



# Optimizing QA Responses: Insights into BERT and RAG-Based Models



# Background and Objectives

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- **Background:**

- Started with a basic BERT model (deepset/bert-base-cased-squad2) for QA tasks.
- Document handling included DOCX, PDF, and Excel formats.
- Limited in handling complex queries and large datasets.

- **Objective:**

- Enhance QA system with a sophisticated Retrieval-Augmented Generation (RAG) model.
- Improve handling of complex queries by combining document retrieval with generative language models.

# Design Decisions and Approach

- **A. Data Processing and Integration:**
- **Document Processing:**
  - Initial: Used pandas, docx, pdfminer for text extraction.
  - Enhanced: Adopted PyPDF2, pptx, and langchain for advanced handling and embedding.
- **Switch to RAG Model:**
  - Initial: Basic BERT model.
  - RAG Model: Integrated RAG with FAISS for similarity search and document retrieval, used HuggingFaceEmbeddings and Cohere.

# RAG Model Integration

## 1. Document Embedding and Indexing:

- **Embedding:** HuggingFaceEmbeddings with sentence-transformers/all-MiniLM-L6-v2.
- **Indexing:** FAISS for fast similarity search.

## 2. Retriever Setup:

- FAISS-based retriever for document retrieval.

## 3. Prompt Template:

- Designed prompt to ensure answers based on context.

## 4. Answer Generation:

- Constructed RAG chain using Cohere, format\_docs, and generate\_answer function.

# API Integration with FastAPI

## 1. API Design:

### • Endpoints:

- POST /answer/: Handles QA requests, generates answers, returns result and latency.
- GET /evaluate\_latency/: Evaluates latency for sample questions.

## 2. Error Handling:

- Managed exceptions and provided informative error messages.

## 3. Latency Measurement:

- Measured latency for QA requests to assess performance.

# Technical Details

## **1. Libraries and Frameworks:**

- HuggingFaceEmbeddings, FAISS, Cohere, langchain, FastAPI.

## **2. Code Implementation:**

- Document processing, RAG chain construction, API endpoints.

# Dataset

## 1. Benchmark Datasets:

- **SQuAD Dataset:**

- **Description:** Stanford Question Answering Dataset (SQuAD) is a widely used benchmark dataset for evaluating QA systems. It contains questions based on paragraphs from Wikipedia articles.
- **Purpose:** Provides a standard for assessing model performance on question-answering tasks.

## 2. Custom QA Dataset:

- **Description:** Created from various document formats including DOCX, PDFs, and Excel files. Contains 48 questions designed to evaluate the model's ability to handle diverse document types.
- **Purpose:** Tailored to test the model's performance on real-world documents and queries beyond the standard SQuAD dataset.

# Performance Evaluation Metrics

## 1. Initial BERT Model Metrics:

- a. **Latency:** Time taken to generate answers using the basic BERT model.
- b. **Accuracy:** Proportion of correct answers among all questions.
- c. **F1 Score:** Harmonic mean of precision and recall, measuring the model's balance between precision and recall.

## 2. RAG Model Metrics:

a. **Latency:** Time taken for the RAG-based model to generate answers. Typically higher due to the complexity of retrieval and generation processes.

### b. Similarity Metrics:

**Average Cosine Similarity:** Measures the cosine of the angle between the embeddings of the generated answer and the reference answers, indicating how similar they are in vector space.

**Average Embedding Similarity:** Measures the similarity between the embeddings of the generated answers and reference answers, indicating the quality of embeddings used.

**Average BERTScore:** Measures the relevance and quality of generated answers using contextual embeddings from the BERT model. Higher BERTScore indicates better alignment with reference answers.



# Summary and Recommendations

- **1. Performance Insights:**
  - Initial BERT model: Faster responses but less accurate for complex queries.
  - RAG model: Sophisticated but higher latency and lower similarity scores.
- **2. Recommendations:**
  - **Optimization:** Reduce latency in retrieval and generation.
  - **Enhancement:** Fine-tune or explore alternative models.
  - **Evaluation:** Continuous evaluation with additional metrics.



THANK YOU

