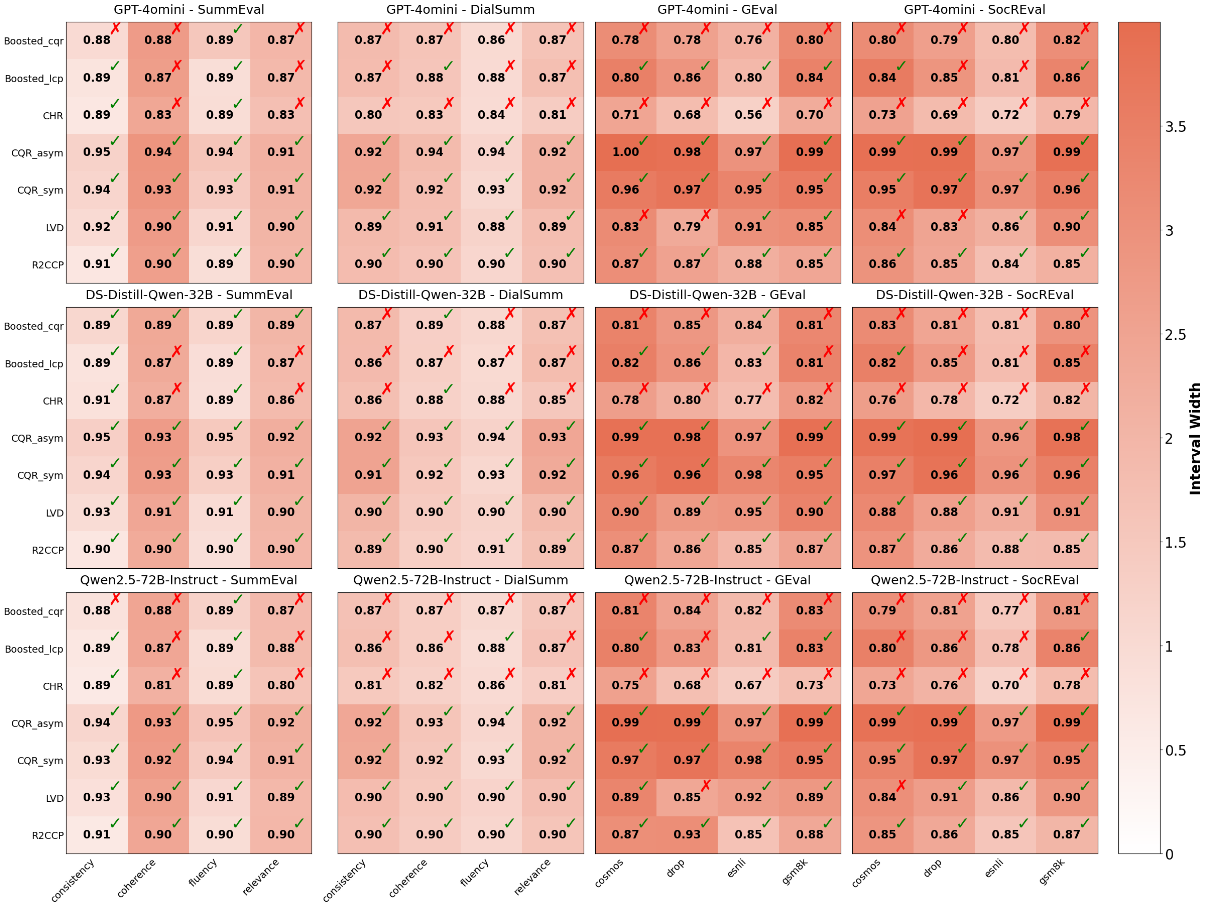

Figure 4: Summary of all experiments regarding continuous interval constructions. Each cell displays the mean coverage of the corresponding conformal prediction method over 30 runs on the given dataset. Cell shading encodes the average interval width, with lighter hues denoting narrower intervals. A ✓ or ✗ in the upper-right corner of each cell denotes whether the coverage criterion is met: ✓ for met; otherwise ✗.

Table 7: GPT-4o vs. GPT-4o mini as LLM judge with five rephrased CoT prompts over 30 different runs.

Prompt	Consistency	Coherence	Fluency	Relevance
		GPT-4o		
CoT 0	$0.84 \pm 0.22/90.06\% \pm 2.03\%$	$3.09 \pm 0.15/89.61\% \pm 2.92\%$	$1.09 \pm 0.22/89.94\% \pm 2.33\%$	$2.41 \pm 0.15/89.52\% \pm 2.94\%$
CoT 1	$0.80 \pm 0.25/89.59\% \pm 2.06\%$	$2.98 \pm 0.16/88.56\% \pm 2.89\%$	$1.05 \pm 0.23/89.95\% \pm 2.00\%$	$2.37 \pm 0.11/89.19\% \pm 2.37\%$
CoT 2	$0.87 \pm 0.29/89.75\% \pm 2.11\%$	$2.98 \pm 0.14/89.35\% \pm 2.81\%$	$1.07 \pm 0.23/90.00\% \pm 2.24\%$	$2.40 \pm 0.16/89.34\% \pm 2.99\%$
CoT 3	$0.88 \pm 0.34/90.05\% \pm 2.13\%$	$3.02 \pm 0.13/89.53\% \pm 2.31\%$	$1.05 \pm 0.27/89.95\% \pm 2.27\%$	$2.38 \pm 0.14/89.65\% \pm 2.81\%$
CoT 4	$0.81 \pm 0.27/89.74\% \pm 2.26\%$	$3.05 \pm 0.13/89.65\% \pm 2.65\%$	$1.05 \pm 0.24/89.80\% \pm 2.10\%$	$2.39 \pm 0.15/89.87\% \pm 3.20\%$
		GPT-4o mini		
CoT 0	$0.83 \pm 0.26/89.65\% \pm 2.44\%$	$2.97 \pm 0.14/88.79\% \pm 2.65\%$	$1.06 \pm 0.24/89.62\% \pm 2.09\%$	$2.36 \pm 0.13/89.76\% \pm 2.48\%$
CoT 1	$0.81 \pm 0.21/89.70\% \pm 2.05\%$	$3.02 \pm 0.16/89.30\% \pm 2.95\%$	$1.07 \pm 0.27/89.87\% \pm 2.26\%$	$2.37 \pm 0.14/89.55\% \pm 2.86\%$
CoT 2	$0.81 \pm 0.24/89.66\% \pm 2.25\%$	$2.98 \pm 0.12/89.13\% \pm 2.55\%$	$1.05 \pm 0.26/89.62\% \pm 2.07\%$	$2.39 \pm 0.13/89.65\% \pm 2.71\%$
CoT 3	$0.88 \pm 0.31/90.09\% \pm 2.18\%$	$3.03 \pm 0.13/89.46\% \pm 2.69\%$	$1.07 \pm 0.26/89.85\% \pm 1.89\%$	$2.42 \pm 0.15/89.83\% \pm 2.67\%$
CoT 4	$0.85 \pm 0.28/89.73\% \pm 2.12\%$	$3.02 \pm 0.12/89.09\% \pm 2.49\%$	$1.09 \pm 0.27/89.77\% \pm 2.24\%$	$2.42 \pm 0.14/89.98\% \pm 2.62\%$

Table 8: Impact of temperature (Tmp.) for different LLM judge over 30 runs with different random seeds. Values in parentheses are p-values for testing whether the coverage equals 0.9. Only DeepSeek-R1-Distill-Qwen-32B exhibits noticeable changes when temperature changes, while the other two are relatively stable.

Tmp.	Consistency	Coherence	Fluency	Relevance
		GPT-4o mini		
0	$0.66 \pm 0.17/90.58\% \pm 2.47\%$ (9e-05)	$2.62 \pm 0.16/89.28\% \pm 3.03\%$ (7e-11)	$0.98 \pm 0.16/90.24\% \pm 2.10\%$ (3e-07)	$2.00 \pm 0.11/89.65\% \pm 2.17\%$ (3e-10)
1	$0.69 \pm 0.19/90.88\% \pm 2.49\%$ (5e-04)	$2.62 \pm 0.15/89.63\% \pm 3.12\%$ (9e-10)	$0.92 \pm 0.16/89.36\% \pm 2.71\%$ (3e-10)	$1.97 \pm 0.12/89.70\% \pm 2.50\%$ (4e-10)
		DeepSeek-R1-Distill-Qwen-32B		
0	$0.69 \pm 0.13/90.44\% \pm 2.10\%$ (6e-05)	$2.30 \pm 0.12/90.12\% \pm 2.13\%$ (2e-08)	$0.89 \pm 0.15/90.09\% \pm 2.08\%$ (5e-04)	$2.00 \pm 0.15/89.84\% \pm 2.90\%$ (4e-08)
1	$0.79 \pm 0.19/90.17\% \pm 2.09\%$ (1e-06)	$2.66 \pm 0.11/90.04\% \pm 1.92\%$ (1e-06)	$1.11 \pm 0.26/90.06\% \pm 1.98\%$ (2e-05)	$2.19 \pm 0.11/90.06\% \pm 2.29\%$ (4e-09)
		Qwen2.5-72B-Instruct		
0	$0.61 \pm 0.13/90.73\% \pm 2.02\%$ (3e-04)	$2.44 \pm 0.14/89.54\% \pm 2.48\%$ (2e-10)	$0.95 \pm 0.12/90.18\% \pm 1.92\%$ (4e-08)	$1.98 \pm 0.12/90.45\% \pm 2.50\%$ (9e-05)
1	$0.61 \pm 0.18/90.29\% \pm 2.09\%$ (3e-04)	$2.69 \pm 0.12/90.56\% \pm 2.16\%$ (2e-02)	$0.93 \pm 0.13/90.65\% \pm 2.29\%$ (5e-04)	$2.01 \pm 0.11/89.91\% \pm 2.73\%$ (2e-06)

Table 9: Two evaluations with the same summarization but different judge scores yield similar evaluations under our framework. In this table, Raw is the raw score in the judgment, weighted is the weighted average based on logits, Con.Interval is the original interval predicted by R2CCP while Dis.Interval is the one after boundary adjustment.

custom_id	Raw	Weighted	Logits (1–5)	Con. Interval	Dis. Interval
93_10_COT2	5	4.64	$-12.69, -9.06, -5.06, -1.06, -0.44$	[4.612, 5]	[4.67, 5]
93_11_COT2	4	4.37	$-11.67, -7.67, -3.67, -0.55, -0.92$	[4.626, 5]	[4.67, 5]

A.9 Additional Results on Discrete Intervals After Boundary Adjustment

Table 13 presents additional experiment results for DialSumm and ROSCOE evaluated with G-Eval after boundary adjustment. Compared to the results in Table 12, boundary adjustment could improve coverage without sacrificing too much or even shorten the interval width, thereby improving the trade-off between coverage and interval width. We also notice that Boosted CQR and Boosted LCP benefit the most from boundary adjustment. After boundary adjustment, prediction intervals of Boosted CQR and Boosted LCP are comparable to that of R2CCP while achieving 90% coverage. However, it should be noted that there is no conformal prediction methods that achieve the best trade-off across different LLM judges.

A.10 Partial Boundary Adjustment is Effective to Mitigate Miscoverage

Owing to the heteroscedastic, and correlated nature of LLM-generated judgments and to the limited calibration set size, prediction intervals before boundary adjustment often fail to achieve 90% coverage. We propose boundary adjustment as a remedy to overcome miscoverage caused by the ordinal, discrete nature of ratings. A standard boundary adjustment could mitigate miscoverage, but it might also introduce bias or fail to satisfy potential user preference for continuous outputs. Here, we explore partial boundary adjustment that adjust the endpoints of a prediction interval by a pre-defined threshold λ. More specifically, only those interval endpoints within absolute distance λ to an integer will be rounded (e.g., $[3.2, 4.9]$ to $[3.2, 5.0]$ for

Table 10: Impact of distribution shift on interval width and coverage. SummEval and DialSumm are used to calibrate each other. We mark coverage $< 85\%$ with gray text, coverage between 85% – 90% with underline and coverage $\geq 90\%$ with the smallest interval width in **bold**.

Model	Fluency	Consistency	Coherence	Relevance
From SummEval to DialSumm: Before boundary adjustment				
GPT-4o mini	1.349 / 79.07%	0.5431 / 18.45%	2.275 / 86.07%	1.912 / 84.81%
DeepSeek-R1-Distill-Qwen-32B	0.6925 / 46.57%	0.5956 / 24.00%	**1.924 / 92.71%**	1.793 / 81.86%
Qwen2.5-72B-Instruct	0.8463 / 47.43%	0.5864 / 20.36%	2.067 / 72.00%	1.978 / 87.43%
From SummEval to DialSumm: After boundary adjustment				
GPT-4o mini	1.352 / 86.50%	0.5233 / 31.26%	2.271 / 89.57%	**1.895 / 91.55%**
DeepSeek-R1-Distill-Qwen-32B	0.6531 / 57.00%	0.5563 / 30.71%	**1.922 / 94.36%**	1.773 / 87.07%
Qwen2.5-72B-Instruct	0.8376 / 62.93%	0.5537 / 30.64%	2.064 / 76.57%	1.980 / 90.29%
From DialSumm to SummEval: Before boundary adjustment				
GPT-4o mini	1.316 / 53.69%	1.837 / 66.50%	1.764 / 56.50%	1.892 / 82.81%
DeepSeek-R1-Distill-Qwen-32B	1.121 / 35.94%	1.880 / 50.38%	1.344 / 52.38%	1.727 / 80.19%
Qwen2.5-72B-Instruct	1.164 / 27.19%	1.596 / 37.75%	1.491 / 48.31%	1.588 / 77.63%
From DialSumm to SummEval: After boundary adjustment				
GPT-4o mini	1.334 / 92.06%	1.849 / 80.50%	1.773 / 63.25%	1.894 / 90.88%
DeepSeek-R1-Distill-Qwen-32B	1.160 / 82.38%	1.878 / 69.94%	1.332 / 60.25%	1.723 / 86.25%
Qwen2.5-72B-Instruct	**1.219 / 90.00%**	1.604 / 59.25%	1.521 / 57.38%	1.562 / 84.50%

$\lambda = 0.1$).

Theoretically, Theorem 1 suggests that such an outward adjustment shifts the quantile level to include more potential labels, thus improving coverage. Empirically, we conduct experiments with vary λ and show the results in Tables 14 and 15. Our results suggest that larger λ often yield greater coverage gains without much increase or even with decrease on average interval width.

A.11 Additional Results on Midpoints Effectiveness

Tables 16, 17 and 18 include additional results on evaluating the effectiveness of interval midpoint under different settings, including on DialSumm, and on ROSCOE evaluated with G-Eval and SocREval. From the tables, we observe similar findings as to our findings in Table 3 that midpoints are consistently less biased evaluation compared to other baseline methods.

A.12 Potential Extension to Multimodal Evaluation

To explore the broader application of our framework, we conduct experiments on GenAI-Bench (Li et al., 2024a), a benchmark designed for vision-language tasks. GenAI-Bench contains 1600 prompt texts, each paired with six model generated images, and each output is rated by three human experts. We prompt Qwen2.5-VL-32B-Instruct (Bai et al., 2025) to assess image-text consistency and apply our framework to construct prediction intervals for evaluations.

Two prompting strategies are considered in this new experiment. The first is a standard prompt (Figure 19), which simply asks the model to assign a quality score. The second is a chain-of-thought (Figure 20), followed a chain-of-thought design that asks the model to reason through a more detailed evaluation process and produce its score. For evaluation, we partition the dataset into two splits (800:800) that serves alternately as calibration and test sets, and employ R2CCP to generate intervals.

For the evaluations by Std_prompt, the original average interval width is 2.43 with a coverage of 0.884, which increase to 2.45 and 0.919 after adjustment. For CoT_prompt, the original interval average width is 2.45 with a coverage of 0.897, improving to 2.47 and 0.929 after adjustment. As shown in Table 20, the midpoints of the intervals yield scores that achieve higher correlations with human ratings and lower error compared to raw or Weighted Avg., demonstrating the effectiveness of our interval-based framework.

Table 11: Comparison of human-based baseline and R2CCP (seed = 42) on SummEval and DialSumm

Evaluator	Method	Consistency	Coherence	Fluency	Relevance
		SummEval			
Human-based	Baseline	0.667 (91.4%)	2.000 (95.6%)	1.333 (96.3%)	2.000 (92.8%)
GPT-4o-mini	R2CCP	0.621 (90.1%)	2.652 (89.9%)	1.135 (93.4%)	2.076 (91.5%)
DSR1-Qwen-32B	R2CCP	0.598 (89.3%)	2.168 (85.8%)	0.850 (90.1%)	2.142 (93.3%)
Qwen-2.5-72B	R2CCP	0.491 (88.9%)	2.429 (88.0%)	0.812 (88.0%)	1.969 (91.4%)
		DialSumm			
Human-based	Baseline	2.667 (95.9%)	2.000 (96.9%)	2.000 (95.1%)	2.667 (95.6%)
GPT-4o-mini	R2CCP	1.799 (91.99%)	1.701 (91.00%)	1.215 (89.71%)	1.580 (85.2%)
DSR1-Qwen-32B	R2CCP	1.912 (88.7%)	1.283 (89.3%)	0.812 (88.0%)	1.805 (89.9%)
Qwen-2.5-72B	R2CCP	1.591 (87.0%)	1.494 (90.3%)	1.136 (90.3%)	1.653 (91.9%)

For other potential applications, one might follow Wang et al. (2025); Wei et al. (2025) to obtain pairwise preference based on our intervals as we mention in Section 3.1. For example, there are 1600 prompt texts for six models to generate images. For each image, we can obtain an interval by our framework. One possible preference learning method is to compute a preference score that measures the overlapping of a pair of intervals. Since we have a calibration set in conformal prediction, we can also calculate a calibrated confidence of preference. Finally, one can generate a preference directed acyclic graph with six edges for each prompt text in this dataset. On such a preference graph, edges are equipped with the features of pointwise evaluations including intervals and raw response while the link direction is the pairwise preference (A is better than B) while the weight is the calibrated confidence. One might also infer a listwise preference rank with highest accumulated confidence based on this graph.

A.13 Prompt Used and Responses from Repromt and Regrade

We adopt G-Eval (Liu et al., 2023) as the main LLM-as-a-judge framework across all tasks and SocREval (He et al., 2024) specifically for reasoning tasks. We make minimal adjuments to the prompt adjustments for each evaluation. Below we provide three representative prompt examples: evaluating relevance on SummEval (Figure 5), evaluating ROSCOE under both G-Eval (Figure 6) and SocREval (Figure 7). It is worth noting that we apply the SummEval prompt template directly to DialSumm. Even though DialSumm is for dialogue summarization rather than news summarization, the resulting intervals on DialSumm still exhibit promising performance.

Table 12: Interval width and coverage on DialSumm and ROSCOE evaluated with G-Eval before boundary adjustment. We mark coverage $< 85\%$ with gray text, coverage between 85% – 90% with underline and coverage $\geq 90\%$ with the smallest interval width in **bold**.

Method	DialSumm Evaluated with G-Eval				ROSCOE Evaluated with G-Eval			
	Consistency	Coherence	Fluency	Relevance	CosmosQA	DROP	e-SNLI	GSM8K
				GPT-4o mini				
CQR	2.41 / 91.99%	1.77 / 92.41%	**1.08 / 93.38%**	2.06 / 91.57%	**3.60 / 96.43%**	**3.77 / 96.54%**	3.35 / 95.31%	**3.58 / 94.83%**
Asym CQR	2.43 / 92.30%	1.87 / 94.00%	1.18 / 94.40%	2.09 / 92.38%	3.95 / 99.56%	3.89 / 98.19%	**2.98 / 96.67%**	3.94 / 99.27%
CHR	1.54 / 80.01%	1.48 / 83.03%	0.99 / 84.01%	1.40 / 80.53%	2.47 / 70.78%	1.82 / 68.44%	1.28 / 55.66%	2.27 / 70.27%
LVD	1.90 / 89.20%	1.75 / 90.67%	1.20 / 88.40%	1.79 / 89.23%	3.18 / 83.44%	2.33 / 79.11%	3.00 / 91.18%	3.10 / 84.50%
Boosted CQR	1.85 / 86.81%	1.61 / 87.26%	1.03 / 86.33%	1.65 / 87.06%	3.12 / 77.99%	2.58 / 78.32%	2.13 / 75.79%	3.20 / 80.03%
Boosted LCP	1.83 / 87.45%	1.59 / 88.30%	1.00 / 87.53%	1.76 / 87.20%	3.45 / 79.66%	2.94 / 86.41%	1.94 / 80.26%	3.42 / 83.53%
R2CCP	**1.84 / 90.13%**	**1.63 / 90.15%**	1.14 / 89.64%	**1.72 / 90.11%**	3.09 / 86.77%	2.54 / 86.70%	2.20 / 88.01%	2.43 / 84.67%
				DeepSeek-R1-Distill-Qwen-32B				
CQR	2.50 / 91.30%	1.51 / 91.85%	**1.11 / 92.83%**	2.33 / 91.69%	**3.62 / 96.29%**	**3.82 / 96.22%**	3.33 / 97.85%	3.54 / 95.27%
Asym CQR	2.52 / 91.92%	1.58 / 93.20%	1.22 / 94.04%	2.42 / 92.51%	3.89 / 98.95%	3.88 / 97.78%	2.95 / 97.15%	3.90 / 99.27%
CHR	1.76 / 86.09%	1.26 / 87.80%	1.06 / 87.79%	1.53 / 85.22%	2.64 / 78.10%	2.19 / 80.13%	1.80 / 77.24%	2.77 / 81.90%
LVD	**2.03 / 90.19%**	**1.41 / 90.29%**	1.22 / 90.41%	**1.87 / 90.01%**	3.31 / 89.52%	2.81 / 88.98%	**2.86 / 94.82%**	**3.39 / 90.07%**
Boosted CQR	1.89 / 87.48%	1.31 / 88.61%	1.11 / 88.07%	1.71 / 87.39%	3.40 / 80.92%	2.84 / 85.02%	2.23 / 83.68%	3.27 / 80.53%
Boosted LCP	1.88 / 86.05%	1.32 / 86.77%	1.02 / 87.28%	1.82 / 87.24%	3.49 / 81.73%	2.94 / 86.06%	1.99 / 83.33%	3.38 / 81.13%
R2CCP	1.86 / 89.22%	1.31 / 89.92%	1.19 / 90.57%	1.70 / 89.39%	3.05 / 86.84%	2.44 / 85.87%	1.96 / 85.43%	2.51 / 86.77%
				Qwen2.5-72B-Instruct				
CQR	2.37 / 91.51%	**1.52 / 91.57%**	**1.06 / 93.11%**	**2.02 / 91.55%**	**3.62 / 96.67%**	3.78 / 96.86%	3.37 / 98.29%	**3.58 / 95.30%**
Asym CQR	2.40 / 91.92%	1.61 / 92.88%	1.14 / 93.87%	2.04 / 92.38%	3.93 / 99.12%	3.92 / 99.17%	2.96 / 97.41%	3.90 / 99.00%
CHR	1.48 / 81.50%	1.25 / 81.88%	1.00 / 85.97%	1.33 / 81.15%	2.59 / 74.97%	1.76 / 68.38%	1.39 / 66.84%	1.76 / 72.57%
LVD	**1.84 / 90.43%**	1.47 / 89.91%	1.20 / 90.26%	1.74 / 89.99%	3.34 / 89.01%	2.41 / 84.57%	**2.65 / 92.41%**	2.83 / 88.50%
Boosted CQR	1.69 / 86.57%	1.35 / 87.06%	1.05 / 87.38%	1.52 / 87.08%	3.35 / 81.02%	2.55 / 83.52%	1.90 / 81.84%	3.18 / 82.70%
Boosted LCP	1.75 / 86.08%	1.35 / 86.29%	0.96 / 87.77%	1.63 / 86.88%	3.45 / 80.41%	2.79 / 83.05%	1.85 / 80.79%	3.42 / 83.47%
R2CCP	1.74 / 89.97%	1.41 / 89.67%	1.14 / 89.70%	1.61 / 89.80%	3.07 / 87.11%	**3.10 / 93.40%**	1.68 / 84.80%	2.38 / 87.53%

Table 13: Interval width and coverage on DialSumm and ROSCOE evaluated with G-Eval after boundary adjustment. We mark coverage $< 85\%$ with gray text, coverage between 85% – 90% with underline and coverage $\geq 90\%$ with the smallest interval width in **bold**.

Method	DialSumm Evaluated with G-Eval				ROSCOE Evaluated with G-Eval			
	Consistency	Coherence	Fluency	Relevance	CosmosQA	DROP	e-SNLI	GSM8K
				GPT-4o mini				
CQR	2.40 / 94.09%	1.76 / 94.50%	1.07 / 95.01%	2.05 / 94.33%	3.60 / 96.60%	3.77 / 96.86%	3.42 / 97.50%	3.57 / 95.10%
Asym CQR	2.43 / 94.34%	1.86 / 95.87%	1.18 / 95.97%	2.08 / 94.68%	3.95 / 99.69%	3.89 / 98.54%	2.99 / 97.54%	3.94 / 99.27%
CHR	1.54 / 86.65%	**1.47 / 90.28%**	0.96 / 89.86%	1.40 / 87.49%	2.48 / 80.31%	1.82 / 78.06%	1.30 / 72.41%	2.25 / 78.90%
LVD	1.90 / 93.81%	1.75 / 94.43%	1.21 / 93.81%	1.80 / 93.77%	3.20 / 91.70%	2.33 / 86.63%	3.01 / 96.89%	3.11 / 89.53%
Boosted CQR	1.85 / 93.33%	1.60 / 93.95%	1.00 / 93.32%	**1.66 / 92.66%**	3.16 / 93.40%	2.60 / 90.51%	2.16 / 89.39%	**3.22 / 90.50%**
Boosted LCP	**1.83 / 92.94%**	1.60 / 93.01%	**0.96 / 93.50%**	1.76 / 91.85%	3.39 / 94.46%	2.97 / 91.71%	**1.96 / 92.32%**	3.32 / 92.87%
R2CCP	1.84 / 93.32%	1.63 / 93.38%	1.15 / 93.28%	1.72 / 93.65%	**3.06 / 90.31%**	**2.52 / 90.48%**	2.16 / 92.35%	2.42 / 86.77%
OrdinalAPS	2.24 / 90.39%	2.03 / 35.69%	1.87 / 60.61%	2.07 / 79.40%	1.79 / 70.61%	1.44 / 78.57%	1.75 / 70.13%	1.36 / 75.03%
OrdinalRC	2.33 / 91.49%	3.17 / 39.46%	2.01 / 64.66%	2.21 / 83.29%	1.94 / 73.16%	1.52 / 80.73%	1.84 / 72.32%	1.44 / 75.47%
				DeepSeek-R1-Distill-Qwen-32B				
CQR	2.49 / 93.67%	1.51 / 94.80%	1.11 / 94.58%	2.31 / 93.54%	3.61 / 96.43%	3.83 / 96.95%	3.32 / 97.98%	3.54 / 95.80%
Asym CQR	2.51 / 93.90%	1.58 / 95.41%	1.22 / 95.61%	2.43 / 94.35%	3.89 / 98.95%	3.88 / 97.87%	2.94 / 97.28%	3.90 / 99.37%
CHR	**1.76 / 90.78%**	**1.25 / 93.09%**	1.03 / 92.48%	**1.53 / 90.65%**	2.66 / 85.95%	2.21 / 87.94%	1.83 / 90.57%	2.75 / 89.17%
LVD	2.04 / 93.87%	1.41 / 95.07%	1.23 / 94.74%	1.87 / 93.86%	3.34 / 94.69%	2.82 / 93.40%	2.87 / 98.55%	3.42 / 95.47%
Boosted CQR	1.89 / 92.91%	1.31 / 94.36%	1.08 / 94.16%	1.71 / 92.95%	3.44 / 94.69%	2.88 / 94.41%	2.27 / 95.44%	3.29 / 93.60%
Boosted LCP	1.87 / 91.83%	1.32 / 93.31%	**0.98 / 93.27%**	1.82 / 91.52%	3.49 / 94.76%	3.03 / 91.27%	2.01 / 92.59%	3.31 / 91.70%
R2CCP	1.85 / 92.87%	1.31 / 93.84%	1.19 / 93.79%	1.70 / 93.23%	3.04 / 91.29%	2.40 / 89.84%	**1.90 / 90.79%**	2.49 / 88.87%
OrdinalAPS	2.05 / 90.05%	3.17 / 90.40%	3.43 / 90.25%	2.17 / 89.90%	**2.90 / 90.99%**	**2.27 / 91.24%**	3.20 / 91.93%	2.98 / 91.93%
OrdinalRC	2.05 / 90.04%	3.17 / 90.30%	3.42 / 89.93%	2.17 / 89.80%	2.79 / 89.59%	2.22 / 90.73%	3.15 / 90.48%	**2.86 / 90.83%**
				Qwen2.5-72B-Instruct				
CQR	2.37 / 94.62%	1.51 / 94.42%	1.06 / 94.40%	2.05 / 94.91%	3.63 / 97.14%	3.78 / 97.14%	3.38 / 98.42%	3.58 / 95.73%
Asym CQR	2.41 / 95.10%	1.61 / 95.21%	1.14 / 95.08%	2.04 / 95.00%	3.93 / 99.42%	3.92 / 99.24%	2.95 / 97.50%	3.89 / 99.07%
CHR	1.48 / 87.99%	1.25 / 89.46%	0.97 / 91.59%	1.34 / 88.06%	2.62 / 83.74%	1.77 / 82.92%	1.43 / 85.31%	1.78 / 82.10%
LVD	1.84 / 94.48%	1.48 / 94.77%	1.20 / 95.10%	1.73 / 94.04%	3.36 / 94.90%	**2.41 / 92.44%**	2.65 / 98.25%	2.83 / 92.47%
Boosted CQR	1.70 / 92.85%	**1.35 / 93.90%**	1.05 / 93.82%	1.52 / 92.95%	3.40 / 94.56%	2.57 / 93.30%	1.92 / 94.47%	3.22 / 92.03%
Boosted LCP	1.76 / 92.50%	**1.35 / 93.38%**	**0.90 / 92.39%**	1.62 / 92.52%	3.45 / 95.24%	2.85 / 90.95%	**1.91 / 92.02%**	3.38 / 92.73%
R2CCP	**1.73 / 93.55%**	1.41 / 93.72%	1.15 / 93.83%	1.60 / 93.17%	3.05 / 90.71%	3.08 / 95.65%	1.59 / 89.67%	2.39 / 89.60%
OrdinalAPS	2.57 / 89.84%	2.88 / 63.10%	2.95 / 75.48%	2.83 / 90.10%	2.78 / 89.42%	**2.02 / 90.95%**	2.79 / 93.25%	**2.46 / 90.30%**
OrdinalRC	2.57 / 89.85%	3.01 / 68.81%	3.09 / 78.40%	2.81 / 89.81%	**2.85 / 90.95%**	1.93 / 89.62%	2.71 / 91.40%	2.60 / 91.63%

Table 14: R2CCP interval width and coverage for summarization tasks under partial boundary adjustment with $\lambda = 0.5,\ 0.1,\ 0$ (no boundary adjustment). Width±std / coverage%±std are computed based on 30 different runs.

Dataset	Dimension	0.167 (Full Adjustment)	0.1	0
		GPT-4o mini		
SummEval	Consistency	0.6753 ± 0.2026 / 92.15% ± 2.25%	0.6800 ± 0.1951 / 91.68% ± 2.33%	0.6858 ± 0.1859 / 90.88% ± 2.49%
	Coherence	2.6186 ± 0.1522 / 92.81% ± 2.37%	2.6201 ± 0.1497 / 91.54% ± 2.69%	2.6243 ± 0.1466 / 89.63% ± 3.12%
	Fluency	0.9116 ± 0.1673 / 90.99% ± 2.06%	0.9166 ± 0.1657 / 90.49% ± 2.29%	0.9213 ± 0.1641 / 89.36% ± 2.71%
	Relevance	1.9688 ± 0.1288 / 93.38% ± 1.96%	1.9693 ± 0.1244 / 91.90% ± 2.19%	1.9705 ± 0.1215 / 89.70% ± 2.50%
DialSumm	Consistency	1.8443 ± 0.1299 / 93.32% ± 1.85%	1.8425 ± 0.1298 / 92.03% ± 1.96%	1.8436 ± 0.1287 / 90.13% ± 2.39%
	Coherence	1.6264 ± 0.1363 / 93.38% ± 2.68%	1.6274 ± 0.1354 / 92.10% ± 3.08%	1.6256 ± 0.1337 / 90.15% ± 3.38%
	Fluency	1.1504 ± 0.1187 / 93.28% ± 2.03%	1.1484 ± 0.1237 / 91.87% ± 2.56%	1.1357 ± 0.1226 / 89.64% ± 2.92%
	Relevance	1.7161 ± 0.1398 / 93.65% ± 2.06%	1.7178 ± 0.1391 / 92.15% ± 2.32%	1.7209 ± 0.1395 / 90.11% ± 2.75%
		DeepSeek-R1-Distill-Qwen-32B		
SummEval	Consistency	0.6804 ± 0.1521 / 91.57% ± 2.17%	0.6876 ± 0.1437 / 91.02% ± 2.11%	0.6941 ± 0.1343 / 90.44% ± 2.09%
	Coherence	2.2972 ± 0.1161 / 93.22% ± 1.65%	2.2994 ± 0.1169 / 91.91% ± 1.88%	2.3042 ± 0.1172 / 90.12% ± 2.13%
	Fluency	0.8886 ± 0.1605 / 91.80% ± 1.82%	0.8907 ± 0.1561 / 91.09% ± 2.00%	0.8926 ± 0.1512 / 90.09% ± 2.08%
	Relevance	1.9935 ± 0.1557 / 92.96% ± 2.09%	1.9951 ± 0.1514 / 91.72% ± 2.35%	1.9984 ± 0.1482 / 89.84% ± 2.90%
DialSumm	Consistency	1.8534 ± 0.1426 / 92.87% ± 2.01%	1.8574 ± 0.1397 / 91.43% ± 2.10%	1.8601 ± 0.1371 / 89.22% ± 2.62%
	Coherence	1.3113 ± 0.1082 / 93.84% ± 1.85%	1.3126 ± 0.1077 / 92.28% ± 2.14%	1.3138 ± 0.1068 / 89.92% ± 2.76%
	Fluency	1.1903 ± 0.1368 / 93.79% ± 1.78%	1.1915 ± 0.1349 / 92.58% ± 2.03%	1.1859 ± 0.1348 / 90.57% ± 2.35%
	Relevance	1.6952 ± 0.1660 / 93.23% ± 1.89%	1.6982 ± 0.1639 / 91.70% ± 2.16%	1.7043 ± 0.1601 / 89.39% ± 2.57%
		Qwen2.5-72B-Instruct		
SummEval	Consistency	0.5876 ± 0.1520 / 91.83% ± 1.92%	0.5973 ± 0.1447 / 91.47% ± 1.88%	0.6122 ± 0.1341 / 90.73% ± 2.02%
	Coherence	2.4308 ± 0.1457 / 92.78% ± 2.07%	2.4331 ± 0.1444 / 91.53% ± 2.19%	2.4367 ± 0.1426 / 89.54% ± 2.48%
	Fluency	0.9494 ± 0.1180 / 92.12% ± 1.46%	0.9500 ± 0.1216 / 91.38% ± 1.76%	0.9527 ± 0.1218 / 90.17% ± 1.92%
	Relevance	1.9765 ± 0.1257 / 93.72% ± 1.78%	1.9776 ± 0.1253 / 92.50% ± 2.06%	1.9789 ± 0.1237 / 90.45% ± 2.49%
DialSumm	Consistency	1.7319 ± 0.1106 / 93.55% ± 1.59%	1.7350 ± 0.1083 / 92.16% ± 1.91%	1.7368 ± 0.1050 / 89.97% ± 2.18%
	Coherence	1.4060 ± 0.1115 / 93.72% ± 1.97%	1.4079 ± 0.1086 / 92.07% ± 2.36%	1.4094 ± 0.1076 / 89.67% ± 2.81%
	Fluency	1.1518 ± 0.1265 / 93.83% ± 2.29%	1.1475 ± 0.1345 / 92.37% ± 2.74%	1.1376 ± 0.1398 / 89.70% ± 3.42%
	Relevance	1.5966 ± 0.1742 / 93.17% ± 2.02%	1.6015 ± 0.1714 / 91.82% ± 2.43%	1.6071 ± 0.1682 / 89.80% ± 2.85%

Table 15: R2CCP interval width and coverage for reasoning tasks under partial boundary adjustment with $\lambda = 0.5,\ 0.1,\ 0$ (no boundary adjustment). Width±std / coverage%±std are computed based on 30 different runs.

Judge	Dataset	0.5	0.1	0
GPT-4o mini				
G-Eval	Cosmos	3.0612 ± 0.5594 / 90.31% ± 7.07%	3.0847 ± 0.5371 / 87.31% ± 8.17%	3.0864 ± 0.5335 / 86.77% ± 7.98%
	DROP	2.5230 ± 0.4804 / 90.48% ± 5.53%	2.5410 ± 0.4402 / 87.30% ± 6.03%	2.5431 ± 0.4363 / 86.70% ± 5.87%
	e-SNLI	2.1562 ± 0.4732 / 92.35% ± 6.88%	2.1932 ± 0.4282 / 88.30% ± 7.15%	2.1953 ± 0.4264 / 88.01% ± 7.17%
	GSM8K	2.4205 ± 0.7782 / 86.77% ± 7.63%	2.4283 ± 0.7639 / 85.10% ± 7.50%	2.4298 ± 0.7626 / 84.67% ± 8.00%
SocREval	Cosmos	2.9294 ± 0.4597 / 89.46% ± 7.01%	2.9586 ± 0.4396 / 86.73% ± 7.80%	2.9618 ± 0.4350 / 85.85% ± 7.79%
	DROP	2.4125 ± 0.8208 / 89.21% ± 9.21%	2.4271 ± 0.7631 / 85.40% ± 10.04%	2.4300 ± 0.7600 / 84.73% ± 9.97%
	e-SNLI	1.7076 ± 0.5804 / 90.11% ± 8.41%	1.7467 ± 0.4878 / 84.99% ± 8.23%	1.7480 ± 0.4842 / 84.02% ± 8.62%
	GSM8K	2.0943 ± 1.1782 / 86.93% ± 8.15%	2.1452 ± 1.0893 / 85.70% ± 7.95%	2.1452 ± 1.0866 / 85.07% ± 7.87%
DeepSeek-R1-Distill-Qwen-32B				
G-Eval	Cosmos	3.0357 ± 0.4873 / 91.29% ± 5.71%	3.0474 ± 0.4629 / 87.35% ± 6.04%	3.0489 ± 0.4601 / 86.84% ± 5.87%
	DROP	2.4000 ± 0.6406 / 89.84% ± 7.80%	2.4360 ± 0.5746 / 86.48% ± 7.94%	2.4385 ± 0.5714 / 85.87% ± 8.05%
	e-SNLI	1.8952 ± 0.4948 / 90.79% ± 7.39%	1.9532 ± 0.4343 / 86.06% ± 6.95%	1.9585 ± 0.4315 / 85.43% ± 7.02%
	GSM8K	2.4865 ± 0.8454 / 88.87% ± 9.31%	2.5067 ± 0.8065 / 87.07% ± 9.04%	2.5078 ± 0.8053 / 86.77% ± 8.89%
SocREval	Cosmos	2.9094 ± 0.6323 / 90.58% ± 7.92%	2.9365 ± 0.5718 / 87.76% ± 8.45%	2.9378 ± 0.5689 / 86.97% ± 8.37%
	DROP	2.2457 ± 0.6021 / 89.97% ± 8.61%	2.2906 ± 0.5369 / 86.92% ± 9.06%	2.2931 ± 0.5342 / 86.35% ± 9.08%
	e-SNLI	1.7965 ± 0.5139 / 92.35% ± 7.77%	1.8413 ± 0.4481 / 88.45% ± 8.00%	1.8450 ± 0.4443 / 87.87% ± 7.92%
	GSM8K	1.8238 ± 1.2189 / 86.93% ± 7.45%	1.8767 ± 1.1507 / 85.67% ± 7.30%	1.8796 ± 1.1480 / 85.33% ± 7.02%
Qwen2.5-72B-Instruct				
G-Eval	Cosmos	3.0529 ± 0.5262 / 90.71% ± 6.80%	3.0624 ± 0.5089 / 87.82% ± 8.11%	3.0652 ± 0.5059 / 87.11% ± 8.10%
	DROP	3.0765 ± 0.9169 / 95.65% ± 5.33%	3.0954 ± 0.8907 / 93.68% ± 7.50%	3.0964 ± 0.8894 / 93.40% ± 7.74%
	e-SNLI	1.5885 ± 0.4282 / 89.67% ± 6.42%	1.6737 ± 0.3734 / 85.28% ± 6.56%	1.6792 ± 0.3694 / 84.80% ± 6.89%
	GSM8K	2.3922 ± 0.6387 / 89.60% ± 4.34%	2.3778 ± 0.6328 / 87.93% ± 5.71%	2.3782 ± 0.6323 / 87.53% ± 5.95%
SocREval	Cosmos	2.8786 ± 0.5572 / 89.29% ± 7.43%	2.8999 ± 0.5210 / 86.16% ± 8.76%	2.8996 ± 0.5176 / 85.34% ± 8.46%
	DROP	2.3446 ± 0.6459 / 90.00% ± 7.90%	2.3832 ± 0.5883 / 86.92% ± 8.14%	2.3852 ± 0.5854 / 86.25% ± 8.22%
	e-SNLI	1.5461 ± 0.6282 / 90.20% ± 8.42%	1.5854 ± 0.5467 / 85.43% ± 8.44%	1.5897 ± 0.5397 / 84.50% ± 8.75%
	GSM8K	1.9602 ± 1.0970 / 88.57% ± 7.01%	2.0026 ± 1.0422 / 87.07% ± 7.14%	2.0015 ± 1.0391 / 86.73% ± 7.09%

Table 16: Midpoints experiment on DialSumm. **Bold** indicates better performance than baselines, underlined denotes comparable performance, and gray indicates worse performance.

Method	Coherence				Consistency				Fluency				Relevance			
	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ
GPT-4o mini																GPT-4o-mini
Raw Score	3.787	1.711	0.205	0.172	1.000	0.772	0.656	0.547	2.111	1.171	0.400	0.344	1.278	0.874	0.668	0.564
Weighted Avg.	3.701	1.699	0.218	0.162	0.825	0.704	0.702	0.546	1.688	1.066	0.434	0.338	1.175	0.855	0.703	0.549
Con R2CCP	**0.344**	**0.454**	**0.396**	**0.300**	**0.391**	**0.489**	0.688	0.532	**0.173**	**0.309**	0.433	0.340	**0.338**	**0.445**	**0.716**	0.563
Dis R2CCP	**0.348**	**0.453**	**0.385**	**0.313**	**0.395**	**0.489**	0.684	**0.553**	**0.178**	**0.309**	0.418	**0.364**	**0.342**	**0.446**	**0.714**	**0.584**
DeepSeek-R1-Distill-Qwen-32B																
Raw Score	2.908	1.412	0.396	0.329	1.422	0.952	0.589	0.497	2.454	1.383	0.414	0.356	1.214	0.829	0.555	0.461
Weighted Avg.	2.149	1.241	0.456	0.343	0.652	0.614	0.642	0.491	2.115	1.287	0.452	0.347	0.674	0.625	0.621	0.476
Con R2CCP	**0.211**	**0.348**	**0.627**	**0.488**	**0.451**	**0.509**	**0.668**	**0.512**	**0.185**	**0.315**	**0.460**	0.356	**0.348**	**0.450**	**0.721**	**0.563**
Dis R2CCP	**0.215**	**0.347**	**0.615**	**0.511**	**0.455**	**0.508**	**0.665**	**0.534**	**0.188**	**0.314**	**0.455**	**0.389**	**0.352**	**0.450**	**0.716**	**0.581**
Qwen2.5-72B-Instruct																
Raw Score	3.934	1.775	0.321	0.267	1.344	0.897	0.704	0.599	2.796	1.420	0.478	0.406	1.812	1.070	0.609	0.521
Weighted Avg.	3.693	1.746	0.358	0.266	1.076	0.819	0.737	0.577	2.575	1.335	0.499	0.386	1.552	1.014	0.660	0.516
Con R2CCP	**0.241**	**0.381**	**0.583**	**0.450**	**0.370**	**0.467**	0.737	0.577	**0.169**	**0.306**	0.489	0.380	**0.311**	**0.424**	**0.727**	**0.578**
Dis R2CCP	**0.245**	**0.380**	**0.574**	**0.471**	**0.373**	**0.467**	0.734	0.594	**0.174**	**0.306**	0.485	**0.419**	**0.315**	**0.424**	**0.722**	**0.594**

Table 17: Midpoints experiment on ROSCOE evaluated by G-Eval. **Bold** indicates better performance than baselines, underlined denotes comparable performance, and gray indicates worse performance.

Method	CosmosQA				DROP				e-SNLI				GSM8k			
	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ
GPT-4o mini																
Raw Score	1.780	1.044	0.483	0.406	1.843	0.951	0.490	0.411	2.719	1.210	0.340	0.288	2.216	0.909	0.586	0.516
Weighted Avg.	1.704	1.065	0.490	0.371	1.651	0.894	0.516	0.391	2.610	1.221	0.357	0.273	2.169	0.936	0.577	0.458
Con R2CCP	2.035	1.223	0.366	0.282	**1.509**	1.034	0.458	0.353	**1.045**	**0.865**	0.239	0.189	2.307	1.282	0.493	0.396
Dis R2CCP	2.044	1.220	0.348	0.293	**1.526**	1.024	0.469	0.402	**1.061**	**0.854**	0.231	0.206	2.317	1.277	0.501	0.434
DeepSeek-R1-Distill-Qwen-32B																
Raw Score	2.353	1.166	0.396	0.335	2.156	0.977	0.478	0.419	3.090	1.466	0.225	0.199	2.300	0.906	0.596	0.538
Weighted Avg.	1.805	1.157	0.462	0.348	1.281	0.913	0.551	0.422	2.144	1.286	0.279	0.214	1.907	1.045	0.602	0.476
Con R2CCP	1.931	1.172	0.440	0.344	1.485	1.003	0.491	0.380	**0.904**	**0.802**	**0.423**	**0.334**	2.232	1.283	0.540	0.432
Dis R2CCP	1.936	**0.999**	0.407	0.345	1.518	0.999	0.478	0.406	**0.916**	**0.792**	**0.405**	**0.355**	2.256	1.281	0.539	0.472
Qwen2.5-72B-Instruct																
Raw Score	1.964	1.179	0.420	0.364	1.797	0.928	0.498	0.421	1.920	1.173	0.359	0.304	1.911	0.820	0.653	0.589
Weighted Avg.	1.840	1.166	0.484	0.367	1.381	0.867	0.569	0.437	1.615	1.101	0.388	0.292	1.767	0.857	0.662	0.529
Con R2CCP	1.992	1.207	0.429	0.329	1.789	1.124	**0.584**	**0.453**	**0.796**	**0.727**	**0.471**	**0.372**	2.021	1.174	0.566	0.460
Dis R2CCP	2.004	1.200	0.390	0.327	1.801	1.121	**0.573**	**0.487**	**0.816**	**0.716**	**0.455**	**0.400**	2.044	1.173	0.578	0.511

Table 18: Midpoints experiment on ROSCOE evaluated by SocREval. **Bold** indicates better performance than baselines, underlined denotes comparable performance, and gray indicates worse performance.

Method	CosmosQA				DROP				e-SNLI				GSM8k			
	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ	MSE	MAE	ρ	τ
GPT-4o mini																
Raw Score	1.780	1.044	0.483	0.406	2.969	1.284	0.202	0.168	1.096	0.841	0.551	0.496	4.103	1.613	0.173	0.148
Weighted Avg.	1.704	1.065	0.490	0.371	1.408	0.905	0.563	0.429	1.054	0.849	0.574	0.460	1.612	0.771	0.649	0.523
Con R2CCP	1.904	1.170	0.430	0.330	1.560	1.017	0.495	0.386	**0.725**	**0.716**	0.509	0.408	2.061	1.154	0.569	0.470
Dis R2CCP	1.917	1.165	0.415	0.348	1.578	1.013	0.493	0.421	**0.753**	**0.711**	0.505	0.453	2.095	1.144	0.589	0.527
DeepSeek-R1-Distill-Qwen-32B																
Raw Score	2.130	1.128	0.500	0.432	1.443	0.803	0.630	0.564	0.693	0.629	0.581	0.531	1.445	0.628	0.707	0.640
Weighted Avg.	2.016	1.107	0.525	0.398	1.446	0.825	0.639	0.503	0.668	0.632	0.622	0.496	1.425	0.645	0.664	0.522
Con R2CCP	**1.853**	1.151	0.468	0.362	**1.264**	0.914	0.602	0.476	0.717	0.708	0.615	0.490	1.849	1.048	0.595	0.477
Dis R2CCP	**1.875**	1.146	0.595	0.515	**1.290**	0.907	0.595	**0.515**	0.734	0.695	0.580	0.517	1.891	1.045	0.637	0.577
Qwen2.5-72B-Instruct																
Raw Score	1.737	0.975	0.533	0.444	1.313	0.730	0.610	0.536	0.590	0.488	0.651	0.591	1.387	0.653	0.730	0.663
Weighted Avg.	1.688	0.986	0.527	0.407	1.290	0.735	0.603	0.475	0.558	0.499	0.665	0.540	1.388	0.659	0.681	0.557
Con R2CCP	1.897	1.162	0.446	0.348	1.378	0.968	0.556	0.456	0.609	0.656	0.597	0.482	1.823	1.063	0.648	0.556
Dis R2CCP	1.910	1.156	0.442	0.375	1.403	0.965	0.541	0.487	0.632	0.652	0.595	0.533	1.849	1.057	0.653	0.596

Table 19: Reprompting the LLM with prediction intervals reinforces its original judgments since initial scores already lie within those intervals, the model makes trivial adjustments, revealing that it might be hard for interval alone to correct inherent bias since there is no significant difference in each metric for comparison.

Dataset	**Width / Coverage**	**Method**	**MSE**	**MAE**	ρ	τ
CosmosQA (Seed = 1)	2.60 / 89.80%	Initial Raw	2.204082	1.163265	0.480293	0.419364
		Reprompt Raw	2.193877	1.153061	0.476310	0.417798
		Initial Weighted	2.052884	1.133203	0.508314	0.390947
		Reprompt Weighted	2.111918	1.167847	0.499106	0.377264
		Majority Vote	2.06124	1.142857	0.453829	0.389735
DROP (Seed = 18)	1.67 / 89.52%	Initial Raw	1.371429	0.800000	0.603949	0.551028
		Reprompt Raw	1.380952	0.809524	0.603821	0.550921
		Initial Weighted	1.333399	0.800079	0.612075	0.485937
		Reprompt Weighted	1.345206	0.814889	0.634605	0.503989
		Majority Vote	1.161904	1.077917	0.636556	0.583316
e-SNLI (Seed = 9)	1.26 / 89.47%	Initial Raw	0.684211	0.631579	0.561363	0.517585
		Reprompt Raw	0.657895	0.631579	0.595460	0.548320
		Initial Weighted	0.610842	0.623154	0.639802	0.512257
		Reprompt Weighted	0.605095	0.638822	0.646223	0.517462
		Majority Vote	0.763158	0.873589	0.548492	0.503363
GSM8K (Seed = 30)	1.14 / 92.00%	Initial Raw	0.860000	0.420000	0.816251	0.747567
		Reprompt Raw	0.850000	0.410000	0.819313	0.755605
		Initial Weighted	0.840141	0.437920	0.763763	0.599531
		Reprompt Weighted	0.833816	0.463369	0.738347	0.590121
		Majority Vote	0.91	0.45	0.817539	0.748547

Table 20: An example of extending our framework to text-image consistency evaluation. This table shows the comparison of correlation and error metrics between model original evaluations and midpoints of intervals.

Method	Pearson	Spearman	Kendall	MSE	MAE	RMSE
Std - Raw Score	0.5311	0.5650	0.4722	0.8978	0.7718	0.9475
Std - Weighted Avg.	0.5820	0.6523	0.4790	0.8204	0.7414	0.9058
Std - Con R2CCP	0.6250	0.6296	0.4574	0.7396	0.6828	0.8600
Std - Dis R2CCP	0.6246	0.6286	0.4747	0.7430	0.6816	0.8620
CoT - Raw Score	0.4932	0.5100	0.4266	1.1778	0.8746	1.0853
CoT - Weighted Avg.	0.5571	0.6017	0.4385	1.1177	0.8490	1.0572
CoT - Con R2CCP	0.6053	0.6096	0.4421	0.7703	0.7083	0.8777
CoT - Dis R2CCP	0.6036	0.6067.	0.4631	0.7752	0.7082	0.8805

Prompt on Relevance of SummEval

You'll be handed a summary of a news article.

Your challenge is to rate how well the summary captures the essence of the article.

Make sure to thoroughly read and understand these instructions before diving in. Keep this guide handy as you work through the task, so you can refer back to it if needed.

Evaluation Criteria:

Relevance (1–5): Does the summary hit the mark by including the most important content from the original article? It should focus on the key details without wandering into irrelevant or repetitive information. If the summary strays or over-explains, it should be rated lower.

How to Evaluate:

1. Read both the source article and the summary attentively.
2. Compare the two, identifying the critical points of the article.
3. Judge how well the summary captures these important points and avoids unnecessary details.
4. Give the summary a relevance score between 1 and 5.

Source Article:
`{{Document}}`

Summary:
`{{Summary}}`

Evaluation Form (ENTER A SCORE BETWEEN 1–5):

Relevance:

Figure 5: Chain-of-thought prompt for evaluating relevance on SummEval.

Prompt on ROSCOE by G-Eval

You will receive a generated response based on the question.

Your mission is to assess whether the generated response answers the question in a well-justified manner.

Please pay close attention to the instructions and keep this guide handy while completing your review. Feel free to refer back to it as needed.

Evaluation Criterion:
Quality (1–5): 1=incomprehensible and wrong, 5=clear and correct

Steps for Evaluation:

1. Carefully read the Situation (Premise) and the Claim (Hypothesis) to understand their key elements.
2. Evaluate the response to determine if it logically connects the Situation to the Claim and sufficiently explains whether the Claim is supported (or not) based on the details provided.
3. Score the response's quality on a scale of 1 to 5, with 1 being the lowest and 5 the highest, based on clarity, correctness, and the justification provided.

Situation (Premise):
{{Premise}}

Claim (Hypothesis):
{{Hypothesis}}

Question:
{{Question}}

Generated response:
{{Response}}

Evaluation Form (Only provide the overall quality score from 1–5 without any text):
Quality:

Figure 6: Chain-of-thought prompt on ROSCOE evaluated with G-Eval.

Prompt on ROSCOE by SocREval

Instruction:

Does the generated response answer the question in a well-justified manner? Please generate your own response for the question first, then conduct a qualitative analysis on the generated response by taking into account your own response, and finally give me an overall quality score in [1, 2, 3, 4, 5] (1=incomprehensible and wrong, 5=clear and correct). Note that you need to consider both the explanation and the answer in the generated response.

Example:

- **Situation (Premise):** Two women are embracing while holding to go packages.
- **Claim (Hypothesis):** Two women are holding packages.
- **Question:** Is the Claim supported by the Situation?
- **Generated response:** The two women are most likely embracing because they are either friends or family. If they were just holding packages, there would be no need for them to embrace. The answer is Yes.
- **Example representation:**
  - "own response": "Yes, the Claim is supported by the Situation. The Situation states that two women are ëmbracing while holding to go packages,ẅhich means they are holding packages. Therefore, the Claim is accurate.",
  - "qualitative analysis": "The generated response starts by making an assumption about why the two women might be embracing, suggesting they could be friends or family. While this could be true, it is not directly relevant to the question asked. The core of the question is about the Claim's accuracy given the Situation. The latter part of the generated response does correctly determine that the answer is Ÿes.Ḧowever, the earlier assumption makes the response longer and potentially more confusing.",
  - "overall quality": 4

Actual Input:

- **Situation (Premise):** `{{Premise}}`
- **Claim (Hypothesis):** `{{Hypothesis}}`
- **Question:** `{{Question}}`
- **Generated response:** `{{Response}}`

Evaluation Request:

Please generate your own response for the question first, then conduct a qualitative analysis on the generated response by taking into account your own response, and finally give me the overall quality of the given generated response for the question by taking into account both your own response and the qualitative analysis based on the instruction and the format of the example representation.

Evaluation Form (Only provide the overall quality score from 1–5 without any text):

Quality:

Figure 7: Chain-of-thought prompt on ROSCOE evaluated with SocREval.

Reprompt on ROSCOE by DeepSeek-R1-Distill-Qwen-32B with SocREval

Let me show you our evaluation record. Based on all these information, make decision and give me final score.

Initial Prompt:
{{Prompt in 1st round}}

Initial Response:
{{Response in 1st round}}

Reprompt and Regrade:

Thank you for your initial evaluation!

To help you arrive at a final score that more closely aligns with human expert judgment, we have constructed a 90% confidence interval for this task using conformal prediction based on your past scoring records. This interval is provided to help you gauge the uncertainty in your recent assessment, which we hope will enhance your evaluation.

Interval Information: The confidence interval we have provided is {{Interval}}. Please keep in mind that there is approximately a 90% probability that the expert's score lies within this interval, and a 10% probability that it lies outside.

— **Your Objective**: Acting as a human expert, use the interval information along with the recent evaluation task to decide whether and how to adjust the initial score.

— Below are some decision-making suggestions for your reference, but we also encourage you to apply your own independent thinking to align as closely as possible with human expert judgment.

Decision-Making Suggestions:

1. **Key Dimensions to Consider**:
   - **Original Score Confidence**: Your confidence level in the score you just assigned;
   - **Interval Position**: Whether the original score falls inside or outside the interval;
   - **Interval Width**: Whether the interval is narrow (e.g., ≤ 2.0) or wide (e.g., ≥ 2.0);
   - **Potential Labels**: What specific label options lie within the interval (e.g., {3.00, 4.00} for an example interval [3,4]).

2. **Advice on Decision, Reasoning, and Explanation**:
   - **High Confidence & Score Within a Narrow Interval**: If the interval is narrow and your score is validated by the interval boundaries, you may confidently retain your original score, provided you believe your evaluation and explanation are seamless. You may also make minor adjustments within the interval where you think the score is most plausible.
   - **High Confidence & Score Outside a Narrow Interval**: Although there is a small probability (<10%) that you are correct, we encourage you to question your initial judgment, reconsider the evaluation, and consider adjusting the score to the most probable point within the interval, or retain the original score with a brief justification.
   - **Low Confidence & Any Interval**: Use the interval to guide a careful re-examination of the task. For example, consider why an expert rating might take a certain value within the interval and whether that reasoning is sound. After reflection, if you find a value most reasonable, you may choose that score.
   - **Challenging the Interval**: You have the right to firmly believe that the true score cannot possibly fall within the provided interval. However, since we guarantee that the interval covers the expert score 90% of the time, your challenge likely indicates an error in expert judgment. If your explanation convinces us, this would be a valuable discovery. Generally, though, we prefer to treat the expert judgment as ground truth.

Please use the suggestions above to produce a **new final score** through a step-by-step chain of thought:
1. Your confidence level in the original score (high/medium/low) and the reason;
2. How the interval width, potential labels and the position of the original score influence your judgment;
3. Your adjustment action (retain/minor adjustment/re-examination/other) and the rationale;
4. The final score you assign.

Finally, please first state your final evaluated score (1–5), followed by your explanation:

Final Score:

Figure 8: Prompt used to reprompt and regrade with prediction interval information. Here we provide a template for reprompting and regrading on ROSCOE by DeepSeek-R1-Distill-Qwen-32B with SocREval.

Reprompt Response of LLM Judge: Ground truth is 1 in this example (DROP of ROSCOE).

Final Score: 2

Explanation:

1. **Confidence Level**: High confidence in the original score of 2. The generated response incorrectly stated the number of losses, which was a clear error.
2. **Interval Consideration**: The confidence interval [1.00, 3.00] suggests that the score is likely within this range. The original score of 2 falls within this interval, aligning with the expert judgment.
3. **Adjustment Action**: Retain the original score of 2. The reasoning remains sound as the generated response had a factual error, leading to a lower quality score.
4. **Rationale**: The generated response's error in interpreting the team's record significantly impacts its quality, justifying the score of 2.

Figure 9: A response of reprompt and regrade with final score and explanations. Initial raw score is 2, initial weighted score is 1.65, and ground truth is 1. Reprompt and regrade strengthens the confidence of LLM judge, since the weighted score changes from 1.65 to 2.04 due to changes in token logits.

Reprompt Response of LLM Judge: Ground truth is 2 in this example (GSM8K of ROSCOE).

Final Score: 2

Explanation: After reviewing the generated response and considering the confidence interval [1.00, 2.00], I remain confident that the original score of 2 is appropriate. The generated response incorrectly calculated the water intake rate and the time taken, leading to an overestimation of the water taken on. The correct approach, as detailed in my own response, results in 16 liters, whereas the generated response arrived at 160 liters. The interval suggests that the score is likely within 1 to 2, and since the response is incorrect but shows some understanding, a score of 2 is justified.

Figure 10: A response of reprompt and regrade with final score and explanations. Initial raw score is 2, initial weighted score is 1.81, and ground truth is 2. Reprompt and regrade strengthens the confidence of LLM judge, since the weighted score changes from 1.81 to 2.02 due to changes in token logits.

Reprompt Response of LLM Judge: Ground truth is 3 in this example (CosmosQA of ROSCOE).

Final Score: 4

Explanation: 1. Confidence in Original Score: High. The initial evaluation correctly identified that Sam's understanding supports the Claim, though it could have elaborated more on the context.
2. Interval Consideration: The interval [1.00, 5.00] is wide, allowing for a range of scores. The original score of 4 falls comfortably within this interval, suggesting it is plausible.
3. Adjustment Action: Retain. The reasoning aligns well with the provided information, and the score accurately reflects the quality of the generated response.
4. Rationale: The generated response correctly answers the question but could have provided more depth. However, it sufficiently supports the Claim, warranting a score of 4.

Figure 11: A response of reprompt and regrade with final score and explanations. Initial raw score is 4, initial weighted score is 3.82, and ground truth is 3. Reprompt and regrade strengthens the confidence of LLM judge, since the weighted score changes from 3.82 to 3.97 due to changes in token logits.

Reprompt Response of LLM Judge: Ground truth is 5 in this example (Consistency of SummEval).

Final Score: 4

Explanation:

1. **Confidence in Original Score**: High. The initial evaluation correctly assessed the summary's accuracy without factual errors.
2. **Omitted Details**: The summary fails to mention Vanessa's profession and the police appeal, which are key elements of the source text.
3. **Interval Consideration**: The confidence interval [4.67, 5.00] indicates that a higher score is possible under the uncertainty model.
4. **Adjustment Action**: Retain. Despite the interval's suggestion, the omission of critical details justifies keeping the score at 4.

Figure 12: A response of reprompt and regrade with final score and explanations. The LLM judge acknowledges the value of prediction interval but resist changing score.

Reprompt Response of LLM Judge: Ground truth is 5 in this example (Consistency of SummEval).

Final Score: 4

Explanation:

1. **Confidence in Original Score**: High. The summary accurately reflects the main points without introducing inaccuracies, though it omits some details.
2. **Interval Consideration**: The interval [4.67, 5.00] suggests a higher score is expected. However, the summary's omission of Pereira's contract and other clubs' interest justifies a slightly lower score.
3. **Adjustment Action**: Retain the original score of 4. The summary's focus on Orlando City's interest makes the omissions acceptable, maintaining consistency without misleading information.
4. **Final Score**: 4. The summary is truthful and consistent, though less comprehensive, warranting a score within the lower end of the interval.

Figure 13: A response of reprompt and regrade with final score and explanations. The LLM judge acknowledges the value of prediction interval but resist changing score.

Reprompt Response of LLM Judge: Ground truth is 5 in this example (Consistency of SummEval).

Final Score: 4

Explanation: The initial score of 4 is within the provided confidence interval [4.67, 5.00], but it's on the lower end. However, the summary accurately reflects the main point without errors, though it lacks some context. Given the interval's guidance, a score of 4 remains appropriate as it aligns with the evaluation criteria.

Figure 14: A response of reprompt and regrade with final score and explanations after moving interval information to the front to avoid position bias. The LLM judge thinks that "4 is within the provided confidence interval [4.67, 5.00]".

Reprompt Response of LLM Judge: Ground truth is 5 in this example (Consistency of SummEval).

Final Score: 4

Explanation: The initial score of 4 is appropriate as the summary accurately reflects the key points without introducing inaccuracies. The confidence interval [4.33, 5.00] suggests a higher score is possible, but the redundancy and omission of details justify maintaining the score at 4.

Figure 15: A response of reprompt and regrade with final score and explanations after moving interval information to the front to avoid position bias. The LLM judge resist changing the score even though it thinks that "[4.33, 5.00] suggests a higher score is possible".

Reprompt Response of LLM Judge: Ground truth is 4.67 in this example (Consistency of SummEval).

Final Score: 4.67

Explanation: The initial score of 4 was based on the summary's accurate reflection of key facts without introducing errors. However, considering the confidence interval [4.67, 5.00], which suggests a high likelihood that the expert score falls within this range, and recognizing that the summary effectively captures the essential details without significant omissions that affect consistency, it is reasonable to adjust the score upward. The summary's completeness, while not perfect, is sufficiently accurate to warrant a higher score within the interval. Therefore, the final score is 4.67.

Figure 16: A response of reprompt and regrade with final score and explanations when the judge can provide intermediate score (not just integer). The judge is willing to raise initial lower score to the lower bound of the interval.

Reprompt Response of LLM Judge: Ground truth is 5 in this example (Consistency of SummEval).

Final Score: 4.33

Explanation:

1. **Confidence in Original Score**: My confidence in the original score of 4 is medium. While the summary is accurate, I recognize that it omits some key details, which might slightly affect its comprehensiveness.
2. **Interval Analysis**: The provided confidence interval is [4.67, 5.00], which is narrow. The original score of 4 falls outside this interval, suggesting that the summary might be more consistent than initially assessed.
3. **Adjustment Consideration**: Given the interval's narrowness and the fact that the original score is outside, I reconsidered the evaluation. The summary's accuracy and adherence to facts are strong, and the omissions, while present, do not introduce inaccuracies. Therefore, a slight adjustment within the interval is warranted.
4. **Final Adjustment**: I adjusted the score to 4.33, reflecting a balance between the summary's accuracy and the minor omissions, while aligning more closely with the confidence interval.

Figure 17: A response of reprompt and regrade with final score and explanations when the judge can provide intermediate score (not just integer). The judge is willing to raise initial lower score but still falls outside of the prediction interval.

Reprompt Response of LLM Judge: Ground truth is 5 in this example (Consistency of SummEval).

Final Score: 4

Explanation:

1. **Confidence Level**: High confidence in the original score of 4. The summary accurately captures the main points without introducing inaccuracies, though it omits some details.
2. **Interval Consideration**: The confidence interval is [4.67, 5.00], which is narrow. The original score of 4 falls outside this interval, suggesting a potential adjustment.
3. **Adjustment Rationale**: Despite the interval suggesting a higher score, the summary's omission of key details justifies a score of 4. The interval may not fully account for the summary's incompleteness, so retaining the original score is appropriate.
4. **Final Decision**: Retain the score of 4, as it aligns with the evaluation criteria and accurately reflects the summary's consistency.

Figure 18: A response of reprompt and regrade with final score and explanations when the judge can provide intermediate score (not just integer). The judge is willing to raise initial lower score but resist changing the score.

Standard Prompt for GenAI-Bench: Text-to-Image Quality

Evaluate the quality between the following text prompt and the corresponding visual generation on a scale of 1 to 5, where 5 is perfect and 1 is poor.

Figure 19: Standard prompt for GenAI-Bench evaluated by Qwen2.5-VL-32B-Instruct.

Chain-of-thought Prompt for GenAI-Bench: Text-to-Image Quality

You will be given:
1) a single generated image I
2) the corresponding prompt P {prompt}

Your task: Output `Quality Score: (1-5)` followed by a concise explanation. Use the five-step chain-of-thought below **silently**, then distill the insight into one short sentence.

Internal CoT Steps (do not output):

1. **Skill Inventory**: Scan P for the typical generation skills it implicitly tests, e.g.
   - Counting (how many objects)
   - Spatial layout (relative positions)
   - Attribute binding (color, material, style)
   - Negation & absence (what must not appear)
   - Action or interaction realism
   - Scene coherence & lighting plausibility

2. **Global Coherence Check**: Does the entire scene feel like one unified photograph / artwork that matches the prompt's mood and setting?

3. **Critical Object Pass**: Identify the 1–3 most semantically heavy objects or relations. Are they present, correctly shaped, and believably integrated?

4. **Fine-Grain Glance**: Spot any subtle oddities (extra limbs, miscounts, impossible lighting, texture smears). Even tiny flaws here can reveal skill gaps.

5. **Holistic Judgment**: Weigh the combined effect: if the key skills are satisfied and the image looks natural $\rightarrow$ 5; mild off-notes $\rightarrow$ 4; clear but non-fatal misses $\rightarrow$ 3; multiple visible failures $\rightarrow$ 2; fundamentally wrong $\rightarrow$ 1.

Output Format (public):
Quality Score: X
Explanation: One short sentence summarizing the overall perception ($\leq$ 25 words).

Figure 20: Chain-of-thought prompt on GenAI-Bench evaluated by Qwen2.5-VL-32B-Instruct.