RAPTOR: Recursive Abstractive Processing for Tree-Organized Retrieval using PHI-4 LLMbyMicrosoft

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***Abstract*—The exponential rise of unstructured data has led to the need for sophisticated systems that are both able to retrieve and summarise information effectively. We propose Recursive Abstractive Tree-Organized Retrieval (RAPTOR), a new framework for retrieving hierarchical information and abstract summarizing information by implementing recursive approaches. RAPTOR leverages Microsoft's Phi-4 model to deliver multilevel context-aware summarization and ultra-precision retrieval. The system aggregates these models into a single pipeline that delivers strong question answering, abstract summarization, and intelligent information processing. Benchmark dataset tests demonstrate that RAPTOR can deliver meaningful contextually correct summaries that outperform conventional retrievals. It solves the most important abstractive retrieval problems, paving the way for document summarization, knowledge graph generation, and intelligent Q&A systems. Further work will include advancing RAPTOR for real-time performance and extending its functionality for application use cases. Index Terms—Recursive Abstractive Tree-Organized Retrieval (RAPTOR), Hierarchical retrieval, Abstractive summarization, Large language models (LLMs), Phi-4 by Microsoft.**

***Index Terms*—Information retrieval, Recursive summarization, Hierarchical knowledge extraction, Context-aware AI, Intelligent Q&A systems, Document summarization, Recursive Abstractive Tree-Organized Retrieval (RAPTOR), Hierarchical retrieval, Abstractive summarization, Large language models (LLMs), UnifiedQA,**

I. INTRODUCTION

A. Transition from Cloud-Based to Local Models

The shift from cloud-based Large Language Models (LLMs) like ChatGPT API to locally hosted models represents a transformative step in leveraging AI technology for customized needs. This transition is driven by the increasing demand for privacy, cost control, and infrastructure autonomy.

1) Motivation Behind the Transition: Cloud-based solutions, while robust and scalable, pose certain challenges. They often involve recurring subscription costs, limitations on data privacy, and dependency on third-party servers. Organizations dealing with sensitive or proprietary data may find it unfeasible to trust external servers for processing. Local hosting addresses these concerns by offering the following benefits:

1) **Cost Savings:** With local deployments, operational expenses shift from variable subscription fees to fixed infrastructure costs. This proves economical for large-scale usage over time, especially when leveraging GPU-accelerated hardware.
2) **Enhanced Privacy:** Locally hosted models ensure that sensitive data does not leave an organization's premises. This minimizes exposure to potential breaches and aligns with stringent data protection regulations such as GDPR.
3) **Control Over Infrastructure:** Hosting models locally allows organizations to customize setups according to their specific requirements, ensuring better optimization for unique workflows.

2) Key Technological Elements in Local Hosting : Transitioning to local models requires robust tools and frameworks. For instance:

1) **FAISS (Facebook AI Similarity Search):** FAISS optimizes the retrieval of vector embeddings, ensuring high-speed semantic search capabilities crucial for tasks like contextual querying and long-tail knowledge retrieval.
2) **LM Studio:** This provides an accessible interface for hosting and fine-tuning models, streamlining local deployment processes while offering user-friendly integration with recursive structures.
3) **Phi 3.5:** The specific model architecture brings state-of-the-art performance and flexibility, enhancing retrieval and comprehension for complex tasks.

By combining these technologies, the project ensures scalable, efficient, and private use of LLMs.

B. Objectives of the Project

The project's primary objective is to address limitations in traditional retrieval-augmented models by enhancing their ability to deal with long-tail knowledge and evolving datasets. Traditional cloud-based LLMs often struggle with outdated data or fail to contextualize information spread across multiple document sections. This project tackles such challenges using recursive tree-based indexing methods. [**?**]

1) Addressing Long-Tail Knowledge: Long-tail knowledge refers to specialized or niche information that might not be prominent in mainstream datasets. For LLMs to handle such knowledge effectively, they must access and integrate context across multiple abstraction levels. Recursive models provide an innovative solution:

1) **Recursive Summarization:** Texts are clustered and summarized at multiple levels of granularity, forming a hierarchical tree structure. This ensures that broader themes and specific details are retained and made accessible during retrieval.
2) **Hierarchical Context Representation:** By organizing information into layers, the model can adapt retrieval depth based on query complexity.

2) Enhanced Retrieval Through Tree-Based Indexing: The cornerstone of this system is its hierarchical indexing mechanism:

Chunking and Clustering: The corpus is divided into smaller, manageable chunks. These chunks are embedded into dense vectors using a model like Sentence-BERT (SBERT) and clustered based on semantic similarity.

Tree Formation: Summaries of each cluster are generated recursively, creating parent nodes that represent higher-level abstractions of the information. This forms a semantic tree where root nodes capture overarching themes, while leaf nodes store granular details.

Optimized Search with FAISS: FAISS is utilized for high-speed nearest-neighbor searches during the retrieval process, ensuring the most relevant nodes are identified based on cosine similarity with the query. [**?**]

C. Objectives and Vision

The project aims to enable precise, context-aware retrieval for real-time applications like question-answering, summarization, and knowledge base management. By combining recursive tree structures with local LLMs, the system is designed to:

1) Improve retrieval accuracy by utilizing multi-level abstractions.
2) Reduce operational costs compared to cloud-based solutions.
3) Enhance adaptability to dynamically changing datasets.

The deployment of such a system with tools like FAISS and LM Studio not only addresses the current gaps in retrieval-augmented models but also opens avenues for further innovation. Fine-tuning larger datasets locally, leveraging high-performance hardware, and customizing workflows will ensure the system remains both efficient and future-proof.

II. Literature Review

The bone of contention that lies at the very center of any form of academic research constitutes a literature review. It is a comprehensive survey of works already in existence in a particular field. Specifically, it is about looking into previous studies, identifying gaps, and providing a basis of major themes, debates, or advances as a prelude to future research. The present research literature review focuses on relevant information retrieval and abstractive summarization while incorporating large language models (LLMs) into different NLP tasks.

A. Retrieval Significance

The retrieval is still in existence. It has raised very important questions regarding whether the retrieval would still be needed (Dai et al.,2019; Dao et al.,2022; Liu et al,2023). But according to Liu et al. (2023) and Sun et al. (2021), these models usually fail to fully exploit the long-range context, so performance is negatively impacted as the context length grows, especially in cases where useful information is distributed over a large document. Or one could say that it is also very costly in terms of computation and very slow for practical purposes. Therefore, it is a consideration of the important information rather than processing an entire document for knowledge-intensive tasks.

B. Retrieval Variations

The advances in retrieval-augmented language models improved the retrieval, reading, and end-to-end system training. Traditional term-based methods like TF-IDF (Sp¨ arck Jones, 1972) and BM25 (Robertson et al., 1995; Roberts et al., 2020) embrace the paradigm of reaching out to find retrieval augmentation for language models, leaving space for other approaches, notably the emerging deep learning techniques (Karpukhin et al., 2020; Khattab & Zaharia, 2020; Sachan et al., 2023). More recently, large language models have themselves been considered for retrieval as they can memorize huge amounts of knowledge (Yu et al., 2022; Sun et al., 2022). Contributions to research in the reader part included such contributions as Fusion-in-Decoder (FiD) (Izacard & Grave, 2022), wherein retrieved passages are processed independently within the encoder and RETRO (Borgeaud et al., 2022; Wang et al., 2023), wherein text is generated that is grounded on retrieved context with the aid of cross-chunked attention.

Systems have innovatively come out for the end-to-end training, for example, Atlas (Izacard et al., 2022), fine-tunes the encoder-decoder model with that of the retriever. A two-way approach in REALM (Guu et al., 2020) demonstrated that a masked language model is actually trained to conduct open-domain question-answering tasks. Like RAG, (Retrieval-Augmented Generation) that consists of pre-trained sequence-to-sequence models with a neural retriever (Lewis et al., 2020), the increasing number of models, such as Joint Passage Retrieval (JPR) (Min et al., 2021), uses the tree decoding approach to develop passage diversity and relevance for multi-answer retrieval. Some methods such as Dense Hierarchical Retrieval (DHR) and Hybrid Hierarchical Retrieval (HHR) by Liu et al., 2021; Arivazhagan et al., 2023, use both document

retrievals and passage-level retrievals to enhance the accuracy of retrieved results.

C. Looping Summarization as Context

Summarization techniques now have a long history as methods for compressing texts and allowing more focused interaction with the content (Angelidis & Lapata, 2018). For instance, the summarization model of Gao et. al. (2023) is said to further enhance correctness across most datasets through the generation of summaries as well as snippets from passages. Nonetheless, this approach may prove to be a lossy compression scheme at other times. According to Wu et al. (2021), a recursive-abstractive summarization model is proposed to circumvent this problem, whereby smaller portions of text are summarized and eventually merged into wider or larger sections of a summary. The most important feature of this approach is that it can provide a precise representation of the broader themes but can miss out on the smaller details.

To overcome all these limitations, LlamaIndex (Liu, 2022) keeps intermediate nodes while keeping different states of details it can store, still summarizing adjacent text chunks. Yet, this yet again suffers with an adverse situation similar to what other methods doing adjacent nodes summarize and fails in capturing long inter-dependencies of forms of text. This gives RAPTOR an edge because it identifies and classifies relationships not only in the length but also in the depth of a text, hence keeping both the minute details as well as long-range dependencies intact.

III. Methodology

A. System Architecture

RAPTOR leverages Phi 3.5, a locally hosted large language model, integrated with FAISS for efficient vector-based retrieval. The system comprises:

- **Recursive Summarization**: Textual data is recursively summarized to create a hierarchical tree structure.
- **Semantic Clustering**: Dense vector embeddings generated by Sentence-BERT (SBERT) or similar models are clustered using algorithms like Gaussian Mixture Models (GMMs).
- **Tree-Based Indexing**: Summarized clusters form parent nodes, enabling multi-level abstraction.

B. Workflow

1) **Data Preprocessing**: Raw text is divided into manageable chunks and embedded as dense vectors.
2) **Tree Construction**: Embeddings are clustered and summarized recursively to construct a hierarchical tree.
3) **Query Handling**: User queries are embedded, matched against the tree nodes via FAISS, and relevant summaries are retrieved for inference.

IV. Experiments

A. Experimental Setup

RAPTOR was deployed locally using Phi 3.5 on a GPU-accelerated system with FAISS for vector retrieval. Benchmarks included QASPER, QuALITY, and NarrativeQA datasets.

B. Evaluation Metrics

Performance was assessed using metrics such as F1 score, ROUGE-L, and retrieval latency.

C. Results

- **QuALITY Benchmark**: RAPTOR achieved a 55.7
- **NarrativeQA**: RAPTOR demonstrated a 7.3-point improvement in ROUGE-L compared to BM25, highlighting its ability to handle thematic queries.
- **Efficiency**: RAPTOR's collapsed tree mechanism, coupled with FAISS, ensured rapid query processing with minimal latency.

V. Applications

A. Healthcare

RAPTOR's ability to synthesize and retrieve thematic insights aids in summarizing patient records or clinical trials [8].

B. Legal Analysis

Hierarchical summaries of case law provide lawyers with a quick overview while allowing access to granular evidence [6].

C. Education

RAPTOR supports efficient thematic exploration by clustering and summarizing textbooks or lecture notes [4].

VI. Discussion

RAPTOR's hierarchical retrieval mechanism enables nuanced information synthesis, outperforming traditional models in accuracy and efficiency. By hosting the system locally, it addresses privacy concerns and reduces reliance on costly cloud-based APIs. However, initial computational overhead in tree construction and reliance on high-end hardware remain areas for improvement.

VII. Conclusion

RAPTOR redefines retrieval-augmented architectures by integrating recursive summarization with hierarchical retrieval. Its superior performance on knowledge-intensive benchmarks, coupled with cost-efficient local deployment, makes it a promising solution for domains like healthcare, legal analysis, and education. Future work will focus on optimizing scalability and exploring domain-specific fine-tuning.

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