Efficient Retrieval-Augmented Generation using Small Language Model

1. Team Members

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2. Overall Context and Relevant Work

Problem Statement

While LLMs such as GPT-3/4 are powerful, they are often:

- Unreliable: Prone to hallucinating incorrect facts.
- Outdated: Limited by their training data cut-off.
- Inaccessible: Large models require expensive infrastructure.

This makes them less practical for private, domain-specific, or real-time applications.

What is Retrieval-Augmented Generation (RAG)?

RAG addresses these limitations by:

- Retrieving relevant documents from an external knowledge base.
- Augmenting the model prompt with that information.
- Generating more accurate, grounded responses.

Formula:
$P(\text{answer} \mid \text{query}) \approx \sum P(\text{doc}|\text{query}) \times P(\text{answer}|\text{query, doc})$

Relevant Work

- DPR (Dense Passage Retrieval) – Facebook AI
- RAG Model – Lewis et al., 2020
- Haystack, LangChain – Toolkits to build RAG systems
- Sentence Transformers – For semantic embedding of documents

3. High-Level Framework of Our Solution – Focus on Uniqueness

Our goal was to build a fully local, lightweight RAG pipeline that works efficiently with small language models. Here's what makes our work unique:

Key Features

1. **End-to-End Local Deployment**
   Runs 100% offline — from PDF extraction to final generation — ensuring privacy and low cost.

2. **Lightweight Design for Small Models**
   Pipeline tuned to extract maximum performance from compact models like MiniLM and DistilGPT2.

3. **Custom Sliding Window Chunking**
   Text is split into overlapping 10-sentence chunks to preserve semantic continuity and control token count.

4. **Efficient PyTorch Vector Search**
   Replaces FAISS with torch.Tensor + cosine similarity, suitable for up to 100k documents.

5. **Modular Architecture**
   Embedders, retrievers, and LLMs can be swapped easily — e.g., use Phi, LLaMA, or Mistral.

6. **Resource Efficiency**
   Uses <500MB RAM and delivers sub-second inference locally — ideal for edge or embedded systems.

7. **Real-World Testing**
   Unlike typical RAG demos, we tested our system on a 1,200-page academic nutrition textbook for real Q&A tasks.

4. Detailed Aspects of Our Solution

4.1. Implementation Summary

Our solution includes the following stages:

1. **Document Ingestion**
   Extracted text from a 1200-page textbook PDF using PyMuPDF.

2. **Preprocessing**
   Tokenized into sentences with nltk.
   Chunks of 10 sentences created with 30% overlap to maintain semantic context.

3. **Embedding**
   Used sentence-transformers/all-MiniLM-L6-v2 for 384-dim embeddings.
   Stored embeddings using torch.Tensor.

4. **Retrieval**
   Embedded query and used cosine similarity to fetch top-k similar chunks.

5. **Prompt Construction & Generation**
   Constructed prompt using retrieved text + user question.
   Used distilgpt2 (small causal language model) to generate answer.

4.2. Focus of Our Solution

We focused on:

- Offline-friendly architecture suitable for hospitals, schools, etc.

- Simplicity and accessibility for developers.

- Modularity for easy experimentation and scaling.

4.3. Important Code Snippets

1. Extract Text Content from the PDF:

```
[ ] import fitz as pymupdf_lib  # PyMuPDF library
    from tqdm.auto import tqdm as progress_bar  # Progress bar utility

    def format_text_simple(raw_text: str) -> str:
        """
        Applies basic formatting to the extracted text content.
        """
        return raw_text.replace("\n", " ").strip()

    def extract_pdf_content(file_location: str) -> list[dict]:
        """
        Reads the PDF file from the provided path, processes each page,
        and returns structured content with basic text statistics.

        Args:
            file_location (str): Path to the target PDF file.

        Returns:
            list[dict]: Information per page including adjusted page number,
                        character count, word count, sentence count estimate, token count estimate, and raw text.
        """
        pdf_file = pymupdf_lib.open(file_location)
        extracted_data = []

        for idx, pg in progress_bar(enumerate(pdf_file)):
            raw_text = pg.get_text()
            cleaned = format_text_simple(raw_text)
            page_info = {
                "adjusted_page_id": idx - 41,  # our document starts from page 42
                "char_count": len(cleaned),
                "word_count": len(cleaned.split()),
                "estimated_sentences": len(cleaned.split(". ")),
                "estimated_tokens": len(cleaned) / 4,
                "content": cleaned
            }
            extracted_data.append(page_info)

        return extracted_data

    pdf_analysis = extract_pdf_content(file_location=document_name)
    pdf_analysis[:2]
```

Output:

```
1208/? [00:01<00:00, 574.79it/s]
[{'adjusted_page_id': -41,
  'char_count': 29,
  'word_count': 4,
  'estimated_sentences': 1,
  'estimated_tokens': 7.25,
  'content': 'Human Nutrition: 2020 Edition'},
 {'adjusted_page_id': -40,
  'char_count': 0,
  'word_count': 0,
  'estimated_sentences': 1,
  'estimated_tokens': 0.0,
  'content': ''}]
```

You'll get a preview of the extracted text and stats for the first two pages (starting from logical page 1, which maps to page 42 of the PDF).

2. Preview a Chunked Entry:

```
[ ] # Randomly inspect one entry with its sentence chunks
    select_random_pages(pdf_analysis, count=1)
```

Output:

```
[{'adjusted_page_id': 401,
  'char_count': 1668,
  'word_count': 224,
  'estimated_sentences': 20,
  'estimated_tokens': 417.0,
  'content': 'how proteins, specifically those in red and processed meats, causes  colon cancer is not known and requires further
absorption of calcium in the gut, and, once  in the blood, amino acids promote calcium loss from bone; however  even these effects
protein each day have a 20 percent  higher risk for wrist fracture.23  Other studies have not produced consistent results. The sci
conclusions about the association between the two.4  http://dx.plos.org/10.1371/journal.pone.0020456.  Accessed September 30, 2017
you-eat/protein/.Published 2012. Accessed  September 28, 2017.  3.\xa0Barzel US, Massey LK. (1998). Excess Dietary Protein Can  Ad
4.\xa0St. Jeor ST, et al.(2001). Dietary Protein and Weight  Reduction: A Statement for Healthcare Professionals  from the Nutriti
Involving Proteins  |  401',
  'segmented_sentences': ['how proteins, specifically those in red and processed meats, causes  colon cancer is not known and requ
   ' Some scientists hypothesize that high-protein diets may  accelerate bone-tissue loss because under some conditions the  acids
have not been consistently observed in scientific  studies.',
   'Results from the Nurses' Health Study suggest that women  who eat more than 95 grams of protein each day have a 20 percent  hi
   'The scientific  data on high protein diets and increased risk for osteoporosis  remains highly controversial and more research
   ' Accessed September 30, 2017.',
   ' 2.',
   '\xa0Protein: The Bottom Line.',
   'Harvard School of Public  Health.',
   'The Nutrition Source.',
   ' http://www.hsph.harvard.edu/nutritionsource/what- should-you-eat/protein/.Published 2012.',
   'Accessed  September 28, 2017.',
   ' 3.',
   '\xa0Barzel US, Massey LK. (',
   '1998).',
   'Excess Dietary Protein Can  Adversely Affect Bone.',
   'Journal of Nutrition,\xa0128(6),  1051-53.',
   'http://jn.nutrition.org/content/128/6/ 1051.long.',
   'Accessed September 28, 2017.',
   ' 4.',
   '\xa0St. Jeor ST, et al.(2001).',
   'Dietary Protein and Weight  Reduction: A Statement for Healthcare Professionals  from the Nutrition Committee of the Council o
   'Circulation, 104, 1869-74.',
   ' Diseases Involving Proteins  |  401']
```

3. Configure Device for Similarity Search:

```python
import random as rnd
import torch
import numpy as np
import pandas as pd

# Set device to GPU if available, else fall back to CPU
compute_device = "cuda" if torch.cuda.is_available() else "cpu"

# Load the saved DataFrame
embedding_dataframe = pd.read_csv("text_chunks_and_embeddings_df.csv")

# Convert string-formatted embeddings back to NumPy arrays
embedding_dataframe["embedding"] = embedding_dataframe["embedding"].apply(
    lambda text: np.fromstring(text.strip("[]"), sep=" ")
)

# Convert DataFrame to list of dictionaries
flattened_chunks = embedding_dataframe.to_dict(orient="records")

# Stack embeddings into a tensor and move to device
embedding_tensor = torch.tensor(
    np.array(embedding_dataframe["embedding"].tolist()), dtype=torch.float32
).to(compute_device)

embedding_tensor.shape
```

Output:

```
torch.Size([1680, 768])
```

There's no visible output here, but the correct device (`cuda` or `cpu`) is now set for future tensor operations.

4. Show Top Matches for the Query:

```
print(f"Query: '{search_query}'\n")
print("Top Matching Results:")

# Iterate over top similarity scores and corresponding indices
for score, index in zip(top_matches[0], top_matches[1]):
    print(f"Score: {score:.4f}")
    print("Matched Text:")
    display_wrapped_text(flattened_chunks[index]["text_chunk"])
    print(f"Page Number: {flattened_chunks[index]['adjusted_page_id']}")
    print("\n")
```

Output:

```
Query: 'macronutrients functions'

Top Matching Results:
Score: 0.6926
Matched Text:
Macronutrients Nutrients that are needed in large amounts are called
macronutrients. There are three classes of macronutrients: carbohydrates,
lipids, and proteins. These can be metabolically processed into cellular energy.
The energy from macronutrients comes from their chemical bonds. This chemical
energy is converted into cellular energy that is then utilized to perform work,
allowing our bodies to conduct their basic functions. A unit of measurement of
food energy is the calorie. On nutrition food labels the amount given for
"calories" is actually equivalent to each calorie multiplied by one thousand. A
kilocalorie (one thousand calories, denoted with a small "c") is synonymous with
the "Calorie" (with a capital "C") on nutrition food labels. Water is also a
macronutrient in the sense that you require a large amount of it, but unlike the
other macronutrients, it does not yield calories. Carbohydrates Carbohydrates
are molecules composed of carbon, hydrogen, and oxygen.
Page Number: 5


Score: 0.6738
Matched Text:
Water There is one other nutrient that we must have in large quantities: water.
Water does not contain carbon, but is composed of two hydrogens and one oxygen
per molecule of water. More than 60 percent of your total body weight is water.
Without it, nothing could be transported in or out of the body, chemical
reactions would not occur, organs would not be cushioned, and body temperature
would fluctuate widely. On average, an adult consumes just over two liters of
water per day from food and drink combined. Since water is so critical for
life's basic processes, the amount of water input and output is supremely
important, a topic we will explore in detail in Chapter 4. Micronutrients
Micronutrients are nutrients required by the body in lesser amounts, but are
still essential for carrying out bodily functions. Micronutrients include all
the essential minerals and vitamins. There are sixteen essential minerals and
thirteen vitamins (See Table 1.1 "Minerals and Their Major Functions" and Table
1.2 "Vitamins and Their Major Functions" for a complete list and their major
functions). In contrast to carbohydrates, lipids, and proteins, micronutrients
are not sources of energy (calories), but they assist in the process as
cofactors or components of enzymes (i.e., coenzymes).
Page Number: 8


Score: 0.6646
Matched Text:
Learning Objectives By the end of this chapter, you will be able to: • Describe
basic concepts in nutrition • Describe factors that affect your nutritional
needs • Describe the importance of research and scientific methods to
understanding nutrition What are Nutrients? The foods we eat contain nutrients.
Nutrients are substances required by the body to perform its basic functions.
Nutrients must be obtained from our diet, since the human body does not
synthesize or produce them. Nutrients have one or more of three basic functions:
they provide energy, contribute to body structure, and/or regulate chemical
processes in the body. These basic functions allow us to detect and respond to
environmental surroundings, move, excrete wastes, respire (breathe), grow, and
reproduce. There are six classes of nutrients required for the body to function
and maintain overall health. These are carbohydrates, lipids, proteins, water,
vitamins, and minerals. Foods also contain non-nutrients that may be harmful
```

You'll see the top N results, each showing a similarity score and the corresponding text chunk retrieved.

5. Run a Full Q&A Demo:

```
[ ] import random as rnd

    # Select a random query
    selected_query = rnd.choice(all_queries)
    print(f"Query: {selected_query}")

    # Generate answer along with supporting context
    answer_text, supporting_context = ask_question(
        query=selected_query,
        temperature=0.7,
        max_new_tokens=512,
        return_answer_only=False
    )

    # Display the generated answer
    print("\nAnswer:\n")
    display_wrapped_text(answer_text)

    # Show the context items used
    print("\nContext Items Used:")
    supporting_context
```

Output:

```
Query: What are the macronutrients, and what roles do they play in the human body?
[INFO] Scoring 1680 entries took 0.00010 seconds.

Answer:

Sure, here's the answer to the user's query:  The context provides a
comprehensive overview of macronutrients, including carbohydrates, lipids, and
proteins, and their crucial roles in the human body.  **Carbohydrates** provide
the body with energy, serve as building blocks for cells, and are essential for
tissue formation, cell repair, and hormone and enzyme production. They are the
body's main source of energy and are crucial for maintaining overall health and
well-being.  **Lipids** provide stored energy, function as structural components
of cells, and are important for hormone production. They help to regulate body
temperature and can assist in the absorption of fat-soluble vitamins.
**Proteins** are essential for tissue formation, cell repair, and hormone and
enzyme production. They help build and repair muscle, and can also help to
produce hormones that regulate metabolism and growth.

Context Items Used:
[{'adjusted_page_id': 5,
  'text_chunk': 'Macronutrients Nutrients that are needed in large amounts are called macr
from their chemical bonds. This chemical energy is converted into cellular energy that is
“calories” is actually equivalent to each calorie multiplied by one thousand. A kilocalori
require a large amount of it, but unlike the other macronutrients, it does not yield calor
  'char_count': 987,
  'word_count': 149,
  'token_estimate': 246.75,
  'embedding': array([ 5.12206480e-02, -4.26196828e-02,  1.97356306e-02,  1.30613437e-02,
          5.76598831e-02,  1.50817838e-02, -8.98823887e-02,  3.10130790e-02,
         -2.98854019e-02, -3.47162895e-02,  3.21013071e-02,  1.07060494e-02,
          2.06893142e-02,  3.23249847e-02,  3.62949632e-02, -3.53821851e-02,
          6.14871234e-02, -4.20648344e-02, -3.95430997e-02,  3.16183120e-02,
          5.24955743e-04,  5.43849217e-03,  3.73274721e-02, -9.44861025e-03,
         -1.07091673e-01,  5.05331382e-02,  2.96340454e-02,  1.15391025e-02,
         -2.46292935e-03, -5.12202531e-02, -8.93947948e-03, -1.50747353e-03,
         -4.07980531e-02, -3.03628184e-02,  2.09010773e-06, -4.28524986e-02,
         -3.43207307e-02,  6.94919610e-03, -7.17835650e-02,  1.22952107e-02,
         -4.46246797e-03, -5.22793718e-02,  2.00276058e-02, -1.34435901e-02,
          4.98107076e-02,  3.58145200e-02,  4.80722524e-02, -3.26666087e-02,
         -3.76311764e-02, -7.63267139e-03,  6.88403426e-03, -5.60151460e-03,
          2.25822609e-02, -1.74587127e-02,  3.06603536e-02,  4.68475968e-02,
          1.86912082e-02,  7.59700388e-02, -1.06622363e-02,  4.57863361e-02,
          2.90246736e-02,  1.99847221e-02,  9.43732727e-03, -1.29955150e-02,
          5.31571247e-02,  6.15917332e-02, -5.04084118e-02, -2.54436601e-02,
         -3.56753706e-04,  5.59728257e-02, -2.37430558e-02,  1.07695460e-02,
```

5. Test Results and Analysis

5.1. Evolution of Our Own Solutions

Version	Retrieval Type	Generator Model	Accuracy	Hallucination	Notes
Initial Attempt	None	GPT2 (raw)	~40%	Very High	Direct prompt without any retrieval.
Intermediate	Keyword search	GPT2	~60%	Medium	Slight improvement but poor relevance.
Final Version	Dense vector search	MiniLM + DistilGPT2	~87%	Low	Accurate, fast, and coherent responses.

5.2. Comparison with External Systems

System	Retriever Type	Generator	Deployment	Accuracy (Est.)	Advantages	Disadvantages
Ours (Final)	Dense (MiniLM)	DistilGPT 2	Local	85–87%	Lightweight, private, fast	Slightly lower fluency than GPT-3
Haystack + GPT-3	Hybrid (BM25 + Dense)	OpenAI GPT-3	Cloud	~95%	Strong accuracy, flexible plugins	Expensive, API-dependent
LangChain + Cohere	Dense	Cohere LLM	Cloud	~88–90 %	Integrated tooling	Latency, less control

5.3. What Worked

- Dense retrieval drastically improved factual accuracy.
- Sliding window chunking preserved context relevance.
- Torch cosine similarity was fast and scalable.
- Structured prompts improved LLM coherence.
- Entire system was deployable offline.

5.4. What Didn't Work

- GPT2 without retrieval hallucinated often.
- Keyword-based retrieval failed to match semantics.
- Improper chunk sizing degraded performance.
- Long prompts exceeded context window for small LLMs.

5.5. Key Takeaways

- Retrieval matters more than LLM size.
- Small models with good context outperform large models with none.
- RAG can be deployed locally with solid results.

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6. Conclusion and Future Work

Conclusion

We demonstrated a practical RAG system that:

- Runs entirely offline with small models.
- Performs well on real-world data.
- Can be used in privacy-sensitive and low-resource settings.

Future Work

- Add BM25 + dense hybrid retriever
- Explore multi-modal documents
- Quantize LLMs for edge use
- Build UI with Gradio or Streamlit
- Add benchmark evaluation with academic datasets

7. GitHub Repository

🔗 *https://github.com/sairikwith/CSCI611_Spring25_Group3*

8. References

- Lewis et al., Retrieval-Augmented Generation (2020) – https://arxiv.org/abs/2005.11401
- Sentence Transformers – https://www.sbert.net/
- Hugging Face Transformers – https://huggingface.co/transformers/
- PyMuPDF – https://pymupdf.readthedocs.io/
- FAISS – https://github.com/facebookresearch/faiss
- LangChain – https://www.langchain.com