Model Consistency as a Cheap yet Predictive Proxy for LLM Elo Scores

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Abstract

New large language models (LLMs) are being released every day. Some perform significantly better or worse than expected given their parameter count. Therefore, there is a need for a method to independently evaluate models. The current best way to evaluate a model is to measure its Elo score by comparing it to other models in a series of contests—an expensive operation since humans are ideally required to compare LLM outputs. We observe that when an LLM is asked to judge such contests, the consistency with which it selects a model as the best in a matchup produces a metric that is 91% correlated with its own human-produced Elo score. This provides a simple proxy for Elo scores that can be computed cheaply, without any human data or prior knowledge.

1 Introduction

The rapid proliferation of large language models (LLMs) makes it increasingly difficult to assess which models are best suited for specific tasks, especially given that some models outperform or underperform relative to their parameter count (Hong et al., 2023; Grattafiori et al., 2024). This challenge has motivated the need for independent, scalable model evaluation methods.

Measuring the intelligence of LLMs has been pursued through various approaches (Peng et al., 2024), from task-specific benchmarks (Hernández-Orallo, 2017) to natural language generation analysis (Papineni et al., 2002). The most prominent approach is human-based evaluation, exemplified by the LMSYS Chatbot Arena Leaderboard (Chiang et al., 2024), where human annotators compare responses from different models to generate Elo scores. However, this process is subjective and, due to its inherent dependence on humans, cannot scale with the increasing number of newly released models that need to be evaluated to keep the Elo scores updated.

To address scalability, researchers have turned to LLMs-as-Judges, replacing human evaluators with high-performing LLMs. While this approach eliminates the need for human data, it introduces biases including position bias (Shi et al., 2024), verbosity bias (Saito et al., 2023), and self-enhancement bias (Xu et al., 2024). More critically, LLM judges show poor alignment with human preferences (Liu et al., 2025), limiting their viability as replacements for human evaluators.

Objective tests like MMLU (Hendrycks et al., 2021) and MedQA (Jin et al., 2020) offer another approach, evaluating domain-specific knowledge without human input. While these benchmarks correlate with human preferences (Holliday et al., 2024), they fail to assess style or complex task performance, and risk overestimating models trained on benchmark data (Zhou et al., 2023).

Despite numerous alternatives, the Elo score method remains the gold standard (Quan et al., 2025; González-Bustamante, 2024; Wu and Aji, 2023) because it captures both stylistic preferences and diverse task capabilities that are difficult to quantify. However, its inherent flaws (Singh et al., 2025) warrant consideration of other properties of LLMs that can approximate the Elo score.

In the following sections, we will introduce our proposed method and its computation, as well as a set of experiments demonstrating the high correlation of our proposed metric with Elo scores. We also provide observations on the type of data that is best suited for producing such results, concluding with perspectives on how our preliminary findings could be further improved.

2 Proposed Method

We propose that an LLM's Consistency—quantified by the variance measured in its pairwise decisions when acting as a judge—can serve as a proxy for measuring its own

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Elo score. This does so without relying on human evaluation, prior knowledge, or susceptibility to traditional data leakage issues and independent judge LLM biases.

2.1 Consistency Formula

Given two models, m_i and m_j, and a model serving as a judge m_{judge}, running a **contest** between that pair of models consists of asking the same question to both models and having the judge pick the best answer (see Section 2.2 for details on the process of running an individual contest). A **matchup** ij is the set of all contests between models m_i and m_j, evaluated by the same judge m_{judge}.

If the judge's aggregated preferences for a matchup yields a probability of winning p_{ij} to m_i, we can model the matchup with a Bernoulli distribution of parameter p_{ij} and variance $p_{ij} \cdot (1 - p_{ij})$. This variance is inversely correlated with the consistency with which the judge selects a model as the winner: it approaches 0.25 if both models are equally likely to win and tends toward 0 if the same model's answer is always preferred.

Given a set of matchups M between models, if we denote n_{ij} as the number of contests between models m_i and m_j, we can compute the average variance across matchups using Equation 1.

$$\overline{\text{Var}}(m_{\text{judge}}, M) = \frac{\sum_{ij \in M} n_{ij} \cdot p_{ij} \cdot (1 - p_{ij})}{\sum_{ij \in M} n_{ij}} \tag{1}$$

This average variance can be used to measure a judge's consistency across the set of matchups M. We can further rescale the variance to make it easier to interpret, producing the **Consistency score** formula in Equation 2, yielding a number between 0 (the judge is entirely random) and 1 (the judge always picks the same models as winners in their respective matchups).

$$\text{Consistency}(m_{\text{judge}}, M) = 1 - 4 \cdot \overline{\text{Var}}(m_{\text{judge}}, M) \tag{2}$$

Hypothesizing that an LLM with a high Elo score, as typically determined over a number of contests, would itself be good at judging such contests, and that a good judge is expected to have low variance, being consistent in its answers, we explored using the Consistency score as a proxy for a model's Elo score.

Consistency scores have the benefit of not requiring any human feedback or prior knowledge of the task (we do not need to evaluate whether the judged models were *correct* in their answers), being cheap and easy to compute (given a number of preexisting answers to questions, we only need to run the judge over each contest, selecting winners), and being applicable to a wide array of tasks, including less well-defined ones where no clear-cut answer may be available (such as complex textual tasks like translation).

To further motivate for our experimentation, we saw that Wen et al. (2025) employs a logical consistency function across many data points to maximize mutual predictability of labeling, implying that the consistency with which a label is estimated gives insight into the capabilities of an LLM for downstream tasks.

2.2 Preference Elicitation

We employ a two-stage chain-of-thought prompting process to elicit preferences from LLMs judging a given contest.

First, the judge LLM is presented with the original user question and both model responses. The judge is then prompted to generate a paragraph of reasoning explaining its preference based on a predefined set of evaluation criteria (see the prompt in Appendix A.1.1).

Second, the judge LLM receives the generated reasoning and is prompted to extract a preference from it, selecting either response '1', '2', or '0' to indicate a tie (see the prompt in Appendix A.1.2).

This two-stage approach has proven necessary because single-pass prompting often led judge LLMs with lower Elo scores to misunderstand the task—either attempting to answer the question themselves or elaborating on the prompt rather than providing a preference. By first generating a justification, we ensure that the judge LLM adheres to the evaluation criteria, reducing preference selection errors.

Additionally, allowing ties prevents artificially inflated variance caused by forcing judges to make arbitrary selections in cases where neither response is clearly preferable. This approach aligns with the LMSYS dataset format, ensuring compatibility and consistency in evaluation.

For each model m_i competing against a model m_j, the probability of m_i winning against m_j (denoted p_{ij}) is computed using Equation 3, based on the number of contests between the two models (n_{ij}), the number of wins of model m_i (Wins_{ij}), and the number of ties (Ties_{ij}, with each tie counted as half a win).

$$p_{ij} = \frac{\text{Wins}_{ij} + 0.5 \cdot \text{Ties}_{ij}}{n_{ij}} \tag{3}$$

Consistent with findings from Shi et al. (2024), we observe a strong positional bias toward the first response in preference elicitation (less pronounced with higher Elo models). To mitigate this bias, we submit an equal number of contests for each possible ordering of models (both ij and ji), thus avoiding artificially increasing the Consistency score of a judge by always placing a judged model in the first position within its contests.

3 Experiments

3.1 Experimental Setup

We employed 24 LLMs, selected to cover a diverse range of Elo scores (listed in Table 1 in section A.2 of the Appendix). These scores range from 1008 to 1315, based on the most recent available LMSYS Chatbot Arena Leaderboard dataset. Each judge LLM was used to evaluate and select preferences between responses generated by other LLMs.

The LMSYS Elo scores are somewhat noisy; Elo scores and model rankings evolve as new models and contests are introduced in the LMSYS Chatbot Arena. As such, we do not expect to perfectly fit any frozen set of Elo scores.

To test our hypothesis, we used contests from the *arena-human-preference-55k* dataset (Chiang et al., 2024), which contains a collection of unique prompts crowdsourced by real human users, paired responses to each prompt from two competing LLMs, along with the identities of the competing LLMs. Although this dataset also includes human preference annotations, these were not used in our study. We used this dataset because it provided us exactly what we needed: pairs of responses from LLMs and a wide range of LLMs responding to prompts that would have minimal overlap with the judge LLMs being evaluated.

From this dataset, we extracted a subset of 2800 question-response pairs involving 35 different LLMs across 140 different matchups, as detailed in Section A.2 of the Appendix. Models were selected so that each pair of models participated in at least 20 contests and that most of these models differed from our 24 judge LLMs[1].

[1]The code and data used in the experiment is available at https://github.com/ashwinsrama/LLM_Consistency

3.2 Correlation with Elo Score

Plotting the Consistency score (defined in Equation 2) of each judge LLM over the full set of matchups against the Elo scores of the judge LLMs (based on the LMSYS Chatbot Arena Leaderboard) yielded a Pearson correlation coefficient of 0.91, as depicted in Figure 1.

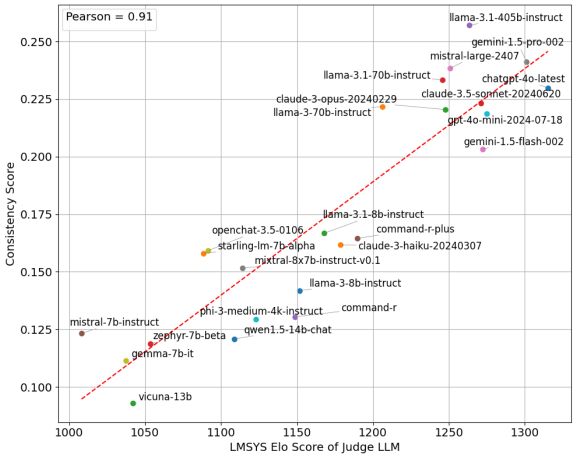

Figure 1: Correlation plot between the Elo score and Consistency score of each judge.

We found similarly high correlations when examining different sets of judge models and using different contests to measure Consistency scores, provided that the models in contest matchups had sufficiently large Elo differences (see Section 3.3) and the judges spanned a diverse range of Elo scores.

While the distribution of judge LLMs was chosen to be uniform across Elo scores, there appear to be roughly three clusters when plotted against Consistency scores: low-performing models (lower part of the plot), medium-performing models, and high-performing models (upper part of the plot).

We found that the correlation between Elo score and Consistency score is significantly lower within each cluster: 0.74, 0.76, and 0.12 for the low-, medium-, and high-performing clusters, respectively (see Appendix A.3 for details). While this is in part due to the small size of these clusters, it suggests that our metric is capable of distinguishing broad differences in model capabilities but is not yet refined enough to differentiate, for example, between the five best models available.

Ranking models by Consistency scores places them on average within 2.8 positions of their Elo ranking, while predicting a model's Elo score based on its Consistency score, using simple linear regression, results in a mean absolute error of 35.2 Elo points.

3.3 Impact of the Contest Data

We further observe a strong and positive correlation when computing the variance (per Equation 1) of judges on *individual* matchups and then plotting the variance of those variances against the difference in Elo scores between the two models in the matched pair (see Figure 2).

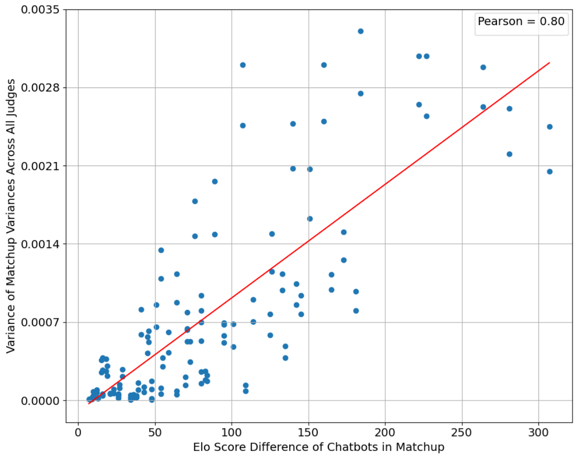

Figure 2: Correlation plot between the difference in Elo scores in a given matchup of two models and the variance of matchup variance computed across all judge LLMs for that matchup.

This is somewhat intuitive: if the two models in a matchup have similar Elo scores, then no judge manages to reliably differentiate them, leading to low consistency across all judges and correspondingly low variance between judges. However, pairs with a larger Elo difference are easier to discriminate, allowing strong judges to excel while weak judges remain unable to consistently pick the better response, thereby increasing the variance on that matchup. This suggests that pairs of models with large Elo differences are the most effective for identifying consistent judges.

Building on this insight, we examined the convergence of our metric by measuring the correlation between Consistency and Elo scores as we increased the number of matchups (see Figure 3), either randomly (blue line, averaged over 25 random matchup orders) or by adding matchups with larger Elo differences first (red line).

Both lines converge to a 0.91 correlation, as they eventually use the same matchups. However, we found that most of the convergence can be achieved using just the 10 matchups with the highest Elo differences, reaching a correlation of 0.88 (see Figure 5 in the Appendix). The judges yield a significantly higher Consistency score compared to the previous correlation plot, because the matchups are easier for judges to be consistent upon. Additionally, we found that using just 30 matchups is sufficient to extract the full information, reaching a 0.91 correlation.

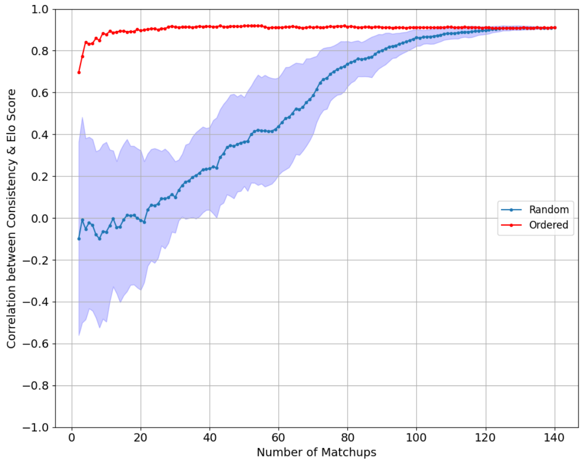

Figure 3: Convergence of the Pearson correlation coefficient between Consistency and Elo scores as the number of matchups used to compute the Consistency scores increases. The blue line is computed over 25 random matchup orders, while the red line is produced by adding the matchups with the highest Elo differences first.

This highlights the importance of the contest data in computing the metric. Matchups between models with widely different Elo scores are necessary to extract information about the judge's ability to discriminate between models, an observation consistent with Gao et al. (2024).

Regarding the number of matchups to be used, it is interesting to note that the sorted matchups convergence curve is essentially monotonous, suggesting that, while adding matchups with lower Elo differences does dilute consistency (as seen in Figure 5), it appears to be an additive operation: adding information without harming the correlation of the metric with Elo scores. This means that additional matchups can be incorporated as long as matchups with high Elo differences are prioritized.

4 Conclusion

We introduce Consistency scores as a simple, scalable metric for estimating LLM intelligence by measuring a model's consistency in preferring the same winner in repeated pairwise matchups. This score strongly correlates with LMSYS Elo scores

($r = 0.91$), achieving a mean prediction error of just 35.2 Elo points—all without requiring human input or prior knowledge of the models.

Our method is efficient to apply: evaluating a new model's Elo score only requires running pairwise comparisons on existing answer sets. It generalizes well across tasks, including subjective ones, though its effectiveness improves when contest data features models with widely differing abilities.

Overall, we believe that Consistency scores present a promising avenue for measuring model intelligence due to their ease of measurement and the strong results observed in this initial exploration. This approach offers a promising direction for automatic LLM evaluation, with future work focused on refining rankings among top-tier models. We hope that further refinements in this direction will lead to a cost-effective and reliable metric for evaluating model intelligence across a diverse range of traditionally challenging tasks.

Limitations

While our work is novel and demonstrates a correlation between judgment consistency and intelligence, there are shortcomings that practitioners should consider when using this metric.

Primarily, the metric lacks the ability to distinguish between top-performing models. As depicted in Appendix A.3, the highest cluster yields a Pearson correlation of 0.12. However, as research labs and companies investigate smaller models—for tasks such as low-power LLM inference, knowledge distillation, and testing fine-tuning algorithms—even the strong correlation within the lower clusters of LLMs makes the metric useful.

Additionally, while the Consistency score is not able to distinguish between models that are very close in Elo score, one should note that Elo scores are a noisy metric, because it is inherently subjective and can change from day-to-day based on the number of human preferences elicited. In fact, the Elo score for each model represented in the LMSYS Chatbot Arena Leaderboard comes with a 95% confidence interval that can drastically change the range of permissible Elo scores and relative ranking of each model.

Looking beyond these limitations, we identify several areas for potential improvement on our existing work that warrant attention.

First, curating dedicated contest sets optimized for information extraction could enhance performance beyond the essentially random data utilized in this study.

Second, a weighting formula could be designed to account for Elo differences in matchups, as pairs with smaller differences yield noisier results and might merit downweighting.

Additionally, prompt engineering may unlock better performance from stronger models, which might currently be constrained by imprecise instructions.

Finally, a more sophisticated uncertainty model leveraging broader contest data could improve robustness. Such a model should incorporate patterns where consistently high-performing models across diverse contests demonstrate greater reliability than those with variable performance.

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A Appendix

A.1 Prompts Used

A.1.1 Reasoning Prompt

```
Please act as an impartial judge and
    evaluate the quality of the
    responses provided by two AI
    assistants to the user question
    displayed below.

[User Question]
{PROMPT}

[The start of Answer #1]
{ANSWER1}
[The end of Answer #1]

[The start of Answer #2]
{ANSWER2}
[The end of Answer #2]

Your task is to determine which of the
    two answers is better, based on the
    following criteria:
- Choose the response that follows the
    user's instructions and answers the
    user's question better.
- Evaluate based on helpfulness,
    relevance, accuracy, depth,
    creativity, and level of detail of
    the responses.
- Do not allow the length or order of
    the responses to influence your
    evaluation.

In 1 paragraph, write out your thought
    process and reasoning for which
    answer better meets the criteria. Do
     not actually answer the original
    question yourself. You are only
    choosing between the two provided
    answers based on how well they meet
    the specified criteria. If both
    answers are comparable such that you
     have no preference, then explain
    that.
```

A.1.2 Preference Prompt

```
Read the following passage:

[Start of Passage]
{REASONING}
[End of Passage]

Indicate which answer the author thinks
    is better. Respond with a single
    integer:
- "1" if the author thinks Answer #1 is
    better.
- "2" if the author thinks Answer #2 is
    better.
- "0" if the author has no preference,
    or thinks the answers are equal.

Your response must be exactly one
    integer (1, 2, or 0). Do not include
     any other text/explanation. The
    author prefers Answer #:
```

A.2 Dataset Used

LLM Name	Elo Score	Consistency Score
chatgpt-4o-latest	1315	0.230
gemini-1.5-pro-002	1301	0.241
gpt-4o-mini-2024-07-18	1275	0.219
gemini-1.5-flash-002	1272	0.203
claude-3.5-sonnet-20240620	1271	0.223
llama-3.1-405b-instruct	1263	0.257
mistral-large-2407	1251	0.238
claude-3-opus-20240229	1248	0.220
llama-3.1-70b-instruct	1246	0.233
llama-3-70b-instruct	1206	0.222
command-r-plus	1190	0.165
claude-3-haiku-20240307	1178	0.162
llama-3.1-8b-instruct	1168	0.167
llama-3-8b-instruct	1152	0.142
command-r	1149	0.130
phi-3-medium-4k-instruct	1123	0.129
mixtral-8x7b-instruct-v0.1	1114	0.152
qwen1.5-14b-chat	1109	0.121
openchat-3.5-0106	1091	0.159
starling-lm-7b-alpha	1088	0.158
zephyr-7b-beta	1053	0.119
vicuna-13b	1042	0.093
gemma-7b-it	1037	0.111
mistral-7b-instruct	1008	0.123

Table 1: List of the LLMs evaluated in our experiments, sorted by their LMSYS Elo scores in descending order. Consistency scores are computed as per Section 3.2.

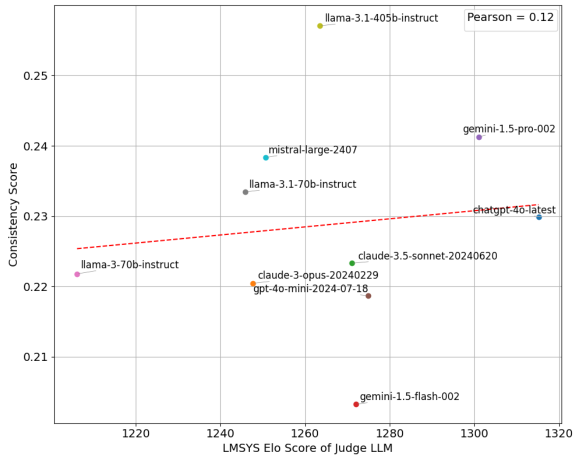
LLM Name	Elo Score
gpt-4-1106-preview	1251
gpt-4-0314	1186
gpt-4-0613	1162
claude-1	1149
mistral-medium	1148
claude-2.0	1132
claude-2.1	1118
gpt-3.5-turbo-0613	1117
mixtral-8x7b-instruct-v0.1	1114
claude-instant-1	1111
gpt-3.5-turbo-0314	1106
wizardlm-70b	1106
tulu-2-dpo-70b	1099
llama-2-70b-chat	1093
vicuna-33b	1091
pplx-70b-online	1078
gpt-3.5-turbo-1106	1068
llama-2-13b-chat	1063
wizardlm-13b	1059
zephyr-7b-beta	1053
codellama-34b-instruct	1042
vicuna-13b	1042
llama-2-7b-chat	1037
mistral-7b-instruct	1008
vicuna-7b	1005
palm-2	1003
koala-13b	964
mpt-7b-chat	927
RWKV-4-Raven-14B	922
oasst-pythia-12b	894
chatglm-6b	879
fastchat-t5-3b	868
stablelm-tuned-alpha-7b	840
dolly-v2-12b	822
llama-13b	799

Table 2: List of LLMs matched in our experiments, sorted by their LMSYS Elo scores in descending order.

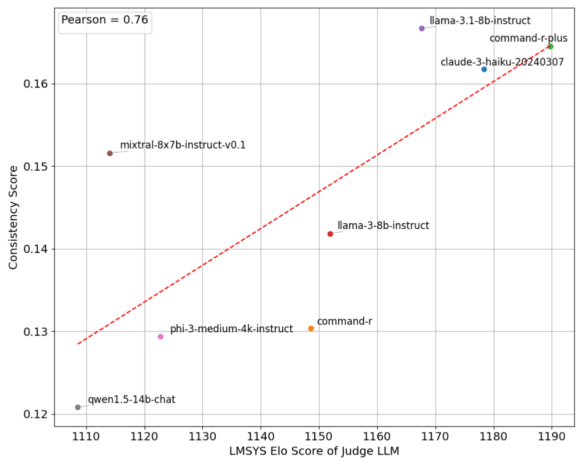
First LLM	Second LLM	Difference in Elo Scores
gpt-4-0314	chatglm-6b	307
fastchat-t5-3b	claude-1	281
RWKV-4-Raven-14B	gpt-4-0314	264
chatglm-6b	gpt-3.5-turbo-0314	227
mpt-7b-chat	claude-1	222
RWKV-4-Raven-14B	gpt-3.5-turbo-0314	184
gpt-4-0314	vicuna-7b	181
fastchat-t5-3b	vicuna-13b	173
koala-13b	llama-13b	165
vicuna-33b	gpt-4-1106-preview	160
tulu-2-dpo-70b	gpt-4-1106-preview	151
palm-2	claude-1	145
koala-13b	dolly-v2-12b	142
gpt-4-1106-preview	claude-instant-1	140
fastchat-t5-3b	palm-2	135
claude-2.1	gpt-4-1106-preview	133
chatglm-6b	vicuna-7b	126
koala-13b	stablelm-tuned-alpha-7b	125
mpt-7b-chat	vicuna-13b	114
gpt-3.5-turbo-0613	mistral-7b-instruct	109
claude-1	vicuna-13b	107
vicuna-7b	gpt-3.5-turbo-0314	101
gpt-4-0613	gpt-3.5-turbo-1106	95
llama-13b	oasst-pythia-12b	95
codellama-34b-instruct	claude-2.0	89
gpt-4-0613	pplx-70b-online	84
RWKV-4-Raven-14B	vicuna-7b	83
gpt-3.5-turbo-0314	gpt-4-0314	80
mistral-medium	gpt-3.5-turbo-1106	80
gpt-3.5-turbo-0613	llama-2-7b-chat	80
palm-2	mpt-7b-chat	76
wizardlm-13b	claude-2.0	73
oasst-pythia-12b	dolly-v2-12b	71
koala-13b	oasst-pythia-12b	71
pplx-70b-online	mistral-medium	70
gpt-3.5-turbo-0613	zephyr-7b-beta	64
wizardlm-70b	codellama-34b-instruct	64
fastchat-t5-3b	mpt-7b-chat	59
mistral-7b-instruct	llama-2-13b-chat	55
stablelm-tuned-alpha-7b	oasst-pythia-12b	54
gpt-3.5-turbo-0613	llama-2-13b-chat	54
llama-2-70b-chat	codellama-34b-instruct	51
gpt-4-0613	mixtral-8x7b-instruct-v0.1	48
wizardlm-13b	wizardlm-70b	48
gpt-3.5-turbo-1106	mixtral-8x7b-instruct-v0.1	46
zephyr-7b-beta	mistral-7b-instruct	45
RWKV-4-Raven-14B	chatglm-6b	43
llama-13b	stablelm-tuned-alpha-7b	41
llama-2-70b-chat	claude-2.0	39
vicuna-13b	palm-2	38
mixtral-8x7b-instruct-v0.1	pplx-70b-online	36
mistral-medium	mixtral-8x7b-instruct-v0.1	34
llama-2-70b-chat	wizardlm-13b	34
mistral-7b-instruct	llama-2-7b-chat	29
vicuna-33b	claude-2.1	27
llama-2-13b-chat	llama-2-7b-chat	26
claude-2.0	wizardlm-70b	26
dolly-v2-12b	llama-13b	23
vicuna-33b	claude-instant-1	21
tulu-2-dpo-70b	claude-2.1	19
dolly-v2-12b	stablelm-tuned-alpha-7b	18
llama-2-7b-chat	zephyr-7b-beta	16
codellama-34b-instruct	wizardlm-13b	16
gpt-4-0613	mistral-medium	15
llama-2-70b-chat	wizardlm-70b	13
claude-instant-1	tulu-2-dpo-70b	12
pplx-70b-online	gpt-3.5-turbo-1106	10
zephyr-7b-beta	llama-2-13b-chat	10
vicuna-33b	tulu-2-dpo-70b	9
claude-2.1	claude-instant-1	7

Table 3: List of matchup pairs used in our experiments, sorted by their LMSYS Elo score difference.

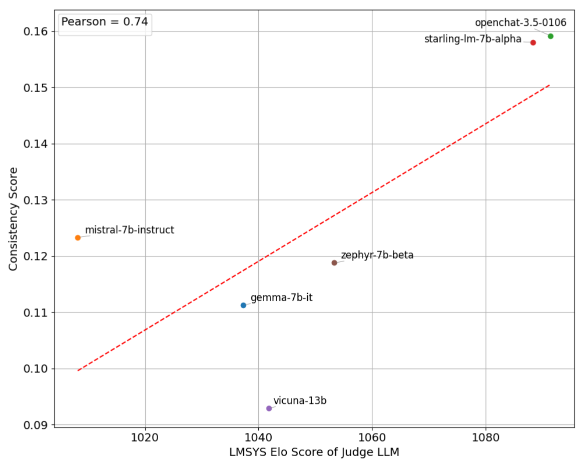
A.3 Correlation Plots



(a) Highest cluster



(b) Middle cluster



(c) Lowest cluster

Figure 4: Correlation plots between Consistency and Elo scores for each judge LLM, grouped into clusters of low-, middle-, and high-performing models.

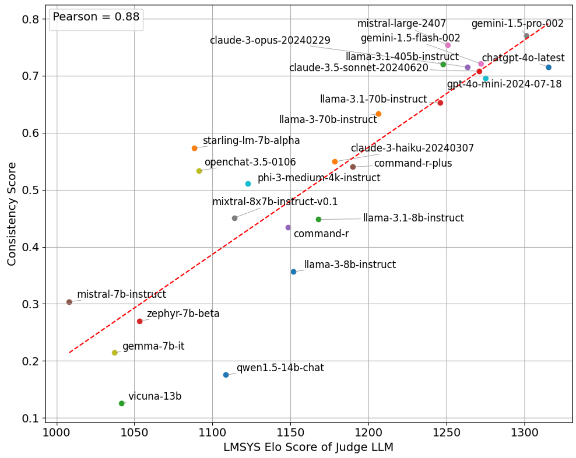


Figure 5: Correlation plot between the Elo and Consistency scores of each judge, computing the Consistency scores using *only* the 10 matchups with the highest Elo differences.