

Faculty of Environmental Sciences  
Chair of Geoinformatics

# LLMs for Conversational Geodata Search

AGILE 2025 Tutorial, Dresden, Germany

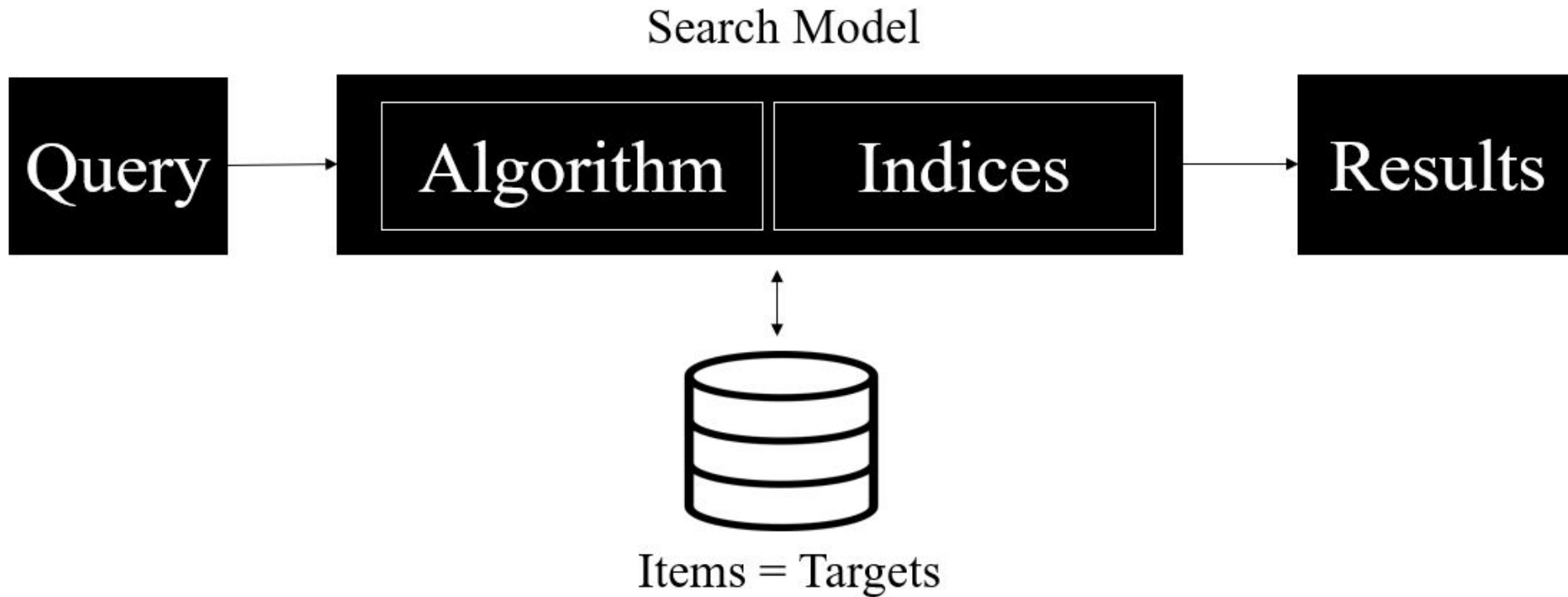
Auriol Degbelo, Simeon Wetzel, Stephan Maes

# Agenda

- Search Targets
- GeoQuery
- Retrieval-Augmented Generation

# Automated Information Retrieval

Key abstract components



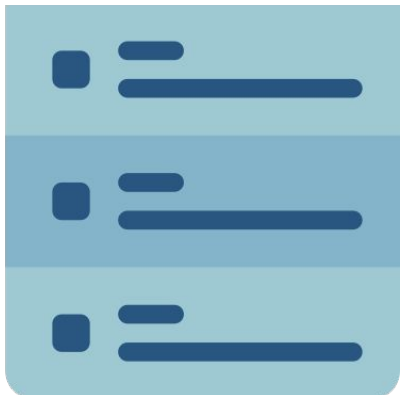
# What are QA Systems?

“Question Answering (QA) Systems can be considered as an extension of Search Engines in the sense, that they aim at automatically **supplying users with precise answers to questions** posed in natural language, instead of simply returning a ranked list of relevant sources based on a set of keywords”. (Dimitrakis et al, 2020)

Where is Dresden located?



Old Search  
Engines



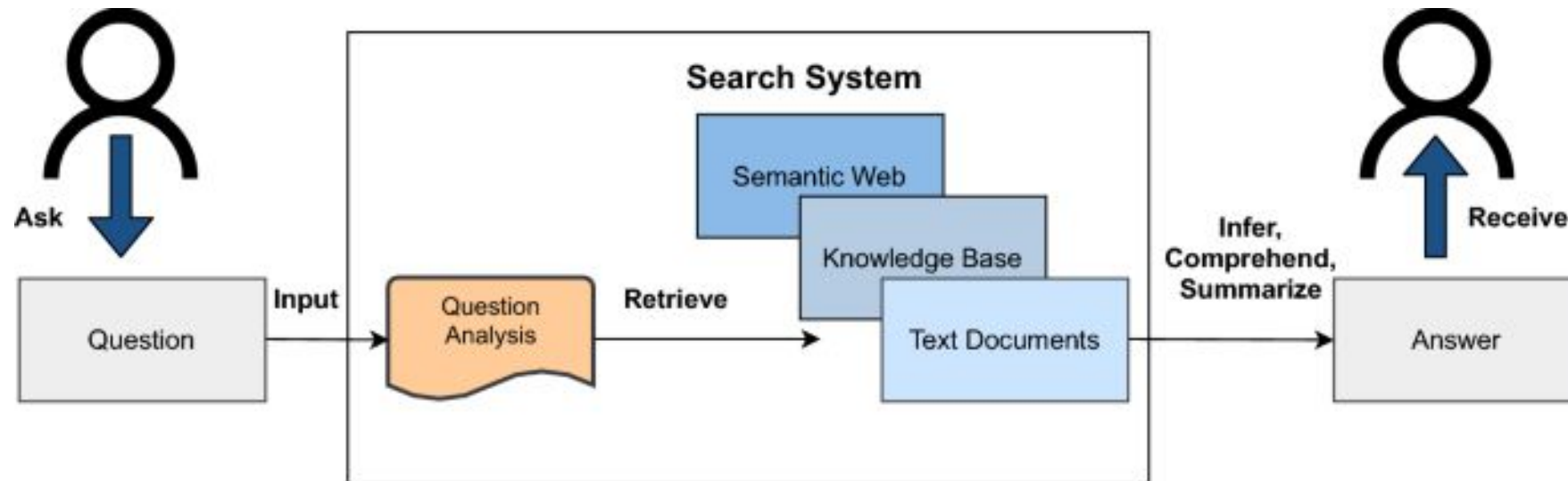
Where is Dresden located? →

Dresden is located in Germany ←

Q&A  
System

# Question Answering Systems

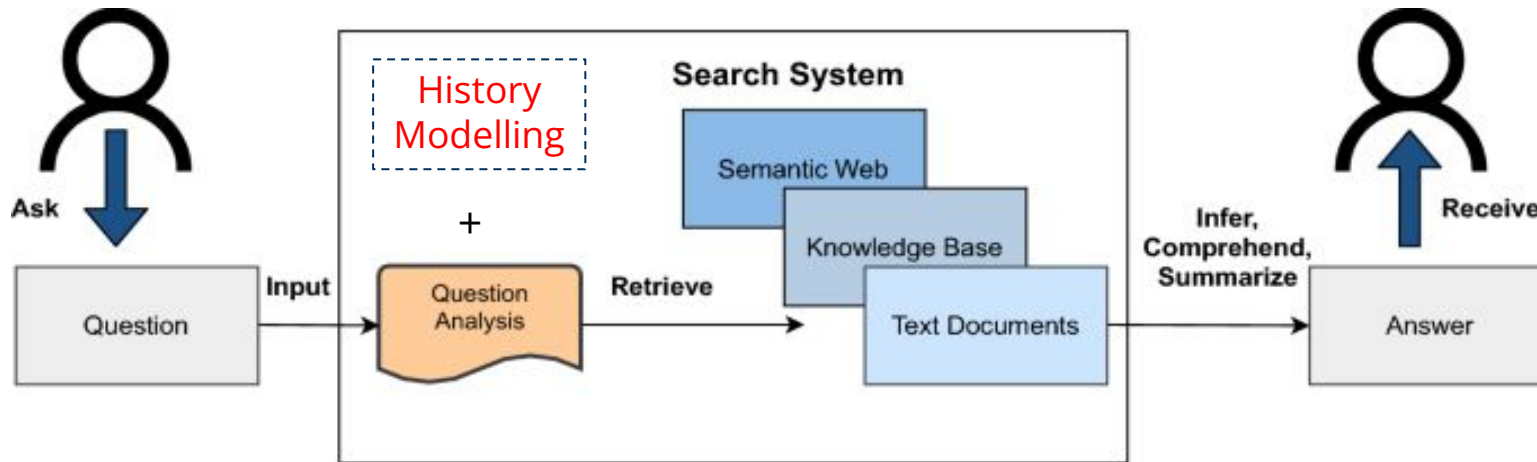
Key abstract components



[Zaib et al, 2022]

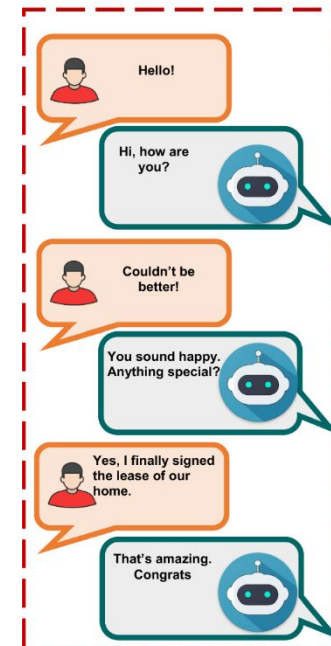
# Conversational Question Answering Systems

Key abstract components

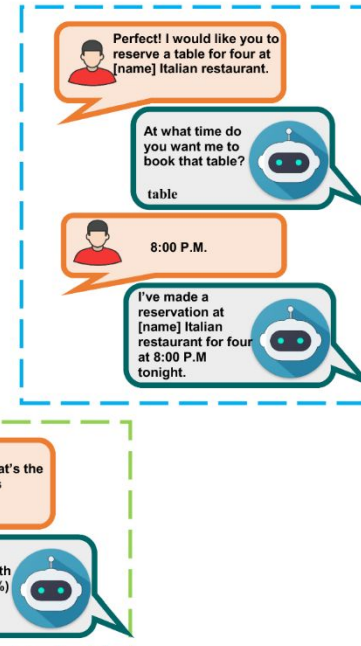


[Zaib et al, 2022]

## Chat-Oriented



## Task-Oriented



# Search Targets, GeoQueries

# Search Target

A search target is a resource searched for.

- Georeferenced datasets
- Georeferenced videos
- Raster maps
- Interactive maps
- Geospatial services (e.g. OGC web services)
- Shapefiles
- Algorithms in scientific papers

▪ ...

Geographic Information Retrieval: Text  
Multimedia Information Retrieval: Audio, Video, ...  
Dataset Search: Dataset

...



# Search target for our scenario: document

metadata

document = id + metadata

Example: id: ('relation', 5651)

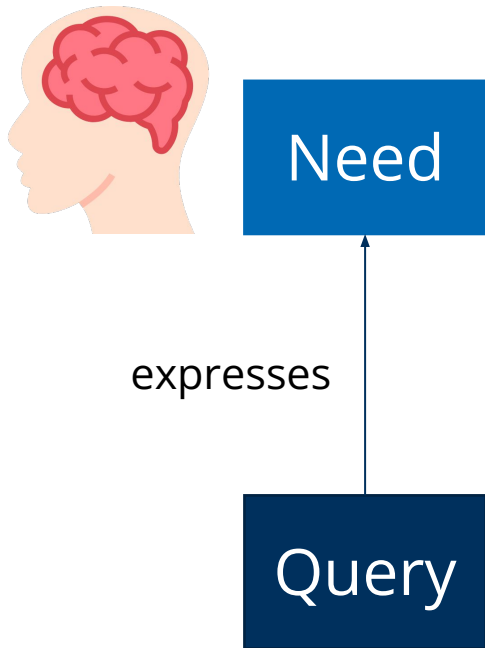
## Visualization



```
{
  'tourism': 'museum',
  'building': 'yes',
  'addr:postcode': '01069',
  'blind:description:de': 'Führungen für Sehgeschädigte und Blinde',
  'fee': 'yes',
  'email': 'service@dhmd.de',
  'addr:housenumber': '1',
  'id': "('relation', 5651)",
  'addr:street': 'Lingnerplatz',
  'heritage': 'yes',
  'dog': 'no',
  'check_date': '2024-03-09',
  'website': 'https://www.dhmd.de',
  'internet_access': 'wlan',
  'name:en': 'German Hygiene Museum',
  'wikidata': 'Q874373',
  'roof:shape': 'flat',
  'roof:colour': '#727466',
  'alt_name:de': 'Hygienemuseum',
  'toilets': 'yes',
  'toilets:wheelchair': 'yes',
  'internet_access:fee': 'no',
  'building:architecture': 'neoclassicism',
  'type': 'multipolygon',
  'wikipedia': 'de:Deutsches Hygiene-Museum',
  'architect': 'Wilhelm Kreis',
  'changing table': 'yes',
  'building description': 'yes',
  'wheelchair': 'yes',
  'opening_hours': 'Tu-Su 10:00-18:00',
  'name': 'Deutsches Hygiene-Museum',
  'geometry': '{"type": "Polygon", "coordinates": [[[13.7455854, 51.0450922], [13.7459654, 51.0449423], [13.7455854, 51.0450922]]]}',
  'internet_access:access': 'customers',
  'check_date:opening_hours': '2022-06-20',
  'start_date': '1928..1930',
  'smoking': 'no',
  'addr:city': 'Dresden',
  'phone': '+49 351 4846400'}
```

# GeoQuery

## Need vs Query



[Baeza-Yates and Ribeiro-Neto, 1999]

***A clear statement in natural language that describes what the user is asking for or wants to know.***

*'I am looking for restaurants near Dresden'.*

***The expression of the user information need in the input language provided by the information system.***

Q1: „restaurant near Dresden“

Q2: SELECT r where ....



# GeoQuery

## Definition

Geoquery = A query that requests location-specific information

= The **expression of the user's need for location-specific information**  
in the input language provided by the information system

# GeoQuery

## Two forms of geoqueries

<theme><relationship><space> [Purves et al, 2018]

(very often <object><relationship><place> [Carniel, 2023])

- Weather *in* Dresden
- Restaurants *near* Dresden
- Castles *inside* Dresden
- Houses *north of* Dresden

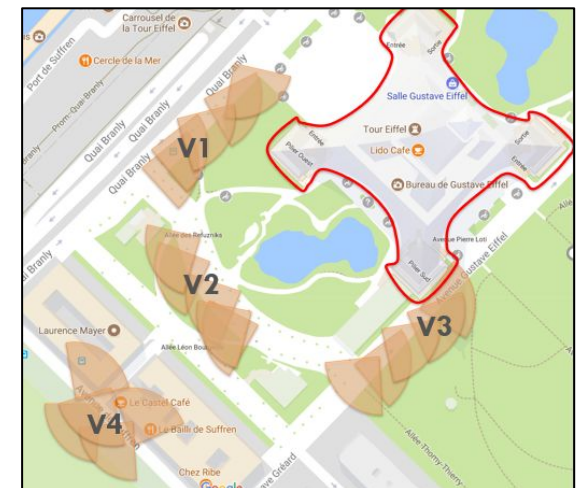
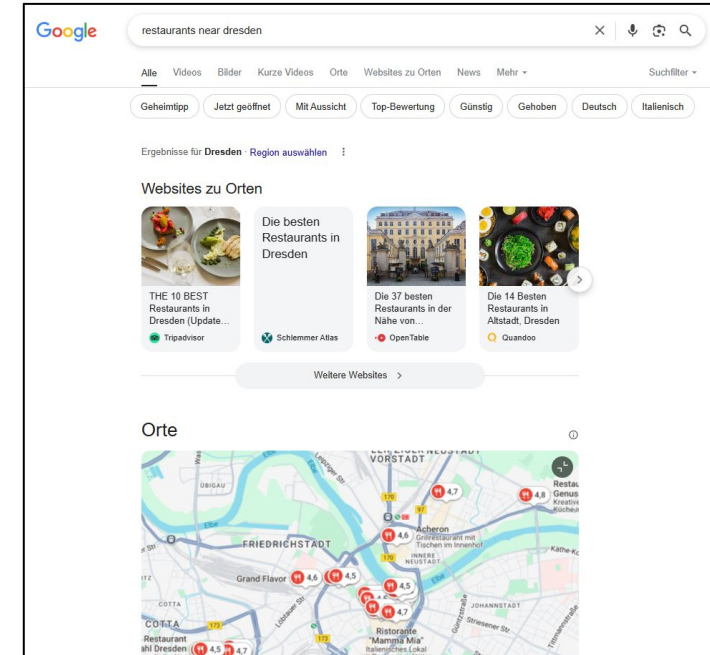
<resources> about <theme><space><time> [Degbelo, 2022]

- Maps about the cities of Prussia in 1830


**Technische Universität Dresden**

Videos about the Eiffel Tower in 2020, whose spatial locations are within *bbox*

Folie 12



# GeoQuery Interpretation

A geoquery has a footprint

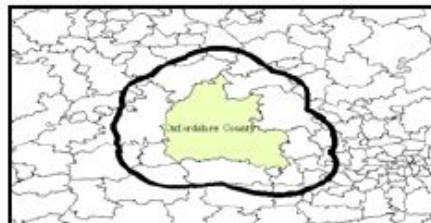
The footprint of a spatial term **P-footprint** indicates the geographical location of the intended place, and is specified in terms of map coordinates with a selected reference system. [Fu et al, 2005]

A query footprint **Q-footprint** defines a geographical space that covers the intended spatial search extent of the query, and it is specified in the form of map coordinates. [Fu et al, 2005]

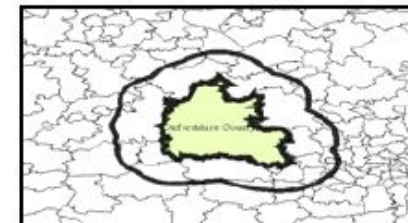
Castles *rel* Oxfordshire

[Fu et al, 2005]

(a) near



(b) outside



(c) north



# Retrieval-Augmented Generation



# Retrieval-Augmented Generation

“RAG is a technique for augmenting LLM knowledge with additional data.

LLMs can reason about wide-ranging topics, but their knowledge is limited to the public data up to a specific point in time that they were trained on. If you want to build AI applications that can reason about **private data or data introduced after a model's cutoff date**, you need to augment the knowledge of the model with the specific information it needs. The process of bringing the appropriate information and inserting it into the model prompt is known as Retrieval Augmented Generation (RAG)”. [\[source\]](#)

**RAG = LLMs + Your Own Data** [CSV, JSON, Webpages, PDF, Graph Data, ... ]

**GeoRAG = LLMs + Your Own Data + Spatially-Explicit Reranking**

# Retrieval-Augmented Generation

A RAG Application typically needs three steps...

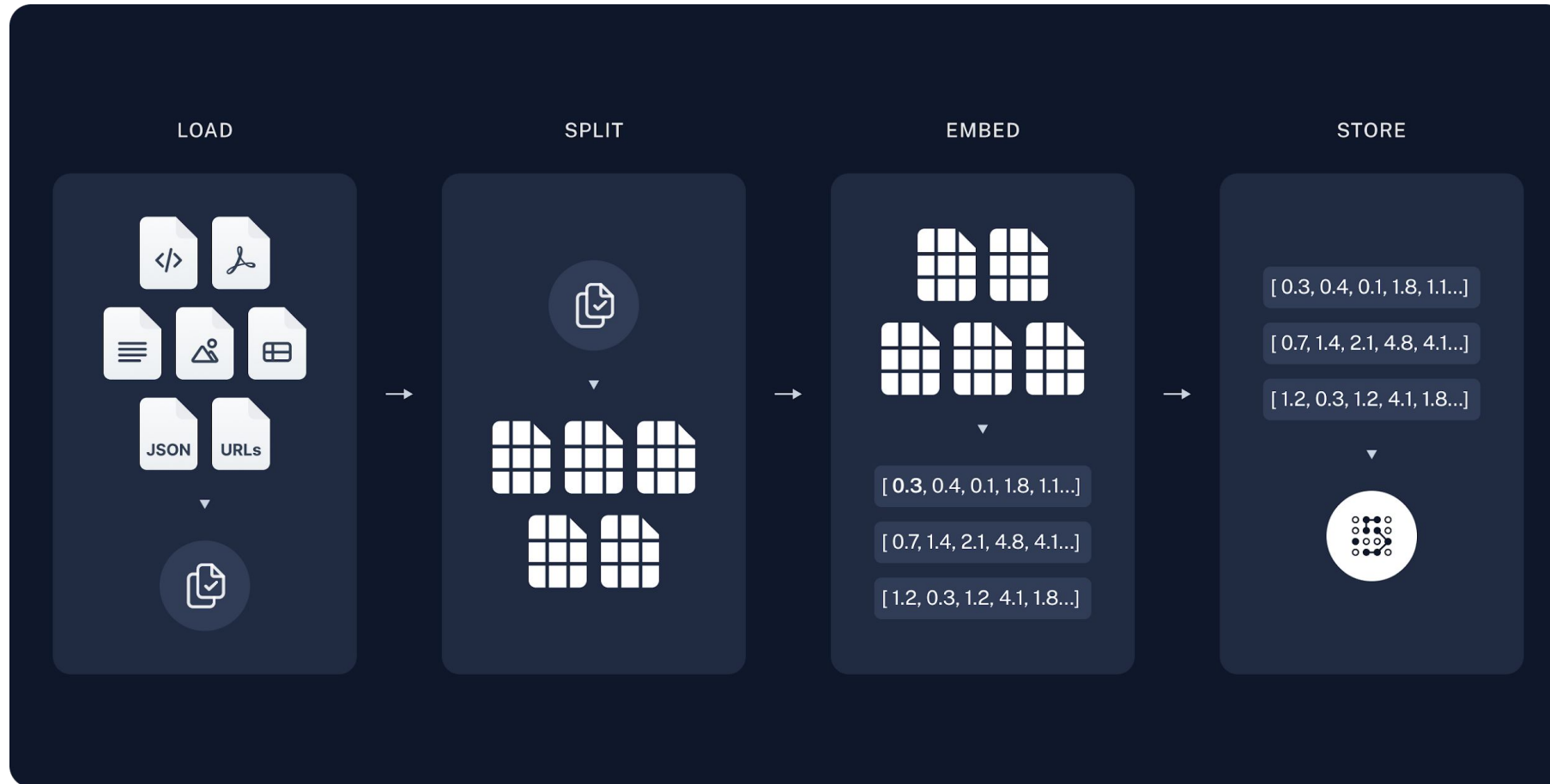
**Indexing** (dividing targets into smaller chunks and storing these, usually before the user query)

**Retrieval** (selection of relevant chunks to the user query)

**Generation** (answer formulation based on the chunks from the previous step)

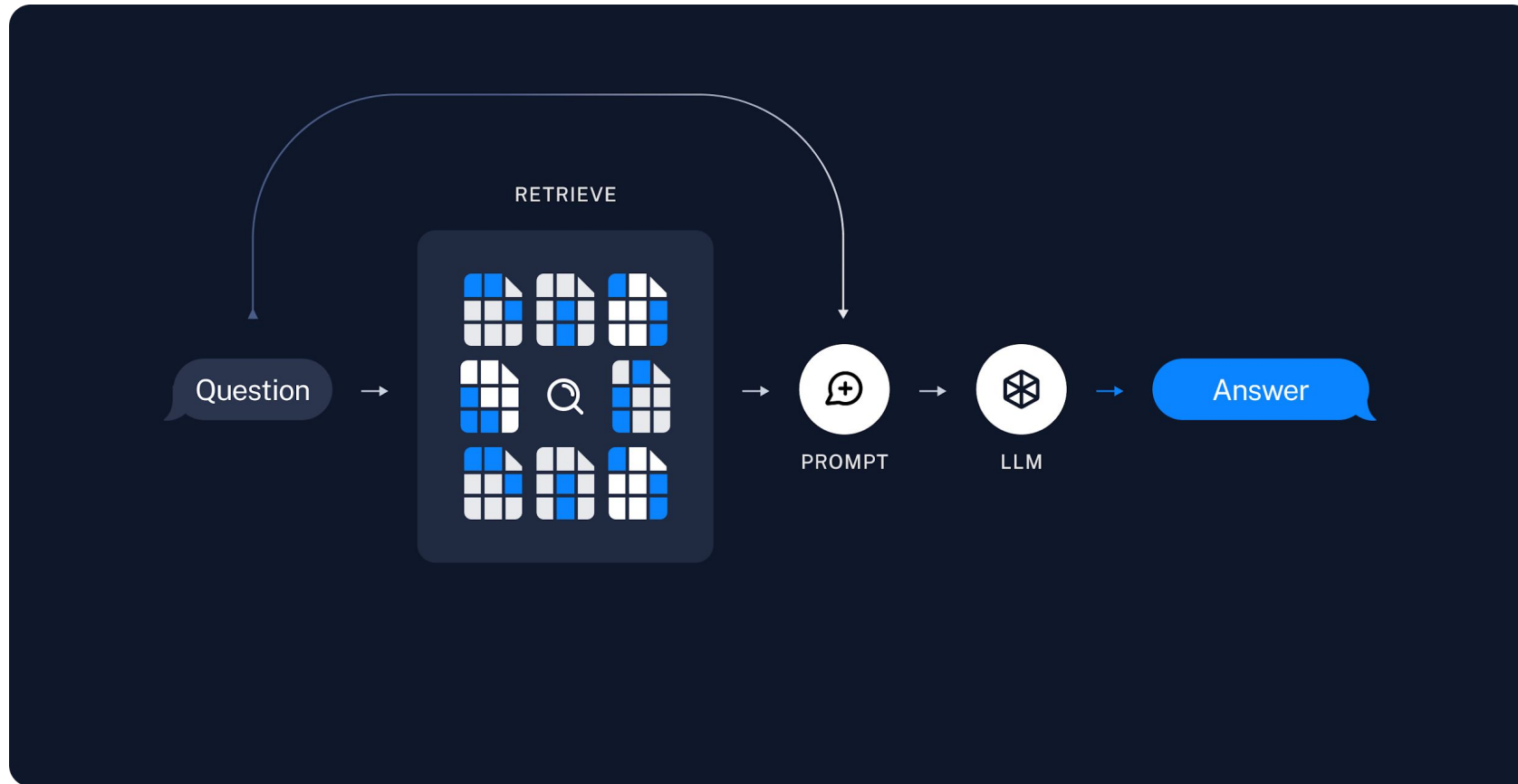


# RAG: Indexing and Storage



<https://python.langchain.com/docs/tutorials/rag/>

# RAG: Retrieval and Generation

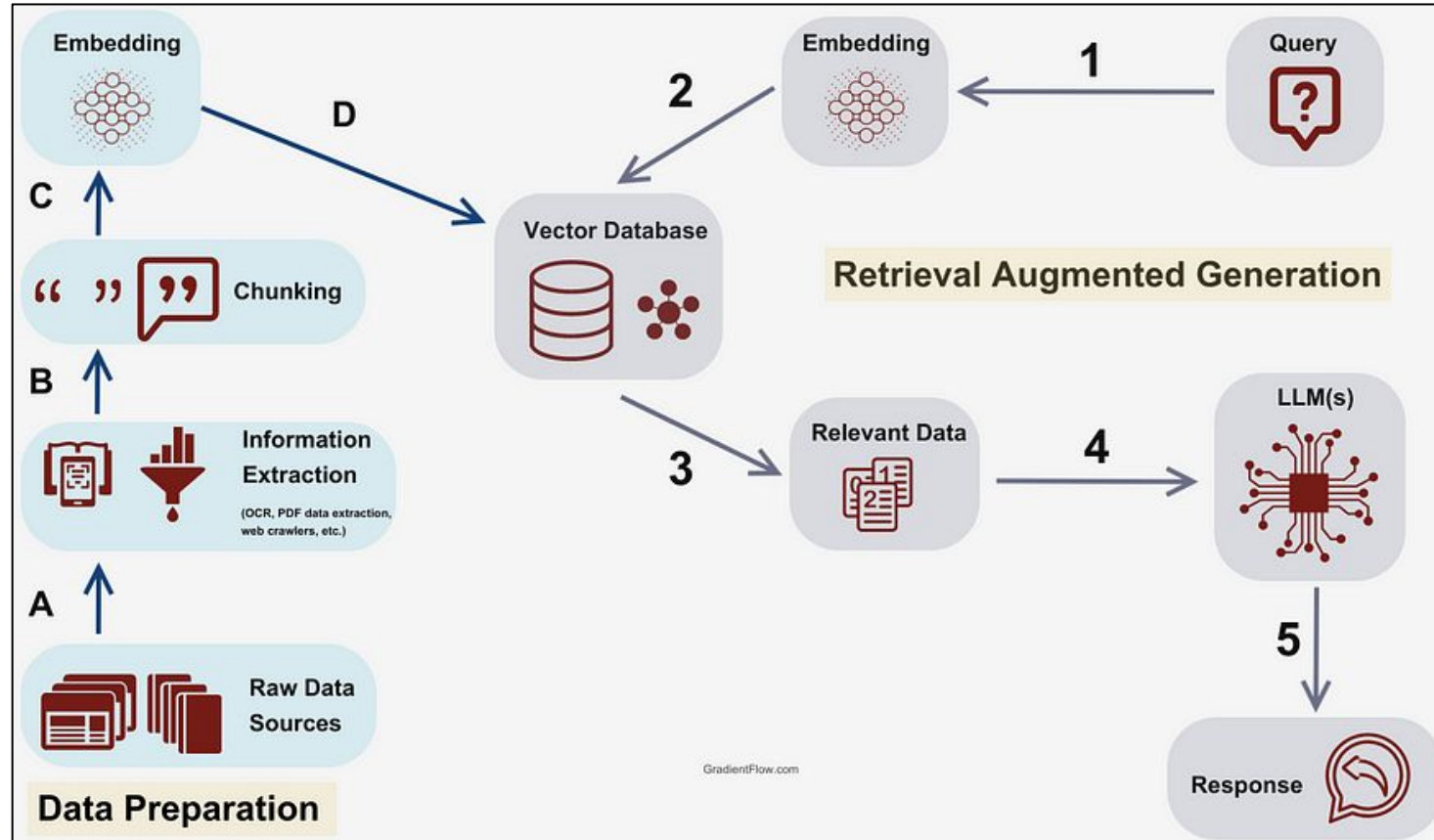


<https://python.langchain.com/docs/tutorials/rag/>

Q: “Who are the authors of this document?”

A: “The authors are...”

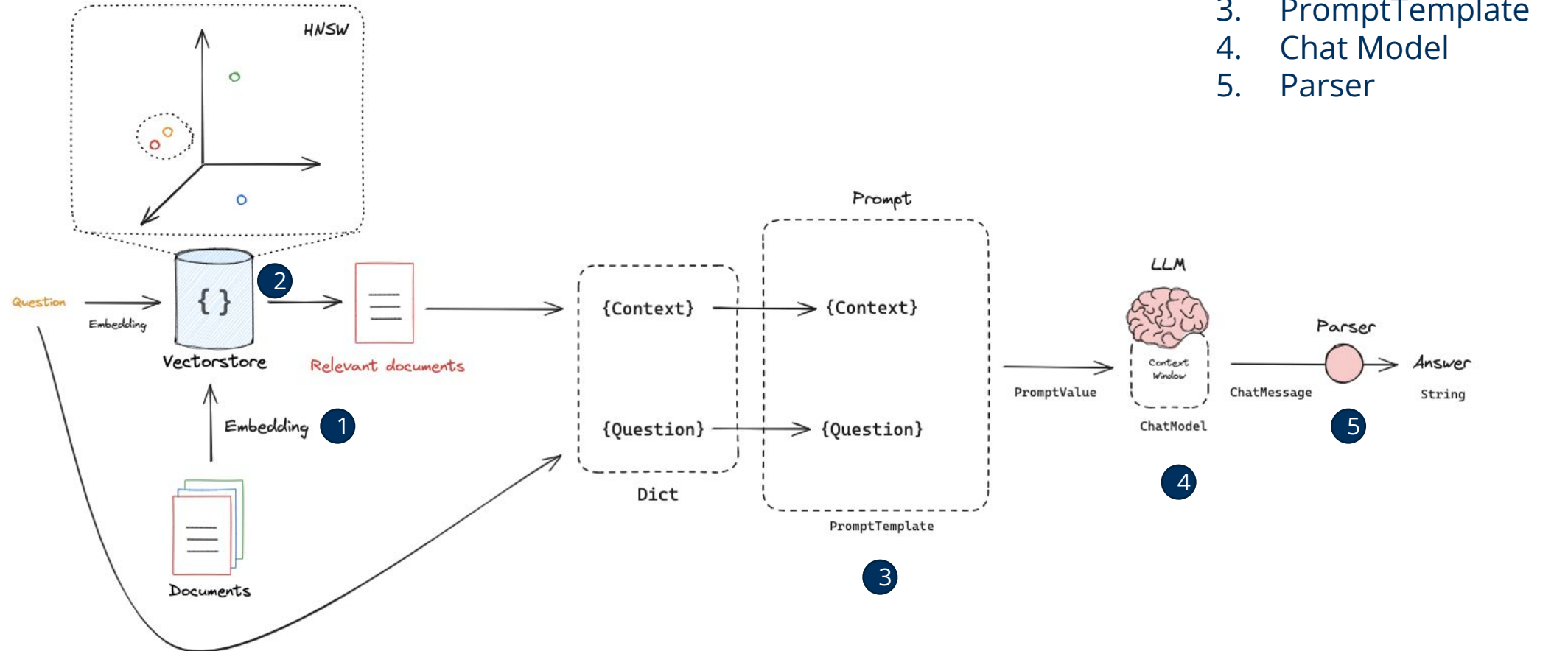
# RAG: All steps at once



<https://aswin19031997.medium.com/enhancing-conversational-ai-with-retrieval-augmented-generation-rag-leveraging-csv-integration-3000322819eb>

# Examples of RAG Architectures

## Basic RAG Architecture



# Our scenario: from search target to embedding

all metadata

selected metadata

embedding

## Text-based metadata only

### Additional examples

Document 1:  
Name: Bürgerhaus Schönborn  
addr:city: Dresden  
addr:country: DE  
addr:housenumber: 6  
addr:postcode: 01465  
addr:street: Seifersdorfer Straße  
amenity: townhall  
building: yes  
source: HiRes aerial imagery  
building\_description: yes

Document 2:  
Name: A-Gebäude  
building: yes  
building\_description: yes

Document 3:  
Name: B-Gebäude  
building: yes  
building\_description: yes

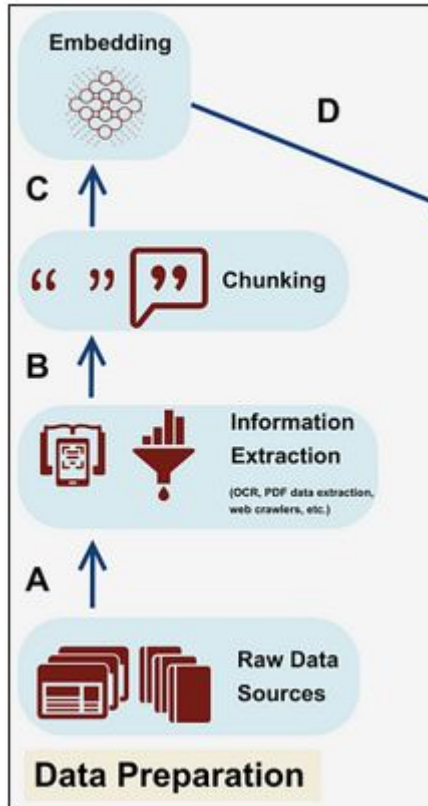
Document 4:  
Name: Geschwisterwohnen WG  
building: yes  
operator: Outlaw  
website: <https://www.outlaw-ggmbh.de/wo>  
building\_description: yes

“An embedding is a numerical representation of a piece of information, for example, text, documents, images, audio” [\[source\]](#)

```
[[-0.02388945  0.05525852 -0.01165488 ...  
[-0.0126876  0.04687412 -0.01050217 ...  
[ 0.00049438  0.11941205  0.00522949 ...  
...  
[-0.03900796 -0.01060951 -0.00738271 ...  
[-0.09598278 -0.06301168 -0.11690582 ...  
[-0.01162949  0.05961934  0.01650903 ...
```



# Embedding model for vector creation



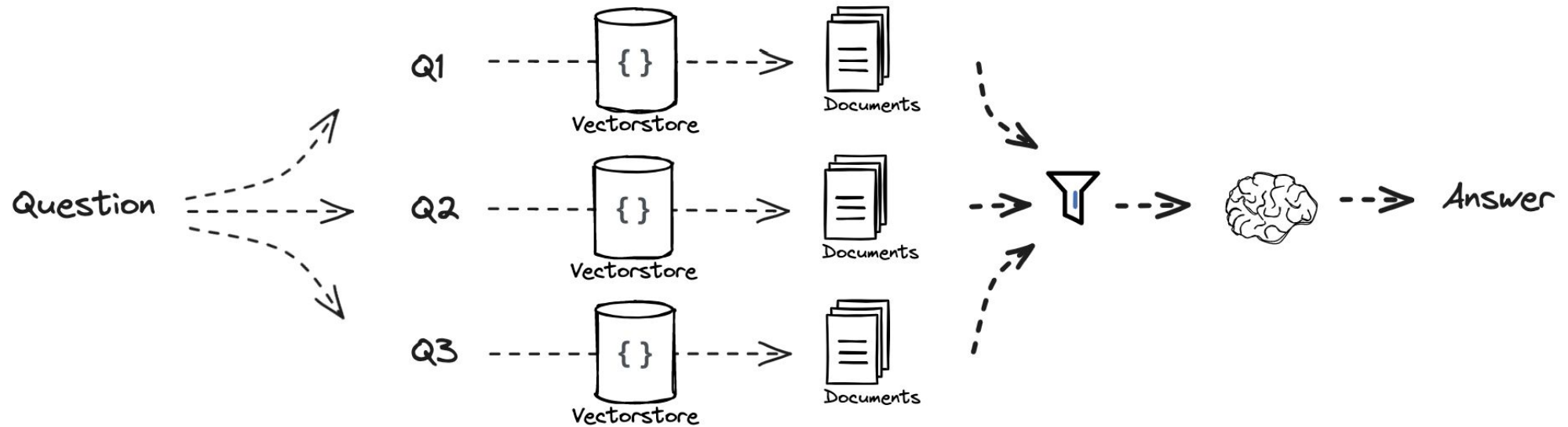
```
from chromadb.utils.embedding_functions import SentenceTransformerEmbeddingFunction

model_name = "paraphrase-multilingual-mpnet-base-v2"

ef = SentenceTransformerEmbeddingFunction(model_name=model_name)
```

# Examples of RAG Architectures

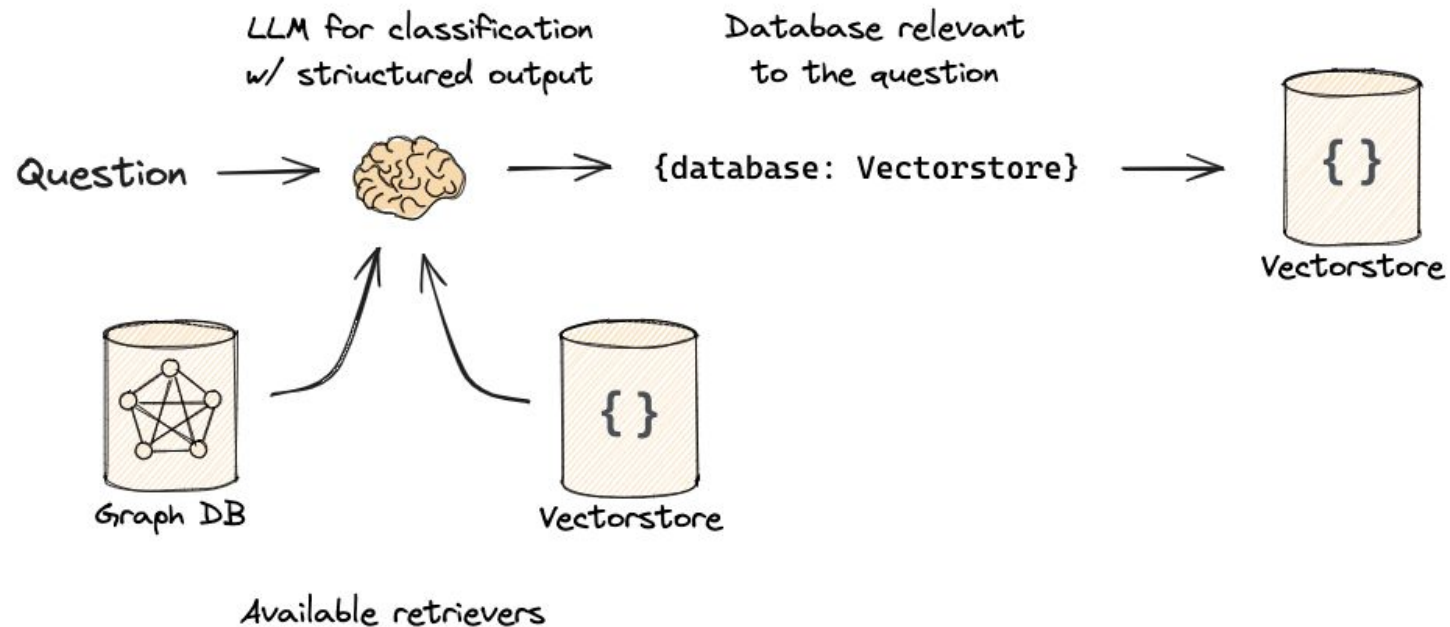
Expansion: RAG Fusion



[https://github.com/langchain-ai/rag-from-scratch/blob/main/rag\\_from\\_scratch\\_5\\_to\\_9.ipynb](https://github.com/langchain-ai/rag-from-scratch/blob/main/rag_from_scratch_5_to_9.ipynb)

# Examples of RAG Architectures

Logical Routing: Let LLM choose DB based on the question

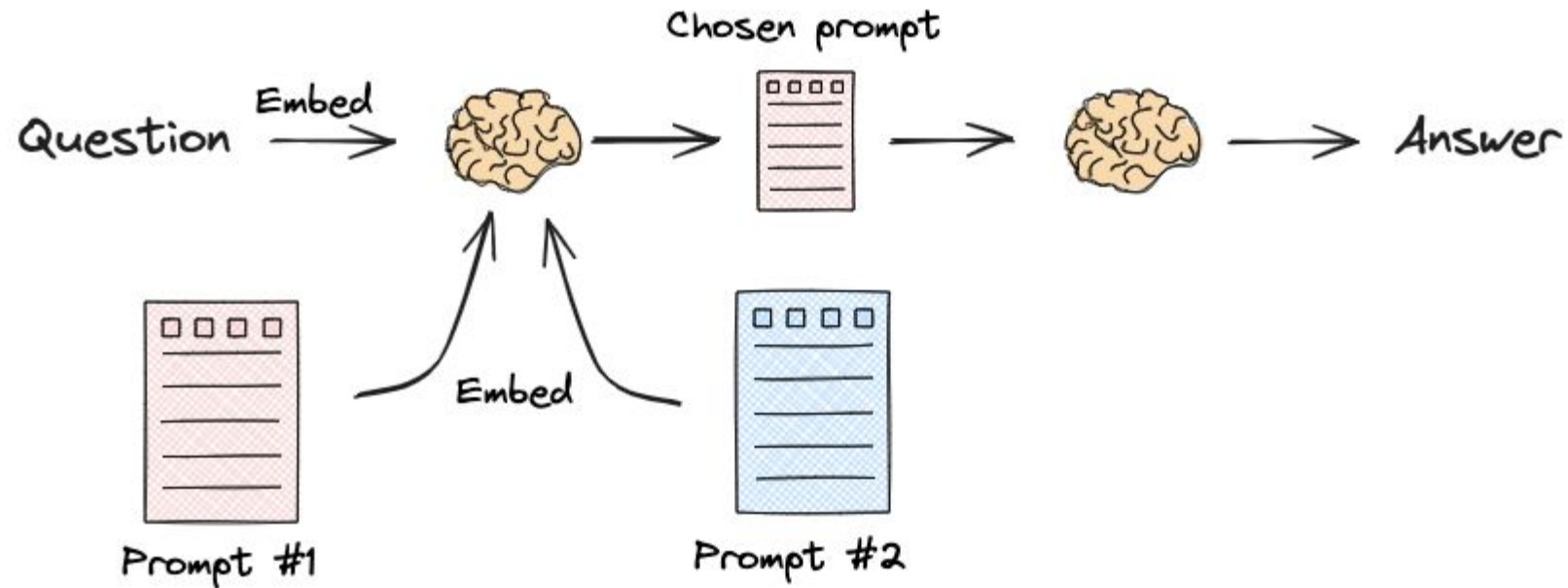


[https://github.com/langchain-ai/rag-from-scratch/blob/main/rag\\_from\\_scratch\\_10\\_and\\_11.ipynb](https://github.com/langchain-ai/rag-from-scratch/blob/main/rag_from_scratch_10_and_11.ipynb)



# Examples of RAG Architectures

Semantic Routing: Embed question and choose prompt based on similarity



[https://github.com/langchain-ai/rag-from-scratch/blob/main/rag\\_from\\_scratch\\_10\\_and\\_11.ipynb](https://github.com/langchain-ai/rag-from-scratch/blob/main/rag_from_scratch_10_and_11.ipynb)

# References

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