

Retrieval-augmented Generation for German official documents

*Topic 13. Retrieval-augmented Generation for
German official documents*

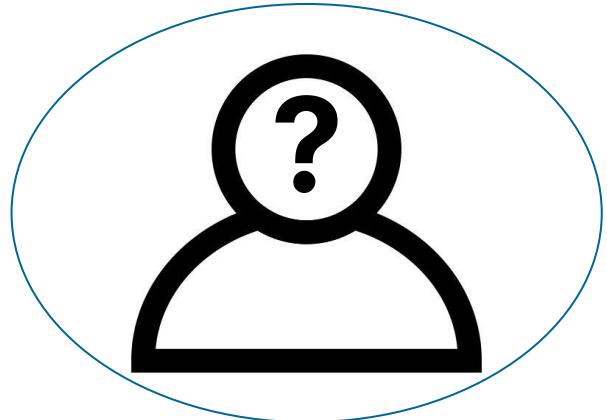
Group 25: Stefan Sick, Diara Rinnerbauer, Valentin Tian

Date: 16/01/2026

Content

- Our Team & Work Distribution
- **Motivation**
- Data
- **Preprocessing Pipeline**
- Milestone 1
- **Milestone 2**
- Additional Approaches
- **Evaluation**
- Key Takeaways

Our Team & Work Distribution



Stefan Sick

- Preprocessing
- Initial Code
- Framework
- LLM-based RAG
- SLM-based RAG
- Evaluation
- Presentation

Diara Rinnerbauer

- Data Gathering
- Preprocessing
- TF-DF based RAG
- Code enhancement
- Evaluation
- Presentation & Report

Valentin Tian

- Preprocessing
- TF-DF based RAG
- LLM-based RAG
- Verbatim RAG
- Code enhancement
- Evaluation
- Presentation & Report

Motivation

- Aim: Develop a RAG system to provide precise answers from official parliamentary protocols.



- **Dataset**
 - German Parliamentary Corpus (GerParCor)
- **Description**
 - the largest German-speaking corpus of parliamentary protocols from three different centuries, on a national and federal level from the countries of Germany, Austria, Switzerland and Liechtenstein.
- **Subset**
 - CH Nationalrat, 100 documents (3.77 Million Tokens)
- **Challenge**
 - Handling domain-specific language and ensuring high factual accuracy in official contexts.

Preprocessing Pipeline (Milestone 1)

- Data extraction
 - Raw texts from 100 .xmi documents
- NLP Processing
 - Stanza German pipeline was used for tokenization, multi-word token (MWT) expansion, POS tagging, and lemmatization
- Standardization
 - Converted into the CoNLL-U format

Classification Task (Milestone 2)

- Rule-based baseline
 - Utilizes TF-IDF (BM25) for vector processing and indexing
- Machine learning baseline
 - Employs the Multilingual E5 Text Embeddings model from Hugging Face for semantic search
- Core components
 - Built with LlamaIndex and LangChain, using Gemini 2.5 Flash as the generative LLM

Questions Set

- Pre-defined set of 20 questions that include:
 - Domain-specific questions derived from the randomly selected documents
 - Hallucination check: question that cannot be answered based on the given documents
 - Questions phrased similarly to the text but contain erroneous implication, e.g. specifics that are not part of the text

Questions Groups	
Facts with numbers	10
Definitional facts	6
No answer in data	4

Automated Evaluation Methodology (Milestone 2)

- LLM-as-a-Teacher
 - LLM generates question-answer pairs directly from the source documents
- RAG Execution
 - The system processes these questions without access to the "truth" labels
- LLM-as-a-Judge
 - LLM scores responses from 0 (False) to 5 (Perfect) based on accuracy and reasoning

Baseline Evaluation Results (Milestone 2)

Quantitative

Metric	Rule based	Machine learning
Mean score	3.6 / 5	4.5 / 5
Delta	-	+.09
Relative improvement	-	+25%
Error reduction	-	64%

Qualitative

- **Correctness:**
 - Most domain-specific questions were answered accurately
- **Numerical sensitivity:**
 - Both systems struggled with precise voting counts when multiple figures appeared in the context
- **Hallucination check:**
 - The models successfully passed tests with out-of-scope questions by stating information was not present

Additional Approaches

- **Verbatim RAG* by KRLabs**
 - No hallucination
 - Direct derivation
- **Local Small Language Model (Llama 3.2)**
 - Open-source/Free
 - Indexing and Retrieval Pipeline with ReRanking
 - Privacy

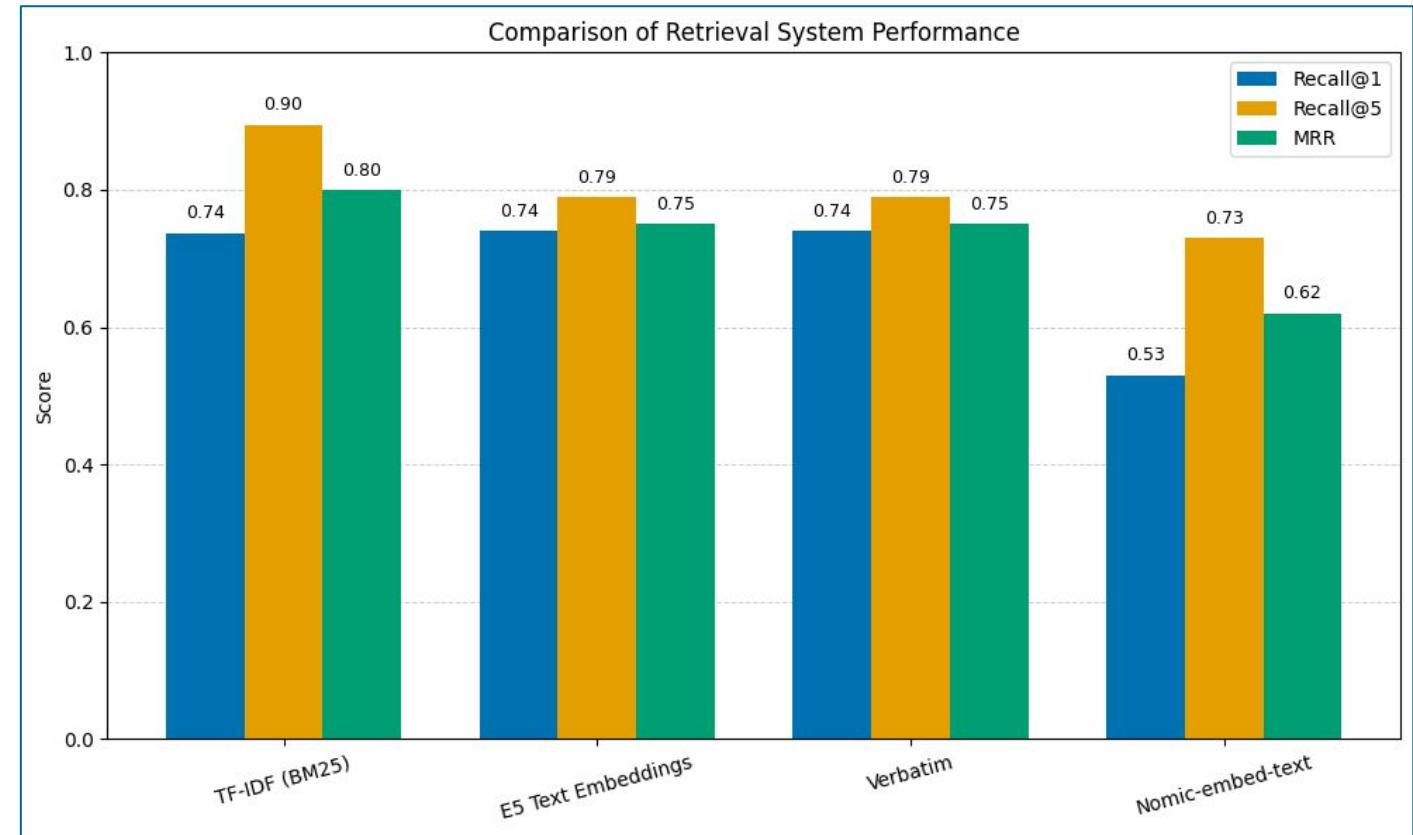
*<https://github.com/KRLabsOrg/verbatim-rag>

RAG Output Format

```
[  
  {  
    "id": 1,  
    "question": "Was war der Ausgang der Abstimmung der Staatspolitischen Kommission über die Handhabung von Volksinitiativen die Grundrechte verletzen?",  
    "source_id": "20111220.gz",  
    "expected_answer": "13 Stimmen Annahme, 8 Stimmen dagegen, 2 Enthaltungen.",  
    "answer": "- Die Staatspolitische Kommission (SPK) stimmte mit 13 zu 8 Stimmen bei 2 Enthaltungen für eine wichtige Etappe im Umgang mit Volksinitiativen",  
    "answer_source_id": [  
      "20111220.gz",  
      "20130321.gz"  
    ],  
    "answer_context_snippets": [  
      {  
        "source_id": "20111220.gz",  
        "snippet": "Die Staatspolitische Kommission schlägt Ihnen mit 13 zu 8 Stimmen bei 2 Enthaltungen eine wichtige Etappe in einem langen Prozess vor, die  
      },  
      {  
        "source_id": "20111220.gz",  
        "snippet": "Als Begründung wird darauf hingewiesen, dass mit dieser Motion die Wahrscheinlichkeit der Einreichung, des Zustandekommens und der Annahr  
      },  
      {  
        "source_id": "20130321.gz",  
        "snippet": "Unsere Kommission hat die Vertreterinnen und Vertreter des Initiativkomitees am 10. Januar angehört und sich danach entschieden, der Init  
      },  
      {  
        "source_id": "20111220.gz",  
        "snippet": "Der Ständerat schlägt vor, analog zum Postulat Heim 09.3118, den Bundesrat eine Vorlage ausarbeiten zu lassen, welche dafür sorgt, dass r  
      },  
      {  
        "source_id": "20111220.gz",  
        "snippet": "Beim Kerngehalt der Volksrechte wird es auch sehr, sehr gefährlich. Wenn ich von Amputation und vom Angriff auf die Volksrechte und die  
      },  
    ]  
},  
],
```

Information Retrieval Evaluation Results

System	Recall@1	Recall@5	MRR
TF-IDF (BM25)	0.737	0.895	0.8
E5 Text Embeddings	0.74	0.79	0.75
Verbatim	0.74	0.79	0.75
Nomic-embed-text	0.53	0.73	0.62



Answer Quality Analysis:

- 1 – True
- 0.5 - Almost True (Noise, additional knowledge/opinion, false citation)
- 0 - False

Question Group	TF-DF (BM25)	E5 Text Embeddings	Verbatim	Nomic-embed-text
Facts with numbers	6/8	6.5/8	3.5/8	1.5/8
Definitional facts	7/10	6/10	6.5/10	4/10
No answer in data	2/2	2/2	2/2	2/2
Total	15/20	14.5/20	12/20	7.5/20
Accuracy	0.75	0.75	0.6	0.375

Key Takeaways

- The quality of the final answer strongly depends on successful document retrieval.
- A robust RAG system must be able to explicitly highlight when the answer is not present in the dataset.
- Evaluating RAG systems is still a non-trivial task and in general manual.
- There is no universal RAG system that performs best across all tasks.
- Different retrieval and generation strategies are optimal for different use cases.

Thank you for your attention!



Retrieval-augmented Generation for German official documents

*Topic 13. Retrieval-augmented Generation for
German official documents*

Group 25: Stefan Sick, Diara Rinnerbauer, Valentin Tian

Date: 16/01/2026