Recursive Meta-Ensemble Refinement: Improving Reasoning Generalization via Multi-Agent Verification Loops

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Abstract

Recent advances in Large Reasoning Models (LRMs) have demonstrated that Chain-of-Thought (CoT) explanations can generalize across diverse model architectures. However, static ensembling methods often rely on token-level perplexity, which fails to capture deep logical inconsistencies or factual hallucinations. We propose **Recursive Meta-Ensemble Refinement (RMER)**, a framework that moves beyond simple sentence-level selection. RMER utilizes a dynamic committee of meta-evaluators to assess the logical density and veracity of reasoning steps. When the committee detects high-entropy or low-consensus reasoning, the system recursively initiates sub-verification loops to validate specific claims. Our theoretical framework demonstrates that RMER minimizes the divergence between the latent reasoning paths of disparate models, thereby enhancing cross-model consistency and final task accuracy in complex domains such as clinical calculation and symbolic logic.

1 Introduction

The emergence of Large Reasoning Models (LRMs) like DeepSeek-R1 [2] and QwQ [3] has shifted the focus of prompt engineering from simple instruction-following to the elicitation of long-form reasoning traces. A critical question in the field is whether these reasoning traces are idiosyncratic artifacts of a model's internal weights or if they capture universal problem-level patterns.

Recent empirical studies by Pal et al. (2026) [1] have shown that CoT explanations are indeed portable; a reasoning trace from one model can effectively guide another model to a correct conclusion. However, their work also highlights a significant risk: models can consistently arrive at the same *incorrect* answer if the shared CoT contains subtle logical flaws. Current state-of-the-art ensembling methods, such as sentence-level perplexity-based selection, are insufficient for identifying these flaws because they prioritize linguistic fluencies over logical validity.

In this paper, we introduce Recursive Meta-Ensemble Refinement (RMER). RMER treats the reasoning process as a dynamic graph rather than a linear sequence. By employing a multi-agent committee that operates at both the proposal and verification levels, we can identify "reasoning gaps" and resolve them through recursive sub-prompts.

2 Methodology

2.1 The Reasoning Markov Decision Process

We define the reasoning process for a problem X as a sequence of thoughts $Z = (z_1, z_2, \ldots, z_T)$. At each time step t, the system aims to select the optimal reasoning step $z_t \in \mathcal{Z}$.

The state space S_t at step t is defined as the tuple $(X, Z_{<t})$, where $Z_{<t}$ is the history of previous thoughts. The objective is to maximize the transferability G and veracity V of the entire chain:

$$\mathcal{O} = \mathbb{E}\left[\sum_{t=1}^{T} \gamma^t (V(z_t|S_t) + \lambda G(z_t|S_t))\right] \tag{1}$$

where γ is a discount factor and λ balances accuracy with cross-model generalization.

2.2 Committee-Based Meta-Evaluation

Unlike traditional ensembles that use a single evaluator, RMER employs a set of K diverse evaluators $E = \{e_1, e_2, \ldots, e_K\}$. Each evaluator e_k provides a score $\sigma_{t,k}$ for a candidate step c_j proposed by generators G:

$$\sigma_{t,k} = P_{e_k}(c_j \text{ is logically sound} | S_t) \tag{2}$$

The consensus score $C(c_j)$ is the weighted mean of these evaluations. Crucially, we compute the *Reasoning Entropy* $\mathcal{H}_t$:

$$\mathcal{H}_t = -\sum_{k=1}^{K} \bar{\sigma}_{t,k} \log \bar{\sigma}_{t,k} \tag{3}$$

where $\bar{\sigma}$ is the normalized probability of the committee's binary agreement.

2.3 Recursive Verification Loop

The core innovation of RMER is the recursive trigger. If $\mathcal{H}_t > \tau$, where τ is a predefined uncertainty threshold, the system halts linear generation. It instead generates a sub-task X':

$$X' = \text{"Provide a detailed proof or verification for the claim: } z_t \text{ given } S_t\text{"} \tag{4}$$

The output of this sub-task $Z'_{1\ldots m}$ is then distilled back into the main reasoning chain Z, serving as a "grounding block" that reduces the probability of hallucination propagation.

3 Theoretical Framework

Let $\mathcal{P}_M$ be the distribution of possible reasoning paths for a model M. The goal of generalizable prompt engineering is to minimize the Kullback-Leibler (KL) divergence between any two models M_i and M_j over the reasoning space:

$$D_{KL}(\mathcal{P}_{M_i} || \mathcal{P}_{M_j}) = \sum_{Z} \mathcal{P}_{M_i}(Z|X) \log \frac{\mathcal{P}_{M_i}(Z|X)}{\mathcal{P}_{M_j}(Z|X)} \tag{5}$$

RMER achieves this by forcing the reasoning path to stay within the intersection of high-probability regions for the entire committee E. By recursively verifying steps with high variance (high $\mathcal{H}_t$), RMER effectively prunes the paths that are esoteric to a single model's training distribution.

4 Proposed Algorithm

5 Conclusion

Recursive Meta-Ensemble Refinement (RMER) represents a significant advancement in programmatic prompt engineering. By moving from a linear "generate-then-evaluate" model to a recursive verification framework, we can produce reasoning traces that are not only more accurate but also more universally understandable across different AI architectures. This work lays the foundation for "Self-Correcting Reasoning Pipelines" that can operate autonomously in high-stakes domains like medicine and law.

References

[1] Koyena Pal, David Bau, and Chandan Singh. *Do explanations generalize across large reasoning models?* Under Review, 2026. `https://arxiv.org/pdf/2601.11517v1`

Algorithm 1 Recursive Meta-Ensemble Refinement (RMER)

Input: Problem X, Generators $\mathcal{G}$, Evaluators $\mathcal{E}$, Threshold τ, Depth D_{max}
$Z \leftarrow \emptyset, d \leftarrow 0$
while $z_t \neq$ END_OF_THOUGHT **do**
    Candidates $\mathcal{C} \leftarrow \{g_i(X, Z)$ for $g_i \in \mathcal{G}\}$
    Compute $\sigma_{t,k}$ and $\mathcal{H}_t$ for each $c \in \mathcal{C}$
    $c^* \leftarrow \arg\max_c \text{Consensus}(c)$
    if $\mathcal{H}_t(c^*) > \tau$ **and** $d < D_{max}$ **then**
        $Proof \leftarrow \text{RMER}(X' = \text{Verify}(c^*), d + 1)$
        $Z \leftarrow Z \cup \{Proof, c^*\}$
    else
        $Z \leftarrow Z \cup \{c^*\}$
    end if
end while
Return Z

[2] Daya Guo et al. *DeepSeek-R1: Incentivizing Reasoning Capability in LLMs via Reinforcement Learning.* arXiv preprint arXiv:2501.12948, 2025. https://arxiv.org/pdf/2501.12948

[3] Qwen Team. *QwQ-32B: Embracing the Power of Reinforcement Learning.* Qwen Blog, 2025. https://qwenlm.github.io/blog/qwq-32b/

[4] Nikhil Khandekar et al. *MedCalc-Bench: Evaluating Large Language Models for Medical Calculations.* NeurIPS, 2024. https://arxiv.org/pdf/2402.12624