Context-augmented Retrieval: A Novel Framework for Fast Information Retrieval based Response Generation using Large Language Model

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ABSTRACT

Generating high-quality answers consistently by providing contextual information embedded in the prompt passed to the Large Language Model (LLM) is dependent on the quality of information retrieval. As the corpus of contextual information grows, the answer/inference quality of Retrieval Augmented Generation (RAG) based Question Answering (QA) systems declines. This work solves this problem by combining classical text classification with the Large Language Model (LLM) to enable quick information retrieval from the vector store and ensure the relevancy of retrieved information. For the same, this work proposes a new approach Context Augmented retrieval (CAR), where partitioning of vector database by real-time classification of information flowing into the corpus is done. CAR demonstrates good quality answer generation along with significant reduction in information retrieval and answer generation time.

CCS CONCEPTS

• Information systems \rightarrow Information retrieval.

KEYWORDS

Large language models(LLMs), Retrieval Augmented Generation(RAG), Natural language processing(NLP), Information retrieval, Generative Pre-Trained Transformers(GPT), Generative AI(Gen AI), Context-augmented Retrieval(CAR)

1 INTRODUCTION

With the launch of OpenAI's ChatGPT, Large Language Models (LLMs) such as the GPT and LLAMA series have garnered significant attention. These LLMs can perform various impressive tasks, including language translation, content summarization, and other functions that typically require human

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intelligence. In certain aspects, these models can sometimes outperform humans. However, LLMs face challenges such as factual hallucination, knowledge obsolescence, and a lack of domain-specific expertise [29][15][35]. Two primary solutions to address these problems are fine-tuning LLMs on domain-specific data and using Retrieval-Augmented Generation (RAG). Based on previous research, RAG is considered the better option [13].

Retrieval-augmented generation (RAG) is an advanced technique in NLP that combines retrieval-based and generative models to improve the quality and accuracy of responses, especially in applications requiring precise information retrieval within a specific knowledge domain (e.g., a book or other provided sources for factual correctness)[14].

Traditional generative models like the GPT series and the LLAMA series generate responses based solely on the input they receive. This can sometimes lead to inaccuracies or hallucinations where the model produces irrelevant information[8][34][30]. In contrast, retrieval-based models focus on fetching relevant information from a pre-existing database, ensuring factual correctness. While generative models can provide faster answers, incorrect information can be more damaging than no information at all.

RAG bridges these two approaches. It employs a retrieval mechanism to fetch relevant documents or passages from a large database based on the input query. These retrieved documents provide factual grounding for response. The generative model takes these documents and generates a contextually appropriate response. A typical RAG workflow is depicted in Figure 1.

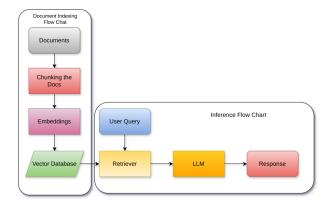


Figure 1: RAG Workflow

The process involves two main steps:

 Retrieval Step: Given an input query, the retrieval component searches a large dataset to find the most relevant documents or passages. This is typically done using techniques like dense passage

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retrieval, which involves embedding the query and documents into a shared vector space and finding the nearest neighbours[20].

 Generation Step: The generative component takes the retrieved documents as additional context and generates a response that is both coherent and informative. This ensures that the response is grounded in the actual content of the retrieved documents, thereby enhancing factual accuracy.

As the size of the knowledge domain increases, so does the noise in the data. This can cause RAG to struggle with large datasets and increase the time needed to retrieve information. These limitations can be addressed through methods such as Agentic RAG or keyword-augmented generation (KAR) and cos-mix[22][28][19].

Agentic RAG involves generating a summary of each retrieved chunk and passing it to an agent LLM that verifies the relevance of the retrieved chunk to the user query. This approach allows for the rejection of irrelevant context and can be done concurrently to minimize computing time. It is particularly helpful for mitigating PDF parsing errors, as this step can summarize garbled text with the question providing context to guide the summary. However, these are recursive and time-consuming procedures.

Keyword-augmented generation (KAR) involves using keywords to augment information retrieval, resulting in reduced latency and retrieval costs. This approach simplifies updating a system with domain-specific knowledge while also making it easier to understand the source of the information. Cosmix involves a hybrid cosine-similarity and distance based approach for efficient retrieval.

Few-shot or zero-shot learning techniques have gained significant attention in Natural Language Processing (NLP) due to their ability to classify text with minimal or no labelled data for the target domain[16][10]. These approaches leverage the power of pre-trained language models, which have been trained on vast amounts of text data, to generalize across domains. This capability is particularly valuable in scenarios where obtaining a large labelled dataset is impractical or time-consuming. For instance, a zero-shot learning model can classify a piece of text that has never been explicitly trained on by using natural language prompts. For example, to classify movie reviews as positive or negative, a prompt like "Classify the following review as positive or negative: [review text]" can be used. The model uses its understanding of language and context to generate the correct classification based on the prompt.

The aforementioned solutions involve LLMs with a high number of parameters, which increases processing time. Therefore, we introduce a query classifier into the existing RAG workflow.

Traditional machine learning models like Random Forest, and Decision Trees have many strengths and can perform various tasks effectively[27] [33] [25] [21] [18]. They excel at handling structured data, such as numbers and categories, making them ideal for tasks like predicting house prices, detecting spam emails, and recommending products. These models can learn patterns from the data they are trained on, allowing them to make accurate predictions and decisions. However, they often face difficulties when dealing with natural language. We can improve their accuracy by integrating advanced NLP techniques[23].

Traditional machine learning algorithms are also known for their interpretability and transparency. Models like Decision Trees provide clear insights into how decisions are made, making them valuable in domains where understanding the reasoning behind predictions is crucial, such as in medical diagnosis or financial risk assessment. Moreover, ensemble methods such as Random Forest combine multiple decision trees to improve robustness and generalization, reducing overfitting and enhancing performance on complex datasets with noisy or incomplete information.

Transformer models like BERT have gained widespread popularity due to their ability to model bidirectional dependencies in language data effectively[11]. By pre-training on large databases of text data using unsupervised

learning objectives like masked language modelling and next-sentence prediction, BERT learns contextual representations of words and sentences that capture their meanings and relationships within the surrounding context. However, BERT's computational complexity and large memory footprint make it challenging to fine-tune specific data[36].

To address this issue, we used a distilled version of BERT, DistilBERT. DistilBERT retains much of BERT's performance while being more computationally efficient and lightweight. By distilling the knowledge from the larger BERT model into a smaller and faster variant, DistilBERT achieves significant speed and memory improvements [32].

Recent works show that, as the size of the vector store increases, the retrieval time also increases[17]. The integration of RAG with models like DistilBERT further enhances the system's efficiency[12]. DistilBERT can help in classifying user queries to identify the relevant domain, and RAG ensures that the responses are grounded in the accurate retrieval of information from the classified domain.

One of the key challenges in dealing with enterprise-specific data is quickly extracting relevant context from the knowledge domain while avoiding confusion between closely related data. Rather than having a single knowledge domain for all categories, a better approach could be to have individual knowledge domains for each respective category and a query classifier to identify the correct knowledge domain. This can reduce retrieval time and improve response quality.

2 METHODOLOGY

In this section, we will detail the methodology and workflow of the contextaugmented RAG system, describing each component and the processes involved, as illustrated in the flowchart (Figure 2).

2.1 Context augmented Retrieval

The Context-augmented Retrieval (CAR) workflow, enhances the system's ability to retrieve the most relevant information using the classifier and thereby generate a response by injecting this into a prompt passed to LLM. The steps are as follows:

- User Query: Query is received and passed to classifier model.
- Query-Index Classification Model: The query is classified into the appropriate domain/category using the classification model, as will be discussed in Section 2.3.
- Index loader: The domain-specific labeled index is loaded to retrieve relevant information corresponding to the user's query. Details about the index generator and classification function are provided in Section 2.2.
- Hybrid Retriever:
 - BM25 retriever: BM25 is a bag-of-words retrieval function that ranks a set of documents based on the query terms appearing in each document, regardless of how close together they occur[1].
 - Vector retriever: Vector retrievers are responsible for fetching the most relevant context given a user query from the nodes.
 Together, both functions ensure the efficient retrieval of context relevant to the given query.
- Query Engine: The retrieved context, together with the query, is subsequently fed into the LLM to generate the coherent response.

2.2 Index Generation and Classification

- Documents segregation: Documents are categorized based on the domain in which they need to be classified. Then each category/domain is assigned a label.
- Directory loader: The documents from each domain are to be separately loaded from their respective directory irrespective of their extensions i.e. pdf, CSV, etc. For each directory, this is performed by SimpleDirectoryLoader from llama-index

Figure 2: This figure provides an analysis of the CAR workflow. Arrows indicate the flow of information from one block to the next, while numbers represent the order in which blocks are triggered.

- Ingestion pipeline: This pipeline loads the required documents and applies the required transformations for it. The following transformations are applied:
 - Entity Extraction: This is a crucial step in the workflow i.e. to identify the keywords like names, dates, location etc. This is done by EntityExtractor in llama-index.
 - Node parser: The documents/paragraphs are divided into chunks that are important for further steps. This task is done by Sentence-Splitter from llama-index.
- Index Generation: The indices for each chunk are generated from
 the tokens using OpenAI's text-embedding-ada-002 embeddings
 with a chunk size limit of 512 tokens, which vectorize the data for
 retrieval. This also ensures to chunk the data without trying to break
 paragraphs sentences and words[2].
- VectorStore: The generated indices are stored in a vector database, and separate databases specific to each domain are labeled accordingly for integration into the workflow.

2.3 Classification Architecture

The queries entered by user are classified using classifier into labels which correspond to the labels provided to indexes created for each category/domain, as shown in Figure 2. The classification architecture consists of the following components:

- (1) Query Classification: This module facilitates query categorization into available domains. Various approaches can be employed, including traditional machine learning models such as:
 - Logistic Regression: A linear model used for binary classification tasks, Logistic Regression estimates probabilities using a logistic function and is effective when the relationship between features and target is linear[3].
 - Multinomial Naive Bayes (MultinomialNB): Based on Bayes' theorem with strong independence assumptions between features, MultinomialNB is suitable for text classification tasks where features are counts or frequencies[4].
 - Gaussian Naive Bayes (GaussianNB): Another variant of Naive Bayes, GaussianNB assumes features follow a Gaussian distribution and is ideal for continuous data where values are real numbers[5].
 - LinearSVC (Linear Support Vector Classifier): A variant of Support Vector Machine (SVM), LinearSVC constructs a linear decision boundary to separate classes and is effective for binary classification tasks with large-scale datasets[6].

And fine-tuned transformer models such as:

 DistilBERT: A distilled version of BERT (Bidirectional Encoder Representations from Transformers), DistilBERT is a transformerbased model pre-trained on large text corpora and fine-tuned for various NLP tasks, achieving state-of-the-art performance in tasks like text classification and question answering.

- By categorizing queries, the system efficiently narrows down the search space, enhancing the precision and focus of the retrieval process.
- (2) Context Retrieval: This module implements the CAR approach. Once the query is classified, the index labeled for the classified query is then used to pass the context embedded in prompt to the LLM for answer generation.

3 PROMPT

The following prompt has been used, the context variable is passed to the prompt as shown in Figure 2.

""" You're an AI assistant to help students learn their course material via convertsations. The following is a friendly conversation between a user and an AI assistant for answering questions related to query. The assistant is talkative and provides lots of specific details in form of bullet points or short paras from the context. Here is the relevant context: {context_str}

Instruction: Based on the above context, provide a detailed answer IN THE USER'S LANGUAGE with logical formation of paragraphs for the user question below. """

4 RESULTS

We conducted a comprehensive comparison between conventional machine learning models and transformer models that have been fine-tuned on a labelled question-domain dataset of 60 questions each of Physics, Chemistry and Nano-science domains and evaluated them in terms of out of sample accuracy, recall and precision.

Table 1: Comparison of Classical Machine Learning Models vs. Fine-Tuned Transformer Model in text classification

Model	Training Accuracy	Testing Accuracy	Recall	Precision
MultinomialNB	1.00	1.00	1.00	1.00
Logistic Regression	1.00	1.00	1.00	1.00
GaussianNB	1.00	0.92	0.92	0.93
LinearSVC	1.00	0.92	0.92	0.93
DistilBERT	1.00	0.42	0.42	0.59

Table 1 illustrates that classical machine learning models surpass finetuned transformer models in classifying user queries, achieving perfect scores of 1 in accuracy, precision, and recall on out of sample data. These results significantly exceed the performance of the fine-tuned models, proving the effectiveness of incorporating this classification approach into the workflow.

When evaluating large datasets like enterprise data, it is often beneficial to categorize the questions, aiding in a more effective assessment of the workflow[9]. In this study, questions were divided into four categories: Reason Dense, Reason Sparse, Factual Dense, and Factual Sparse. These

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categories represent reasoning and factual questions, distinguished by the frequency of the answer's occurrence (sparse and dense) within the entire embedding space of documents. Next, response/answer to 60 questions of each category were evaluated separately to analyse the response time of CAR workflow and quality of answers using CAR.

Table 2: Comparison of Information Retrieval Time: CAR vs RAG

Query Type	Avg. % Change in Retrieval time	
Reason, Dense	-50.35%	
Reason, Sparse	-48.98%	
Factual, Dense	-57.97%	
Factual, Sparse	-48.13%	

Table 3: Comparison of Response Generation Time: CAR vs RAG

Query Type	Avg. % change in Inference time	
Reason, Dense	-5.17%	
Reason, Sparse	-8.36%	
Factual, Dense	-12.58%	
Factual, Sparse	-0.88%	

Table 2 demonstrates that implementing conventional machine learning models to predict category/domain of query with appropriately segregated content (labelled domain index) can significantly reduce retrieval time. This is evidenced by a reduction in retrieval time exceeding $\sim\!50\%$. Similarly, from Table 3 we can see that the response generation/inference time also reduced in the range of $\sim 1\text{-}12~\%$.

Table 4: Comparison of CSGA: CAR vs RAG

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Query Type	Avg. CAR CSGA	Avg. RAG CSGA
Reason, Dense	0.86	0.87
Reason, Sparse	0.86	0.87
Factual, Dense	0.85	0.86
Factual, Sparse	0.85	0.86

Cosine similarity with ground truth answer (CSGA) score is a metric which gives comparable measure of quality of LLM generated response like DeepEval [7][9]. It is calculated by finding the cosine similarity between the vectorized ground truth answer and the generated answer. As shown in Table 4, the CSGA score for CAR is comparable to RAG, indicating minimal impact on answer quality.

Besides, human evaluation involving two human evaluators (independent evaluation by each evaluator) was also performed for answers generated using RAG and CAR workflow. Special care was taken while capturing human feedback by randomizing the appearance of answers from CAR and RAG for both evaluators. This human evaluation is necessary and generally more superior to traditional evaluation metrics, as it ensures a more accurate and reliable assessment of the response quality [26].

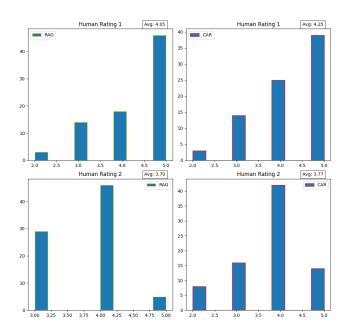


Figure 3: Human Evaluation: RAG vs CAR

As illustrated in Figure 3, the RAG workflow based response generation has a higher number of questions with the highest rating. However, on average, the ratings of the answers generated using CAR based response generation surpass those of the RAG, as it has a greater number of questions rated in the range of 3-4 compared to RAG based response generation.

5 DISCUSSION

As indicated in Table 1, traditional machine learning models outperform fine-tuned transformer models in classifying user queries. Several factors might contribute to this discrepancy. Due to the lack of enterprise specific dataset and the complexity of transformer architectures, it can lead to overfitting, resulting in poorer performance compared to traditional models[24]. This is also evident from the fact that accuracy over training/in-sample data is higher for fine-tuned DistilBERT compared to accuracy over test data/out of sample data. Additionally, traditional machine learning models benefit from hand-crafted features obtained through feature engineering, whereas transformer models rely on learning features directly from the data[31], hence they require more data to learn features. These factors may explain the performance differences observed between the models.

Table 2 and Table 3 shows a significant reduction in both inference and retrieval times respectively. The decrease in retrieval time is due to the model now retrieving from a smaller corpus rather than the entire dataset. The reduction in inference time can be attributed to the minimized noise in the retrieved context, ensuring that only highly relevant information is used to generate the answer.

Figure 3 reveals that the RAG model received higher ratings for a greater number of questions. This can be attributed to human evaluators tendency to assign higher ratings to longer answers. Since the context corpus was reduced, the answer length decreased, leading to lower ratings. If we increase the corpus for each domain, we can expect an improvement in ratings of CAR model. There is also a slight improvement in the average ratings of CAR generated answers compared to the RAG for some questions. This improvement can be attributed to the model's ability to retrieve concise information, which reduces noise in retrieval. As a result, the model generates more concise answers that are relevant to the query, thereby increasing the average ratings.

Table 4 shows that the cosine similarity with the ground truth remains relatively same between CAR and RAG. CSGA score for CAR answers also shows stability (low variance) for different answers, which can be attributed to the efficacy of CAR in generating response from LLM. However, CAR generated answers on average is slightly lower (~ 1%), which can be explained by the fact that the ground truth answers used to calculate the CSGA score are based on the RAG approach applied over GPT-4??. In RAG, context retrieval happens over the entire corpus and it may encompass more information compared to CAR. This will result in lower overlap between vectors of CAR generated answers and ground truth answers. However, due to the category/domain classification being performed in proposed CAR with perfect accuracy for every query, answers are always generated on the relevant context lowering any possible hallucination and our results demonstrate CAR answer quality is very similar to those of traditional RAG.

6 CONCLUSION

In this paper, we have proposed an novel approach to retrieve context for generating answer from LLM. It integrates query classification based context retrieval with LLM based inference to improve the relevance of responses as well as decrease the response time. The key findings from our investigation are as follows:

- This work demonstrates that the use of machine learning models over fine-tuned BERT model for classification of user queries is more suitable for enterprise specific concise dataset.
- Context augmented retrieval effectively leads to lower retrieval times ($\sim 50\%$) and lower response time ($\sim 7\%$) without impacting the answer quality
- Cosine similarity with ground truth answer remained almost similar between CAR and RAG generated responses (average difference of ~ 0.8%). Same is corroborated by human rating of responses too.

Future work will explore how to respond to queries which may span multiple categories/domains by automatically generating relevant labels. For the same, alternative multi-label classification model need to be investigated and integrated with LLM based inference for efficient answering of questions belonging multiple categories over expansive dataset.

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