Track: Research

Team (18) Members:

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[Research Question] How can iterative query formulation enhance retrieval-augmented question-answering systems to address knowledge gaps in multi-hop knowledge retrieval processes?

[Explanation] In the field of artificial intelligence, retrieval-augmented techniques for large language models are being developed to improve their ability to utilize external knowledge, particularly for addressing complex questions and avoiding inaccuracies. While current research mainly focuses on retrieving relevant information, our approach aims to address the need for multi-hop knowledge retrieval by proposing iterative query formulation. This method prioritizes identifying and filling knowledge gaps systematically, thus enhancing the effectiveness of knowledge-intensive question-answering tasks while minimizing redundancy in retrieved data.

[Significance] This research question is significant as it addresses a critical challenge in artificial intelligence, particularly in large language models (LLMs). Current techniques for retrieval-augmented question answering often struggle with addressing knowledge gaps, resulting in incomplete or inaccurate answers, especially for complex, multi-hop questions. By focusing on iterative query formulation, we aim to reduce this issue and improve the capability of LLMs to provide more reliable and comprehensive responses.

[Novelty]

- [1] introduces a methodology using ground-truth evidence passages, treating them as sequential links to retrieve the next relevant passage.
- [2] & [4] highlight the importance of generating intermediate answers to facilitate finding subsequent relevant passages but don't explicitly address iterative query refinement based on knowledge gaps.
- [3] utilizes LLMs to generate follow-up questions iteratively, guiding retrieval of additional passages, but primarily relies on simple prompting techniques lacking targeted gap identification and filling.

Our research may set itself apart by concentrating on the development of iterative query formulation strategies that specifically aim to uncover and address 'gap knowledge'. This approach is designed to systematically refine the information retrieval process, ensuring that each iteration brings forth new and pertinent information rather than reiterating content previously retrieved.

[Approach] To address the absence of predefined gap-focused questions in current QA datasets, we propose a reinforcement learning from human feedback (RLHF) approach for training a query encoder. This method employs Proximal Policy Optimization (PPO) to fine-tune LLMs, incentivizing them to generate precise gap questions by rewarding their ability to retrieve highly relevant and gap-filling knowledge from external sources. Unlike static prompt-based methods, this dynamic approach encourages the LLM to continuously improve its ability to identify and address knowledge gaps without the need for labor-intensive question preparation.

[Framework]

- Subquestion Generation: Our framework employs an LLM to generate subquestions bridging the knowledge gap between available and required information.
- Reward Calculation: Generated subquestions act as queries to extract relevant passages, with alignment between retrieved passages and knowledge gaps quantitatively assessed for reward calculation.
- Optimization via PPO: We fine-tune the LLM using reward scores within a Proximal Policy Optimization framework, iteratively adjusting parameters to optimize generation of gap-focused queries.

[Evaluation] We plan to evaluate the efficacy of our approach in terms of two main aspects: how effectively it can find relevant information and how accurately it can answer questions. Besides, we use the metric defined in [3]. The metric is fundamentally the accuracy of the LLM in answering 2-hop compositional questions like “What is the calling code of the birthplace of Frida Kahlo?”. Additionally, we will record the perplexity assigned to the answer to 1-hop questions. We can then compare our approach with recent existing methods [1-4].

[Timeline]

Week 1: Complete an expanded literature review and finalize the project's design. Develop the weak supervision mechanism and reward system for fine-tuning.
Week 2: Build and test the initial prototype. Conduct evaluations comparing our approach against baseline methods.
Week 3: Analyze the experimental findings. Refine our approach based on evaluation outcomes.
Week 4: Run our approach on different benchmarking datasets. Complete project report.

[Task Division]

Shreya Matta: Literature Review, Conceptualization, Data Collection, Experiment Design.
Palvi Shroff: Literature review, Testing, Feedback Integration.
Taobo Liao: Literature review, Model development, Data analysis.
Kashob Kumar Roy: Literature review, Model development, Experimental Analysis.

Reference papers:

[1] Answering Complex Open-Domain Questions with Multi-Hop Dense Retrieval
[2] Interleaving Retrieval with Chain-of-Thought Reasoning for Knowledge-Intensive Multi-Step Questions
[3] Measuring and Narrowing the Compositionality Gap in Language Models
[4] Enhancing Retrieval-Augmented Large Language Models with Iterative Retrieval-Generation Synergy
[5] Training language models to follow instructions with human feedback