Experimental Setup and Results Analysis for an Application of LLM-RAG

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Abstract. We present the details of experimental evaluation of a system design that leverages LLMs and Retrieval Augmented Generation (RAG) to reduce the bid analysis and evaluation effort in context of government procurement processes. We describe the selection of test data and pre-processing required to conduct the experiments. The important observations about the system's performance have also been discussed.

Keywords: e-procurement · tender bids · Large Language models · Retrieval-augmented generation

1 Introduction

The Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) have gained popularity for a variety of applications pertaining to contextualized question answering. This paper describes the details of experimental evaluation of a system [1] that leverages LLMs and RAG to speed up the analysis of bid documents in context of a procurement business process.

2 System under evaluation

The high-level architecture of the evaluated system is shown in Fig. 1 (this is replicated from the original paper [1]).

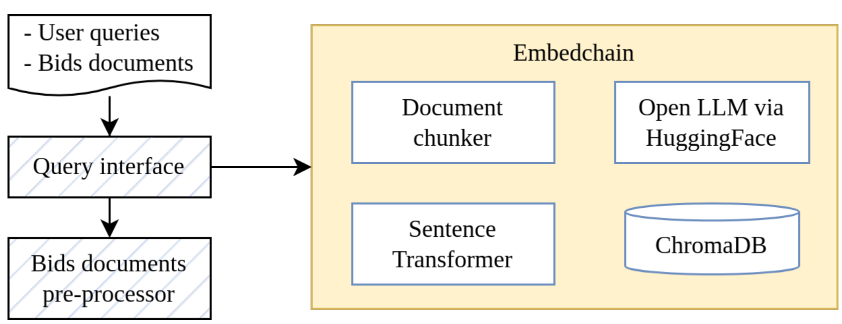

Fig. 1: High-level architecture

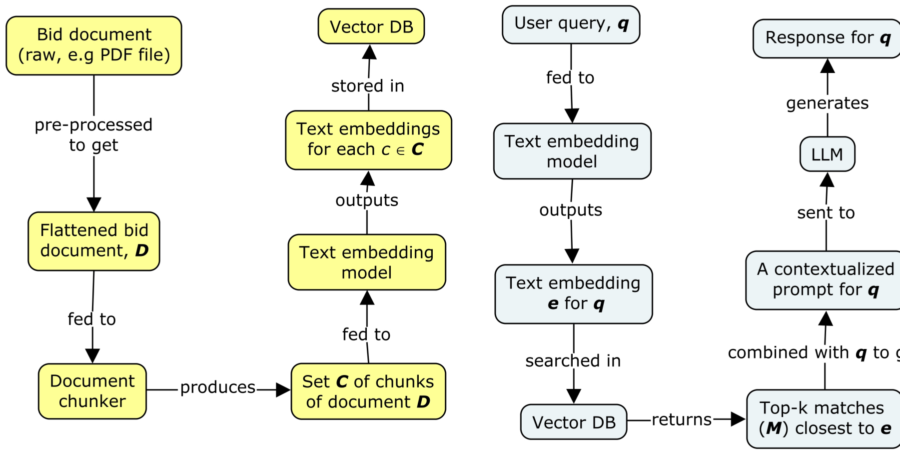

Fig. 2: Logical flow of module interactions.

Tabular data found in the input documents was converted to descriptive sentences using rule-based templates. A simple rule that was used involved concatenating the value in a table cell with the corresponding table header cell value. Example: the data from first row of Table-1 can be transformed into the following text:
Drug name is Paracetamol, Expiry Date is 2027-03-30, Batch No. is AW33456.

Table 1: Sample tabular data

S.No	Drug Name	Expiry Date	Batch No.
1	Paracetamol	2027-03-30	AW33456
2	Acepik-P	2026-12-23	BGT67565

More complex rules can be used as needed based on the data present in the bid documents.

3 Experimental Evaluation

We conducted experiments to evaluate the effectiveness and efficiency of our proposed system compared to baseline methods. Metrics such as answer accuracy and response time are measured to assess the system's performance across query types and bid documents. Below, we outline the key components and methodologies for conducting the experimental evaluation:

3.1 Dataset Selection

Dataset selection was made for two primary purposes: **(i)** Assessing the efficacy of the proposed system on a reasonable sample of read bids documents taken from diverse domains, and **(ii)** Identifying the effects of different structural properties of a bid document on the performance of the proposed system. The structural properties include the number of pages and tables in a document, the relative number of words in tables, and the body of the document.

For meeting purpose (i) above, we chose the bids documents such that they were representative of the bids spanning different domains, such as bids for large construction contracts, computer hardware purchases, outsourcing contracts, and so on (see Table-2). We ensured the dataset included a sufficient number of documents to provide a comprehensive evaluation of the system's performance.

For purpose (ii), we used synthesized bid documents that had the desired properties (e.g., number of pages, tables, and words, etc.). These bid documents were generated using an LLM (we used ChatGPT 3.5 free version and locally deployed Llama [2]) and manually edited as needed.

Table 2: Details of real bid documents.

Tender domain	**No. of bid documents**
Turnkey building construction project	16
Computers/servers purchase	25
Data networking installation in large buildings	13
Transportation services contract	10
HVAC maintenance contract	15
Specialized equipment purchase	22

3.2 Query Generation

The analysis of bid documents involved crafting queries that aligned with both the specified bid evaluation criteria and the broader procurement guidelines set by regulatory bodies. These queries were designed to encompass a diverse array of informational requirements and intricacies found within the bid documents, ensuring coverage of various topics, concepts, and interconnections.

Example tender The following publicly available tender document is an example of a common scenario: `https://www.iith.ac.in/assets/files/tenders/T089R%20Tendernotice_1.pdf`. Chapter 4 of this tender contains several criteria in a tabular format that the bidders are required to conform in a format as indicated in "ANNEXURE–A" of the above tender.

For testing our system with a tender scenario like the above one, we can easily derive the following queries using the above tender's information:

1. *How many channels does the quoted EEG medical grade system have?*
2. *What is the Sampling rate of the quoted EEG medical grade system?*
3. *What is the WiFi Operating time quoted?*

These queries (and many more) were inputted into our system when testing it with the synthetic and real bid documents.

3.3 Evaluation Metrics and Results

We established specific metrics to gauge the system's effectiveness in responding to queries:

1. **Accuracy:** Quantifying the system's correctness in providing answers compared to human-generated or ground truth responses.
2. **Response Time:** Assessing the duration taken by the system to process and furnish answers.

As a benchmark for comparison, we employed manual scrutiny of bid documents by human experts. Notably, this method attains a perfect accuracy rate of 100%, albeit it typically operates at a slower pace in bid evaluation, particularly in generating responses to queries.

Evaluation with real tenders data Table-3 shows the information about the bid documents, evaluation queries, and other structural properties of the documents that we tested with.

Testing with synthetic documents We generated synthetic documents using LLMs (viz. ChatGPT 3.5 and Llama 2 [2] open source) and edited manually as needed. The following structural properties were varied when generating these documents: i) No. of pages, ii) No. of tables in the document, iii) Proportion of the number of words that appeared in the tables vs. the rest of the body of a document.

3.4 Experimental Observations and Analysis

Our focus in the experiments was mainly to assess a) the accuracy of the answers our system produced for the given set of queries for a given bid document and b) the response time or speed to getting those answers.

Table-3 shows the data about the bid documents, evaluation queries, and the accuracy across the domains that we considered. Following are the key insights that we have from the data:

1. Accuracy of the answers appears to be better when the tabular data is flattened.
2. There is no significant trend or variation in accuracy across domains of the bid documents.

Table 3: Bid documents and performance data across domains.

Domain of the tender	Turnkey building construction project	Computers/servers purchase	Data networking installation in large buildings	Transportation services contract	HVAC maintenance contract	Specialized equipment purchase
No. of documents	16	25	13	10	15	22
Avg. queries per document	16	16	15	14	16	16
Avg. pages per document	29	26	25	22	26	28
Avg. tables per document	11	11	10	10	12	9
Avg. words per document, W^b	6553	6632	6550	5811	5462	5498
Avg. words in tables per document, W^t	2195	2155	1094	2841	1977	973
Avg. accuracy with flattened tables	0.85	0.91	0.94	0.88	0.95	0.93
Avg. accuracy without table flattening	0.82	0.84	0.92	0.8	0.91	0.89
Avg. query response time (ms)	1561	1896	1683	2001	1942	1821

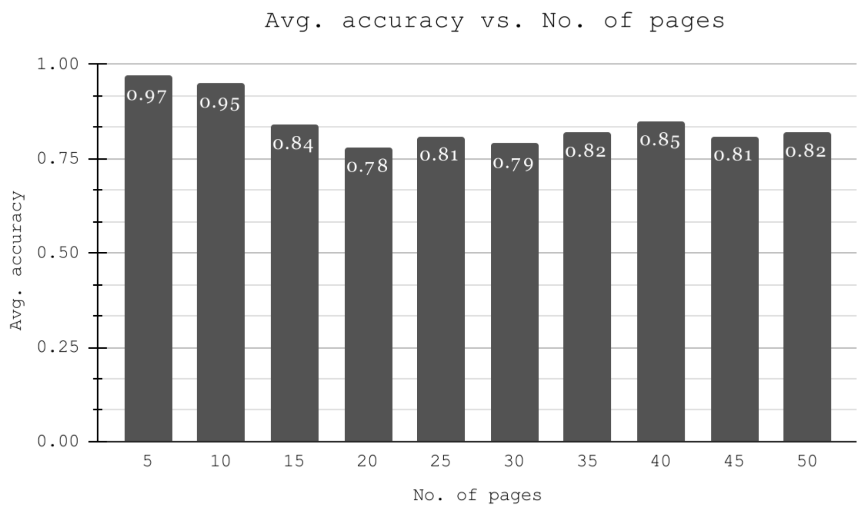

Fig. 3: With Avg. words/page = 250,
Avg. tables/page = 0.4,
$W^t/W^b = 0.4$

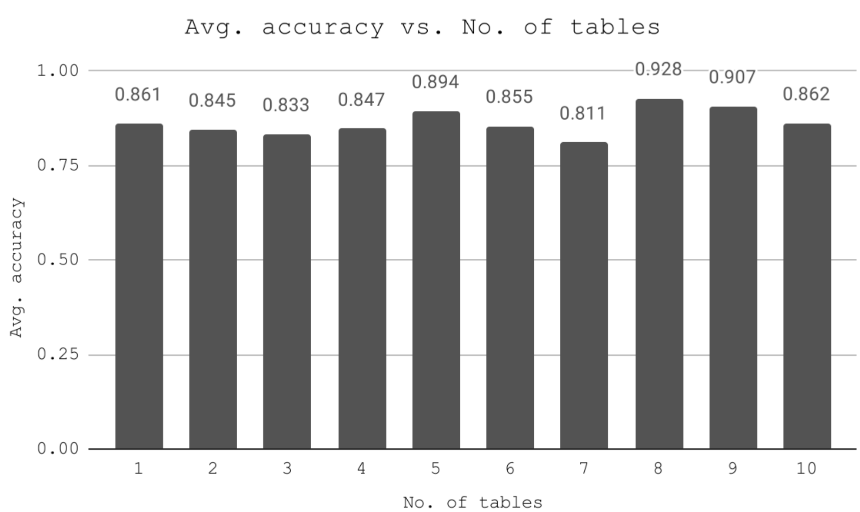

Fig. 4: With No. of pages = 20,
Avg. words/page = 250,
$W^t/W^b = 0.4$

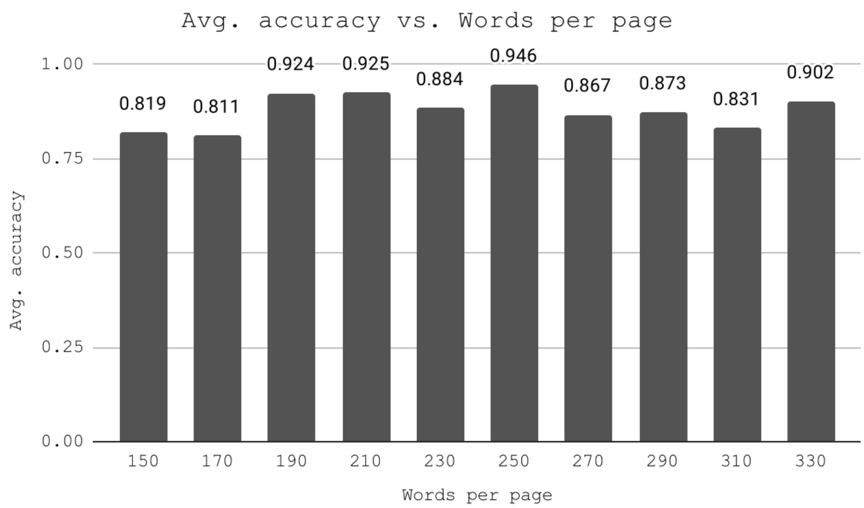

Fig. 5: With No. of pages = 20,
Avg. tables/page = 0.4,
$W^t/W^b = 0.4$

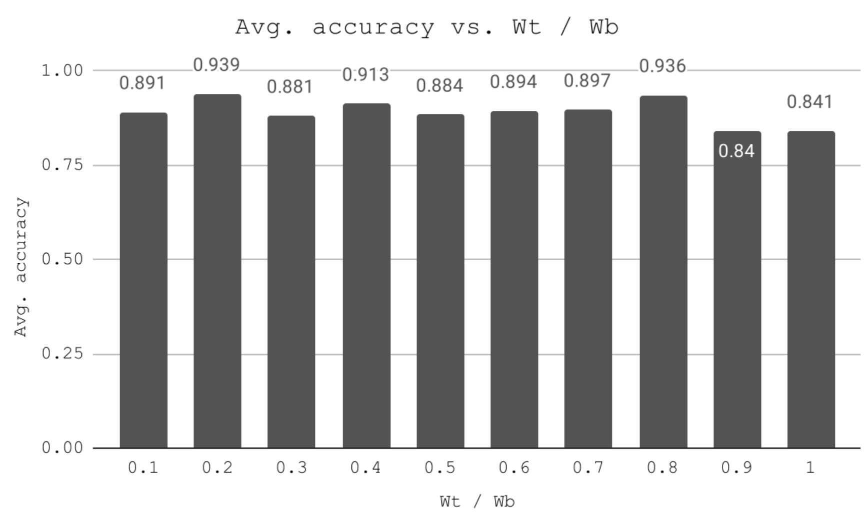

Fig. 6: With No. of pages = 20,
Avg. words/page = 250,
Avg. tables/page = 0.4

3. The accuracy of answers appears to plateau out (see Fig. 3, 4, 5 and 6) in almost all the cases of synthetic documents. The variation in accuracy does not show any significant trend.

The above observations suggest that, except for the flattening of tabular data, other structural properties of the bid documents and even the domains do not affect the accuracy of the query results.

4 Conclusions

We have described the experimental setup that can be used to evaluate the given [1] RAG based system that leverages LLMs to speed up the analysis of tender bids documents. Variation of various aspects of the input documents has been explored in the experiments. Our experiments with actual as well as synthetic bid documents show that the proposed system accuracy of 80% and above can easily be achieved by using lightweight open-source LLMs.

References

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