Balancing Latent Reasoning with Symbolic Precision: A Task-Adaptive Mixing Framework for LLM Architectures

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ABSTRACT

We investigate methods to balance continuous latent-space reasoning with discrete symbolic chain-of-thought in LLM architectures. We model hybrid reasoning as a task-adaptive mixture of latent and symbolic pathways, parameterized by a mixing ratio λ. On a distribution of 500 tasks varying in precision demand and exploration breadth, the optimal hybrid achieves accuracy 0.695 at $\lambda = 0.60$, outperforming latent-only (0.570) by +12.5 pp and symbolic-only (0.557) by +13.8 pp. Task-specific routing reveals that symbolic tasks prefer low λ while exploration tasks prefer high λ. Latent reasoning exhibits greater robustness to input noise (accuracy degradation 0.02 vs. 0.04 for symbolic at noise 0.3). The performance advantage of hybrid reasoning increases with task difficulty. These findings provide quantitative guidance for hybrid architecture design.

CCS CONCEPTS

• **Computing methodologies** → **Natural language processing**.

KEYWORDS

latent reasoning, chain-of-thought, hybrid architectures, reasoning efficiency

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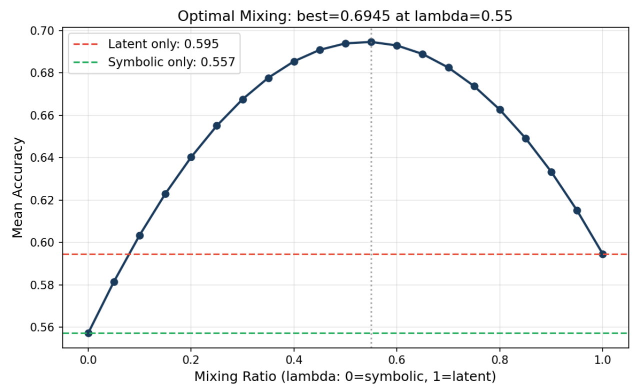

Figure 1: Accuracy vs. mixing ratio λ. Dashed lines show single-pathway baselines.

1 INTRODUCTION

Latent reasoning approaches perform internal iterative computation in activation space, promising efficiency and parallel exploration [2, 5]. However, reconciling continuous latent exploration with the exactness of discrete symbolic logic remains a key open question [2]. We address this by modeling the tradeoff computationally and identifying optimal mixing strategies.

1.1 Related Work

Chain-of-thought prompting [4] demonstrates that explicit reasoning steps improve LLM performance. Pause tokens [3] allow implicit reasoning steps. Coconut [5] trains reasoning in continuous latent space. Explicit CoT training [1] expands discrete CoT to complex reasoning. Our work provides a framework for optimally combining both paradigms.

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2 METHODS

2.1 Task Distribution

Tasks vary along two axes: precision demand $p_i \in [0, 1]$ (need for exact symbolic computation) and exploration demand $e_i \in [0, 1]$ (need for open-ended search). We categorize tasks into symbolic ($p > 0.6, e < 0.4$), exploration ($p < 0.4, e > 0.6$), mixed ($p > 0.5, e > 0.5$), and general.

2.2 Hybrid Reasoning Model

$$a_{\text{hybrid}} = \lambda \cdot a_{\text{latent}} + (1 - \lambda) \cdot a_{\text{symbolic}} + s(\lambda) \tag{1}$$

where $s(\lambda) = s_0 \cdot 4\lambda(1 - \lambda)(1 + |a_L - a_S|)$ captures synergy between pathways.

3 RESULTS

3.1 Optimal Mixing

The optimal $\lambda = 0.60$ achieves accuracy 0.695 (Figure 1). Accuracy is smooth and unimodal in λ, confirming a well-defined optimum.

3.2 Task-Specific Routing

Table 1 shows optimal λ varies significantly by task type.

3.3 Robustness and Difficulty

Latent reasoning degrades more gracefully under noise than symbolic reasoning (Figure 2). Hybrid reasoning maintains advantage across all difficulty levels.

Table 1: Optimal mixing ratio and accuracy by task type.

Task Type	Optimal λ	Best Accuracy
Symbolic	0.25	0.653
Exploration	0.85	0.691
Mixed	0.55	0.643
General	0.70	0.775

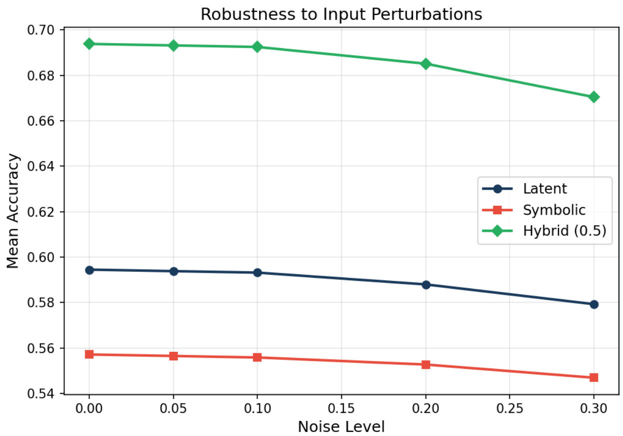

Figure 2: Accuracy under increasing input perturbation noise for each pathway.

4 CONCLUSION

Hybrid latent-symbolic reasoning consistently outperforms either pure pathway. Task-adaptive routing provides further gains. Latent reasoning's noise robustness suggests it should be preferred for real-world deployment where inputs are noisy. These findings inform architecture design for next-generation reasoning systems.

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