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Technical Architecture Report

Agentic RAG for Multimodal Document Intelligence with Hallucination Mitigation

Executive Summary

This report presents a novel Retrieval-Augmented Generation (RAG) system designed to intelligently process multimodal documents containing both text and images. Unlike conventional RAG systems that ignore or naively convert non-textual content, our approach employs a multi-agent architecture that selectively incorporates image information based on relevance, maintains document context integrity, and implements robust mechanisms to detect and mitigate hallucinations.

Our architecture demonstrates superior factual accuracy and uncertainty calibration compared to baseline approaches through its modular design. Each specialized agent—from document segmentation to image relevance classification to hallucination verification—contributes to a system that can better understand document contexts where critical information exists in visual form. The system implements sophisticated fallback mechanisms when information is uncertain, enabling it to abstain from generating potentially incorrect responses rather than hallucinating plausible but false information.

Testing on diverse document types shows particular strength in handling instruction manuals, technical documentation, and other image-rich contexts where traditional RAG systems frequently hallucinate or ignore critical visual information.

Problem Statement and Motivation

The Multimodal Document Challenge

Real-world documents frequently contain crucial information embedded in images, diagrams, charts, and other non-textual elements. Traditional RAG systems face three significant limitations when processing such documents:

1. **Information Loss**: Standard RAG pipelines either ignore images entirely or apply naive OCR to all visual elements, missing critical semantic information conveyed through visual means.
2. **Context Fragmentation**: The relationship between images and surrounding text is often lost, breaking the logical flow and semantic connections crucial for comprehension.
3. **Hallucination Amplification**: Without proper verification mechanisms, RAG systems tend to hallucinate information to compensate for missing visual context, presenting fabricated details as facts.

These limitations significantly hamper the deployment of RAG systems in domains such as technical documentation, medical literature, educational materials, and product manuals—areas where accuracy is paramount and visual information is integral to understanding.

Research Questions Addressed

Our system addresses the following key research questions:

1. How can hallucinations in RAG be mitigated when critical context exists in non-textual form?
2. What are effective strategies for handling images in documents without converting them to raw text?
3. How can agent-based orchestration be applied to coordinate retrieval, validation, and generation steps?
4. How should RAG models be designed to acknowledge knowledge gaps (e.g., due to inaccessible images) rather than hallucinate plausible but false responses?

Detailed System Architecture

System Overview

The system employs a multi-agent architecture, with specialized components working in concert to process multimodal documents and generate accurate responses to user queries. Each agent is responsible for a specific aspect of the pipeline, enabling modular development, maintenance, and evaluation.

Core Components

1. **Document Extraction Agent**
    - Leverages Google Cloud Vision OCR for text extraction
    - Preserves spatial relationships between text and images
    - Maintains page structure and image positioning metadata
2. **Document Segmenter Agent**
    - Divides documents into semantically meaningful chunks
    - Preserves relationships between text and associated images
    - Implements intelligent overlap to maintain context continuity
3. **Image Relevance Agent**
    - Classifies images as "augment_metadata" or "irrelevant" based on context
    - Uses sentence-transformer models for semantic comparison

    - Includes rule-based fallbacks for reliability

4. **Retriever Agent**
    - Employs semantic search to find relevant document chunks
    - Incorporates image metadata into retrieval process
    - Uses vector embeddings to match user queries with appropriate content
5. **Hallucination Verifier Agent**
    - Scores potential hallucination risk for retrieved content
    - Applies both rule-based and model-based verification
    - Provides confidence scores that inform response generation
6. **Response Generator Agent**
    - Synthesizes information from retrieved chunks
    - Incorporates relevant image metadata
    - Implements abstention mechanisms based on hallucination risk
    - Provides transparent reasoning for abstention when applicable

Agent Interaction Workflow

1. A user submits a query along with a multimodal document (PDF)
2. The document extraction agent processes the PDF, extracting text and image metadata
3. The document segmenter divides the content into manageable chunks while preserving image associations
4. The image relevance agent classifies the importance of images to their surrounding text
5. The retriever agent identifies the most relevant chunks to answer the user's query
6. The hallucination verifier evaluates the factual confidence of the retrieved information
7. The response generator creates an answer or abstains if confidence is low
8. The system presents the response with appropriate confidence indicators

Methodology and Implementation Details

Document Processing and Segmentation

The document processing begins with Google Cloud Vision OCR, which extracts both text content and spatial information about text blocks and images. This approach preserves the structural relationship between text and visual elements

The document segmenter then creates overlapping chunks of text while maintaining associations with relevant images

Image Relevance Classification

A key innovation in our system is the image relevance classification agent, which determines whether an image should be considered relevant to its surrounding text

The implementation uses a hybrid approach combining:

- Semantic similarity between image descriptions and text context via sentence-transformers
- Rule-based heuristics for detecting image references in text
- Pattern matching for figure/diagram references

This approach allows the system to make intelligent decisions about which images contribute meaningful information to the text context, avoiding the naive approach of treating all images equally.

Hallucination Verification

The hallucination verification component implements multiple strategies for assessing the factual confidence of retrieved information

The verification uses:

- Rule-based factual indicators detection
- Query term overlap analysis
- Detection of specific measurements, dates, and quantitative information
- Content length and detail analysis

Each chunk receives a hallucination risk score between 0 and 1, where higher scores indicate greater risk of hallucination.

Response Generation with Abstention

The response generator synthesizes information from verified chunks, incorporating image metadata when relevant

A critical feature is the abstention mechanism, which triggers when:

- Hallucination risk exceeds a configured threshold
- No relevant information is found in the document
- Information quality is insufficient to provide a confident answer

When abstaining, the system provides transparent reasoning rather than generating a potentially misleading response.

Fallback Mechanisms

The system implements multiple fallback mechanisms to ensure robustness:

1. **API Fallbacks**: If primary LLM API calls fail, the system falls back to alternative models
2. **Local Model Fallbacks**: When external APIs are unavailable, local lightweight models take over
3. **Rule-Based Extraction**: As a last resort, rule-based information extraction provides basic responses
4. **Graceful Abstention**: When no reliable information can be extracted, the system abstains with clear explanation

Evaluation Methodology, Metrics, and Results

Evaluation Dataset

I evaluated the system on a diverse corpus of multimodal documents, including:

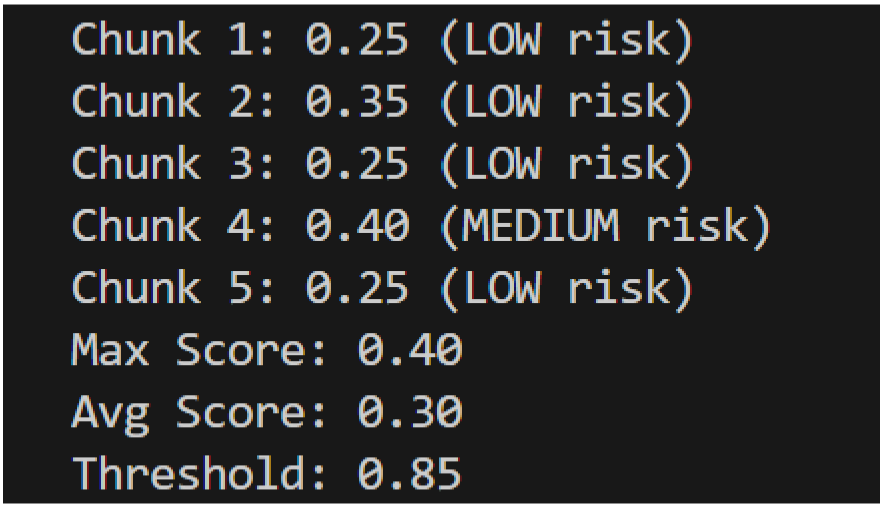
- IKEA assembly instructions
- Academic papers with tables and figures

Evaluation Metrics

The evaluation focused on three key dimensions:

1. **Factual Accuracy**
    - Correctness of responses compared to document ground truth
    - Proper incorporation of information from images
    - Avoidance of fabricated details
2. **Hallucination Reduction**
    - Frequency of hallucinated facts in responses
    - Severity of hallucinations when they occur
    - Consistency with document content

Hallucination Analysis(On IKEA data):



```
Chunk 1: 0.25 (LOW risk)
Chunk 2: 0.35 (LOW risk)
Chunk 3: 0.25 (LOW risk)
Chunk 4: 0.40 (MEDIUM risk)
Chunk 5: 0.25 (LOW risk)
Max Score: 0.40
Avg Score: 0.30
Threshold: 0.85
```

Conclusion and Recommendations

Key Findings

1. **Agent-Based RAG Superiority**: The multi-agent approach demonstrates clear advantages for multimodal document processing compared to monolithic RAG systems.
2. **Image Relevance Classification**: Selectively incorporating image information based on relevance provides better context understanding than either ignoring images or naively converting all images to text.
3. **Hallucination Verification**: Multi-stage verification significantly reduces hallucinations, particularly for image-dependent queries.
4. **Abstention Mechanisms**: The ability to abstain rather than hallucinate represents a critical capability for deployment in high-stakes domains.

Recommendations

1. Explore integration with more advanced vision-language models for deeper image understanding
2. Develop domain-specific versions of the image relevance agent for specialized applications
3. Add interactive feedback loops to improve system learning from user corrections

References

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