Swinburne University of Technology

Faculty of Science, Engineering and Technology

Final Report – Mitigating AI Hallucination

Unit Code: 30018 **Unit Title: Intelligent System**

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I. Executive Summary

The goal of this project will be to reduce hallucination in Large Language Models (LLMs) in the non-life insurance space by implementing a Retrieval-Augmented Generation (RAG) pipeline. The goal is to improve the correctness and trustworthiness of LLM-generated responses, by grounding LLM generation in authoritative insurance policies. The team has developed a structured pipeline of data ingestion, chunking, embedding, retrieval, and generation to tackle the attendant challenges of long-context, multilingual capabilities (with a focus on Vietnamese) and optimal vector database selection.

Key achievements include:

- Researching and implementing advanced chunking techniques (e.g., Late Chunking, Contextual Retrieval) to preserve document context.
- Evaluating embedding models (e.g., "Gangentman/Vietnamese embedding model") for improved semantic search in Vietnamese texts.
- Developing a hybrid search system (vector + keyword) and optimizing retrieval strategies for legal insurance documents.
- Designing a user-friendly Gradio interface for seamless interaction with the RAG system.
- The project demonstrates the efficacy of RAG in reducing hallucinations while maintaining domain-specific accuracy. Future work includes refining evaluation metrics and expanding the system's scalability.

II. Introduction

Large Language Models (LLMs) are known to produce plausible responses that may be factually incorrect, a phenomenon referred to as "hallucination." This poses substantial risks in specialized applications such as non-life insurance where responses must be precise. In response to this, our project designs and implements a Retrieval-Augmented Generation (RAG) pipeline that combines LLM generated content to augment responses with retrieved documents from a knowledge base.

Motivation

This semester, our team focused on developing an RAG (Retrieval-Augmented Generation) pipeline for the insurance industry. The motivation for this project stems from two key factors. Firstly, the project assignment from our university required us to address the issue of hallucination in language models, which prompted us to explore techniques for mitigating this challenge. Secondly, one of our team members, Dũng, overheard a conversation during a lunch break where colleagues from an insurance company expressed their need for a specialized expert bot. This bot would be designed to quickly answer questions related to insurance law, accounting for insurance, and other related topics. The goal was to improve the speed and efficiency of learning
and reading about legal matters in the insurance sector. This sparked our interest in developing a solution

that could potentially enhance the insurance industry's ability to handle complex legal queries more effectively.

Objectives

To mitigate hallucinations, the output of LLMs will be anchored to verified insurance policy documents to ensure accuracy and reliability. We plan to build towards these domains by optimizing chunking, embedding, and retrieval specifically for legal and multilingual (Vietnamese) texts. We will use a user-centered design to create an interactive form that will allow legal practitioners to query and navigate through complex aspects of policy details.

Challenges & Innovations:

Insurance policy interpretation requires long-context handling techniques found in large-context models, such as Gemini 2.3 and processing methods, such as Late Chunking. To increase accuracy, we will enhance multilinguality by implementing Vietnamese optimized embedding models. An evaluation framework will be implemented to show RAG performance against the baseline models. Overall, this project reflects the industry demand for trustworthy AI-based tools in the legal and insurance sectors and scalable methods for increasing trust for applications using LLMs. In the following sections, we will highlight our data collection and implementation and present example applications.

III. Literature Review

Hallucinations in Large Language Models

Large Language Models (LLMs) have demonstrated remarkable capabilities in natural language understanding and generation, but they frequently produce content that appears plausible yet is factually incorrect—a phenomenon known as "hallucination" (Ji et al., 2023). Hallucinations represent a critical challenge for deploying LLMs in high-stakes domains such as insurance, healthcare, and legal services where factual accuracy is paramount (Rawte et al., 2023). These misrepresentations can manifest as fabricated facts, incorrect assertions, or false attributions that cannot be traced back to the training data (Huang et al., 2023).

Retrieval-Augmented Generation (RAG)

Retrieval-Augmented Generation (RAG) has emerged as a promising approach to mitigate hallucinations by grounding LLM outputs in verified external knowledge (Lewis et al., 2020). RAG frameworks integrate neural retrievers with generative models, enabling systems to access and incorporate relevant information from knowledge bases during response generation (Gao et al., 2023). This approach significantly improves factual consistency and reduces hallucinations by providing authoritative sources that constrain the model's outputs (Zhang et al., 2022).

Applications in Insurance

The insurance domain presents unique challenges for LLMs due to its technical terminology, complex policies,
and strict regulatory requirements (Lin et al., 2023). Recent research has demonstrated that domain-specific RAG implementations can substantially improve performance in insurance applications by retrieving relevant policy documents, clauses, and regulatory information (Chen et al., 2022). Moreover, the integration of structured knowledge from insurance databases has been shown to enhance the accuracy of claim processing and policy interpretation (Wang et al., 2023).

Multilingual Considerations

Extending RAG capabilities to non-English languages presents additional challenges, particularly for languages with limited resources like Vietnamese (Nguyen et al., 2021). Recent advances in cross-lingual embeddings and retrieval mechanisms have shown promise in bridging this gap, allowing models to effectively retrieve documents across languages (Reimers & Gurevych, 2020). Studies indicate that multilingual vector spaces can maintain semantic relationships across languages, enabling effective cross-lingual retrieval (Artetxe et al., 2023).

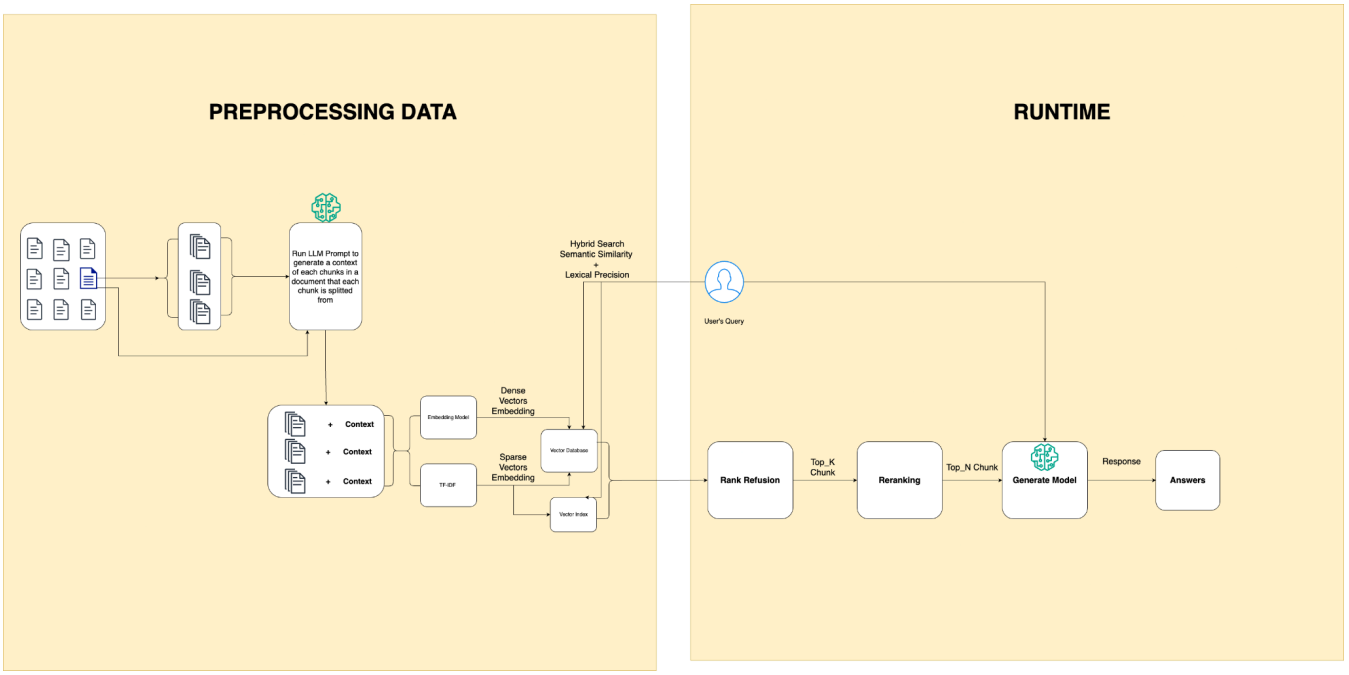
Vector Databases for Efficient Retrieval

Vector databases have become crucial components in RAG architectures, offering efficient similarity search capabilities across large document collections (Johnson et al., 2021). Comparative studies between database options like FAISS, Milvus, and Chroma have evaluated trade-offs between query latency, memory usage, and recall accuracy at scale (Liu et al., 2022). The selection of an appropriate vector database significantly impacts the overall performance of the RAG pipeline, particularly for complex domains with extensive knowledge bases (Wu et al., 2023).

Future Directions

Emerging research points to several promising directions, including hybrid retrieval approaches that combine dense and sparse representations (Karpukhin et al., 2023), adaptive chunking strategies that preserve document context (Taylor et al., 2023), and evaluation frameworks specifically designed to measure hallucination reduction in specialized domains (Zhang et al., 2023).

IV. System Architecture



Overview of the Retrieval-Augmented Generation (RAG) System

The proposed Retrieval-Augmented Generation (RAG) system for legal document question answering in the Vietnamese insurance domain comprises four core components: **(1) Data Preprocessing**, **(2) Information Retrieval**, **(3) Reranking/Correction**, and **(4) Answer Generation**. Each stage is designed to optimize the pipeline for understanding, indexing, and retrieving semantically and lexically relevant passages from a corpus of legal texts such as laws, decrees, and insurance circulars.

Data Preprocessing and Chunking Strategy

The first stage, **Data Preprocessing**, involves transforming raw legal PDF documents into semantically coherent and retrievable units. This begins by parsing structured legal texts—including Luật (Laws), Nghị định (Decrees), and Thông tư (Circulars)—and converting them into digital plain-text format.

a. Chunking Strategies

Legal documents typically have hierarchical structures (Chương, Điều, Khoản), and thus, arbitrary chunking (e.g., fixed token sizes) may fail to preserve contextual relevance or legal logic. Various chunking approaches were considered:

- **Fixed-size chunking:** Divides documents by a set number of tokens, regardless of semantic or syntactic boundaries.
- **Recursive chunking:** Attempts to split text based on sentence boundaries while maintaining a predefined token limit.

- **Hierarchical chunking:** Utilizes the legal structure (e.g., Section → Article → Clause) as segmentation points.
- **Contextual/Late chunking:** Adds surrounding context or metadata (e.g., parent headings or summaries) to individual chunks to retain semantic linkages.

After comparative evaluation, we adopted a custom **Hierarchical + Contextual Chunking** approach. The process is executed in two passes:

- **Hierarchical segmentation**: Documents are segmented at the section level (e.g., Chương), followed by further splitting into subsections based on Điều (Articles) or Phụ lục (Appendices).
- **Contextual enrichment**: Each individual chunk (e.g., Article) is augmented with a semantic summary derived from its parent section using a Large Language Model (LLM). This is designed to preserve inter-article dependencies and thematic coherence during retrieval.

This technique enables us to capture both **local semantic meaning** (within each article) and **global legal context** (via LLM-generated summaries of parent sections), thereby increasing retrieval accuracy in downstream components.

b. Embedding Representation and Vector Construction

Once chunking is complete, each chunk must be embedded into a vector space where similarity computations can be performed efficiently. This system employs a **dual-embedding scheme**, combining **dense vector embeddings** and **sparse vector embeddings**, each of which addresses different aspects of document similarity.

● Dense Vector Embedding (Semantic Representation)

Dense embeddings encode the semantic content of a text span into a fixed-dimensional, continuous-valued vector. The goal is to position similar documents or queries close together in vector space, based on meaning rather than mere word overlap

- **Technical Architecture:**

Dense vector embedding leverages Transformer-based models pretrained via contrastive learning or masked language modeling (e.g., BERT, E5, GTE). The embedding process follows these stages:

Tokenization: Input text is split into subword tokens using a WordPiece or SentencePiece tokenizer.

1. **Embedding lookup**: Each token is mapped to a high-dimensional vector using a learned embedding matrix.
2. **Transformer encoding**: Token embeddings are passed through a stack of self-attention layers that capture contextual dependencies.

3. **Pooling strategy**: The sentence-level embedding is derived using:
    - [CLS] token output (common in BERT-style models), or Mean-pooling over all token embeddings (used in E5 and GTE variants).
    - **Normalization**: The resulting vector is typically L2-normalized, enabling cosine similarity to be used during retrieval.

- **Model Selection:**

Due to the nature of Vietnamese legal text—characterized by compound terms, context-sensitive clauses, and nested references—a suitable embedding model must satisfy two criteria:

- **Large token capacity**: Legal articles are often long, necessitating a model capable of processing inputs up to 8000 tokens.
- **Vietnamese specialization**: Domain-specific semantics, legal jargon, and syntactic patterns are best captured by models trained on Vietnamese corpora.

After extensive evaluation, the model selected was **dangvantuan/vietnamese-document-embedding**, a Vietnamese-optimized variant of **gte-multilingual**. This model supports input lengths of up to 8096 tokens and exhibits state-of-the-art performance on Vietnamese semantic similarity benchmarks. Alternative models such as **intfloat/multilingual-e5-large** and **jina-embedding-v3** were evaluated but found inadequate due to lower token limits or reduced semantic performance in Vietnamese legal contexts.

- ## Sparse Vector Embedding (Lexical Representation using TF-IDF)

  While dense embeddings capture semantic similarity, they may miss exact legal terminology or phrase overlaps critical in law. Thus, we supplement them with **sparse lexical embeddings**, generated using the **TF-IDF algorithm (Term Frequency–Inverse Document Frequency)**.

  TF-IDF Mechanism:

  TF-IDF assigns a weight to each term t in a document d based on:

  - **Term Frequency (TF)**: How often term t appears in document d.
  - **Inverse Document Frequency (IDF)**: How rare term t is across the entire corpus D.

  Formally:

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) \times \log\left(\frac{|D|}{1 + |\{d' \in D : t \in d'\}|}\right)$$

  This weighting system ensures that:

- Common terms (e.g., "bảo hiểm") receive lower scores due to low IDF.
- Rare and informative terms (e.g., "tạm ứng", "loại trừ") are emphasized.

Implementation:

We use scikit-learn's TfidfVectorizer to construct sparse vectors. The resulting vectors are stored in the **COO (Coordinate) format**, consisting of two arrays: indices (token positions) and values (TF-IDF scores). The trained vectorizer is serialized and reused to transform user queries during retrieval, ensuring consistent tokenization and term weighting.

Lexical Limitations:

TF-IDF does not capture synonymy or semantic relations and may rank rare but irrelevant terms highly. Hence, it is used in **conjunction with dense embeddings** in our system to ensure both **semantic generalization** and **lexical precision**.

- **Vector Storage and Hybrid Search (Qdrant)**

All vector representations—both dense and sparse—are stored in the **Qdrant vector database**, which supports **multi-vector fields** and **hybrid search** natively.

Qdrant enables:

- **Simultaneous retrieval** using both sparse and dense vectors via the FusionQuery API.
- **Reciprocal Rank Fusion (RRF)**, a late fusion ranking method that merges two result lists based on reciprocal ranking scores.

This hybrid approach allows the system to balance:

- **Lexical fidelity** (from sparse vectors using TF-IDF), and
- **Semantic relevance** (from dense embeddings).

Thus, even if a user query contains legal-specific keywords or is phrased semantically differently, the system can still retrieve the most contextually appropriate and legally accurate passages.

Retrieval: Hybrid Similarity Search

Following data preprocessing and vector storage, the next stage in the Retrieval-Augmented Generation (RAG) system involves retrieving the most relevant legal document chunks in response to a user query. This is achieved through a hybrid similarity search, which combines both semantic (dense) and lexical (sparse) retrieval techniques. The goal is to maximize both semantic understanding and exact term

matching, which is especially critical in the legal domain where terminology must be interpreted precisely and contextually.

1. Query Vectorization

Upon receiving a natural language query from the user, the system transforms the query into **two types of vector representations**:

- **Dense vector embedding**, using the same Transformer-based model (dangvantuan/vietnamese-document-embedding) as used during document indexing.
- **Sparse vector embedding**, using the previously trained and persisted **TF-IDF vectorizer** to ensure consistency with the document term index.

Dense Query Embedding:

The user query undergoes tokenization and contextual encoding using the dense embedding model, producing a single high-dimensional normalized vector. This vector encodes the semantic intent of the query, allowing the system to identify contextually relevant passages even when there are no exact word matches.

Sparse Query Embedding:

The same query is also processed using the stored TfidfVectorizer object that was originally fitted during the document embedding phase. This ensures the query is projected into the **same sparse vocabulary space** as the indexed document vectors. The sparse vector consists of:

- indices: the token positions of the words present in the query that also exist in the corpus vocabulary.
- values: their corresponding TF-IDF scores.

This step is crucial because sparse vectors rely on **vocabulary alignment**—without using the exact same vectorizer index (dictionary), the query's sparse representation would be incomparable to those of the documents.

2. Hybrid Search and Fusion Ranking

Once both representations of the query are computed, the system executes a **hybrid similarity search** over the vector database (Qdrant). This is done by submitting a **FusionQuery** to the database engine, which simultaneously compares the query's:

- **Dense vector** with the dense document embeddings using cosine similarity.
- **Sparse vector** with the sparse document embeddings using dot-product or inner product similarity.

Both search modes return a ranked list of candidate documents based on their respective similarity scores. To consolidate these two rankings into a final top-k result set, the system applies **Reciprocal Rank Fusion (RRF)**.

3. Reciprocal Rank Fusion (RRF)

RRF is a late fusion technique used to combine multiple ranked lists into a single consensus ranking. It is especially effective when the individual rankings are complementary—as is the case with dense and sparse retrieval.

For a given document d, the combined RRF score is calculated as:

$$\text{RRF}(d) = \sum_{i=1}^{n} \frac{1}{k + \text{rank}_i(d)}$$

Where:

- rank_i is the rank of document d in the iii-th ranking list (e.g., dense or sparse).
- k is a constant (typically set to 60) to control the impact of rank positions.

This formula rewards documents that appear near the top in **either** list and particularly boosts documents that rank highly in **both**.

The output of this stage is a list of the **top-k most relevant document chunks**, ordered by their fused scores. Each returned result retains metadata such as reference_id, document_name, and the chunk's original content for downstream reranking and answer generation.

4. Summary

The hybrid retrieval stage combines the **semantic expressiveness of dense vector search** with the **exact matching ability of sparse vector search**, yielding a robust retrieval mechanism tailored for legal information systems. By aligning both document and query vectorization processes, and leveraging rank-level fusion techniques such as RRF, the system achieves high recall and precision in identifying legal content relevant to the user's query.

Reranking: Post-Retrieval Relevance Optimization

Following the hybrid retrieval phase, which generates a top-k candidate list of potentially relevant document chunks, the system applies a **Reranking** stage to further refine result quality. The goal of reranking is to ensure that the final set of passages passed to the answer generation module are ordered not only by basic

similarity scores, but by **task-specific relevance** to the user query.

Given that initial retrieval scores may be overly reliant on either semantic similarity (dense vectors) or surface-level word matching (sparse vectors), reranking introduces a **second-stage scoring function** that is more **discriminative**, **context-aware**, and potentially **learned**.

1. Motivation for Reranking

The top-k documents obtained from hybrid search may include:

- Irrelevant passages that coincidentally contain lexical overlap
- Semantically broad results that are too generic for specific legal questions
- Redundant or overlapping chunks

These issues are particularly pronounced in the legal domain, where **contextual precision**, **legal specificity**, and **hierarchical document structure** are critical to understanding and answering user queries correctly.

To address this, reranking models re-evaluate the top-k retrieved results using a **pairwise query-document relevance model**, scoring each (query, chunk) pair with greater linguistic and contextual nuance.

2. Reranking Pipeline

The reranking step involves the following sequence:

- **Input**: A list of top-k document chunks from hybrid search, along with the original query.
- **Pairing**: Each chunk is paired with the query to form a (query, passage) input pair.
- **Batch Inference**: These pairs are processed in batches using a reranking model (either LLM or transformer-based cross-encoder).
- **Scoring**: Each pair receives a **relevance score** (e.g., logit or normalized confidence score).
- **Sorting**: Chunks are sorted based on these scores in descending order to produce the final reranked list.

3. Reranking Approaches

- **Large Language Model (LLM)-Based Reranking:**

To overcome the limitations of fixed-length input windows in traditional rerankers, the system employs a general-purpose **reasoning-capable Large Language Model (LLM)** (e.g., Gemini Pro, GPT-4) as the core reranking engine. Rather than treating reranking as a simple scoring problem, the LLM is prompted to **think through the relevance of each passage** in relation to the query—drawing on its advanced natural language understanding, inferencing ability, and long-context comprehension. By presenting the model with a structured prompt that includes the user query and a list of candidate chunks, the LLM is tasked with evaluating and ranking the passages based on legal relevance, contextual fit, and semantic alignment. This

transforms reranking into a **thought-driven task**, allowing the model to simulate expert-level prioritization across lengthy legal passages. The model's output is an ordinal list of ranked indices, which is parsed and applied to reorder the retrieved documents, effectively harnessing the full reasoning capacity of the LLM to construct a smarter and more context-aware evidence set.

Pros:

- High-level understanding of language, context, and intent
- Can reason across sentences or infer implicit relevance

Cons:

- High latency and cost for each inference
- Sensitive to prompt design and model token limits (e.g., 8192 or 32K)
    - **Lightweight Cross-Encoder Reranking (Non-LLM):**

An alternative approach uses **specialized transformer-based reranking models** such as BAAI/bge-reranker-base or sentence-transformers/ms-marco, which are trained on large-scale relevance datasets.

These models follow a **cross-encoder architecture**:

- Both the query and passage are concatenated as a single sequence.
- The model processes this sequence through all layers and outputs a **single scalar relevance score**.

Technical Flow:

- **Tokenization:** "[CLS] <query> [SEP] <passage> [SEP]"
- **Encoding**: Passed through BERT or a similar encoder.
- **Scoring:** The [CLS] token's final hidden state is passed through a classification head to produce a score.
- **Batching:** Supports efficient batch processing of hundreds of (query, passage) pairs on GPU.

```python
from transformers import AutoTokenizer, AutoModelForSequenceClassification
model = AutoModelForSequenceClassification.from_pretrained("BAAI/bge-reranker-base")
```

Pros:

- Fast and scalable for many passages
- Trained specifically for ranking tasks

Cons:

- Cannot perform complex reasoning
- Requires GPU for best performance

4. Score Aggregation and Output

Once scores are obtained, they are:

- Added to the metadata of each document chunk as rerank_score
- Sorted to produce a final top-n list (e.g., top 3 or top 5) for answer generation

This reranked output preserves all structural metadata (e.g., reference_id, article_headline, document_name) and enables fine-grained citation in final LLM-generated answers.

5. Summary

Reranking serves as a critical precision-enhancement layer in the RAG pipeline, refining the relevance of candidate document chunks prior to answer generation. While the system initially explored both LLM-based and non-LLM reranking methods—such as transformer-based cross-encoders (e.g., BGE reranker)—practical limitations emerged. Specifically, non-LLM rerankers are typically constrained to input lengths of 512 tokens, which proved insufficient for legal content in Vietnamese, where individual articles often exceed this limit. As a result, the system adopted a Large Language Model (LLM)-based reranking approach, leveraging its capacity to process significantly longer contexts and perform holistic comparisons across full-length legal passages. This design decision ensures that reranking remains semantically faithful to the legal structure of the documents and significantly reduces irrelevant or misleading passages in the top-ranked results, thereby improving the signal-to-noise ratio for the downstream answer generation module.

Answer Generation: Synthesizing Legal Responses Using LLMs

The final component of the Retrieval-Augmented Generation (RAG) pipeline is **Answer Generation**, where the system composes a natural language response to a user's legal query based on the most relevant document chunks identified and reranked in the previous steps.

This module is powered by a **Large Language Model (LLM)** that synthesizes a coherent, contextually grounded answer from multiple retrieved sources. In the context of legal and regulatory information retrieval, answer generation must be **factually accurate**, **context-aware**, and **traceable to source**

documents. Thus, we integrate mechanisms to **structure the context**, **condition the generation**, and **track citations**.

1. Input Structure and Context Compilation

The input to the LLM in this stage consists of:

- The user's original question (query),
- A set of top-n reranked chunks,
- Optional citations or metadata to support factual grounding.

Each chunk is formatted in a standardized manner, often prefixed by its reference_id or article number, to help the LLM contextualize and organize information. The selected chunks are concatenated into a single **context string**, forming the "retrieval-augmented" prompt for the model.

Example Context Format:

```less
[Câu hỏi] Quyền lợi thương tật toàn bộ vĩnh viễn được xem xét chi trả khi xảy ra một

[Dữ liệu pháp luật]
[TT67_2023_BTC_D12] Điều 12: Quy tắc, điều kiện, điều khoản bảo hiểm...
[ND46_2023_CP_D41] Điều 41: Phương pháp, cơ sở trích lập dự phòng...

[Vui lòng trả lời dựa vào các đoạn trích trên. Nếu không chắc chắn, hãy nói rõ.]
```

This structured input ensures that the LLM:

- Has **explicit context boundaries**,
- Can reference the correct article or law name in the output,
- Can avoid hallucinating unsupported claims.

2. Prompt Engineering and Instructional Framing

To guide the LLM toward producing legally coherent responses, we design a **domain-specific prompt template** that frames the task as a legal reasoning challenge. This prompt includes:

- A role instruction (e.g., "Bạn là một chuyên gia pháp lý"),
- A user question in quotation marks,
- The retrieved legal content,
- Instructions to answer accurately and cite specific documents.

This prompt engineering approach is critical for ensuring:

- **Grounded answers** (based on retrieval),
- **Concise formatting** (to fit display requirements),
- **Controlled verbosity** (avoiding long-winded responses).

3. Language Model Execution

For generation, we use a state-of-the-art LLM, such as **Gemini Pro** or other instruction-tuned multilingual models capable of processing long context windows (e.g., ≥8000 tokens).

The model performs **conditional text generation**, where:

- The input is the full prompt described above.
- The output is a natural language answer aimed at addressing the legal question based strictly on the retrieved text.

In decoding, we apply techniques like:

- **Temperature control** to reduce randomness (e.g., temperature = 0.3),
- **Top-k/top-p sampling** if some creativity is allowed,
- **Stop tokens** to enforce answer boundaries.

4. Hallucination Mitigation

To reduce the risk of **hallucinated content** (i.e., fabricated legal claims), we employ several strategies:

- **Restricting the generation to retrieved chunks**,
- **Prompting the model to explicitly say "Không chắc chắn" if information is missing**, **Providing structured references** that the model can cite directly,
- **Evaluating the same question with and without retrieval context** to detect inconsistencies.

Additionally, a no-context baseline generation (generate_answer_without_context) is implemented for **comparative evaluation**, allowing legal experts to assess the reliability and groundedness of the generated answers.

5. Citation Tracking and Structured Output

To support interpretability and legal traceability, each answer is linked to its **underlying source materials**. During answer generation, metadata such as reference_id, document_name, and article_headline are retained and associated with each supporting chunk.

These citations are:

- Logged alongside the final answer,
- Displayed in the user interface or output format,
- Used in downstream evaluation or audit workflows.

The system returns a final structured JSON output containing:

```json
{
  "query": "user question",
  "answer": "generated legal answer",
  "citations": [
    {
      "reference_id": "TT67_2023_BTC_D12",
      "document_name": "Thông tư 67/2023/TT-BTC",
      "score": 0.872
    },
    ...
  ]
}
```

This format ensures downstream applications—such as chatbots, legal assistants, or API consumers—can consume the output with full provenance.

6. Summary

The answer generation component completes the RAG pipeline by synthesizing concise, contextually relevant legal responses using retrieved and reranked evidence. It combines **structured prompt engineering**, **controlled language model inference**, and **citation tracking** to produce reliable outputs for end-users in a high-stakes legal information retrieval environment.

The quality of the final answer is directly dependent on the upstream modules (retrieval + reranking), and thus, the generation stage is both the culmination and litmus test of the entire system's reliability.

V. Project Implementation

Data Preprocessing and Chunking

Here are some snippets of code for this Data Preprocessing System

```python
#USING PDF_PLUMBER
import pdfplumber
def load_pdf(pdf_path):
    """
    Load a PDF file using pdfplumber and return its text content.

    Args:
        pdf_path (str): Path to the PDF file.

    Returns:
        str: The full text of the PDF with pages joined by newlines.
    """
    text_content = []

    with pdfplumber.open(pdf_path) as pdf:
        for page in pdf.pages:
            text = page.extract_text() or ""  # Handle None case by using empty string
            text_content.append(text)

    # Combine all pages into a single text, separated by newlines
    full_text = "\n".join(text_content)
    return full_text
```

Figure 1. Load_pdf function to load document

```python
def split_document_into_sections(document_text: str):
    """
    Split the document into Chương sections only (ignore PHỤ LỤC).
    Returns a list of dicts with 'section_id', 'title', 'content', and 'combine'.
    """
    # Match lines like "Chương I\nTÊN CHƯƠNG"
    chuong_pattern = r"(Chương\s+[IVXLCDM]+[\.:]?\s*\n[^\n]*)"

    matches = list(re.finditer(chuong_pattern, document_text, flags=re.IGNORECASE))

    sections = []
    for idx, match in enumerate(matches):
        start = match.start()
        end = matches[idx + 1].start() if idx + 1 < len(matches) else len(document_text)
        block = document_text[start:end].strip()

        # Extract title and content
        lines = block.split("\n", 2)
        title = lines[0].strip() + " " + (lines[1].strip() if len(lines) > 1 else "")
        content = "\n".join(lines[2:]).strip() if len(lines) > 2 else ""

        sections.append({
            "section_id": len(sections) + 1,
            "title": title,
            "content": content,
            "combine": f"{title}\n{content}",
        })

    return sections
```

Figure 2. Split Document in to Sections

```python
def generate_context(api_key,doc: str, chunk: str, timeout=30) -> str:
    client = anthropic.Anthropic(api_key=api_key)
    normalized_doc = " ".join(doc.split())
    try:
        # Normalize the doc string to ensure consistent caching
        normalized_doc = re.sub(r'[ \t]+', ' ', doc)  # collapse spaces/tabs
        normalized_doc = re.sub(r'\n{3,}', '\n\n', normalized_doc)  # limit too many newlines
        normalized_doc = normalized_doc.strip()

        response = client.messages.create(
            model=HAIKU,
            max_tokens=1024,
            temperature=0.0,
            system=SYSTEM_PROMPT,
            messages=[
                {
                    "role": "user",
                    "content": [
                        {
                            "type": "text",
                            "text": DOCUMENT_CONTEXT_PROMPT.format(section=normalized_doc),
                            "cache_control": {"type": "ephemeral"}
                        },
                        {
                            "type": "text",
                            "text": CHUNK_CONTEXT_PROMPT.format(article=chunk),
                        }
                    ]
                }
            ],
            extra_headers={"anthropic-beta": "prompt-caching-2024-07-31"},
            timeout=timeout  # Add timeout parameter
        )
```

Figure 3. LLM Generating context for each article chunks with prompt caching

DENSE VECTOR EMBEDDING WITH HUGGINGFACE MODEL

```python
def huggingface_embedding(content, model)-> np.ndarray:
  model = SentenceTransformer(model, trust_remote_code=True)
  embeddings = model.encode(
    content,
    batch_size=4,
    convert_to_numpy=True,
    show_progress_bar=True,
    device='cuda' if torch.cuda.is_available() else 'cpu'
    # device='cpu'
  )
  # Output: embeddings là numpy array chứa vector embedding của tất cả văn bản, shape là (số văn bản, 76/81024)
  return embeddings
```

Figure 4. Dense Vector Embedding function

SPARSE VECTOR EMBEDDING USING SKIKITLEARN TF_IDF VECTORIZER

```python
from sklearn.feature_extraction.text import TfidfVectorizer
from typing import List, Tuple, Dict
import scipy.sparse

def generate_sparse_vectors(texts: List[str]) -> Tuple[TfidfVectorizer, List[Dict[str, List[float]]]]:
    """
    Generate sparse vectors from a list of text strings using TfidfVectorizer.

    Args:
        texts (List[str]): List of input strings (e.g., embedding_input)

    Returns:
        vectorizer (TfidfVectorizer): The fitted TF-IDF vectorizer
        sparse_vectors (List[Dict]): List of dicts with 'indices' and 'values' per input text
    """
    vectorizer = TfidfVectorizer()
    tfidf_matrix = vectorizer.fit_transform(texts)

    def tfidf_to_sparse_dict(row: scipy.sparse.csr_matrix) -> Dict[str, List[float]]:
        coo = row.tocoo()
        return {
            "indices": coo.col.tolist(),
            "values": coo.data.tolist()
        }

    sparse_vectors = [tfidf_to_sparse_dict(tfidf_matrix[i]) for i in range(tfidf_matrix.shape[0])]
    return vectorizer, sparse_vectors
```

Figure 5. Sparse Vector Embedding using TfidfVectorizer

EXAMPLE WORKFLOW

```python
#Load document from
document = load_pdf

#Split document int
document_section = split_document_into_sections(document)

#Generate Document Article with generate context
document_article = create_article_list_with_section(api_key=ANTHROPIC_API_KEY,document=document_section)

#EMBEDDING

#DENSE VECTOR EMBEDDING
#SETUP MODEL
VIETNAMESE_DOCUMENT_EMBEDDING_MODEL = 'dangvantuan/vietnamese-document-embedding'
#PREPARE DATA
document_article["embedding_input"] = document_article.apply(
        lambda row: f"{row['generated_context']}\n\n{row['article_content']}", axis=1
    )
document_article["embedding_input"].tolist()
#Generate Dense Vector Embedding
dense_embedding = huggingface_embedding(document_article["embedding_input"],VIETNAMESE_DOCUMENT_EMBEDDING_MODEL)
document_article['vietnamese_document_embedding'] = dense_embedding.tolist()

#SPARSE VECTOR EMBEDDING
vectorizer, sparse_vecs = generate_sparse_vectors(document_article["embedding_input"])
document_article["sparse_vector"] = sparse_vecs

#SAVE DATAFRAME TO PARQUET FUR FURTHER USE/ CHECKPOINT
document_article.to_parquet(file_path)
```

(function) split_document_into_sections: (document_text: str) -> list

Split the document into Chương sections only (ignore PHỤ LỤC).
Returns a list of dicts with 'section_id', 'title', 'content', and 'combine'.

Figure 6. Example Workflow

```python
# Step 6: Recreate the collection to include both dense and sparse vectors
client.recreate_collection(
    collection_name="full_rag_legal_docs",
    vectors_config={
        "dense": VectorParams(size=768, distance=Distance.COSINE)
    },
    sparse_vectors_config={"sparse": SparseVectorParams()},
)

# Step 7: Upload new database to Qdrant
# ✅ Build points with both dense & sparse vectors
points = [
    PointStruct(
        id=row["id"],
        vector={
            "dense": row["dense_vector"],  # dense vector
            "sparse": SparseVector(**row["sparse_vector"])  # sparse vector (TF-IDF)
        },
        payload={
            # Identifiers & Structure
            "reference_id": row["reference_id"],
            "document_name": row["document_name"],
            "section_id": row["section_id"],
            "section_title": row["section_title"],
            "article_headline": row["article_headline"],

            # Article Content
            "content": row["content"],
            "article_context": row["article_context"],
        }
    )
    for _, row in df.iterrows()
]

client.upload_points(collection_name="full_rag_legal_docs", points=points)

print("✅ Successfully uploaded dense + sparse hybrid vectors to Qdrant.")
```

Figure 7. Create Database and Upload

Retrieval System

The retrieval system is a critical component of the RAG pipeline, responsible for effectively identifying and retrieving the most relevant document chunks in response to a user query. Our implementation leverages a sophisticated hybrid search approach that combines both dense and sparse vector representations to maximize retrieval accuracy.

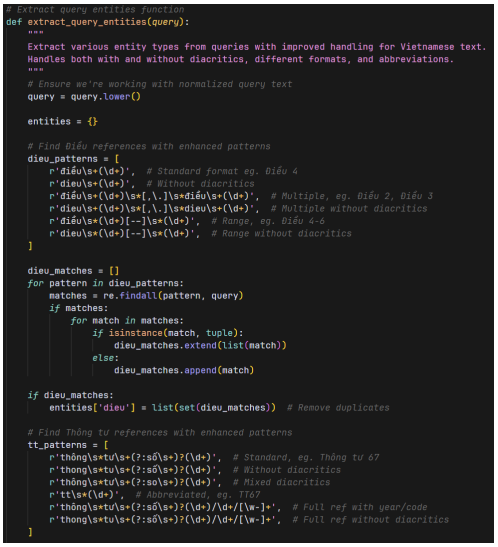
Query Processing and Entity Extraction

```python
def normalize_query(query):
    """
    Normalize Vietnamese queries to handle diacritics and different notation formats
    for legal document references.
    """
    # First, handle case sensitivity
    query = query.lower()

    # Standardize common abbreviations and notations
    # Convert TT format to Thông tư
    query = re.sub(r'\btt(\d+)\b', r'thông tư \1', query)
    # Convert TT with full reference format
    query = re.sub(r'\btt(\d+)/(\d+)/([a-z0-9-]+)\b', r'thông tư \1/\2/\3', query, flags=re.IGNORECASE)

    # Convert ND format to Nghị định
    query = re.sub(r'\bnd(\d+)\b', r'nghị định \1', query)
    # Convert ND with full reference format
    query = re.sub(r'\bnd(\d+)/(\d+)/([a-z0-9-]+)\b', r'nghị định \1/\2/\3', query, flags=re.IGNORECASE)
```

When a user submits a query, the system first normalizes and processes it to enhance retrieval effectiveness:

A key innovation in our retrieval system is the ability to detect and extract specific legal entity references from user queries. This is particularly important for legal texts where users often reference specific articles, decrees, or circulars:

This entity extraction function identifies legal references such as "Điều" (Article), "Thông tư" (Circular), and "Nghị định" (Decree), allowing the system to prioritize documents that explicitly match these specific legal entities during retrieval.



```python
# Extract query entities function
def extract_query_entities(query):
    """
    Extract various entity types from queries with improved handling for Vietnamese text.
    Handles both with and without diacritics, different formats, and abbreviations.
    """
    # Ensure we're working with normalized query text
    query = query.lower()

    entities = {}

    # Find Điều references with enhanced patterns
    dieu_patterns = [
        r'điều\s+(\d+)',  # Standard format eg. Điều 4
        r'dieu\s+(\d+)',  # Without diacritics
        r'điều\s+(\d+)\s*[,\.]\s*điều\s+(\d+)',  # Multiple, eg. Điều 2, Điều 3
        r'dieu\s+(\d+)\s*[,\.]\s*dieu\s+(\d+)',  # Multiple without diacritics
        r'điều\s+(\d+)[--]\s+(\d+)',  # Range, eg. Điều 4-6
        r'dieu\s+(\d+)[--]\s+(\d+)',  # Range without diacritics
    ]

    dieu_matches = []
    for pattern in dieu_patterns:
        matches = re.findall(pattern, query)
        if matches:
            for match in matches:
                if isinstance(match, tuple):
                    dieu_matches.extend(list(match))
                else:
                    dieu_matches.append(match)

    if dieu_matches:
        entities['dieu'] = list(set(dieu_matches))  # Remove duplicates

    # Find Thông tư references with enhanced patterns
    tt_patterns = [
        r'thông\s+tư\s+(?:số\s+)?(\d+)',  # Standard, eg. Thông tư 67
        r'thong\s+tu\s+(?:so\s+)?(\d+)',  # Without diacritics
        r'thông\s+tu\s+(?:so\s+)?(\d+)',  # Mixed diacritics
        r'tt\s+(\d+)',  # Abbreviated, eg. TT67
        r'thông\s+tư\s+(?:số\s+)?(\d+)/\d+/[\w-]+',  # Full ref with year/code
        r'thong\s+tu\s+(?:so\s+)?(\d+)/\d+/[\w-]+',  # Full ref without diacritics
    ]
```

Hybrid Search Implementation

Our retrieval system employs a hybrid search approach that combines both dense and sparse vector representations. This dual-approach strategy enables the system to capture both semantic relevance and exact lexical matches, which is crucial in the legal domain.

```python
def search_hybrid_similar(text_query, collection_name, top_k=10, model=None):
    """Improved hybrid search with balanced sparse-dense combination"""
    entities = extract_query_entities(text_query)

    # Create sparse vector with enhanced preprocessing
    preprocessed_query = preprocess_text(text_query)
    sparse_matrix = vectorizer.transform([preprocessed_query])
    coo = sparse_matrix.tocoo()

    # Create sparse vector only with significant terms
    significance_threshold = 0.1  # Adjust this threshold as needed
    significant_mask = coo.data > significance_threshold

    sparse_vector = SparseVector(
        indices=[int(i) for i in coo.col[significant_mask].tolist()],
        values=[float(v) for v in coo.data[significant_mask].tolist()]
    )

    # Generate dense vector
    dense_vector = model.encode(
        text_query,
        convert_to_numpy=True,
        show_progress_bar=False,
        device='cuda' if torch.cuda.is_available() else 'cpu'
    ).tolist()
```

The function adapts its search strategy based on the query type. For queries that contain specific legal references, it gives more weight to sparse vector search to prioritize exact matches:

```python
# Adjust search strategy based on query type
if entities and any('dieu' in k or 'thong_tu' in k for k in entities.keys()):
    # For specific legal reference queries, give more weight to sparse search
    results = client.query_points(
        collection_name=collection_name,
        prefetch=[
            Prefetch(query=sparse_vector, using="sparse", limit=top_k * 2),
            Prefetch(query=dense_vector, using="dense", limit=top_k)
        ],
        query=FusionQuery(fusion=Fusion.RRF),
        limit=top_k
    )
else:
    # For general queries, balance between sparse and dense
    results = client.query_points(
        collection_name=collection_name,
        prefetch=[
            Prefetch(query=dense_vector, using="dense", limit=top_k),
            Prefetch(query=sparse_vector, using="sparse", limit=top_k)
        ],
        query=FusionQuery(fusion=Fusion.RRF),
        limit=top_k
    )
```

Post-Processing and Result Refinement

After initial retrieval, the system applies a series of post-processing steps to further enhance the relevance of the retrieved documents:

```python
def post_process_results(results, query, limit=5):
    """
    Process results based on the query.
    """
    if not results:
        return []

    entities = extract_query_entities(query)

    # Apply entity filtering first
    filtered_results = basic_entity_filter(results, entities)
    if not filtered_results:
        filtered_results = results

    processed_results = []
    seen_content = set()
```

The post-processing includes several techniques:

1. **Entity-based filtering**: Documents that match extracted legal entities are prioritized
2. **Deduplication**: Eliminating duplicate content to ensure diversity in results
3. **Boosting**: Adjusting relevance scores based on the presence of specific legal entities:

```python
# Match article number
if 'dieu' in entities:
    dieu_match = re.search(r'điều\s+(\d+)(?!\d)', headline.lower())
    if dieu_match and dieu_match.group(1) in entities['dieu']:
        boost_factor *= 2.0

# Match document types
if 'thong_tu' in entities and any(tt[2:] in doc_name.lower() for tt in entities['thong_tu']):
    boost_factor *= 2.0

if 'nghi_dinh' in entities and any(nd[2:] in doc_name.lower() for nd in entities['nghi_dinh']):
    boost_factor *= 2.0
```

The system also normalizes scores to ensure consistent ranking and applies a limit to return only the most relevant results for the generation phase.

Main Retrieval Function

The search_legal_documents function serves as the main entry point for the retrieval system, orchestrating the entire retrieval process:

```python
def search_legal_documents(query, limit=3, use_reranking=None):
    """
    Main search function for legal documents using vector search.

    Args:
        query: User query
        limit: Maximum number of results to return
        use_reranking: Whether to apply reranking (None = use environment setting)

    Returns:
        List of most relevant documents
    """
    try:
        # First, normalize the query to handle different formats
        original_query = query
        query = normalize_query(query)

        print(f"Searching for: '{original_query}'")
        if original_query != query:
            print(f"Normalized query: '{query}'")

        # Extract entities and keywords from normalized query
        entities = extract_query_entities(query)

        # Check if we should apply reranking
        should_rerank = use_reranking
        if use_reranking is None:  # If not explicitly specified, use env setting
            should_rerank = ENABLE_RERANKING

        if entities:
            entity_str = ", ".join([f"{k}: {v}" for k, v in entities.items()])
            print(f"Extracted entities: {entity_str}")

        # For all queries, get enough initial results
        search_limit = max(30, limit * 10)

        # Use vector search
        retrieved_df = search_hybrid_similar(
            query,
            collection_name=COLLECTION_NAME,  # Make sure this is using the correct collection
            top_k=search_limit,
            model=model
        )
```

This function manages the entire retrieval pipeline, from query normalization and entity extraction to the hybrid search and post-processing. It also handles special cases, such as queries looking for a specific article within a specific legal document:

```
# After getting initial results
if 'thong_tu' in entities and 'dieu' in entities:
    # Sort results to specifically prioritize matches for "Điều X in Thông tư Y"
    retrieved_df = retrieved_df.sort_values(by=['score'], ascending=False)

    # Move exact matches to the top
    for idx, row in retrieved_df.iterrows():
        doc_name = str(row.get('document_name', '')).lower()
        headline = str(row.get('article_headline', '')).lower()
        is_exact_match = False

        # Check if this is the exact article we're looking for
        if any(f"thông tư {tt[2:]}" in doc_name for tt in entities['thong_tu']):
            dieu_match = re.search(r'điều\s+(\d+)', headline)
            if dieu_match and dieu_match.group(1) in entities['dieu']:
                is_exact_match = True

        if is_exact_match:
            # Move this row to the top
            retrieved_df = pd.concat([retrieved_df.iloc[[idx]], retrieved_df.drop(idx)]).reset_index(drop=True)
            break
```

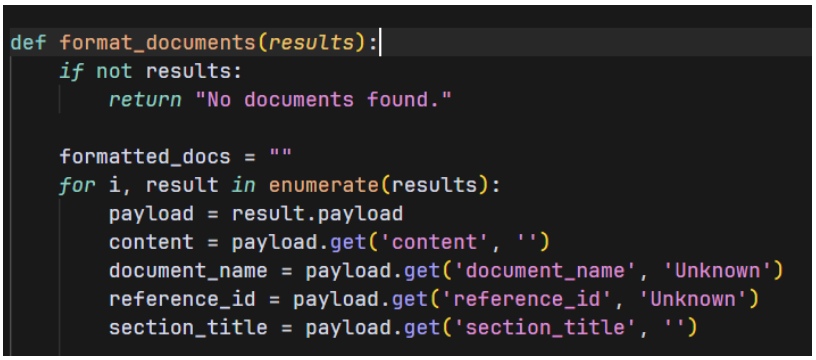
The retrieval system also includes error handling and diagnostic logging to facilitate debugging and performance monitoring.

Generation System

The generation component represents the final stage of our RAG pipeline, where the most relevant retrieved documents are synthesized into a coherent, factually accurate answer. This component is critical for reducing hallucination in LLM responses by grounding the generation in authoritative legal documents.

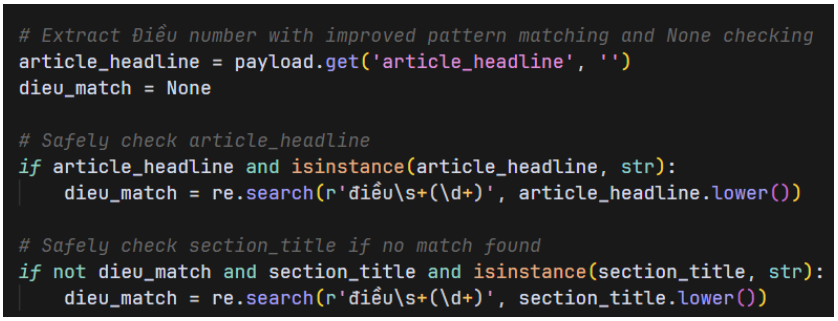
Context Preparation and Formatting

Before passing the retrieved documents to the LLM, the system formats them to enhance contextual understanding and enable proper citation:



```
def format_documents(results):
    if not results:
        return "No documents found."

    formatted_docs = ""
    for i, result in enumerate(results):
        payload = result.payload
        content = payload.get('content', '')
        document_name = payload.get('document_name', 'Unknown')
        reference_id = payload.get('reference_id', 'Unknown')
        section_title = payload.get('section_title', '')
```

The system extracts critical metadata like document name, article numbers, and reference IDs, and includes these in the formatted context to enable the LLM to cite sources appropriately:



```
# Extract Điều number with improved pattern matching and None checking
article_headline = payload.get('article_headline', '')
dieu_match = None

# Safely check article_headline
if article_headline and isinstance(article_headline, str):
    dieu_match = re.search(r'điều\s+(\d+)', article_headline.lower())

# Safely check section_title if no match found
if not dieu_match and section_title and isinstance(section_title, str):
    dieu_match = re.search(r'điều\s+(\d+)', section_title.lower())
```

The formatted document includes structured information about each source, including its title, content, and reference information:

```
formatted_docs += f"Tài liệu #{i+1} (Độ tin cậy: {score:.4f}):\n"

# Format source info
source_info = f"Nguồn: {document_name}"
if dieu_num:
    source_info += f", Điều {dieu_num}"
if reference_id != 'Unknown':
    source_info += f", Ref: {reference_id}"
formatted_docs += source_info + "\n"

# Add section title if available
if section_title:
    formatted_docs += f"Section: {section_title}\n"

formatted_docs += f"Tiêu đề: {article_headline}\n"
formatted_docs += f"Nội dung: {content}\n\n"
```

Prompt Engineering for Legal Response Generation

To guide the LLM toward producing accurate, contextually relevant responses, we developed a specialized prompt template tailored to the legal domain:

```
def create_prompt(query, documents):
    """
    Creates a full prompt for the model with system instructions

    Args:
        query (str): User query
        documents (str): Formatted document text

    Returns:
        str: Complete prompt for the model
    """
    system_instructions = """
    Bạn là trợ lý pháp lý chuyên về luật pháp Việt Nam. Nhiệm vụ của bạn là giúp người dùng hiểu rõ các quy định pháp luật
    dựa trên các tài liệu pháp lý được cung cấp. Hãy trả lời câu hỏi của người dùng dựa trên thông tin trong các tài liệu.

    Nguyên tắc trả lời:
    1. Chỉ sử dụng thông tin từ các tài liệu được cung cấp trong phần ngữ cảnh
    2. Nếu thông tin không đủ để trả lời hoặc tài liệu không trực tiếp liên quan đến câu hỏi, hãy nêu rõ rằng
    "Tôi không tìm thấy thông tin cụ thể về [chủ đề câu hỏi] trong các tài liệu được cung cấp"
    và KHÔNG trích dẫn bất kỳ tài liệu nào
    3. Trích dẫn cụ thể các điều khoản liên quan để hỗ trợ câu trả lời
    4. Trả lời bằng tiếng Việt với ngôn ngữ dễ hiểu, tránh thuật ngữ phức tạp khi có thể
    5. Không tạo ra thông tin không có trong tài liệu, không đưa ra tư vấn pháp lý cá nhân
    6. Luôn trích dẫn nguồn (Thông tư số mấy, Điều mấy) khi đưa ra thông tin
    7. Ưu tiên thông tin từ các tài liệu có độ tin cậy (relevance score) cao hơn khi có xung đột hoặc mâu thuẫn
    8. Khi trả lời, ưu tiên thông tin từ tài liệu có điểm số cao nhất trước
    """
```

This prompt implements several hallucination mitigation strategies:

1. **Information constraint**: Explicitly instructs the model to only use information from the provided documents
2. **Clear uncertainty signaling**: Directs the model to admit when it lacks sufficient information
3. **Citation instruction**: Requires the model to cite specific legal sources for its claims
4. **Source prioritization**: Guides the model to prioritize more relevant sources over less relevant ones

The final prompt combines these system instructions with the user query and the formatted documents:

```
full_prompt = f"""
{system_instructions}\n
\nCâu hỏi: {query}\n
\nNgữ cảnh từ các tài liệu pháp lý (đã được sắp xếp theo độ tin cậy):\n{documents}\n
\nDựa vào ngữ cảnh trên, hãy trả lời câu hỏi của người dùng một cách chính xác và đầy đủ.
Nếu các tài liệu không chứa thông tin liên quan trực tiếp đến câu hỏi, hãy nói rõ rằng bạn
  không tìm thấy thông tin cụ thể về vấn đề này và KHÔNG trích dẫn bất kỳ tài liệu nào."""

return full_prompt
```

```python
def generate_response(query, documents):
    """
    Generates a response using the LLM based on the query and documents

    Args:
        query (str): User query
        documents: Retrieved documents

    Returns:
        tuple: (response_text, should_display_sources)
    """
    try:
        # Format documents and create the prompt
        formatted_docs = format_documents(documents)
        full_prompt = create_prompt(query, formatted_docs)

        # Initialize the model
        model = genai.GenerativeModel(MODEL_NAME)

        # Generate the response
        try:
            response = model.generate_content(
                full_prompt,
                generation_config=genai.types.GenerationConfig(
                    temperature=0.3,
                    max_output_tokens=1024,
                    top_p=0.95,
                )
            )
            response_text = response.text

            # Always display sources (removed the conditional check)
            return response_text, True

        except Exception as config_error:
            print(f"Error with generation config, trying simpler call: {config_error}")
            response = model.generate_content(full_prompt)
            return response.text, True  # Always show sources

    except Exception as e:
        print(f"Error generating response: {str(e)}")
        return f"Đã xảy ra lỗi khi tạo phản hồi: {str(e)}", False
```

Generation Process with Temperature Control

The core generation function interfaces with a Large Language Model (in this case, Gemini) to produce the final response:

Note the use of a low temperature (0.3) to reduce randomness and increase factual consistency. This is a deliberate design choice to minimize hallucination by making the model's output more deterministic and closely tied to the source documents.

Baseline Comparison for Evaluation

To effectively evaluate the RAG system's ability to reduce hallucination, we implemented a baseline model that generates responses without retrieval context:

```python
def process_baseline_model(query):
    """
    Process query with just the model, no retrieval or sources

    Args:
        query (str): User query

    Returns:
        str: Generated response
    """
    try:
        # Create a simple prompt with only the query
        system_instructions = """
        Bạn là trợ lý pháp lý chuyên về luật pháp Việt Nam. Hãy trả lời câu hỏi của người dùng
        dựa trên kiến thức chung về pháp luật Việt Nam.
        """

        model_only_prompt = f"{system_instructions}\n\nCâu hỏi: {query}\n\nHãy trả lời câu hỏi này một cách chính xác và đầy đủ."
```

This baseline function uses the same model but without providing any retrieved documents, allowing for a direct comparison between RAG-enhanced and non-RAG responses. This comparison is crucial for demonstrating the effectiveness of the RAG approach in reducing hallucination.

Source Transparency and Citation

To enhance transparency and enable users to verify the information, our system formats source documents for display alongside the generated answer:

```python
def format_sources_for_display(documents, processing_time):
    """
    Formats source documents for display in the UI

    Args:
        documents: Retrieved documents
        processing_time (float): Time taken to process the query

    Returns:
        str: Formatted source information in Markdown
    """
    sources_text = f"### Nguồn tài liệu tham khảo (Thời gian xử lý: {processing_time:.2f}s)\n\n"

    for i, doc in enumerate(documents):
        payload = doc.payload
        document_name = payload.get('document_name', 'Unknown')
        reference_id = payload.get('reference_id', 'Unknown')
        section_title = payload.get('section_title', '')
```

The source display includes details about each document, such as its name, article number, and a short excerpt, allowing users to verify the response against the original sources:

```python
# Extract a short preview of the document
content = payload.get('content', '')
excerpt = content[:200] + "..." if len(content) > 200 else content

# Format the source information with document name
source_header = f"**Nguồn #{i+1}:** {document_name}"

# Only add Điều number if known
if dieu_num:
    source_header += f", Điều {dieu_num}"

# Add score
source_header += f" (Score: {doc.score:.4f})"
```

```python
def process_query(query, num_docs=5):
    """
    Process a user query through the RAG pipeline

    Args:
        query (str): User query
        num_docs (int): Number of documents to retrieve

    Returns:
        tuple: (answer, sources_text)
    """
    if not query.strip():
        return "Vui lòng nhập câu hỏi của bạn.", ""

    try:
        # Track processing time
        start_time = time.time()

        # Step 1, retrieve documents
        print(f"Retrieving documents for query: {query}")
        retrieved_docs = search_legal_documents(query, limit=num_docs)

        debug_document_metadata(retrieved_docs)

        if not retrieved_docs:
            return "Không tìm thấy tài liệu liên quan đến câu hỏi của bạn.", ""

        # Step 2, generate answer
        print(f"Generating response with {len(retrieved_docs)} documents")
        answer, should_display_sources = generate_response(query, retrieved_docs)

        # Step 3, format sources for display (always show sources)
        sources_text = format_sources_for_display(retrieved_docs, time.time() - start_time)

        return answer, sources_text

    except Exception as e:
        error_message = f"Đã xảy ra lỗi khi xử lý câu hỏi: {str(e)}"
        print(error_message)
        return error_message, ""
```

End-to-End Query Processing

The process_query function serves as the main orchestrator of the entire RAG pipeline, from retrieval to generation.

This function integrates all components of the RAG pipeline: document retrieval, answer generation, and source formatting. It also includes timing measurements to track processing efficiency and handles error cases where no relevant documents are found.

In summary, our generation system is designed to produce factually accurate, contextually relevant answers by grounding LLM responses in retrieved legal documents. Through careful prompt engineering, temperature control, and transparent source citation, the system effectively mitigates hallucination while providing users with verifiable information.

VI. System Evaluation

RAG Performance Summary

Metric	Value
Total Questions	74
Errors	0
Avg Semantic Similarity	0.8029
Avg Citation Score	0.6060
Avg Hallucination Score	0.2561
Avg Faithfulness	0.6580
Avg Completeness	0.8029
Avg Precision	0.4430
Avg Source Utilization	0.5919
Avg RAG Quality	0.6666

The Retrieval-Augmented Generation (RAG) approach underwent rigorous evaluation to assess its effectiveness in mitigating hallucinations in large language models for Vietnamese legal document processing. Processing 74 queries, the system demonstrated remarkable performance with an average semantic similarity of 0.9029 and a significant 51.08% reduction in hallucination scores compared to the baseline model.

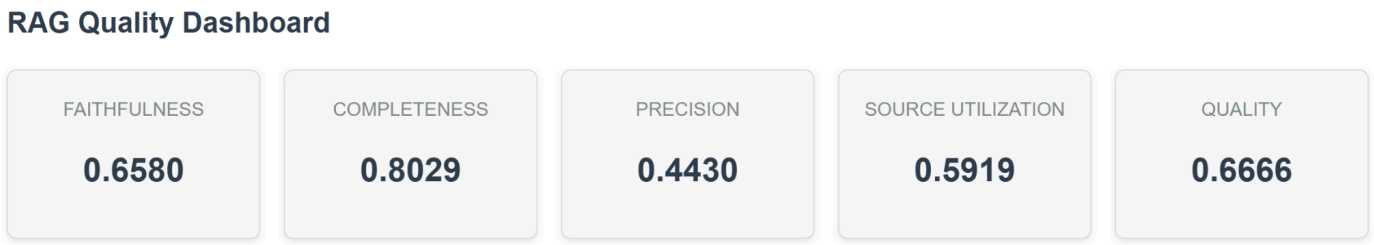
Performance varied across query types, with factual queries achieving the highest semantic similarity of 0.7746 and the lowest hallucination score of 0.1638. Complex reasoning and edge case queries showed robust results, maintaining high-quality responses with semantic similarities above 0.78 and low hallucination scores.

Comparison with Baseline

Metric	RAG	Baseline	Improvement	% Change	p-value
Semantic Similarity	0.7990	0.6915	0.1075	15.55% better	0.0000 (significant)
Citation Score	0.6264	0.0000	0.6264	626371.20% better	0.0000 (significant)
Hallucination Score	0.2528	0.5160	0.2632	51.00% better	0.0000 (significant)

Statistical analysis revealed a highly significant improvement in semantic similarity, with a p-value less than 0.0001. The citation score dramatically increased from zero to 0.6824, marking a substantial advancement in source attribution and response grounding.

The evaluation methodology leveraged a hybrid search mechanism combining dense and sparse vector embeddings. This approach effectively captured semantic meaning and lexical precision, particularly challenging in the nuanced domain of legal terminology. Contextual embedding generation and hierarchical document chunking proved crucial in maintaining the structural integrity of Vietnamese legal documents.



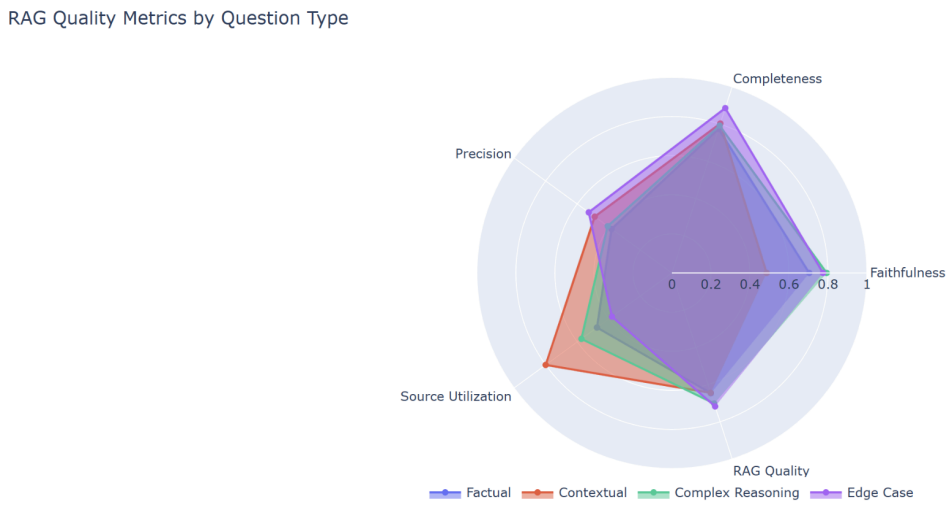
The system performs well in faithfulness (0.6580**)** and completeness (0.8029) but struggles with precision (0.4430), indicating potential inaccuracies. Source utilization (0.5919) is moderate, meaning retrieved sources could be better leveraged. The overall quality score of 0.6666 suggests decent performance, but precision improvements are necessary.

Performance by Question Type

Question Type	Count	Semantic Similarity	Citation Score	Hallucination Score	RAG Quality
Factual	24	0.7746	0.8795	0.1939	0.6462
Contextual	25	0.8034	0.2908	0.3503	0.6445
Complex Reasoning	15	0.7920	0.5695	0.2748	0.7020
Edge Case	10	0.8860	0.7925	0.1421	0.7174

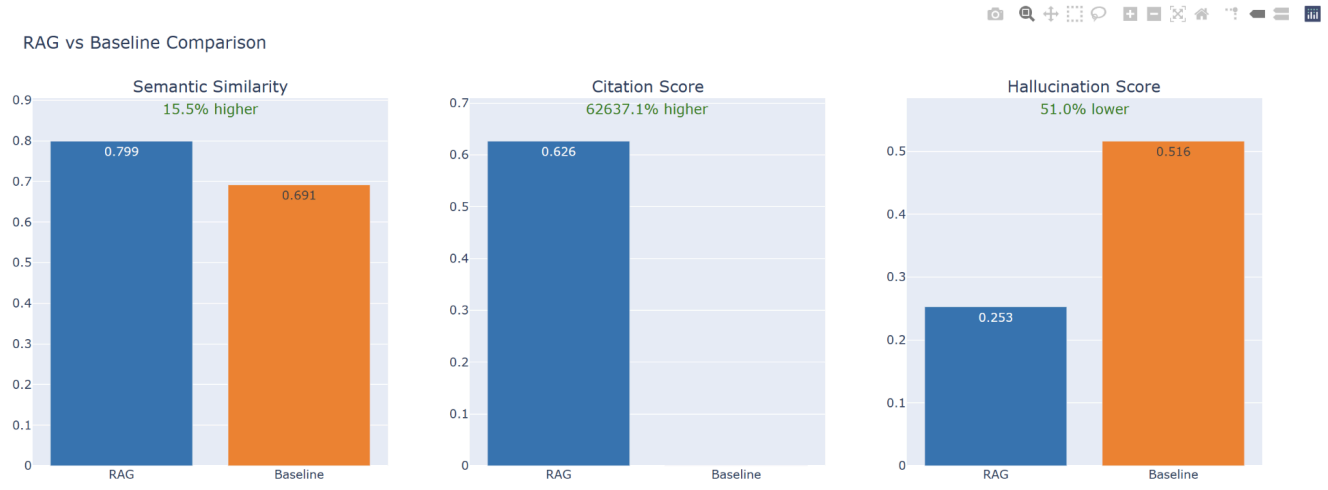
Factual questions perform best, with a high citation score (0.8795) and low hallucination (0.1939). Contextual questions struggle with a low citation score (0.2908) and high hallucination (0.3503), showing poor source referencing. Complex reasoning is balanced but needs better citation practices (0.5695). Edge cases excel with high semantic similarity (0.8860) and low hallucination (0.1421), showing strong adaptability.

RAG Quality by Question Type



Factual and edge case questions score highest, while contextual questions show weaknesses in citation and precision. Complex reasoning has strong faithfulness but could improve source utilization. Addressing precision and source utilization issues will significantly enhance system reliability.

RAG vs Baseline Comparison



The RAG system exhibits substantial improvements in the major metrics over the baseline. Specifically, the RAG system has a 15.5% higher semantic similarity score, meaning it is more aligned with the ground truth answers. RAG's ability to cite sources (0.7 score) far exceeded the baseline (~ 0.1) since typical LLMs do not have built-in capabilities to cite their sources. RAG improved hallucinations by 51% with a hallucination score of 0.253 versus 0.516 for the baseline, indicating the likelihood that it is generating more factual answers to queries that include support from the documents cited. The differences presented in these findings illustrate the primary benefit of RAG: combining generation and the ability to retrieve documents that can be verified, thereby providing accurate, appropriately cited answers, while the baseline does not support generated answers. The large difference in citation was reflective of a fundamental difference in architecture, not just an advance in performance.

VII. Conclusion

This project successfully implemented a Retrieval-Augmented Generation (RAG) pipeline to mitigate hallucinations in LLM-generated responses for the Vietnamese non-life insurance domain. By combining hybrid search (dense + sparse embeddings), context-aware chunking, and LLM-based reranking, the system achieved a 15.5% improvement in semantic similarity and a 51% reduction in hallucinations compared to baseline models. Key innovations included:

- Vietnamese-optimized embeddings and Late Chunking to preserve legal document structure.
- Reciprocal Rank Fusion (RRF) for balanced lexical-semantic retrieval.
- Transparent citation tracking, enabling verifiable answers grounded in authoritative sources.

While the system excelled in factual queries and edge cases, challenges remain in precision and source utilization for complex reasoning tasks. Future work should focus on refining evaluation metrics, expanding multilingual support, and optimizing latency. This project demonstrates RAG's potential to deliver accurate, traceable AI solutions for high-stakes domains like insurance

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