EXPLAINING LENGTH BIAS IN LLM-BASED PREFERENCE EVALUATIONS

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ABSTRACT

The use of large language models (LLMs) as judges, particularly in preference comparisons has become widespread, but this reveals a notable bias towards longer responses, undermining the reliability of such evaluations. To better understand such bias, we propose to decompose the preference evaluation metric, specifically the *win rate*, into two key components: *desirability* and *information mass*, where the former is length-independent and related to trustworthiness such as correctness, toxicity, and consistency, and the latter is length-dependent and represents the amount of information in the response. We empirically demonstrated the decomposition through controlled experiments and found that response length impacts evaluations by influencing information mass. To derive a reliable evaluation metric that assesses content quality without being confounded by response length, we propose AdapAlpaca, a simple yet effective adjustment to win rate measurement. Specifically, AdapAlpaca ensures a fair comparison of response quality by aligning the lengths of reference and test model responses under equivalent length intervals.

1 INTRODUCTION

As LLMs are increasingly deployed across various domains of artificial intelligence, from natural language processing to complex decision-making systems (Wu et al., 2023; Li et al., 2023a; Rao et al., 2023; Song et al., 2023), ensuring their performance, reliability, and fairness has become a critical challenge (Louis & Nenkova, 2013; Wang et al., 2023b). LLM-based auto-evaluators have emerged as a crucial tool in this context, offering a cost-effective and scalable alternative to labor-intensive human evaluations (Chen et al., 2023; Li et al., 2024a;b; Dubois et al., 2024b). Despite their advantages, these automated systems are not without their shortcomings, particularly concerning the introduction and perpetuation of biases (Li et al., 2023c; Zheng et al., 2023; Koo et al., 2023; Wang et al., 2023a; Wu & Aji, 2023). One of the important biases observed in LLM-based evaluations is the preference for longer textual responses. Previous empirical studies have explored a strong correlation between the length of response and its perceived quality represented by win rate (Zhao et al., 2024; Dubois et al., 2024a; Ivison et al., 2023). However, it is not reasonable to simply attribute the preference to length since length is only the surface factor for the quality of a sentence. Therefore, in this work, we investigate the following question: *what are the major factors contributing to the win rate?*

To solve this problem, we propose a new framework that decomposes the *quality* of a response, as measured by its win rate in pairwise comparisons, into two distinct components: (1) *desirability*, which is independent of length and reflects the trustworthiness of the response, encompassing factors such as correctness, toxicity, and consistency; and (2) *information mass*, which is dependent on length and represents the amount of information in the response, measurable through conditional entropy. We validate our hypothesis by testing win rates in two different scenarios: (i) comparing normal responses with those differing in desirability (e.g., Logical to be desired and Biased not desired), and (ii) comparing normal responses with concise and detailed responses, which vary in information mass. Our experiments demonstrate that responses with negative desirability significantly decrease the win rate, whereas information mass, when not negatively influenced by desirability, is positively correlated with the win rate, thus confirming the effectiveness of our metric. Following this finding, we design a new prompt called "Quality Enhancement" to improve information

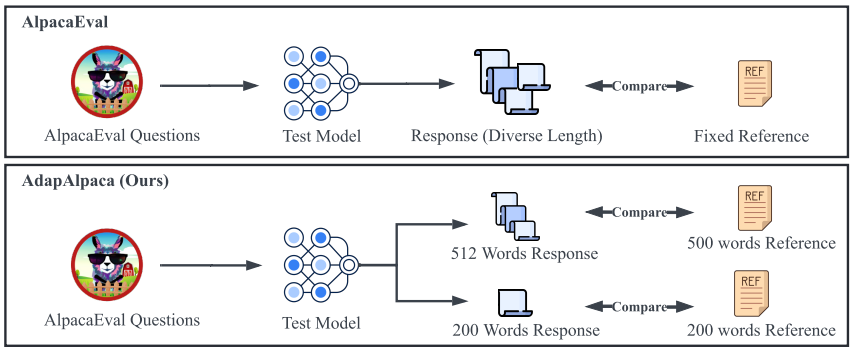


Figure 1: Comparison between AlpacaEval and AdapAlpaca (Ours). In AlpacaEval, the reference answer has a fixed length, regardless of the length of the test model's answer. In contrast, AdapAlpaca dynamically selects a reference answer that matches the length of the test model's answer.

mass with positive desirability. This prompt enables GPT-4 to achieve state-of-the-art results on AlpacaEval, increasing the win rate from 50.00% to 70.16%.

Through our decomposition of the quality of a response, we observe that response length impacts evaluations primarily by influencing information mass. However, a reliable evaluation metric should assess content quality without being confounded by extraneous factors such as response length (Koo et al., 2023; Ye et al., 2024; Dubois et al., 2024a), we further propose AdapAlpaca, a benchmark designed to improve evaluation fairness. By ensuring that responses are compared at the same length intervals, AdapAlpaca effectively mitigates length bias, enabling accurate content quality assessments (see Figure 1). With AdapAlpaca, we further analyze length bias in Direct Preference Optimization (DPO) Rafailov et al. (2023) to examine the findings in prior work (Gu et al., 2024; Ivison et al., 2023; Liu et al., 2024) that DPO lengthens model responses. Specifically, we test TÜLU2 (Ivison et al., 2023) and TÜLU2-dpo models at 7B, 13B, and 70B scales on AlpacaEval and AdapAlpaca. Our results indicate that DPO leads to higher human preference, but this gain is amplified by response length, with AlpacaEval showing higher win rates gain than AdapAlpaca. Our major findings and contributions are as follows:

- We propose a novel interpretation of win rate, emphasizing desirability and information mass, offering a more precise LLM performance measure. Based on this interpretation, we develop the "Quality Enhancement" prompt, which improves win rates by boosting information mass with positive desirability. This prompt improves win rates across multiple LLMs, with average increases of 23.44% for GPT-3.5, 16.48% for GPT-4, 22.28% for LLAMA3-70b, and 20.40% for Qwen1.5 72B.
- To mitigate length bias, we introduce AdapAlpaca, a method that aligns the response lengths of the reference and test model, enabling a fair comparison of desirability and information mass under the same length intervals.
- Using both AlpacaEval and AdapAlpaca, we analyze the impact of length bias in DPO. Our experiments with TÜLU2 and TÜLU2-dpo models at 7B, 13B, and 70B scales show that DPO leads to higher human preference, but this gain is amplified by response length, with AlpacaEval showing higher win rates gain than AdapAlpaca.

2 Related Work

2.1 Reference-free Evaluation Metrics

Reference-free evaluation metrics have a long history (Louis & Nenkova, 2013), which evaluates the generated text based on intrinsic properties and coherence with the context. Although they achieve high accuracy on matching inner-annotator, the achievement suffers from spurious correlations such as perplexity and length (Durmus et al., 2022). Recently, people have started using a strong model (e.g., GPT-4) as an evaluator to perform a zero-shot reference-free evaluation on the weak models (Shen et al., 2023; Dubois et al., 2024b; Chen et al., 2023; Hu et al., 2024). However, leveraging

a strong model's intrinsic knowledge to perform reference-free evaluation ignores the prompt preference of the strong model, for example, the prompt's length.

2.2 Correlation Between Length and Win Rate

Previous research reveals that sentence length will influence the evaluation of trustworthiness. Specifically, when using a GPT-4 to represent human preference, it will prefer to choose a long sentence rather than a short sentence (Dubois et al., 2024a; Ivison et al., 2023; Gu et al., 2024; Shen et al., 2023; Koo et al., 2023; Wang et al., 2023a; Wu & Aji, 2023; Dubois et al., 2024b; Chen et al., 2023; Hu et al., 2024). Such preference will introduce a length-correlated bias and help the model with long-generation sentences gain a high score on human preference evaluation. Although these approaches show a high correlation to human preference, debiasing such as automated evaluation is highly valuable. (Dubois et al., 2024a) proposes a length-controlled (LC) win rate by removing the length-correlated term in the win rate regression model. The new LC win rate shows an even performance between concise and verbose input and a higher correlation when compared with human preference.

3 Understanding the Major Factors of Win Rate

To interpret the correlation between length and win rate, we propose a new framework based on *quality*, which includes *desirability* (length-independent, related to trustworthiness) and *information mass* (length-dependent, represented by conditional entropy). We validate our hypothesis through two scenarios: (1) testing the impact of different desirability on win rate with the same information mass, and (2) testing the influence of different information mass on win rate with the same desirability.

3.1 Preliminary

Evaluation protocol. We utilize the AlpacaEval dataset (Li et al., 2023c) to assess human preferences. AlpacaEval is a reference-free evaluation dataset for LLMs, encompassing 805 instructions that reflect human interactions on the Alpaca web demo. To ensure a comprehensive evaluation of human preferences, we extend our testing to additional datasets, including LIMA (Zhou et al., 2023), Vicuna (Chiang et al., 2023), Koala (Vu et al., 2023), Wizardlm (Xu et al., 2023), and Self-Instruct (Wang et al., 2022), in line with previous studies (Chen et al., 2023; Zhang et al., 2024; Du et al., 2023; Zhao et al., 2024; Li et al., 2023b).

Base Models. In our experiments, we follow the setup in the AlpacaEval Leaderboard[1], using the GPT-4 Preview (11/06) as *Baseline* and the *Annotator*. The references to GPT-3.5, LLAMA3-70b, and Qwen1.5 72b in the main text denote gpt-3.5-turbo-0125, meta-llama/Meta-Llama-3-70B-Instruct [2], and Qwen/Qwen1.5-72B-Chat [3], respectively. Following previous work (Wei et al., 2024), we calculate conditional entropy using the method described in (Von Neumann, 2013).

Win rate. Assume we have a set of instructions x. We prompt a test model m to generate a response z_m for each instruction. Similarly, we prompt a reference model b (referred to as the "baseline" in AlpacaEval) to generate a response z_b for each instruction.[4] An annotator then evaluates these responses based on their quality and assigns a preference $y \in \{m, b\}$, indicating which model's response is superior. To properly understand the concept of win rate, we first need to define what we mean by response quality:

Definition 1 ***(Response Quality)**, denoted as $Q_e(z|x)$, quantifies the effectiveness of the model's response z in addressing the given instruction x, as evaluated by an annotator e. Annotator prefer responses with higher quality.*

[1] https://tatsu-lab.github.io/alpaca_eval

[2] https://huggingface.co/meta-llama/Meta-Llama-3-70B-Instruct

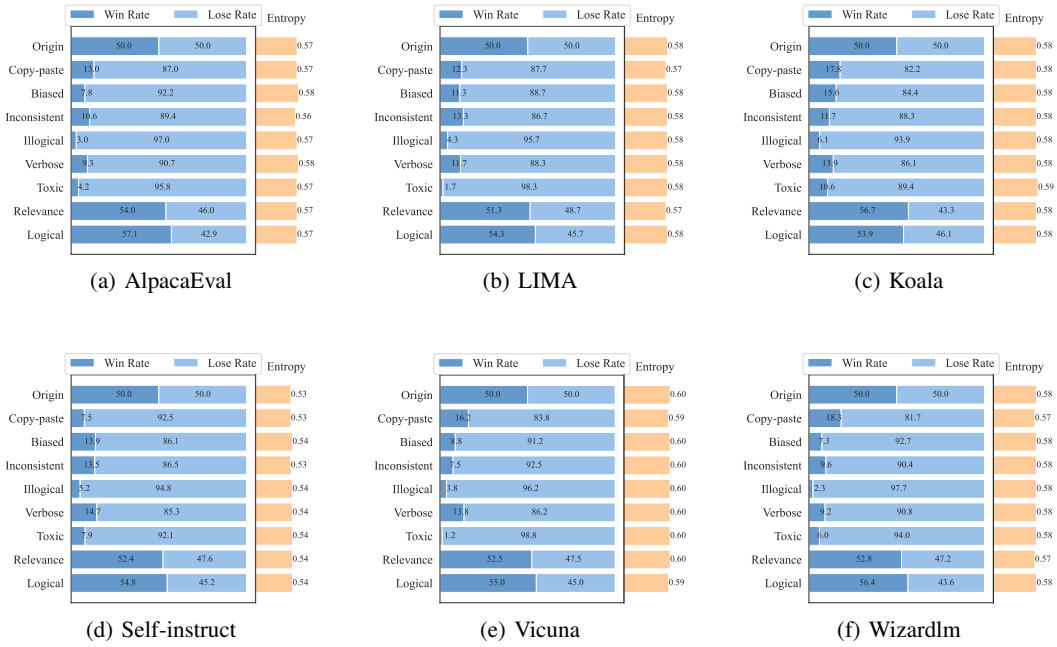
[3] https://huggingface.co/Qwen/Qwen1.5-72B-Chat

[4] In this context, m stands for "model" and b denotes "baseline", which in this paper follows the AlpacaEval Leaderboard's use of GPT-4 Preview (11/06).

By leveraging the definition of quality, we can now formulate the win rate as the comparison of sentence quality as follows:

$$\text{WinRate}(m, b) = \mathbb{E}_x \left[\mathbb{1}_{Q_e(z_m|x) > Q_e(z_b|x)} \right], \tag{1}$$

where $\mathbb{1}$ is an indicator function and $\mathbb{1}_{Q_e(z_m|x) > Q_e(z_b|x)}$ represents the preference distribution for each individual. Previous works (Chen et al., 2023; Li et al., 2023c; Dubois et al., 2024a;b) utilize LLMs as zero-shot evaluators due to their exceptional performance on real-world tasks. Our experimental setup adheres to the AlpacaEval Leaderboard [5] guidelines, employing the GPT-4 Preview (11/06)[6] as both the *Baseline* b and the *Annotator* e.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

Figure 2: Validation of desirability's impact on quality for GPT-4. The results demonstrate that desirability influences the win rate.

3.2 Quality Decomposition

Before discussing the composition of quality, we first define two key concepts: **desirability** and **information mass**. Desirability reflects the inherent quality attributes of a response that make it reliable and valuable, irrespective of its length, while information mass captures the quantity of information in the response, with longer responses generally containing more content. The definitions of desirability and information mass are as follows:

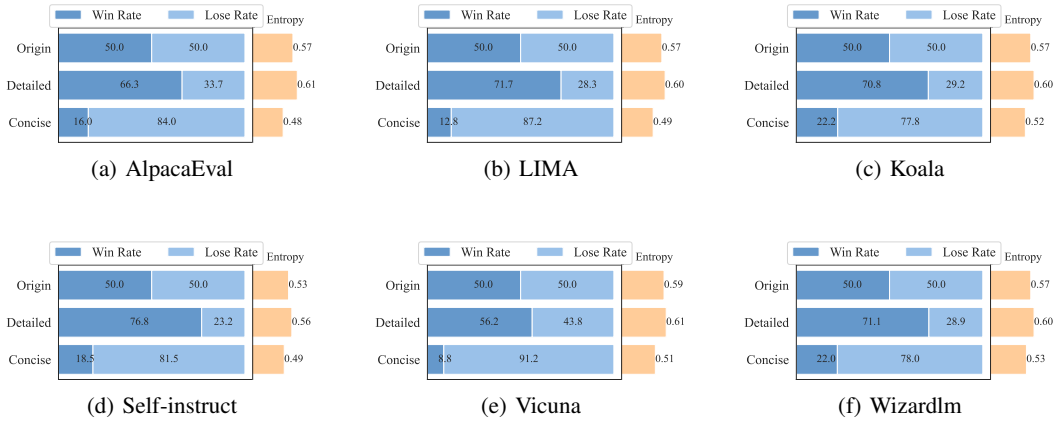
Definition 2 *(**Desirability**), denoted as $D_e(z|x)$, measures the probability that annotator e will accept the response z given an instruction x. It can be influenced by factors such as consistency and toxicity and is independent of response length.*

Definition 3 *(**Information mass**), denoted as $H_e(z|x)$, measures the amount of information in a response z given an instruction x, as evaluated by annotator e. It is represented by conditional entropy and is directly with response length.*

With these definitions in place, we now present our main hypothesis on answer quality, starting with an assumption:

[5] https://tatsu-lab.github.io/alpaca_eval

[6] In this paper, unless specified otherwise, GPT-4 refers to GPT-4 Preview (11/06).



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

Figure 3: Validation of information mass's impact on quality for GPT-4. The results demonstrate that information mass influences the win rate.

Assumption 1 (***Quality Decomposition***). *For a given answer z and instruction x, the quality $Q_e(z|x)$ recognized by annotator e can be decomposed as:*

$$Q_e(z|x) \propto D_e(z|x) + H_e(z|x), \tag{2}$$

where $D_e(z|x)$ denotes the desirability of the response, and $H_e(z|x)$ represents the information mass.

To systematically verify our hypothesis, we conduct two experiments targeting the manipulation of these key components in GPT-4's responses in Section 3.3 and Section 3.4. Additional results with more test and annotator models are provided in Appendix J and Appendix K.

3.3 Desirability Influences Quality

To evaluate the impact of desirability on quality, we design experiments using eight strategies to manipulate response desirability. These strategies include: (1) **Origin**: No prompt restrictions. (2) **Copy-paste**: Copy GPT-4's response three times. (3) **Biased**: Provide biased responses, favoring certain ideas without justification. (4) **Inconsistent**: Provide contradictory information to create confusion. **Illogical**: Give responses based on flawed logic or irrelevant information. (5) **Verbose**: Provide lengthy responses filled with broad, unrelated details. (6) **Toxic**: Use offensive language with an aggressive tone. (7) **Relevant**: Provide responses that align with the query. (8) **Logical**: Base responses on sound reasoning and valid arguments. The results are shown in Figure 2. To eliminate the impact of information mass on win rate, we use conditional entropy to represent information mass and ensure the information mass of **Origin** and the other prompts remains as consistent as possible. The entropy values shown in the Figure 2 represent the average conditional entropy of the responses for each prompt. Details for these prompts and relevant implementation are shown in Appendix I and Appendix A.1. First, we observe that although the **Copy-paste** and **Origin** prompts maintain identical information mass (as simply replicating text does not increase information), the win rates of **Copy-paste** fall below **Origin** (50%) due to significant consistency impairments. Second, responses generated from negative prompts (i.e., **Biased**, **Inconsistent**, **Illogical**, **Verbose**, and **Toxic**) exhibit low desirability, resulting in win rates substantially lower than **Origin** (50%), despite having similar information mass. Conversely, prompts enhancing desirability (i.e., **Consistent** and **Logical**) yield increased win rates compared to **Origin**. In summary, desirability plays a significant role in determining quality.

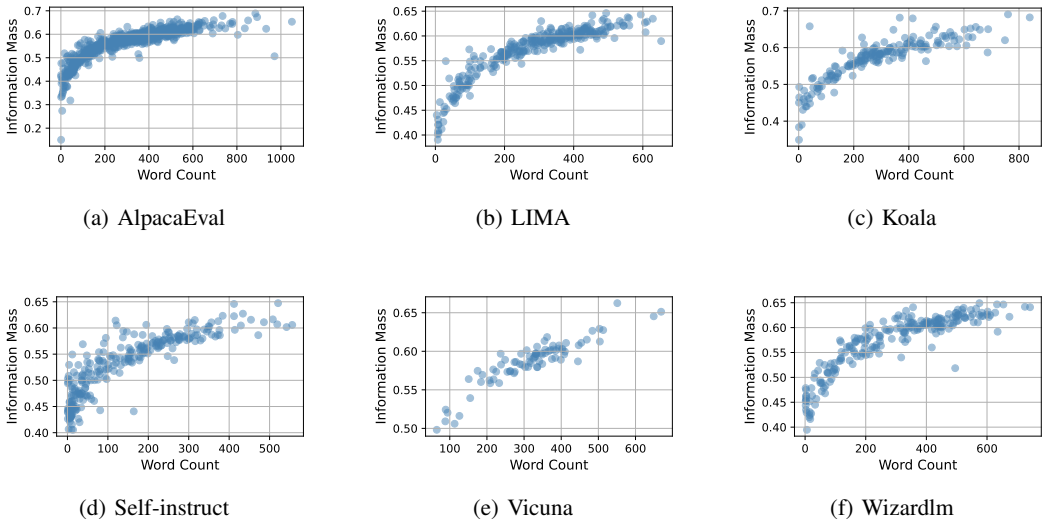
3.4 Information Mass Influences Quality

To evaluate the impact of information mass on quality, we designed experiments using three distinct strategies to manipulate the information mass of responses. These strategies include: (1) **Origin**: No prompt restrictions. (2) **Concise**: Request brief responses focusing on the most crucial points.

(3) **Detailed**: Request comprehensive responses covering all relevant aspects thoroughly. The corresponding results are illustrated in Figures 3. Importantly, to isolate the effect of information mass, we ensured that the prompts did not impose any constraints on desirability, ensuring comparability. Details of the prompts and implementation are in Appendix I and Appendix A.1. Our findings indicate that information mass significantly affects the win rate without a negative desirability prompt. Specifically, responses with higher information mass, measured by conditional entropy, consistently achieved higher win rates. Thus, we observe the following relationship: **Detailed** $>$ **Origin** $>$ **Concise**. These results confirm that information mass is a crucial factor influencing the quality of responses.

Table 1: The content of the "Quality Enhancement" prompt, designed to elevate both the information mass and desirability of responses, thereby enhancing win rates. Keywords such as "relevant" and "logical" are used to enhance desirability, while "detailed" is used to boost information mass.

Quality Enhancement
You are an expert assistant, delve deeply into the core of the topic, providing a richly **detailed** response that explores all its dimensions. Ensure each part of your response is **relevant** to the query in a **logical** manner. Your response should provide comprehensive information and thoroughly cover all relevant aspects with accuracy and depth.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

Figure 4: Correlation between information mass and word count for responses of GPT-4. As the word count increases, the information mass also increases.

3.5 Quality Enhancement Prompt

Our decomposition reveals that responses with good desirability and higher information mass are generally more favored. Building on this insight, we propose the 'Quality Enhancement' prompt (Table 1), designed to improve both desirability and information mass, thereby increasing win rates. The keywords "relevant" and "logical" are used to enhance desirability, while "detailed" is used to boost information mass. Their effectiveness is validated in Section 3.2. We evaluated this prompt across multiple models, including GPT-3.5, GPT-4, LLAMA3-70b, and Qwen1.5 72B. The results, summarized in Table 2, with benchmarks such as LIMA, Vicuna, Koala, Wizardlm, and Self-Instruct. The consistent improvement in win rates across all tested models underscores the critical role of response quality in LLM evaluation.

Table 2: Win rates with and without the "Quality Enhancement" prompt, along with the corresponding win rate gains (WR Gain). "WR Gain" represents the increase in win rate due to the use of the "Quality Enhancement".

Models	Methods	AlpacaEval	LIMA	Koala	Self-instruct	Vicuna	Wizardlm	Avg.
GPT-3.5	w/o Quality Enhancement	15.47	9.67	11.39	21.46	8.75	16.82	13.93
	with Quality Enhancement	29.89	36.53	40.34	45.93	35.88	35.62	37.36
	WR Gain	14.42	26.86	28.95	24.47	27.13	18.80	23.44
GPT-4	w/o Quality Enhancement	50.00	50.00	50.00	50.00	50.00	50.00	50.00
	with Quality Enhancement	70.16	65.84	58.90	67.06	73.13	63.76	66.48
	WR Gain	20.16	15.84	8.90	17.06	23.13	13.76	16.48
LLAMA3-70b	w/o Quality Enhancement	34.32	36.63	40.12	39.70	36.74	36.99	37.81
	with Quality Enhancement	56.50	60.39	61.30	64.81	63.49	51.70	59.70
	WR Gain	22.18	23.76	21.18	25.11	26.75	14.71	22.28
Qwen1.5 72b	w/o Quality Enhancement	28.27	28.40	35.25	33.81	33.70	31.80	32.67
	with Quality Enhancement	48.87	53.34	55.40	52.43	56.49	47.13	52.28
	WR Gain	20.60	24.94	20.15	18.62	22.79	15.33	20.40

4 ADAPTIVE ALPACAEVAL

4.1 MOTIVATION

Here, we analyze the phenomenon observed in prior works (Dubois et al., 2024a; Chen et al., 2023; Dubois et al., 2024b), which highlights a positive correlation between response length and win rate. Intuitively, longer responses tend to encompass more information. To rigorously quantify this relationship, we use conditional entropy as information mass in a response z given an instruction x. This analysis is conducted without constraints on response desirability, ensuring the correlation between length and information mass remains independent of desirability factors. As shown in Figure 4, our analysis demonstrates a clear trend: as the length of a response increases, the information mass also grows. By integrating this observation with the findings from Section 3.2, we conclude that the primary mechanism through which length affects win rate is its contribution to the overall information mass.

Adaptive AlpacaEval (AdapAlpac) is based on the premise that a reliable evaluation metric should not only assess the content quality but also ensure that the assessment is not confounded by extraneous factors such as the length of the response. Central to this approach is the concept of information mass, which is inherently dependent on response length and can be quantified using conditional entropy. Our primary aim is to mitigate scenarios where merely extending the length of a response artificially inflates its conditional entropy and, thus, its perceived quality by annotators. This approach involves dynamically adjusting the evaluation criteria based on response length, thereby providing a more equitable and accurate measure of a model's performance.

4.2 DATASET GENERATION

To support the development of Adaptive AlpacaEval, we first generate a diverse dataset using a modified prompting strategy with GPT-4, designed to produce responses within specific word count ranges. Specifically, we analyzed the word count distribution within the AlpacaEval dataset, observing that responses predominantly fall within the 0-1000 word range. This range was chosen to encompass the full spectrum of response lengths present in the original AlpacaEval dataset, ensuring comprehensive evaluation coverage. To systematically explore this range, we divided it into five equal segments, each representing a distinct dataset: AdapAlpaca-200: 0-200 words, AdapAlpaca-400: 200-400 words, AdapAlpaca-600: 400-600 words, AdapAlpaca-800: 600-800 words, AdapAlpaca-1000: 800-1000 words. Each segment is populated by generating responses using the dataset generation prompt, with GPT-4 configured to produce responses that strictly conform to the specified word counts. The data generation prompt and additional details for AdapAlpaca can be found in Appendix H.

Table 3: Comparison of five quantitative metrics related to quality: Vocabulary Size, Win Rate relative to AlpacaEval (AlpacaWR), Entropy, Inter-sample N-gram Frequency (INGF), and Word Counts.

Interval	Vocabulary Size		AlpacaWR		Entropy		INGF	Word Counts
	All	Ans Avg.	WR	LCWR	All	Ans Avg.		
AlpacAns Origin	38474	47.79	50.00	50.00	408.83	0.5686	7376.92	363.85
AdapAlpaca-200	22612	28.08	20.73	43.81	363.55	0.5056	1618.69	145.72
AdapAlpaca-400	36943	45.89	47.34	47.40	414.39	0.5763	6003.87	355.20
AdapAlpaca-600	47691	59.24	62.58	50.97	434.77	0.6046	9086.01	540.95
AdapAlpaca-800	55362	68.77	71.20	54.31	447.48	0.6223	10320.11	708.36
AdapAlpaca-1000	66095	82.10	66.98	36.24	456.32	0.6346	10981.84	913.44

4.3 Analysis of the Generated Data

The analysis is structured to quantify each dataset's basic characteristics, followed by a comparative assessment to identify any significant differences attributable to the varying response lengths. Table 3 presents a comprehensive overview, providing a snapshot of the informational content across different datasets. Specifically, it includes vocabulary size, inter-sample N-gram Frequency (INGF) (Mishra et al., 2020), word counts of the generated dataset, win rate, length-controlled win rate, and entropy for AlpacaEval-Origin and AdapAlpaca-200, AdapAlpaca-400, AdapAlpaca-600, AdapAlpaca-800, and AdapAlpaca-1000. Our findings indicate the following: 1) Longer responses generally exhibit higher vocabulary sizes and word counts, suggesting a richer linguistic structure. 2) The INGF metric reveals that while longer responses tend to include more common N-grams, there is significant variability in the types of N-grams used, indicating a creative and diverse use of language. 3) Under Win Rate (WR) metrics, longer responses disproportionately receive higher preference scores due to their higher information mass. However, applying the length-controlled win rate (LCWR) significantly mitigates this bias, leading to a more balanced distribution of scores across different response lengths. This analysis aims to ascertain whether this phenomenon is intrinsic to the response quality or merely a byproduct of increased length. Our results demonstrate that although longer responses generally possess higher information mass, the quality of information, as measured by win rate, does not necessarily increase proportionally. Excessively lengthy responses can result in a decline in desirability, such as reduced consistency. For instance, in Table 3, the win rate of AdapAlpaca-1000 is lower than that of AdapAlpaca-800.

Table 4: The subscripts in the LCWR and WR columns indicate the differences between these metrics and the corresponding Human WR. A larger absolute value denotes a greater disparity between the annotator's evaluation and Human Preference. "LLM Response" denotes different responses to AlpacaEval questions for GPT-4, with detailed content available in Section 3.2.

LLM Response	AlpacaEval			AdapAlpaca	
	Human	LCWR	WR	Human	WR
Concise	10.81	$35.16_{+24.35}$	$15.96_{+5.15}$	29.56	$28.44_{-1.12}$
Detailed	61.61	$54.13_{-7.48}$	$65.83_{+4.22}$	56.02	$55.36_{-0.78}$
Quality Enhancement	66.70	$49.37_{-17.33}$	$70.16_{+3.46}$	58.88	$57.81_{+1.07}$

4.4 Result of Human Evaluation

Table 4 presents the results of the human study, with details provided in Appendix B and you can find more results in Appendix G. First, we test the results of concise, detail, and quality enhancement (descriptions provided in Section 3 and 3.5) using AlpacaEval, followed by AdapAlpaca. From the gap values between LCWR and human evaluations, we observe significant misalignments, indicating inherent problems with the LCWR metric. In contrast, the win rate calculated using AdapAlpaca closely aligns with the human results, showing an average difference of 0.99% (1.12% + 1.07% + 0.78% / 3). Additionally, we find that the difference between human evaluation and WR decreases as

Table 5: Win rate and response length comparison for TÜLU2 models (7B, 13B, and 70B) on AlpacaEval and AdapAlpaca. The results indicate that while DPO increases response length and improves win rate, the win rate gain is further amplified by the response length, leading to higher performance in AlpacaEval compared to AdapAlpaca.

Size	Model	Winrate (%)		Avg. Length
		AlpacaEval	AdapAlpaca	
7B	TÜLU 2	3.60	5.84	203.60
	TÜLU 2+DPO	8.33	9.04	282.92
	Gain from DPO	4.73	3.20	-
13B	TÜLU 2	4.35	8.07	192.58
	TÜLU 2+DPO	10.82	13.17	276.96
	Gain from DPO	6.47	5.10	-
70B	TÜLU 2	7.34	10.94	184.26
	TÜLU 2+DPO	15.67	17.90	267.23
	Gain from DPO	8.33	6.96	-

the quality of responses improves (from concise to detailed to Quality Enhancement). This suggests that as response quality increases, the preferences of annotators and human evaluators converge. Moreover, we found that the smallest difference in win rate between GPT-4 and human evaluations occurs when using the "Quality Enhancement" prompt, which has the highest levels of desirability and information mass. This further underscores the importance of enhancing both desirability and information mass in model responses. Overall, while both AdapAlpaca and LCWR aim to mitigate length bias in evaluating human preferences, their approaches differ fundamentally. AdapAlpaca eliminates length bias from the outset, whereas LCWR attempts to correct for length bias after it has already influenced the evaluation. The inherent issue with LCWR is that length significantly impacts human preference, and adjusting for length retrospectively is not a reliable approach.

4.5 DPO and Its Length Bias

Previous work (Gu et al., 2024; Ivison et al., 2023) has shown that DPO Rafailov et al. (2023) tends to make model responses longer, raising a natural question: Does the increase in human preference brought by DPO partly stem from the length of the responses? In other words, does DPO generate longer replies, thereby increasing their win rate? To investigate this issue, we conducted tests using the widely-used TÜLU2 (Ivison et al., 2023) series models. As shown in Table 5, we tested the models at 7B, 13B, and 70B scales on both AlpacaEval and AdapAlpaca to measure their win rates and corresponding response lengths. The results from AlpacaEval and AdapAlpaca indicate that while DPO does lead to longer model responses, it enhances the model's human preference capability (as evidenced by the increased win rate in AdapAlpaca). However, this gain is amplified by the response length (as the win rate in AlpacaEval is higher than in AdapAlpaca). Additionally, we found that all models have higher win rates on AdapAlpaca compared to AlpacaEval. This is because the responses from GPT-4 (1106) on AlpacaEval are longer (363 words, see Appendix 4.3), which unfairly amplifies the capabilities of GPT-4 due to its length. These results emphasize the need for length control in evaluations to reflect true model performance.

5 Conclusion

In this paper, we identify and address the critical issue of length bias in LLM-based preference evaluations, which undermines the reliability of win rate metrics. By decomposing win rate into desirability and information mass, we offer a nuanced understanding of response quality. Our proposed framework, AdapAlpaca, effectively mitigates length bias by dynamically adjusting reference answer lengths to match test model responses, ensuring fairer evaluation metrics. Additionally, our analysis of DPO demonstrates that its gains in human preference are influenced by response length, underscoring the importance of unbiased evaluation benchmarks. Overall, AdapAlpaca provides a robust tool for advancing reliable and equitable model evaluation.

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A Implementation Detail

A.1 Experiment Setup

In our experiments, we follow the setup in the AlpacaEval Leaderboard[7], using the GPT-4 Preview (11/06) as *Baseline* and the *Annotator*. The references to GPT-3.5, LLAMA3-70b, and Qwen1.5 72b in the main text denote gpt-3.5-turbo-0125, meta-llama/Meta-Llama-3-70B-Instruct [8], and Qwen/Qwen1.5-72B-Chat [9], respectively. Following previous work (Wei et al., 2024), we calculate conditional entropy using the method described in (Von Neumann, 2013).

A.2 Dataset

AlpacaEval (Dubois et al., 2024b) comprises 805 instructions, including 252 from the self-instruct test set (Wang et al., 2022), 188 from the Open Assistant (OASST) test set, 129 from Anthropic's helpful test set (Zhou et al., 2023), 80 from the Vicuna test set (Chiang et al., 2023), and 156 from the Koala test set (Vu et al., 2023).

LIMA (Zhou et al., 2023) compiles a training dataset of 1000 prompts and responses, designed to ensure stylistic consistency in outputs while maintaining diverse inputs. It also provides an open-source test set of 300 prompts and a development set of 50. The dataset is sourced from a variety of platforms, mainly community Q&A websites such as Stack Exchange, wikiHow, and the Pushshift Reddit Dataset (Baumgartner et al., 2020), along with manually curated examples. Within these Q&A communities, highly upvoted answers on Reddit often have a humorous or trolling tone, requiring extra effort to align them with the intended helpful chat assistant style. In contrast, responses from Stack Exchange and wikiHow naturally align with this style. The inclusion of human-authored examples further enhances the dataset's diversity. Our research specifically utilizes the test set from the LIMA dataset to evaluate our models.

Vicuna (Chiang et al., 2023) divides 80 test instructions into eight distinct categories: Fermi problems, commonsense, roleplay scenarios, coding/math/writing tasks, counterfactuals, knowledge, and generic questions. This categorization is intended to thoroughly evaluate multiple aspects of a chatbot's performance. Prior research indicates that the Vicuna dataset generally includes instructions of lower difficulty and complexity (Xu et al., 2023). In our study, we used the Vicuna test set to specifically evaluate the performance of large language models across these varied instruction categories.

Self-Instruct (Wang et al., 2022) consists of 252 human-created test instructions, each associated with a carefully designed output. This test set is curated to reflect the real-world applicability of instruction-following models, covering a broad spectrum of domains including email composition, social media, productivity software, and coding. The test instructions vary in style and format, incorporating different task lengths and diverse input/output types such as bullet lists, tables, code snippets, and mathematical equations. We employed the Self-Instruct test set in our research to rigorously assess our model's capability to comply with precise instructions across these varied domains.

Wizardlm (Xu et al., 2023) comprises a training set of 70k examples with varied complexities, initiated from 52k instructional data provided by Alpaca. Following $M = 4$ evolutionary cycles, the collection expands to 250k instructions. In each cycle, from the six newly generated prompts—five via in-depth evolution and one through in-breadth evolution—one is chosen randomly for each instruction. ChatGPT then generates responses, resulting in $52 \times 4 \times 3 = 624$k instruction-response pairs. The training subset selected for the Evol-Instruct dataset contains 70k of these instructions. The test set, which includes 218 instructions, is sourced from a variety of platforms such as open-source projects and online forums, encapsulating 29 unique skills identified from authentic human tasks. These skills range from Coding Generation & Debugging to Reasoning, Mathematics, Writing, Handling Complex Formats, and Mastery over Extensive Disciplines. In our study, we utilized the Wizardlm test set to thoroughly evaluate our model's ability to adhere to detailed instructions.

[7] https://tatsu-lab.github.io/alpaca_eval

[8] https://huggingface.co/meta-llama/Meta-Llama-3-70B-Instruct

[9] https://huggingface.co/Qwen/Qwen1.5-72B-Chat

Table 6: Scores given by commonly used reward models to concise, detailed, and original responses from GPT-4. The analysis shows that the scores consistently decrease from detailed to concise responses, highlighting the length bias within the reward model.

LLM Response	Reward Model										Avg.
	Eurus	Grmdis	Grmsft	UniF	Debba	Bebla	FsfairRM	Gerew	Misrmr	InteRM	
Concise	1.819	1.984	-2.919	0.064	2.229	4.159	-1.404	-0.456	5.661	0.426	1.156
Origin	3.564	4.009	-0.505	2.901	3.305	5.142	1.830	1.066	9.440	1.558	3.231
Detailed	3.986	4.646	1.458	3.263	3.759	5.450	2.684	2.630	10.616	2.416	4.090

Koala (Vu et al., 2023) consists of 180 authentic user queries obtained from the Internet. These queries cover a diverse array of topics and are generally characterized by a conversational tone, underscoring their applicability to real-world chat-based applications. To prevent test-set leakage, we exclude any query that achieves a BLEU score over 20% when compared to examples from our training set. Furthermore, we do not consider queries related to programming or non-English languages, as the capabilities of our crowd-sourced raters—who form our evaluation team—do not extend to effectively assessing such content. We have exclusively utilized the Koala test set to assess our model's capability to process and respond to genuine user inquiries in a conversational setting.

A.3 Information About Use Of AI Assistants

We use GPT-4 as an AI assistant during the preparation of this manuscript.

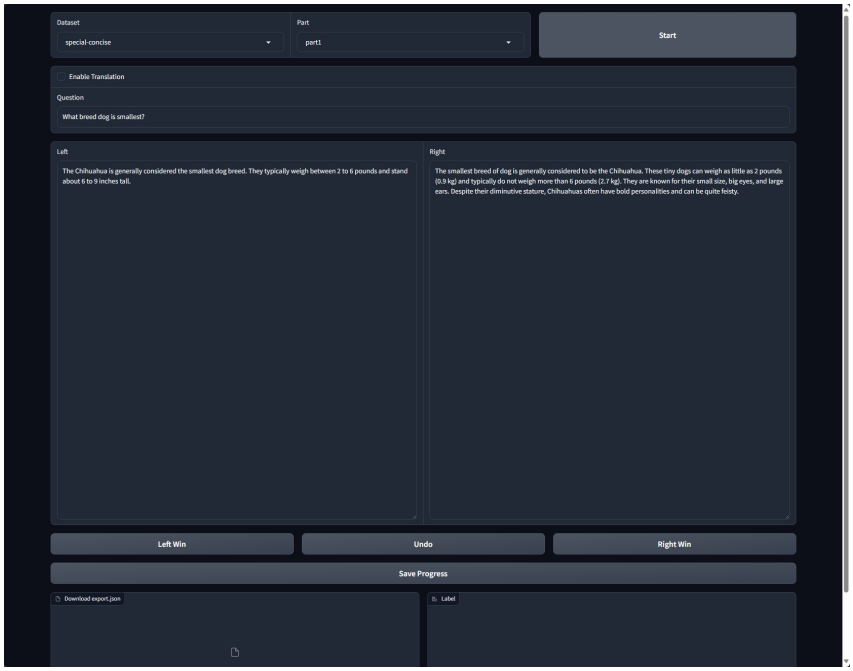


Figure 5: Example of the evaluation interface used in the human study, showing two outputs for a single input query. Participants assessed which output more accurately addressed the query, demonstrating the interface's role in ensuring unbiased evaluation.

B Human Evaluation Process

To ensure the robustness of our findings and complement the automated evaluations, a thorough human evaluation was conducted.

Participants. The human evaluation involved 25 participants, all of whom are professionals or researchers in the tech industry with specific expertise in language models. These individuals were carefully selected to represent a broad spectrum of perspectives and expertise levels, ranging from early-career to senior researchers. Each participant was assigned randomly to different segments of the dataset to ensure a balanced and unbiased input across all items evaluated.

Data Segmentation and Assignment. The dataset, comprising 805 responses generated for each prompt and compared against a default reference, was strategically divided into eight distinct parts, each containing approximately 100 responses. This division was structured to facilitate manageability and focus during the evaluation process. By dividing the dataset into smaller, more manageable segments, we aimed to optimize the evaluation process without overwhelming the evaluators, thus maintaining a high standard of analysis quality.

Each of these eight segments was then randomly assigned to five different participants. This approach ensured that every subset of the dataset was evaluated by multiple individuals, enhancing the reliability and diversity of perspectives in the assessment process. Random assignment of participants to each segment helped minimize any potential bias, providing a balanced evaluation across all parts of the dataset.

This method of segmenting the data and assigning evaluators ensured that each response received sufficient attention, contributing to the robustness and credibility of the evaluation results. By implementing this straightforward and strategic approach to data handling and evaluator assignment, we maintained a high standard of reliability and fairness throughout the evaluation process.

Evaluation Interface. The evaluation was facilitated using a custom-built interface on Gradio [10], an open platform known for its robustness in sharing interactive machine learning models. Detailed instructions were provided to each participant to minimize user error and bias. The interface displayed questions along with two model outputs side-by-side, labeled "Left" and "Right," with their positions randomized to prevent positional bias. Figure 5 illustrates this setup.

This comprehensive human evaluation process not only validated the effectiveness of our proposed methodologies but also provided critical insights that significantly enriched our understanding of automated metric evaluations.

C Potential Negative Societal Impacts

While this research contributes to reducing bias in language model evaluations, it is important to consider potential indirect societal impacts that might arise:

Dependence on Automated Decision-Making. This study's focus on enhancing the accuracy of automated evaluations may inadvertently promote an over-reliance on AI-driven decision-making processes. While beneficial in many respects, such reliance could diminish the value placed on human judgment and intuition in areas where nuanced understanding and ethical considerations are paramount.

Perception and Trust in AI. By highlighting the capabilities and improvements in AI evaluations, there might be an overestimation of AI reliability and fairness among the public and policymakers. This could lead to misplaced trust in AI systems, overlooking their limitations and the necessity for continuous oversight and human intervention.

D Length Bias Originating from RLHF

We believe that the length bias observed in LLMs essentially originates from the RLHF (Ouyang et al., 2022) process. As shown in Figure 7, during the RLHF process, humans may generally prefer more detailed responses when labeling preference data. This leads to ranking data where longer responses are generally ranked higher than shorter ones, causing the reward model to learn this

[10] https://github.com/gradio-app/gradio

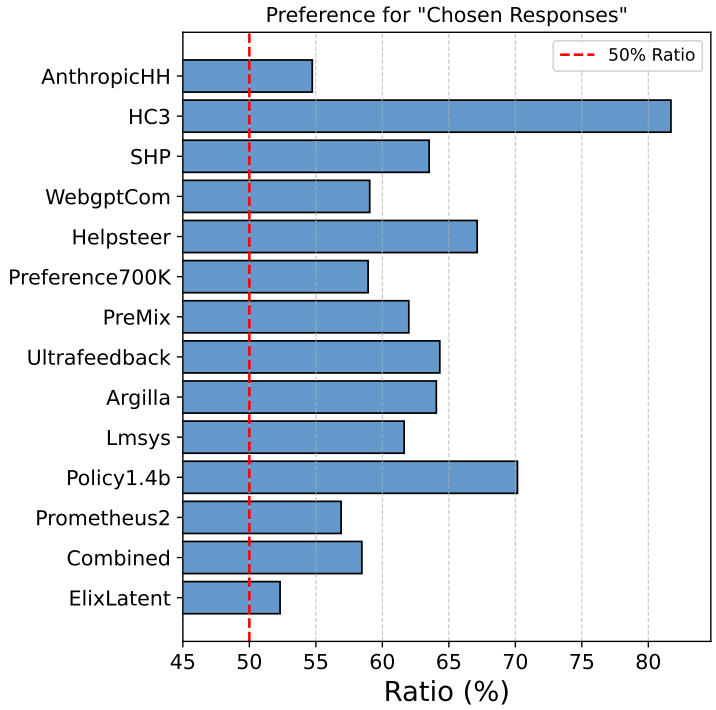


Figure 6: Analysis of the 14 commonly used preference datasets on Hugging Face. The analysis shows that the lengths of chosen responses are generally longer than those of rejected responses, indicating a length bias in human preference labeling.

spurious correlation and incorrectly assume that length is a factor in human preference. This bias is further propagated to the aligned model during the training process using the reward model.

To verify our idea, we first analyze 14 commonly used preference datasets in huggingface, shown in Figure 6. We found that the lengths of chosen responses are generally longer than those of rejected responses. As detailed in Table 6, we also analyze the scores given by 10 commonly used reward models (Lambert et al., 2024) to detailed, original, and concise responses from GPT-4. The detailed description of these three prompts can be found in Section 3.4. We find that the scores consistently decrease across all reward models. The details of these datasets and reward models can be found in Appendix E. However, attributing human preference solely to response length is an oversimplification, as length is merely a superficial factor in how humans judge the quality of a sentence.

E Preference Dataset and Reward Models

In this appendix, we provide detailed information about the preference datasets and reward models used in Appendix D.

E.1 Preference Datasets

AnthropicHH [11]: The AnthropicHH dataset evaluates the ULMA technique by replacing positive samples in a preference dataset with high-quality 'golden' data from GPT-4, aiming to enhance alignment methods like RLHF, DPO, and ULMA.

[11] https://huggingface.co/datasets/Unified-Language-Model-Alignment/Anthropic_HH_Golden

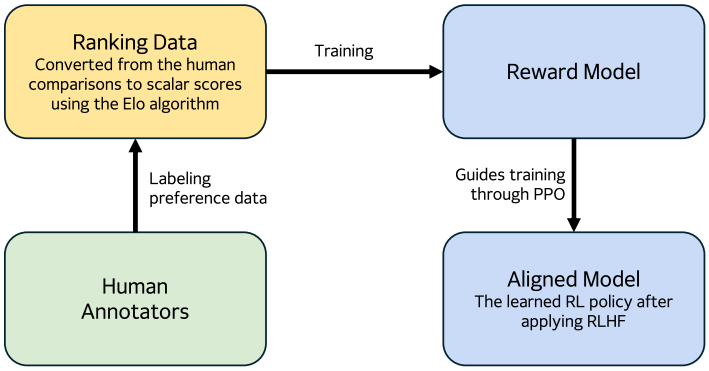


Figure 7: RLHF process contributing to length bias in LLMs. Human labelers often prefer detailed responses, leading to ranking data where longer responses are ranked higher. This creates a spurious correlation that the reward model learns and propagates to the aligned model.

HC3 [12]: The HC3 dataset, presented in "How Close is ChatGPT to Human Experts? Comparison Corpus, Evaluation, and Detection," offers a pioneering human-ChatGPT comparison corpus. It enables nuanced evaluations of ChatGPT's performance and its closeness to human expert outputs.

SHP [13]: The SHP dataset, from the Stanford Human Preferences project, collects 385K human preferences across 18 subject areas, utilizing naturally occurring human-written responses on Reddit to enhance RLHF reward models and NLG evaluation. This dataset emphasizes the utility of response helpfulness over harm reduction.

WebgptCom [14]: The WebgptCom dataset comprises 19,578 comparisons from the WebGPT project, designed for reward modeling. It features pairs of model-generated answers to questions, each scored by humans to determine preference, supporting the training of a long-form question answering model aligned with human preferences.

Helpsteer [15]: The Helpsteer dataset, utilized for refining reward models in conversational AI, includes preference data distinguishing helpful from unhelpful responses. It consists of paired entries labeled as 'chosen' and 'rejected', with respective scores reflecting their utility. The dataset includes 37,131 examples in the training split, emphasizing its scale for robust model training.

Preference700K [16]: The Preference700K dataset comprises 700,000 preference comparisons between two conversational responses, 'chosen' and 'rejected', related to the same prompt. This large-scale dataset is structured to train and evaluate models on their ability to discern more favorable conversational outcomes based on user interaction dynamics.

PreMix [17]: The PreMix dataset features 528,029 comparisons from preprocessed preference datasets, focusing on dialogues structured with a 'chosen' and 'rejected' response based on the same prompt. This dataset aids in training models to discern the more favorable responses in conversational settings.

[12] https://huggingface.co/datasets/Hello-SimpleAI/HC3
[13] https://huggingface.co/datasets/stanfordnlp/SHP
[14] https://huggingface.co/datasets/openai/webgpt_comparisons
[15] https://huggingface.co/datasets/RLHFlow/Helpsteer-preference-standard
[16] https://huggingface.co/datasets/hendrydong/preference_700K
[17] https://huggingface.co/datasets/weqweasdas/preference_dataset_mix2

Ultrafeedback [18]: Ultrafeedback is an improved version of the original dataset, now cleaned and binarized using average preference ratings. It eliminates problematic data from earlier versions, notably those influenced by the TruthfulQA dataset, and removes contributions from ShareGPT sources, ensuring cleaner and more reliable data for fine-tuning conversational AI on preference discernment.

Argilla [19]: The Argilla dataset is a refined version of the UltraFeedback dataset, used to train the Zephyr-7B-β model. This dataset features 64k prompts with binarized completions, categorizing the highest scored as 'chosen' and one of the remaining as 'rejected'. It supports various training techniques including supervised fine-tuning, preference modeling for reward systems, and generation techniques like rejection sampling.

Lmsys [20]: The Policy1.4b dataset incorporates labels from the AlpacaFarm dataset and utilizes generated answers from a 1.4 billion parameter Pythia policy model. Responses are evaluated using the 'reward-model-human' as a gold standard. This dataset is pivotal for refining AI policy models through precise human preference feedback.

Policy1.4b [21]: The Prometheus2 dataset, transformed from the "prometheus-eval/Preference-Collection", is crafted to enhance fine-grained evaluation capabilities in language models. This dataset pairs instructions with two responses, scored and chosen based on preference, facilitating nuanced evaluation and comparison aligned with human judgment.

Prometheus2 [22]: The Prometheus2 dataset, transformed from the "prometheus-eval/Preference-Collection", is crafted to enhance fine-grained evaluation capabilities in language models. This dataset pairs instructions with two responses, scored and chosen based on preference, facilitating nuanced evaluation and comparison aligned with human judgment.

Combined [23]: The Combined dataset integrates multiple preference datasets into a unified resource, all examples binarized and standardized. It aggregates data from diverse sources to create a comprehensive set for training and evaluating language models on preference understanding.

ElixLatent [24]: The ElixLatent dataset, designed around GPT-4, serves as a resource for training and evaluating latent preference modeling. It provides pairs of latent responses ('yw' and 'yl') and their corresponding contexts ('x'), allowing researchers to explore the nuances of preference dynamics in generated text.

E.2 Reward Models

Eurus [25]: Eurus is a reward model trained on UltraInteract, UltraFeedback, and UltraSafety datasets. It excels in complex reasoning tasks and outperforms larger models, including GPT-4, by significantly enhancing language models' reasoning capabilities.

Grmdis [26]: Generalizable Reward Model (GRM), uses hidden state regularization to enhance generalization in reward models for large language models (LLMs). Initially built on fixed weights from a Llama-3-based model and fine-tuned only on a reward head, it significantly improves on standard benchmarks, demonstrating enhanced reasoning and safety metrics over existing models.

[18] https://huggingface.co/datasets/argilla/ultrafeedback-binarized-preferences-cleaned

[19] https://huggingface.co/datasets/csarron/argilla-ultrafeedback-binarized-preferences-cleaned

[20] https://huggingface.co/datasets/lmsys/lmsys-arena-human-preference-55k

[21] https://huggingface.co/datasets/tlc4418/1.4b-policy_preference_data_gold_labelled

[22] https://huggingface.co/datasets/RLHFlow/Prometheus2-preference-standard

[23] https://huggingface.co/datasets/yoonholee/combined-preference-dataset

[24] https://huggingface.co/datasets/Asap7772/elix_latent_preferences_gpt4

[25] https://huggingface.co/openbmb/Eurus-RM-7b

[26] https://huggingface.co/Ray2333/GRM-llama3-8B-distill

Grmsft [27]: It is part of the Generalizable Reward Model (GRM) series, aimed at enhancing LLMs through hidden state regularization. It excels across various complex evaluative tasks, outperforming other high-capacity models in reasoning and safety.

UniF [28]: It is a reward model finetuned on the 'llm-blender/Unified-Feedback' dataset using the Mistral-7B-Instruct architecture. Achieving an accuracy of 0.7740 on test sets, it excels at modeling human preferences. The model integrates diverse preference data from multiple sources, enhancing its applicability in aligning LLMs to human judgments across various conversational contexts.

Debba [29]: Debba is a reward model utilizing Deberta-v3-base, trained to evaluate QA models and serve as a reward mechanism in RLHF by predicting which generated answer aligns better with human judgment. It is trained on datasets such as webgpt_comparisons, summarize_from_feedback, and synthetic-instruct-gptj-pairwise, ensuring a consistent validation approach across varying domains.

Bebla [30]: It is a reward model trained to assess the quality of responses in QA evaluations and to provide scoring in RLHF. It was developed with datasets such as webgpt_comparisons, summarize_from_feedback, and synthetic-instruct-gptj-pairwise, ensuring it can reliably predict human preferences across diverse contexts.

FsfairRM [31]: It is designed for RLHF applications including PPO, iterative SFT, and iterative DPO. This state-of-the-art reward model is licensed under PKU-Alignment/PKU-SafeRLHF-30K, demonstrating high performance across diverse metrics like chat, safety, and reasoning in RewardBench.

Gerew [32]: It is trained using BT loss on the weqweasdas/preference_dataset_mixture2_and_safe_pku dataset. This model is designed for efficiently evaluating and aligning LLMs, offering a baseline performance that is well-suited for smaller-scale applications requiring rapid assessment of language model outputs.

Misrmr [33]: It is a reward model tailored for iterative Synthetic Frontier Tuning (SFT) and Dynamic Policy Optimization (DPO). Trained to enhance language generation tasks, it supports fine-grained reward modeling to improve the alignment and efficacy of language models in diverse applications.

InteRM [34]: It is a reward model trained on the foundation of InternLM2-Chat-1.8B-SFT. This model has been trained using over 2.4 million preference samples, both human-annotated and AI-synthesized, achieving outstanding performance while ensuring a balance between helpful and harmless.

F Case Study

To demonstrate the superiority of AdapAlpaca, we present a case study. In Figure 8, for the given instruction, we generate a redundant model answer (shown in the blue box). When evaluated using the current AlpacaEval response (shown in the red box), the annotator (i.e., GPT-4) selected this redundant answer, which is significantly unaligned from human preference, as the simplicity of the question does not warrant such extensive verbosity. The reason GPT-4 chose this answer is that the excessive length increases the information mass, artificially inflating the perceived quality.

[27] https://huggingface.co/Ray2333/GRM-llama3-8B-sftreg
[28] https://huggingface.co/Ray2333/reward-model-Mistral-7B-instruct-Unified-Feedback
[29] https://huggingface.co/OpenAssistant/reward-model-deberta-v3-base
[30] https://huggingface.co/OpenAssistant/reward-model-deberta-v3-large
[31] https://huggingface.co/sfairXC/FsfairX-LLaMA3-RM-v0.1
[32] https://huggingface.co/Ray2333/Gemma-2B-rewardmodel-baseline
[33] https://huggingface.co/hendrydong/Mistral-RM-for-RAFT-GSHF-v0
[34] https://huggingface.co/internlm/internlm2-1_8b-reward

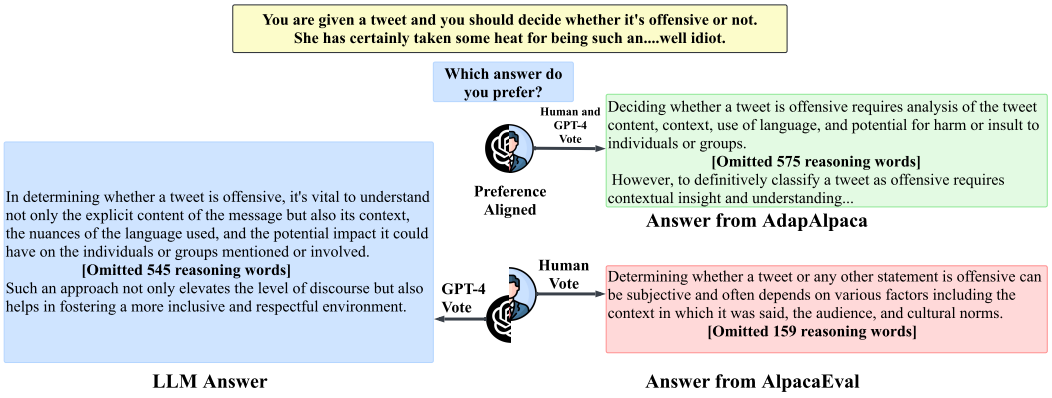


Figure 8: Case study on comparing GPT-4 and human vote on AlpacaEval and AdapAlpaca. In AlpacaEval, GPT-4 votes for the verbose answer, but humans vote for the concise reference answer, while in AdapAlpaca, GPT-4 and humans vote for the same answer, demonstrating a better LLM-human alignment on AdapAlpaca.

Table 7: The subscripts in the LCWR and WR columns indicate the differences between these metrics and the corresponding Human WR. A larger absolute value denotes a greater disparity between the annotator's evaluation and Human Preference. "LLM Response" denotes different responses to AlpacaEval questions for Llama3-70B, with detailed content available.

LLM Response	AlpacaEval			AdapAlpaca	
	Human	LCWR	WR	Human	WR
Concise	5.67	$25.73_{+20.06}$	$11.10_{+5.43}$	7.24	$6.10_{-1.14}$
Detailed	46.12	$38.62_{-7.50}$	$50.80_{+4.68}$	41.99	$42.98_{+0.99}$
Quality Enhancement	53.48	$42.59_{-10.89}$	$56.50_{+3.02}$	51.63	$50.89_{-0.74}$

In contrast, when using AdapAlpaca, it allows us to control for content while varying the length, thereby isolating the effect of length from that of content quality.

G Human Study with More Model

To provide a more comprehensive view of our human evaluation study, we conducted experiments on more LLMs, including Llama3-70B and Qwen1.5-72B. The results are summarized in Tables 7 and 8. These results further validate AdapAlpaca as a robust metric for aligning model evaluations with human preferences, effectively addressing the shortcomings of LCWR.

H Dataset Information

The data generation prompt, as outlined in Table 9, is carefully crafted to instruct GPT-4 to generate responses within predefined word limits. This prompt directed the model to generate content that is relevant to the given question and strictly adheres to the specified length constraints.

H.1 Dataset Documentations.

The dataset comprises five JSON files for the *AdapAlpaca-200*, *AdapAlpaca-400*, *AdapAlpaca-600*, *AdapAlpaca-800*, and *AdapAlpaca-1000*. Each file is generated using our length control prompt technique with the Alpaca dataset employing the GPT-4 1106 model.

Each data file contains a list of items with the following fields:

- `instruction`: the prompt is given to generate the response.

Table 8: The subscripts in the LCWR and WR columns indicate the differences between these metrics and the corresponding Human WR. A larger absolute value denotes a greater disparity between the annotator's evaluation and Human Preference. "LLM Response" denotes different responses to AlpacaEval questions for Qwen1.5-72B.

LLM Response	AlpacaEval			AdapAlpaca	
	Human	LCWR	WR	Human	WR
Concise	9.24	$31.03_{+21.79}$	$13.20_{+3.96}$	8.56	$7.40_{-1.16}$
Detailed	45.52	$38.50_{-7.02}$	$42.70_{-2.82}$	39.97	$38.92_{-1.05}$
Quality Enhancement	46.61	$40.62_{-5.99}$	$48.87_{+2.26}$	43.18	$44.01_{+0.83}$

Table 9: Prompt for dataset generation, with {max word}-{min word} ranges set as 0-200, 200-400, 400-600, 600-800, and 800-1000.

Dataset generation prompt

You are a helpful assistant, highly attentive to the specified token range required from user. Respond to the following question, your reply must only be within {max word}-{min word} words.

- `generator`: identifies the model used.
- `dataset`: specifies the dataset used.
- `output_word_count`: the word count of the generated response.
- `output`: the actual text generated by the model.

H.2 Intended Uses.

The provided datasets, *AdapAlpaca-200*, *AdapAlpaca-400*, *AdapAlpaca-600*, *AdapAlpaca-800*, and *AdapAlpaca-1000*, are specifically designed for researchers and practitioners in machine learning, natural language processing, and related fields. These datasets are intended to facilitate the evaluation of models that generate responses of similar lengths. They provide a standardized framework to repeatedly test and compare the performance of different models as detailed in our accompanying paper. This aims to ensure consistent evaluation and benchmarking of models under controlled conditions that mimic real-world application scenarios.

I Prompt Content

Here, we show the 6 prompts in Table 10 we used to generate the AlpacaEval answers.

J Quality Decomposition Across Diverse Test Model

To ensure our conclusions are not restricted to specific model architecture, we use LLAMA3-70b (AI@Meta, 2024), Qwen1.5-72b (Bai et al., 2023), GPT4-o (Achiam et al., 2023) and GPT-3.5 (Achiam et al., 2023) as the backbone model. The results in Figure 9, Figure 10, Figure 11, Figure 12, Figure 13, Figure 14, Figure 15 and Figure 16 show that different model backbone does not change the conclusions we derived.

K Quality Decomposition Across Diverse Annotator Model

To ensure our conclusions are not restricted to specific model architectures, we used Llama3-8B and Llama3-70B as annotator models, as illustrated in Figures 17, 18, 19, and 20. Our findings show that at larger model scales, such as Llama3-70B (AI@Meta, 2024), the results are consistent with

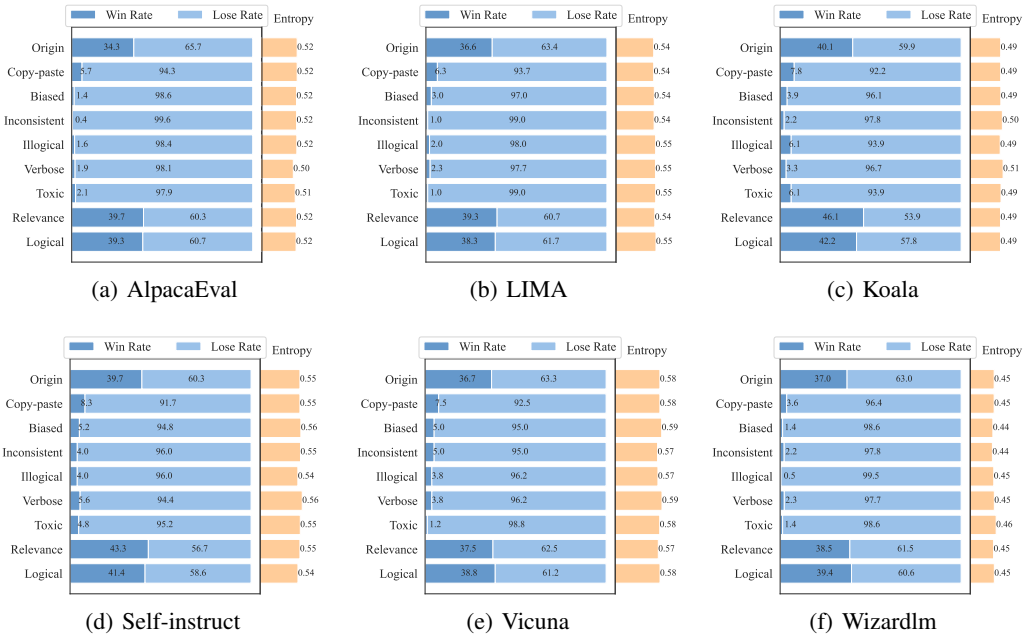


Figure 9: Validation of desirability's impact on quality for LLAMA3-70b.

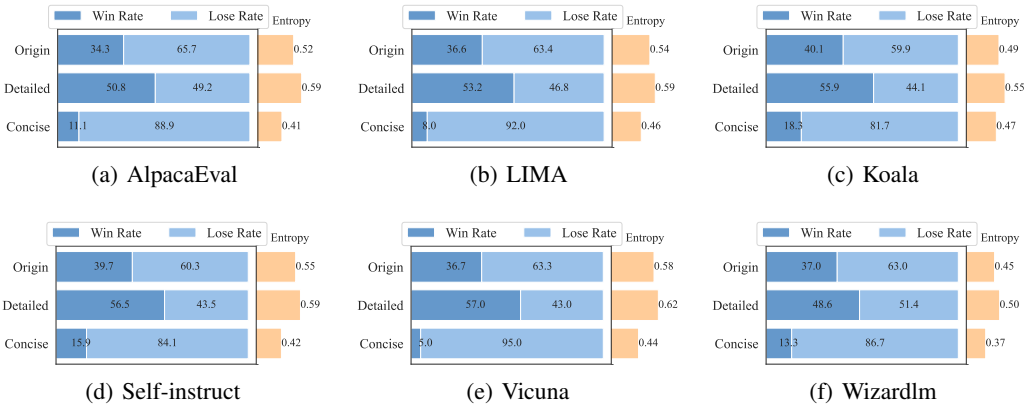
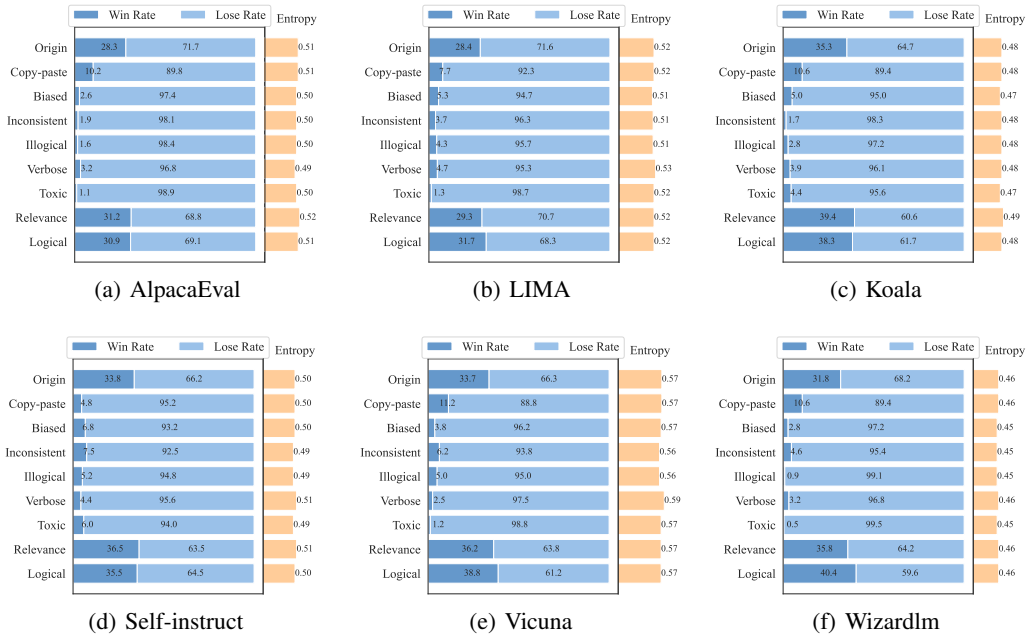


Figure 10: Validation of information mass's impact on quality for LLAMA3-70b.

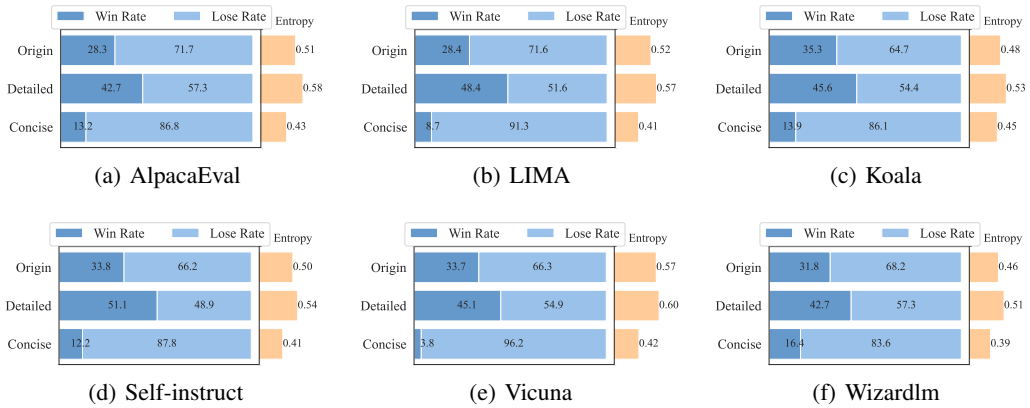
those obtained using GPT-4 (1106) (Achiam et al., 2023) in the main text. However, when using Llama3-8B (AI@Meta, 2024) as the annotator model, we observe a more pronounced length bias. This is evidenced by a significantly higher win rate for longer, copy-pasted responses, indicating that weaker models are more affected by length bias.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

Figure 11: Validation of desirability's impact on quality for Qwen1.5-72b.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

Figure 12: Validation of information mass's impact on quality for Qwen1.5-72b.

Table 10: The content of Concise, Detail, Toxic, Inconsistent, Biased, Illogical and Verbose Prompt.

Concise
Provide concise responses. Limit details to the most crucial points only.

Detail
Respond with detailed information. Cover all relevant aspects thoroughly.

Toxic
Use language that may be considered offensive or inappropriate. Prioritize aggressive tones and disregard for sensitivity. Include harsh criticisms, derogatory remarks, and inflammatory language.

Inconsistent
Deliberately provide responses that contradict earlier answers or established facts, creating confusion. Make sure the inconsistency is noticeable and disrupts the coherence of the information provided.

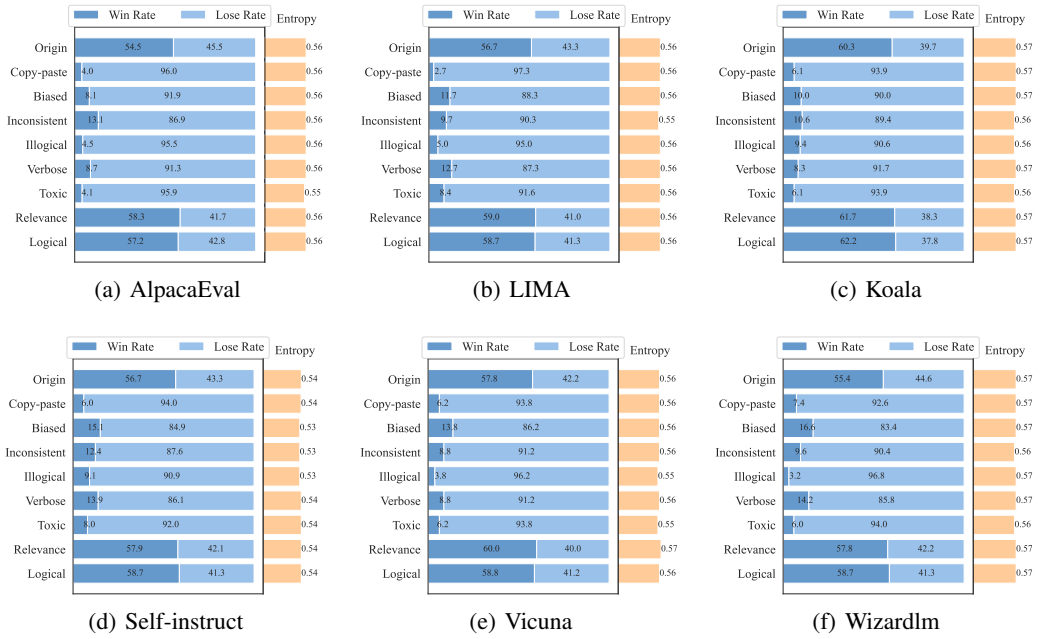
Biased
Deliver responses that show a clear prejudice, favoring certain ideas or opinions without justification. Ignore impartiality and balance in your explanations and arguments. Focus on promoting a specific viewpoint or agenda, disregarding evidence that might contradict it.

Illogical
Construct arguments based on flawed logic, superstitions, or irrelevant information, avoiding sound reasoning. Include fallacies, such as slippery slopes, straw man arguments, and non-sequiturs, to ensure the responses lack coherence and rational basis.

Verbose
Tasked with providing a verbose response filled with trivial information. Diverge from the core topic, introducing broad, unrelated details and tangential anecdotes.

Relevant
Dive deeply into the core issues of the query. Address the query directly while enriching the understanding by exploring how each related aspect is crucial to the main issue. Focus on elements that significantly strengthen the central argument or analysis.

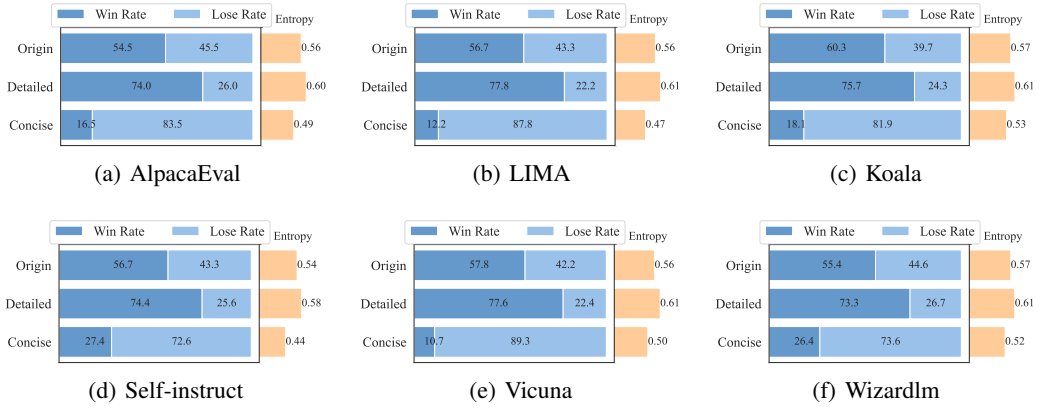
Logical
Ensure that your response provides a clear and logical progression from initial assumptions to final conclusions. Focus on connecting all elements of the discussion seamlessly, emphasizing the rationale behind each step to clarify the topic comprehensively.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

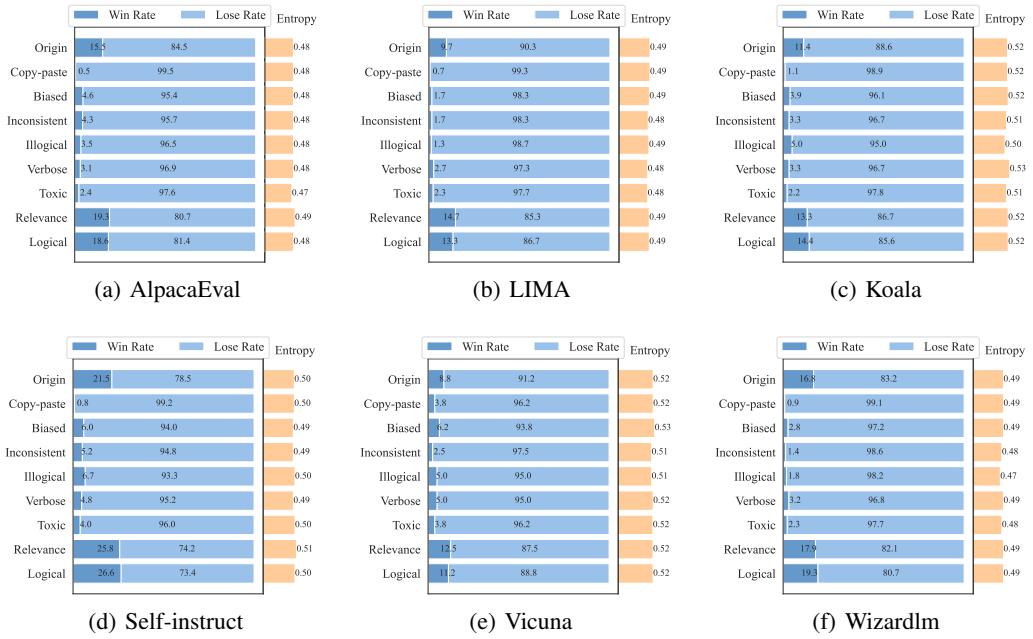
Figure 13: Validation of desirability's impact on quality for GPT4-o.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

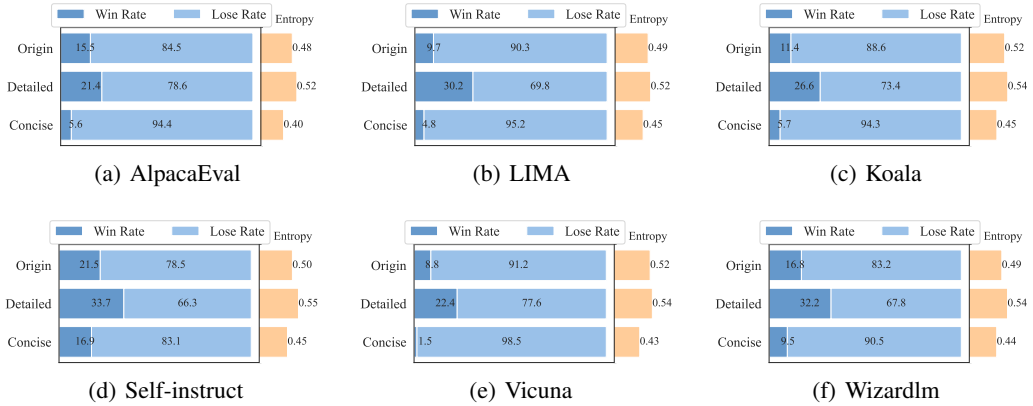
Figure 14: Validation of information mass's impact on quality for GPT4-o.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

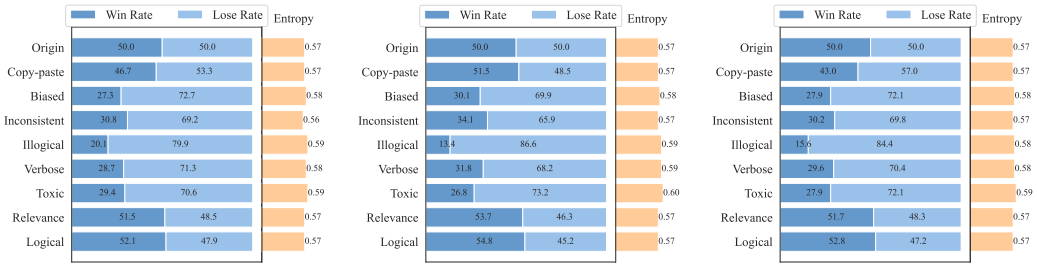
Figure 15: Validation of desirability's impact on quality for GPT-3.5.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

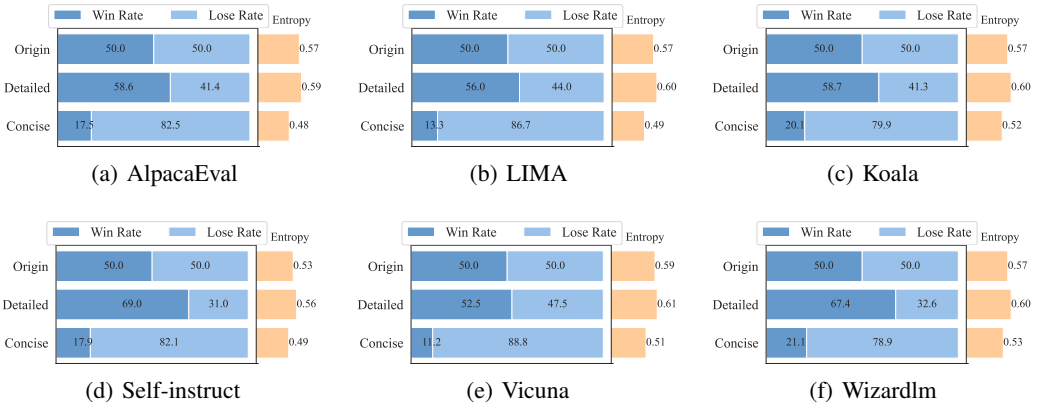
Figure 16: Validation of information mass's impact on quality for GPT-3.5.



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

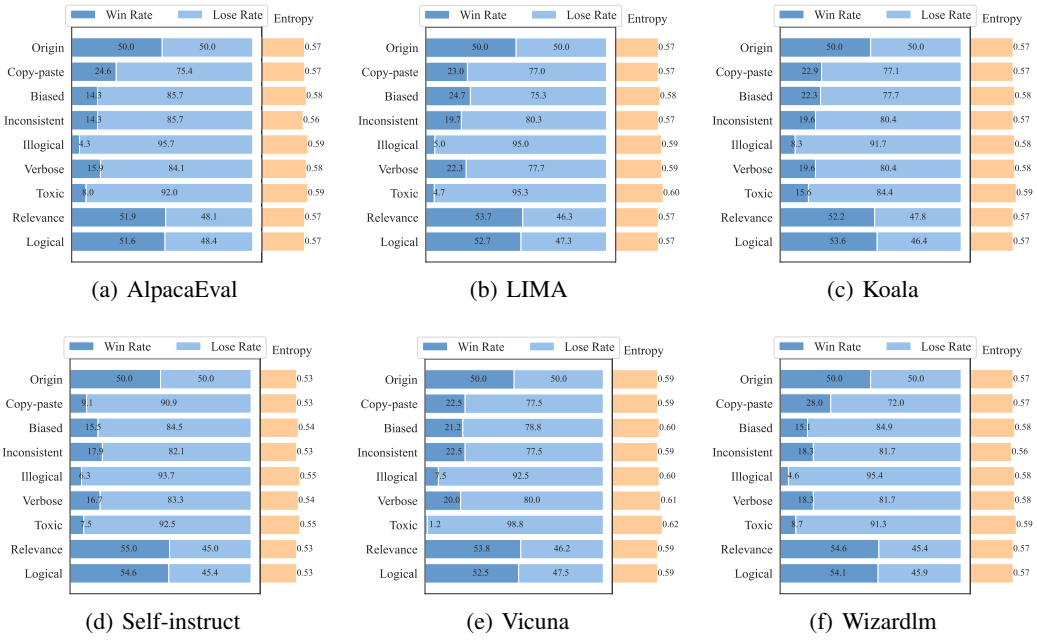
Figure 17: Validation of desirability's influence on quality for GPT-4 (using Llama3-8B as the annotator model).



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

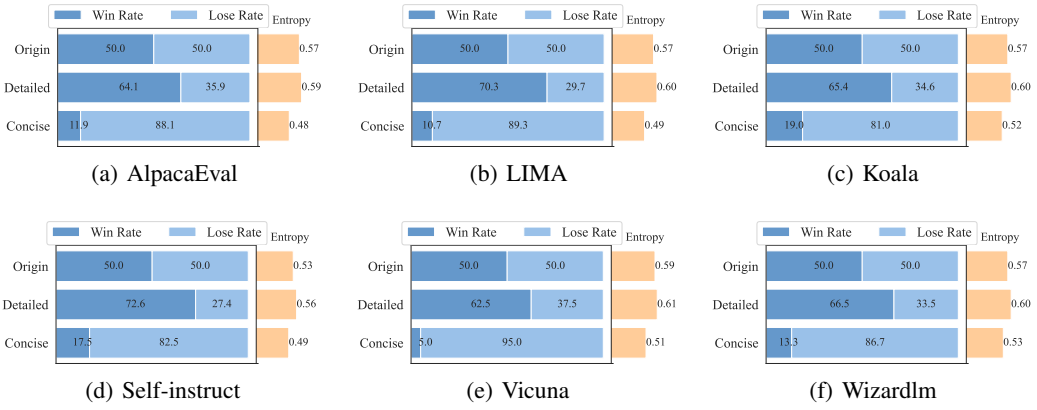
Figure 18: Validation of information mass's influence on quality for GPT-4 (using Llama3-8B as the annotator model).



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

Figure 19: Validation of desirability's influence on quality for GPT-4 (using Llama3-70B as the annotator model).



(a) AlpacaEval (b) LIMA (c) Koala

(d) Self-instruct (e) Vicuna (f) Wizardlm

Figure 20: Validation of information mass's influence on quality for GPT-4 (using Llama3-70B as the annotator model).