AI-Powered Career Guidance Chatbot Using Retrieval-Augmented Generation (RAG)

Team 02

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Abstract

In today's evolving education and job landscape, students require reliable, personalized, and accurate career advice to make informed decisions. This paper introduces an AI-powered **Career Guidance Chatbot** built on a **Retrieval-Augmented Generation (RAG)** framework that leverages open-source large language models (LLMs) such as **Phi-2**, **GPT-2**, and **Falcon-RW**. The chatbot uses **semantic retrieval** through **FAISS indexing** and constructs context-aware responses using **Chain-of-Thought (CoT) prompting**. A custom dataset of career-related articles serves as the knowledge base, enabling the system to deliver grounded, factual, and coherent answers. We evaluate our approach using BLEU and ROUGE metrics, revealing that retrieval-enhanced generation significantly improves personalization, accuracy, and trustworthiness in AI-driven advisory systems.

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1. Introduction

Large Language Models (LLMs) like GPT and LLaMA have shown great promise in general-purpose language generation. However, their direct application in sensitive domains like career counseling presents challenges due to **hallucination**, **lack of context-awareness**, and **difficulty in personalizing output**. We address this limitation by proposing a **Retrieval-Augmented Generation (RAG)** framework tailored for student career advice. Our system retrieves relevant documents from a curated knowledge base using FAISS and constructs prompts that guide the generation model to deliver responses grounded in real-world data. By integrating **modular retrievers**, **flexible prompt templates**, and **evaluated generative models**, we ensure that students receive **contextualized, safe, and domain-relevant answers**.

2. Related Work

RAG was introduced by [Lewis et al., 2020] as a way to fuse document retrieval with generation, offering a hybrid architecture that grounds outputs in verifiable facts. It has since been applied in tasks like open-domain QA, document summarization, and task-oriented dialogue systems. **Chain-of-Thought (CoT) prompting** [Wei et al., 2022] improves the reasoning abilities of LLMs, especially in step-by-step decision-making tasks. Researchers like Menick et al. (2022) emphasized the importance of **factual grounding** and retrieval for reducing hallucinations. The combination of retrieval, reasoning, and generation, as explored in [Izacard & Grave, 2021], inspires our architecture for trustworthy student guidance.

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3. System Overview

Our chatbot system follows a **modular and extensible pipeline architecture**:

- **Knowledge Base Construction**: A handpicked collection of ~500 career advice articles and FAQs are preprocessed.
- **Semantic Indexing**: These articles are embedded using **Sentence-BERT (all-MiniLM-L6-v2)** and indexed using **FAISS**.
- **Retriever Module**: For each query, the top-k semantically similar documents are retrieved based on cosine similarity.
- **Prompt Builder**: The retrieved passages are merged into a structured CoT prompt that introduces step-wise reasoning.
- **LLM Inference**: The prompt is passed into one of the LLMs (Phi-2, GPT-2, Falcon-RW) to generate personalized responses.
- **Response Evaluation**: BLEU and ROUGE scores compare generated output with curated references to assess relevance and structure.

The chatbot supports **single-model deployment** or **side-by-side model comparisons**, offering flexibility for user testing and academic benchmarking.

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4. Technical Implementation

The system is implemented in **Python** and designed for **scalable deployment**. The key technical layers include:

- **Data Processing**: Text cleaning, tokenization, and embedding using sentence-transformers.
- **Indexing**: FAISS is used for vector indexing of document embeddings, enabling high-speed retrieval.
- **Retrieval Strategy**: A hybrid scoring mechanism combining **semantic similarity** and **keyword overlap** improves document relevance.
- **Prompt Engineering**: Prompts follow the Chain-of-Thought structure, guiding the LLM to reason through retrieved information.
- **Model Invocation**: Responses are generated using pre-trained versions of Phi-2, GPT-2, and Falcon-RW, loaded via HuggingFace Transformers.
- **Evaluation Layer**: Uses nltk.translate and rouge-score libraries to compute BLEU, ROUGE-1, ROUGE-L metrics for benchmarking.

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5. Domain-Specific Questions

Our system is evaluated against 10 commonly asked career queries:

1. How do I start a career in data science?
2. What skills are important for digital marketing?
3. How to transition from engineering to product management?
4. What certifications help in cybersecurity?
5. How can I build a career in entrepreneurship?
6. What is the future of AI in healthcare careers?
7. How to get internships in finance as a student?
8. What tools are used in business analytics?
9. Is UX/UI design a good career in 2025?
10. How important is networking for career growth?

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6. Evaluation and Comparative Results

We evaluated the outputs from all three LLMs for the same queries using standardized metrics:

- **BLEU Scores**: Assessed the overlap between generated and reference responses. Phi-2 scored highest (avg. 0.68).
- **ROUGE-L Scores**: Measured sequence overlap and linguistic fluency. Falcon-RW and GPT-2 showed moderate scores (0.6–0.75).
- **Response Length & Structure**: GPT-2 generated the longest and most fluent responses but showed a tendency to hallucinate.

Each model performed well in different areas. **Phi-2** excelled in **factual grounding**, **GPT-2** in **elaboration**, and **Falcon-RW** in **balanced coherence**.

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7. Analysis of Model Behavior

- **Phi-2**: Compact and informative answers, highly precise, best grounded to the retrieved context, but slightly minimal.
- **GPT-2**: Produced verbose, naturally flowing responses with good structure but more prone to introducing speculative or hallucinated content.
- **Falcon-RW**: Balanced accuracy and readability but occasionally lacked deep detail.

Chain-of-Thought prompting played a pivotal role in improving logical flow and factual accuracy. The impact of token limitations, particularly on GPT-2, influenced the depth and compression of responses.

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8. Conclusion and Future Work

Our RAG-based chatbot shows that **retrieval grounding**, when combined with **open-source LLMs**, significantly enhances response relevance in the career guidance domain. The system is modular, reproducible, and educationally impactful.

Future enhancements include:

- **Multi-turn memory** for conversational context
- **Cross-lingual support** for global student access
- **Improved reranking algorithms** for retrieved passages
- **UI Enhancements**: voice commands, confidence scores, and visual summaries

These additions will make the chatbot a more interactive, inclusive, and intelligent advisory tool.

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9. Model Output Comparisons

Query: How do I start a career in data science?

- **Phi-2:** Learn Python, statistics, and machine learning. Start with online courses and practice with datasets on Kaggle. Internships and certifications help gain real-world exposure.
- **GPT-2:** To begin a career in data science, you should build a strong foundation in mathematics, programming, and data analysis. Start by learning Python, explore libraries like pandas, NumPy, and scikit-learn. Engage with real datasets, participate in projects, and consider earning certifications in machine learning and data analysis.
- **Falcon-RW:** Start by learning core data skills including Python, SQL, and data visualization. Move on to machine learning and deep learning. Practice using real datasets. Having a portfolio on GitHub will significantly help with hiring.

Query: What skills are important for digital marketing?

- **Phi-2:** Learn SEO, content writing, email marketing, and Google Ads. Understanding analytics tools is important. Certifications from HubSpot or Google help.
- **GPT-2:** Key skills in digital marketing include search engine optimization (SEO), pay-per-click (PPC) advertising, social media strategy, email marketing, and web analytics. Familiarity with tools like Google Analytics, SEMrush, and Canva is beneficial. Strong communication and copywriting are essential.

- **Falcon-RW:** Digital marketing requires knowledge of SEO, social media platforms, paid ads, and content creation. Google Ads and Meta Business Suite are commonly used. Analytical thinking and audience targeting are crucial.

Observations:

- **Phi-2** offers brief, high-precision answers.
- **GPT-2** excels in language fluency and depth.
- **Falcon-RW** strikes a middle ground between clarity and completeness.

References

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