

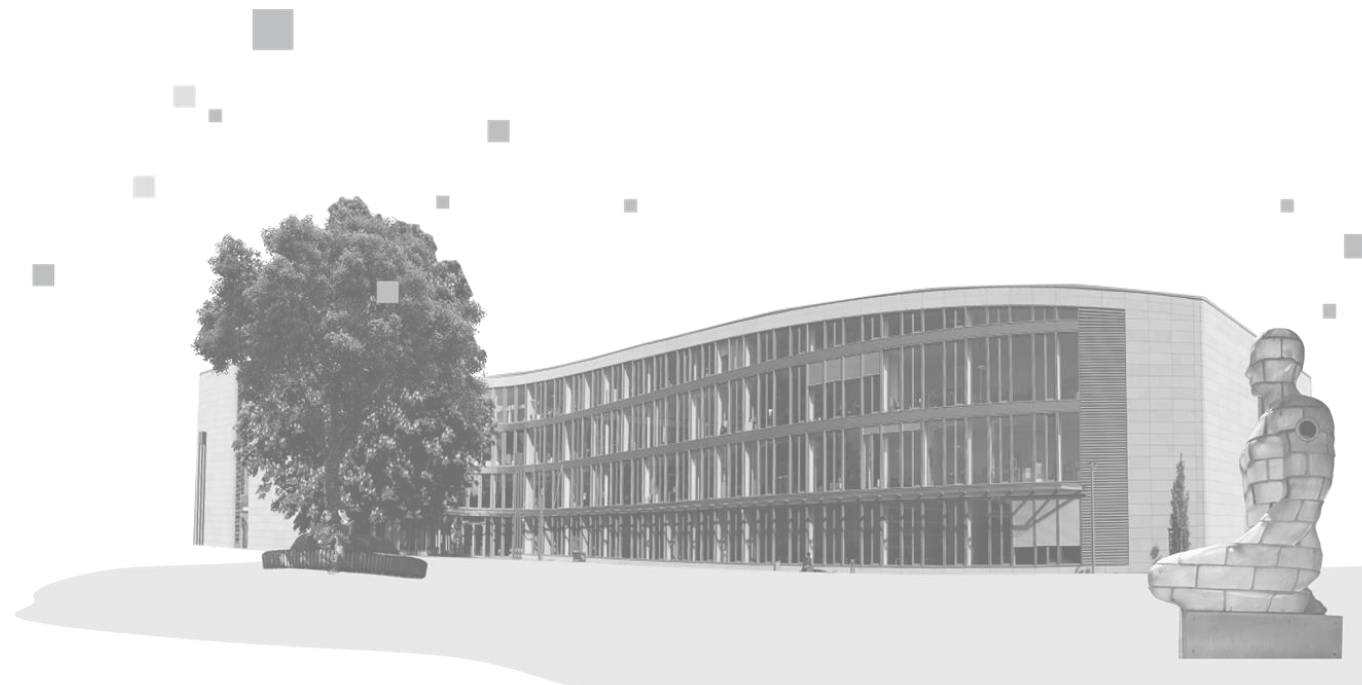
Efficient Information Retrieval from Documents with AI

Local Retrieval-Augmented Generation

Hanno Müller
hanno.mueller@hpi.de

Design IT.
Create Knowledge.

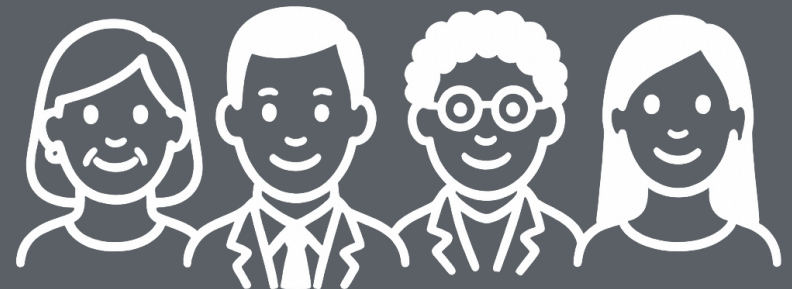
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Who are you?

What do you know about RAG?

From **which documents** do you want
to retrieve information?



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Motivation

- AI Service Centre documents over **1,000 hours** of interaction with clients from a wide range of domains, including:
 - SMEs / NGOs / associations / large enterprises / freelancers
 - Start-Ups
 - Academia
 - Municipal, state, and federal authorities
- Large share of requests revolved around questions about **RAG**, such as its benefits and feasibility.
- AI Service Centre has partnered up for RAG **pilot projects** with Deutscher Bundestag, Landtag Brandenburg, Brandenburger Umweltministerium, fghgsd (IT Baseline Protection)

Gefördert durch:

What is RAG?

- Retrieval-Augmented Generation (RAG) enhances LLM performance by enabling LLMs to access **external information** from multiple sources.

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ChatGPT 5.1

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✓ What is RAG — core definition

- RAG stands for *Retrieval-Augmented Generation*. laizee.ai +2
- At its core, RAG is a hybrid AI approach: it combines **information retrieval (IR)** — i.e. searching external data sources — with **text generation** by a large language model (LLM). Elastic +2
- Instead of relying only on the fixed knowledge encoded in the LLM's parameters from pre-training, RAG lets the model "look up" relevant, up-to-date or domain-specific information at inference time. Wikipedia +2

In short: RAG is about letting generative models access external knowledge sources so their outputs are grounded, more accurate, and context-relevant.

slides_english.pdf PDF

+ Ask anything

ChatGPT can make mistakes. Check important info. See [Cookie Preferences](#).

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What is RAG?

- Retrieval-Augmented Generation (RAG) enhances LLM performance by enabling LLMs to access **external information** from multiple sources.

→ *Generation that is augmented by retrieval*

1. **Information Retrieval** from, e.g., internet, uploaded documents, local documents, live databases such as SQL
2. **Text Generation**, taking into account retrieved information

- Separation of data and model
- Answers go beyond training data without additional model training
- Less hallucinations

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External Systems

- RAG run externally / in cloud (e.g., SaaS applications)

PRO:

- Easy to scale
- No hardware or maintenance
- Advanced toolkit available

CONTRA:

- May be expensive
- Dependence on provider
- Data leaves your environment → privacy concerns

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On-premise Systems

- RAG run on-premise (servers you control)

PRO:

- High data protection & compliance
- Predictable (fixed) costs
- Integration with internal systems

CONTRA:

- High infrastructure cost (investment cost & maintenance)
- Slower innovation cycles
- Difficult to scale (but hybrid on-premise/cloud possible)

Gefördert durch:

Local Systems

- RAG run locally (e.g., laptop or tower with dedicated GPU)

PRO:

- Full data protection & compliance
- Fast prototyping
- (Almost) no ongoing costs

CONTRA:

- Limited performance w.r.t. model size & latency
- Not scalable
- May require strong technical skills

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LEARNING GOALS

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Learnings

- Understand the fundamentals of RAG
 - Embeddings
 - Vector databases
 - Information retrieval
 - Prompt engineering
- Increase awareness for the requirements for (your own) RAG
 - e.g., document preprocessing
 - e.g., creating vector databases
 - e.g., prompt engineering

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Agenda

1. General Introduction (20 minutes)
2. Demonstration of RAG (20 minutes)
3. Interactive Notebook (20 minutes)
4. Customise RAG (20 minutes)
5. RAG Evaluation (20 minutes)
6. Discussion (20 minutes)

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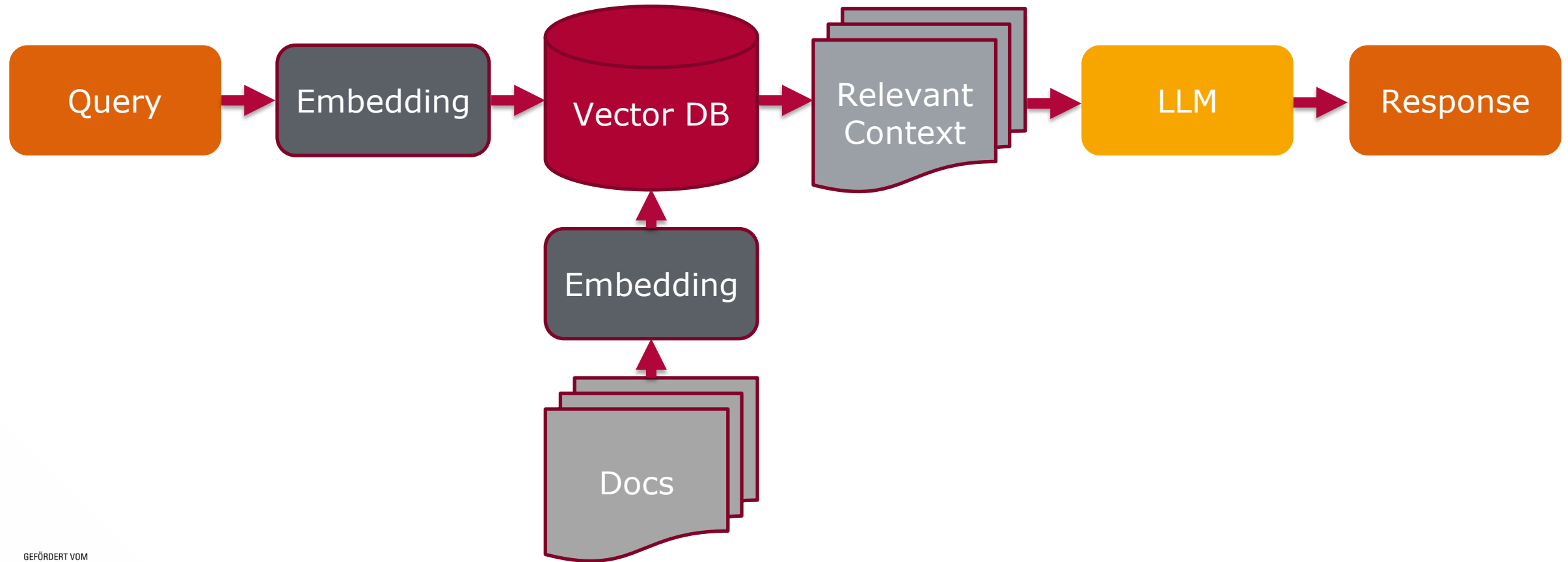


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CONFIGURATION

Chat History ☒

RAG ☒

Retrieval Mode ☐

CHATS

Chat Just now

⚙ Settings

Llama 3.2 3B Instruct ▼

Ask a question about your documents... (Enter to send, Ctrl+Enter for new line)

Send

Hands-On

https://github.com/aihpi/workshop-rag/blob/main/learning-materials/01_workflow.ipynb

<https://github.com/aihpi/>

→ repositories

→ workshop-rag

→ learning-materials

→ 01_workflow.ipynb

GEFÖRDERT VOM



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Data

- ‚Good‘ documents are **machine readable** and enable easy extraction of structure (sections, subsections, headers, metadata)
- ‚Bad‘ documents require **manually crafted processing algorithms**; algorithms may exist but usually function unsatisfactory
- Documents can be categorised in:
 - Text documents (including Tables)
 - Visual documents (scanned documents, figures, diagrams, illustration)

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Evaluation

- RAG can perform insufficiently due to
 1. **Retrieval** problems
 - Retrieving irrelevant information
 - Missing relevant information
 - 'Lost in the middle'¹
 2. **Augmentation** problems
 - e.g., gaps between retrieved information are not coherently filled
 3. **Generation** problems
 - e.g., hallucinations

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¹ Liu, N. F., Lin, K., Hewitt, J., Paranjape, A., Bevilacqua, M., Petroni, F., & Liang, P. (2024). Lost in the middle: How language models use long contexts. *Transactions of the Association for Computational Linguistics*, 12, 157-173.

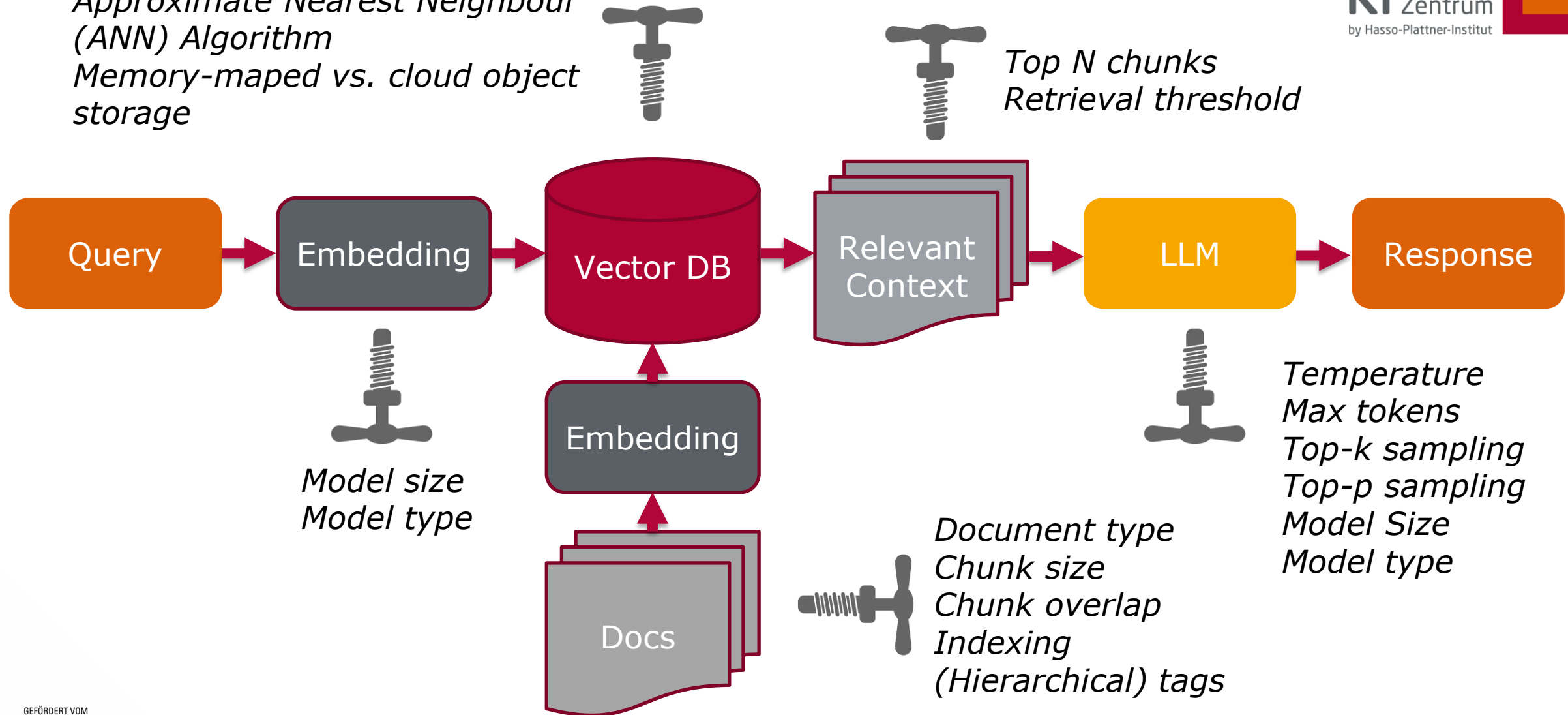
Evaluation Frameworks

- Evaluation frameworks enable to test RAG system on predefined context data and questions answer pairs, e.g.,
 - <https://docs.ragas.io/en/stable/>
 - <https://www.quotientai.co/>
- Performance may drastically differ between **test data vs. real data**
 - create individual test data
 - manually investigate performance
 - Deconstruction of retrieval, augmentation, generation
 - User feedback

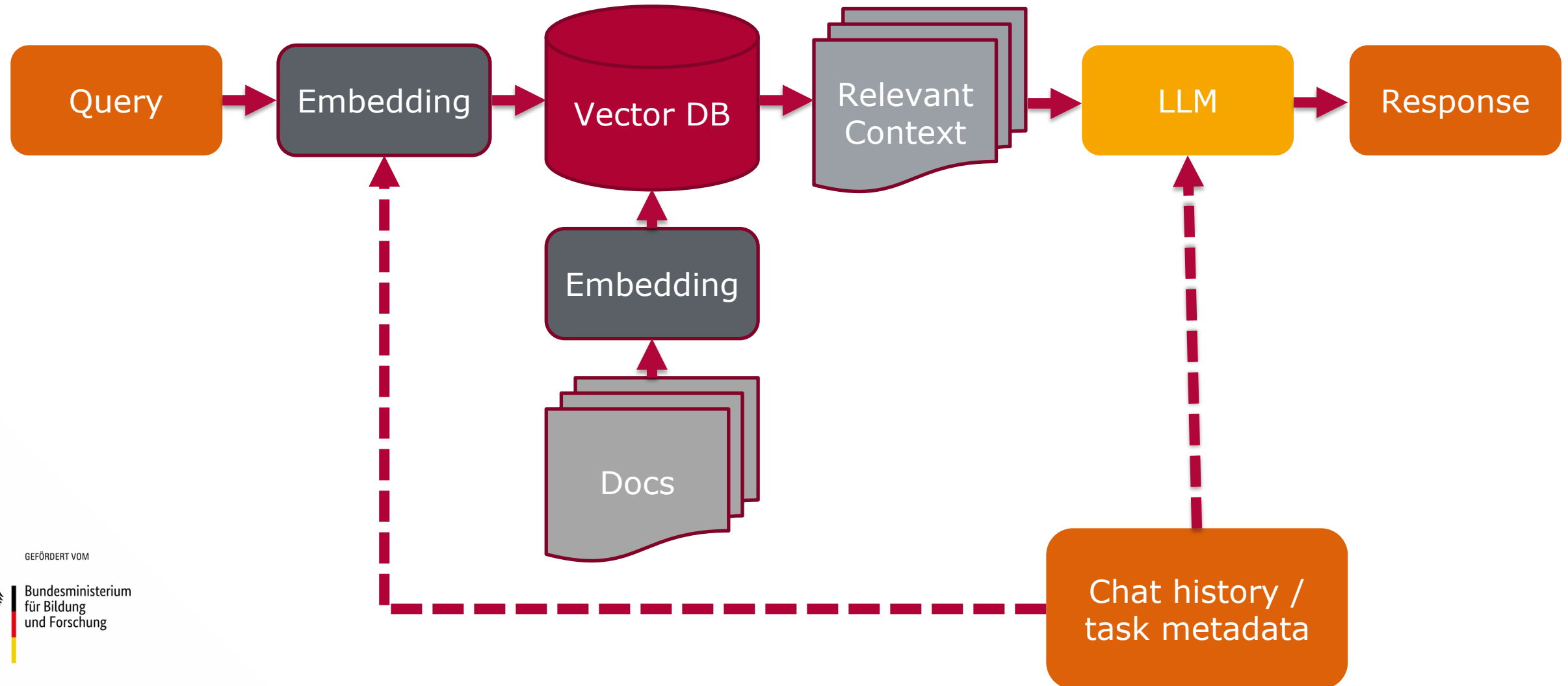
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Approximate Nearest Neighbour (ANN) Algorithm

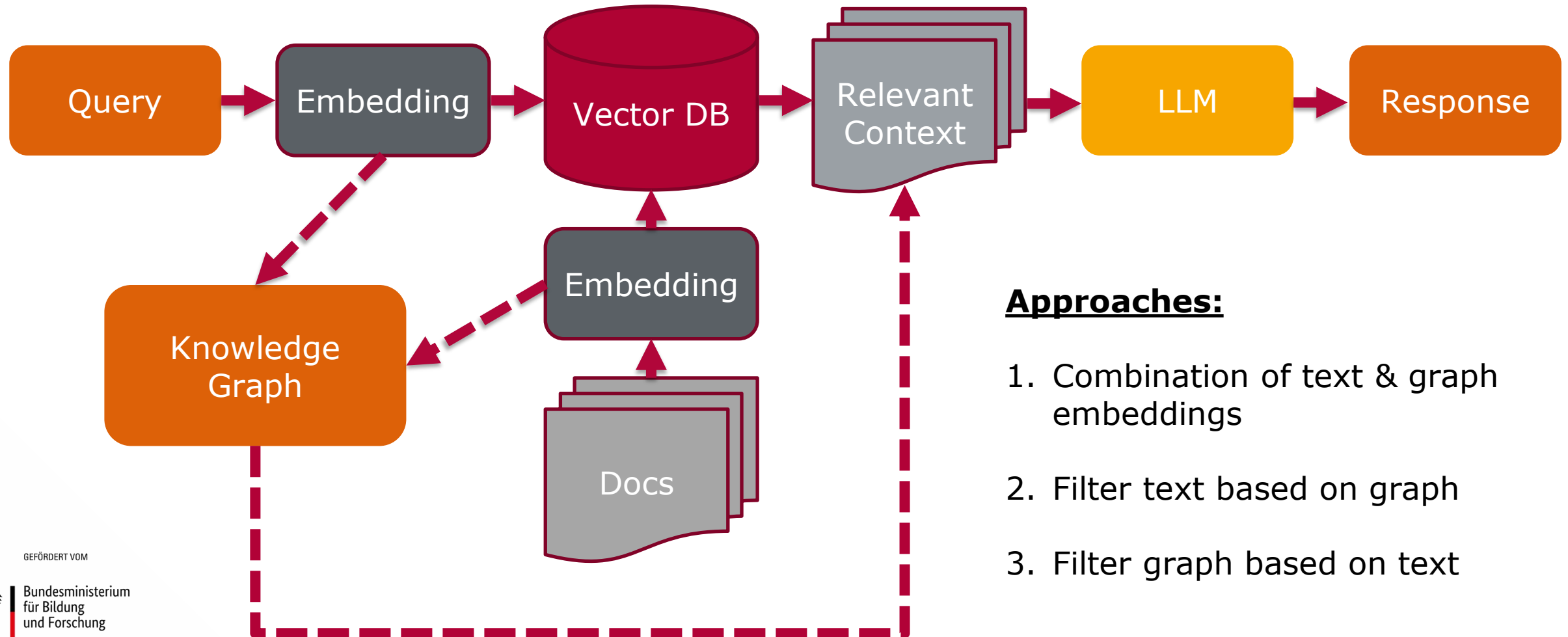
Memory-mapped vs. cloud object storage



Context RAG



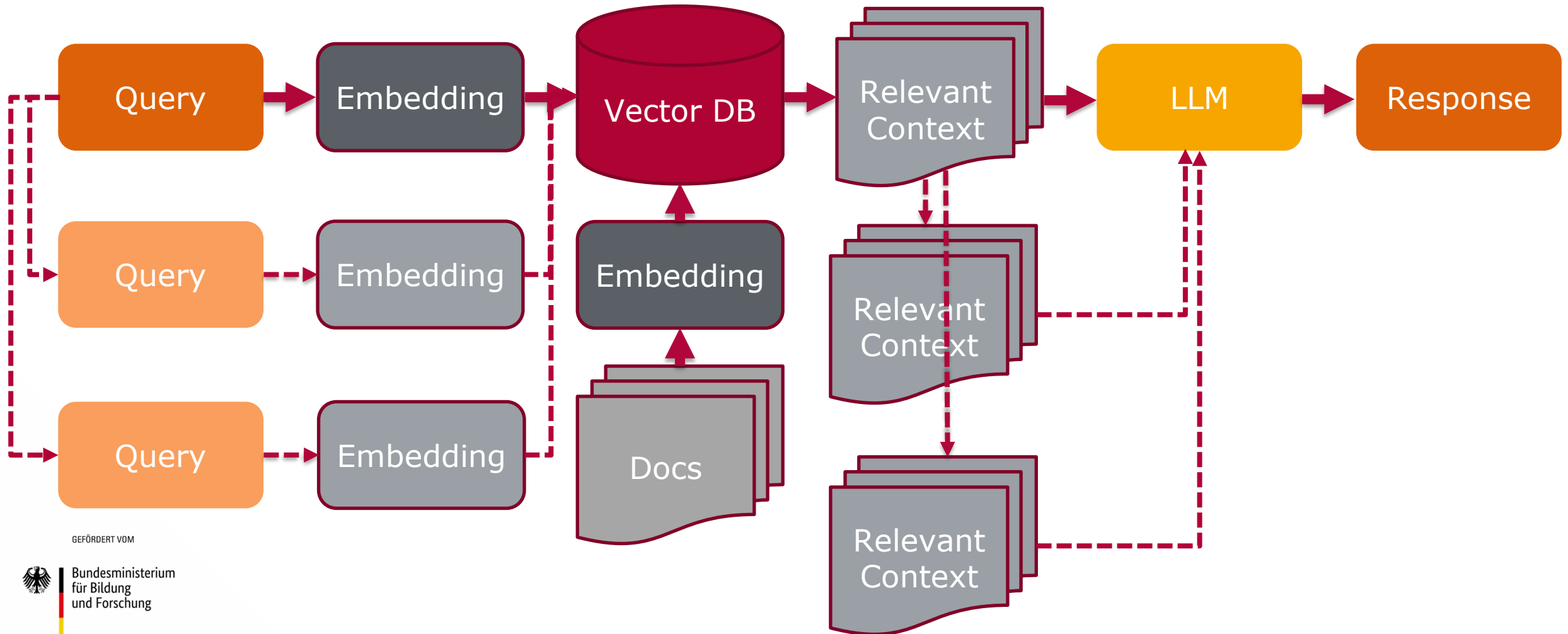
Graph RAG



Approaches:

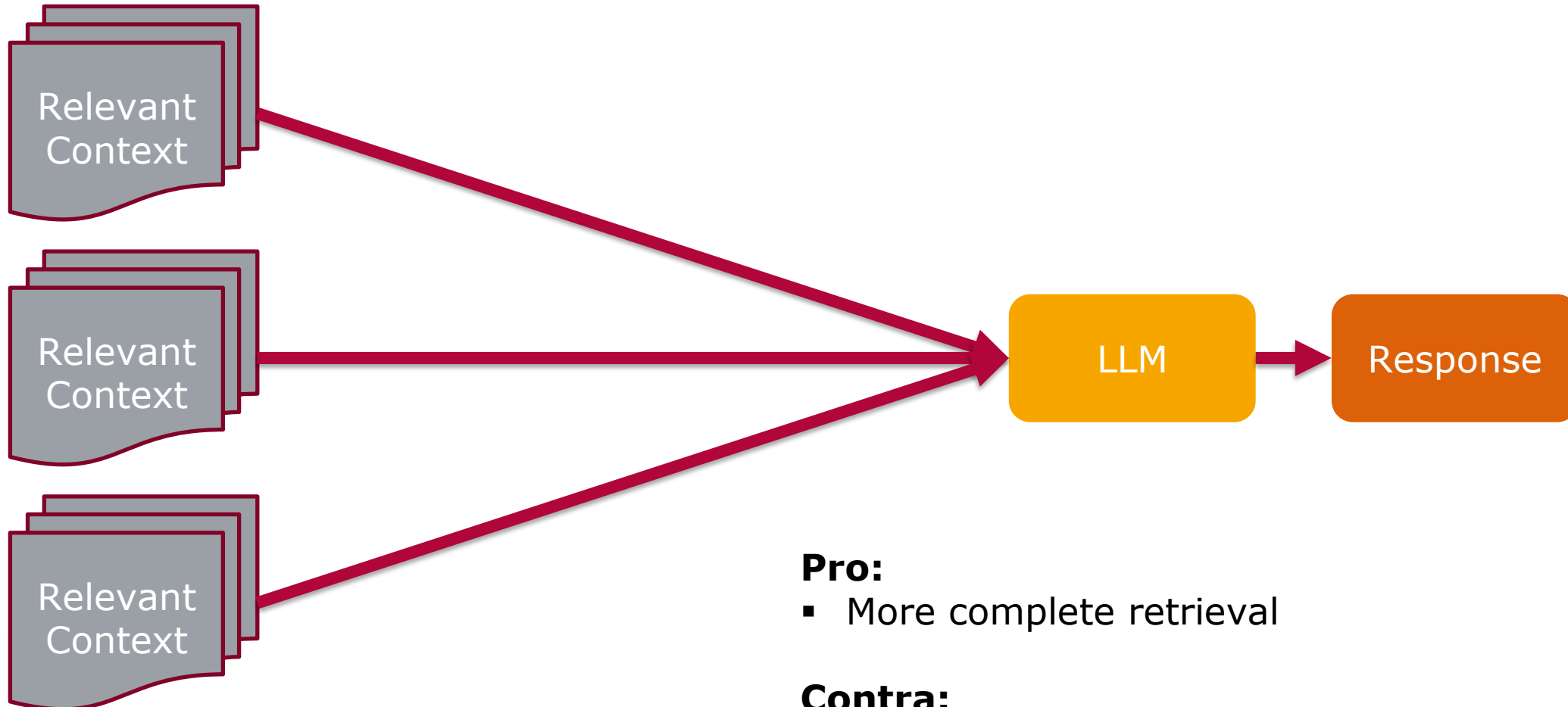
1. Combination of text & graph embeddings
2. Filter text based on graph
3. Filter graph based on text

Query Transformations



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Multi Query



Pro:

- More complete retrieval

Contra:

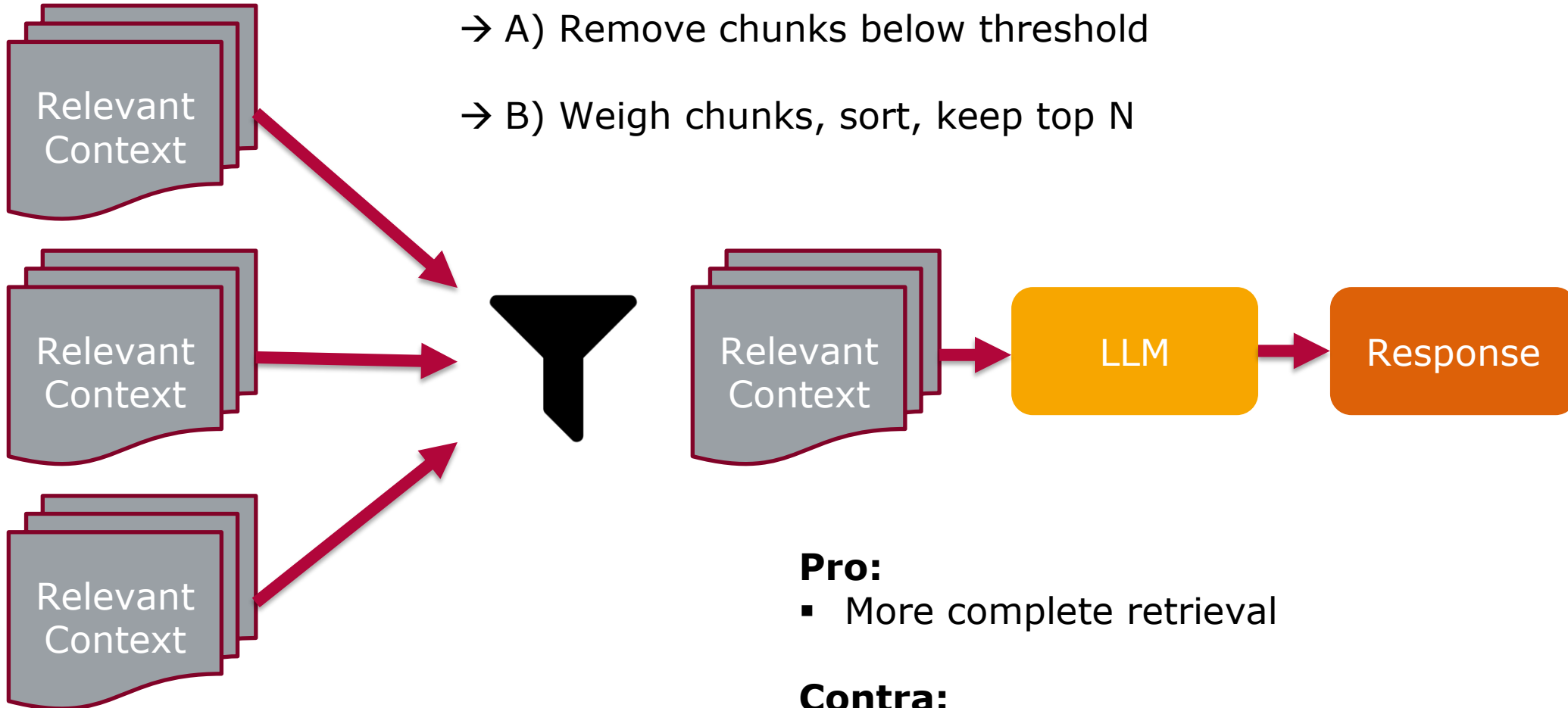
- 'Lost in the middle'
- More irrelevant retrieval
- Challenging for LLM context window

Filtering

Filtering can be based on how often an information chunk is retrieved.

→ A) Remove chunks below threshold

→ B) Weigh chunks, sort, keep top N



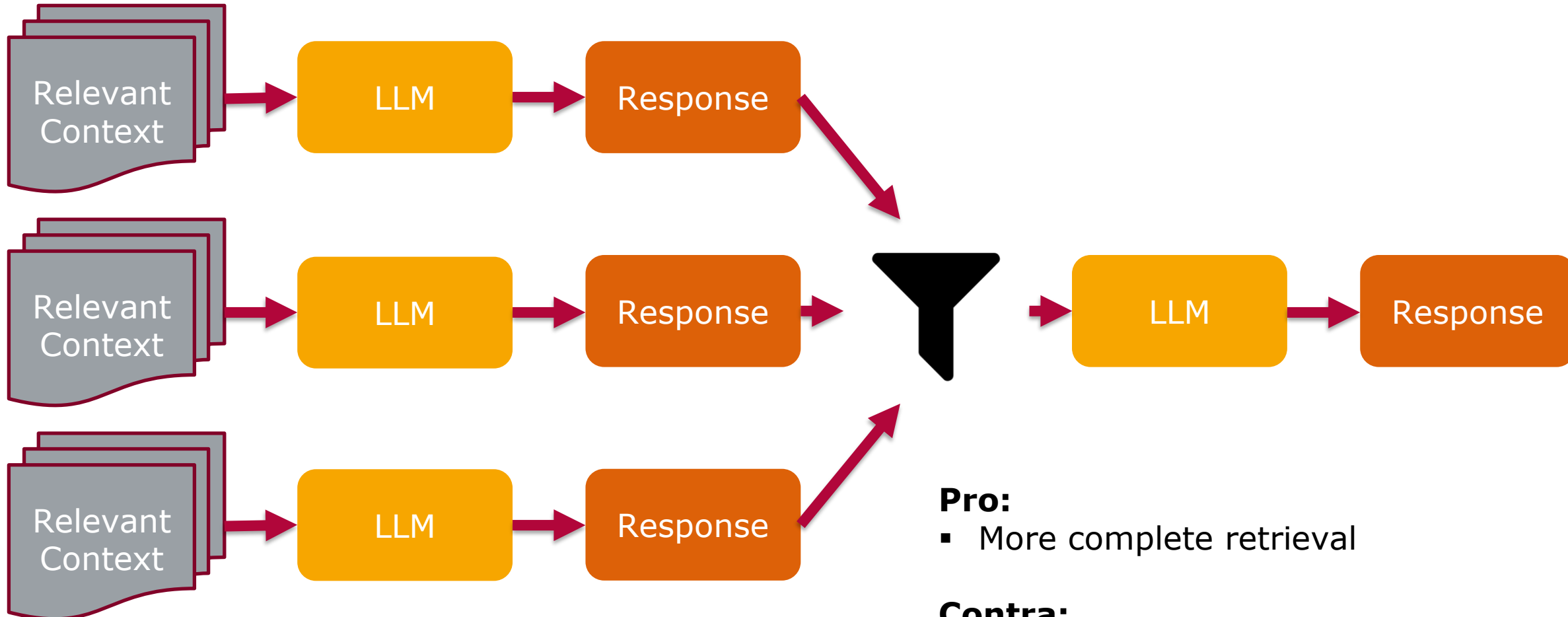
Pro:

- More complete retrieval

Contra:

- Only works when all relevant information can be retrieved from (paraphrased) query

Multi Response



Pro:

- More complete retrieval

Contra:

- High LLM usages → large costs
- Seldomly better than simpler architectures



DISCUSSION

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kisz@hpi.de

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