Decentralized Arena: Towards Democratic and Scalable Automatic Evaluation of Language Models

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Abstract

The recent explosion of large language models (LLMs), each with its own general or specialized strengths, makes scalable, reliable benchmarking more urgent than ever. Standard practices nowadays face fundamental trade-offs: closed-ended question-based benchmarks (*e.g.,* MMLU) struggle with saturation as newer models emerge, while crowd-sourced leaderboards (*e.g.,* Chatbot Arena) rely on costly and slow human judges. Recently, automated methods (*e.g.,* LLM-as-a-judge) shed light on the scalability, but risk bias by relying on one or a few "authority" models. To tackle these issues, we propose Decentralized Arena (DE-ARENA), a fully automated framework leveraging collective intelligence from all LLMs to evaluate each other. It mitigates single-model judge bias by democratic, pairwise evaluation, and remains efficient at scale through two key components: (1) a coarse-to-fine algorithm for fast ranking of new models with sub-quadratic complexity, and (2) an automatic question selection strategy for the construction of new evaluation dimensions. Extensive experiments across 66 LLMs demonstrate that DE-ARENA achieves 97% correlation with human judge, while significantly reducing the cost.

1 Introduction

In recent years, the community has developed thousands of large language models (LLMs) (Achiam et al., 2023; Bai et al., 2023; Liu et al., 2024) with ever-stronger general and specialized capabilities. To deploy these models in the real world effectively, we must assess and rank their performance accurately. Concretely, existing work mostly collects a set of related high-quality questions, then judges the outputs of LLM to estimate the corresponding specialized capability (Guha et al., 2024; Xie et al., 2023; Rajkumar et al., 2022). By involving humans to vote on the preference of all LLM pairs (*i.e.,* deciding which LLM's output "wins"), Chatbot Arena (Chiang et al., 2024) provides robust and reliable leaderboards, yielding one of the most popular LLM benchmarks.

Recently, with the increasing usage of LLMs in a variety of applications and real-world tasks (Hou et al., 2024; Taylor et al., 2022; Du et al., 2024), it's crucial to evaluate their capabilities on fine-grained dimensions, *e.g.,* math reasoning, physical science, and more specialized branches, such as algebra and astrophysics. However, it is rather costly (both in terms of time and financially) for Chatbot Arena and other human-annotation-based benchmarks to support evaluating thousands of LLMs in thousands of fine-grained dimensions, *i.e.,* millions or even billions of human votes required. Moreover, human judgments also exhibit variability and subtle subjectivity, particularly when frontier models sometimes deploy persuasive "sycophantic" language (Sharma et al., 2023) or other surface cues that may bias annotators toward incorrect but agreeable responses (Schoch et al., 2020). To address them, researchers have studied automatic evaluation methods, typically selecting one (or few) "strongest" LLMs (*e.g.,* GPT-4) as judges to evaluate all model pairs (Dubois et al., 2024; Li et al., 2023c). However, judge models can be biased, *e.g.,* prefer outputs that resemble its own style (Zheng et al., 2023; Panickssery et al., 2024). Optimizing models based on such evaluations could end up with overfitting to the judge biases.

To achieve the goal of reliable and scalable evaluation across various dimensions, we propose Decentralized Arena (De-Arena), an automatic evaluation method based on the "wisdom of the crowds". Table 1 illustrates the main difference between De-Arena and other benchmarks. The core idea behind De-Arena is to use the collective intelligence of all LLMs to evaluate and compare themselves. This forms a democratic system where *all LLMs to be evaluated are also judges to evaluate others*, leading to fairer rankings than the automatic methods relying on a few centralized "authority" judge mod-

Benchmarks	Judges	Auto Eval	Auto Data	Open ended
Compass Arena	Human	✗	✗	✓
Chatbot Arena	Human	✗	✗	✓
MixEval	-	✓	✓	✗
LiveBench	-	✓	✗	✗
Alpaca Eval	GPT-4	✓	✗	✓
WildBench	GPT-4	✓	✗	✓
BiGGen Bench	GPT-4	✓	✗	✓
PRD	Five LLMs	✓	✗	✓
Auto Arena	Five LLMs	✓	✓	✓
De-Arena	All LLMs	✓	✓	✓

Table 1: Comparison of representative LLM benchmarks based on the types of judge models, whether automatically evaluating LLMs, selecting the data, or using open-ended questions.

els (Salminen et al., 2015; Surowiecki, 2004). This should address the single-judge bias or the bias from a similar model family (Goel et al., 2025). Additionally, its automatic benchmarking process also supports *scaling up the number of test LLMs and dimensions* with a lower cost than collecting large-scale human annotations.

To implement our De-Arena, a naive approach is to utilize all the LLMs to judge all other model pairs (similar to Chatbot Arena), based on manually crafted or selected high-quality questions. However, it would lead to a prohibitively expensive time complexity of $\mathcal{O}(n^3k)$[1]. To make De-Arena a more efficient and fully automatic paradigm, we devised (1) *the coarse-to-fine incremental ranking algorithm* and (2) *the representative question selection strategy*. Concretely, in our ranking strategy, the LLMs will be incrementally inserted into the rank list (*i.e.,* one by one), by first finding the rough position via binary search and then fine-grained in-window ranking. Such a way naturally supports gradually growing the rank list by adding the latest LLMs, and the low complexity of binary search (*i.e.,* $\mathcal{O}(kn\log n)$) helps greatly reduce the time cost. We later empirically show that even the coarse-grained step (i.e., binary insertion) can achieve highly capable performance, thanks to the diverse set of judges. Besides efficiency, we introduce an adaptive weight mechanism and ELo system to re-weight judges dynamically (akin to PageRank), making De-Arena more reliable.

For question selection, our De-Arena leverages the above ranking strategy to select a few representative questions that lead to more consistent results, as the majority. In this way, we ensure that the new evaluation dimensions can be automatically built by selecting a few high-value ones from the collected question candidates. Based on the above designs in De-Arena, we automatically construct nine fine-grained dimensions, and efficiently evaluate 66 LLMs on them (as shown in Table 12). Experimental results demonstrate the effectiveness of our method, achieving up to 97% correlation with human-annotation-based Chatbot Arena in the overall dimension (shown in Table 2), with a cost similar to existing benchmarks (shown in Figure 2b). Extensive studies also reveal that our method can significantly reduce the bias from a single-LLM judge (Table 3 and Table 11), and becomes more stable and accurate as the number of models increases (Figure 3), demonstrating its reliability and stability. Ablation study shows that the performance is robust against choices of multi-judges (e.g., randomly selected judges), indicating that our De-Arena is robust to potential group bias as well (Goel et al., 2025).

2 Related Work

LLM Evaluation and Benchmark. Early work (Zhao et al., 2019; Zhang et al., 2019; Yuan et al., 2021) on evaluating language models primarily focuses on the quality of the generated text, considering the fluency and relevance. In recent years, large language models (LLMs) that have undergone pre-training on large-scale corpus, have demonstrated expert-level text generation abilities (OpenAI, 2024a; AI@Meta, 2024), and exhibited strong advanced capabilities (Song et al., 2023; OpenAI, 2024b), such as reasoning and planning. Thus, a surge of benchmarks are proposed to assess the multi-aspect capabilities of LLMs, which are either based on closed-ended (Wang et al., 2024; Rein et al., 2024) or open-ended questions (Chiang et al., 2024). The first type of benchmarks relies on close-ended questions with accurate answers to evaluate LLMs, which simplifies the evaluation process. However, due to the simple formats of the closed-ended questions, they cannot fully estimate the true user preferences of LLMs in applications (Wu et al., 2024), and may also be hacked through training on similar data (Sainz et al., 2023). To address this, Chatbot Arena (Chiang et al., 2024) collects open-ended questions, and invites humans to vote on each pair of LLMs based on their

[1] n and k refer to the number of models and questions.

outputs. However, human annotation is costly, and also makes the overall evaluation results difficult to reproduce. Therefore, a surge of automatic evaluation benchmarks has emerged, employing a strong LLM (e.g., GPT-4 (Zheng et al., 2023; Li et al., 2023c)) or a fine-tuned specialized LLM (Li et al., 2023a; Kim et al., 2024b) to replace human judges. Despite the low cost, single-LLM judge-based methods may suffer from the evaluation bias, *e.g.,* self-enhancement bias (Zheng et al., 2023) and verbosity bias (Saito et al., 2023). Recent attempts, such as PRD (Li et al., 2023b) and Auto-Arena (Zhao et al., 2024) have explored multi-LLM judgment to mitigate these issues. However, using more LLMs as judges would significantly increase the computational and resource cost, limiting the scalability for evaluating a large number of LLMs and new dimensions.

Collective Intelligence. Collective intelligence arises when multiple agents collaborate or compete in decentralized networks, often producing more accurate judgments than any single expert alone (Surowiecki, 2004; Yao et al., 2024). Research in crowd-based systems (Salminen et al., 2015), multi-agent systems (Brigui-Chtioui and Saad, 2011), and swarm intelligence (Chakraborty and Kar, 2017; Gloor, 2006) shows that collecting diverse perspectives can mitigate individual errors and biases, particularly where no centralized controller is present. For instance, natural examples of ant colonies and bird flocks reveal that complex problems can be addressed effectively through simple agent interactions (Gloor, 2006). In this paper, we extend the principles of collective intelligence to LLM evaluation. We design a large-scale decentralized system in which LLMs simultaneously serve as judges and participants. Because each LLM has a distinct training background, aggregating their judgments reduces the influence of single model bias. Our experiments highlight that evaluation reliability consistently improves with the number of involved models, demonstrating the potential of collective intelligence to enable more robust, accurate, and scalable LLM benchmarking.

3 Decentralized Arena

This section introduces the detailed design of our Decentralized Arena (De-Arena). In De-Arena, we focus on the idea of decentralization that uses all LLMs as judges to vote on other model pairs, based on high-quality questions in each dimension. It can reduce the cost of gathering human annotations, and also avoid the bias that may arise from relying on a single or a small number of judge models. To achieve it, we devise the coarse-to-fine incremental sort algorithm to efficiently rank a large number of LLMs, and the automatic question selection algorithm to select representative data for building new evaluation dimension. The overview of our De-Arena is shown in Figure 1.

3.1 Coarse-to-fine Incremental Ranking

Given a set of LLMs $\{m_i\}_{i=1}^n$, we aim to sort them into a ranking list $[m_1, \cdots, m_n]$, according to their performance on the collected k questions. Considering that a surge of stronger LLMs will be developed in the near future, we devise an LLM sort algorithm that supports the incremental insertion of new LLMs into the ranking list. Concretely, we begin with a small set of "seed" models (*i.e.,* 6 models), which are ranked using a full-sample pairwise comparison method. In this process, each of the 6 models evaluates and ranks all the other models, excluding itself. Other models are then incrementally inserted into the rank list, one by one, where all models in the list act as judges to help find the position. To efficiently insert a new model into the list, we devise the coarse-grained binary search and fine-grained in-window reranking strategies.

Coarse-grained Ranking with Binary Search. Given the current ranking list $[m_1, \cdots, m_t]$ with t models, we aim to find the rough position of the $t+1$-th model in an efficient way. As the ranking list is ordered, we utilize the binary search algorithm (Lin, 2019), which can quickly narrow down the search space via the logarithmic time complexity. Concretely, we first compare the new model with the one in the $t/2$-th position of the ranking list, where all other models in the list serve as judges. Given the collected k questions, all the judge LLMs vote on the outputs of the two models (*i.e.,* deciding whose output "wins"). If the new LLM owns more wins, we repeat the above step to find the position of the new LLM in the first half list $[m_1, \cdots, m_{t/2-1}]$. Otherwise, we repeat it in $[m_{t/2+1}, \cdots, m_t]$. This loop will continues until narrowing the search space into a certain position, which is the rough position of the model. The time complexity of this binary search is $\mathcal{O}(kn \log n)$.

Fine-grained In-window Reranking. After obtaining the rough position of the new model, we continue to check whether it is suitable and make

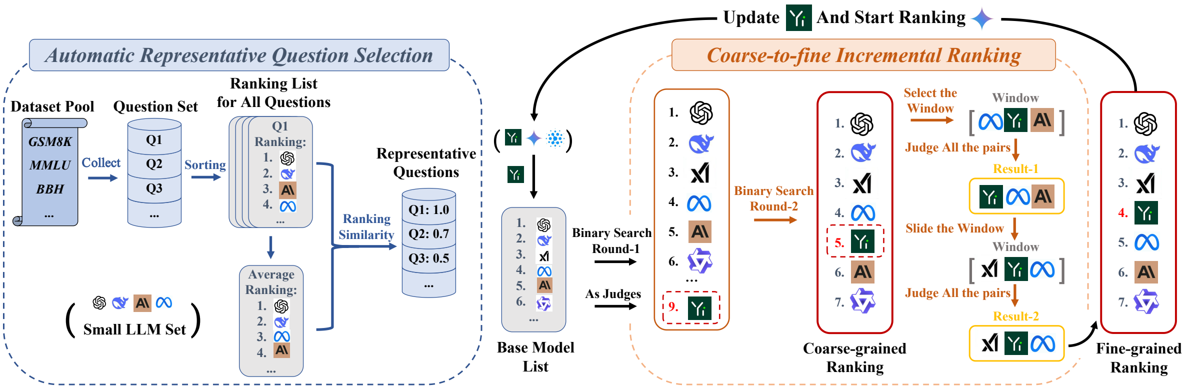


Figure 1: The overview of our method, consisting of the automatic question selection strategy (left) and the coarse-to-fine incremental ranking algorithm (right). Here, we show an example that creates a new dimension based on open-source datasets, and one of the insert iterations for adding the model Yi into the previous ranking list.

refinement if necessary. Here, the new model is compared against its adjacent peers within a defined local window (*e.g.,* two models before and after it in the ranking list). The rationale is that these nearby LLMs often own similar capabilities to the new one, whose positions in the ranking list are the hardest to distinguish, warranting closer comparison. Concretely, we first compare the new LLM with other in-window models using the collected k questions and rerank them, where all other models outside this window serve as judges. If the in-window reranking step leads to a change in the new LLM's position, the process will be repeated within the updated window until the ranking list stabilizes. This functions like a sliding window, guiding the LLM crowd to focus on the most ambiguous comparison pairs, thereby ensuring accurate rankings while significantly reducing computational costs.

Score Generation and Style Control. After obtaining the ranking list and pairwise comparison results of all LLM candidates, we follow the methodology used in Chatbot Arena that computes corresponding Elo scores to finalize the ranking results:

$$R'_{\mathrm{A}} = R_{\mathrm{A}} + K \cdot \left(S_{\mathrm{A}} - \frac{1}{1 + 10^{(R_{\mathrm{B}} - R_{\mathrm{A}})/400}} \right) \quad (1)$$

where R_A is the Elo score of model A that is iteratively updated based on the comparison results, R'_A denotes the updated Elo rating of model A after a pairwise comparison. S_A is a bool value that denotes if model A wins the comparison, and K is the coefficient for the score update. As we cannot compare all the model pairs, we follow Chatbot Arena, which uses logistic regression to fit the collected comparison data and estimate the Elo score (Elo, 1967). Here, we consider that the reliability of different LLMs as judges varies. Therefore, we introduce weights in the loss function. Our rationale is that an LLM with a higher Elo score is more likely to be a qualified judge; hence, we utilize the normalized Elo score as the weight in the loss function. Furthermore, whenever the Elo scores are updated, we dynamically adjust each model's weight based on its new score. We also follow Chatbot Arena, which incorporates a style control mechanism to reduce the influence of output style.

3.2 Automatic Questions Selection

To enable scalability in adding arbitrary new evaluation dimensions in De-Arena, we devise an automatic representative question selection algorithm. To build a new dimension, users only need to collect relevant open-ended questions from open-source datasets. Then, we utilize the ranking results of LLMs to identify the most representative questions as high-quality examples for evaluation.

Open-ended Questions Collecting. Thanks to the rich open-source datasets in the community, it is easy to search for and collect various relevant open-source datasets for a certain dimension. However, the collected examples may differ in the formats, *e.g.*,, multi-choice and open-ended questions. In De-Arena, as we can leverage LLMs to compare the outputs of model pairs, we standardize all the data into the open-ended question format by using GPT-4 with an appropriate prompt.

Ranking-based Representative Questions Selection. Considering the diverse quality and large scale of the collected questions, we aim to select a few of the most representative ones for testing

Benchmarks	15 LLMs		30 LLMs		66 LLMs		Avg.
	Overall	Math	Overall	Math	Overall	Math	
CompassAcademic	0.660	-	0.674	-	-	-	-
BFCL	0.798	-	0.813	-	-	-	-
OpenLLM	0.892	-	0.800	-	0.797	-	-
Helm Lite	0.725	0.656	0.748	0.660	0.750	0.665	0.701
LiveBench	0.906	0.900	0.920	0.913	0.925	0.916	0.913
EQ Bench	0.911	-	0.860	-	0.865	-	-
MMLU PRO	0.952	-	0.897	-	0.897	-	-
MixEval	0.954	-	0.963	-	0.965	-	-
BigGen Bench (Prometheus 2)	0.908	-	0.924	-	0.924	-	-
BigGen Bench	0.919	-	0.930	-	0.931	-	-
Alpaca Eval 2.0	0.921	-	0.935	-	0.935	-	-
WildBench	0.894	0.917	0.907	0.932	0.910	0.934	0.916
PRD	0.851	0.904	0.892	0.916	-	-	-
Auto Arena	0.938	-	-	-	-	-	-
De-Arena	**0.957**	**0.939**	**0.967**	**0.952**	**0.974**	**0.959**	**0.958**

Table 2: Results of the automatic evaluation benchmarks with Chatbot Arena (Spearman Correlation). We report the results from the settings of testing 15, 30, and 66 LLMs. Bold indicates the best results in each group.

LLMs. Instead of randomly sampling, we design a ranking-based method to select questions that lead to consistent ranking lists, ensuring high data quality. Concretely, for each question q in the collection, we first utilize our ranking algorithm in Section 3.1 to produce the ranking list of a small set of LLMs, denoted as L. Then, we compute the average ranking list for all questions by simply accumulating the position of all LLMs and then sorting them, denoted as $\hat{L}$. Next, we compute the Spearman correlation ρ between the ranking list of each question and the average list, and use the scores to select representative questions:

$$\rho(L, \hat{L}) = 1 - \frac{6\sum_{i=1}^{n}(r(L, m_i) - r(\hat{L}, m_i))^2}{n\,(n^2-1)}, \quad (2)$$

where $r(L, m)$ returns the position of model m in the list, n is the model number. Then, questions with higher correlation scores are selected, as they are more capable of representing the "majority" preference by yielding ranking results that are highly consistent with the average model rankings.

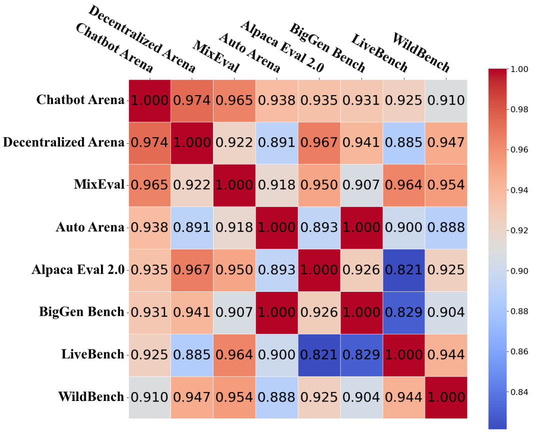
4 Experiments

4.1 Main Experiments

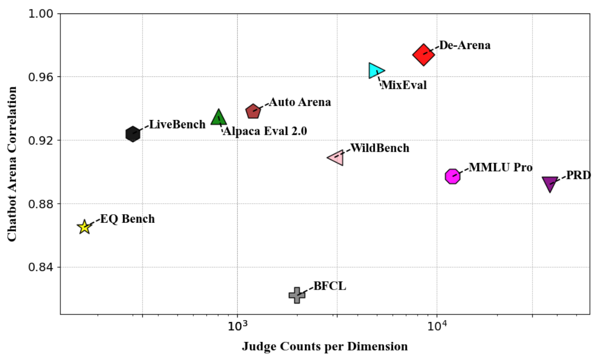
Experimental Setup. We compare our approach with three types of automatic evaluation benchmarks: Closed-ended Dataset-based Benchmarks, Single-LLM Judge-based Benchmarks, and Multi-LLM Judge-based Benchmarks. From these categories, we respectively select 8, 4, and 2 representative and recently proposed benchmarks for comparison. Descriptions of each baseline are provided in Appendix H, while detailed evaluation settings and implementation details are presented in Appendix I and Appendix J.

Main Results Analysis. The comparison results of different benchmarks are shown in Table 2. First, we observe that multi-LLM judge-based benchmarks generally perform better than single-LLM judge-based ones. This indicates that incorporating multiple LLMs as judges improves the consistency between automated evaluation results and human preferences. Such a way can reduce the preference bias from only one judge model. Second, by collecting high-quality questions for evaluation, MixEval and WildBench outperform other closed-ended and single-LLM judge-based benchmarks, respectively. MixEval carefully controls its query distribution to match with real-world user queries, while WildBench collects massive real-world tasks (*i.e.,* 1024). It demonstrates the importance of selecting proper datasets for evaluation.

Besides, our De-Arena surpasses all baselines in most evaluation settings and the average value. In De-Arena, we extend the multi-LLM judge strategy into a more democratic paradigm where all LLMs are both the judges and are to be evaluated, to further reduce the bias. Furthermore, we devise an automatic question selection strategy that uses the correlation of ranking results to find the most representative questions for evaluation. These strategies greatly improve the reliability and scalability of our method, in contrast to baselines that require human



(a) Benchmark Spearman correlation.



(b) Benchmark cost and performance.

Figure 2: (a) Spearman correlation between different LLM benchmarks in the overall dimension. (b) Benchmark cost and performance comparison in the overall dimension, where we show the average judge counts of each model and the correlation with Chatbot Arena.

Methods	MT-Bench		Math	
	Corr↑	R-Diff↓	Corr↑	R-Diff↓
LLaMA-3-70B	0.815	1.71	0.934	1.14
Gemma-2-27B	0.930	1.29	0.932	1.00
Qwen2-70B	0.938	1.00	0.942	1.14
De-Arena	**0.956**	1.00	**0.952**	1.00

Table 3: Judge methods vs. Chatbot Arena: Correlation (↑) and Rank Difference (↓).

involvement or massive data.

In addition, with the increasing of test LLM number, the difficulty of accurately ranking all LLMs also increases. As a result, the correlation scores of most baselines with Chatbot Arena have also decreased. Here, we can see that our De-Arena can achieve a stable performance and even perform better in the math dimension. The reason is that the involvement of more LLMs also introduces more judge models, which can reduce the bias caused by a few judges, further improving the reliability. We also report the correlation between our De-Arena and other best-performing six benchmarks in Figure 2a. Our De-Arena always has a high correlation with all the benchmarks, *i.e.,* > 0.85. It indicates the effectiveness of our method for producing reliable ranking results, as existing benchmarks, echoing with the superior performance in Table 2.

4.2 Further Analysis

Reducing Single-Judge Biases. In De-Arena, our major contribution is to utilize all LLMs as judges to democratically vote all the model pairs, reducing the single-judge evaluation bias and improving reliability. To study it, we compare our De-Arena with several of its variations using a single LLM as the judge, including LLaMA-3-70B, Gemma-2-27B, Qwen2-70B-inst, GPT-4o-2024-08-06. Here, we report the Spearman correlation and the difference in the ranked LLMs between all methods with Chatbot Arena. As presented in Table 3, the performance of our De-Arena is consistently better than all other variations, with higher Spearman correlation and lower rank difference. It indicates that our democratic voting strategy can avoid the ranking results being biased by the preference of few LLMs. Also, in our case study, we find that LLaMA-3-70B and Gemma-2-27B are prone to vote for themselves and the same series of LLMs, causing their ranks to rise drastically.

Cost and Scalability Study. In De-Arena, we devise the coarse-to-fine ranking algorithm and question selection strategy to reduce the cost of scaling the LLM number. To evaluate this efficiency, we estimate the cost of our De-Arena with other benchmarks for comparison. As it is hard to compute the detailed cost, we count the average comparison number of each LLM, which is relevant to the number of test questions and voting counts. As shown in Figure 2b, our De-Arena achieves the best performance among all benchmarks, with slightly higher cost than single-LLM judge-based ones. The reason is that we employ the representative question selection strategy to reduce the number of test questions (*e.g.,* 100 instances), and also the ranking algorithm to reduce the voting counts of judge models. The above designs

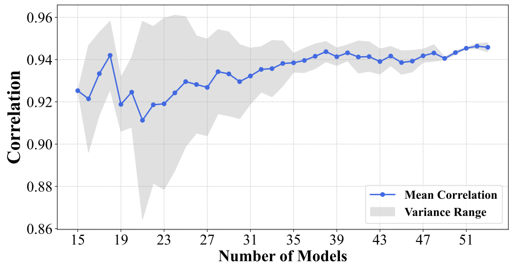
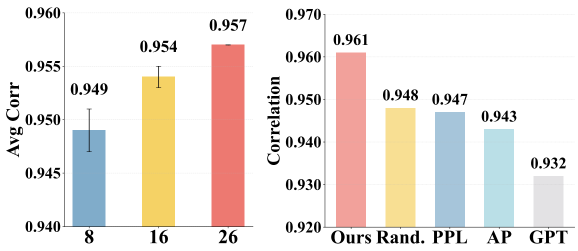


Figure 3: De-Arena's mean (blue curve) and variance (shaded area) of Chatbot Arena correlation in the MT-bench dimension, with the increase in LLM number.



(a) Corr. w.r.t model num (b) Corr. w.r.t select methods

Figure 4: (a) Spearman correlation with Chatbot Arena across varying judge model number. (b) Spearman correlation for different question selection methods, with AP representing Anchor Point.

greatly reduce the cost from both sides. Besides, as De-Arena has the lower cost and higher correlation with Chatbot Arena, it shows strong potential as an effective and scalable automatic counterpart for broader real-world applications.

Convergence Study. As our De-Arena adopts the coarse-to-fine incremental ranking strategy, the insertion order of LLMs might affect the stability of the final ranking results. To study it, we run our method five times, using different random seeds to shuffle the insertion order, and compute the mean and variance correlations with Chatbot Arena, in the MT-bench dimension. As shown in Figure 3, we can see that with the involvement of more models, our ranking results become more stable and robust with higher correlation and lower variance. It demonstrates the scalability of our decentralized evaluation strategy with the scaling of LLMs. The more models participate in the evaluation process, the more reliable and trustworthy the final ranking results for all models become.

Robustness against Potential Group Biases. Since De-Arena leverages the collective intelligence of LLMs to judge each other, it effectively mitigates single-judge biases. To further assess its robustness and potential group biases, we varied the number of judge models across three settings: 8, 16, and 26. For the 8 and 16 settings, we randomly sampled five different judge sets to evaluate stability; for 26, we used all suitable open-source models. The final outcomes are presented in Figure 4a. We observe that the performance consistently improves as the number of judge models increases, with the best performance achieved when the number reaches 26. This can be attributed to the fact that a larger number of judge models enables a more democratic and decentralized evaluation process. As the judge pool grows, the collective intelligence effect becomes more pronounced, which helps to further mitigate the biases of individual models. Meanwhile, since the group consists of highly diverse models, group biases are minimally introduced. This highlights the strong robustness of using multiple judges in the evaluation process.

Methods	MT-Bench		Math	
	Corr↑	Judges↓	Corr↑	Judges↓
Ours	**0.957**	521495	**0.962**	808074
- w/o Fine	0.952	320715	0.961	489741
- w/o Coarse	0.954	352245	0.959	520580
- Full Sample	0.956	2245874	**0.962**	3660355

Table 4: Correlations (Corr) and rank differences (R-Diff) between different judge methods and Chatbot Arena. ↑ and ↓ denote the higher and the lower the better, respectively.

4.3 Ablation and Variation Study

Coarse-to-fine Ranking Algorithm. To study the effectiveness of our coarse-to-fine ranking algorithm, we remove the coarse-grained binary search ranking and fine-grained in-window reranking strategies, to build two variations for comparison: (1) *w/o Coarse*: ours without coarse-grained binary search; (2) *w/o Fine*: ours without fine-grained in-window reranking. Besides, we also built the variation that uses all LLMs to vote all the LLM pairs, namely (3) *Full Ranking*: ours with full ranking. We conduct the experiments on MT-Bench and Math dimensions, and report the correlation with Chatbot Arena and the number of judges. As shown in Table 4, among all the variations, our De-Arena can well balance the performance and the cost. In De-Arena, both the coarse-grained binary search and the fine-grained in-window reranking algorithms contribute to performance improvement while only slightly increasing the number of judge.

	MT-Bench	Algerba	Geometry	Probability
Avg Corr	0.957	0.942	0.956	0.961
Std	0.0019	0.0021	0.0015	0.0016

Table 5: Stability study of coarse-to-fine ranking algorithm. In each dimension, we conduct five random trials by shuffling the insertion order of models.

	Ours	- w/o Fine	- w/o Coarse
Avg Corr	0.957	0.953	0.955
Std	0.0019	0.0031	0.0029

Table 6: Stability study under variations of the coarse-to-fine ranking algorithm. Each dimension, we conduct five random trials by shuffling the insertion order.

Without these strategies, the variation that needs to fully rank all model pairs greatly increases the cost ($\times 4$ judge counts). In Appendix C, we conduct additional experiments to further investigate the accuracy of the binary search step.

Stability Study of Coarse-to-fine Ranking Algorithm In De-Arena, we adopt an incremental insertion approach, where models are inserted in varying orders and ranked accordingly. To assess the stability of our algorithm, we conduct experiments showing that the insertion order has minimal impact on the final rankings. Specifically, we perform five random shuffles of the insertion order and compute the Spearman correlation with Chatbot Arena rankings. As shown in Table 5, correlation remains consistently high with very low standard deviation, confirming the robustness of the coarse-to-fine ranking algorithm. To further validate stability, we apply the same randomized insertion experiments to our algorithm variations under MT-Bench. As shown in Table 6, although the variations do not perform as well as the full algorithm, their standard deviations remain very low, indicating strong stability. Therefore, the full coarse-to-fine ranking algorithm demonstrates the best performance and is well-suited for scenarios that require highly accurate and stable rankings.

Question Selection Algorithm. To evaluate the effectiveness of our representative question selection algorithm, we compare it with several variations using different strategies: (1) *Random* that randomly selects the questions; (2) *Perplexity* that uses the perplexity of LLaMA-3-8B (AI@Meta, 2024) to rank and select the top ones; (3) *Anchor point* (Vivek et al., 2024) that selects an optimal subset of sub-problems to represent the full dataset; (4) *GPT-4* that crafts prompts to guide GPT-4 to rank and select the top ones. Here, we utilize them to select 32 questions from the 80 questions in MT-Bench. As shown in Figure 4b, all the variations perform worse than De-Arena, indicating the effectiveness of our question selection algorithm. Here, random is a robust baseline that outperform other variations, while our methods lead to a higher correlation with Chatbot Arena. The reason is that we focus on selecting the most representative questions reflecting the majority based on ranking similarity. This approach effectively identifies the most useful ones for testing.

Dimension	with Elo Weights	No Weights
MT-Bench	**0.957**	0.949
Math	**0.959**	0.953

Table 7: Ablation study results about the Elo weight in different dimensions.

Weights for Judge Models. In De-Arena, we recognize that models differ in their ability to judge LLMs, so we introduce a weighting mechanism that assigns higher weights to stronger models and lower weights to weaker ones. To study its effectiveness, we remove it and compare the performance changes in the MT-Bench and three math sub-dimensions. As shown in Table 7, removing the weights would lead to decrease in the correlation score. It indicates the effectiveness of the weighting mechanism we implemented.

5 Conclusion

In this paper, we propose De-Arena, a democratic and fully automatic LLM evaluation system where the models to be evaluated can also evaluate each other. To make it a more efficient and automatic system, we devised the coarse-to-fine incremental ranking and representative question selection strategies. These innovations enable De-Arena to scale effectively to a large number of LLMs and support evaluation across fine-grained, diverse dimensions Extensive experiments have verified the reliability and scalability of our De-Arena. In the future, we will extend our De-Arena by including more LLMs and useful evaluation dimensions, supporting fully automatic new dimension discovery and evaluation, and further exploring the evaluation of super-human intelligence.

6 Limitations

Our De-Arena aspires to reshape LLM benchmarking by harnessing collective intelligence rather than relying on few "authority" models or costly human annotation. It may carry several potential limitations:

• By involving every participating LLM as both evaluator and evaluated, De-Arena aims to reduce single-model dominance and mitigate systemic biases. It encourages more equitable participation and transparent performance comparisons, fostering an environment in which models from diverse teams—industry, academia, or open-source communities—can be assessed on a level playing field.

• Traditional benchmarking often depends on extensive human annotation, which can be labor-intensive, subjective, and slow. De-Arena's automatic evaluation minimizes human oversight and lowers costs, potentially democratizing access to robust evaluation for smaller research groups or underfunded institutions and easing the ethical burden associated with human annotators' time and well-being.

• In contrast to single-judge approaches, a decentralized, multi-LLM system spreads accountability across many models. When combined with transparency about each model's contributions to a final ranking, the system can better highlight disagreements or harmful biases among models. This collective responsibility promotes more nuanced scrutiny of anomalies or potentially harmful content.

• While distributing decision-making reduces reliance on any single model's biases, emergent group biases can still arise if many models share similar training data or user bases. Continued research is needed to detect and mitigate these collective distortions, especially for underrepresented languages or cultural contexts.

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Dimension	Length	Header	List	Bold	All
MT-Bench	**0.933**	0.914	0.911	0.897	0.932
Algebra	0.909	0.909	0.909	**0.911**	0.906
Probability	0.934	0.930	0.929	0.929	**0.935**
Geometry	0.932	**0.934**	0.933	0.932	0.924

Table 8: Style control ablation study results across different dimensions. Each column represents a different style control method applied, and All denotes controlling all of them.

Window size	MT-Bench		Math	
	Corr↑	Judges↓	Corr↑	Judges↓
1	**0.957**	521495	**0.962**	808074
2	0.953	684460	0.960	1069615
3	0.955	892260	0.960	1284068

Table 9: Hyperparameter tuning results about window size.

A Style Control Study

Due to variations in training data, different models often exhibit distinct output styles. Following the approach of Chatbot Arena, we defined four styles (*i.e.,* Length, Header, List, Bold) and calculated the correlation between these styles and the Chatbot Arena style control. Also, we add the results by controlling all the them.

As the results shown in Table 8, we can see that controlling all of the styles can achieve better performance in all these dimensions. In contrast, only using one of them would have an improvement on a certain dimension, but might also affect the performance in other ones. It indicates that controlling all styles is capable of well balancing the capability in all evaluation aspects.

B Hyper-parameter Tuning

In De-Arena, the window size and base model number are two hyper-parameters that control the cost of in-window reranking and the initial ranking list, respectively. Here, we study their best settings by varying them in $[1, 2, 3]$ and $[3, 6, 9, 12]$, respectively. As the results shown in Table 9, setting the window size to 1 can lead to the fewest judge counts, and also achieve a good correlation score, which well balances the performance and the cost. As shown in Table 10, we can observe that using 6 base models can achieve the best performance. The reason is that too few or too many models would cause the instability of the ranking list during incrementally inserting new models.

Base Model Number	3	6	9	12
MT-Bench	0.948	**0.957**	0.952	0.954
Math	0.961	**0.962**	0.960	0.960

Table 10: Hyperparameter tuning results about base model number.

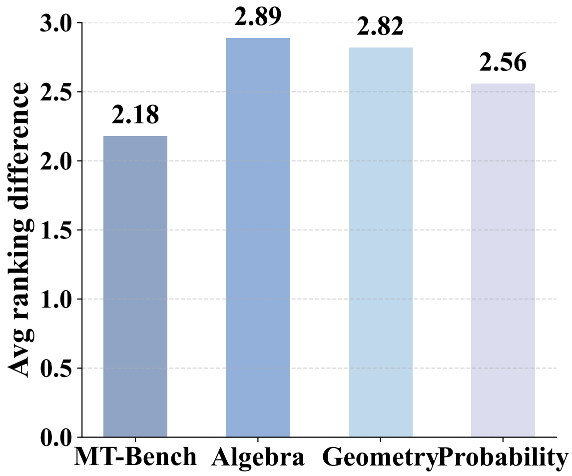

Figure 5: Binary search ranking differences between binary search and ground truth in four dimensions.

C Accuracy Study of Coarse-grained Binary Search

De-Arena heavily relies on the Coarse-to-Fine Ranking Algorithm, with the accuracy of the binary search in the first step being crucial for identifying the approximate ranking range of models. To better demonstrate the accuracy of the binary search, we monitor the absolute difference between the binary search ranking and the ground truth ranking during the insertion process across four dimensions. Finally, we compute the average ranking difference for all models. As the results shown in Figure 5, the coarse-grained binary search ranking for each model across all dimensions is very close to its ground truth ranking. With the subsequent fine-grained ranking adjustments, the accuracy of the rankings is further improved.

D Comparison-count Distribution.

Our De-Arena adopts the coarse-to-fine ranking algorithm, which can allocate more comparisons on the hard-to-distinguish LLM pairs with neighboring positions in the ranking list. To study it, we visualize the comparison-count distribution for all LLMs in Figure 6. We can observe that the collective LLM intelligence automatically focuses primarily on the neighboring LLM pairs (those

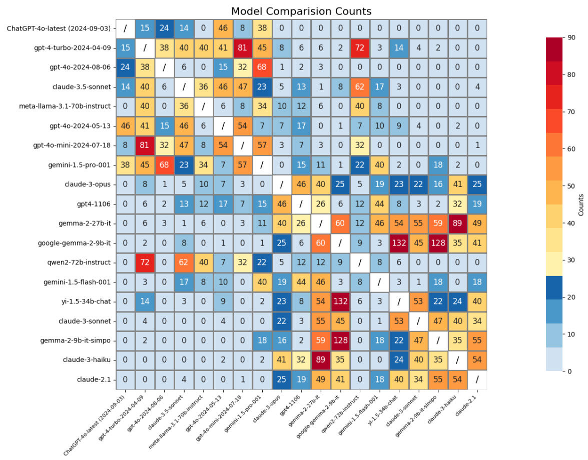

Figure 6: The distribution map of the LLM comparison counts in the MT-Bench dimension.

Results from De-Arena	Results using LLaMA-3-70B
o1-mini	llama-3-70b-instruct
o1-preview	meta-llama-3.3-70b-instruct
gpt-4o-2024-05-13	o1-mini
meta-llama-3.3-70b-instruct	gpt-4o-2024-08-06
gpt-4o-2024-08-06	o1-preview
qwen2-72b-instruct	gpt-4o-2024-05-13
gemma-2-27b-it	qwen2-72b-instruct
gemma-2-2b-it	gemma-2-27b-it
llama-3-70b-instruct	gemma-2-2b-it
gemma-1.1-7b-it	gemma-1.1-7b-it
gemma-1.1-2b-it	gemma-1.1-2b-it
qwen2.5-1.5b	llama2-7b-chat
llama2-7b-chat	llama2-13b-chat
llama2-13b-chat	qwen2.5-1.5b
qwen1.5-4b-chat	qwen1.5-4b-chat

Table 11: Comparison of the ranking results using LLaMA-3-70B as the judge and our method, respectively.

close to the diagonal), which are also equivalent to those with near 50% win rates in Figure 8. In contrast, comparisons between LLMs with large performance gaps are sparse (or even omitted), reducing the overall computation cost. Such a distribution is all thanks to our ranking algorithm, where the binary search and in-window reranking help reduce the unnecessary comparisons with predictable results and concentrate on the ambiguous pairs.

Questions with the Higher and Lower Scores

Selected Question with Higher Score:
- You have been tasked with designing a solar-powered water heating system for a residential building. Describe the key components and considerations you would include in your design. Design a five-step workflow.

Unselected Question with Lower Score:
- What is the central dogma of molecular biology? What processes are involved? Who named this?

E Case Study for Question Selection

To better show the effectiveness of our representative question selection algorithm, we show the questions with the higher and lower scores using our method in the above example. We can observe that the selected question with the higher score is indeed with higher quality. It contains more detailed task description and requires multiple special knowledge to solve it. In contrast, for the question with the lower score, its required knowledge is relatively limited. As no clear instruction is given, it is not easy to distinguish the quality of the potential outputs from LLMs.

F Case Study for Ranking Results

To study the ranking bias in single-LLM judge based methods and our approach, we show the ranking results using only LLaMA-3-70B as the judge and our De-Arena in Table 11. In the ranking list using LLaMA-3-70B as the judge, LLaMA-3-70B itself and its fine-tuned version Meta-LLaMA-3.3-70B-instruct are both ranked into the first and second positions, respectively. It demonstrates the existence of the evaluation bias for single-LLM judge based methods. In contrast, our De-Arena can produce a more reliable ranking results, which is more consistent as human preference (as shown in Table 3). It demonstrates that using more LLMs as judges is promising to obtain more reliable ranking results than using one or few judge models.

G Fine-grained Dimension Correlation

Our approach achieves high correlations with human judge based Chatbot Arena (95% in the "Overall" dimension). Here, we further report the correlation between each dimension from our De-Arena and the dimensions from Chatbot Arena (*i.e.,* Overall and Math) in Figure 7. We can see that the correlation scores are always high across these dimensions (> 0.85), indicating the consistency of our automatic ranking results and human preference. For the fine-grained sub-dimensions about a certain capability (*i.e.,* math, reasoning, and science), their correlations are also relatively higher.

H Baseline Details

• *Closed-ended Datasets based Benchmarks.*

(1) **CompassAcademic** (Contributors, 2023) selects a set of open-source datasets and benchmarks and integrates them to evaluate LLMs. (2) **BFCL** (Yan et al., 2024) evaluates LLMs' ability to accurately call functions in real-world data. (3) **Helm Lite** (Liang et al., 2022) is a lightweight benchmark consisting of nine scenarios, including math reasoning, medical QA, and long context QA. (4) **LiveBench** (White et al., 2024) contains 18 diverse tasks across 6 categories, which minimizes potential contamination by releasing new questions monthly. (5) **EQ Bench** (Paech, 2023) is an emotional intelligence benchmark for evaluating LLMs' ability to understand complex emotions and social interactions. (6) **MMLU PRO** (Wang et al., 2024) is an enhanced benchmark based on MMLU (Hendrycks et al., 2020), to evaluate the language understanding abilities across broader and more challenging tasks. (7) **MixEval** (Ni et al., 2024) collects user queries from the web and matches them with similar queries from existing benchmarks, to bridge the gap between real-world user queries and ground-truth-based evaluation. (8) **OpenLLM** (Fourrier et al., 2024) consists of commonly used datasets such as IFEval, BBH, MATH, GPQA, and MUSR, which compares LLMs in their own open and reproducible settings.

• *Single-LLM Judge based Benchmarks.*

(1)**BiGGen Bench** (Kim et al., 2024a) evaluates 9 core capabilities of LLMs, including instruction following, planning, reasoning, and others, using GPT-4 as the judge model along with instance-specific evaluation criteria. Meanwhile, (2) **BiGGen Bench (Prometheus 2)** employs Prometheus 2 (Kim et al., 2024b) as the judge model, serving as a complement to the original benchmark. (3) **Alpaca Eval 2.0** (Dubois et al., 2024) employs GPT-4-Turbo as the judge and computes the win rates of the LLMs against GPT-4-Turbo for ranking. (4) **WildBench** (Lin et al., 2024) compares LLMs with three baseline models: GPT-4-Turbo, Claude3-Haiku, and Llama-2-70B on 1024 challenging real-world tasks. GPT-4-turbo is used as a judge to evaluate all the LLM pairs.

• *Multi-LLM Judge based Benchmarks.*

(1) **PRD** (Li et al., 2023b) uses peer LLMs for weighted rankings of all LLMs, enabling fairer and more accurate assessments. (2) **Auto Arena** (Zhao et al., 2024) employs a committee of five strongest LLMs to evaluate other LLMs across 8 task categories.

I Evaluation Settings

To provide a comprehensive comparison, we design three settings that evaluate 15, 30, and 66 LLMs, respectively, and report the performance on the overall and math dimensions. Following existing work (Ni et al., 2024), we compute the Spearman Correlation between the ranking list from all benchmarks and the latest Chatbot Arena leaderboard. Since Chatbot Arena rankings are based on human annotation, this approach allows us to estimate the correlation between automatic evaluation and human preferences. Considering that the set of evaluated LLMs differs among benchmarks, we select the shared set of LLMs between the benchmark and Chatbot Arena to compute the correlation.

J Implementation Details

For PRD, we re-implement it using the same hyperparameter setting in the original paper. For other baseline methods, we collect the results from their official leaderboards. For our De-Arena, we construct nine fine-grained dimensions using the data selection method in Section 3.2, namely math algebra, math geometry, math probability, logic reasoning, social reasoning, science chemistry, science biology, science physics, and MT-bench. We involve 15 open-source models in the data selection process to reduce the time cost. For evaluation, we test 66 models in total and set the window size for fine-grained reranking to 1. In the main experiments, we use the average rank of all nine dimensions as our final Overall rank, and the average rank of the three math sub-dimensions as our final Math rank. In the evaluation stage, for each benchmark, we identify and select the most relevant dimension provided by that benchmark and compare its results with the Chatbot Arena's Overall and Math dimensions, for calculating the correlation.

K De-Arena Leaderboard

We show the detailed ranking results (*i.e.,* Elo scores) of all the evaluation dimensions from our De-Arena leaderboard in Table 12. It consists of the results from the dimensions of MT-Bench, Math (including Algebra, Probability, and Geometry three sub-dimensions), Reasoning (including Social and Logic), Science (including Biology, Chemistry, and Physics). We also show the average scores for all dimensions as the overall score. With the fine-grained sub-dimensions about math, reasoning, and science, we can have a comprehensive understanding of the detailed capabilities of LLMs, enabling to select the most suitable ones in specific tasks and scenarios.

L Visualization of Win-rate Distribution

To better understand the results of our De-Arena, we also collect the win-rate of all LLM pairs and draw the distribution map in Figure 8. We can see that the neighboring models in the ranking list (close to the diagonal), generally have near 50% win rates. It indicates that they are the more hard-to-distinguish ones than others with long distances, and they need more times of comparisons for determining their position in the ranking list. This echos to the results in Figure 6, where we can see that these neighboring models are also assigned with more comparison counts in our approach.

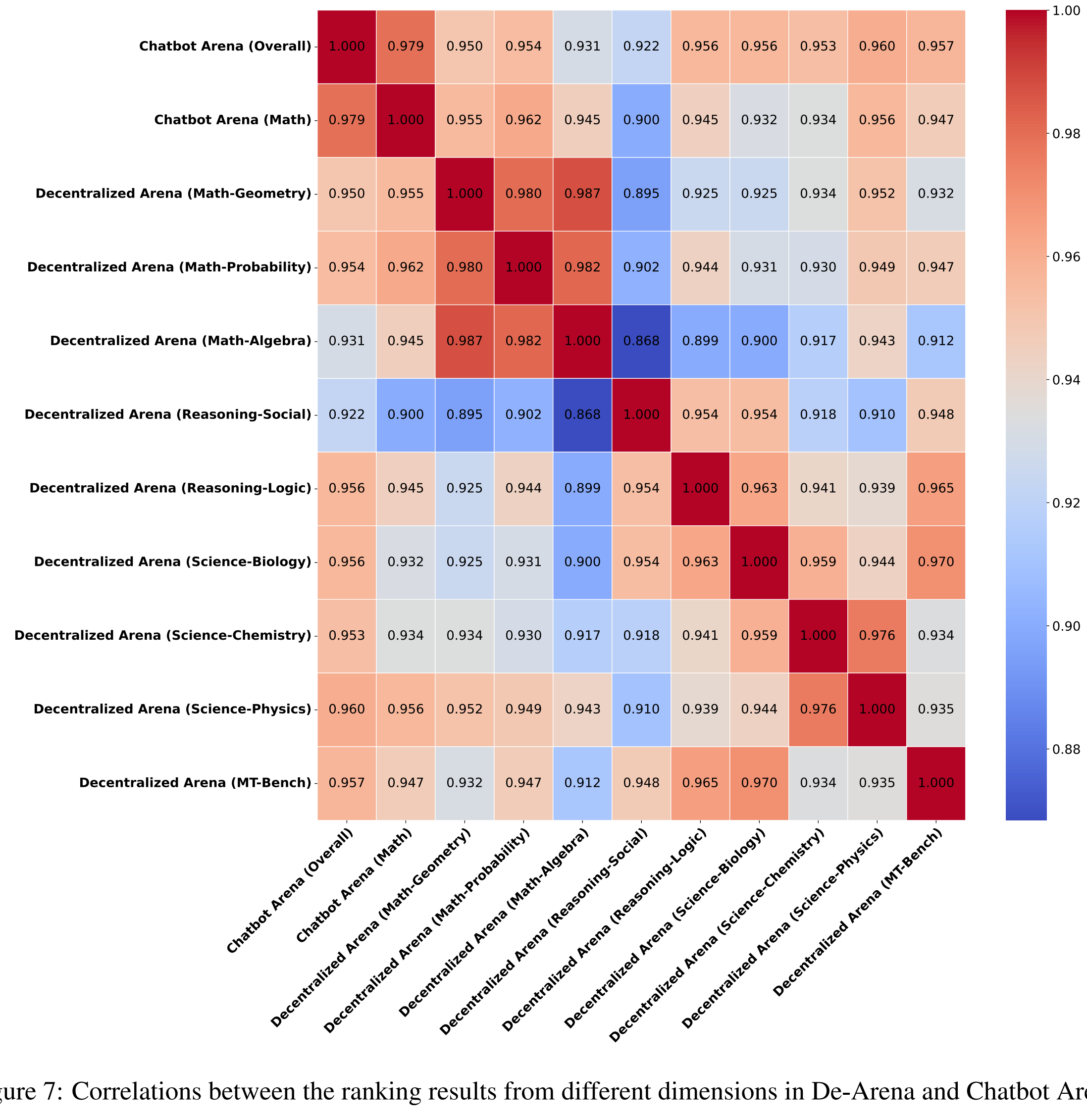

Figure 7: Correlations between the ranking results from different dimensions in De-Arena and Chatbot Arena.

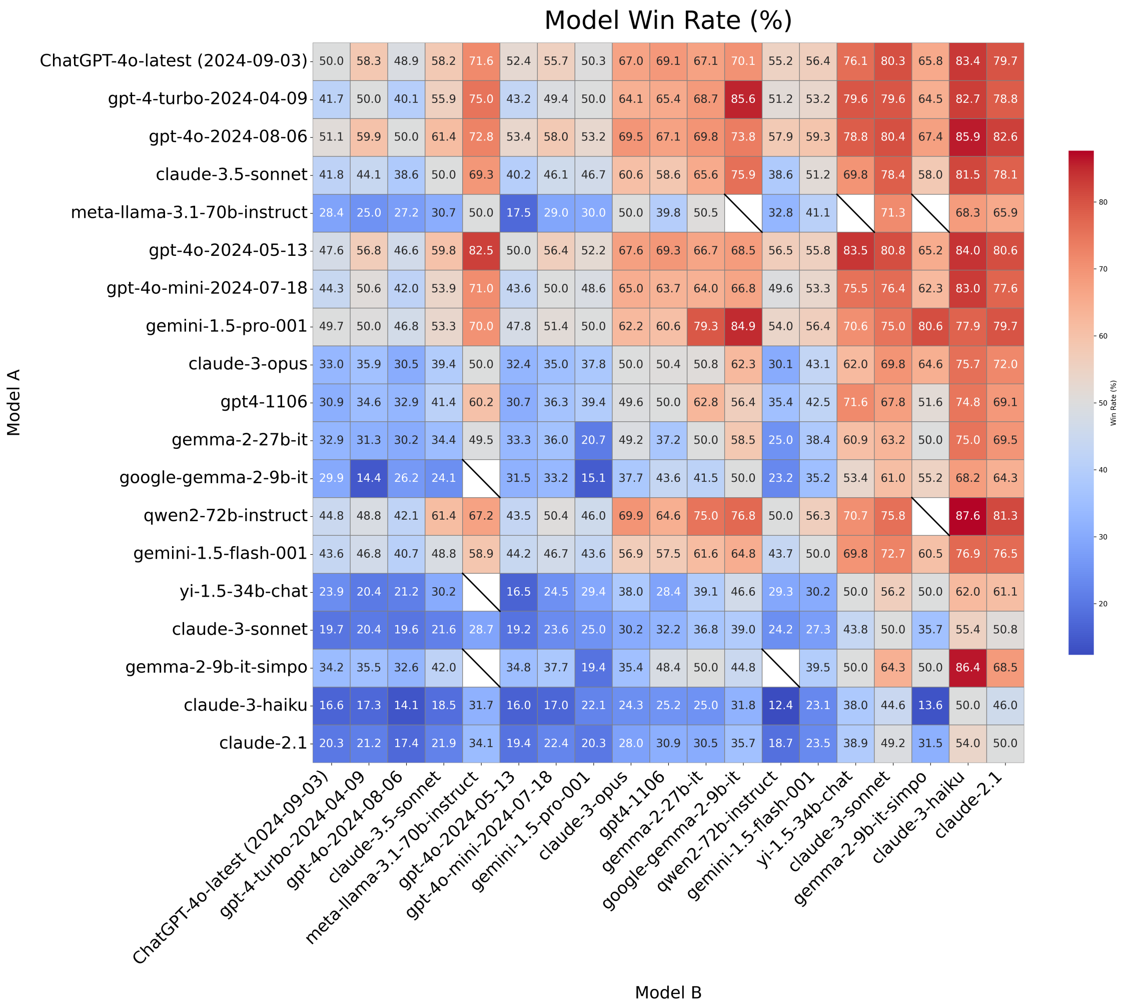

Figure 8: Win-rate distribution map for the evaluated LLMs using De-Arena.

Model	Avg	Algebra	Probability	Geometry	Social	Logical	Biology	Chemistry	Physics	MT-Bench
ChatGPT-4o-latest (2024-09-03)	93.97611237	93.25223834	90.8076583	85.98448817	86.71827446	100	100	100	98.62585524	90.39649681
o1-mini	93.49965051	100	100	100	89.87352647	94.97639081	95.62385008	75.21644169	-	92.30699507
o1-preview	91.78818444	93.72198245	94.02361667	89.49116499	89.48962613	93.65959665	94.74772613	-	-	87.38357803
yi-lightning	90.39547454	92.29959103	93.09112725	86.21341092	92.57263596	88.97256711	88.06702943	91.27789372	88.37342652	92.69158893
glm-4-plus	89.83614921	89.16383214	81.98647507	83.72554158	100	94.93241923	90.77110696	88.62203483	93.85598831	85.46794477
gpt-4o-2024-05-13	87.24525238	93.62469055	88.55622014	86.39564946	77.75644714	85.5560242	88.41283385	87.05454646	96.41218435	81.43867531
claude-3.5-sonnet-20241022	86.18487078	85.70322602	85.82789712	81.08853546	89.24744502	-	83.01772535	89.50095243	100	75.09318483
claude-3.5-sonnet	86.0533705	84.97424618	80.51555832	81.47663229	92.88930807	88.7379798	85.15229796	87.25551817	91.66450066	81.81429306
nemotron-70b	85.70411922	82.07750032	81.70841233	76.85175181	94.53145012	88.98770368	85.27553532	76.19278843	85.71193093	100
gpt-4-turbo-2024-04-09	85.44134591	88.24008459	87.79500275	83.43704168	82.55003583	86.58929024	87.99407319	79.24268595	90.17692838	82.94697059
gemini-1.5-pro-001	83.84274456	93.28632947	79.80140526	85.73710469	85.13995771	79.22139256	86.46757085	-	87.24190789	73.84628802
gpt-4o-2024-08-06	83.58357517	95.45825213	86.52136129	89.90076493	74.61636352	77.39296389	77.05217011	80.41289146	92.27434298	78.62306627
meta-llama-3.3-70b-instruct	81.64213667	88.05191213	81.50070219	76.01034051	93.37347192	80.58107374	80.49115306	72.91567181	82.81423433	79.04067033
gpt-4o-mini-2024-07-18	81.62911065	91.90507855	87.46593196	83.73769897	75.21167553	78.08781194	75.84538799	76.10327227	89.37924614	76.92589247
llama-3.1-tulu-3-70b	80.69260189	83.20202637	80.99912888	81.36555176	73.0850881	81.7890594	83.98513871	79.25643379	82.99883141	79.55215858
gemini-1.5-flash-001	78.66833532	83.971693	75.58450378	81.10124024	82.10090965	75.78605523	78.77971787	79.59254762	79.80184306	71.29650746
qwen2-72b-instruct	78.48455626	95.56883255	86.58621783	83.69563472	69.74028595	73.75123543	73.12077365	73.36129808	78.81838628	71.71834187
claude-3-opus	78.10866978	77.77044272	77.4873327	74.31586807	82.3069533	79.40132155	75.88174054	80.34596587	82.54044867	72.9279546
gemma-2-9b-it-simpo	77.31789719	77.09186481	69.27464096	72.17173541	83.46348374	68.03070404	86.46613755	81.56961063	80.47500035	-
gpt4-1106	77.14331181	82.62125793	76.45691542	75.25907271	67.72358159	76.19284396	78.53497849	73.3599233	82.95606466	81.18516826
gemma-2-27b-it	74.9744008	79.32429033	74.68913171	72.95412253	75.46769179	75.72526971	77.38686738	74.41991612	74.4943143	70.30800333
meta-llama-3.1-70b-instruct	74.81908103	82.65410121	75.1056567	73.267449	71.7164733	75.28740754	72.90888115	71.61528424	75.99739508	-
yi-1.5-34b-chat	71.26419157	67.61590435	71.75031051	68.92660537	75.57098544	69.26273322	77.29432239	66.96425091	70.395733	73.59687895
google-gemma-2-9b-it	70.77950078	69.24880738	73.41916217	70.79663106	80.30676405	76.08614138	74.7058259	63.4394147	60.1404845	68.87227591
llama-3-70b-instruct	70.20905093	63.68177551	63.49465684	62.46945654	72.63114143	77.9502143	74.4856376	74.30515962	75.03715503	67.82626154
claude-3-sonnet	69.41240667	62.36474989	62.50401897	61.45200594	75.6759593	70.94830758	77.32499969	71.37876596	71.92772412	71.13512857
claude-3-haiku	65.60203719	59.59236589	58.39414152	56.83290624	76.22751044	66.38556042	73.9756324	65.90048762	66.54094904	66.56878114
llama-3.1-tulu-3-8b	64.13924992	74.7934719	69.57294421	72.08700434	49.9473266	42.15176782	68.92413911	62.85180162	70.70292737	66.2218663
qwen1.5-72b-chat	62.17737731	71.70038733	60.5941344	65.90803703	65.20990412	38.87873049	63.5728462	63.18615677	62.19290741	68.35329203
claude-2.0	60.07907816	53.95876732	54.59652028	57.90072173	69.89646107	58.37909426	65.6804687	60.83364251	66.59410047	52.87192713
ministral-8b-it	59.8488688	61.63242352	58.725246	69.64691693	52.54413325	59.03562429	62.66986324	57.89155735	55.91787053	60.57618413
qwen1.5-32b-chat	59.06682296	70.78787721	60.35928986	61.69634576	57.70118438	41.23076181	59.40325534	54.81117145	63.07920208	62.53231871
meta-llama-3.1-8b-instruct	58.47833266	65.33759004	60.96410289	63.03060773	48.09357333	56.38560314	59.60200084	55.86477681	50.78809065	66.23864855
claude-2.1	58.08029878	58.04833618	51.47446438	61.04594773	46.53270297	61.44324545	63.62055392	56.78385236	68.43538787	55.33819815
qwq-32b-preview	57.7441793	71.64275748	65.35384041	58.87771141	48.61002573	54.23148211	53.47734778	46.74960749	56.92639997	63.8284413
qwen2.5-1.5b	53.92178189	80.25022034	71.83262853	72.94135308	43.70205398	36.95513268	44.12989317	43.1067093	52.16952909	40.2085168
llama3-8b-instruct	52.91726564	46.66264507	40.01343217	44.11394158	51.5703736	58.94572886	60.93646636	57.92241191	56.85879525	59.23159592
starling-lm-7b-beta	52.3307152	52.84886768	46.5522985	51.13239206	51.61448852	48.63101151	58.5348304	50.50725399	44.75096252	66.40433164
qwen1.5-14b-chat	51.7844422	60.51769951	48.74784967	53.57316657	46.29169097	35.3542195	52.46656265	50.86736939	54.73141043	63.51001115
mistral-8x7b-instruct-v0.1	51.55563155	51.29291916	48.27727168	49.19273323	42.54964874	39.00128601	62.82428402	56.26412563	55.53066816	59.06774734
gpt3.5-turbo-0125	50.18821862	65.17729038	58.53802397	62.28075511	41.45152348	25.14406855	46.55809712	51.41965985	50.59440643	50.53014266
command-r-(08-2024)	48.62671709	46.83436386	42.80091277	52.40409927	46.35774401	27.95956428	55.60311141	51.79248215	50.9690958	62.9190803
openchat-3.5-0106	47.43100598	50.5316225	46.18623367	46.49040206	43.70677816	39.44367439	55.48276235	43.37252958	43.15194557	58.51310554
gemma-2-2b-it	46.87564068	38.8089853	39.96987681	45.64812266	60.09115358	41.30384584	62.65299225	38.62991027	24.78287364	69.99300579
command-r-(04-2024)	45.65347002	33.00394744	37.6909176	38.12742778	46.5288232	36.53973546	56.21337898	52.08000978	52.33467243	58.36231751
gemini-1.0-pro-001	45.55337569	51.6275763	37.0959279	50.19526563	29.97602848	27.69158385	43.65118076	55.27507409	60.00746246	54.46028173
openchat-3.5	45.32554772	46.43700574	40.73751634	46.11460291	48.03856938	37.81208901	43.51031422	44.62699512	44.5992235	56.05361328
gemma-1.1-7b-it	45.08073221	45.73849545	38.11118608	39.98693207	30.0216809	38.86595628	52.31782605	52.65411393	51.64818503	56.38221413
starling-lm-7b-alpha	42.04507999	42.84399348	40.46448993	39.9951744	45.99949677	32.59182068	46.24425706	38.73575836	35.37621299	56.15451622
mistral-7b-instruct-2	36.96477144	26.08274886	32.40740394	24.48546791	33.65114071	30.10038709	46.41225983	40.51553273	45.39716673	53.63083522
llama-3.2-3b-it	35.00733269	58.69046044	44.10665702	-	16.95381455	12.75038565	28.53090391	37.646318	33.86613149	47.51399047
vicuna-33b	34.88330747	27.47528016	29.6760891	25.60995953	42.34355432	23.15924552	47.12097365	33.63396701	34.13729337	50.79340454
gemma-7b-it	32.62523838	24.22405867	24.14389506	28.60141294	36.71945984	27.42936244	34.3566972	35.61243194	35.37364385	47.16618346
llama-3.2-1b-it	31.50652515	48.19647744	35.35718488	38.4098706	22.37884882	14.82696436	30.66596363	28.17342475	18.52660051	47.02339137
smollm2-1.7b	29.77883794	41.41094808	34.66233542	40.86703593	24.65541733	14.47158568	28.68894368	21.27370007	24.5651071	37.41446812
mistral-7b-instruct-1	25.18022546	24.28958881	30.91573756	21.30326088	25.0166404	19.58058203	27.73220177	21.1732995	19.77456982	36.83614841
vicuna-13b	24.54431725	23.01589211	17.95905259	22.98158082	24.22989261	19.67247727	34.52179233	23.25790538	23.32247878	31.93778333
gemma-1.1-2b-it	22.23412728	13.45837587	7.880815666	21.50934176	28.61649971	11.99679124	28.48075179	22.20401391	24.68483409	41.27572145
qwen1.5-4b-chat	21.64067671	33.87561687	19.1517295	25.22230824	32.39522118	14.53055119	14.20140305	18.12674834	17.35368952	19.90882249
llama2-7b-chat	20.37432805	12.45837033	8.124426409	9.546107548	23.34687358	19.83603456	30.18764134	22.86497137	15.31628193	41.68824533
llama2-13b-chat	19.7016256	7.162722477	13.89583417	9.340440711	23.72229041	24.18676702	26.80803286	18.33849082	12.95980209	40.90024986
gemma-2b-it	18.70510718	12.73154473	7.739314245	25.55963926	20.20062881	6.432548745	19.03185637	18.14493366	20.88252343	37.62297534
vicuna-7b	17.98491319	8.77942567	8.020707561	9.731584621	22.36270901	14.08926915	28.51353075	21.44761184	16.70282166	32.21655842
zephyr-7b-beta	14.57067856	16.3116851	10.09469635	13.2538558	0	9.979969635	22.337812	20.35092805	18.4166841	20.39047603
koala-13b	9.409161591	2.531969921	4.683320295	2.659127343	20.54769134	9.810835924	19.26051579	5.954307371	3.708961286	15.52572505
openassistant-pythia-12b	0.405780038	0	0	0	3.652020346	0	0	0	0	0

Table 12: De-Arena Leaderboard on nine fine-grained dimensions.