

# Arena-Lite: Efficient and Reliable Large Language Model Evaluation via Tournament-Based Direct Comparisons

Seonil Son<sup>1\*</sup>, Ju-Min Oh<sup>1†</sup>, Heegon Jin<sup>1‡</sup>,  
Cheolhun Jang<sup>1</sup>, Jeongbeom Jeong<sup>1</sup>, Kuntae Kim<sup>1§</sup>  
<sup>1</sup>NCSOFT

Correspondence: seonil.calendar@gmail.com

## Abstract

As Large Language Models (LLMs) expand across domains, LLM judges have become essential for systems evaluation. Current benchmarks typically compare system outputs against baselines. This baseline-mediated approach, though convenient, yields lower reliability than direct comparison between systems. We propose Arena-Lite which integrates tournament structure on top of head-to-head comparison. The application of a tournament structure and direct comparison eliminates the need for baseline outputs, reduces the number of required comparisons, and allows higher reliability in system rankings. We conducted two experiments: (1) controlled stochastic modeling and (2) empirical validation with a real LLM judge. Those experiments collectively demonstrate that Arena-Lite consistently achieves higher reliability with fewer comparisons, even with smaller datasets or weaker judges. We release an easy-to-use web demonstration and code to foster adoption of Arena-Lite, streamlining model selection across research and industry communities. Arena-Lite demo and code are available on <https://huggingface.co/spaces/NCSOFT/ArenaLite>

## 1 Introduction

LLMs excel in diverse tasks, from chatbots to code generation, due to their powerful generative capabilities (Ouyang et al., 2022; Roziere et al., 2023). As their versatility grows, accurately evaluating their performance becomes critical. To address this, benchmarks like MMLU and BigBench have emerged to assess LLM capabilities across various domains (Hendrycks et al., 2020; Srivastava et al., 2023). Many of these benchmarks, such as those for arithmetic or code execution (e.g., GSM-Hard,

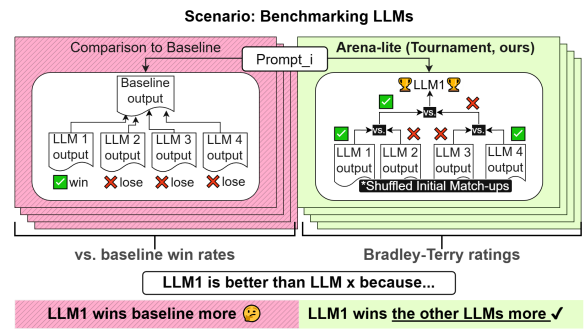


Figure 1: Arena-Lite directly compares LLM response pairs over multiple single-elimination tournaments rather than comparing responses to baseline outputs. In terms of deciding whether a certain LLM is better or worse compared to the other one, we suggest direct head-to-head comparison is more intuitive and results in better separability.

	Total no. matches (↓)	No. matches per LLM participant (↑)
Current Practice	$n_{\text{model}} \cdot  X $	$ X $
Arena-Lite (ours)	$(n_{\text{model}} - 1) \cdot  X $	$[ X ,  X  * \lceil \log_2 n_{\text{model}} \rceil]$

Table 1: Comparison between Current practice of benchmarking (comparing to baseline outputs) and Arena-Lite.  $|X|$  and  $n_{\text{model}}$  represents size of benchmark dataset, and number of candidate LLMs to rank respectively. Arena-Lite, always save  $|X|$  number of comparisons for benchmarking, while allows more matches per LLM participant thanks to head-to-head comparison.

HumanEval (Gao et al., 2022; Chen et al., 2021)), use automated scoring to evaluate problem-solving skills. However, their focus is not on quality of generated content or limited to the cases where the generated contents are automatically evaluated (e.g. programming), which are mostly not the case for variety of generation tasks. The Chatbot Arena, a leading platform for reliable human evaluation of LLMs, has set a standard by collecting extensive human annotations (Chiang et al., 2024). Yet, its resource-intensive approach has prompted efforts to replicate its rankings using LLM judges as a cost-

\*Current institution: RLWORLD Inc.

†Current institution: Samsung AI Research

‡Current institution: Global AI Platform

§Current institution: Samsung Life Insurance

effective alternative (Li et al., 2024, 2023). These methods, however, rely on baseline-mediated comparisons—comparing LLM outputs to a leading proprietary model’s outputs—which sacrifice reliability.

Current benchmarks relying on baseline often rank LLMs by their win rate against baseline responses from an leading proprietary models. This approach has two advantages: it scales linearly with the number of LLMs and provides a consistent quality standard. However, we argue that comparing LLMs directly against each other is inherently more reliable than using baseline outputs, which can introduce noise coming from weak transitivity (Xu et al., 2025) of human preferences on LLM responses. To address this, we propose Arena-Lite, a novel evaluation framework that uses direct, head-to-head comparisons organized in a tournament structure. By eliminating the need for baseline outputs, Arena-Lite reduces the number of comparisons required while achieving stronger alignment with human-established rankings, such as those from Chatbot Arena.

Arena-Lite conducts single-elimination tournaments among participating LLMs for each prompt. From the match results, we can compute Bradley-Terry preference ratings for the final ranking (Bradley and Terry, 1952). This results in a single scalar per model that captures relative performance between any model counterpart, enabling accurate and efficient ranking. We validate Arena-Lite through two experiments. The first experiment, stochastic modeling of LLM competition (Section 4.2) demonstrates that tournament-based direct comparison method outperforms baseline-mediated method under various conditions, including different numbers of LLM participants, dataset rows used, and judge accuracies. Second, our empirical experiment (Section 4.3) shows that Arena-Lite achieves higher correlation with Chatbot Arena’s rankings than standard approaches using baseline outputs (Table 1) attested toward number of LLM as judges. These results collectively highlight Arena-Lite’s ability to deliver reliable rankings with fewer comparisons, even with smaller datasets or weaker judges over various generation tasks.

Our contributions are threefold:

1. We introduce Arena-Lite, a tournament-based framework for direct LLM comparisons, offering greater reliability than baseline-mediated approaches.
2. We rigorously demonstrate, through both com-

prehensive modeling and empirical experiments, that Arena-Lite achieves more accurate LLM rankings while requiring fewer comparisons than prevalent practices, particularly those relying on common baseline model outputs.

3. We open-source a functional demo and the complete code for Arena-Lite (<https://huggingface.co/spaces/NCSOFT/ArenaLite>), enabling researchers and industry practitioners to easily host and utilize our framework for streamlined LLM evaluation.

## 2 Preliminaries: Quantifying Generative Performance

Quantifying the generative capabilities of LLMs is an inherently challenging task. The evaluation is complicated by the stochasticity of model outputs and the subjectivity of human judgments. To approximate real-world performance, a common methodology involves assessing model outputs across a diverse range of prompts. In this context, two metrics are widely utilized: the **win rate**, which measures the frequency of preference for a model’s output over a baseline, and the **Bradley-Terry model**, which is employed to infer a latent skill rating for each model based on pairwise comparisons.

### 2.1 Measuring Win rate over baseline outputs

Benchmarks like AlpacaEval and Arena-Hard-Auto assess LLM response quality by comparing it to baseline responses from proprietary model (Li et al., 2023, 2024). An LLM judge evaluates whether the candidate LLM’s response outperforms the baseline for a given prompt. The win rate—the proportion of prompts where the LLM’s response is preferred—serves as a measure of its generative ability. While this approach is straightforward and scalable, it introduces noise coming from mediated comparisons.

### 2.2 Bradley-Terry Model Preference for LLM Rating

The Bradley-Terry (BT) model (Bradley and Terry, 1952) is widely used to infer baseline-mediated rankings of LLMs from pairwise comparisons. Chatbot Arena adopts the BT model rather than the classical Elo system (Elo and Sloan, 1978), but both Elo and BT models are useful for expecting

probability of match outcome based on a score difference, though they differ in update rules and statistical assumptions.

In the BT model, each LLM is assigned a latent score representing its proficiency. Given LLMs  $i$  and  $j$  with scores  $R_i$  and  $R_j$ , respectively, the probability that LLM  $i$  is preferred over LLM  $j$  is modeled as:

$$P(i > j) = \frac{1}{1 + 10^{(R_j - R_i)/400}}. \quad (1)$$

This formulation closely resembles the Elo win-probability function, reinforcing the intuitive connection between the two.

Chatbot Arena uses this BT-based formulation to rank LLMs by aggregating human preferences collected through pairwise matchups (Chiang et al., 2024). Users are shown responses from two anonymized models to the same prompt and asked to select which response they prefer. The accumulated judgments are then used to fit BT scores, producing a leaderboard that reflects relative model performance.

While this approach requires a substantial number of human evaluations to ensure reliability, it captures nuanced quality differences between models more effectively than purely automatic benchmarks. Arena-Lite, introduced in the next section, builds on the same BT modeling framework but seeks to reduce the number of required comparisons by using tournament-structured match-making.

### 3 Arena-Lite

To address the high annotation cost of Chatbot Arena while preserving evaluation reliability, we propose Arena-Lite. Arena-Lite introduces a tournament-based approach for efficient and reliable LLM evaluation using a single-elimination structure. Unlike baseline-mediated evaluations that compare model outputs to a baseline, Arena-Lite directly compares outputs from different models through head-to-head matchups for each prompt in benchmark datasets. Repeated tournaments across the dataset produce consistent leaderboards reflecting models' fundamental performance.

We first discuss limitations of baseline-mediated evaluations (Section 3.1). Next, we describe how Arena-Lite conducts tournaments to generate ratings (Section 3.2, Algorithm 1). Finally, we highlight similarities between the single-elimination

structure and merge sort, explaining why aggregated tournaments yield reliable LLM rankings (Section 3.3).

#### 3.1 Comparing to Baseline outputs is not Always Helpful

Although baseline outputs are a standard way to evaluate and rank LLMs, they introduce potential failure modes. Beyond the fact that a single baseline output might not capture every dimension of appropriate answers, relying solely on a baseline output can lead to unreliable rankings of LLMs.

Consider an ideal scenario with a judge capable of perfectly distinguishing the quality of any two outputs. If we choose to compare LLM responses directly to rank them using BT preference (Equation 1), all head-to-head comparisons are utilized. In contrast, baseline-mediated evaluation for differentiating LLMs can exhibit failure modes, as shown in Equation 2.

$$\begin{array}{l} M_1(X_i) \\ \text{vs. } \rightarrow \\ M_2(X_i) \end{array} \quad \left\{ \begin{array}{ll} M_1(X_i) > Y_i > M_2(X_i) & (\text{helpful}) \\ M_1(X_i) < Y_i < M_2(X_i) & (\text{helpful}) \\ M_1(X_i), M_2(X_i) > Y_i & (\text{unhelpful}) \\ M_1(X_i), M_2(X_i) < Y_i & (\text{unhelpful}) \end{array} \right. \quad (2)$$

When the baseline output ( $Y_i$ ) for a prompt ( $X_i$ ) successfully disambiguates the pair of LLM responses  $M_1(X_i)$  and  $M_2(X_i)$  (as in the first and second cases), comparison to the baseline is effective for benchmarking. Otherwise, these comparisons do not help differentiate LLM performance. Consequently, the baseline-mediated approach provides less information for ranking when multiple responses are either both correct or both incorrect relative to the baseline.

#### 3.2 Tournaments of LLMs over multiple prompts to preference ratings

Figure 1 and Algorithm 1 illustrate how Arena-Lite benchmarks LLMs via a tournament approach. Here,  $|X|$  denotes the number of prompts in the benchmark dataset. Running Arena-Lite hosts tournaments among participant LLMs for every prompt in the dataset.

The use of tournament structures for LLM benchmarking offers both benefits and challenges. A major advantage of a single-elimination tournament is efficiency. As shown in Table 1, the number of matches scales linearly with the number of participants and even lower compared to using baseline

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**Algorithm 1** Tournament-Based Model Evaluation

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**Require:** Models  $M = \{m_1, m_2, \dots, m_n\}$ ,Prompts  $X = \{x_1, x_2, \dots, x_k\}$ **Ensure:** Bradley-Terry preference ratings

```
1: Initialize  $R \leftarrow \emptyset$ 
2: for each  $x_j \in X$  do
3:    $\text{next\_power} \leftarrow 2^{\lceil \log_2(|M|) \rceil}$ 
4:    $\text{n\_byes} \leftarrow \text{next\_power} - |M|$ 
5:    $M' \leftarrow M \cup \{\text{None}\}_{\text{n\_byes}}$ 
6:   Randomly shuffle  $M'$ 
7:    $\text{winner} \leftarrow \text{SINGLEELIM}(M', x_j)$ 
8: end for
9: return  $\text{COMPUTE BTM}(R)$  ▷ Eq. (1)

10: function  $\text{SINGLEELIM}(M', x)$ 
11:   if  $|M'| = 2$  then
12:      $\text{result} \leftarrow \text{MATCH}(M'[0], M'[1], x)$ 
13:     if  $\text{None} \notin M'$  then
14:       Add result to  $R$ 
15:     end if
16:     if  $\text{result} = \text{None}$  then return  $[\text{None}]$ 
17:     elsereturn  $[\text{result}[0]]$ 
18:     end if
19:   else
20:      $\text{mid} \leftarrow \lfloor |M'|/2 \rfloor$ 
21:      $\text{left} \leftarrow \text{SINGLEELIM}(M'[:\text{mid}], x)$ 
22:      $\text{right} \leftarrow \text{SINGLEELIM}(M'[\text{mid}:], x)$ 
23:     return  $\text{SINGLEELIM}(\text{left} \cup \text{right}, x)$ 
24:   end if
25: end function

26: function  $\text{MATCH}(m_i, m_j, x)$ 
27:   if  $m_i = \text{None}$  and  $m_j = \text{None}$  then
28:     return  $\text{None}$ 
29:   else if  $m_i = \text{None}$  or  $m_j = \text{None}$  then
30:     return  $m_i$  if  $m_j = \text{None}$  else  $m_j$ 
31:   else
32:      $O_i \leftarrow m_i(x), O_j \leftarrow m_j(x)$ 
33:     if  $O_j > O_i$  then return  $(m_j, m_i)$ 
34:     elsereturn  $(m_i, m_j)$ 
35:     ▷ returns (winner, loser) tuple
36:   end if
37: end function
```

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outputs. However, single elimination tournament only identifies a champion, leaving the relative ordering of other participants unclear.

To retain tournament's efficiency while obtaining a fine-grained ranking, we propose aggregating tournament results over multiple prompts with randomized initial match-ups for each prompt. Performing multiple tournaments with random initialization offers several benefits:

1. It resolves ties among non-champion participants from previous tournaments.
2. It mitigates the impact of unfavorable match-ups in any single tournament.
3. Aggregating match results allows for precise win rate estimation via BT preference, resulting in a well-aligned overall ranking.
4. More matches are allocated to high-performing participants while ensuring every participant is evaluated at least once per prompt (Table 1).

In Section 3.3, we further explain how aggregating multiple tournaments could yield reliable ranking of LLMs. We also provide further analysis on number of comparisons performed over tournaments of Arena-Lite comparing to merge sort, offering a comprehensive view of the method's efficiency and effectiveness.

### 3.3 Why Aggregating Multiple Tournaments Yields Reliable Rankings

A key challenge in LLM evaluation is to derive a reliable ranking from a feasible number of pairwise comparisons. Our tournament-based approach, Arena-Lite, is designed to efficiently sample these comparisons. In a single tournament with  $n$  models, each model participates in a minimum of one match and a maximum of  $\lceil \log_2 n_{\text{model}} \rceil$  matches. When conducted over a benchmark with  $|X|$  distinct prompts, the total number of evaluations per model is bounded within the interval  $[|X|, |X| * \lceil \log_2 n_{\text{model}} \rceil]$  as presented in Table 1. However, the efficiency of this tournament structure raises a critical question: how does this limited sampling produce a statistically reliable global ranking?

To achieve reliable rankings of LLMs, our approach aggregates match outcomes from multiple tournaments, lesser than a full grid comparisons, but effectively approximating the complete set of pairwise comparisons required for merge sort. We outline the rationale in four key points:



**Merge Sort Baseline** A single-elimination tournament mirrors the merging steps of merge sort, which requires  $\mathcal{O}(n \log n)$  comparisons with no duplicate match-ups to rank  $n$  models. However, a single tournament omits many comparisons, covering only the minimal match-ups needed to determine a winner.

**Recovering Comparisons via Aggregation** By aggregating tournaments over diverse prompts, we can recover missed pairwise match-ups that should have occurred. Assuming match outcomes are prompt-independent (as BT model assumes), matches across prompts are considered equivalent. With  $|X|$  prompts (typically hundreds to thousands) and  $n_{\text{model}}$  models (tens), only random initial match-ups totaling  $|X| \cdot \lfloor \frac{n_{\text{model}}}{2} \rfloor$ . This exceeds the  $\binom{n_{\text{model}}}{2}$  possible combination, ensuring broad coverage.

**Sufficiency of Comparisons** The aggregated match-ups not only cover the necessary comparisons but also surpass the  $\mathcal{O}(n \log n)$  requirement of merge sort. Moreover, each unique model pair competes in average  $|X|/(n_{\text{model}} - 1)$  to  $\frac{|X| \log_2 n_{\text{model}}}{n_{\text{model}} - 1}$  matches<sup>1</sup> across the benchmark, a frequency mostly sufficient for accurate win rate estimation.

**Refinement for Reliability** The remaining matches, totaling  $|X| \cdot (n_{\text{model}} - 1)$ , further refine the ranking by enhancing win rate estimates, especially among top-performing models, reducing noise and ensuring robustness akin to Arena-Lite’s sampling strategy.

In summary, aggregating multiple tournaments reconstructs the full set of comparisons needed for a merge sort-like ranking while providing enough repeated match-ups to ensure accurate win rate estimations. This dual mechanism yields reliable and robust LLM rankings across the benchmark.

## 4 Experiments

We conducted two experiments to evaluate Arena-Lite against baseline-mediated benchmarking. The first experiment (Section 4.2) utilized a stochastic model to simulate LLM competitions, comparing Arena-Lite’s tournament-based direct comparison with baseline-mediated evaluation. This controlled setup allowed us to test Arena-Lite’s design principles, such as the effectiveness of direct versus

mediated comparison (Section 3.1) and tournament-based sampling (3.3), while isolating variables and minimizing noise, such as LLM judge biases (Park et al., 2024). The second experiment (Section 4.3) validates Arena-Lite empirically using various LLMs as judges and public benchmark data. We tested models including gpt-4o, gpt-4o-mini, Claude3.5, Qwen2.5, Llama3.1, and Gemma2 to assess Arena-Lite’s effectiveness against standard benchmarking practices. Together, these experiments demonstrate the superior reliability and efficiency of Arena-Lite’s tournament approach. Section 4.1 outlines shared experimental settings, followed by detailed descriptions of each experiment in subsequent subsections.

### 4.1 Chatbot Arena Leaderboard as Ground-Truth Rankings

We benchmark Arena-Lite and baseline-mediated evaluation against rankings from the Chatbot Arena leaderboard, widely recognized for its reliability due to extensive human preference annotations. With a large volume of votes across diverse prompts, these rankings provide a robust ground truth for model comparisons.

### 4.2 Experiment 1: Controlled Stochastic Modeling of LLM Competitions

We suggest a simple stochastic model based on the Bradley-Terry (BT) framework to compare Arena-Lite’s approach with baseline-mediated evaluation. This experiment simulates prompt-agnostic LLM competitions which follows the Bradley-Terry model’s presumption, with outcomes determined by a judge following Equation 3. The judge’s decision is based on the BT preference difference ( $\Delta_{ij}$ ) between models  $i$  and  $j$ , and the judge’s accuracy ( $P_{\text{judge}}$ ):

$$\begin{aligned} P_{\text{predict}}(i > j) &= P_{\text{judge}} \times P_{\text{gt}}(i > j) \\ &= P_{\text{judge}} \times \frac{1}{1 + 10^{\Delta_{ij}/400}} \end{aligned} \quad (3)$$

With the model of judge above (Equation 3), we simulate both Arena-Lite’s tournament-based approach and baseline-mediated approaches according to the following initial conditions and procedures.

#### Initial conditions:

- **Ground-Truth BT Preference:** We extracted BT preferences from the English category of

<sup>1</sup>These estimates are computed by number of matches a model undergoes which is  $\lfloor |X| \rfloor \cdot \lfloor |X| * \lfloor \log_2 n_{\text{model}} \rfloor \rfloor$ , divided by number of possible opponents for a model,  $n_{\text{model}} - 1$

Chatbot Arena (as of June 23), derived from approximately 60% of user-submitted judgments. These preferences serve as both the initial model parameters and the ground-truth rankings for evaluation.

- **Judge Accuracy ( $P_{\text{judge}}$ ):** We varied judge accuracy from 0.6 to 0.9.
- **Number of LLMs ( $n_{\text{model}}$ ) and Dataset Size ( $|X|$ ):** We adjusted the number of participating LLMs and benchmark dataset sizes to assess the robustness of both approaches in data-poor and data-rich settings.

### Simulation Procedure:

1. Select participant LLMs and their BT preferences.
2. Compute expected win rates ( $P_{\text{gt}}$ ) using Equation 3.
3. Sample match outcomes based on  $P_{\text{predict}}$  (Equation 3), determined by the BT preference rating gap ( $\Delta_{ij}$ ) and judge accuracy ( $P_{\text{judge}}$ ).
4. Repeat for the specified number of test prompts ( $|X|$ ).
5. Compute scores:
  - **Baseline-mediated:** Win rate against a reference model (gpt-4-1106-preview, rating 1233).
  - **Arena-Lite:** BT preference from all tournament match outcomes.
6. Rank models based on scores.
7. Calculate Spearman correlation between simulated and ground-truth rankings.

We conducted 50 trials per configuration to account for stochasticity in initial tournament brackets and judging process.

## 4.3 Experiment 2: Empirical Validation of Arena-Lite with real LLM Judge

To empirically validate our proposal, we evaluated the reliability of both Arena-Lite and baseline-mediated approach over the top 19 models from the Chatbot Arena leaderboards. This experiment employs actual prompt inputs and LLM outputs, distinguishing it from the earlier simulation study.

### 4.3.1 Dataset: Test Prompts and LLM Responses Used

Testing the benchmarking approaches requires: (1) test prompts and (2) the corresponding responses

from LLMs. For the benchmark dataset, we selected Arena-Hard-Auto (Li et al., 2024). The prompts in Arena-Hard-Auto were carefully curated from Chatbot Arena user queries. This dataset consists of 500 prompts—two instances for each of 250 subtopics. Although AlpacaEval (Li et al., 2023), which comprises 800 prompt-reference pairs, could serve as a viable testbed, we opted for Arena-Hard-Auto because its design aligns more closely with Chatbot Arena. Arena-Hard-Auto uses responses from gpt-4-0314 as the baseline outputs. For ranking, we utilized the reserved outputs of the top 20 (=19 + baseline) models from the Arena-Hard-Auto Browser.<sup>2</sup>

### 4.3.2 Participant LLMs

For ranking, we selected 19 LLMs from the top of the ChatBot Arena leaderboard in the *hard prompts* category, as these models most closely align with Arena-Hard-Auto.

### 4.3.3 LLM Judges

We used several aligned LLMs as judges for testing both benchmarking approaches. LLMs of our choice are gpt-4o family of models (OpenAI et al., 2024), Claude3.5, and a selection of open-weight models: Qwen2.5 (Qwen et al., 2025), Llama3.1 (Grattafiori et al., 2024), and Gemma2 (Team et al., 2024). For pairwise comparisons of responses, we employed the judging prompt suggested in LLMBar (Zeng et al., 2024) (See Appendix A.8.2). The same judge prompt was applied consistently across both the tournament and baseline-mediated approaches. To mitigate position bias (Wu and Aji, 2023), the order of model responses was alternated during evaluation. Further details on the LLM-as-a-judge configuration are provided in Appendix A.8.

The two experimental settings are summarized as follows:

**Experiment 1 (Modeling Experiment):** This experiment uses the ground truth BT preference of the models to initialize the simulation. We vary control parameters for the benchmarking approaches—including the judge’s accuracy ( $P_{\text{judge}}$ ), the number of test prompts used ( $|X|$ ), and the number of participant LLMs ( $n_{\text{model}}$ )—to determine which benchmarking approach more accurately reproduces the participants’ ranking. For

<sup>2</sup>Extracted from the 2024 Jul 6 commit (fd42026).

each configuration, we conduct 50 trials of experiments.

**Experiment 2 (Empirical Validation):** This experiment assesses the two benchmarking approaches using empirical runs with various LLM judges. We select the top 19 LLMs from Chatbot Arena and used their reserved outputs on Arena-Hard-Auto test prompts. For both the tournament and baseline-mediated approaches, we employ the Spearman correlation coefficient to measure how well the results align with the ground truth leaderboard rankings. In our empirical study, we conduct 500 trials for each experimental setting.

## 5 Results and Discussion

We assess the reliability and robustness of Arena-Lite as a means for LLM benchmarking, comparing it against the current baseline-mediated approach. Our results from both simulation study and empirical runs indicate that the tournament approach of Arena-Lite yields rankings that align more closely with the ground-truth Chatbot Arena leaderboards. We present our findings using whisker plots and tables in the following sections.

### 5.1 Experiment 1: Modeling Experiment Results

Figure 2 illustrates noticeable differences in Spearman correlation, indicating that the tournament approach is more reliable than the baseline-mediated method. The consistent performance gap across various conditions—namely, the number of participants, the number of test prompts, and judge accuracy ( $n_{\text{model}}$ ,  $|X|$ , and  $P_{\text{judge}}$ )—demonstrates the robustness of the tournament approach. Although the simulation simplifies real-world complexity, a similar performance gap was observed in the empirical findings (Experiment 2, Figure 3). This consistency suggests that the robust performance of Arena-Lite is not coincidental or limited to a specific empirical setting of ours.

### 5.2 Experiment 2: Empirical Validation Results

As hinted in the previous section, the empirical results in Figure 3 show that Arena-Lite consistently outperforms the baseline-mediated approach. Although the performance gaps are less pronounced than in the simulation, the same trend persists. In Table 2, we report the median values for Arena-Lite and the baseline-mediated approach using the

gpt-4o family of judges while varying the number of test prompts ( $|X|$ ). These results consistently demonstrate that Arena-Lite outperforms the baseline-mediated method. Note that Arena-Lite shows similar or superior reliability even in extreme data-poor benchmark condition ( $|X| = 50$ ).

Table 3 presents the outcomes when using other LLMs as judges, with a fixed number of prompts ( $|X| = 500$ ). The results for Claude3.5-sonnet, Llama3.1-8b, and Qwen2.5-7b follow a similar trend. However, smaller models (Gemma2-2b and Qwen2.5-0.5b) appears to be less reliable as an LLM judge. Hence, we recommend using evaluation-specialized judge LLMs or, at least, generative judge models with around 7B parameters regardless of using Arena-Lite or considering baseline-mediated approach.

Spearman corr. ( $\uparrow$ )	$ X  = 50$	100	250	475	500
baseline-mediated (4o)	0.895	0.935	<b>0.963</b>	0.966	0.964
Arena-Lite (4o)	<b>0.905</b>	<b>0.940</b>	0.960	<b>0.970</b>	<b>0.970</b>
baseline-mediated (4o-mini)	0.895	0.908	0.917	0.916	0.912
Arena-Lite (4o-mini)	<b>0.901</b>	<b>0.919</b>	<b>0.931</b>	<b>0.933</b>	<b>0.933</b>

Table 2: Robustness of ranking methods to benchmark set size,  $|X|$  (Experiment 2, Sec. 4.3). The table shows the median Spearman correlation ( $\uparrow$ ) from 500 trials. Arena-Lite consistently achieves higher correlation than the baseline-mediated approach across all dataset sizes ( $|X|$ ), demonstrating its superior reliability and robustness for ranking LLMs.

$ X  = 500$	claude3.5 sonnet	llama3.1 8b-it	qwen2.5 7b-it	qwen2.5 0.5b-it	gemma2 2b-it
baseline-mediated	0.924	0.820	0.756	0.089	<b>0.592</b>
Arena-Lite	<b>0.930</b>	<b>0.850</b>	<b>0.811</b>	-0.124	0.552

Table 3: Robustness of ranking methods to the choice of judge LLM (Experiment 2, Sec. 4.3). The table shows the Spearman correlation ( $\uparrow$ ) between ground-truth LLM rankings and the results from each method. The values are medians from 500 trials. The results suggest that around 7B parameters-large LLMs is a viable minimum threshold for a reliable judge. Full results for other benchmark sizes are available in Appendix, Table ??.

### 5.3 Incorporating a New LLM into an Existing Leaderboard

While our main focus has been on ranking multiple LLMs at once, it is also useful to consider the common scenario of adding a single new model to an existing leaderboard, which is also frequent use-case. We explored two approaches: (1) a *binary search*-like placement method, and (2) using the top-performing model response as a baseline. Our

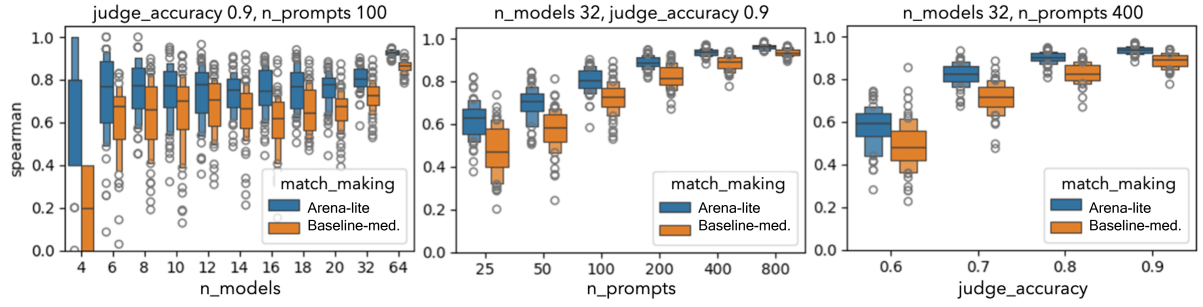


Figure 2: Comparison of LLM ranking reliability between Arena-Lite and a baseline method in a stochastic simulation (Experiment 1, Sec. 4.2). Ranking reliability is measured by the Spearman correlation ( $\uparrow$ ) between the competition-derived ranking and the ground-truth ranking. Each box plot summarizes the results from 50 trials. The subplots analyze the effect of varying (from left to right) the number of competing models ( $n_{\text{models}}$ ), the number of prompts ( $n_{\text{prompts}}$ ), and the accuracy of the judge ( $P_{\text{judge}}$ ). The single-elimination structure of Arena-Lite results in consistently higher correlation scores.

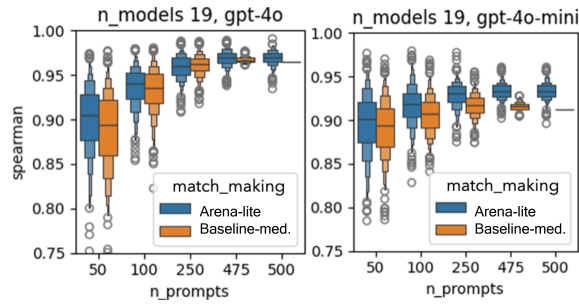


Figure 3: Ranking reliability of Arena-Lite vs. utilizing baseline outputs. Arena-Lite consistently demonstrates higher Spearman’s rank correlation across numbers of benchmark prompts ( $|X|$ ), indicating more reliable ranking. The evaluation was performed using gpt-4o (left) and gpt-4o-mini (right) as judge models, with a fixed number of models ( $n_{\text{models}}=19$ ). Each box plot summarizes the results of 50 runs. (Experiment 2, Sec. 4.3).

findings indicate that the later approach is more reliable (Table 5, Appendix). Further details and discussions are provided in Appendix A.6.

## 6 Related Works

### 6.1 LLM-as-a-Judge for Systems Ranking

Utilizing LLM-as-a-Judge as a building block for systems ranking has become a common practice in the LLM benchmarking community. Several studies have investigated how LLM judges compare to human evaluators, examining their similarities and differences (Park et al., 2024), as well as how these differences impact system rankings (e.g., JuS-Rank (Gera et al., 2024), (Gao et al., 2025)). Our research extends these approaches by proposing a method that orchestrates LLM-as-a-Judge through a well-established tournament structure to derive rankings among systems.

### 6.2 Efficient and Reliable Evaluation

There is a growing body of research focused on optimizing the number of evaluations while maintaining reliability when using LLM-as-a-Judge for system ranking. Perlitz et al. proposed a metric called DIoR to quantify the relationship between computational costs and system ranking reliability. UniCBE (Yuan et al., 2025) introduced a method to analyze the relationship between reliability and the number of judge evaluations based on uncertainty. BenchBench (Perlitz et al., 2024b) systematically analyzed consistency across benchmarks and provided a package to facilitate this analysis. tinyBenchmarks (Maia Polo et al., 2024) explored strategies to minimize the number of evaluations across various established benchmarks. Arena-Lite relates to these studies in that it leverages the properties of tournament structures and direct comparisons to achieve more reliable results with fewer judge evaluations.

## 7 Conclusion

We introduced Arena-Lite, an efficient and reliable framework for evaluating Large Language Models (LLMs) through tournament-based direct comparisons. By eliminating the need for baseline outputs and adopting head-to-head comparison, Arena-Lite achieves higher reliability in system rankings with reduced number of comparisons. Our experiments, encompassing controlled stochastic modeling and empirical validation with various LLM judges, confirm that Arena-Lite consistently outperforms standard baseline-mediated evaluation methods, even with smaller datasets or weaker judges. The release of an accessible web demonstration and code



supports the adoption of Arena-Lite to help streamlining model development cycle across research and industry. Future work will extend Arena-Lite’s application to diverse domains, including multi-modal LLM evaluation involving visual or audio inputs and outputs.

## Limitations

While we conducted extensive testing to assess the robustness of Arena-Lite tournaments—including 50 and 500 trials for Experiment 1 and Experiment 2, respectively—some inherent sources of randomness remain, such as variation due to initial match bracket assignments. The randomness in bracket assignment is added for adopting tournament structure of Arena-Lite and may influence outcome stability. Future work could explore more informative or adaptive matchmaking strategies that improve ranking fidelity beyond what is achievable with single-elimination formats, potentially within the same or even fewer number of matches.

## References

- Ralph Allan Bradley and Milton E. Terry. 1952. [Rank analysis of incomplete block designs: I. the method of paired comparisons](#). *Biometrika*, 39(3/4):324–345.
- Mark Chen, Jerry Tworek, Heewoo Jun, Qiming Yuan, Henrique Ponde de Oliveira Pinto, Jared Kaplan, Harri Edwards, Yuri Burda, Nicholas Joseph, Greg Brockman, Alex Ray, Raul Puri, Gretchen Krueger, Michael Petrov, Heidy Khlaaf, Girish Sastry, Pamela Mishkin, Brooke Chan, Scott Gray, Nick Ryder, Mikhail Pavlov, Alethea Power, Lukasz Kaiser, Mohammad Bavarian, Clemens Winter, Philippe Tillet, Felipe Petroski Such, Dave Cummings, Matthias Plappert, Fotios Chantzis, Elizabeth Barnes, Ariel Herbert-Voss, William Hebgen Guss, Alex Nichol, Alex Paino, Nikolas Tezak, Jie Tang, Igor Babuschkin, Suchir Balaji, Shantanu Jain, William Saunders, Christopher Hesse, Andrew N. Carr, Jan Leike, Josh Achiam, Vedant Misra, Evan Morikawa, Alec Radford, Matthew Knight, Miles Brundage, Mira Murati, Katie Mayer, Peter Welinder, Bob McGrew, Dario Amodei, Sam McCandlish, Ilya Sutskever, and Wojciech Zaremba. 2021. Evaluating large language models trained on code. *arXiv preprint arXiv:2107.03374*.
- Wei-Lin Chiang, Lianmin Zheng, Ying Sheng, Anastasios Nikolas Angelopoulos, Tianle Li, Dacheng Li, Hao Zhang, Banghua Zhu, Michael Jordan, Joseph E. Gonzalez, and Ion Stoica. 2024. [Chatbot arena: An open platform for evaluating llms by human preference](#). *Preprint*, arXiv:2403.04132.
- Arpad E Elo and Sam Sloan. 1978. The rating of chess-players: Past and present. (*No Title*).
- Luyu Gao, Aman Madaan, Shuyan Zhou, Uri Alon, Pengfei Liu, Yiming Yang, Jamie Callan, and Graham Neubig. 2022. Pal: Program-aided language models. *arXiv preprint arXiv:2211.10435*.
- Mingqi Gao, Yixin Liu, Xinyu Hu, Xiaojun Wan, Jonathan Bragg, and Arman Cohan. 2025. [Re-evaluating automatic LLM system ranking for alignment with human preference](#). In *Findings of the Association for Computational Linguistics: NAACL 2025*, pages 4605–4629, Albuquerque, New Mexico. Association for Computational Linguistics.
- Ariel Gera, Odellia Boni, Yotam Perlitz, Roy Bar-Haim, Lilach Eden, and Asaf Yehudai. 2024. Justrank: Benchmarking llm judges for system ranking. *arXiv preprint arXiv:2412.09569*.
- Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, Amy Yang, Angela Fan, Anirudh Goyal, Anthony Hartshorn, Aobo Yang, Archi Mitra, Archie Sravankumar, Artem Korenev, Arthur Hinsvark, Arun Rao, Aston Zhang, Aurelien Rodriguez, Austen Gregerson, Ava Spataru, Baptiste Roziere, Bethany Biron, Binh Tang, Bobbie Chern, Charlotte Caucheteux, Chaya Nayak, Chloe Bi, Chris Marra, Chris McConnell, Christian Keller, Christophe Touret, Chunyang Wu, Corinne Wong, Cristian Canton Ferrer, Cyrus Nikolaidis, Damien Al-lonsius, Daniel Song, Danielle Pintz, Danny Livshits, Danny Wyatt, David Esiobu, Dhruv Choudhary, Dhruv Mahajan, Diego Garcia-Olano, Diego Perino, Dieuwke Hupkes, Egor Lakomkin, Ehab AlBadawy, Elina Lobanova, Emily Dinan, Eric Michael Smith, Filip Radenovic, Francisco Guzmán, Frank Zhang, Gabriel Synnaeve, Gabrielle Lee, Georgia Lewis Anderson, Govind Thattai, Graeme Nail, Gregoire Mialon, Guan Pang, Guillem Cucurell, Hailey Nguyen, Hannah Korevaar, Hu Xu, Hugu Touvron, Iliyan Zarov, Imanol Arrieta Ibarra, Isabel Kloumann, Ishan Misra, Ivan Evtimov, Jack Zhang, Jade Copet, Jaewon Lee, Jan Geffert, Jana Vranes, Jason Park, Jay Mahadeokar, Jeet Shah, Jelmer van der Linde, Jennifer Billock, Jenny Hong, Jenya Lee, Jeremy Fu, Jianfeng Chi, Jianyu Huang, Jiawen Liu, Jie Wang, Jiecao Yu, Joanna Bitton, Joe Spisak, Jongsoo Park, Joseph Rocca, Joshua Johnstun, Joshua Saxe, Junteng Jia, Kalyan Vasuden Alwala, Karthik Prasad, Kartikeya Upasani, Kate Plawiak, Ke Li, Kenneth Heafield, Kevin Stone, Khalid El-Arini, Krithika Iyer, Kshitiz Malik, Kuenley Chiu, Kunal Bhalla, Kushal Lakhotia, Lauren Rantala-Yeary, Laurens van der Maaten, Lawrence Chen, Liang Tan, Liz Jenkins, Louis Martin, Lovish Madaan, Lubo Malo, Lukas Blecher, Lukas Landzaat, Luke de Oliveira, Madeline Muzzi, Mahesh Pasupuleti, Mannat Singh, Manohar Paluri, Marcin Kardas, Maria Tsimpoukelli, Mathew Oldham, Mathieu Rita, Maya Pavlova, Melanie Kam-badur, Mike Lewis, Min Si, Mitesh Kumar Singh,

Mona Hassan, Naman Goyal, Narjes Torabi, Nikolay Bashlykov, Nikolay Bogoychev, Niladri Chatterji, Ning Zhang, Olivier Duchenne, Onur Çelebi, Patrick Alrassy, Pengchuan Zhang, Pengwei Li, Petar Vasic, Peter Weng, Prajjwal Bhargava, Pratik Dubal, Praveen Krishnan, Punit Singh Koura, Puxin Xu, Qing He, Qingxiao Dong, Ragavan Srinivasan, Raj Ganapathy, Ramon Calderer, Ricardo Silveira Cabral, Robert Stojnic, Roberta Raileanu, Rohan Maheswari, Rohit Girdhar, Rohit Patel, Romain Sauvestre, Ronnie Polidoro, Roshan Sumbaly, Ross Taylor, Ruan Silva, Rui Hou, Rui Wang, Saghar Hosseini, Sahana Chennabasappa, Sanjay Singh, Sean Bell, Seohyun Sonia Kim, Sergey Edunov, Shaoliang Nie, Sharan Narang, Sharath Rapparth, Sheng Shen, Shengye Wan, Shruti Bhosale, Shun Zhang, Simon Vandenhende, Soumya Batra, Spencer Whitman, Sten Sootla, Stephane Collot, Suchin Gururangan, Sydney Borodinsky, Tamar Herman, Tara Fowler, Tarek Sheasha, Thomas Georgiou, Thomas Scialom, Tobias Speckbacher, Todor Mihaylov, Tong Xiao, Ujjwal Karn, Vedanuj Goswami, Vibhor Gupta, Vignesh Ramanathan, Viktor Kerkez, Vincent Gouget, Virginie Do, Vish Vogeti, Vitor Albiero, Vladan Petrovic, Weiwei Chu, Wenhan Xiong, Wenyan Fu, Whitney Meers, Xavier Martinet, Xiaodong Wang, Xiaofang Wang, Xiaoqing Ellen Tan, Xide Xia, Xinfeng Xie, Xuchao Jia, Xuewei Wang, Yaelle Goldschlag, Yashesh Gaur, Yasmine Babaei, Yi Wen, Yiwen Song, Yuchen Zhang, Yue Li, Yuning Mao, Zacharie Delpierre Coudert, Zheng Yan, Zhengxing Chen, Zoe Papakipos, Aaditya Singh, Aayushi Srivastava, Abha Jain, Adam Kelsey, Adam Shajnfeld, Adithya Gangidi, Adolfo Victoria, Ahuva Goldstand, Ajay Menon, Ajay Sharma, Alex Boesenberg, Alexei Baevski, Allie Feinstein, Amanda Kallet, Amit Sangani, Amos Teo, Anam Yunus, Andrei Lupu, Andres Alvarado, Andrew Caples, Andrew Gu, Andrew Ho, Andrew Poulton, Andrew Ryan, Ankit Ramchandani, Annie Dong, Annie Franco, Anuj Goyal, Aparajita Saraf, Arkabandhu Chowdhury, Ashley Gabriel, Ashwin Bharambe, Assaf Eisenman, Azadeh Yazdan, Beau James, Ben Maurer, Benjamin Leonhardt, Bernie Huang, Beth Loyd, Beto De Paola, Bhargavi Paranjape, Bing Liu, Bo Wu, Boyu Ni, Braden Hancock, Bram Wasti, Brandon Spence, Brani Stojkovic, Brian Gamido, Britt Montalvo, Carl Parker, Carly Burton, Catalina Mejia, Ce Liu, Changan Wang, Changkyu Kim, Chao Zhou, Chester Hu, Ching-Hsiang Chu, Chris Cai, Chris Tindal, Christoph Feichtenhofer, Cynthia Gao, Damon Civin, Dana Beaty, Daniel Kreymer, Daniel Li, David Adkins, David Xu, Davide Testuggine, Delia David, Devi Parikh, Diana Liskovich, Didem Foss, Dingkan Wang, Duc Le, Dustin Holland, Edward Dowling, Eissa Jamil, Elaine Montgomery, Eleonora Presani, Emily Hahn, Emily Wood, Eric-Tuan Le, Erik Brinkman, Esteban Arcaute, Evan Dunbar, Evan Smothers, Fei Sun, Felix Kreuk, Feng Tian, Filippas Kokkinos, Firat Ozgenel, Francesco Caggioni, Frank Kanayet, Frank Seide, Gabriela Medina Florez, Gabriella Schwarz, Gada Badeer, Georgia Swee, Gil Halpern, Grant Herman, Grigory Sizov, Guangyi, Zhang, Guna Lakshminarayanan, Hakan Inan, Hamid Shojanaz-

eri, Han Zou, Hannah Wang, Hanwen Zha, Haroun Habeeb, Harrison Rudolph, Helen Suk, Henry Aspegren, Hunter Goldman, Hongyuan Zhan, Ibrahim Damlaj, Igor Molybog, Igor Tufanov, Ilias Leontiadis, Irina-Elena Veliche, Itai Gat, Jake Weissman, James Geboski, James Kohli, Janice Lam, Japhet Asher, Jean-Baptiste Gaya, Jeff Marcus, Jeff Tang, Jennifer Chan, Jenny Zhen, Jeremy Reizenstein, Jeremy Teboul, Jessica Zhong, Jian Jin, Jingyi Yang, Joe Cummings, Jon Carvill, Jon Shepard, Jonathan McPhie, Jonathan Torres, Josh Ginsburg, Junjie Wang, Kai Wu, Kam Hou U, Karan Saxena, Kartikay Khandelwal, Katayoun Zand, Kathy Matosich, Kaushik Veeraraghavan, Kelly Michelena, Keqian Li, Kiran Jagadeesh, Kun Huang, Kunal Chawla, Kyle Huang, Lailin Chen, Lakshya Garg, Lavender A, Leandro Silva, Lee Bell, Lei Zhang, Liangpeng Guo, Licheng Yu, Liron Moshkovich, Luca Wehrstedt, Madian Khabza, Manav Avalani, Manish Bhatt, Martynas Mankus, Matan Hasson, Matthew Lennie, Matthias Reso, Maxim Groshev, Maxim Naumov, Maya Lathi, Meghan Keneally, Miao Liu, Michael L. Seltzer, Michal Valko, Michelle Restrepo, Mihir Patel, Mik Vyatskov, Mikayel Samvelyan, Mike Clark, Mike Macey, Mike Wang, Miquel Jubert Hermoso, Mo Metanat, Mohammad Rastegari, Munish Bansal, Nandhini Santhanam, Natascha Parks, Natasha White, Navyata Bawa, Nayan Singhal, Nick Egebo, Nicolas Usunier, Nikhil Mehta, Nikolay Pavlovich Laptev, Ning Dong, Norman Cheng, Oleg Chernoguz, Olivia Hart, Omkar Salpekar, Ozlem Kalinli, Parkin Kent, Parth Parekh, Paul Saab, Pavan Balaji, Pedro Rittner, Philip Bontrager, Pierre Roux, Piotr Dollar, Polina Zvyagina, Prashant Ratanchandani, Pritish Yuvraj, Qian Liang, Rachad Alao, Rachel Rodriguez, Rafi Ayub, Raghotham Murthy, Raghu Nayani, Rahul Mitra, Rangaprabhu Parthasarathy, Raymond Li, Rebekkah Hogan, Robin Battey, Rocky Wang, Russ Howes, Ruty Rinott, Sachin Mehta, Sachin Siby, Sai Jayesh Bondu, Samyak Datta, Sara Chugh, Sara Hunt, Sargun Dhillon, Sasha Sidorov, Satadru Pan, Saurabh Mahajan, Saurabh Verma, Seiji Yamamoto, Sharadh Ramaswamy, Shaun Lindsay, Shaun Lindsay, Sheng Feng, Shenghao Lin, Shengxin Cindy Zha, Shishir Patil, Shiva Shankar, Shuqiang Zhang, Shuqiang Zhang, Sinong Wang, Sneha Agarwal, Soji Sajuyigbe, Soumith Chintala, Stephanie Max, Stephen Chen, Steve Kehoe, Steve Satterfield, Sudarshan Govindaprasad, Sumit Gupta, Summer Deng, Sungmin Cho, Sunny Virk, Suraj Subramanian, Sy Choudhury, Sydney Goldman, Tal Remez, Tamar Glaser, Tamara Best, Thilo Koehler, Thomas Robinson, Tianhe Li, Tianjun Zhang, Tim Matthews, Timothy Chou, Tzook Shaked, Varun Vontimitta, Victoria Ajayi, Victoria Montanez, Vijai Mohan, Vinay Satish Kumar, Vishal Mangla, Vlad Ionescu, Vlad Poenaru, Vlad Tiberiu Mihailescu, Vladimir Ivanov, Wei Li, Wenchen Wang, Wenwen Jiang, Wes Bouaziz, Will Constable, Xiao Cheng Tang, Xiaojian Wu, Xiaolan Wang, Xilun Wu, Xinbo Gao, Yaniv Kleinman, Yanjun Chen, Ye Hu, Ye Jia, Ye Qi, Yenda Li, Yilin Zhang, Ying Zhang, Yossi Adi, Youngjin Nam, Yu, Wang, Yu Zhao, Yuchen Hao, Yundi Qian, Yunlu Li, Yuzi He, Zach Rait, Zachary

- DeVito, Zef Rosnbrick, Zhaoduo Wen, Zhenyu Yang, Zhiwei Zhao, and Zhiyu Ma. 2024. [The llama 3 herd of models](#). *Preprint*, arXiv:2407.21783.
- Dan Hendrycks, Collin Burns, Steven Basart, Andy Zou, Mantas Mazeika, Dawn Song, and Jacob Steinhardt. 2020. Measuring massive multitask language understanding. In *International Conference on Learning Representations*.
- Tianle Li, Wei-Lin Chiang, Evan Frick, Lisa Dunlap, Banghua Zhu, Joseph E. Gonzalez, and Ion Stoica. 2024. [From live data to high-quality benchmarks: The arena-hard pipeline](#).
- Xuechen Li, Tianyi Zhang, Yann Dubois, Rohan Taori, Ishaan Gulrajani, Carlos Guestrin, Percy Liang, and Tatsunori B. Hashimoto. 2023. AlpacaEval: An automatic evaluator of instruction-following models. [https://github.com/tatsu-lab/alpaca\\_eval](https://github.com/tatsu-lab/alpaca_eval).
- Felipe Maia Polo, Lucas Weber, Leshem Choshen, Yuekai Sun, Gongjun Xu, and Mikhail Yurochkin. 2024. tinybenchmarks: evaluating llms with fewer examples. *arXiv preprint arXiv:2402.14992*.
- OpenAI, :, Aaron Hurst, Adam Lerer, Adam P. Goucher, Adam Perelman, Aditya Ramesh, Aidan Clark, AJ Ostrow, Akila Welihinda, Alan Hayes, Alec Radford, Aleksander Madry, Alex Baker-Whitcomb, Alex Beutel, Alex Borzunov, Alex Carney, Alex Chow, Alex Kirillov, Alex Nichol, Alex Paino, Alex Renzin, Alex Tachard Passos, Alexander Kirillov, Alexi Christakis, Alexis Conneau, Ali Kamali, Allan Jabri, Allison Moyer, Allison Tam, Amadou Crookes, Amin Tootoochian, Amin Tootoonchian, Ananya Kumar, Andrea Vallone, Andrej Karpathy, Andrew Braunstein, Andrew Cann, Andrew Codisoti, Andrew Galu, Andrew Kondrich, Andrew Tulloch, Andrey Mishchenko, Angela Baek, Angela Jiang, Antoine Pelisse, Antonia Woodford, Anuj Gosalia, Arka Dhar, Ashley Pantuliano, Avi Nayak, Avital Oliver, Barret Zoph, Behrooz Ghorbani, Ben Leimberger, Ben Rossen, Ben Sokolowsky, Ben Wang, Benjamin Zweig, Beth Hoover, Blake Samic, Bob McGrew, Bobby Spero, Bogo Gertler, Bowen Cheng, Brad Lightcap, Brandon Walkin, Brendan Quinn, Brian Guarraci, Brian Hsu, Bright Kellogg, Brydon Eastman, Camillo Lugaresi, Carroll Wainwright, Cary Bassin, Cary Hudson, Casey Chu, Chad Nelson, Chak Li, Chan Jun Shern, Channing Conger, Charlotte Barette, Chelsea Voss, Chen Ding, Cheng Lu, Chong Zhang, Chris Beaumont, Chris Hallacy, Chris Koch, Christian Gibson, Christina Kim, Christine Choi, Christine McLeavey, Christopher Hesse, Claudia Fischer, Clemens Winter, Coley Czarnecki, Colin Jarvis, Colin Wei, Constantin Koumouzelis, Dane Sherburn, Daniel Kappler, Daniel Levin, Daniel Levy, David Carr, David Farhi, David Mely, David Robinson, David Sasaki, Denny Jin, Dev Valladares, Dimitris Tsipras, Doug Li, Duc Phong Nguyen, Duncan Findlay, Edede Oiwoh, Edmund Wong, Ehsan Asdar, Elizabeth Proehl, Elizabeth Yang, Eric Antonow, Eric Kramer, Eric Peterson, Eric Sigler, Eric Wallace, Eugene Brevdo, Evan Mays, Farzad Khorasani, Felipe Petroski Such, Filippo Raso, Francis Zhang, Fred von Lohmann, Freddie Sulit, Gabriel Goh, Gene Oden, Geoff Salmon, Giulio Starace, Greg Brockman, Hadi Salman, Haiming Bao, Haitang Hu, Hannah Wong, Haoyu Wang, Heather Schmidt, Heather Whitney, Heewoo Jun, Hendrik Kirchner, Henrique Ponde de Oliveira Pinto, Hongyu Ren, Huiwen Chang, Hyung Won Chung, Ian Kivlichan, Ian O’Connell, Ian O’Connell, Ian Osband, Ian Silber, Ian Sohl, Ibrahim Okuyucu, Ikai Lan, Ilya Kostrikov, Ilya Sutskever, Ingmar Kanitscheider, Ishaan Gulrajani, Jacob Coxon, Jacob Menick, Jakub Pachocki, James Aung, James Betker, James Crooks, James Lennon, Jamie Kiros, Jan Leike, Jane Park, Jason Kwon, Jason Phang, Jason Teplitz, Jason Wei, Jason Wolfe, Jay Chen, Jeff Harris, Jenia Varavva, Jessica Gan Lee, Jessica Shieh, Ji Lin, Jiahui Yu, Jiayi Weng, Jie Tang, Jieqi Yu, Joanne Jang, Joaquin Quinonero Candela, Joe Beutler, Joe Landers, Joel Parish, Johannes Heidecke, John Schulman, Jonathan Lachman, Jonathan McKay, Jonathan Uesato, Jonathan Ward, Jong Wook Kim, Joost Huizinga, Jordan Sitkin, Jos Kraaijeveld, Josh Gross, Josh Kaplan, Josh Snyder, Joshua Achiam, Joy Jiao, Joyce Lee, Juntang Zhuang, Justyn Harriman, Kai Fricke, Kai Hayashi, Karan Singhal, Katy Shi, Kavin Karthik, Kayla Wood, Kendra Rimbach, Kenny Hsu, Kenny Nguyen, Keren Gu-Lemberg, Kevin Button, Kevin Liu, Kiel Howe, Krithika Muthukumar, Kyle Luther, Lama Ahmad, Larry Kai, Lauren Itow, Lauren Workman, Leher Pathak, Leo Chen, Li Jing, Lia Guy, Liam Fedus, Liang Zhou, Lien Mamitsuka, Lilian Weng, Lindsay McCallum, Lindsey Held, Long Ouyang, Louis Feuvrier, Lu Zhang, Lukas Kondrasiuk, Lukasz Kaiser, Luke Hewitt, Luke Metz, Lyric Doshi, Mada Aflak, Maddie Simens, Madelaine Boyd, Madeleine Thompson, Marat Dukhan, Mark Chen, Mark Gray, Mark Hudnall, Marvin Zhang, Marwan Aljube, Mateusz Litwin, Matthew Zeng, Max Johnson, Maya Shetty, Mayank Gupta, Meghan Shah, Mehmet Yatbaz, Meng Jia Yang, Mengchao Zhong, Mia Glaese, Mianna Chen, Michael Janer, Michael Lampe, Michael Petrov, Michael Wu, Michele Wang, Michelle Fradin, Michelle Pokrass, Miguel Castro, Miguel Oom Temudo de Castro, Mikhail Pavlov, Miles Brundage, Miles Wang, Minal Khan, Mira Murati, Mo Bavarian, Molly Lin, Murat Yesildal, Nacho Soto, Natalia Gimelshein, Natalie Cone, Natalie Staudacher, Natalie Summers, Natan LaFontaine, Neil Chowdhury, Nick Ryder, Nick Stathas, Nick Turley, Nik Tezak, Niko Felix, Nithanth Kudige, Nitish Keskar, Noah Deutsch, Noel Bundick, Nora Puckett, Ofir Nachum, Ola Okelola, Oleg Boiko, Oleg Murk, Oliver Jaffe, Olivia Watkins, Olivier Godement, Owen Campbell-Moore, Patrick Chao, Paul McMillan, Pavel Belov, Peng Su, Peter Bak, Peter Bakkum, Peter Deng, Peter Dolan, Peter Hoeschele, Peter Welinder, Phil Tillet, Philip Pronin, Philippe Tillet, Prafulla Dhariwal, Qiming Yuan, Rachel Dias, Rachel Lim, Rahul Arora, Rajan Troll, Randall Lin, Rapha Gontijo Lopes, Raul Puri, Reah Miyara, Reimar Leike, Renaud Gaubert, Reza Zamani, Ricky Wang, Rob Donnelly, Rob Honsby, Rocky Smith, Rohan Sahai, Rohit Ramchan-

- dani, Romain Huet, Rory Carmichael, Rowan Zellers, Roy Chen, Ruby Chen, Ruslan Nigmatullin, Ryan Cheu, Saachi Jain, Sam Altman, Sam Schoenholz, Sam Toizer, Samuel Miserendino, Sandhini Agarwal, Sara Culver, Scott Ethersmith, Scott Gray, Sean Grove, Sean Metzger, Shamez Hermani, Shantanu Jain, Shengjia Zhao, Sherwin Wu, Shino Jomoto, Shiron Wu, Shuaiqi, Xia, Sonia Phene, Spencer Papay, Srinivas Narayanan, Steve Coffey, Steve Lee, Stewart Hall, Suchir Balaji, Tal Broda, Tal Stramer, Tao Xu, Tarun Gogineni, Taya Christianson, Ted Sanders, Tejal Patwardhan, Thomas Cunningham, Thomas Degry, Thomas Dimson, Thomas Raoux, Thomas Shadwell, Tianhao Zheng, Todd Underwood, Todor Markov, Toki Sherbakov, Tom Rubin, Tom Stasi, Tomer Kaftan, Tristan Heywood, Troy Peterson, Tyce Walters, Tyna Eloundou, Valerie Qi, Veit Moeller, Vinnie Monaco, Vishal Kuo, Vlad Fomenko, Wayne Chang, Weiye Zheng, Wenda Zhou, Wesam Manassra, Will Sheu, Wojciech Zaremba, Yash Patil, Yilei Qian, Yongjik Kim, Youlong Cheng, Yu Zhang, Yuchen He, Yuchen Zhang, Yujia Jin, Yunxing Dai, and Yury Malkov. 2024. [Gpt-4o system card](#). *Preprint*, arXiv:2410.21276.
- Long Ouyang, Jeffrey Wu, Xu Jiang, Diogo Almeida, Carroll Wainwright, Pamela Mishkin, Chong Zhang, Sandhini Agarwal, Katarina Slama, Alex Ray, et al. 2022. Training language models to follow instructions with human feedback. *Advances in neural information processing systems*, 35:27730–27744.
- Junsoo Park, Seungyeon Jwa, Meiying Ren, Daeyoung Kim, and Sanghyuk Choi. 2024. [Offsetbias: Leveraging debiased data for tuning evaluators](#). *Preprint*, arXiv:2407.06551.
- Yotam Perlitz, Elron Bandel, Ariel Gera, Ofir Arviv, Liat Ein-Dor, Eyal Shnarch, Noam Slonim, Michal Shmueli-Scheuer, and Leshem Choshen. 2024a. [Efficient benchmarking \(of language models\)](#). In *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pages 2519–2536, Mexico City, Mexico. Association for Computational Linguistics.
- Yotam Perlitz, Ariel Gera, Ofir Arviv, Asaf Yehudai, Elron Bandel, Eyal Shnarch, Michal Shmueli-Scheuer, and Leshem Choshen. 2024b. [Do these llm benchmarks agree? fixing benchmark evaluation with benchbench](#). *Preprint*, arXiv:2407.13696.
- 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, Jiayi 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](#). *Preprint*, arXiv:2412.15115.
- Baptiste Roziere, Jonas Gehring, Fabian Gloeckle, Sten Sootla, Itai Gat, Xiaoqing Ellen Tan, Yossi Adi, Jingyu Liu, Tal Remez, Jérémy Rapin, et al. 2023. Code llama: Open foundation models for code. *arXiv preprint arXiv:2308.12950*.
- Aarohi Srivastava, Abhinav Rastogi, Abhishek Rao, Abu Awal Md Shoeb, Abubakar Abid, Adam Fisch, Adam R Brown, Adam Santoro, Aditya Gupta, Adrià Garriga-Alonso, et al. 2023. Beyond the imitation game: Quantifying and extrapolating the capabilities of language models. *Transactions on Machine Learning Research*.
- Gemma Team, Morgane Riviere, Shreya Pathak, Pier Giuseppe Sessa, Cassidy Hardin, Surya Bhupatiraju, Léonard Hussenot, Thomas Mesnard, Bobak Shahriari, Alexandre Ramé, Johan Ferret, Peter Liu, Pouya Tafti, Abe Friesen, Michelle Casbon, Sabela Ramos, Ravin Kumar, Charline Le Lan, Sammy Jerome, Anton Tsitsulin, Nino Vieillard, Piotr Stanczyk, Sertan Girgin, Nikola Momchev, Matt Hoffman, Shantanu Thakoor, Jean-Bastien Grill, Behnam Neyshabur, Olivier Bachem, Alanna Walton, Aliaksei Severyn, Alicia Parrish, Aliya Ahmad, Allen Hutchison, Alvin Abdagic, Amanda Carl, Amy Shen, Andy Brock, Andy Coenen, Anthony Laforge, Antonia Paterson, Ben Bastian, Bilal Piot, Bo Wu, Brandon Royal, Charlie Chen, Chintu Kumar, Chris Perry, Chris Welty, Christopher A. Choquette-Choo, Danila Sinopalnikov, David Weinberger, Dimple Vijaykumar, Dominika Rogozińska, Dustin Herbison, Elisa Bandy, Emma Wang, Eric Noland, Erica Moreira, Evan Senter, Evgenii Eltyshiev, Francesco Visin, Gabriel Rasskin, Gary Wei, Glenn Cameron, Gus Martins, Hadi Hashemi, Hanna Klimczak-Plucińska, Harleen Batra, Harsh Dhand, Ivan Nardini, Jacinda Mein, Jack Zhou, James Svensson, Jeff Stanway, Jetha Chan, Jin Peng Zhou, Joana Carrasqueira, Joana Iljazi, Jocelyn Becker, Joe Fernandez, Joost van Amersfoort, Josh Gordon, Josh Lipschultz, Josh Newlan, Ju yeong Ji, Kareem Mohamed, Kartikeya Badola, Kat Black, Katie Millican, Keelin McDonnell, Kelvin Nguyen, Kiranbir Sodhia, Kish Greene, Lars Lowe Sjoesund, Lauren Usui, Laurent Sifre, Lena Heuermann, Leticia Lago, Lilly McNealus, Livio Baldini Soares, Logan Kilpatrick, Lucas Dixon, Luciano Martins, Machel Reid, Manvinder Singh, Mark Iverson, Martin Görner, Mat Velloso, Mateo Wirth, Matt Davidow, Matt Miller, Matthew Rahtz, Matthew Watson, Meg Risdal, Mehran Kazemi, Michael Moynihan, Ming Zhang, Minsuk Kahng, Minwoo Park, Mofi Rahman, Mohit Khatwani, Natalie Dao, Nenshad Bardoliwalla, Nesh Devanathan, Neta Dumai, Nilay Chauhan, Oscar Wahltinez, Pankil Botarda, Parker Barnes, Paul Barham, Paul Michel, Pengchong Jin, Petko Georgiev, Phil Culliton, Pradeep Kupala, Ramona Comanescu, Ramona Merhej, Reena Jana, Reza Ardeshtir Rokni, Rishabh Agarwal, Ryan Mullins, Samaneh Saadat, Sara Mc Carthy, Sarah Cogan, Sarah Perrin, Sébastien M. R. Arnold, Sebastian Krause, Shengyang Dai, Shruti Garg, Shruti Sheth, Sue Ronstrom, Susan Chan, Timothy Jor-



dan, Ting Yu, Tom Eccles, Tom Hennigan, Tomas Kocisky, Tulsee Doshi, Vihan Jain, Vikas Yadav, Vilobh Meshram, Vishal Dharmadhikari, Warren Barkley, Wei Wei, Wenming Ye, Woohyun Han, Woosuk Kwon, Xiang Xu, Zhe Shen, Zhitao Gong, Zichuan Wei, Victor Cotruta, Phoebe Kirk, Anand Rao, Minh Giang, Ludovic Peran, Tris Warkentin, Eli Collins, Joelle Barral, Zoubin Ghahramani, Raia Hadsell, D. Sculley, Jeanine Banks, Anca Dragan, Slav Petrov, Oriol Vinyals, Jeff Dean, Demis Hassabis, Koray Kavukcuoglu, Clement Farabet, Elena Buchatskaya, Sebastian Borgeaud, Noah Fiedel, Armand Joulin, Kathleen Kenealy, Robert Dadashi, and Alek Andreev. 2024. [Gemma 2: Improving open language models at a practical size](#). *Preprint*, arXiv:2408.00118.

Minghao Wu and Alham Fikri Aji. 2023. [Style over substance: Evaluation biases for large language models](#). *Preprint*, arXiv:2307.03025.

Yi Xu, Laura Ruis, Tim Rocktäschel, and Robert Kirk. 2025. [Investigating non-transitivity in llm-as-a-judge](#). *Preprint*, arXiv:2502.14074.

Peiwen Yuan, Shaoxiong Feng, Yiwei Li, Xinglin Wang, Yueqi Zhang, Jiayi Shi, Chuyi Tan, Boyuan Pan, Yao Hu, and Kan Li. 2025. [Unicbe: An uniformity-driven comparing based evaluation framework with unified multi-objective optimization](#). *Preprint*, arXiv:2502.11454.

Zhiyuan Zeng, Jiatong Yu, Tianyu Gao, Yu Meng, Tanya Goyal, and Danqi Chen. 2024. Evaluating large language models at evaluating instruction following. In *International Conference on Learning Representations (ICLR)*.

## A Appendix

### A.1 Arena-Lite Web Demo

We provide screenshots of Arena-Lite web demo here ([link to Huggingface Space](#)). You could try or locally host Arena-Lite according to its documentation. It is quite easy to use and do not require much of resources to host.

Arena-Lite provides the benchmark result (Figure 4) with helpful visualization interface that enables walking through the matches and tournaments one by one (Figure 5) and match statistics between LLMs (Figure 6). We also provide visualization that helps examining potential bias of LLM Judge being used (Figure 7).

#### A.1.1 Starter Prompt Set

We provide several judge prompts that we have used for specific target tasks. Some of those are for quite specialized tasks, and some might work for evaluating general instruction following. You could customize your own judge prompt based on

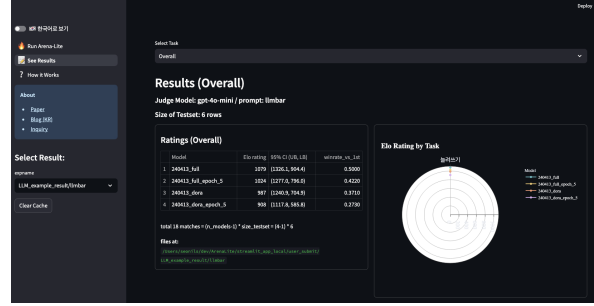


Figure 4: Arena-Lite web screenshot 1: At the top of the result page, one can see the leaderboard of LLMs with their BT preference. If the benchmark dataset has subcategories, radar chart (right) is also visible.

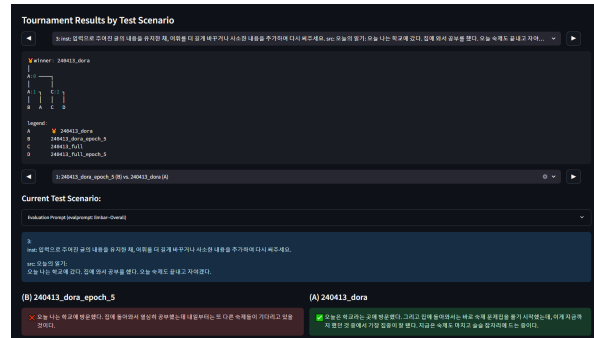


Figure 5: Arena-Lite web screenshot 2: User can walk through the matches and tournaments one by one. Match brackets is visualized briefly with text UI and user can select any specific match to see the details (e.g. match result, prompt, and model outputs).

your evaluation needs according to the documentation. The list of the judge prompts we provide is as follows, and one could see the detailed prompts at yaml files [here](#).

1. llmbar prompt (Figure A.8.2) and conciser version of the prompt, llmbar\_brief. Those are for evaluating instruction following.
2. translation\_pair prompt for selecting translation models trained on game-specialized parallel corpora,
3. rag\_pair\_kr prompt for evaluating knowledge groundedness of korean RAG models over chatting scenario,
4. translation\_fortunecookie prompt which was crafted for evaluating translation models specialized for translating fortune-tellings, and
5. post\_edit prompt for evaluating conversation revision based on given persona of a speakers given in a instruction, which is quite specialized use case.



Figure 6: Arena-Lite web screenshot 3: User can see the match statistics between LLMs (i.e. win rate between model pairs, number of matches per pair and per model).

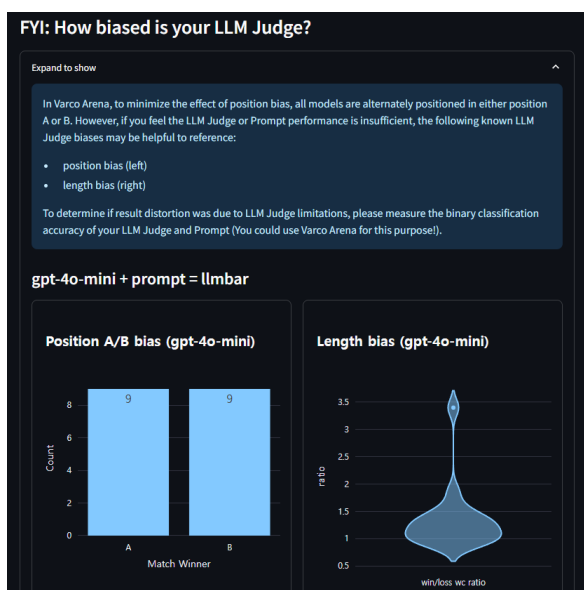


Figure 7: Arena-Lite web screenshot 4: User can see the LLM Judge’s examine how biased the LLM judge being used. The demo provides clues for potential bias toward response length and position.

## A.2 Full table for Experiment 2

Here is the extended results of Experiment 2 (Section 4.3) presented in Table 3. Aligned LLMs smaller than 7B parameters struggles to work as a proper Judge. Otherwise, Arena-Lite method excels over common practice of using outputs from proprietary as baselines.

Dataset size	method	claude 3.5 sonnet	llama3.1 8b-it	qwen2.5 7b-it	qwen2.5 0.5b-it	gemma2 2b-it
50	baseline-mediated	.896	.656	.492	.010	.064
	Arena-Lite (ours)	<b>.897</b>	<b>.715</b>	<b>.544</b>	-0.051	-0.088
100	baseline-mediated	.912	.732	.596	.002	.079
	Arena-Lite (ours)	<b>.918</b>	<b>.780</b>	<b>.656</b>	-0.068	-0.090
250	baseline-mediated	.924	.801	.700	.045	<b>.560</b>
	Arena-Lite (ours)	<b>.929</b>	<b>.830</b>	<b>.760</b>	-0.131	.551
475	baseline-mediated	.924	.819	.708	.083	.112
	Arena-Lite (ours)	<b>.930</b>	<b>.845</b>	<b>.810</b>	-0.131	-0.009
500	baseline-mediated	.924	.820	.756	.089	<b>.592</b>
	Arena-Lite (ours)	<b>.930</b>	<b>.850</b>	<b>.811</b>	-0.124	.551

Table 4: Extended results for comparing Arena-Lite to baseline-mediated method of using outputs from proprietary models as an baseline. We tested other LLMs as judge over various size of benchmark datasets.

### A.3 Machine Requirements for Experiments

Except the part we inferenced open-weight models such as Llama, Qwen and Gemma, our experiments are mostly do not require GPU usage. Inference are done on one A100 GPU, but T4 would be enough for reproducing our experiments. Otherwise, our experiments require querying API and post-processing those with CPU. Experiments could be run on personal desktops. The lowest specification of the machine we deployed had i5-8400 CPU, 16 GiB RAM.

### A.4 Assuring Statistical Significance of the Results within Budget for proprietary models

To ensure a statistically significant number of trials for each experiment while staying within budget, we utilize OpenAI’s Batch API to prepare full-grid match outcomes (i.e., all-play-all matches for every prompt) in a cache file, allowing us to reuse these outcomes. Each empirical experiment consists of 500 trials per setting, with results represented using whisker plots or summary statistics such as median values. When experimenting with a subset of the Arena-Hard-Auto benchmark ( $|X| < 500$ ), we sample a stratified subset of the benchmark dataset for each new trial.

### A.5 BT preference from Arena-Lite compared to Human Annotations

Figure 8 shows the BT preference computed out of Arena-Lite. For judge, we used gpt-4o. As mentioned in the caption, the BT preference are bootstrapped median value from 500 trials. 95% confidence intervals also plotted as an error bar, which look negligible in scale compared to observed values. Matches are performed over Arena-Hard-Auto benchmark dataset (500 prompts).

### A.6 Binary search vs. Win rate over baseline

#### A.6.1 Binary Search

We tried binary search placement of a newly added LLM to the leaderboard without baseline output in Table 6. Details of how we implemented binary search are attached in Algorithm 2, Appendix. It turns out that binary search based on already built leaderboard ranks is not as reliable compared to utilizing the best model’s outputs as a baseline. Therefore, when adding a newcomer LLM to pre-existent leaderboard, we could utilize the already submitted responses as a baseline from the 1st placed LLM.

---

#### Algorithm 2 Binary Search for Enlisting new LLM to a leaderboard

---

**Require:** Leaderboard  $L$ , new model  $m_{\text{new}}$ , test prompts  $X$ , outputs  $O_{ij}$ , assumes  $|X| > |L| > n_{\text{comparisons}}$

**Ensure:** Updated leaderboard  $L'$  with  $m_{\text{new}}$  placed

```

1:  $n_{\text{comparisons}} \leftarrow \lfloor \log_2(|L|) \rfloor$ 
2:  $n_{\text{matches}} \leftarrow \lfloor |X| / n_{\text{comparisons}} \rfloor$ 
3: function BINARYSEARCHPLACEMENT( $L, m_{\text{new}}$ )
4:    $X \leftarrow \text{Shuffle}(X)$ 
5:    $X \leftarrow \text{concat}(X; X)$ 
6:    $\text{low} \leftarrow 0$ 
7:    $\text{high} \leftarrow |L| - 1$ 
8:   while  $\text{low} \leq \text{high}$  do
9:      $\text{mid} \leftarrow \lfloor (\text{low} + \text{high}) / 2 \rfloor$ 
10:     $\text{wins} \leftarrow 0$ 
11:    for  $i \leftarrow 1$  to  $n_{\text{matches}}$  do
12:       $x \leftarrow X.\text{pop}()$ 
13:      if  $\text{Match}(m_{\text{new}}, L[\text{mid}], x) = m_{\text{new}}$  then
14:         $\text{wins} \leftarrow \text{wins} + 1$ 
15:      end if
16:    end for
17:    if  $\text{wins} > n_{\text{matches}} / 2$  then
18:       $\text{high} \leftarrow \text{mid} - 1$ 
19:    else if  $\text{wins} < n_{\text{matches}} / 2$  then
20:       $\text{low} \leftarrow \text{mid} + 1$ 
21:    else if  $|X| > 0$  then
22:      continue ▷ Ensure tie
23:    else
24:      return  $\text{mid}$ ,  $\text{tie}$  ▷ Tie
25:    end if
26:  end while
27:  return  $\text{low}$ ,  $\text{non-tie}$  ▷ Position found
28: end function
29: function UPDATELEADERBOARD( $L, m_{\text{new}}$ )
30:    $\text{position}, \text{istie} \leftarrow$ 
31:     BinarySearchPlacement( $L, m_{\text{new}}$ )
32:    $L' \leftarrow L.\text{insert}(\text{position}, m_{\text{new}}, \text{istie})$ 
33:   return  $L'$ 
34: end function

```

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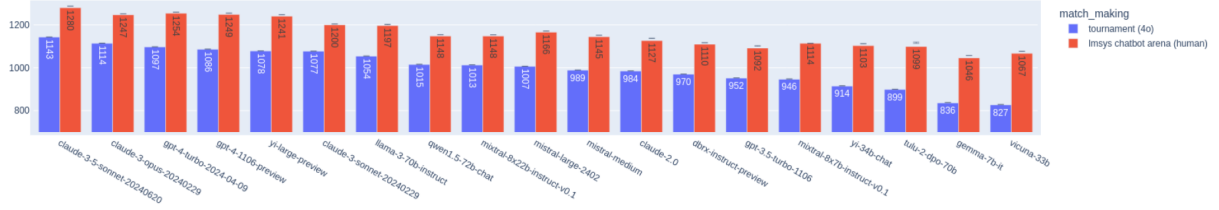


Figure 8: BT preference of the model with gpt-4o judge on the full set of Arena-Hard-Auto (Li et al., 2024) prompts. Arena-Lite result (bootstrapped median over 1000 samples of 500 trials) is in blue, plotted alongside the ratings from the ground truth leaderboard in red (Chatbot Arena, *Hard prompts category*). Error bars are 95% confidence intervals.

$ \Delta_{\text{rank}} $ ( $\downarrow$ )	gt=1-6	7-13	14-19 (20)	total avg.
binary search (4o)	<b>0.92</b>	1.84	2.13	1.72
comp. to 1st (4o)	1.98	<b>1.55</b>	<b>1.57</b>	<b>1.39</b>
binary search (4o-mini)	1.27	1.82	<b>1.21</b>	1.5
comp. to 1st (4o-mini)	<b>1.00</b>	<b>1.43</b>	1.43	<b>1.37</b>

Table 5: Comparison of the binary search method versus using the top-performing model’s response as a baseline (*comp. to 1st*) for inserting a new LLM into the leaderboard. We report the mean rank deviation ( $|\Delta_{\text{rank}}|$ ) from the ground-truth leaderboard as an additional error metric. For further details, see Algorithm 2 in Appendix.

$ \Delta_{\text{rank}} $ ( $\downarrow$ )	gt=1	2	3	4	5	6	avg.
binary search (4o)	0.09 (.04/-0.03)	1.24 (.14/-14)	<b>1.75</b> (.09/-0.09)	<b>1.55</b> (.07/-0.06)	1.26 (.08/-0.08)	1.10 (.10/-0.09)	<b>0.92</b>
anchored (4o)	<b>0.00</b> (0.00/0.00)	<b>1.01</b> (0.01/-0.01)	1.95 (0.02/-0.02)	2.00 (0.00/0.00)	<b>0.96</b> (0.02/-0.02)	<b>0.30</b> (0.04/-0.04)	1.98
binary search (4o-mini)	0.52 (.09/-0.07)	0.85 (.12/-11)	0.59 (.10/-0.09)	2.03 (.02/-0.02)	1.20 (.05/-0.05)	2.45 (.07/-0.06)	1.27
anchored (4o-mini)	0.00 (0.00/0.00)	0.00 (0.00/0.00)	1.00 (0.00/0.00)	2.00 (0.00/0.00)	2.00 (0.00/0.00)	1.00 (0.00/0.00)	<b>1.00</b>

### A.6.2 Comparing to the most Performant Model so far: Converting Ratings Table back to Win Rates

Assuming we preserved a set of match results and model outputs from the last benchmarking, we could benefit from those to perform insertion. One could pick an appropriate *anchor* LLM as a baseline in a leaderboard to estimate the skill of a newcomer. Using previous matches from the tournaments that built the leaderboard could be used for estimating win rates over the baseline. This is the same as converting the preference ratings table into a win rate leaderboard. Since the leaderboard is not built with full-grid matches but with tournaments, there would be some missing matches against the baseline regardless we have picked. There are two ways to estimate the win rate over the baseline model. We could just count the matches given are enough in amount, or we could also convert BT preference back to  $P(i > a)$  to use it directly for scoring for the model ranks in the leaderboard. Reminding that BT preference rating is for expecting a likely outcome of the match, this should work. After this win rate of the newcomer model  $P^*(n > a) = \frac{\text{count}(n \text{ wins})}{|X|}$  could be directly compared for enlisting.

7	8	9	10	11	12	13	avg.
1.31 (.10/-10)	1.27 (.11/-11)	2.22 (.14/-12)	1.74 (.09/-0.09)	2.27 (.12/-11)	2.23 (.12/-12)	1.86 (.07/-0.07)	1.84
0.30 (0.04/-0.04)	3.68 (0.04/-0.04)	1.09 (0.03/-0.03)	1.03 (0.02/-0.01)	2.97 (0.02/-0.02)	0.78 (0.05/-0.05)	1.00 (0.00/0.00)	<b>1.55</b>
0.69 (.07/-0.06)	0.85 (.09/-0.09)	3.89 (.12/-11)	1.95 (.06/-0.05)	2.10 (.03/-0.03)	2.37 (.10/-11)	0.88 (.12/-11)	1.82
0.51 (0.49/-0.51)	0.52 (0.48/-0.52)	3.50 (0.49/-0.51)	1.00 (0.00/0.00)	1.00 (0.00/0.00)	3.00 (0.00/0.00)	0.50 (0.50/-0.50)	<b>1.43</b>

14	15	16	17	18	19	20	avg.
1.40 (.04/-0.05)	3.07 (.11/-11)	0.80 (.08/-0.09)	1.47 (.05/-0.04)	5.00 (.11/-11)	0.96 (.08/-0.09)	-	2.13
2.00 (0.00/0.00)	2.00 (0.00/0.00)	1.00 (0.00/0.00)	1.21 (0.03/-0.04)	3.00 (0.00/0.00)	0.21 (0.04/-0.03)	-	<b>1.57</b>
1.45 (.07/-0.08)	4.20 (.17/-17)	0.19 (.07/-0.06)	0.08 (.03/-0.02)	1.09 (.05/-0.05)	1.08 (.05/-0.05)	0.40 (.07/-0.07)	<b>1.21</b>
1.00 (0.00/0.00)	2.00 (0.00/0.00)	2.00 (0.00/0.00)	1.00 (0.00/0.00)	1.00 (0.00/0.00)	3.00 (0.00/0.00)	0.00 (0.00/0.00)	1.43

Table 6: Binary search vs. *Anchored comparison*: Mean rank deviation ( $|\Delta_{\text{rank}}|$ ) from ground-truth leaderboard. Result of binary search placement and anchored comparison insert by gpt-4o[-mini] judge are provided with bootstrapped 95% confidence interval (500 trials, 1000 samples,  $|X|=500$ , Arena-Hard-Auto (Li et al., 2024)).

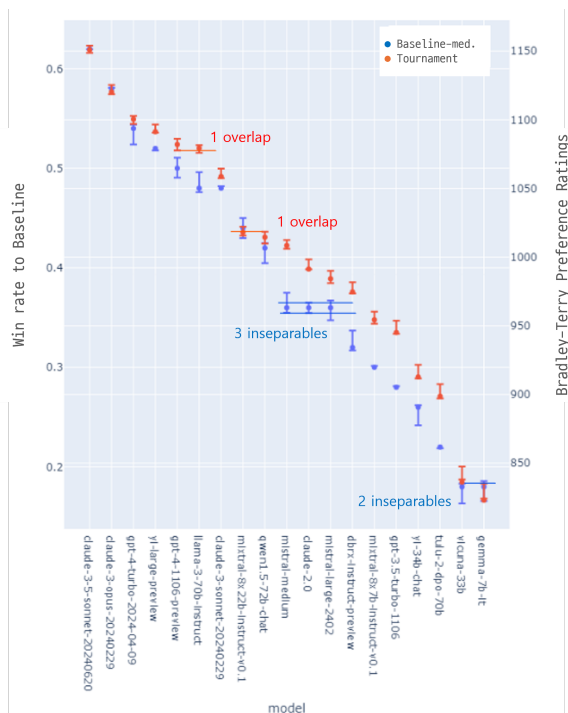


Figure 9: gpt-4o result of *anchored comparison* and tournament approach. 1000 bootstrapped median from 500 observations used for confidence interval estimation.

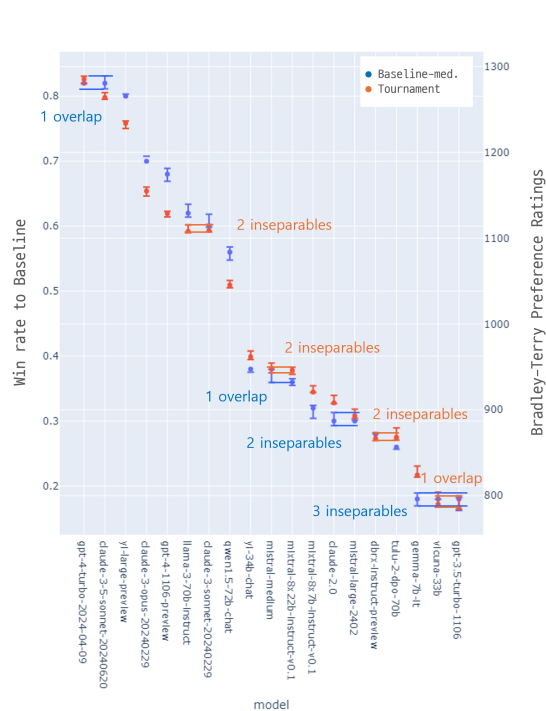


Figure 10: gpt-4o result of *anchored comparison* and tournament approach. 1000 bootstrapped median from 500 observations used for confidence interval estimation.

## A.7 Separability In terms of Confidence Interval

To see how well the two benchmarking approach (*anchored comparison* and tournament approach) separates LLMs in adjacent ranks, we provide scatter plot of Elo rating and win rate paired with error bar (95% confidence interval). We present the both results of using gpt-4o (Figure 9) and gpt-4o-mini (Figure 9) as a judge. Inside the each plot, inseparables indicates the cases where any pair of datapoint co-cludes each other within their range of error bars, and overlap means a certain datapoint is within some other's range of error, when it is one-sided.

## A.8 Judge configuration

### A.8.1 Evaluation Prompt

We use the prompt from LLMBAR. The prompt depicted in Figure A.8.2. We added 4 questions for criteria of our own to Metrics.txt prompt of (Zeng et al., 2024). You can refer to the original prompt in LLMBAR github.

### A.8.2 Decoding Parameters

We did not configure decoding parameters of judge LLMs (gpt-4o[-mini]), which its temperature de-

faults to 1. The only parameter we have adjusted is maximum number of tokens to be generated, which for our prompt is less than 6 (i.e. The output of our prompt is (a) or (b)). To avoid position bias, we alternated the position of the responses from a certain model across the benchmark prompt.

```
PROMPTS = [ # metrics.txt from LLMBAR
{
"role": "system", "content": "You are a helpful assistant in evaluating the quality of the outputs for a given instruction. Your goal is to select the best output for the given instruction.",
},
{
"role": "user", "content": ""Select the Output (a) or Output (b) that is better for the given instruction. The two outputs are generated by two different AI chatbots respectively.
```

Here are some rules of the evaluation:

- (1) You should prioritize evaluating whether the output honestly/precisely/closely executes the instruction, then consider its helpfulness, accuracy, level of detail, harmlessness, etc.
- (2) Outputs should NOT contain more/less than what the instruction asks for, as such outputs do NOT precisely execute the instruction.
- (3) You should avoid any potential bias and your judgment should be as objective as possible. For example, the order in which the outputs were presented should NOT affect your judgment, as Output (a) and Output (b) are **\*\*equally likely\*\*** to be the better.

Do NOT provide any explanation for your choice.

Do NOT say both / neither are good.

You should answer using ONLY "Output (a)" or "Output (b)". Do NOT output any other words.

```
# Instruction:
instruction
```

```
# Output (a):
response_a
```

```
# Output (b):
response_b
```

```
# Questions about Outputs:
```

Here are at most three questions about the outputs, which are presented from most important to least important. You can do the evaluation based on thinking about all the questions.

- Does the output well satisfy the intent of the user request?
- If applicable, is the output well-grounded in the given context information?
- Does the output itself satisfy the requirements of good writing in terms of:
  - 1) Coherence
  - 2) Logicality
  - 3) Plausibility
  - 4) Interestingness

```
# Which is better, Output (a) or Output (b)? Your response should be either "Output (a)" or
"Output (b)": "",
},
] # prompt ends here
```

LLMBar prompt of our use. We used metric variant suggested in original LLMBar paper. More preset prompts are in our Arena-Lite Demo and source (<https://huggingface.co/spaces/NCSOFT/ArenaLite>)