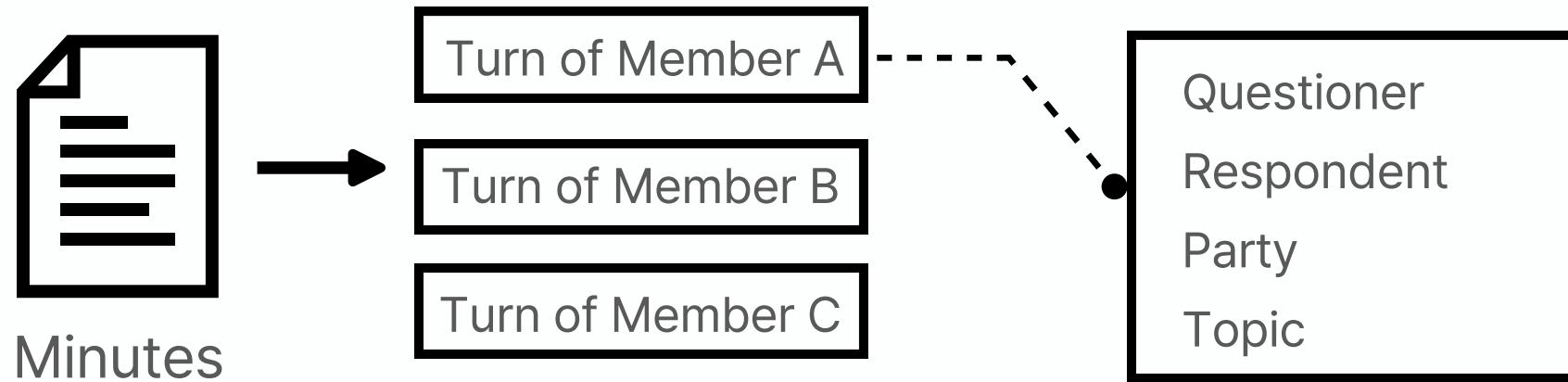


Introduction

Legislative minutes consist of question-and-answer exchanges between council members and executive officials, containing diverse opinions and issue-raising related to public services. However, most citizens, as well as journalists, do not have enough time to read and interpret them properly.

To address this limitation, this study aims to implement a RAG system that summarizes and reconstructs legislative minutes into news-style articles from perspectives that many people may find relevant.

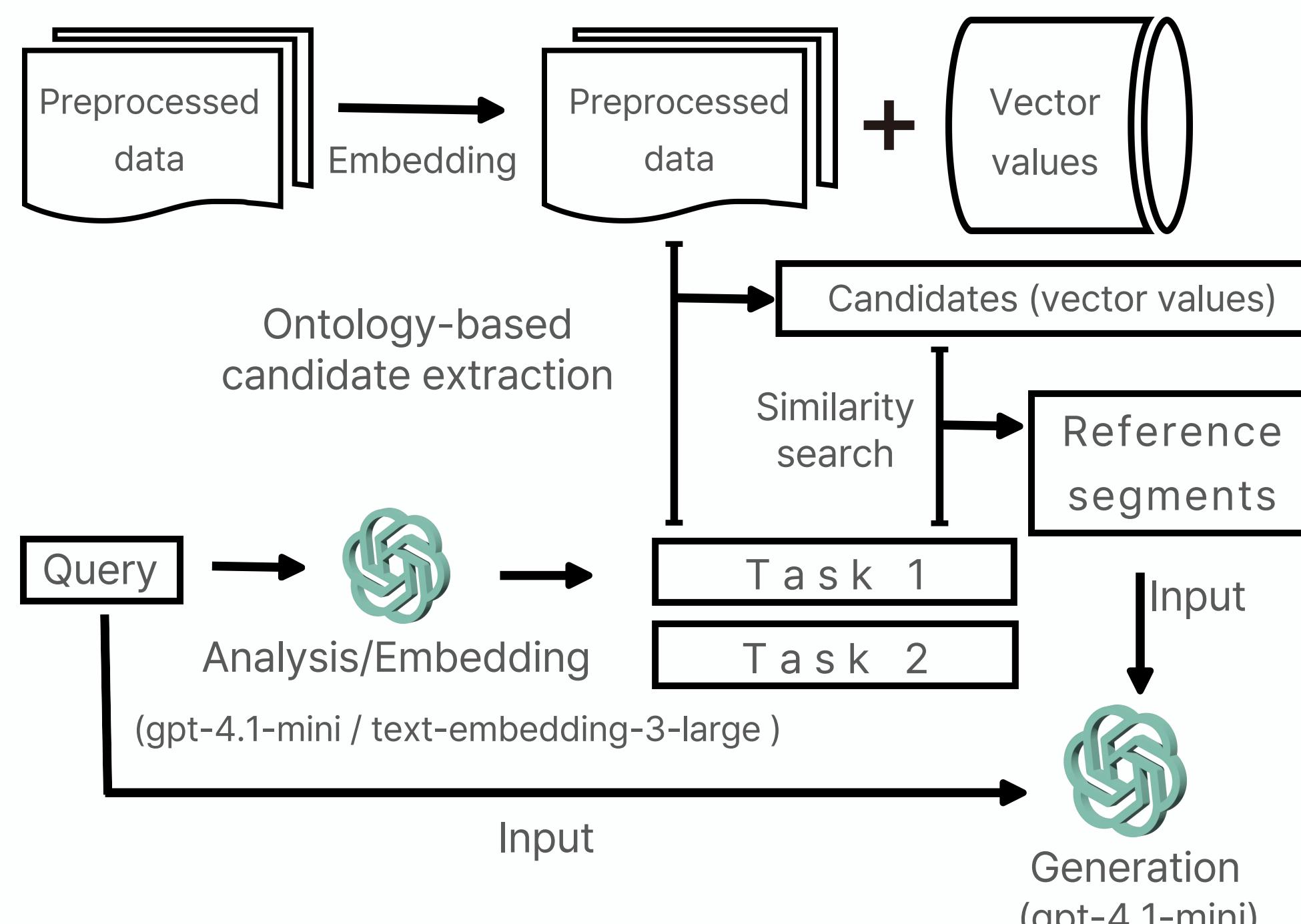
Data Preprocessing



Legislative minutes can be divided into segments based on the chairperson's procedural statements, and this study uses these segmented units as the minimum retrieval units. From each segment, an LLM is then applied to extract information such as the speaker and the topic.

Because calling an LLM through an API incurs costs in this extraction process, this study employs the open-source model gpt-oss-20b to reduce these expenses.

RAG Architecture



Each input query is first analyzed and transformed by an LLM into a task representation suitable for similarity-based retrieval. For each task, up to five reference segments are retrieved through an embedding-based similarity search. The retrieved segments, together with the original query, are then provided to the LLM to generate a news-style article. The LLM used for this process was accessed via API calls to gpt-4.1-mini, and text embeddings were computed using text-embedding-3-large.

Evaluation

Evaluation Target

In this study, we evaluated the quality of reference segments retrieved in response to 100 example queries, using the plenary records of the Gwangju Metropolitan Council and the Seoul Metropolitan Council collected from July 2022 to October 2025. We compared the performance of a Naive RAG approach—which embeds the meeting minutes without any preprocessing and conducts similarity search solely based on the embedding vectors—with that of the Ontology RAG system developed in this research.

Evaluation Method and Criteria

Example Query

What is the view of Member A (XX Party, OO Council) on the topic □□?

Evaluation (gpt-4.1-mini)

- Did it correctly identify the speaker, council, and party?
- Do the topics of the query and the reference segment match?

Example Reference Segment

Content in which B (XX Party, OO Council) spoke on the topic □□

Evaluation Queries (100 items)

- Content on a specific topic discussed in a specific council: (Council + Topic): 40 items
- Content in which a specific speaker mentions a specific topic: (Person + Topic): 20 items
- A specific party's stance on a specific topic (Party + Topic): 10 items
- Differences in stance between two entities: (Person, Council, or Party + Topic): 30 items

Conclusion

Metric	Naive	Ontology	Change
Factual Error Rate	32.2%	7.05%	-25.15%
Average relevance score	5.77/10	6.54/10	+7.66%

Ontology RAG returned no reference segments for 15 of the queries, indicating that the information requested in those queries did not exist in the minutes. In contrast, Naive RAG, relying solely on similarity search, retrieved completely incorrect segments as reference candidates. These segments were additionally classified as errors and assigned a relevance score of zero.

The evaluation results show a substantial reduction in factual error rates, along with a consistent improvement in the average relevance score.



The code, data, and evaluation results used in this study are publicly available on GitHub. Detailed documentation translated into multiple languages is also provided.