Better by Comparison: Retrieval-Augmented Contrastive Reasoning for Automatic Prompt Optimization

Juhyeon Lee*
Peking University
Beijing, China
juhyeonlee@pku.edu.cn

Wonduk Seo* Enhans Seoul, South Korea wonduk@enhans.ai Hyunjin An Enhans Seoul, South Korea hyunjin@enhans.ai Seunghyun Lee Enhans Seoul, South Korea seunghyun@enhans.ai Yi Bu† Peking University Beijing, China buyi@pku.edu.cn

Abstract-Automatic prompt optimization has recently emerged as a strategy for improving the quality of prompts used in Large Language Models (LLMs), with the goal of generating more accurate and useful responses. However, most prior work focuses on direct prompt refinement or model finetuning, overlooking the potential of leveraging LLMs' inherent reasoning capability to learn from contrasting examples. In this paper, we present Contrastive Reasoning Prompt Optimization (CRPO), a novel framework that formulates prompt optimization as a retrieval-augmented reasoning process. Our approach retrieves top-k reference prompts from the HelpSteer2 dataset, an open-source collection annotated for helpfulness, correctness, coherence, complexity, and verbosity, and constructs two complementary optimization paradigms: (1) tiered contrastive reasoning, where the LLM compares high-, medium-, and lowquality prompts to refine its own generation through reflective reasoning, and (2) multi-metric contrastive reasoning, where the LLM analyzes the best prompts along each evaluation dimension and integrates their strengths into an optimized prompt. By explicitly contrasting high- and low-quality exemplars, CRPO enables the model to deduce why certain prompts succeed while others fail, thereby achieving more robust and interpretable optimization. Experimental results on the HelpSteer2 benchmark demonstrate that CRPO significantly outperforms baselines. Our findings highlight the promise of contrastive, retrieval-augmented reasoning for advancing automatic prompt optimization.

Index Terms—Automatic Prompt Optimization, Contrastive Reasoning, Retrieval-Augmented Generation, Large Language Models (LLMs), Helpfulness Alignment.

I. INTRODUCTION

Large Language Models (LLMs) have demonstrated remarkable capabilities across a wide spectrum of natural language processing (NLP) tasks, including reasoning, summarization, and code generation. However, their performance is highly sensitive to the quality of the input prompt [1, 2]. As a result, automatic refining prompts to elicit better responses has become a critical research direction.

Early approaches to automatic prompt optimization explored continuous soft prompt tuning [3–5] or discrete search over token combinations [6–8]. While effective in scenarios with

The authors denoted as * have contributed equally to this work. Author order is determined alphabetically by first name.

access to model gradients (white-box settings), these methods are inapplicable to black-box LLMs (e.g., those accessed via API), where internal states are inaccessible. More recently, optimization has shifted toward black-box prompting methods, where models iteratively explore candidate prompts through trial-and-error [9, 10]. Representative frameworks include PromptAgent [11], which formulates prompt optimization as a Monte Carlo Tree Search planning problem to simulate human trial-and-error exploration; Hierarchical Multi-Agent Workflows (HMAW) [12], which adopt a CEO–Manager–Worker structure to decompose optimization into hierarchical roles; and MASS [13], which leverages topology optimization across multiple agents for selecting effective prompts.

Another line of work views LLMs themselves as optimizers. For instance, OPRO [14] treats prompt optimization as a natural language optimization task, where the LLM iteratively generates new solutions conditioned on previously evaluated prompts. Similarly, PromptBreeder [15] evolves a population of prompts through mutation and selection to improve robustness, and AMPO [16] applies a multi-branch structure that grows and prunes prompts like a tree.

Despite these advances, current methods share several key limitations: (1) They often optimize prompts in isolation, failing to learn from the comparative lessons offered by better and worse exemplars; (2) Many approaches also depend on handcrafted optimization pipelines, reducing their generality and scalability across domains; (3) Finally, most existing methods focus primarily on improving answer quality, often neglecting human-centered dimensions such as interpretability and usability, which are essential for practical deployment in real-world human–AI interaction.

To address these limitations, we introduce **Contrastive Reasoning Prompt Optimization (CRPO)**, a retrieval-augmented framework that explicitly leverages contrastive reasoning across prompts of varying quality. Instead of fine-tuning the LLM, our method retrieves top-k reference prompts from the HelpSteer2 dataset [17], which is an open-source benchmark annotated for helpfulness, correctness, coherence, complexity, and verbosity, and performs two novel optimization strategies: (1) *tiered contrastive reasoning*, where the model reflects

[†] denotes corresponding author.

on high-, medium-, and low-quality exemplars to refine its own generation, and (2) *multi-metric contrastive reasoning*, where the best prompts along individual metrics are analyzed and integrated into an optimized prompt. CPRO enhances prompt quality without requiring model parameter updates by reasoning explicitly about why certain prompts succeed and others fail.

Extensive experiments on HelpSteer2 show that CPO consistently outperforms our baselines, including (1) direct generation, (2) Chain-of-Thought prompting (CoT) [18], and simple retrieval-based augmentation. These results demonstrate the promise of contrastive, retrieval-augmented optimization for aligning LLM outputs toward more helpful, factually correct, and coherent responses.

II. DATASET

We conduct our experiments on the **HelpSteer2** dataset [17], a benchmark designed for evaluating prompt optimization and response helpfulness in Large Language Models (LLMs). The dataset consists of human-annotated prompt–response pairs and is divided into training and validation splits. Specifically, it contains a **training set of 20.3k rows** and a **validation set of 1.04k rows**, which we adopt for retrieval and evaluation, respectively.

Each prompt–response pair in HelpSteer2 is annotated across five evaluation dimensions. Scores for each attribute range from **0** (lowest) to **4** (highest), providing a fine-grained scale of response quality. These annotations capture diverse aspects of quality, making the dataset suitable for studying contrastive reasoning in prompt optimization.

Attribute	Description
Helpfulness	Overall helpfulness of the response to the prompt.
Correctness	Inclusion of all pertinent facts without errors.
Coherence	Consistency and clarity of expression.
Complexity	Intellectual depth required to write the response (e.g., basic
Verbosity	competency vs. domain expertise). Amount of detail included in the response relative to what is asked.

TABLE I: **HelpSteer2 Annotation Dimensions.** Five human-annotated metrics, each scored on a 0–4 scale.

III. METHODOLOGY

We formulate the problem of prompt optimization problem not as directly fine-tuning model parameters, but as a task that maximizes the inherent reasoning capability of LLMs by facilitating learning from reference examplars. Specifically, our framework **Contrastive Reasoning Prompt Optimization** (**CRPO**) first retrieves the top-k relevant prompts from the *HelpSteer2* training set, and then applies contrastive reasoning to construct optimized prompts. We design two complementary variants, illustrated in Figure 1.

A. Retrieval of Reference Prompts

Given an input query q, CRPO retrieves a set of reference prompts $\{p_1, \ldots, p_k\}$ using a retriever:

$$\mathcal{R}(q) = \{p_1, \dots, p_k\}, \quad p_i \in \text{HelpSteer2.}$$
 (1)

Each p_i is annotated along five evaluation dimensions $\mathcal{M} = \{\text{help, corr, coh, comp, verb}\}$. To ensure sufficient coverage across all dimensions, we require $k \geq 5$, so that at least one candidate prompt is available per metric. These exemplars serve as contrasting cases that enable the LLM to perform explicit reasoning.

B. Variant 1: Tiered Contrastive Reasoning

We partition $\mathcal{R}(q)$ into three tiers according to overall quality scores. Specifically, for each retrieved prompt p_i , we compute its average score across all five evaluation dimensions:

$$Avg(p_i) = \frac{1}{|\mathcal{M}|} \sum_{m \in \mathcal{M}} Score(p_i, m), \tag{2}$$

where $\mathcal{M} = \{\text{help, corr, coh, comp, verb}\}$. Prompts are then partitioned into high-quality (P^H) , medium-quality (P^M) , and low-quality (P^L) tiers based on quantile thresholds of $\operatorname{Avg}(p_i)$. The optimized prompt p^* is generated via contrastive reasoning:

$$p^* = f_{\theta}(\text{Reflect}(P^H, P^M, P^L)), \tag{3}$$

where f_{θ} is the LLM and Reflect(·) instructs the model to (i) avoid weaknesses in P^L , (ii) adopt strengths from P^H , and (iii) use P^M as a stabilizing anchor that reduces bias. In particular, incorporating P^M prevents overfitting to extreme cases, ensuring balanced refinement that maintains robustness while still progressing toward high-quality prompts.

C. Variant 2: Multi-Metric Contrastive Reasoning

For each metric $m \in \mathcal{M}$, we select the top prompt:

$$P^m = \arg\max_{p_i \in \mathcal{R}(q)} \mathbf{Score}(p_i, m).$$

The optimized prompt is then constructed as:

$$p^* = f_{\theta} \left(\text{Integrate}(P^{\text{help}}, P^{\text{corr}}, P^{\text{coh}}, P^{\text{comp}}, P^{\text{verb}}) \right), \tag{4}$$

where $Integrate(\cdot)$ encourages the LLM to combine complementary strengths across evaluation axes.

D. Evaluation Method

Effectiveness is assessed by directly feeding the original prompt p and the optimized prompt p^* into the evaluation model \mathcal{E} as a pair. The evaluation model then outputs comparative scores across the five annotated dimensions \mathcal{M} :

$$Score(p, p^*) = [s_{help}, s_{corr}, s_{coh}, s_{comp}, s_{verb}],$$
 (5)

where each $s_m \in [0, 4]$ for $m \in \mathcal{M}$.

To ensure consistency, these raw scores are normalized to the [0,1] range and aggregated as described in Section 4. Improvements are thus attributed to contrastive reasoning in

¹Detailed implementations of baselines are detailed in Section IV.

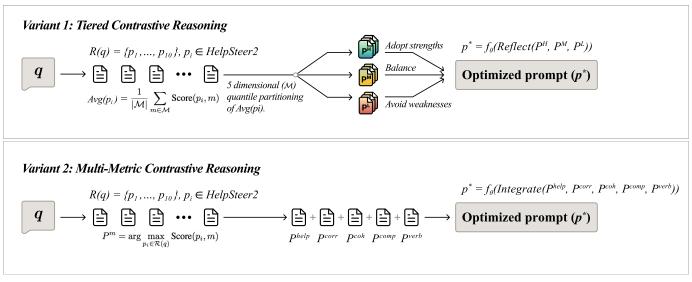


Fig. 1: Overview of CRPO: The framework of CRPO-Tiered Contrastive Reasoning(top) and CRPO-Multi-Metric Contrastive Reasoning(bottom).

CRPO, since the evaluation model judges p^* relative to p under identical conditions.

Algorithm 1 Contrastive Reasoning Prompt Optimization

Require: Query q, Retriever \mathcal{R} , LLM f_{θ} , Evaluation Model \mathcal{E} , Metrics \mathcal{M} , Top-k

// Retrieval Stage

- 1: Retrieve prompts: $\mathcal{R}(q) = \{p_1, \dots, p_k\}$ // Variant 1: Tiered Contrastive Reasoning
- 2: Partition $\mathcal{R}(q)$ into P^H, P^M, P^L 3: $p_{\text{tier}}^* \leftarrow f_{\theta}(\text{Reflect}(P^H, P^M, P^L))$ // Variant 2: Multi-Metric Contrastive Reasoning
- 4: for each metric $m \in \mathcal{M}$ do
- $P^m \leftarrow \arg\max_{p_i \in \mathcal{R}(q)} \operatorname{Score}(p_i, m)$
- 6: end for
- 7: $p_{\text{metric}}^* \leftarrow f_{\theta}(\text{Integrate}(P^m, \forall m \in \mathcal{M}))$ // Evaluation
- 8: Evaluate: Score(\hat{y}) = $\mathcal{E}(p, p^*)$

IV. EXPERIMENTS

A. Setup

We conduct experiments on the *HelpSteer2* dataset to evaluate the effectiveness of our proposed Contrastive Reasoning Prompt Optimization (CRPO). All experiments are designed to ensure fairness in comparison with baseline methods by using the same retrieval pool and evaluation settings.

- 1) LLM and Retrieval Models: For generations, we utilize two representative large language models:
 - GPT-40 [19]: accessed via API, configured with temperature = 0 to ensure deterministic outputs. All other hyperparameters are kept at their default settings.
 - LLaMA 3-8B [20]: an open-source instruction-tuned model, also set with temperature = 0 for reproducibility.

For retrieval, we adopt the BM25 retriever, which selects top-k reference prompts $\{p_1,\ldots,p_k\}$ for each query. We set k = 10 across all experiments, ensuring sufficient coverage across the 5 evaluation dimensions while maintaining efficiency.

- 2) Evaluation Model: For evaluation, we adopt the ArmoRM-Llama3-8B-v0.1 reward model [21], a recently proposed interpretable multi-objective reward model that leverages absolute ratings across human-interpretable dimensions. ArmoRM has demonstrated superior performance on the benchmark dataset, achieving over 90\% accuracy and ranking among the top reward models available. We adopt ArmoRM as the automatic judge for assessing the quality of generated responses.
- 3) Evaluation Metrics: Each response in the HelpSteer2 dataset is annotated across 5 dimensions, with scores ranging from 0 to 4. To normalize across dimensions, we first scale each score by dividing by 4, mapping it to the range [0, 1].

Formally, for a given response \hat{y} , the normalized score is computed as:

$$Score(\hat{y}) = \frac{1}{|\mathcal{M}|} \sum_{m \in \mathcal{M}} \frac{s_m(\hat{y})}{4}, \tag{6}$$

where $s_m(\hat{y})$ denotes the raw score of \hat{y} under metric m. This yields a final evaluation score between 0 and 1, reflecting the overall quality of a response by equally weighting all dimensions.

- 4) Baselines: We compare CRPO against three representative baselines:
 - Direct Generation: the LLM generates a response directly from the query without any retrieval or optimiza-
 - **Chain-of-Thought** (CoT): the LLM is instructed to reason step-by-step before producing a final response.

Model	Helpfulness	Correctness	Coherence	Complexity	Verbosity	Avg. Score
GPT-4o						
Direct Generation	0.3655	0.4349	0.7669	0.4050	0.6638	0.5272
Chain-of-Thought (CoT)	0.3660	0.4329	0.7675	0.3998	0.6666	0.5266
Retrieval Augmented Generation (RAG)	0.4903	0.5745	0.8642	0.4161	0.6567	0.6003
CRPO-Tiered Contrastive Reasoning [†]	0.5253	0.6065	0.8817	0.4474	0.7168	0.6355
CRPO-Multi-Metric Contrastive Reasoning [†]	0.5158	0.5964	0.8758	0.4316	0.6780	0.6195
LLaMA 3-8B						•
Direct Generation	0.3438	0.4101	0.7526	0.4025	0.6602	0.5138
Chain-of-Thought (CoT)	0.3432	0.4067	0.7554	0.4107	0.6657	0.5163
Retrieval Augmented Generation (RAG)	0.3422	0.4161	0.7607	0.4003	0.6492	0.5137
CRPO-Tiered Contrastive Reasoning [†]	0.4224	0.5023	0.8092	0.4243	0.6685	0.5654
CRPO-Multi-Metric Contrastive Reasoning [†]	0.3990	<u>0.4711</u>	0.7989	<u>0.4172</u>	0.6564	<u>0.5485</u>

TABLE II: Comparison across five evaluation metrics—helpfulness, correctness, coherence, complexity, and verbosity—and their mean (*Avg. Score*). Results are reported separately for GPT-40 and LLaMA-3-8B. The best value within each language model is **bold**, the second best is underlined, and methods marked with † denote our proposed CRPO variants.

• Retrieval-Augmented Generation (RAG): the LLM receives the query along with the top-k retrieved prompts (with k = 10, for fair comparison).

To ensure fairness, all methods are evaluated using the same retrieval pool and judged by the same evaluation model. The quality of generated responses is mapped to the metrics provided in *HelpSteer2*, which includes five dimensions: helpfulness, correctness, coherence, complexity, and verbosity.

B. Main Experiment Results

Baseline methods demonstrate modest, albeit limited improvements. Direct generation often produces shallow or inconsistent outputs, since no external context is used. Chain-of-Thought (CoT) prompting encourages stepwise reasoning but tends toward verbosity and repetition without improving factuality. Retrieval-Augmented Generation (RAG) provides contextual grounding through exemplars, but introduces redundancy and lacks a clear mechanism to filter high-quality signals. Thus, while baselines improve over the previous ones, they remain insufficient for producing balanced prompts.

In contrast, CRPO addresses these shortcomings through explicit contrastive reasoning. The multi-metric variant integrates the strongest exemplars along helpfulness, correctness, coherence, complexity, and verbosity, ensuring complementary strengths are preserved. The tiered variant contrasts high, medium-, and low-quality prompts, adopting strengths from the best, avoiding weaknesses from the worst, and stabilizing with medium-quality anchors. Together, these strategies yield prompts that are more robust, interpretable, and human-aligned than those produced by direct generation, CoT, or RAG.

C. Ablation studies

1) Trimaximal-Prompt Selection (TPS): To assess the role of contrastive reasoning, we conduct an ablation where CRPO is reduced to using only the top-3 highest-ranked prompts, without tiered or multi-metric reasoning. As shown in Figure 2, this simplified method performs worse across evaluation metrics, confirming that simple ranking is insufficient.

In contrast, both CRPO variants consistently outperform the ablated setting by explicitly reasoning over contrasts—adopting strengths from high-quality prompts, avoiding weaknesses from low-quality ones, and integrating complementary aspects across dimensions. This result shows that the gains of CRPO stem not from retrieval alone, but from its reflective reasoning process, which yields more stable and interpretable optimization.

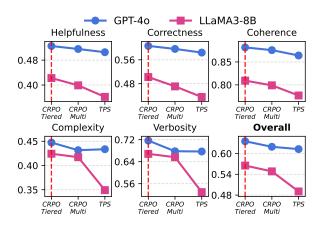


Fig. 2: **Ablation 1.** Performance comparison of the simplified method vs CRPO variants. **Overall** stands for the average score of 5 metrics.

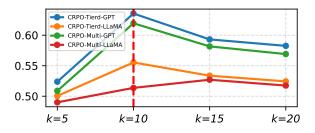


Fig. 3: **Ablation 2.** Overall score comparison across Top-K settings in the RAG stage of CRPO, averaged over five metrics.

2) Optimal K validation: To identify the optimal evidence of retrieved pool size in our RAG framework, we evaluate CRPO with $k \in \{5, 10, 15, 20\}$. As shown in Figure 3, performance improves when moving from a small evidence set to a moderate pool, but declines as the pool grows further. Fixing k=10 yields the best trade-off between evidence diversity and inference cost, producing the most stable gains across language models and CRPO variants. This suggests the same phenomenon occurs regardless of model type, and in a limited context, overstretching the evidence tends to degrade the performance. Accordingly, we set the default Top-K to k=10.

V. CONCLUSION & LIMITATIONS

In this paper, we introduced **Contrastive Reasoning Prompt Optimization (CRPO)**, a retrieval-augmented framework that improves prompt quality through tiered and multimetric contrastive reasoning. By explicitly reflecting on high, medium-, and low-quality prompts, as well as integrating strengths across multiple evaluation dimensions, CRPO enables LLMs to generate more robust and human-aligned outputs without fine-tuning. Experimental results on the Help-Steer2 dataset show that CRPO consistently outperforms baselines, including direct generation, CoT prompting, and simple retrieval augmentation, with ablation studies confirming the central role of contrastive reasoning in these gains.

While CRPO effectively enhances prompt optimization through tiered and multi-metric contrastive reasoning, several limitations remain. First, CRPO's performance is tied to the *HelpSteer2* dataset; while richly annotated, it may not generalize to all domains or user interaction styles encountered in practice. Second, CRPO operates in a single-turn setting, leaving its extension to multi-turn or task-specific dialogue scenarios unexplored. Third, our method leverages general-purpose retrieval (BM25), and future work could examine whether neural or hybrid retrievers provide further gains. Finally, CRPO's evaluation depends on a reward model; thus, complementary human qualitative analysis would provide deeper insights into interpretability and practical usefulness.

REFERENCES

- [1] Z. Zhao, E. Wallace, S. Feng, D. Klein, and S. Singh, "Calibrate before use: Improving few-shot performance of language models," in *International conference on machine learning*, pp. 12697–12706, PMLR, 2021.
- [2] Y. Lu, M. Bartolo, A. Moore, S. Riedel, and P. Stenetorp, "Fantastically ordered prompts and where to find them: Overcoming few-shot prompt order sensitivity," *arXiv* preprint arXiv:2104.08786, 2021.
- [3] B. Lester, R. Al-Rfou, and N. Constant, "The power of scale for parameter-efficient prompt tuning," *arXiv* preprint arXiv:2104.08691, 2021.
- [4] X. L. Li and P. Liang, "Prefix-tuning: Optimizing continuous prompts for generation," *arXiv* preprint *arXiv*:2101.00190, 2021.

- [5] E. J. Hu, Y. Shen, P. Wallis, Z. Allen-Zhu, Y. Li, S. Wang, L. Wang, W. Chen, *et al.*, "Lora: Low-rank adaptation of large language models.," *ICLR*, vol. 1, no. 2, p. 3, 2022.
- [6] T. Shin, Y. Razeghi, R. L. Logan IV, E. Wallace, and S. Singh, "Autoprompt: Eliciting knowledge from language models with automatically generated prompts," arXiv preprint arXiv:2010.15980, 2020.
- [7] M. Deng, J. Wang, C.-P. Hsieh, Y. Wang, H. Guo, T. Shu, M. Song, E. P. Xing, and Z. Hu, "Rlprompt: Optimizing discrete text prompts with reinforcement learning," arXiv preprint arXiv:2205.12548, 2022.
- [8] T. Zhang, X. Wang, D. Zhou, D. Schuurmans, and J. E. Gonzalez, "Tempera: Test-time prompting via reinforcement learning," *arXiv preprint arXiv:2211.11890*, 2022.
- [9] Y. Zhou, A. I. Muresanu, Z. Han, K. Paster, S. Pitis, H. Chan, and J. Ba, "Large language models are human-level prompt engineers," in *The eleventh international conference on learning representations*, 2022.
- [10] R. Pryzant, D. Iter, J. Li, Y. T. Lee, C. Zhu, and M. Zeng, "Automatic prompt optimization with" gradient descent" and beam search," *arXiv preprint arXiv:2305.03495*, 2023.
- [11] X. Wang, C. Li, Z. Wang, F. Bai, H. Luo, J. Zhang, N. Jojic, E. P. Xing, and Z. Hu, "Promptagent: Strategic planning with language models enables expert-level prompt optimization," arXiv preprint arXiv:2310.16427, 2023.
- [12] Y. Liu, J. Singh, G. Liu, A. Payani, and L. Zheng, "Towards hierarchical multi-agent workflows for zero-shot prompt optimization," arXiv preprint arXiv:2405.20252, 2024.
- [13] H. Zhou, X. Wan, R. Sun, H. Palangi, S. Iqbal, I. Vulić, A. Korhonen, and S. Ö. Arık, "Multi-agent design: Optimizing agents with better prompts and topologies," *arXiv* preprint arXiv:2502.02533, 2025.
- [14] C. Yang, X. Wang, Y. Lu, H. Liu, Q. V. Le, D. Zhou, and X. Chen, "Large language models as optimizers," in *The Twelfth International Conference on Learning Representations*, 2023.
- [15] C. Fernando, D. Banarse, H. Michalewski, S. Osindero, and T. Rocktäschel, "Promptbreeder: Self-referential self-improvement via prompt evolution," arXiv preprint arXiv:2309.16797, 2023.
- [16] S. Yang, Y. Wu, Y. Gao, Z. Zhou, B. B. Zhu, X. Sun, J.-G. Lou, Z. Ding, A. Hu, Y. Fang, et al., "Ampo: Automatic multi-branched prompt optimization," arXiv preprint arXiv:2410.08696, 2024.
- [17] Z. Wang, Y. Dong, O. Delalleau, J. Zeng, G. Shen, D. Egert, J. Zhang, M. N. Sreedhar, and O. Kuchaiev, "Helpsteer 2: Open-source dataset for training topperforming reward models," *Advances in Neural Information Processing Systems*, vol. 37, pp. 1474–1501, 2024.
- [18] J. Wei, X. Wang, D. Schuurmans, M. Bosma, F. Xia, E. Chi, Q. V. Le, D. Zhou, et al., "Chain-of-thought prompting elicits reasoning in large language models,"

- Advances in neural information processing systems, vol. 35, pp. 24824–24837, 2022.
- [19] J. Achiam, S. Adler, S. Agarwal, L. Ahmad, I. Akkaya, F. L. Aleman, D. Almeida, J. Altenschmidt, S. Altman, S. Anadkat, et al., "Gpt-4 technical report," arXiv preprint arXiv:2303.08774, 2023.
- [20] H. Touvron, T. Lavril, G. Izacard, X. Martinet, M.-A. Lachaux, T. Lacroix, N. G. Baptiste Rozière, E. Hambro, F. Azhar, A. Rodriguez, A. Joulin, E. Grave, and G. Lample, "Llama: Open and efficient foundation language models." arXiv preprint, 2023.
- [21] H. Wang, W. Xiong, T. Xie, H. Zhao, and T. Zhang, "Interpretable preferences via multi-objective reward modeling and mixture-of-experts," *arXiv preprint* arXiv:2406.12845, 2024.