Best-of-L: Cross-Lingual Reward Modeling for Mathematical Reasoning

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Abstract

While the reasoning abilities of large language models (LLMs) continue to advance, it remains underexplored how such abilities vary across languages in multilingual LLMs and whether different languages generate distinct reasoning paths. In this work, we explore how reasoning knowledge in different languages complements one another. We propose a novel cross-lingual reward modeling framework that aggregates reasoning signals across languages to enhance mathematical reasoning. Our results show a substantial improvement (about 10 scores) in multilingual mathematical reasoning performance compared to using reward modeling within a single language, benefiting even high-resource languages. While English often exhibits the highest performance in multilingual models, we find that cross-lingual sampling benefits English particularly under low sampling budgets. Our findings reveal new opportunities to improve multilingual reasoning by leveraging the complementary strengths of diverse languages.

1 Introduction

Recently, many studies have focused on improving reasoning ability (Ranaldi and Freitas, 2024; Byun et al., 2024) or identifying key factors behind it (Ko et al., 2024). Yet, reasoning research has largely centered on English models, with multilingual models receiving comparatively little attention. Among the few, Shi et al. (2023) have shown that multilingual large language models (LLMs) have strong reasoning capabilities, even for underrepresented languages. Further progress has been made to improve multilingual math reasoning through self-consistency.(Lai et al., 2025), multilingual instruction-tuning, (Chen et al., 2024; Lai and Nissim, 2024), and preference optimization methods (She et al., 2024; Dang et al., 2024a; Yang et al., 2025). Building on prior work using reward modeling to enhance math reasoning in English LLMs (Cobbe et al., 2021; Shen et al., 2021; Hosseini et al., 2024; Zhang et al., 2024; Setlur et al., 2025), Hong et al. (2025) examined the transferability of English reward models to other languages. Building on this line of work, Wang et al. (2025) extended reward models to multilingual setups (multilingual reward model), but still limited sampling and scoring to a single language. We expand this perspective by exploring how multilingual LLMs can utilize the reasoning traces generated in multiple languages for the same question (Figure 1).

To this end, we first study to what extent languages could potentially complement each other's mathematical reasoning skills. Interestingly, we find that even low-resource languages sometimes succeed where high-resource languages fail, suggesting that their reasoning signals could provide valuable complementary information (Figure 5).

Motivated by the above finding, we propose a cross-lingual outcome reward modeling (ORM) framework to harness the *Best-of-Languages* performance, in which we train a multilingual verifier to score the correctness of reasoning traces. At inference, we sample candidate solutions in multiple languages and select the highest-scoring one. To the best of our knowledge, we are the first to propose a cross-lingual reward model that leverages complementary reasoning skills across languages.

Our results show cross-lingual ORM improves performance by over 10% and 15% compared to average results of multilingual ORM and the self-consistency baseline, respectively. Further analysis reveals that expanding the language pool consistently enhances the framework's performance.

Through an ablation study, we find that cross-language sampling even benefits English, especially under low-budget settings. We show that, while having English in the language pool of the cross-lingual ORM sampling positively affects the performance, some selection of non-English pools outperforms other pools containing English, sup-

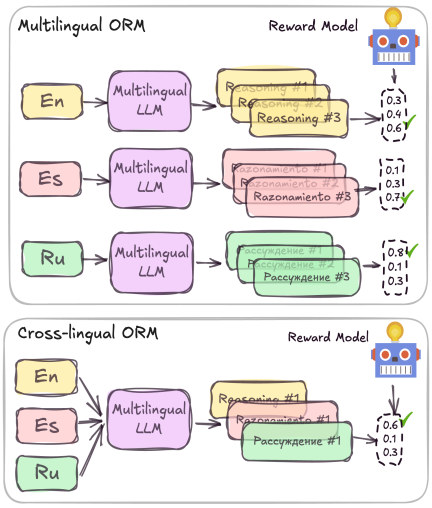

Figure 1: Illustration of multilingual ORM, where the verifier ranks responses within each language, and cross-lingual ORM (ours), where the verifier ranks responses across languages for the same question.

porting our argument that languages have complementary reasoning skills in multilingual models.

2 Related Work

Reward modeling has become a powerful approach to enhance multilingual reasoning. Prior work studied its cross-lingual transferability (Hong et al., 2025; Wu et al., 2024), where a reward model trained in one language is applied to another. These methods generally involve two stages: training the reward model (monolingual or multilingual) and sampling candidate solutions, which typically operate within a single language. For instance, *monolingual ORM* trains and samples in one language (Wang et al., 2025), while *multilingual ORM* trains the reward model on multiple languages but still ranks samples within each language. We instead introduce *cross-lingual ORM* which, like Wang et al. (2025),trains a reward model on multiple languages, but ranks solutions *across* languages for each question. Our framework is based on our observation that utilizing multiple languages has the potential to enhance reasoning performance, similar to the concurrent work (Hong et al., 2025).

3 Methodology

Reward models are extensively being used as a verifier in math reasoning tasks to evaluate the correctness of a given answer. Based on the evaluation setup, reward models can be process-based, where the model assesses the reasoning step by step (called PRMs) (Lightman et al., 2024; Luo et al., 2024), while outcome reward models (ORMs) evaluate the entire reasoning (Cobbe et al., 2021; Shen et al., 2021; Hosseini et al., 2024; Zhang et al., 2024; Setlur et al., 2025). In this work, we focus on the latter and propose a novel cross-lingual outcome reward modeling framework that leverages complementary reasoning signals across languages.

3.1 Cross-lingual Reward Modeling

Our framework is the cross-lingual version of the *Best-of-N* (Lightman et al., 2024), ranking the generated answers for a given question across a set of languages and selecting the highest-scored one.

Given a math question q and a generated candidate answer a, we train a discriminative verifier to predict whether the generated reasoning is correct. More specifically, we train an LLM as the verifier using binary cross-entropy loss: $\mathcal{L}_{ORM} = -[y \cdot \log(\hat{y}) + (1-y) \cdot \log(1-\hat{y})]$. At inference, we use the verifier scores to rank a set of candidate answers in different languages for a given question using the probability that the model put on the correct class, and then, we select the answer with the highest probability.

Training Data Generation. We use the Google Translate version of GSM8K training set in 8 languages, which includes around 7.5k examples per language of high-quality grade school math problems created by human writers (Cobbe et al., 2021) for our verifier training set (Lai and Nissim, 2024). We then prompt 3 models, the instruction-tuned version of Aya-Expanse 8B (Dang et al., 2024b), Llama3.1 8B (Grattafiori et al., 2024), and Qwen2.5 7B (Team, 2024), using the GSM8K training set in the covered languages to generate responses with step-by-step reasoning. We automatically labeled the generated reasoning paths as correct or incorrect based on the correctness of the final answer. Using generations from multiple models allows us to increase the size and diversity of the training set. To make a balanced dataset, we use the same number of correct and incorrect samples for each language, resulting in a set of around 88k samples for training.

Cross-lingual ORM We use the Qwen2.5-Instruct 3B model (Team, 2024) as the base of our reward model (verifier), as it has the widest officially supported language coverage among recent multilingual LLMs. We fine-tune it using the afore-

	En.	Avg.	SC	Multi-ORM	Cross-ORM	Pass@8-Multi	Pass@8-Cross
Aya-Expanse-8b	79.6	63.4	58.3	73.3	**83.2**	82.4	**93.2**
Llama3.1-8b	80.4	64.0	71.6	76.2	**84.0**	86.9	**92.4**
Ministral-8b	82.0	65.1	70.3	76.4	**87.6**	84.3	**93.4**
Qwen2.5-7b	85.2	72.2	74.4	81.3	**92.4**	87.2	**96.4**
Phi3-7b	90.0	69.3	74.2	79.5	**92.8**	85.3	**96.8**
Llama3.2-3b	72.4	56.0	63.0	70.3	**77.2**	80.3	**88.8**

Table 1: The leftmost columns represent the English performance and the average performance of all the languages. *SC* denotes average self-consistency accuracy. *Pass@8-cross* outperforms the average *pass@8-multi*, indicating the complementary math reasoning skills across languages. Our proposed framework, *Crosslingual-ORM*, also exceeds the average *Multilingual-ORM* accuracy by a large margin.

mentioned training set[1]. To make a fair comparison, we use the same verifier for all experiments, including multilingual and cross-lingual ORM.

4 Experiments

4.1 Experimental setups

To study the chain-of-thought math reasoning ability of LLMs, we employ the MGSM (Multilingual Grade School Math) dataset (Shi et al., 2023). Following the original recipe of using MGSM (Shi et al., 2023), we prompt LLMs under the *Native-CoT* setting using 8-shots for all experiments[2].

Models. We have carried out our analysis and experiments using a wide range of instruction-tuned multilingual models, including Aya-Expanse 8B (Dang et al., 2024b), Llama3.1 8B (Grattafiori et al., 2024), Qwen2.5 7B (Team, 2024), Ministral 8B[3], phi-3 7B (Abdin et al., 2024), and Llama 3.2 3b[4].

4.1.1 Baselines.

We evaluate our cross-lingual ORM framework against the following baselines:

Self-consistency. A simple, yet effective approach in chain-of-thought (CoT) prompting is self-consistency (Wang et al., 2023; Yao et al., 2023). This baseline performs majority voting across a batch of sampled answers ($N = 8$) for each language, without any reward model.

Multilingual-ORM Also known as *Best-of-N* technique, where the multilingual verifier scores N different samples within a language and selects the one with the highest score (Wang et al., 2025). We use $N = 8$, generated with a temperature sampling of $T = 0.7$, and truncated at the top-p ($p = 0.95$) for all experiments (including the self-consistency baseline)[5]. We exclude the monolingual ORM baseline, where a separate RM is trained for each language and performs within-language sampling, as previous work reports that its performance is consistently lower than that of multilingual ORM (Wang et al., 2025).

4.2 Results and Findings

LLMs exhibit complementary mathematical reasoning skills across languages. To investigate the similarity of reasoning knowledge across languages, we employ pass@k, a well-established metric used to approximate the upper-bound performance of LLMs when generating multiple answers (Hosseini et al., 2024; Li et al., 2025). This allows us to measure the degree of potential complementarity between languages in multilingual LLMs as it considers a question solved if at least one of the answers in different languages is correct. In Table 1, we report pass@8 scores across languages (pass@8-Cross) and the average pass@8 scores across different samples within languages (pass@8-Multi).[6] we observe that Pass@8-Cross outperforms the performances of individual languages, suggesting that even high-resource languages can potentially benefit from other languages.

Sampling across languages is superior to sampling within a language. Building on our analysis, we employ the cross-lingual verifier described in Sec. 3.1 to see how languages benefit each other in practice. The middle part of Table 1 summarizes the accuracy of our cross-lingual ORM under

[1] Refer to the appendix A for details.
[2] Dataset details in the appendix A.
[3] https://huggingface.co/mistralai/Ministral-8B-Instruct-2410
[4] https://huggingface.co/meta-llama/Llama-3.2-3B-Instruct
[5] We abbreviate Cross-lingual and Multilingual as Cross and Multi in tables and figures for brevity.
[6] Per-language results are in the Appendix.

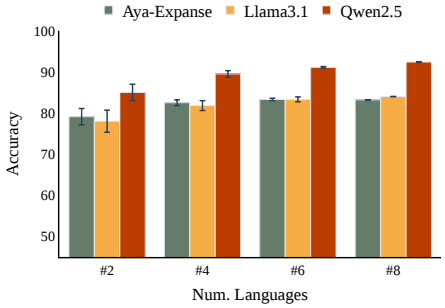

Figure 2: The mean and standard deviation cross-lingual ORM accuracy using different numbers of languages.

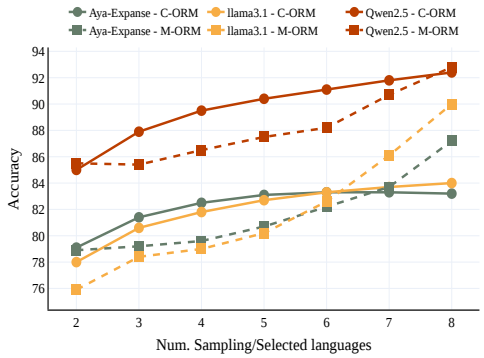

Figure 3: Comparing the accuracy of using cross-lingual ORM and multilingual ORM on English using the same number of languages and samples.

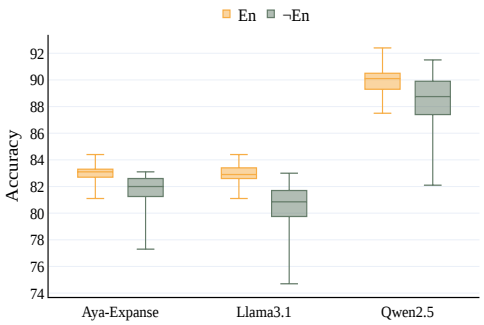

Figure 4: Average cross-lingual ORM performance across language pools of size 2–7, with and without English. English generally helps, but some non-English sets outperform English-inclusive ones.

within- and across-language settings. As shown, Cross-ORM clearly outperforms the average performance of ORM-Multi, with the largest benefits for non-English languages. These results suggest that leveraging cross-lingual signals is more effective than relying solely on monolingual reasoning, especially for underrepresented languages.

Increasing the pool of languages enhances the cross-lingual ORM performance. To understand the impact of language pool size, we show the average performance for all possible language combinations at different pool sizes in Figure 2. As expected, the results demonstrate that adding more languages improves cross-lingual ORM performance up to a certain point, after which the additional gains become negligible.

Sampling across languages benefits English as well. While our earlier analysis shows that cross-lingual ORM exceeds the average performance of multilingual ORM, its accuracy still lags behind that of English ORM. To better understand under what conditions other languages might benefit English, we compare the performance of English ORM (i.e., generating multiple answers in English) and cross-lingual ORM under different sampling budgets in Figure 3. Based on the results, we observe that cross-lingual ORM outperforms English ORM at low sampling budgets. However, this advantage fades as the number of samples increases. We suspect that additional sampling from other languages becomes redundant once English samples already cover a wide range of reasoning paths.

Including English in language pools is generally helpful, yet it does not always lead to superior performance. To examine the effect of including English in the language pools for the cross-lingual ORM setup, we report the mean and standard deviation of accuracy across all possible language pools with a size of 2 to 7 with and without English in Figure 4. As expected, including English generally improves cross-lingual ORM performance. However, this is not always the case; some language pools without English perform better than certain groups that include English, as reflected in the standard deviation of the non-English groups.

5 Conclusion

In this paper, we present a novel cross-lingual reward modeling framework that effectively leverages complementary mathematical reasoning skills across languages in multilingual LLMs. Our experiments show that cross-lingual reward modeling benefits even high-resource languages like English under low-budget inference settings. Furthermore, our findings show that languages mutually enhance each other's reasoning abilities. Our results pave the way for future research into the similarities and differences of reasoning patterns across languages to improve multilingual reasoning models.

6 Limitations

A limitation of our work is that we focused solely on math reasoning tasks, and future research could explore other downstream tasks to broaden the applicability of our approach. Additionally, we used only eight languages, so expanding the number and diversity of languages would be important to further enhance our understanding of multilingual reasoning in LLMs. Another limitation is that we did not investigate the underlying reasoning patterns across languages, which could provide valuable insights for improving multilingual reasoning performance.

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A Experimental Setups

A.1 Cross-lingual ORM setups

We fine-tune our verifier for 5 epochs, with AdamW, a learning rate of $2e$-4, and a batch size of 96. Since the main task is binary classification and to make fine-tuning efficient, we fine-tune with LoRA (Hu et al., 2022) with a rank of 16 and scaling factor of 32.

The MGSM dataset covers 11 languages, including English(en), Spanish(es), French(fr), German(de), Russian(ru), Chinese(zh), Japanese(ja), and Thai(th), with 250 examples for each. We exclude Swahili, Telugu, and Bengali, as multilingual LLMs perform poorly on these languages. Thus, training a reward model (verifier) that already does not have acceptable linguistic knowledge on certain languages for a reasoning task is not practical. Nevertheless, our selection includes languages from diverse language families and writing scripts (Lai et al., 2025). We have used the evaluation harness framework for our experiments and reported exact-match scores (Gao et al., 2024) .

B Full Results

Question:

Melanie is a door-to-door saleswoman. She sold a third of her vacuum cleaners at the green house, 2 more to the red house, and half of what was left at the orange house. If Melanie has 5 vacuum cleaners left, how many did she start with?

English Response:

Melanie sold a third of her vacuum cleaners at the green house. That means she sold 1/3 of her vacuum cleaners. 1/3 of 5 is 5/3, which is 1.67. Melanie sold 1.67 vacuum cleaners at the green house. She had 5 left, so she had 5 + 1.67 = 6.67 vacuum cleaners before the green house. She sold 2 more at the red house, so she had 6.67 - 2 = 4.67 vacuum cleaners before the red house. She sold half of what was left at the orange house. Half of 4.67 is 2.335. Melanie had 4.67 - 2.335 = 2.335 vacuum cleaners left. Melanie had 5 vacuum cleaners left, so she must have had 5 + 2.335 = 7.335 vacuum cleaners before the orange house. Melanie had 7.335 vacuum cleaners before the orange house. The answer is 7.335.

Japanese Response:

緑の家で3分の1の掃除機を売った場合、3/1*3=9個の掃除機を売ったことになります。赤の家で2台を売ったので、合計9+2=11台を売ったことになります。オレンジの家で残りの半分を売った場合、残りの半分は 1/2*5=2.5 となり、オレンジの家で 2.5 台を売ったことになります。合計で、メラニーは 11+2.5=13.5 台の掃除機を売りました。掃除機は整数でなければならないため、彼女は 13 台の掃除機を売りました。彼女は 5 台の掃除機を手元に残したため、彼女は 13+5=18 台の掃除機を持っていました。答えは18です。

Google translation of Japanese Response:

If she sells one-third of the vacuums at the green house, she has sold 3/1*3=9 vacuums. She sells two at the red house, so she has sold a total of 9+2=11 vacuums. If she sells the other half at the orange house, the remaining half is 1/2*5=2.5, so she has sold 2.5 at the orange house. In total, Melanie has sold 11+2.5=13.5 vacuums. Because vacuums must be whole numbers, she has sold 13 vacuums. She has 5 vacuums left, so she has 13+5=18 vacuums. The answer is 18.

Figure 5: A cherry-picked example of Llama 3.1's responses to the same question in English and Japanese, where the English answer is incorrect but the Japanese response is correct, illustrating the complementary reasoning skills across languages.

	en	fr	es	de	ru	zh	ja	th	avg.
					Aya-Expanse-8b				
CoT	76.6 ±1.1	65.1 ±2.0	73.0 ±1.8	68.8 ±1.9	67.6 ±2.5	63.7 ±0.8	57.7 ±1.2	19.7 ±1.8	61.5
SC	84.0	70.8	76.8	76.8	73.6	71.2	67.2	23.2	58.3
					Llama3.1-8b				
CoT	75.0±1.7	60.4±1.4	66.8±1.9	59.6±3.8	61.1±2.8	57.5±2.3	46.9±2.6	47.4±1.1	59.4
SC	84.8	72.4	80.0	74.0	74.0	69.6	58.8	59.2	71.6
					Ministral-8b				
CoT	77.4±1.5	65.1±0.7	71.4±1.3	64.9±1.8	65.4±0.8	58.8±1.7	43.8±1.9	44.5±1.1	61.4
SC	87.2	72.0	80.0	74.0	75.2	67.6	55.2	54.0	70.3
					Qwen2.5-7b				
CoT	84.3±1.0	70.2±1.8	76.3±2.3	63.8±1.2	69.0±1.7	67.8±1.7	63.7±1.4	51.8±1.3	68.4
SC	89.2	73.6	82.8	70.8	73.6	75.6	70.0	59.6	74.4
					Phi3-7b				
CoT	87.6±1.8	77.0±2.3	83.7±1.7	77.3±0.9	71.6±1.8	69.2±2.3	58.0±1.4	18.2±1.3	67.8
SC	92.8	84.4	88.4	83.6	82.8	74.4	65.6	23.6	74.2
					Llama3.2-3b				
CoT	65.6±1.1	51.0±2.7	56.4±1.0	52.4±1.1	53.1±2.4	48.8±2.1	32.0±1.7	44.1±1.9	50.4
SC	79.2	60.4	70.8	67.2	65.6	62.8	44.4	55.6	63.0

Table 2: Vanilla Chain-of-thought(CoT) performance and self-consistency (SC) on MGSM.

	en	fr	es	de	ru	zh	ja	th	avg.
Aya-Expanse-8b	94.4	85.6	90.8	89.2	87.6	84.4	82.4	44.4	82.3
Llama3.1-8b	94.8	85.2	92.4	89.2	92.0	86.8	74.8	80.0	86.9
Ministral-8b	94.4	85.6	91.6	85.2	86.4	86.4	73.2	71.6	84.3
Qwen2.5-7b	95.6	84.0	94.4	85.2	87.6	91.2	84.0	75.6	81.3
phi3-3b	96.4	92.0	95.6	90.8	92.0	88.4	84.8	42.0	85.3
Llama3.2-3b	91.6	78.8	85.6	83.2	82.8	80.8	66.0	73.6	80.3

Table 3: Comparison of Pass@8-Multi across different languages on the MGSM task.

	en	fr	es	de	ru	zh	ja	th	avg.
Aya-Expanse-8b	87.2	76.4	83.2	76.8	78.4	76.0	71.2	37.2	73.3
Llama3.1-8b	90.0	77.6	84.0	60.4	80.0	78.8	68.4	70.0	76.2
Ministral-8b	91.2	76.0	87.6	77.6	77.2	78.0	60.4	62.8	76.4
Qwen2.5-7b	92.8	80.0	86.4	74.8	82.4	85.2	76.0	72.4	81.3
Phi3-7b	94.0	86.8	91.2	86.0	84.0	83.2	75.6	35.2	79.5
Llama3.2-3b	83.2	70.0	76.4	62.4	75.2	70.8	56.8	67.2	70.3

Table 4: Comparison of Multi-ORM across different languages on the MGSM task.

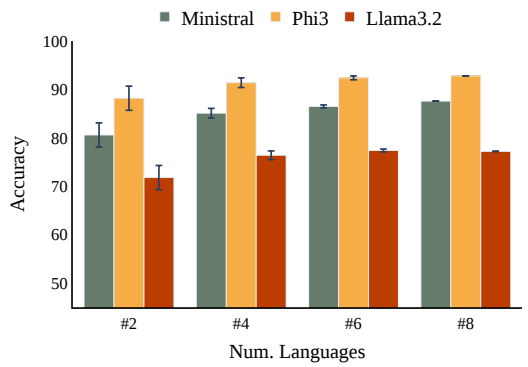

Figure 6: The average and standard deviation cross-lingual ORM performance using different numbers of languages.

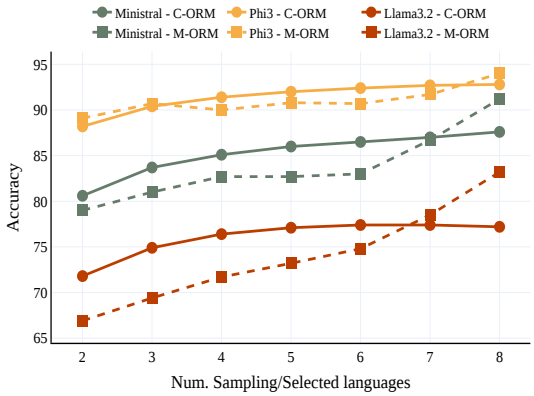

Figure 7: Comparing the accuracy of cross-lingual ORM and multilingual ORM of English using the same number of languages and samples.

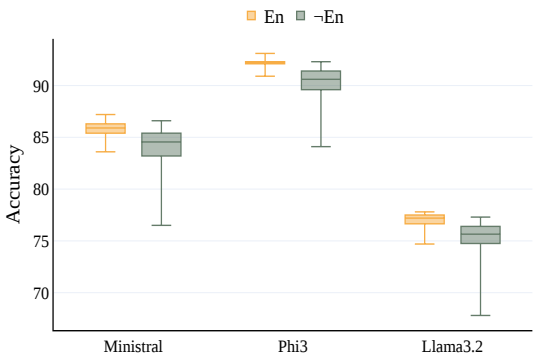

Figure 8: Comparing the role of English on the performance.