Project Proposal

Adaptive Reasoning: Optimizing Efficiency and Accuracy via a Hybrid Chain-of-Thought and Tree-of-Thought Framework

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Abstract

Large Language Models (LLMs) demonstrate strong reasoning abilities using prompting strategies such as Chain-of-Thought (CoT) and Tree-of-Thought (ToT). While ToT provides superior accuracy through multi-path exploration, it is computationally expensive. CoT, although efficient, struggles with complex reasoning tasks. This project proposes an **Adaptive Hybrid Framework** that dynamically switches between CoT and ToT based on problem complexity. A lightweight *Router Model* is trained to classify tasks as "Easy" or "Hard," enabling the system to select the optimal reasoning strategy. The framework will be evaluated on standard math reasoning benchmarks to establish improved trade-offs between accuracy and computational cost.

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I. Introduction

Advanced prompting techniques such as CoT and ToT have transformed multi-step reasoning in LLMs.

- **CoT** produces a linear reasoning chain suitable for straightforward tasks.
- **ToT** explores multiple reasoning branches and self-evaluates, yielding higher performance for difficult problems but with significant computational overhead.

However, the absence of an adaptive mechanism leads to inefficiency, as using a single strategy for all tasks is suboptimal. This project addresses this limitation by proposing a hybrid framework that predicts task difficulty and chooses the appropriate reasoning method to optimize inference time, accuracy, and token usage.

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II. Problem Statement and Objectives

Problem Statement

ToT achieves high accuracy but requires excessive computation, whereas CoT is efficient but fails on harder problems. A unified solution is needed to balance these strengths and weaknesses.

Objectives

1. **Benchmark CoT vs. ToT** on math reasoning datasets.
2. **Develop a Router Model** capable of classifying “Easy” vs. “Hard” problems.
3. **Evaluate the Hybrid System** to show near-ToT accuracy with reduced computational cost.

III. Methodology

A. Datasets

The system will be evaluated using math word-problem datasets:

- GSM8K
- SVAMP
- Math23K
- MGSM
  These datasets provide coverage across robustness, generalization, and multilingual settings.

B. Baseline Models

- LLaMA-3 (Groq API) for inference
- GPT-4 for ground-truth reasoning generation

C. Proposed Hybrid Framework

The project involves three main phases:

1. **Phase 1: Data Labeling**
   - Run CoT and ToT on the training set.
   - Label tasks as *Easy* if CoT succeeds; *Hard* if ToT succeeds but CoT fails.
2. **Phase 2: Router Training**
   - Train a lightweight model (e.g., DistilBERT or Feed-Forward Network) to classify tasks.
3. **Phase 3: Adaptive Inference**
   - Input → Router → Strategy Selection (CoT or ToT) → Final Answer.

This dynamic selection is the core contribution of the project.

IV. Evaluation Metrics

Evaluation will be performed using:

1. **Accuracy** – percentage of correctly solved problems.
2. **Efficiency** – measured via inference time and token cost.
3. **Faithfulness** – alignment of the reasoning steps with ground-truth solutions.

V. Expected Outcomes

The expected contributions include:

1. A comparative analysis demonstrating limitations of using CoT or ToT alone.
2. A functional Router Model capable of difficulty classification.
3. A Hybrid System achieving near-ToT accuracy while reducing computational cost by **40–50%**.

VI. Project Timeline

Week	**Task**
1–2	Literature review & dataset labeling
3–4	Baseline evaluation (CoT vs. ToT)
5–6	Router model training
7–8	Final testing & report writing

VII. Conclusion

This project introduces a scalable and adaptive reasoning framework for LLMs by combining the efficiency of CoT with the depth of ToT. The proposed hybrid approach aims to significantly improve performance on mathematical reasoning tasks while minimizing computational overhead. The findings are expected to provide meaningful contributions to future LLM reasoning research.