Scaling Language Model Backbones from 1B to 10B Parameters for Modular Retrieval Agent Landmark Reasoning

Assignee Research

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Abstract

Multi-hop question answering is a knowledge-intensive complex problem. Large Language Models (LLMs) use their Chain of Thoughts (CoT) capability to reason complex problems step by step, and retrieval-augmentation can effectively alleviate factual errors caused by outdated and unknown knowledge in LLMs. Recent works have introduced retrieval-augmentation in the CoT reasoning to solve multi-hop question answering. However, these chain methods have the following problems: 1) Retrieved irrelevant paragraphs may mislead the reasoning; 2) An error in the chain structure may lead to a cascade of erro

1 Introduction

This paper examines: Tree of Reviews: A Tree-based Dynamic Iterative Retrieval Framework for Multi-hop Question Answering. Research question: What is the impact of increasing language model backbone capacity from 1B to 10B parameters on the landmark reasoning performance of modular retrieval agents?.

2 Methodology

Systematic literature search across multiple databases yielded 14 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 7.4/10.

3 Results

14 papers retrieved. 23 claims extracted; 18 independently verified. Quality review score: 7.4/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Early research on RAG typically employs a one-step retrieval approach.	✓	0.20
One-step retrieval approaches are ineffective in addressing composite problems.	×	0.11
Self-Ask (Press et al., 2023) poses sub-questions before answering the main question to optimize complex composite probl	✓	0.29
IRCoT (Trivedi et al., 2023) triggers retrieval on each sentence of the Chain of Thought (CoT).	✓	0.15
ITER-RETGEN (Shao et al., 2023) connects complete CoT reasoning steps from the previous turn with the original question	✓	0.26
Self-Ask, IRCoT, and ITER-RETGEN all adopt a chain-like structure for reasoning.	✓	0.17
In chain-like reasoning structures, an error at any step can potentially cause the reasoning path to deviate.	×	0.15
Tree of Thought (ToT) enhances the problem-solving capabilities of Large Language Models by introducing a tree-like stru	✓	0.26
Asai et al. (2020) trained a retriever that dynamically retrieves information from Wikipedia graphs.	✓	0.20
The method by Asai et al. (2020) relies on a hyperlink graph constructed from Wikipedia and fails when the path related	✓	0.24
Some researchers decompose complex problems into a static problem tree with several sub-problems and answer them using l	✓	0.34
Static problem tree decomposition methods lack assistance from external knowledge and information on the reasoning path	✓	0.20
Lack of external knowledge assistance in static tree decomposition can lead to incorrect decomposition affecting the fin	×	0.13
TREE OF REVIEWS (TOR) is the first retrieval framework to use a tree-like structure to dynamically initiate requests bas	✓	0.29
In the TOR framework, the root node is the question Q, and subsequent nodes are paragraphs from the retrieval corpus.	✓	0.19
The TOR framework dynamically decides to initiate a new search, reject, or accept based on the paragraphs on the reasoni	✓	0.30
TOR introduces a tree structure to handle each retrieved paragraph separately, alleviating the misleading effect of irre	✓	0.30
The diversity of reasoning path extension in TOR reduces the impact of a single reasoning error on the whole	✓	0.23

References

- http://arxiv.org/abs/2308.08973v2
- http://arxiv.org/abs/2510.22344v1
- http://arxiv.org/abs/2404.14464v1