**Frankfurt University
of Applied Sciences**

– Faculty of Computer Science and Engineering –

Evaluating the Role of Chunk Size in Retrieval-Augmented Generation (RAG)

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Declaration

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Frankfurt, 21. January 2025

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Abstract

The study investigates the impact of chunk size on RAG-generated responses, focusing on key metrics such as retrieval and response accuracy, retrieval and response time, hallucination rates, and contextual relevance. For constructing the knowledge base, the structured **'christti/squad-augmented-v2'** dataset was used as a test dataset. Two known chunking strategies, PAGE (also referred to as document-based chunking) and fixed-size chunking with SMALL, MEDIUM, and LARGE chunk sizes, were used. For the evaluation, 90 random questions were selected, and responses for each chunk type were generated. Various metrics, such as ROUGE, BERT, BERT, and LLM-as-a-Judge, were used to evaluate the generated responses. The analysis revealed that chunk size significantly influences RAG performance. Smaller chunks improve response time and precision but require more retrieval time due to greater overhead, while larger chunks achieve better retrieval efficiency but often fail to align well with specific queries. Document chunks tend to be the most effective in maintaining high retrieval and response accuracy, while medium chunks maintain a balance between contextual breadth and query relevance. The findings suggest the need for domain-specific adaptation, dynamic chunking strategies, and alignment between contexts and queries to enhance the efficiency and accuracy of RAG systems across diverse applications.

Chapter 1

Introduction

1.1 Background and Context

Introduction to Large Language Models

Large Language Model (LLM) are advanced AI systems capable of analyzing and generating human language. They can intelligently analyze text to produce coherent responses and execute various language-related tasks. In the business world, LLMs can unlock valuable insights from vast amounts of text data, automate time-consuming tasks, and enhance customer experiences through more personalized and efficient interactions.[22]

Limitations of Standalone Large Language Models

However, despite their power, LLMs face critical limitations when they are used as a standalone system. In many cases, LLM generate responses that sound plausible but are factually incorrect. This phenomenon is known as hallucination. This occurs because LLM rely on pre-trained data, which may not contain all the necessary knowledge to accurately answer domain-specific questions. [7][43] Additionally, pre-trained LLM are limited by the static knowledge they acquired during training. They cannot access recent developments or specialized domain knowledge that wasn't included in their training data. [7][43] Furthermore, many real-world applications, such as legal, medical, or technical fields, require domain-specific expertise. LLM alone may lack the depth that may necessary to handle such specialized queries effectively. [7] Moreover, in question-answering tasks, users often expect accurate, up-to-date, and contextually relevant responses. [43]

Introduction to the Retrieval-Augmented Generation

To overcome these limitations, a new paradigm called Retrieval-Augmented Generation (RAG) has been introduced. RAG is a framework which is designed to enhance the performance of LLM by incorporating an external mechanism. Instead of completely depending on the pre-trained knowledge base within the model, RAG retrieves relevant document chunks from external knowledge bases based on semantic similarity calculations. This enables LLM to access and incorporate up-to-date, domain-specific information into their responses. By referencing external knowledge, RAG addresses a significant limitation of traditional LLM: their tendency to generate factually incorrect content when they are faced with queries that are not in their training data. The retrieved information from the external knowledge base grounds the LLM's responses, reducing the problem of hallucinations. Due to this integration, RAG has become a widely adopted technology, particularly in advancing chatbot capabilities and improving the practical applicability of LLM in real-world applications.[7]

Challenges in RAG Implementation

However, with the development of RAG technique, new challenges have emerged. A reliable retrieval pipeline is crucial for building effective RAG-based applications. The quality of the final answer highly depends on the relevance of the retrieved text to the user's query. If the retriever fails to identify relevant information from the knowledge bases, the LLM may generate inaccurate or misleading responses.[29] One of the most crucial factors that directly influences the performance of semantic retrieval is chunk size.[16] In the chunking process, a large corpus of text data is divided into smaller and semantically meaningful units.[46] Smaller chunks contain more focused and context-specific information, improving the relevance of retrieved results. However, they may lack the broader context necessary to answer certain queries. Conversely, larger chunks include more context, some of which may not be relevant to the specific query. This can lead to less accurate similarity scores and potentially less useful results for RAG.[16]

1.2 Motivation

The evaluation of the impact of chunk size on RAG systems is highly significant because it directly affects the performance and reliability of applications such as chatbots and QA systems. In RAG-based systems, LLM are enhanced by integrating external knowledge sources which enable them to generate more accurate and contextually relevant responses. [30]
However, the effectiveness of this integration can be influenced by the chunk size, or how the corpus data is segmented. [7] In real-world applications like chatbots, the precision and relevance of responses are crucial. Improper chunking may lead to the retrieval of irrelevant or incomplete information which results in responses that are factually incorrect or lack coherence. [43] For example, in customer support scenarios, a chatbot must access specific sections of the knowledge base to accurately answer user queries. Because of large chunk size the system may retrieve unnecessary information which may overwhelm the user with irrelevant details. [16] On the other hand, if the chunks are too small, critical context may be missed by the retrieval system which may lead to incomplete answers. [30] Effective chunking ensures that the system can extract relevant documents without being misled by irrelevant content. [43] This precision affects the system's ability to provide more accurate and concise answers. [7]

Therefore, understanding and optimizing chunk size is essential for improving the performance of RAG-based applications. By ensuring optimal chunk sizes, developers can improve the accuracy of information retrieval and build efficient AI-driven communication tools. [30]

1.3 Research Problem

1.3.1 Main Research Question

The main question of this research is to evaluate the influence of chunk size on the accuracy, relevance, and efficiency of responses generated by RAG models in open-domain question answering.

1.3.2 Supporting Questions

In order to thoroughly address this primary question, the following supporting questions will also be explored:

- **Impact on Factual Accuracy:** How does chunk size affect the factual accuracy of RAG-generated answers?
- **Retrieval accuracy:** How does chunk size influence retrieval efficiency and accuracy? Specifically, does using smaller chunks yield more relevant context from vector search compared to larger chunks?
- **Mitigating Hallucinations:** Are shorter or longer chunk size more effective in minimizing hallucinations in generated responses?

- **Recommended Chunk Size:** What is a recommended chunk size to effectively balance retrieval efficiency and response quality in RAG models?
- **Performance Metrics:** Does chunk size impact the generation speed and real-time applicability of RAG-based systems?
- **Context vs. Irrelevance:** How do larger chunks compare to smaller ones in contributing irrelevant details that may affect response quality?

1.4 Objectives

The objectives of this thesis are designed to systematically investigate the role of chunk size on the performance of RAG based systems. Each of these objectives is specifically tailored to assess a crucial aspect of model performance:

1.4.1 Evaluate Chunk size and Accuracy

One of the primary objectives of this thesis is to assess how different chunk sizes, such as short, medium, and long, affect the quality and factual accuracy of RAG-generated responses. Chunk size directly impacts the contextual information available to the model during generation.[16] This objective focuses on quantifying the effects of chunk size on accuracy through rigorous experimentation. In the evaluation, metrics such as Precision, Recall, F1-score, BLEU, BERT score, and ROUGE will be employed to assess the impact of chunk size on RAG based system.

1.4.2 Analyze Hallucination Rates

RAG systems, like many other generative models often produce hallucinations—responses containing fabricated or unsupported or irrelevant information. These hallucinations can undermine the trustworthiness and usability of the system.[31] This objective intends to evaluate and classify the prevalence of hallucination as a function of chunk size. Hallucinations will be categorized into two classes:

- **Intrinsic hallucinations**, these errors may arise from the generative model, often resulting from pre-trained biases or insufficient contextual understanding.[31]
- **Extrinsic hallucinations**, these errors are a consequence of the system's reliance on incomplete, irrelevant, or noisy information extracted from its knowledge base.[31] The system's inability to accurately identify and filter out such information can lead to the generation of misleading outputs.

1.4.3 Assess Retrieval and Generation Speed

Efficiency is a vital factor in the development of RAG based systems, most importantly in real-time applications. Different chunk sizes impact the speed of retrieval and response generation.[34] The aim of this objective is, to measure the retrieval times and the generation speeds for each chunk size to find out the trade-offs between speed and quality, that are highly required in real-time applications. These assessments will provide insights into the feasibility of RAG systems for real-time use cases.

Chapter 2

Literature Review

2.1 Foundational Studies

In this section the key foundational works that form the basis of RAG systems will be explained briefly. Focus will be on two particularly relevant studies. These studies provide a strong foundation for understanding the core concepts and challenges in RAG research.

Mix-of-Granularity: Optimize the Chunking Granularity for Retrieval-Augmented Generation

Zijie Zhong et al.[47] introduces the Mix-of-Granularity (MoG) approach. In this approach chunk sizes are dynamically adjusted based on the query requirements to optimize RAG performance. This study highlights the trade-offs between retrieval efficiency and response quality. A hierarchical retrieval framework is used to achieve MoG that combines smaller chunks for precision with larger chunks for context, which dynamically balances granularity to suit different tasks. This study establishes a strong evidence that chunk size directly impacts retrieval speed, hallucination rates, and the overall factual accuracy of generated responses. This research provides critical insights into the effects of chunk granularity, that forms a theoretical basis for examining chunk size systematically.

Financial Report Chunking for Effective Retrieval-Augmented Generation

Another Study [14], which was conducted by Antonio Jimeno Yepes et al. that experimented chunking strategies specifically in the context of financial documents. Their study highlights the impact of chunk size on RAG systems, particularly while dealing with complex, structured data. They propose methodologies for chunking financial reports into semantically coherent segments, which demonstrate that appropriate chunk sizes improve retrieval relevance and generative accuracy while reducing hallucinations. This work also highlights the challenges in processing lengthy financial documents, that emphases the need for tailored chunking strategies to ensure performance in domain-specific applications.

These foundational studies lay the groundwork for understanding how chunk size affects RAG models, particularly in diverse and complex domains such as open-domain QA and structured document retrieval.

2.2 Related Work

This section explores relevant literature that intersects with the research focus, which offer insights into document retrieval, generative systems, and the specific influence of document characteristics like length or chunk size.

Document Retrieval and QA Systems

Extensive research has been carried out to improve document retrieval methods for question-answering (QA) systems. Works like "End-to-End Open-Domain Question Answering with Retrieval-Augmented Generation"[11] examine how retrieval quality directly impacts the accuracy and relevance of QA outputs. Additionally, advancements in vector-based retrieval models, such as ColBERT[15], emphasize the importance of granularity in retrieval tasks. These studies highlight the importance of retrieval units, such as chunks or passages, that shape the performance and accuracy of QA systems.

Impact of Document Length on Model Performance

Research such as "Document Length and Relevance in Neural Information Retrieval"[19] and "Chunking Strategies in Long Document Processing"[5] analyze how document length and chunk size affect model performance. The findings of these studies suggest that shorter documents generally provide clearer and more focused context, whereas longer documents are more likely to include unnecessary details that can weaken the quality of responses. The highlight of these studies suggests how to find the balance between extracting rich contextual information and minimizing noise, which is crucial for determining optimal chunk sizes in RAG systems.

Hallucinations in Generative Models

The problem of hallucinations, where generative models produce incorrect or fabricated information, has drawn considerable attention. Research by Ji et al.[13] categorizes hallucinations into intrinsic and extrinsic types as well as explores strategies to mitigate them. In the context of RAG, studies such as "A comprehensive survey of hallucination mitigation techniques in large language models"[41] show how retrieval quality and document characteristics contribute to minimize hallucination rates. These insights provide a foundation for examining how chunk size influences the probability of hallucinations in RAG-generated responses.

This literature review provides the theoretical basis for this thesis by connecting foundational studies with recent advancements in document retrieval and generative systems. The findings of these studies suggest a critical need to evaluate chunk size as a factor that influences RAG performance, to address key issues such as retrieval efficiency, response quality, and mitigation of hallucination.

2.3 Gap Analysis

Although Retrieval-Augmented Generation(RAG) has shown significant potential in improving the quality of response generated by LLM, it's unclear what effect different chunk sizes have on retrieval relevance, generative accuracy, and hallucination mitigation. Existing studies, such as those by Zijie Zhong et al. [47] and Antonio Jimeno Yepes et al.[14], focus on specific applications but do not provide an unified framework for evaluating chunk size across diverse contexts. Moreover, the relationship between chunk size and hallucination mitigation, specifically its impact on the grounding of generative outputs, requires further investigation. Furthermore, the trade-off between context richness and noise introduced by varying chunk sizes has not been systematically analyzed. This research aims to fill these gaps by offering a systematic evaluation of the impact of chunk size in RAG systems, with experiments performed on Q & A datasets to address key issues such as retrieval efficiency, response quality, contextual accuracy and the hallucination rates.

Chapter 3

Theoretical Background

3.1 RAG architecture

Retrieval-Augmented Generation (RAG) expands the abilities of Large Language models by enabling them to incorporate real-world data and dynamic knowledge.[7, 4] While language models like GPT-3 can generate impressive text, their performance is constrained by the specific information they were trained on. Additionally, their context window[18], which refers to the limited amount of text they can process at once, hinders their ability to effectively utilize vast knowledge bases. RAG addresses this limitation by adding a retrieval process that searches in a vector database for relevant information, which is then combined with the original query before being sent to the language model.[4]

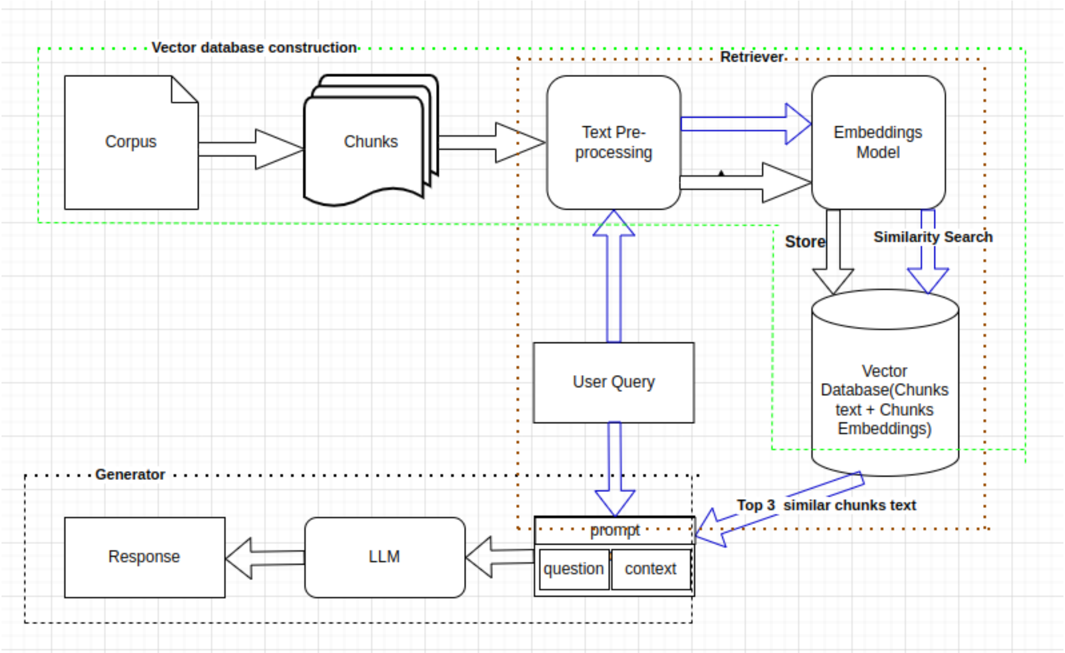

Figure 3.1: RAG architecture

The process starts with Vector Database Construction, where a large corpus is split into smaller chunks. These chunks undergo text pre-processing and are converted into vector embeddings using an embedding model. Both the textual chunks and their vector embeddings are stored in a Vector Database, enabling similarity search for future queries. The foundation of a RAG architecture lies in two key components: the **retriever** and the **generator**.[4] To understand how it works, let's take a closer look at the roles of each.

Retriever

When a user submits a query, the Retriever processes the query by transforming it into a vector representation using the same embedding model. This ensures compatibility with the vectorized documents stored in the database. A similarity search is then performed to identify the top relevant chunks based on their vector similarity scores. These chunks are retrieved and passed as context, along with the original query, to the Generator.[4]

Generator

The Generator uses the retrieved top relevant chunks to produce a final answer by synthesizing and expressing the information in natural language. It depends on a LLM such as GPT, or BART which is trained on massive datasets to generate human-like text. The generator takes both the query and the relevant contexts which were retrieved by the retriever as an input to produce a coherent and informative response.[4] Effective prompt engineering plays a crucial role in order to provide the generator proper guidelines to focus on the right context and produce precise outputs, especially when complex or ambiguous queries are processed. By carefully designing prompts, developers can better guide the LLM to utilize the retrieved knowledge effectively and ensure the generated response aligns with the intended requirements.[2]

3.2 Sentence Embeddings

Sentence embeddings are numerical representations of sentences, where each sentence is assigned to a point in a high-dimensional vector space. Unlike traditional methods like bag-of-words or TF-IDF, which focus mostly on the presence or frequency of individual words, sentence embeddings capture the semantic meaning of the entire sentence. These embeddings enable the comparison of sentences based on their semantic similarity, which facilitates tasks such as text similarity, clustering, semantic search, and question-answer retrieval.[37] Sentence embeddings are generated by transforming text into high-dimensional vectors. The closer two sentences are in this vector space, the more semantically similar they are. For instance, the sentences 'What is AI?' and 'Explain artificial intelligence' would produce embeddings that are close together because they express similar meanings.[27] Sentence embeddings are essential for many NLP applications that require an understanding of the semantic meaning of sentences.[36]

3.3 Bag of N-grams

The Bag of N-Grams Model is a method in NLP, which is used to represent text as a vector, which are contiguous sequences of words or characters. When n=1, these are referred to as uni-grams, representing individual words from the text. Let's consider two sentences "the cat sat on the mat" and "the dog sat on the mat". The Vector representation of these two sentence is following.[12]

Uni-gram Vocabulary	**The cat sat on the mat**	**The dog sat on the mat**
The	1	1
cat	1	0
dog	0	1
sat	1	1
on	1	1
the	1	1
mat	1	1

Table 3.1: Uni-gram Frequency Representation of Two Texts.

3.4 Sentence Transformer

One of the popular Python libraries for computing dense vector representations of sentences is SentenceTransformer, which facilitates various NLP tasks.[26] It is equipped with the pre-trained model **"all-MiniLM-L6-v2"**, which ensures a balance between computational efficiency and performance. This model is based on a distilled version of BERT and outputs 384-dimensional vector embeddings that capture the semantic meaning of entire sentences.[32][42]

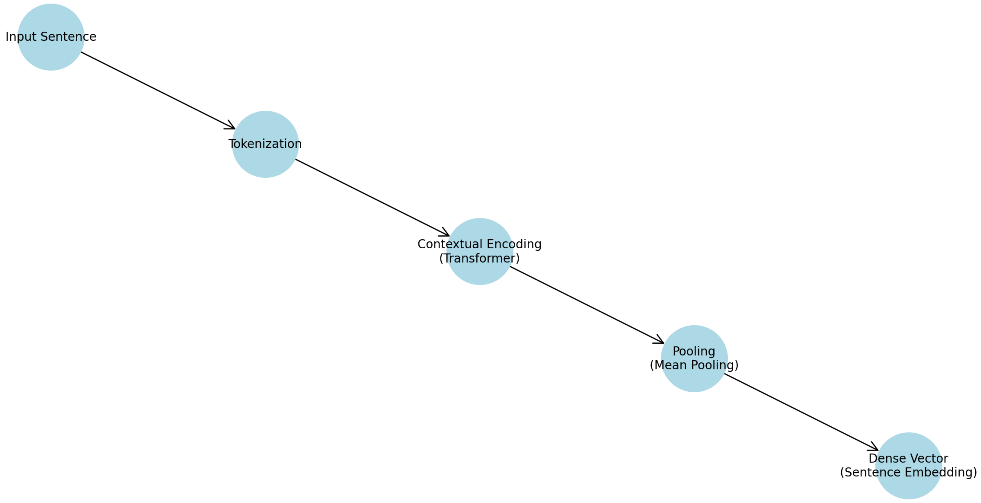

Figure 3.2: Working Procedure of SentenceTransformer

The model starts by breaking the sentence into tokens and using contextual encoding to understand semantic relationships. Afterward, it applies mean pooling to the token embeddings, resulting in a concise and meaningful representation of the sentence.[25]

3.5 Vector Search

Vector search is a method for exploring unstructured data by measuring the similarity between vector embeddings. These vector embeddings are numerical representations of data, such as text, documents, images, or audio. Vector search uses similarity measures to identify patterns and retrieve relevant information, which is useful for text-based applications like semantic search, recommendation systems, or information retrieval systems. Vector Search relies on similarity measures such as Euclidean Distance, Dot Product, or Cosine Similarity to compare vector embeddings. The choice of method depends on the nature of the dataset and the specific task requirements.[20] In the following section, we will discuss Cosine Similarity in more detail, as it is also used in the implementation of the retrieval system for this study.

3.5.1 Cosine Similarity

Cosine Similarity measures how similar two vectors are by looking at their direction, not their length. It is particularly suitable for text embeddings as it can capture semantic similarities while ignoring vector magnitude, which may vary due to sentence length or structure.[38] This measure produces a similarity score between -1 and 1, where higher values indicate closer alignment, which makes it ideal for text-based applications like document search.[20] For vector a and b with dimensions n, cosine similarity can be defined as:

$$\cos\theta = \frac{(a_1 \cdot b_1) + (a_2 \cdot b_2) + \cdots + (a_n \cdot b_n)}{\sqrt{(a_1^2 + a_2^2 \ldots a_n^2) \cdot (b_1^2 + b_2^2 \ldots b_n^2)}}$$

3.6 Chunking in RAG

3.6.1 Introduction to Chunking

Chunking, also called LLM chunking, which involves breaking down large amounts of text into smaller, more manageable chunks.[23] By breaking down textual data into coherent paragraphs, sentences, or token-limited segments, chunking facilitates precise query matching while maintaining logical coherence and reducing noise.[3] This allows each chunk to be individually indexed and easily retrieved when required. This technique significantly improves RAG systems by making retrieval faster, more accurate, and by ensuring that information is evenly distributed across the entire dataset. In practice, as Lewis et al.[17] showed, splitting a massive dataset like Wikipedia into 100-word chunks creates millions of smaller, searchable documents for retrieval process.[23] This highlights the importance of chunking for handling large datasets, maintaining context, and providing relevant answers.[3]

3.6.2 Chunking Strategies

RAG systems use various chunking strategies to optimize information retrieval and processing. Some of the chunking strategies, which are commonly used in RAG system are, Fixed-Size Chunking, Recursive-Based Chunking, Document-Based Chunking, Semantic Chunking, and Hybrid Chunking. For this study, Document-Based and Fixed-Size Chunking were used. In the following section, this chunking strategies will be discussed in detail.

Fixed-Size Chunking

Fixed-size chunking involves breaking down text into chunks of a fixed size, which is measured by the number of tokens, words, or characters. For example, a document could be broken down into chunks of 800 tokens each, without considering where sentences or paragraphs end. Although this approach is easy to implement and computationally efficient, it can divide sentences and coherent units of information, potentially resulting in a loss of context.[23].

Document-Based Chunking

In document-based chunking, the contextual data is divided minimally, or even treated as a single chunk, to ensure that the document's overall structure and context remain unchanged. This strategy is especially useful for content with a clear structure, such as legal or medical documents. However, it can be less efficient for large documents that exceed token limits.[23]

3.6.3 Impact of chunk size on RAG

The chunks size has a vital role in both the retrieval and generation stages of a RAG system. Finding the right balance in chunk size is essential to ensure that the system performs in an optimal way. As chunk size has direct impact on the granularity of retrieved information and the coherence of generated responses.[6, 40]

Impact on Information Retrieval

Larger Chunks: Larger chunks contain more context, which makes them effective for the retrieval of comprehensive information relevant to answer complex queries. This large context can include extra details that may be critical for understanding.[47, 40] But the inclusion of extra information may reduce retrieval granularity, which may lead to the retrieval of unnecessary content. This makes larger chunks less precise for specific or targeted queries.[14, 40]

Smaller Chunks: Smaller chunks allow the retrieval of more precise and specific pieces of information. This makes them ideal for the scenarios where accurate and targeted information is needed.[47, 39] However, context within smaller chunks is limited, which may result in incomplete information retrieval. This reduces their usefulness for broad-context queries.[6, 40]

Impact on Generation

Larger Chunks: Larger chunks provide the model more context during the generation, as a result the risk of hallucinations or incomplete responses can be reduced. This is especially useful for generating detailed outputs.[14] But the larger context may sometimes overwhelm the model, which may lead to exceeding the input token limit of the language model. For instance, GPT-4o has a token limit of 4096 tokens, and if the input text exceeds this limit, the model will truncate the excess tokens. This can result in truncation or inefficiencies in processing.[47, 40, 1]

Smaller Chunk: Smaller chunks provide precise and focused information to the model, which can improve the precision of generated responses. They are effective for answering simple queries requiring straightforward answers.[6, 40] However, due to lack of sufficient context, smaller chunks may lead to less accurate or simplistic answers.[14, 40]

Impact on retrieval time and response time

Response time is directly influenced by the chunk size in RAG. Larger chunk sizes provide more context for the LLM, improving response quality but potentially increasing processing time, as higher token count requires greater memory consumption and computational resources, such as CPU and GPU power. This trade-off between deeper contextual understanding and responsiveness becomes more pronounced with larger chunk sizes.[39]

The size of the chunks also highly affects the retrieval speed. Because it influences how frequently the system needs to search and the complexity of those searches. Larger chunks require more memory and computational power(e.g, CPU,GPU), whereas smaller chunks can lead to more frequent searches.[40]

3.7 Few Shot Prompting

Few Shot Prompting provides the LLM with multiple examples to clarify the task and enhance its understanding, which improves the quality of its responses. This approach demonstrates the expected input-output relationship through concrete examples, which enables the model to align its output with the desired format and context.[28]

3.8 Evaluation Metrics

In order to evaluate RAG systems nuanced metrics to measure the effectiveness of both the retrieval and generation components are required. The choice of metrics directly impacts how well these systems align with real-world requirements. Below is a detailed overview of evaluation metrics that will be used to evaluate our RAG system.

3.8.1 Retrieval Metrics

Precision

Measures the fraction of retrieved chunks that are relevant to answer the query.[44]

$$\text{Precision} = \frac{\text{Number of relevant retrieved chunks}}{\text{Total number of retrieved chunks}} \tag{3.1}$$

Recall

Recall calculates the system's ability to get all relevant chunks for a given query, ensuring completeness.[44]

$$\text{Recall} = \frac{\text{Number of relevant retrieved chunks}}{\text{Total number of relevant chunks in the knowledge base}} \tag{3.2}$$

3.8.2 Generation Metrics

BLEU

The BLEU score calculates the quality of LLM generated text by comparing it with reference text. It evaluates n-gram overlap between reference text and generated text with brevity penalties for overly short responses.[44, 9]

$$p_n = \frac{\text{Count of overlapping n-grams}}{\text{Total n-grams in candidate}} \tag{3.3}$$

$$B.P = \exp(1 - \frac{r}{c}) \text{ if } (c < r) \tag{3.4}$$

$$\text{BLEU} = BP \cdot \exp\left(\frac{1}{N}\sum_{n=1}^{N} \log P_n\right) \tag{3.5}$$

Here, B.P = Brevity penalties, c = candidate length, r = reference length, P_n = Precision for n-grams.
B.P is used to resolve the issue of short responses. When this penalty is not used, a language model might generate very short outputs (e.g., a single word) that overlap perfectly with the reference text but fail to convey the full meaning. When $c = r$ then B.P is 1, no penalized is applied. But when $c < r$, the penalty is applied, which reduces the BLEU score proportionally to how short the candidate text is compared to the reference. The B.P ensures that such excessively short outputs are penalized.[21]

ROUGE

ROUGE assesses the overlap between system-generated text and human reference texts, frequently employed in summarization tasks.[44] There are various ROUGE variants, such as ROUGE-1, ROUGE-S, ROUGE-L, and ROUGE-N. However, for our experiment, we will focus exclusively on ROUGE-1. ROUGE-1 measures overlap of uni-grams between the generated text and reference[10]

$$\text{ROUGE-1} = \frac{\text{Overlapping unigrams}}{\text{Total unigrams in candidate}} \tag{3.6}$$

BERTScore

Unlike traditional metrics like BLEU or ROUGE, which rely on n-gram overlaps, BERTScore uses contextual embeddings from transformer-based models like BERT to capture the semantic similarity between the two texts.[45, 44]

$$R = \frac{1}{|R|} \sum_{r \in R} \max_{c \in C} \text{cosine\_similarity}(E_r, E_c) \tag{3.7}$$

$$P = \frac{1}{|C|} \sum_{c \in C} \max_{r \in R} \text{cosine\_similarity}(E_c, E_r) \tag{3.8}$$

$$F_1 \text{ score} = \frac{2 \cdot P \cdot R}{P + R} \tag{3.9}$$

Where, C = Tokens in the candidate, R = Tokens in the reference, E_c, E_r : Embeddings of candidate and reference tokens, P = Precision, and R = Recall.

Human Evaluation

Human evaluation remains the best standard for assessing generative quality, Human can manually judge coherence, relevance, and fluency.

LLM as a Judge

LLM can also be used to evaluate generated text based on detailed prompts and criteria such as coherence and fluency.[44]

3.8.3 Speed Metrics

Retrieval time

This measures the time taken to fetch relevant chunks from the knowledge base.[40]

Response time

This evaluates the time taken for the language model to produce a response after retrieving the context for a given query.[39]

Chapter 4

Methodology

4.1 High Level Overview

This study investigates the influence of chunk size on the performance of RAG system, with a focus on key metrics including response accuracy, retrieval accuracy, hallucination rate, response time, and retrieval time. To facilitate this analysis, a knowledge base was constructed using the **"christti/squad-augmented-v2"** dataset, where the first 820 unique contexts were concatenated in order to form a single corpus. After analyzing the length of all the contexts, two distinct chunking strategies were developed, and a series of text pre-processing steps were performed on the resulting chunks. Vector embeddings were calculated for each chunk by using `Sentence Transformer` and stored them in a local database. The RAG architecture was implemented by selecting the most relevant chunks based on cosine similarity with the user query's embedding and generating responses for each chunk type. An Evaluation dataset was prepared by using a sample of 90 randomly selected questions from the test dataset. The performance of RAG system was assessed across metrics such as accuracy, retrieval time, and response time for evaluating the effect of chunking strategy on generated responses. In the following sections, each step of the methodology will be elaborated in detail to provide a comprehensive understanding of the research process.

4.2 Preparing the Knowledge Base

4.2.1 Dataset Selection

The **"christti/squad-augmented-v2"** dataset, which is an extension of the Stanford Question Answering Dataset (SQuAD), is an excellent choice for evaluating RAG system. This dataset contains a diverse collection of human-created contexts, each of them is paired with a question and a corresponding answer. These contexts cover a wide range of topics and are semantically rich and coherent. With so many different kinds of context, different chunk sizes can be experimented without losing the semantic meaning. Furthermore, the dataset is aligned with real-world question-answering scenarios and it is highly adopted in NLP research, which establish it as a trustworthy and dependable benchmark for assessing retrieval accuracy, contextual response quality, and hallucination rate. Moreover, its structured format simplifies text pre-processing and embedding generation.[24]

4.2.2 Corpus Construction

The dataset contains a total of 100,132 distinct contexts. For the purpose of this study, the first 820 contexts were selected as the basis for analysis. In order to construct the knowledge base, a corpus was formed, which is defined as a structured collection of texts.[8] This corpus was generated by concatenating all the selected contexts into a single unified text. The following code demonstrates the process of corpus construction.

Listing 1 Python code snippet: Corpus Formation

```python
# Load the dataset
ds = load_dataset("christti/squad-augmented-v2")
df = pd.DataFrame(ds["train"])

# Select first 820 unique contexts
contexts = df['context'].unique()[:820]

# construct the corpus
corpus = ' '.join([context for context in contexts])
```

4.2.3 Chunking Strategy

To facilitate RAG experiments, the corpus was divided into different chunk sizes. In order to evaluate the impact of chunk size on RAG this study considers two types of chunking strategies: page based chunking which follows document based chunking approach, and fixed-size chunking categorized with small, medium, and large chunk size.

Page Based Chunking

Each row in the dataset represents an unique context, which is treated as a single page. This approach aligns with one of the commonly used chunking strategies in NLP tasks, where each context is treated as an independent unit for retrieval and generation.

Determination of Chunk Sizes

For the sake of defining chunk sizes for small, medium, and large, the lengths of contexts in the dataset were analyzed. A descriptive statistical analysis of the character lengths was performed, which reveals the following:

Statistic	**Value**
Count	820.000000
Mean	731.360976
Standard Deviation (std)	358.499497
Minimum (min)	154.000000
25th Percentile (25%)	468.750000
Median (50%)	667.000000
75th Percentile (75%)	912.500000
Maximum (max)	3076.000000

Table 4.1: Statistical Analysis of Context Lengths in the Dataset.

Based on this analysis:

- **Small Chunks:** Defined as 250–500 characters, representing shorter passages near the 25th percentile of context lengths.

- **Medium Chunks:** Defined as 500–800 characters, corresponding to documents near the mean and median lengths.
- **Large Chunks:** Defined as 800–1,200 characters, encompassing longer documents that approach the 75th percentile or exceed the mean.

Chunk Overlaps

For ensuring the continuity of information across chunk boundaries, overlapping text was introduced. Overlaps were set proportionally to the chunk size, where the need to preserve semantic coherence was considered.

- **Small chunks:** 50–100 characters overlap.
- **Medium chunks:** 100–150 characters overlap.
- **Large chunks:** 150–200 characters overlap.

Implementation of Fixed-Size Chunking Strategy

For segmenting the corpus into chunks of a given chunk size `RecursiveCharacterTextSplitter` was used. `RecursiveCharacterTextSplitter` is implemented in the LangChain library, which is built using Python. In chunking process, a large corpus is broken down into smaller chunks by recursively dividing it using a hierarchical approach. It begins with larger units (e.g, paragraphs) and progressively splits into smaller parts (e.g, words) until the chunks meet the provided chunk size. For preserving the contextual balance between chunks, an overlap is often introduced, where a fixed-size portion of the text is shared between consecutive chunks. It is particularly useful for preparing text for downstream tasks such as language modeling, summarization, or document retrieval.[33]

4.2.4 Embedding Generation

After dividing the corpus into chunks of various sizes, each chunk was converted into a vector. However, before performing this conversion, comprehensive text pre-processing was applied to ensure the quality and consistency of the input data, as text pre-processing is crucial for enhancing the efficiency and accuracy of retrieval-based tasks. The pre-processing phase involved several steps, including removing HTML tags, URLs, punctuation, and stopwords, followed by applying stemming to standardize word forms and lemmatization to ensure linguistic consistency. After pre-processing, each chunk was converted into a vector using the `SentenceTransformer`, a Python module widely used for generating high-quality sentence embeddings.

4.2.5 Vector Database Construction

To facilitate efficient vector search in the RAG pipeline, a database table named `text_vectors` was created. This table functions as a storage repository for all chunked text and their associated vector representations, which facilitates efficient and streamlined retrieval processes. The table is created on a local database and is structured as follows:

Field	**Type**
id	int
chunk_text	text
chunk_type	enum('PAGE', 'SMALL', 'MEDIUM', 'LARGE')
embedding	blob

Table 4.2: Schema of the `text_vectors` table for vector database construction.

- **id:** A unique integer identifier for each entry, serving as the primary key.

- **chunk_text:** A column of type text that stores the chunked text data.
- **chunk_type:** An enumerated column indicating the type of chunk (PAGE, SMALL, MEDIUM, LARGE), which facilitates the identification and retrieval of specific chunk types.
- **embedding:** A binary large object (BLOB) column containing the vector representation of the corresponding chunk text.

This table design ensures that chunks of various types can be effectively retrieved, and their embeddings can be used for similarity-based operations in the RAG pipeline. The distribution of chunks by chunk type in the vector database is shown in the bar diagram below, highlighting the frequency of each chunk type (SMALL, MEDIUM, LARGE, PAGE).

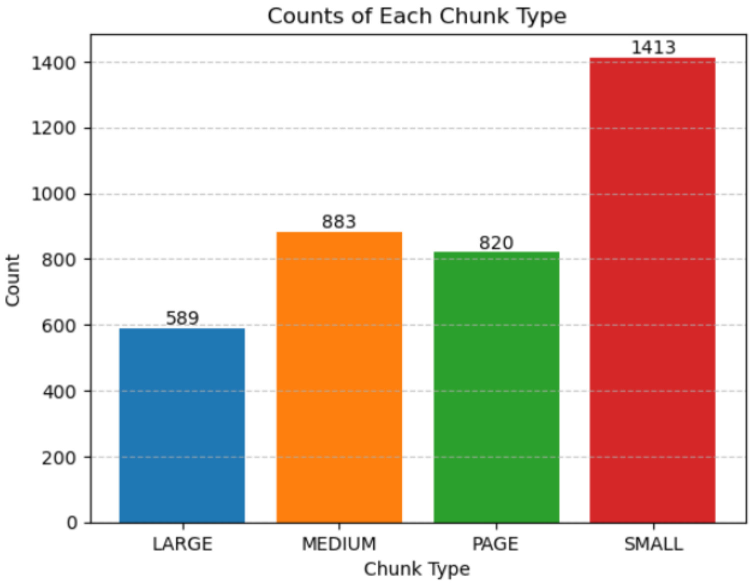

Figure 4.1: Distribution of Chunks by Chunk Type in the Vector Database

4.3 Implementation of RAG Architecture

The implementation of RAG architecture consists of two key components: **retrieval** and **generation**. These components work together to fetch relevant contextual information from a pre-constructed knowledge base and generate high-quality responses to user queries. The RAG pipeline is triggered whenever a user submits a query, initiating the retrieval and generation processes to deliver a contextually accurate response.

4.3.1 Retriever

The retrieval process identifies and retrieves the most relevant chunks from the vector database based on the user query and specified chunk type. The following code snippet demonstrates the retrieval process:

Listing 2 Python code snippet: Implementation of retrieval process

```python
def get_context_by_chunk_type(chunk_type:str, query_text:str)->dict:
    start_time = time.time()

    # Get database connection
    connection = database_connection()
    cursor = connection.cursor()

    # get chunks by chunk type
    cursor.execute("SELECT * FROM text_vectors WHERE chunk_type=%s", (chunk_type,))

    # Retrieve chunks
    rows = cursor.fetchall()

    # Convert user query into vector
    clean_query = preprocess_text(query_text.lower())
    model = SentenceTransformer("all-MiniLM-L6-v2")
    query_vector = model.encode(clean_query)

    # Perform vector search
    similar: list[Similar_Text] = []
    for row in rows:
        # Calculate cosine similarity
        sim_score = cosine_similarity(pickle.loads(row[3]), query_vector)
        similar.append(Similar_Text(row[1], sim_score=sim_score))

    # Sort chunks by similarity score
    similar.sort(key=lambda similar: similar.sim_score, reverse=True)

    # Combine most 3 relevant chunks
    text = "/n".join([sm.text for sm in similar[:3]])
    end_time = time.time()

    # calculate retrieval time
    delta= end_time - start_time
    # return relevant chunks and retrieval time
    return {"retrieval_time": delta, "text": text}
```

This process, implemented in the `get_context_by_chunk_type()` function, follows these steps:

- **Database Query:** The function connects to the vector database and retrieves entries matching the specified chunk type (PAGE, SMALL, MEDIUM, or LARGE).
- **Query Preprocessing:** The user query is preprocessed to ensure consistency with the stored chunks by converting it to lowercase and cleaning it using text preprocessing techniques.
- **Query Vectorization:** The preprocessed query is converted into a vector representation using the `SentenceTransformer`.
- **Cosine Similarity Calculation:** The similarity score between the query vector and each chunk's vector is computed to determine relevance.
- **Sorting and Selection:** The chunks are sorted by similarity scores in descending order, and the top three chunks are concatenated to form the context for the generation component.

4.3.2 Generator

The generation component builds on the retrieved chunks by using them as input to a language model to produce a response to the user query. The following code snippet demonstrates the generation process:

Listing 3 Python code snippet: Generating response for a query.

```python
def chat_with_ai(user_query: str, chunk_type: str, ref_ans: str)->dict:
    # Get OpenAI API key
    openai_api_key = os.environ["OPENAI_API_KEY"]

    # Get relevant chunks
    result = get_context_by_chunk_type(chunk_type, user_query)

    # Format the prompt
    prompt_template = ChatPromptTemplate.from_template(PROMPT_TEMPLATE)
    prompt = prompt_template.format(context=result["text"], question=user_query)

    # Initialze LLM( modle gpt-4o )
    model = ChatOpenAI(openai_api_key=openai_api_key, model_name="gpt-4o")

    # Generate response
    start_time = time.time()
    response_text = model.invoke(prompt)
    end_time = time.time()

    # Calculate response time
    delta = end_time - start_time

    # Return response time and generated response
    return {"response_time": delta, "response": response_text.content}
```

The function includes the following steps:

- **Chunk Integration:** The retrieved chunks are integrated into a predefined prompt template that combines context, user query, and additional instructions.
- **Prompt Construction:** The `ChatPromptTemplate` from LangChain dynamically formats the prompt to include the context and query seamlessly.
- **Response Generation:** The prompt is sent to OpenAI's GPT-4 model (gpt-4o) through the `ChatOpenAI` class to generate response based on the given context.
- **Response Timing:** The function measures and returns the time taken by the model to generate the response.
- **Output Formatting:** The response text and timing information are returned for further evaluation.

4.4 Preparing Evaluation Dataset

To facilitate the analysis of how varying chunk sizes impact the responses generated by RAG system, a structured evaluation dataset was prepared. To prepare the evaluation dataset, 90 questions and their corresponding reference answers were selected from the test dataset. For each question, the system generated four distinct responses, each corresponding to a different chunking strategy: **PAGE**, **SMALL**, **MEDIUM**, and **LARGE**. The generated responses, along with additional metadata, were systematically stored in a database table named `evaluate_answer`. This table was designed with the following schema:

Field	Type
id	int
ref_answer	text
chunk_type	enum('PAGE', 'SMALL', 'MEDIUM', 'LARGE')
llm_response	text
response_time	double
retrieval_time	double

Table 4.3: Schema of the `evaluate_answer` table for constructing the evaluation dataset.

- **id:** A unique identifier for each record in the table, serving as the primary key.
- **ref_answer:** The reference answer corresponding to the question, serving as a benchmark for comparison.
- **chunk_type:** The type of chunking strategy employed for generating the LLM response.
- **llm_response:** The response generated by the LLM for the specific chunking strategy.
- **response_time:** The time taken by the LLM to generate the response, measured in seconds.
- **retrieval_time:** The time taken for the retrieval process during the RAG pipeline, also measured in seconds.

4.5 Designing an LLM Evaluation Framework

In the evaluation dataset, questions, reference answers, and four LLM-generated responses corresponding to each chunk type (small, medium, large, page) were stored. To analyze the impact of chunk size on the performance of RAG system, a series of experiments will be conducted focusing on retrieval accuracy, retrieval speed, response time, hallucination rate, and contextual accuracy. To support these experiments, the LLM-generated responses were thoroughly examined manually.

Question	LLM Response	Reference Answer
When did Beyoncé release her single 'Formation'?	On February 6, 2016, one day before her Super Bowl performance.	Formation was released by Beyoncé in February 2016.
When did Beyoncé release her single 'Formation'?	Unknown based on the Context provided.	Formation was released by Beyoncé in February 2016.
Which music video sparked speculation about Beyoncé's relationship with Jay Z?	03 Bonnie & Clyde	The music video for '03 Bonnie & Clyde' where Beyoncé appeared as Jay Z's girlfriend.
Which music video sparked speculation about Beyoncé's relationship with Jay Z?	Drunk in Love	The music video for '03 Bonnie & Clyde' where Beyoncé appeared as Jay Z's girlfriend.

Table 4.4: Examples of Questions, Reference Answers, and LLM Responses

The table above shows that in some cases, the LLM did not even attempt to answer the questions due to the lack of relevant context provided to it. In other instances, the LLM provided partial answers, while in some cases, it gave completely incorrect answers. However, there are also many instances where the LLM answered the questions accurately and completely. Based on these observations, the generated responses can be categorized into four distinct groups. This categorization provides a systematic framework for analyzing LLM performance across key metrics, such as retrieval accuracy, contextual accuracy, and hallucination rate.

- **Category 1:** This category includes responses where the LLM answered the question completely and accurately. These responses will be treated as retrieval successes and will not be counted while measuring hallucination rate.
- **Category 2:** Responses in this category are partially correct but they do not provide the complete information required to fully answer the question. This suggests that either the provided context was only partially relevant, or hallucination occurred during the response generation. These responses will be considered as a retrieval success, as some relevant context was retrieved. They will also contribute to measure the hallucination rate, as the incomplete answer indicates that the model depended on irrelevant information.
- **Category 3:** This category includes responses where the LLM did not attempt to answer the question due to the absence of relevant context. This indicates inaccuracies in the retrieval process, as the similarity search failed to retrieve the necessary context for answering the question. These responses will be used to measure retrieval inaccuracy. However, they will be excluded when measuring contextual accuracy and hallucination rate, as there is no generated content to evaluate contextual accuracy and hallucination rate.
- **Category 4:** Responses in this category are incorrect or unrelated to the reference answer. Since the LLM attempted to answer the question, it suggests that some relevant context was retrieved, but it might have been noisy or not sufficiently relevant. Additionally, these responses suggest that hallucination occurred during the generation process. Therefore, this category will be considered as a retrieval success and will also contribute to calculate the hallucination rate, as the model failed to produce a meaningful response based on the given context.

To categorize responses and identify the type of hallucination, a detailed analysis of each response is needed, along with a clear understanding of the definitions for intrinsic and extrinsic hallucinations. If this is done manually, it becomes impractical and inefficient for large-scale datasets. To address this challenge, an LLM with an appropriately designed prompt was used as a judge to automatically categorize responses and determine the type of hallucination.

4.6 Implementation of LLM Evaluation Framework

A few-shot structured prompt is used to give the LLM proper guidelines to categorize the responses and to identify the hallucination type based on predefined criteria. This few-shot approach provides the model with sufficient context and examples, which enables consistent and accurate evaluations across the dataset. Below is the prompt used:

```
prompt_template ="""
   You are tasked with evaluating the quality of a single response generated by a language model (LLM).
   Each evaluation involves a question, a reference answer, and one LLM-generated response. Your job is to evaluate the
   response based on the criteria provided below.
   ---
   ### **Evaluation Criteria**
   1. **Answer Accuracy**:
   - **1**: The response answers the question accurately.
   - **2**: The response partially answers the question.
   - **3**: The response cannot answer the question from the given context.
   - **4**: The response answers the question but is completely unrelated to the reference answer.

   2. **Hallucination Type**:
   - **N/A** if **Answer Accuracy** = 1 or 3.
   - If **Answer Accuracy** = 2 or 4, classify the hallucination type as:
     - **Intrinsic**: The response is incomplete or incorrect due to limitations in the generative model (e.g.,
     biases, insufficient reasoning).
     - **Extrinsic**: The response is incomplete or incorrect due to reliance on irrelevant, incomplete, or
     noisy retrieval from the context.
     - **Intrinsic Extrinsic**: Both intrinsic and extrinsic factors contribute to the hallucination.
     ---
    ### **Examples**
    #### **Example 1**
    - **Question:** What title did People magazine award Beyoncé in 2012?
    - **Reference Answer:** People magazine named her the 'World's Most Beautiful Woman' in 2012.
    - **LLM Response:** "Based exclusively on the Context provided, the title People magazine awarded Beyoncé
    in 2012 is not mentioned."

    **Example Output 1**:
    {{
    "answer_accuracy": 3,
    "hallucination_type": "N/A"
    }}
    #### **Example 2**
    - **Question:** What title did People magazine award Beyoncé in 2012?
    - **Reference Answer:** People magazine named her the 'World's Most Beautiful Woman' in 2012.
    - **LLM Response:** "Sexiest Woman of the 21st Century""

    **Example Output 2**:
    {{
        "answer_accuracy": 4,
        "hallucination_type": "Intrinsic"
    }}
    ### Your output must be in JSON Format.
    ### Output Format:
    {{
        "answer_accuracy": 1/2/3/4,
        "hallucination_type": "Intrinsic"/"N/A"/"Extrinsic"/"Extrinsic Intrinsic"
    }}
    ### Inputs:
    - **Question:** {question}
    - **Reference Answer:** {reference_answer}
    - **LLM Responses:**
        {response}

"""
```

In the prompt, a brief description of the task was provided. The criteria for evaluating answer accuracy and the definition of hallucination types were clearly explained. For better clarification, some examples with a question, a reference answer, and a LLM response, along with the expected output format, were included. For categorizing and identifying hallucination types in each response, this prompt was dynamically populated with inputs (question, reference answer, and LLM response). The formatted prompt was passed to the LLM, which generated a JSON output containing the response accuracy and hallucination type. This consistent output format later helped to extract the answer accuracy and hallucination type from generated responses. After extracting all the answer accuracies and hallucination types, the `evaluate_answer` table (Table 4.3) was extended. Two new columns, named `hallucination_type` and `answer_accuracy`, were added to the table, which will serve as key factors in further experiments.

4.7 Evaluation Metrics: Application and Measurement

4.7.1 Retrieval & Response Time

Retrieval time was calculated in seconds during the retrieval process, as shown in (code snippet 2). It represents the time taken to retrieve all the chunks from the vector database, calculate cosine similarity, and sort the chunks based on similarity scores to extract the top 3 relevant chunks for a given user query. The numerical mean was calculated, grouped by chunk type, to compare the impact of chunk size on retrieval time.

Response time was measured in seconds during the response generation by the LLM, as shown in (code snippet 3) which represents the time taken by the LLM to generate a response for a given context and user query. The numerical mean of the response time was calculated for each chunk type for further analysis.

4.7.2 Retrieval Accuracy

Retrieval accuracy was measured by using two key metrics: **Precision** (defined in Equation 3.8.1) and **Recall** (defined in Equation 3.2). To calculate precision and recall, the number of relevant and irrelevant retrieved chunks for each chunk type was determined. To measure the number of irrelevant chunks for each chunk type, the count of responses categorized with an `answer_accuracy` of 3 (as discussed in Section 4.5) was counted. Similarly, responses with `answer_accuracy` categorized as 1, 2, or 4 (as discussed in Section 4.5) were used to calculate the number of irrelevant chunks for each chunk type.

4.7.3 Hallucination Rate

The hallucination rate was calculated by analyzing responses with an `answer_accuracy` of 2 or 4, as these responses were partially or completely incorrect, while excluding those marked as **N/A**. Hallucinations were classified into three categories: Intrinsic, Extrinsic, and Intrinsic Extrinsic, (as defined in Section 4.6). The dataset was systematically grouped by `chunk_type` and `hallucination_type`, and the frequency of each hallucination type was computed to determine its proportion within each chunk type.

4.7.4 Response Correctness

Response correctness was evaluated by calculating the ratio of correctly answered responses (`answer_accuracy` of 1 or 2), as defined in Section 4.6, to the total of correctly and incorrectly answered responses (`answer_accuracy` of 1, 2, or 4) for each `chunk_type`.

4.7.5 Contextual Accuracy

For evaluating the contextual accuracy of the generated responses metrics such as ROUGE-1, BLEU, and BERT score were used. This evaluation focused on the responses, which were categorized with an `answer_accuracy` of 1, 2 and 4(as defined in Section 4.5). Below, the implementation and application of these metrics are described in detail.

ROUGE-1

As previously defined in Section 3.6, ROUGE-1 evaluates the uni-gram overlap between the generated and reference texts by providing three key metrics: precision, recall, and F1-score. In the implementation (Listing 4), the rouge_scorer module is used to compute ROUGE-1 scores with stemming enabled to handle variations in word forms.

Listing 4 Python code snippet: Calculating ROUGE-1.

```python
from rouge_score import rouge_scorer
from typing import Tuple

def rouge1(reference: str, candidate: str) -> Tuple[float, float, float]:
    # Create a RougeScorer object configured to calculate ROUGE-1 with stemming enabled
    scorer = rouge_scorer.RougeScorer(['rouge1'], use_stemmer=True)

    # Calculate the ROUGE-1 score between the reference and candidate texts
    result = scorer.score(reference, candidate)

    # Extract precision, recall, and F1-score from the result
    precision,recall,f1_score = result['rouge1'].precision,result['rouge1'].recall,result['rouge1'].fmeasure

    # Return precision, recall, and F1-score as a tuple
    return precision, recall, f1_score
```

The values can be interpreted as follows: a high precision indicates that most unigrams in the generated text are relevant and present in the reference text, a high recall signifies that the generated text includes most unigrams from the reference text, and a high F1-score reflects a balanced performance between precision and recall.[10]

BLEU Score

As previously defined in Section 3.5, BLEU Score measures the quality of LLM generated text by measuring n-grams overlap with a reference text with brevity penalties. For the implementation the sentence_bleu function from the NLTK library was used, which takes tokenized inputs and computes the BLEU score with optional weights for uni-grams, bi-grams, tri-grams, and four-grams.BLEU Score ranges from 0 to 1, where higher score indicates the strong similarity between reference and candidate text.[21]

Listing 5 Python code snippet: Calculating BLEU Score.

```python
from nltk.translate.bleu_score import sentence_bleu, SmoothingFunction

def bleu_score(reference: str, candidate: str) -> float:
    # Tokenize the reference and candidate
    reference_tokens = [reference.split()]
    candidate_tokens = candidate.split()

    # Apply smoothing to handle edge cases
    smoothing_function = SmoothingFunction().method1

    # Calculate BLEU score
    bleu = sentence_bleu(reference_tokens, candidate_tokens, smoothing_function=smoothing_function)
    return bleu
```

To demonstrate the functioning of the sentence_bleu metric, a reference answer and a generated response from the evaluation dataset are selected and are presented below.

Example Calculation:
Inputs:

- **Reference Text:** "The music video for 03 Bonnie & Clyde where Beyoncé appeared as Jay Z's girlfriend."
- **Tokenized Reference:** [`The`, `music`, `video`, `for`, `03`, `Bonnie`, `&`, `Clyde'`, `where`, `Beyoncé`, `appeared`, `as`, `Jay`, `Z's`, `girlfriend.`]
- **Reference Length:** 15 tokens.
- **Candidate Text:** "03 Bonnie & Clyde"
- **Tokenized Candidate:** [`03`, `Bonnie`, `&`, `Clyde`]
- **Candidate Length:** 4 tokens.

1-gram Precision:

$$p_1 = \frac{3}{4} = 0.75 \tag{4.1}$$

2-gram Precision:

$$p_2 = \frac{1}{3} \approx 0.333 \tag{4.2}$$

3-gram Precision:

$$p_3 = 0.0 \tag{4.3}$$

4-gram Precision:

$$p_4 = 0.0 \tag{4.4}$$

Brevity Penalty:

$$\text{BP} = e^{(1-\frac{15}{4})} = e^{-2.75} \approx 0.063 \tag{4.5}$$

Final BLEU Score:

$$\text{BLEU} = \text{BP} \cdot \exp\left(\frac{1}{4} \cdot (\log 0.75 + \log 0.333)\right) \approx 0.011 \tag{4.6}$$

BERT Score

For the implementation the `score` function from `bert_score` module was utilized. This function returns three key metrics: precision, recall, and F1_score.

Listing 6 Python code snippet: Calculating BERT Score.

```python
from bert_score import score
from typing import Tuple

def bert_score(reference: str, candidate: str)->Tuple(float, float, float):
    # BERTScore requires inputs as lists of strings
    references = [ref]
    candidates = [candidate]

    # Calculate BERTScore
    result = score(candidates, references, lang="en", verbose=False)
    # extract measures from result
    precision, recall, f1_score = result[0].item(), result[1].item(), result[2].item()

    # Return the precision, recall, and f1_score as a float
    return precision, recall, f1_score
```

Calculating BERTScore is a three-step process. These steps are detailed as follows:

- **Tokenization:** Input texts are tokenized using the roberta-large tokenizer, which converts the reference and candidate texts into lists of tokens.
- **Embedding Generation:** The roberta-large model is used to calculate contextual embeddings for each token, which ensures the semantic and contextual meanings of the tokens within their respective sentences.
- **Cosine Similarity:** As discussed in Section 3.8, pairwise cosine similarities are calculated for all candidate-reference token pairs. For each candidate token, the maximum similarity score is recorded.

4.8 Tech-stack

This section outlines the key tools, libraries, and hardware environment used to perform the experiments.

Tool/Framework	Usage in the Project
Python	Primary programming language used to develop and implement the project.
datasets	For loading the test dataset.
pandas	For data manipulation and data analysis.
numpy	For array manipulations and numerical computations.
langchain	To interact with OpenAI models for response generation, in order to format Prompt template, and to implement recursive chunking strategy.
flask	For implementing REST APIs in order to make CRUD services available from other programms.
mysql.connector	For connecting and managing the MySQL database.
sentence_transformers	For generating vector embeddings from text.
python-dotenv	For loading environment variables stored in .env files.
nltk	For natural language processing tasks, such as BLEU score computation.
rouge_score	For evaluating generated text using ROUGE metrics.
bert_score	For evaluating the semantic similarity of text using BERT embeddings.
requests	For making HTTP requests in various processes.
matplotlib	For visualizing data and analysis results.
Ubuntu/Linux	Operating system with 8 GB Storage capacity was used to run all tools and frameworks.
VS-Code	IDE used for writing, debugging, and managing project code.
Jupyter Notebook	Interactive environment for running and visualizing Python code during development and experimentation.

Table 4.5: Tools and frameworks used in the project and their purposes.

Chapter 5

Results and Analysis

5.1 Retrieval & Response Time

This section analyzes the impact of chunk size on retrieval and response times in RAG system. The analysis focuses on four chunk types and summarizes the mean retrieval time, response time, and the number of chunks for each chunk type.

Retrieval Time

Retrieval time refers to the time required by the retrieval system to fetch similar chunks from the vector database for a given query. The retrieval time analysis, as illustrated in the diagram, does not indicate a strong trend across chunk types, except for LARGE and SMALL chunks.

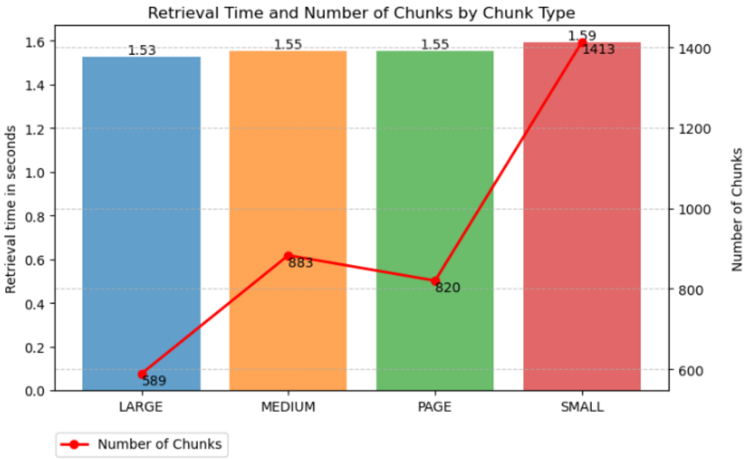

Figure 5.1: Mean Retrieval Time by Chunk type

The retrieval time is highest for SMALL chunks and lowest for LARGE chunks. This behavior is due to the vectorization process, where the `Sentence Transformer` (defined in Section 3.4) was used. The transformer converts text of any length into a fixed-size vector with dimensions (1,384). As a result, the comparison time remains consistent regardless of chunk size. However, the SMALL chunk type, with the highest number of chunks, produces greater overhead in retrieval process(fetching chunks from the database, calculating cosine similarity, and sorting chunks based on similarity scores)(shown in code snippet 2). Conversely, the LARGE chunk type, with the fewest chunks, demonstrates the lowest retrieval time due to reduced retrieval overhead.

Response Time

The response time analysis, as visualized in the diagram, shows a general trend where response time decreases as the chunk size becomes smaller. The response time is highest for LARGE chunks and lowest for SMALL chunks. SMALL chunks result in faster response times, in spite of having a higher number of chunks, because the LLM model processes smaller and more concise inputs.

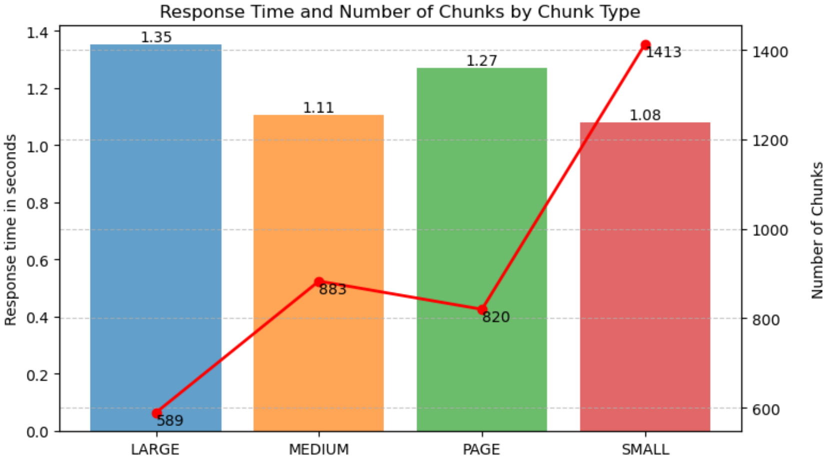

Figure 5.2: Mean Response Time by Chunk type

On the other hand, LARGE chunks take longer response times as the LLM model requires more computational resources (time and memory) to process large input.

5.2 Retrieval Accuracy

Retrieval accuracy is the ability of the RAG system to retrieve relevant chunks for a given query from the vector database. The below diagrams present the retrieval metrics, including the number of retrieved irrelevant and relevant chunks, precision, and recall for each chunk type. In contrast to SMALL and LARGE chunks, which have the lowest precision and recall,

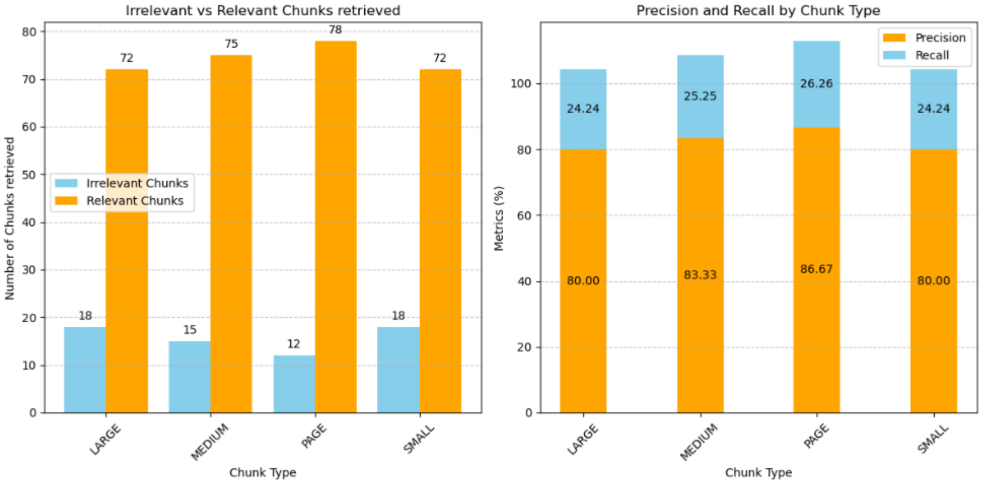

Figure 5.3: Retrieval Accuracy for each chunk type

the PAGE chunk type achieves the highest precision(86.67%) and recall(26.26%) by correctly retrieving 78 relevant chunks. The performance difference is due to the way the queries were formed in the test dataset. Specifically, each user query was formulated from a single page or context, which is closely aligned with the PAGE chunk type. This alignment enables the retrieval system to find out relevant chunks more effectively, which results in higher retrieval accuracy for PAGE chunks.

MEDIUM chunks also perform well, achieving precision (83.33%) and recall (25.25%) by successfully retrieving 75 relevant and 15 irrelevant chunks. This performance is due to the balance between contextual breadth. MEDIUM chunks supplies sufficient context to match the focused nature of the Q&A queries.

Conversely, SMALL and LARGE chunk types achieve lower precision and recall. In case of SMALL chunks, the retrieval system must search through a large number of chunks, which often includes text segments that are less contextually aligned with the query and often lack sufficient context, as each chunk contains only a small portion of the original text, which increases the likelihood of retrieving irrelevant chunks. [35] Similarly, for LARGE chunks, as the Q & A queries are more focused and precise, they are not likely to align perfectly with the broader content in LARGE chunks. This mismatch leads to lower precision, as fewer similar chunks are retrieved.

5.3 Hallucination Analysis

In Hallucination analysis, the reasons for incorrect or incomplete responses generated by the RAG system were examined and they were categorized as Intrinsic, Extrinsic, or Intrinsic-Extrinsic hallucinations, as defined in Section 4.6. The diagram below illustrates the hallucination distribution and hallucination types for different chunk types.

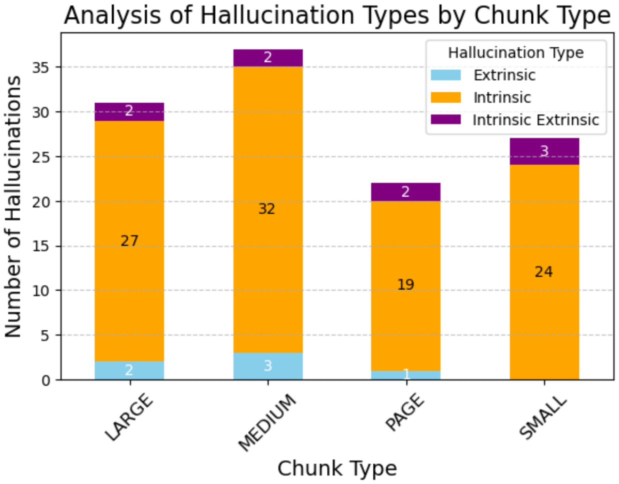

Figure 5.4: Hallucination rate and types

In the case of the PAGE chunk type, the frequency of hallucinations across all categories is lower, which is due to a strong alignment between the query and the context, as each query was directly formulated from a specific page or context within the dataset, resulting in higher overall accuracy. Conversely, LARGE and MEDIUM chunks show the higher number of intrinsic hallucinations, as their relatively larger size often fails to provide sufficient context for reasoning. Furthermore, their broad content misalignment with precise Q&A queries, which leads to a higher frequency of intrinsic hallucinations. Intrinsic hallucinations dominate across all chunk types because the generative model has limitations, such as difficulties with reasoning, biases, and trouble while understanding or combining incomplete or unclear information, even though the retrieved chunks are relevant.

5.4 Response Correctness

Response correctness evaluates how accurately the RAG system generates responses for queries, considering both correct and incorrect answers. The diagrams below summarize the precision and distribution of correct and incorrect responses across different chunk types. The PAGE chunk type achieves the highest precision (92.31%) with only 6 incorrect responses, which again reflects strong query-context alignment.

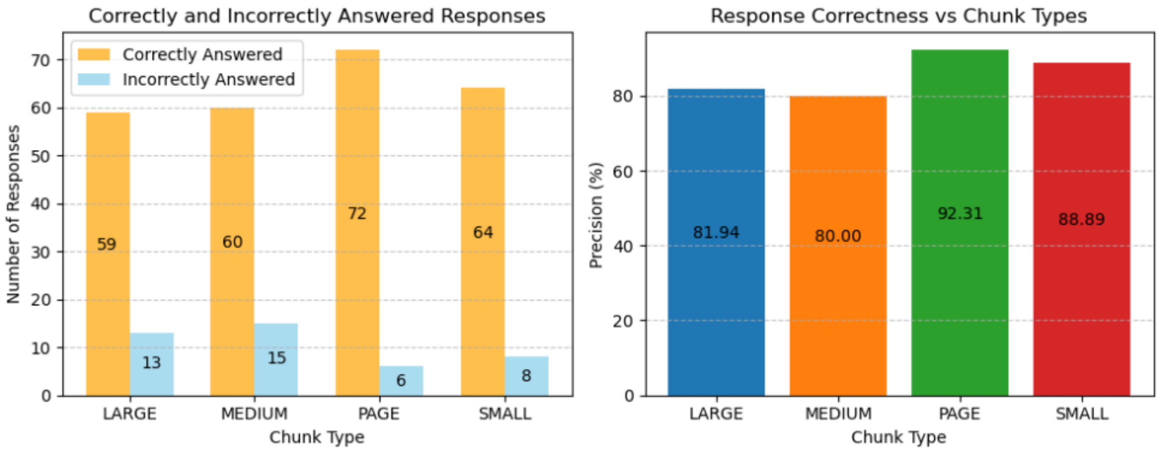

Figure 5.5: Response Correctness

SMALL chunks also perform well, with a precision of 88.89%, that is due to their focused content and the Q&A nature of the queries. However, their limited context occasionally leads to a lack of reasoning, which causes 8 incorrect responses. Conversely, LARGE and MEDIUM chunks show lower precision (81.94% and 80.00%, respectively) due to their larger or medium-sized content, which is not aligned with precise Q&A queries. As a result, 13 and 15 incorrect responses were generated.

5.5 Contextual Accuracy

To measure the ability of the RAG system to maintain semantic and contextual alignment between reference answer and generated responses, Contextual Accuracy was analyzed. The diagrams below illustrate the ROUGE-1, BLEU, and BERT scores across different chunk types, which demonstrates their effectiveness in generating accurate and contextually relevant responses.

The PAGE chunk type represents the highest contextual accuracy by achieving top scores across all metrics. For ROUGE-1, it achieves the highest F-measure (52%), Recall (59%), and Precision (65%), which indicates a strong reference answer and generated response alignment. Similarly, PAGE performs also well in BLEU (22.21%) and BERT scores (90.97% Recall, 90.24% F-measure), which indicates its semantic and sentence-level similarity.

Like PAGE chunk type the SMALL chunk type also performs well, with ROUGE-1 scores close to PAGE and slightly lower BLEU (20.72%) and BERT (89.82% F-measure) scores. Its relatively small focused content enables effective handling of Q&A queries in spite of minor limitations in context breadth.

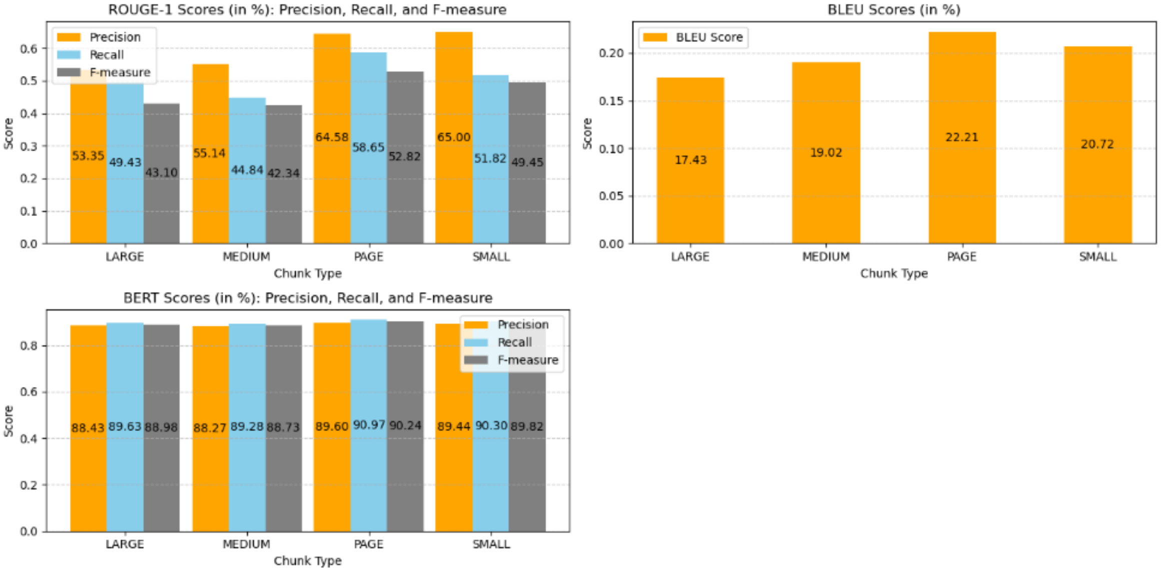

Figure 5.6: Contextual Accuracy

In contrast, MEDIUM and LARGE chunks show lower contextual accuracy, with ROUGE-1 scores (F-measure 42-44%, Recall 44-49%, Precision 53-55%) and BLEU scores (19.02% and 17.43%, respectively), which indicates weaker generated response and reference answer alignment due to broader content. However, when analyzing BERT scores, the variations across chunk types are relatively minor compared to ROUGE-1 and BLEU scores. All chunk types achieve high BERT scores. This indicates that the RAG system maintains strong semantic alignment across all chunk types, even for chunks like LARGE and MEDIUM, which otherwise struggle with query-context alignment in ROUGE-1 and BLEU metrics. This consistency in BERT scores suggests that while broader chunks may fail in precise alignment, they still retain semantic coherence at a high level.

Chapter 6

Discussion

6.1 Overview

In this chapter, the findings will be synthesized to show how they fulfill the research objectives and are compared with the existing theoretical framework. Here, the effect of chunk size on key aspects of RAG systems, including retrieval and response times, response accuracy, retrieval accuracy, hallucination rates, and contextual relevance, will be analyzed. Furthermore, the findings will be compared with existing literature to provide a broader perspective. The study's implications for RAG system and limitations will also be highlighted.

6.2 Interpretation of Results

Retrieval and Response Time

The results of the study show clear patterns in retrieval and response times that are influenced by the chunk size. Although there is no strong trend across chunk types, small time difference in retrieval time was observed for LARGE and SMALL chunks. Larger chunks achieved the fastest retrieval times because there were fewer chunks in the vector database, which reduced the time required for vector search. On the other hand, smaller chunks took the longest retrieval time because the larger number of chunks required more searching and computation, as illustrated in Figure 5.1.

Response times were faster with smaller chunks because the short and focused inputs could easily be processed by the language model. Conversely, larger chunks required more time for response generation due to the greater computational effort needed to handle larger inputs, as showed in Figure 5.2.

The findings align with the study of Zijie Zhong et al. (2024)[47], as discussed in Sections 3.6.3 and 2.1, who highlighted a trade-off between retrieval speed and response quality based on chunk size. Retrieval is faster with larger chunks but requires more processing time to generate a response, as observed in this study. Similarly, the study of Antonio Jimeno Yepes et al. (2024)[14] highlighted that smaller chunks improve retrieval relevance but with higher retrieval time, which is consistent with this study's findings.

Retrieval Accuracy

According to the results of this study, PAGE chunks achieved the highest retrieval accuracy, followed by MEDIUM chunks, while SMALL and LARGE chunks demonstrated lower precision and recall. These findings support foundational studies like Zijie Zhong et al. (2024)[47] and Antonio Jimeno Yepes et al. (2024)[14], which highlighted the critical role of chunk granularity in order to determine retrieval accuracy, as described in Sections 3.6.3 and 2.1. The performance of PAGE and MEDIUM chunks indicates the importance of alignment o f chunk structure with query formulation and achieving a balance between contextual breadth and query focus, respectively.

Hallucination Analysis

The analysis showed that PAGE chunks had the lowest hallucination rates, while LARGE and MEDIUM chunks exhibited higher intrinsic hallucination rates. Intrinsic hallucinations were prevalent across all chunk types, as illustrated in Figure 5.4. These findings are consistent with studies such as Ji et al. (2023)[13] and the work 'A comprehensive survey of hallucination mitigation techniques in large language models' (2024)[41], which investigated how retrieval quality and chunk characteristics affect hallucination rates, as discussed in Section 2.1.

Contextual Accuracy and Response Correctness

PAGE chunks had the most accurate responses and best contextual alignment, followed by SMALL chunks. MEDIUM and LARGE chunks, however, showed lower precision and weaker alignment. PAGE chunks scored the highest on metrics like ROUGE-1, BLEU, and BERT, which indicates better semantic and contextual alignment. SMALL chunks also performed well but had slightly lower scores compared to PAGE. Although MEDIUM and LARGE chunks lacked precise alignment, their BERT scores showed strong semantic coherence, as showed in Figures 5.6 and 5.5. Research like “Document Length and Relevance in Neural Information Retrieval”[19] and “Chunking Strategies in Long Document Processing”[5] similarly highlighted the trade-offs between precision and contextual richness, as well as the role of context alignment, as discussed in Section 2.2, consistent with these findings.

6.3 Implications for RAG System

The findings of this study provide several practical insights and implications regarding the impact of chunk sizes on RAG systems:

- **Task-Specific Chunking:** PAGE chunks demonstrated excellent retrieval accuracy and response correctness, which make them well-suited for tasks where queries are closely aligned with contexts, such as structured document processing. In terms of real-time question-answering applications, SMALL chunks can be beneficial as they provide faster response times and focused information. MEDIUM chunks provide a balanced approach, which supports both broader contextual understanding and query focus.
- **Optimizing Retrieval and Response Trade-Offs:** SMALL chunks ensure relatively better precision and faster responses but increase retrieval time due to large number of chunks. PAGE chunks offer strong context alignment and accuracy but may slow down response generation. MEDIUM chunks balance context and efficiency. Dynamical adjustment between these chunk types may allows RAG systems to optimize performance based on query demands.
- **Reducing Hallucinations with Context Alignment:** The low hallucination rates in PAGE and SMALL chunks highlight the importance of the alignment of the chunk content with the query and maintaining focused information, respectively. Task-specific chunking methods and improved query-context alignment during retrieval can help minimize hallucinations and enhance response reliability.
- **Balancing Context and Precision:** The findings indicate that broader chunks, such as LARGE and MEDIUM, face challenges with precise alignment, which affects response correctness and contextual accuracy.
- **Metrics-Driven Improvements:** Although broader chunks scored lower on metrics like ROUGE-1 and BLEU, the high BERT scores across all chunk types suggest that semantic coherence is still maintained.

6.4 Limitations

Although the study provides valuable insights into the role of chunk size in RAG system performance, certain limitations should be considered:

Constraints of Test Dataset

In this study, the **'christti/squad-augmented-v2'** dataset was used, where the contexts and questions are well-structured and focused on a specific domain. However, in real-life applications, documents are often not well-structured and questions are not always aligned with the context. Therefore, the results of this study may not generalize to other domains with diverse document formats, content structures, or query types.

Simplistic Retrieval Model

The retrieval process in this study relied only on cosine similarity, where `Sentence Transformer` was used for calculating vector embeddings. Although this approach is effective, it did not utilized the advanced retrieval methods that could lead to greater accuracy in RAG systems. For instance, advanced vector databases such as **Chroma**, which is integrated with efficient retrieval methods such as approximate nearest neighbor (ANN) search algorithms (e.g., HNSW, FAISS), could improve retrieval speed and accuracy. Additionally, advanced retrievers, which can be fine-tuned like Dense Passage Retrieval (DPR) or Col-BERT and are pre-trained to optimize relevance for specific datasets, could also be employed to enhance retrieval precision.

Focus on Predefined Metrics

In this study, metrics such as retrieval and response accuracy, hallucination rates, and response times were primarily evaluated. However, other metrics, such as user satisfaction, user feedback-based assessments, were not considered, which could provide a more holistic understanding of system performance.

Financial and Resource Constraints

Although the test dataset contains 100,132 unique contexts, only 820 unique contexts were used to construct the knowledge base. This limitation was due to the memory and computational constraints of the local machine on which the experiment was conducted. As a result, the entire dataset could not be used for a broader experiment.

Additionally, to evaluate the impact of chunk size on RAG-generated responses, only 90 randomly selected questions from the test dataset were used. This was because OpenAI's API was used for generating responses, which charges money based on the number of tokens processed. For the same financial and resource constraints, advanced embedding models and sophisticated vector search techniques, as mentioned in Section 6.4, could not be employed.

Potential Biases in Query Design

Queries were formulated from the same dataset used to create the knowledge base, which potentially introduces a bias favoring alignment with PAGE chunks. In real-world scenarios, queries are often uncertain and random, and users may ask questions unrelated to the dataset, which could lead to different results.

Chapter 7

Conclusion

7.1 Summary

Based on the findings of this study, it can be concluded that the chunk size is a critical factor, which has a vital role in determining the performance of RAG systems. The better performance of PAGE chunks in retrieval accuracy and correctness suggests that they could be a good choice for structured and specific tasks where queries are well aligned with contexts. SMALL chunks also demonstrated improved response times and better response correctness, which indicates that they could be potentially suitable for real-time applications, despite slightly higher retrieval times. MEDIUM chunks demonstrated moderate performance by maintaining balance between contextual understanding and retrieval precision, whereas LARGE chunks struggled with precision and correctness due to broader content misalignment.

Common Challenges in RAG system such as hallucinations and the trade-offs between retrieval speed and response accuracy were also examined in this study. The results showed that PAGE and SMALL chunks minimized hallucination rates, emphasizing the importance of context alignment and focused information retrieval. These limitations, however, can be addressed in future work by leveraging advanced computational resources and expanded datasets for more comprehensive evaluations.

The research provided valuable practical implications for dynamic chunking strategies and domain-specific optimizations, despite certain limitations related to computational and financial constraints, which restricted the size and scope of the dataset and evaluation. The study contributes to the broader understanding of how chunk size influences the efficiency and reliability of RAG systems, which paves the way for improved applications in domains where precise and contextually relevant AI-generated outputs are required.

7.2 Future Work

Exploration of Domain-Specific Applications

Instead of focusing on a specific domain, future work may analyze chunking across diverse domains such as legal documents, medical documents, and financial documents. In these fields, the documents are often structured, and the queries can be more complex. As a result, precise alignment between queries and context is required. For instance, in legal document retrieval, smaller chunks might achieve higher precision by easily finding specific clauses or references. On the other hand, larger chunks might provide a broader understanding of content where multi-clause reasoning is required. In medical applications, where accuracy and comprehensive responses must be ensured, chunking strategies with balanced precision might be helpful to generate responses related to patient history or clinical trials.

Incorporation of Dynamic Chunking

From this study, we have seen that various chunking strategies are suitable for various tasks. For instance, small chunks may achieve more precision while answering Q&A-type queries, while large chunks may gain more contextual accuracy when a broader understanding of the context is required, such as generating a summary on a specific topic. Document chunking could also be suitable when there is alignment between queries and context/document. Therefore, a method to adapt chunk sizes in real time based on the task provided is required, which can be achieved by implementing dynamic chunking techniques that offer significant potential for optimizing the performance of RAG systems. The adjustment of the structure of the document, such as splitting dense paragraphs or concatenating sparse sections, can be implemented using dynamic chunking.

Larger and More Diverse Evaluation Dataset

For more generalization and robustness of the experiment to evaluate the impact of chunk size on RAG-generated responses, future studies can be conducted on a significantly larger set of contexts and queries to ensure statistical reliability of the results. In order to test real-world scenarios, open-domain and ambiguous queries could be included. Additionally, queries that require an understanding of time-based relationships, such as tracking changes in financial trends or interpreting legal case histories, could be considered.

Evaluation of Advanced Retrieval Models

One of the most important components in RAG architecture is the Retriever. For implementing this component in this study, only cosine similarity was used, which is a very basic retrieval process. In future work, the exploration of advanced retrieval techniques may enhance retrieval precision and efficiency in RAG systems. For instance, hybrid search techniques combine sparse methods like BM25 with dense vector retrieval to improve retrieval performance. For example, sparse methods may handle keyword-based queries, while dense methods could be used to retrieve semantically similar content. Advanced domain-specific embeddings (e.g., SciBERT for scientific documents or LegaBERT for legal documents) could also be very helpful to achieve better semantic alignment and retrieval precision.

List of Abbreviations

AI Artificial Intelligence. 2, 3, 8, 35

API Application Programming Interface. 26, 34

BART Bidirectional and Auto-Regressive Transformer. 8

BERT Bidirectional Encoder Representations from Transformers. 1, 4, 6, 9, 13, 23, 25, 26, 30, 31, 33, 34, 36

BLEU Bilingual evaluation understudy. 4, 12, 13, 23, 24, 26, 30, 31, 33

CoI Contextualized Late Interaction. 6, 34

CPU Central Processing Units. 11

CRUD Create, Read, Update, and Delete. 26

FAISS Facebook AI Similarity Search. 34

GPT Generative pre-trained transformer. 7, 8, 11, 19

GPU Graphics Processing Units. 11

HNSW Hierarchical Navigable Small World. 34

HTML HyperText Markup Language. 16

HTTP HyperText Transfer Protocol. 26

IDE Integrated development environment. 26

JSON JavaScript Object Notation. 22

LLM Large Language Model. 1–3, 6, 8, 10–13, 20–24, 28

MoG Mix-of-Granularity. 5

NLP natural language processing (NLP). 8, 9, 14, 15

NLTK Natural Language Toolkit. 24

QA Questions & Answers. 3, 5, 6

RAG Retrieval-Augmented Generation. 1–7, 10–12, 14–17, 19, 20, 27–36

REST Representational State Transfer. 26

ROUGE Recall-Oriented Understudy for Gisting Evaluation.. 1, 4, 13, 23, 24, 26, 30, 31, 33

SQL Structured Query Language. 26

TF-IDF Term Frequency - Inverse Document Frequency. 8

URL Uniform Resource Locator. 16

Bibliography

[1] Josh Achiam et al. "Gpt-4 technical report." In: *arXiv preprint arXiv:2303.08774* (2023).

[2] Xavier Amatriain. "Prompt Design and Engineering: Introduction and Advanced Methods." In: *arXiv preprint* 2401.14423v3 (2024). Accessed on November 27, 2024. URL: https://arxiv.org/html/2401.14423v3.

[3] Sharmila Ananthasayanam. *7 Chunking Strategies in RAG You Need To Know*. Accessed October 2, 2024. 2024. URL: https://www.f22labs.com/blogs/7-chunking-strategies-in-rag-you-need-to-know/?utm_source=chatgpt.com.

[4] Sabrina Aquino. *What is RAG: Understanding Retrieval-Augmented Generation*. Accessed: 2024-03-19. 2024. URL: https://qdrant.tech/articles/what-is-rag-in-ai/.

[5] Junwei Chen, Yuxuan Xu, and Qi Zhang. "Chunking Strategies in Long Document Processing." In: *Journal of Computational Linguistics* (2023).

[6] Paulo Finardi et al. "The Chronicles of RAG: The Retriever, the Chunk and the Generator." In: *arXiv preprint arXiv:2401.07883* (2024).

[7] Yunfan Gao et al. "Retrieval-Augmented Generation for Large Language Models: A Survey." In: *arXiv preprint arXiv:2301.12730* (2023). URL: https://arxiv.org/abs/2301.12730.

[8] Geeks for Geeks Teams. *NLP — Benutzerdefiniertes Korpus*. Accessed February 20, 2019. 2019. URL: https://www.geeksforgeeks.org/nlp-custom-corpus/.

[9] Geeks for Geeks Teams. *NLP – BLEU-Score zur Bewertung neuronaler maschineller Übersetzung – Python*. Accessed March 8, 2024. 2024. URL: https://www.geeksforgeeks.org/nlp-bleu-score-for-evaluating-neural-machine-translation-python/.

[10] Geeks for Geeks Teams. *Verständnis des BLEU- und ROUGE-Scores zur NLP-Bewertung*. Accessed October 4, 2024. 2024. URL: https://www.geeksforgeeks.org/understanding-bleu-and-rouge-score-for-nlp-evaluation/.

[11] Gautier Izacard and Edouard Grave. "End-to-End Open-Domain Question Answering with Retrieval-Augmented Generation." In: *Advances in Neural Information Processing Systems (NeurIPS)*. 2021.

[12] Javatpoint. *Bag of N-Grams Model*. https://www.javatpoint.com/bag-of-n-grams-model?utm_source=chatgpt.com. Accessed: December 2, 2024. 2024.

[13] Zhijing Ji, M Lee, and et al. "Categorizing and Mitigating Hallucinations in Generative Models." In: *Proceedings of the Association for Computational Linguistics (ACL)*. 2023.

[14] Antonio Jimeno Yepes et al. "Financial Report Chunking for Effective Retrieval-Augmented Generation." In: *ArXiv preprint* (2024). URL: https://arxiv.org/abs/2402.05131.

[15] Omar Khattab and Matei Zaharia. "ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction Over BERT." In: *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. 2020.

[16] Lam Hoang. *How Chunk Sizes Affect Semantic Retrieval Results*. Mar. 11, 2024. URL: https://ai.plainenglish.io/investigating-chunk-size-on-semantic-results-b465867d8ca1.

[17] Patrick Lewis et al. "Retrieval-augmented generation for knowledge-intensive nlp tasks." In: *Advances in Neural Information Processing Systems* 33 (2020), pp. 9459–9474.

[18] Hugo Lu. *Understanding the Context Window in OpenAI Models*. Accessed: 2024-07-25. 2023. URL: https://www.getorchestra.io/guides/understanding-the-context-window-in-openai-models#:~:text=The%20context%20window%20refers%20to%20the%20maximum%20amount,models%2C%20each%20with%20different%20capabilities%20and%20context%20windows..

[19] Sean MacAvaney, Robbie McDonald, and Andrew Yates. "Document Length and Relevance in Neural Information Retrieval." In: *Journal of Information Retrieval* (2020).

[20] Nathan Crone Neil Kanungo. *How Vector Databases Search by Similarity: A Comprehensive Primer*. Accessed: 2023-08-25. 2023. URL: https://medium.com/kx-systems/how-vector-databases-search-by-similarity-a-comprehensive-primer-c4b80d13ce63.

[21] Kishore Papineni et al. "Bleu: a Method for Automatic Evaluation of Machine Translation." In: *Proceedings of the 40th Annual Meeting of the Association for Computational Linguistics*. Ed. by Pierre Isabelle, Eugene Charniak, and Dekang Lin. Philadelphia, Pennsylvania, USA: Association for Computational Linguistics, July 2002. DOI: 10.3115/1073083.1073135. URL: https://aclanthology.org/P02-1040.

[22] Patricia Kelbert, Dr. Julien Siebert, Lisa Jöckel. *Was ist ein Large Language Model (LLM)?* Dec. 12, 2023. URL: https://www.iese.fraunhofer.de/blog/large-language-models-ki-sprachmodelle/ (visited on 11/22/2024).

[23] Rahul. *A Guide to Chunking Strategies for Retrieval Augmented Generation (RAG)*. Accessed May 15, 2024. 2024. URL: https://zilliz.com/learn/guide-to-chunking-strategies-for-rag?utm_source=chatgpt.com.

[24] P Rajpurkar. "Squad: 100,000+ questions for machine comprehension of text." In: *arXiv preprint arXiv:1606.05250* (2016). Accessed: December 20, 2024.

[25] Nils Reimers and Iryna Gurevych. *SentenceTransformers: Architecture and Pooling Strategies*. Accessed November 27, 2024. 2019. URL: https://www.sbert.net/docs/usage.html#sentence-embeddings.

[26] Nils Reimers and Iryna Gurevych. *SentenceTransformers: Multilingual Sentence Embeddings using BERT and RoBERTa*. Accessed November 27, 2024. 2019. URL: https://www.sbert.net.

[27] Oscar Sanseviero. *Introduction to Sentence Embeddings*. Accessed November 27, 2024. 2023. URL: https://osanseviero.github.io/hackerllama/blog/posts/sentence_embeddings/.

[28] Sander Schulhoff. *Few Shot Prompting*. Accessed August 7, 2024. 2024. URL: https://learnprompting.org/de/docs/basics/few_shot.

[29] Ishneet Sukhvinder Singh et al. "ChunkRAG: Novel LLM-Chunk Filtering Method for RAG Systems." In: *arXiv preprint arXiv:2410.19572* (2024). DOI: 10.48550/arXiv.2410.19572. URL: https://doi.org/10.48550/arXiv.2410.19572.

[30] Ishneet Sukhvinder Singh et al. "ChunkRAG: Novel LLM-Chunk Filtering Method for RAG Systems." In: *arXiv preprint arXiv:2410.19572* (2024). DOI: 10.48550/arXiv.2410.19572. URL: https://doi.org/10.48550/arXiv.2410.19572.

[31] DL Staff. "Understanding Intrinsic and Extrinsic Hallucinations in NLP." In: *Communications of the ACM* 66.12 (2023), pp. 202–215. URL: https://dl.acm.org/doi/pdf/10.1145/3632410.3633297.

[32] Hugging Face Team. *Pretrained Model: all-MiniLM-L6-v2*. Accessed November 27, 2024. 2023. URL: https://www.sbert.net/docs/pretrained_models.html#all-minilm-l6-v2.

[33] langchain team. *How to recursively split text by characters*. Accessed November 29, 2024. 2024. URL: https://python.langchain.com/docs/how_to/recursive_text_splitter/?utm_source=chatgpt.com.

[34] LlamaIndex Team. *Evaluating the Ideal Chunk Size for a RAG System Using LlamaIndex*. Accessed: 2024-11-23. 2023. URL: https://www.llamaindex.ai/blog/evaluating-the-ideal-chunk-size-for-a-rag-system-using-llamaindex-6207e5d3fec5.

[35] restack team. "Chunking Techniques in Retrieval-Augmented Generation." In: (2024). Accessed: December 20, 2024.

[36] SBERT Team. *Sentence Transformers Documentation*. Accessed November 27, 2024. 2023. URL: https://www.sbert.net/.

[37] TAUS Blog Team. *What Are Sentence Embeddings and Their Applications?* Accessed November 27, 2024. 2023. URL: `https://www.taus.net/resources/blog/what-are-sentence-embeddings-and-their-applications`.

[38] Zilliz Blog Team. "Similarity Metrics for Vector Search." In: *Zilliz Blog* (2024). Accessed on November 27, 2024. URL: `https://zilliz.com/blog/similarity-metrics-for-vector-search`.

[39] Ravi Theja. *Evaluating the Ideal Chunk Size for a RAG System using LlamaIndex*. Accessed October 5, 2023. 2023. URL: `https://www.llamaindex.ai/blog/evaluating-the-ideal-chunk-size-for-a-rag-system-using-llamaindex-6207e5d3fec5?utm_source=chatgpt.com`.

[40] Ravi Theja. *Evaluating the ideal chunk size for a rag system*. Accessed February 20, 2024. 2024. URL: `https://vectorize.io/evaluating-the-ideal-chunk-size-for-a-rag-system/#:~:text=Additionally%2C%20the%20chunk%20size%20impacts%20the%20efficiency%20of,sizes%20may%20result%20in%20more%20frequent%20retrieval%20queries.`.

[41] SM Tonmoy et al. "A comprehensive survey of hallucination mitigation techniques in large language models." In: *arXiv preprint arXiv:2401.01313* (2024).

[42] Wenhui Wang et al. "Minilm: Deep self-attention distillation for task-agnostic compression of pre-trained transformers." In: *Advances in Neural Information Processing Systems* 33 (2020).

[43] Hao Yu et al. "Evaluation of Retrieval-Augmented Generation: A Survey." In: *arXiv preprint arXiv:2301.07297* (2023). URL: `https://arxiv.org/abs/2301.07297`.

[44] Hao Yu et al. "Evaluation of Retrieval-Augmented Generation: A Survey." In: *arXiv preprint arXiv:2405.07437* (2024).

[45] Tianyi Zhang et al. "Bertscore: Evaluating text generation with bert." In: *arXiv preprint arXiv:1904.09675* (2019).

[46] Tong Zhang, Fred Damerau, and David Johnson. "Text chunking based on a generalization of Winnow." In: *Journal of Machine Learning Research* 2.4 (2002).

[47] Zijie Zhong et al. "Mix-of-Granularity: Optimize the Chunking Granularity for Retrieval-Augmented Generation." In: *arXiv preprint arXiv:2406.00456* (2024).