”Talk to your Data”:
Signifikant bessere LLM-RAG-Lösungen
durch Real-World Tipps

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Talk to your data:
Signifikant bessere LLM-RAG-Lösungen durch Real-World Tipps

- Was Sie ERWARTET
  - Hintergrundwissen und Theorie zu RAG
  - Überblick über Semantische Suche
  - Probleme die auftreten können
  - Pragmatische Methoden für die Verwendung eigener Daten im RAG
  - Demos (Python)

- Was Sie NICHT erwartet
  - ChatGPT, CoPilot(s)
  - Grundlagen von ML
  - Deep Dives in LLMs, Vektor-Datenbanken, LangChain

”Talk to your Data”:
Signifikant bessere LLM-RAG-Lösungen durch Real-World Tipps

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- Generative AI in business settings
- Flexible and scalable backends
- All things .NET

- Pragmatic end-to-end architectures
- Developer productivity
- Software quality

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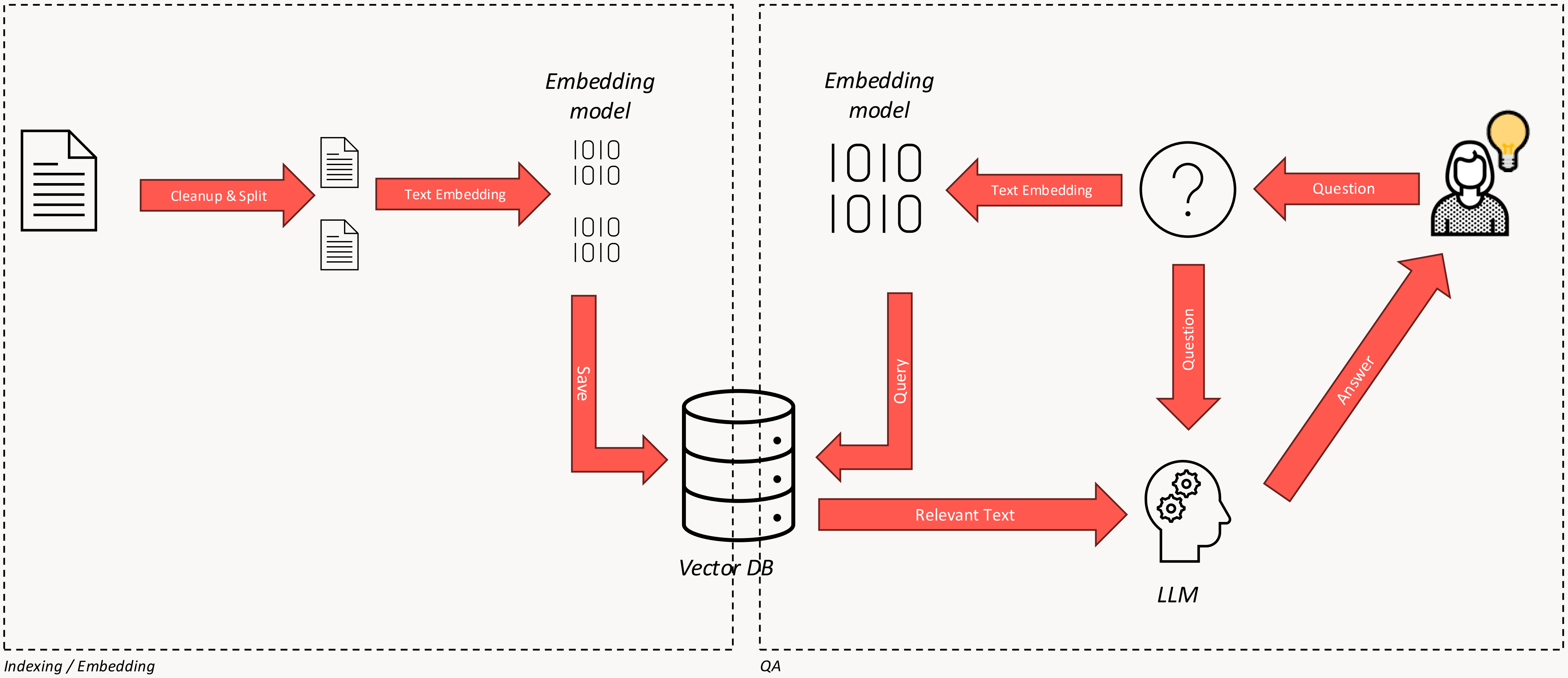
Agenda

- Short introduction to RAG
- Embeddings (and a bit of theory 😱)
- Indexing
- Retrieval
- Not good enough? – Indexing II
    - HyDE & alternative indexing methods
- Conclusion

Introduction

Use case: Retrieval-augmented generation (RAG)



Alternative: Agentic RAG

- Search is provided as a tool to the LLM
- LLM then can decide to call the tool to search on its own
- LLM also decides the search term (could be problematic)

Semantic Search

- Classic search: lexical
  - Compares words, parts of words and variants
  - Classic SQL: WHERE 'content' LIKE '%searchterm%'
  - We can search only for things where we know that it is somewhere in the text

- New: Semantic search
  - Compares for the same contextual meaning
    - "Das Rudel rollt das runde Gerät auf dem Rasen herum"
    - "The pack enjoys rolling a round thing on the green grass"
    - "Die Hunde spielen auf der Wiese mit dem Ball"
    - "The dogs play with the ball on the meadow"

Semantic Search

- How to grasp “semantics”?

- Computers only calculate on numbers
  - Computing is “applied mathematics”

- AI also only calculates on numbers

Semantic Search

- We need a numeric representation of text
  - Tokens
- We need a numeric representation of meaning
  - Embeddings

Tokens

- Similar to char tables (e.g. ASCII), just with larger elements
- Tokens are parts of text
    - Words
    - Syllables
    - Punctuation
    - …
- Tokens are translated to token IDs

- Example: https://platform.openai.com/tokenizer

Embeddings

Embedding (math.)

- Topologic: Value of a high dimensional space is "embedded" into a lower dimensional space
- Natural / human language is very complex (high dimensional)
  - Task: Map high complexity to lower complexity / dimensions
- Injective function
- Similar to hash, or a lossy compression

Embeddings

- Embedding model (specialized ML model) converting text into a numeric representation of its meaning

- Representation is a Vector in an n-dimensional space
  - n floating point values
  - OpenAI
    - “text-embedding-ada-002” uses 1536 dimensions
    - “text-embedding-3-small” 512 and 1536
    - “text-embedding-3-large” 256, 1024 and 3072
  - Huggingface models have a very wide range of dimensions

https://huggingface.co/spaces/mteb/leaderboard & https://openai.com/blog/new-embedding-models-and-api-updates

Embeddings

- Embedding models are unique

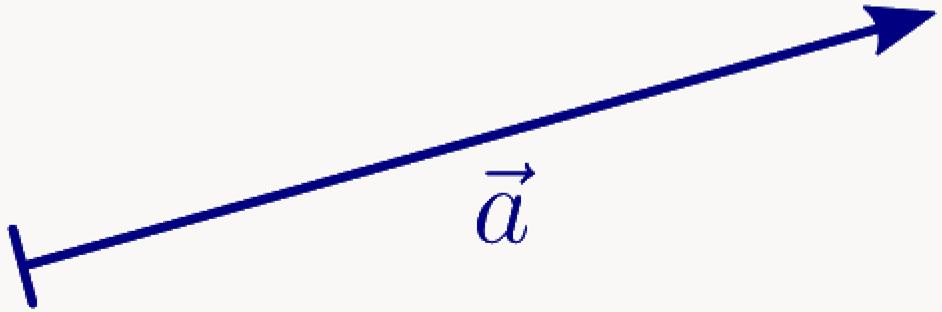
- Each dimension has a different meaning, individual to the model
- Vectors from different models are incompatible with each other
  - they live in different vector spaces

- Some embedding models are multi-language, but not all

- In an LLM, also the first step is to embed the input into a lower dimensional space

What is a vector?

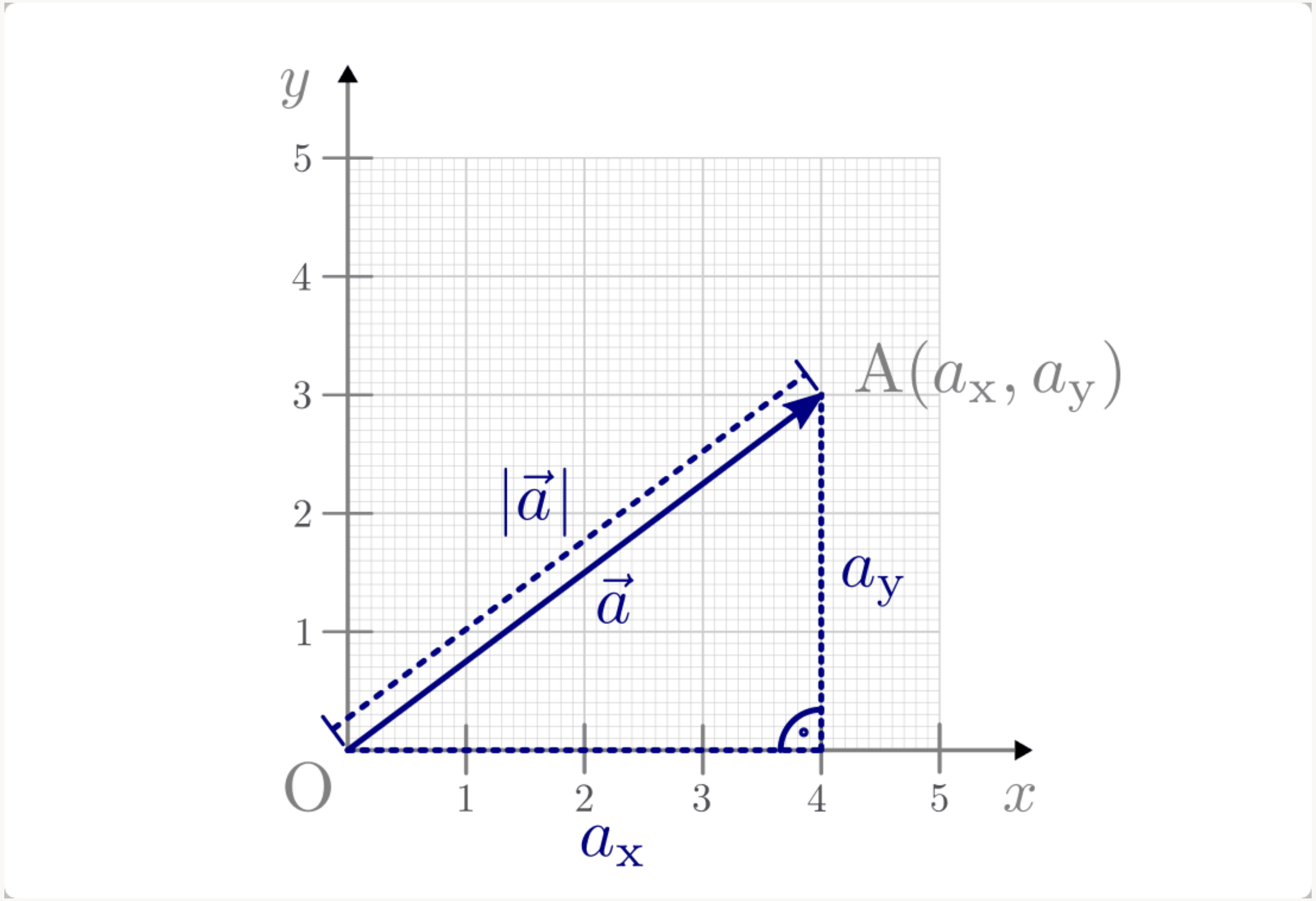
- Mathematical quantity with a direction and length
- $\vec{a} = \binom{a_x}{a_y}$



https://mathinsight.org/vector_introduction

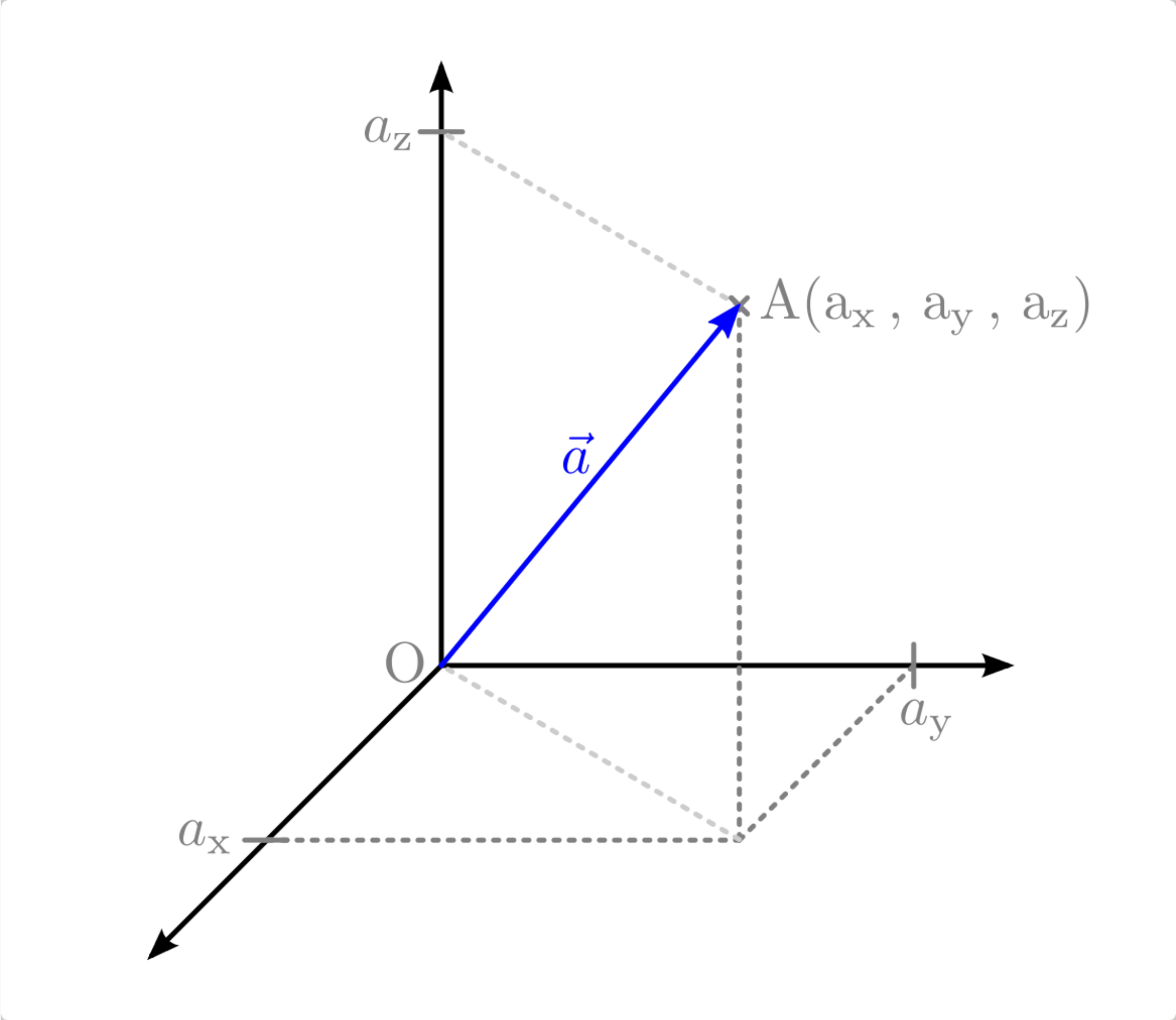
Vectors in 2D

$$\vec{a} = \begin{pmatrix} a_x \\ a_y \end{pmatrix}$$



Vectors in 3D

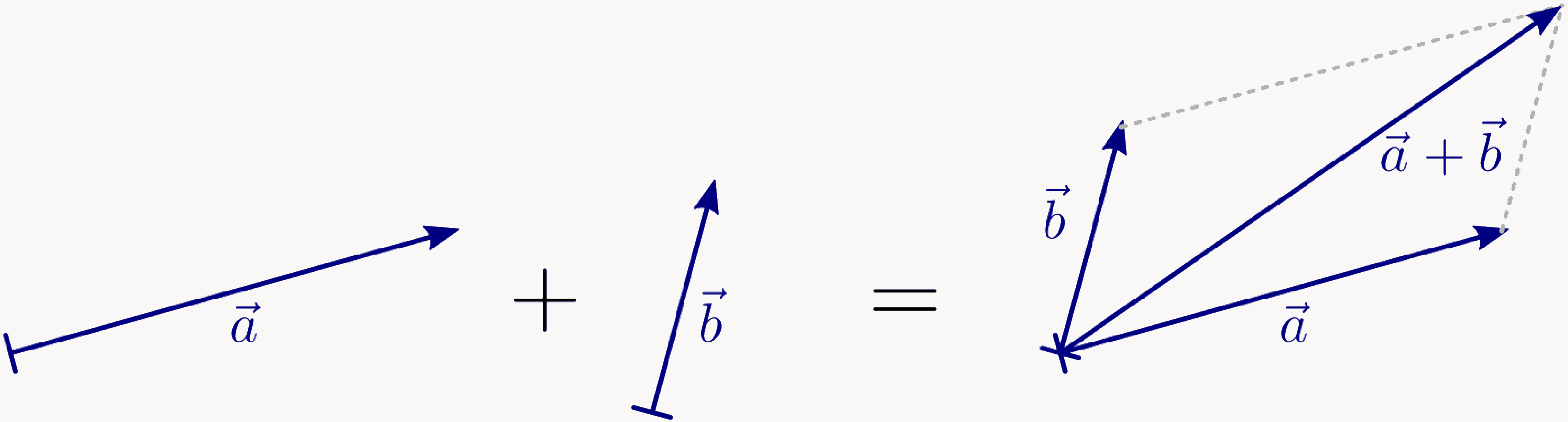
$$\vec{a} = \begin{pmatrix} a_x \\ a_y \\ a_z \end{pmatrix}$$



Vectors in multidimensional space

$$\vec{a} = \begin{pmatrix} a_u \\ a_v \\ a_w \\ a_x \\ a_y \\ a_z \end{pmatrix}$$

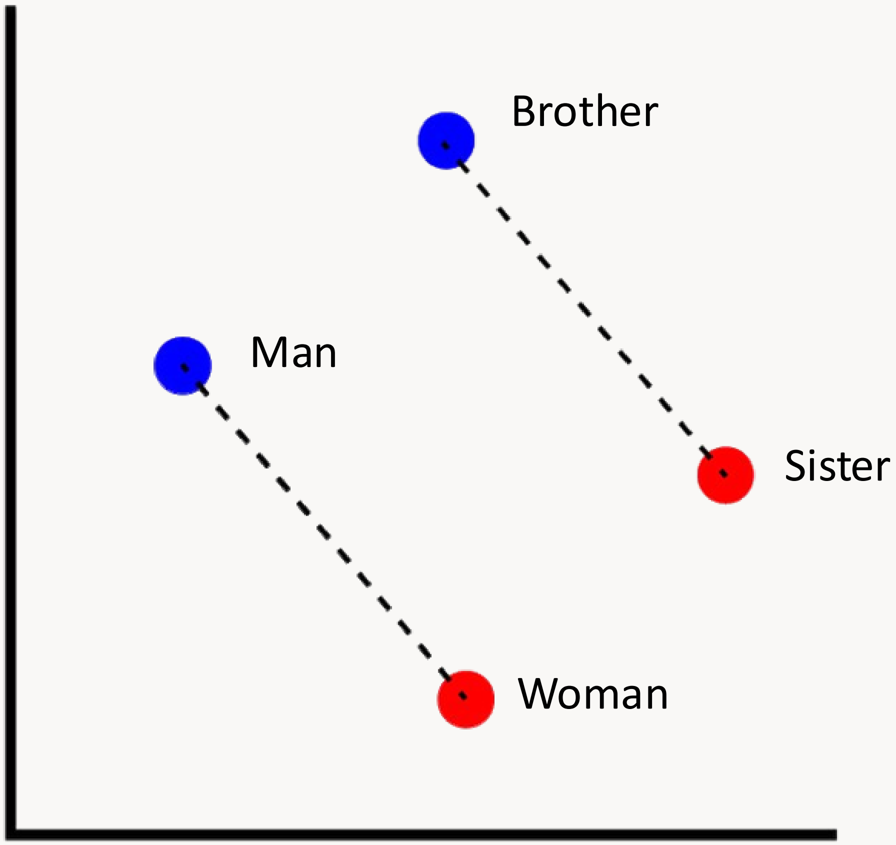
Calculation with vectors



Word2Vec

Mikolov et al., Google, 2013

$$Brother - Man + Woman \approx Sister$$



https://arxiv.org/abs/1301.3781

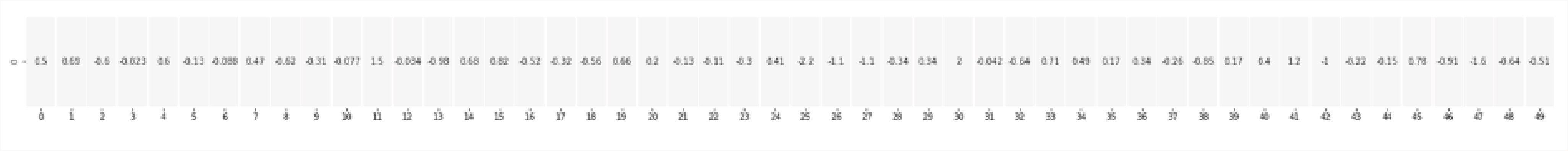
Embedding-Model

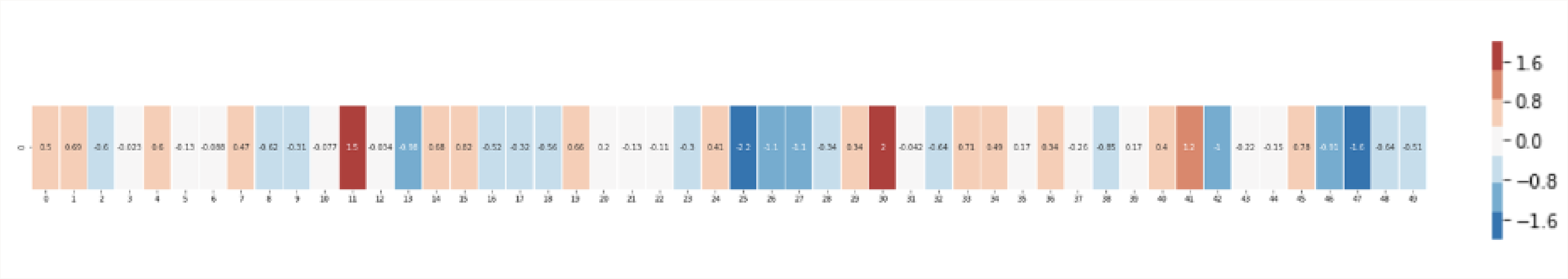
- Task: Create a vector from an input
  - Extract meaning / semantics
- Embedding models usually are very shallow & fast
  Word2Vec is only two layers
- Similar to the first step of an LLM
  - Convert text to values for input layer
- This comparison is very simplified, but one could say:
  - The embedding model ‘maps’ the meaning into the model’s ‘brain’

Vectors from your Embedding-Model

Embedding-Model

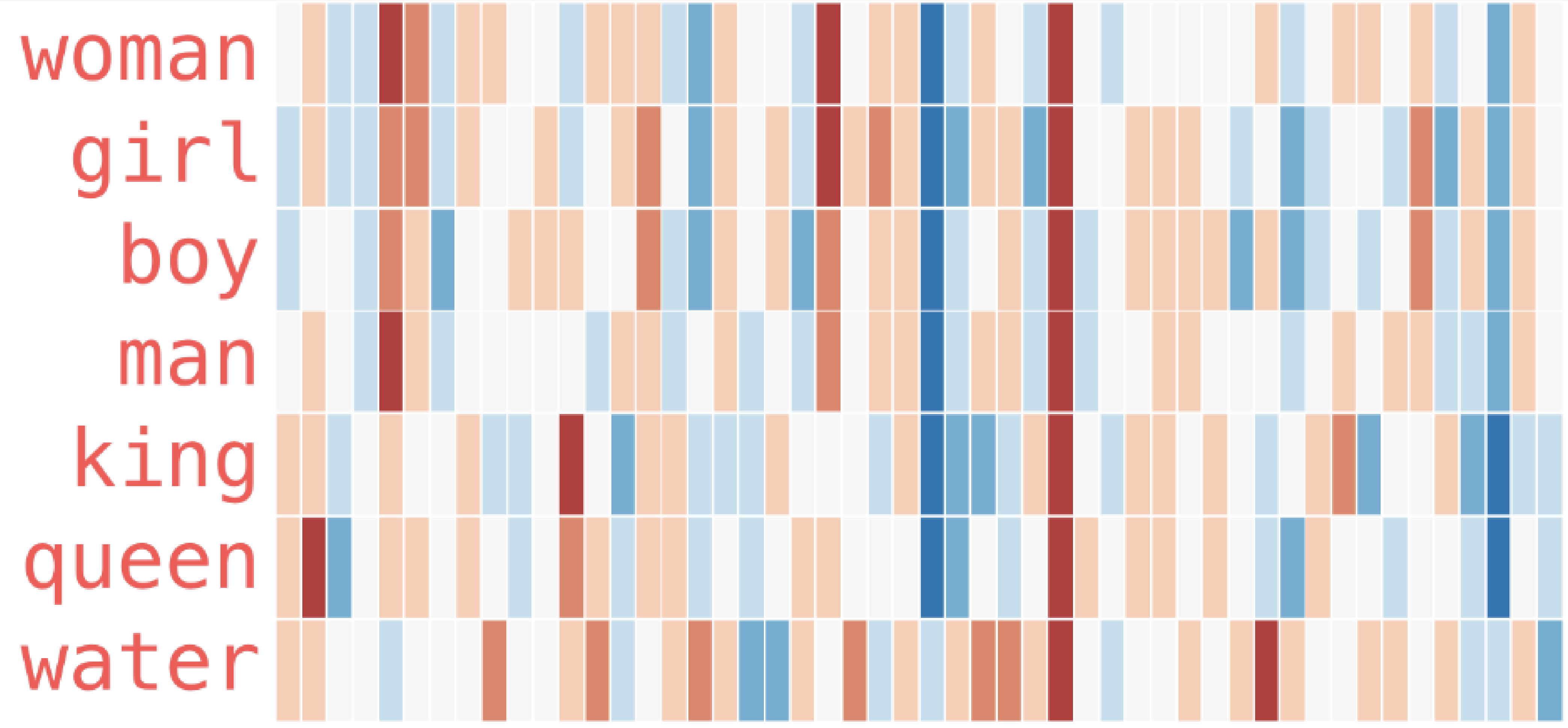
[0.50451 , 0.68607 , -0.59517 , -0.022801, 0.60046 , -0.13498 , -0.08813 , 0.47377 , -0.61798 , -0.31012 , -0.076666, 1.493 , -0.034189, -0.98173 , 0.68229 , 0.81722 , -0.51874 , -0.31503 , -0.55809 , 0.66421 , 0.1961 , -0.13495 , -0.11476 , -0.30344 , 0.41177 , -2.223 , -1.0756 , -1.0783 , -0.34354 , 0.33505 , 1.9927 , -0.04234 , -0.64319 , 0.71125 , 0.49159 , 0.16754 , 0.34344 , -0.25663 , -0.8523 , 0.1661 , 0.40102 , 1.1685 , -1.0137 , -0.21585 , -0.15155 , 0.78321 , -0.91241 , -1.6106 , -0.64426 , -0.51042]





http://jalammar.github.io/illustrated-word2vec/

Embedding-Model



http://jalammar.github.io/illustrated-word2vec/

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Important

- Select your Embedding Model carefully for your use case

- e.g.
  - intfloat/multilingual-e5-large-instruct ~ 50 %
  - T-Systems-onsite/german-roberta-sentence-transformer-v2 < 70 %
  - danielheinz/e5-base-sts-en-de > 80 %
  - BAAI/bge-m3 > 95 %

- Maybe fine-tuning of the embedding model might be an option
- As of now: Treat embedding models as exchangeable commodities!

Recap Embeddings

- Embedding model: “Analog to digital converter for text”

- Embeds the high-dimensional natural language meaning into a lower dimensional-space (the model’s ‘brain’)

- No magic, just applied mathematics
- Math. representation: Vector of n dimensions
- Technical representation: array of floating point numbers

Demo

Embeddings

Sentence Transformers, local embedding model

Other use-cases:

- Similarity determination
- Semantic search
- Semantic routing
  Semantically determine the knowledge base / source for a query
- Semantic caching
  Can be used to cache answers for similar search queries
- Categorization
- Keyword determination by contextual similarity
- etc.

Improvement Process

Improvement Process

- We have a LOT of variables
  - Chunk size
  - Chunking strategy
  - Embedding model
  - Retrieval methods
    - How many documents are retrieved (n)
    - Embedding-only
    - Hybrid search
    - Reranking (yes / no, model, amount…)
  - Plain RAG vs. Agentic RAG
  - Potential transformations
  - Potential knowledge graphs

Improvement Process

- This is (computer) **science** and software **engineering**
- We need to perfectly know what works, and what does not work
- We need reproducible experiments
- We need to **measure** our stuff

Improvement Process

- Create, maintain and compare metrics
- One possibilty for Python: https://www.ragas.io/

Indexing

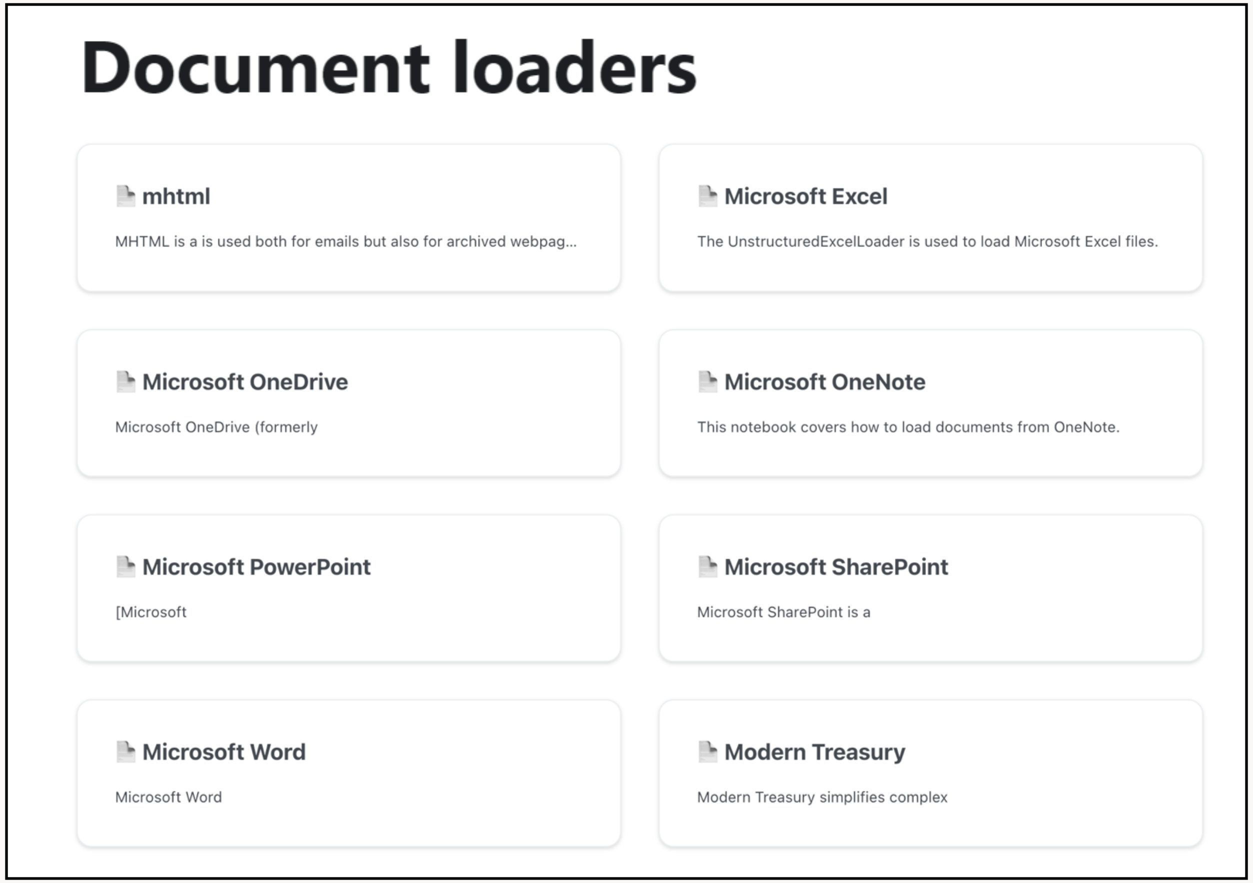
Indexing

Consists of

- Loading
- Clean-up
- Splitting
- Embedding
- Storing

Loading

- Import documents from different sources, in different formats
- LangChain has very strong support for loading data
- Support for cleanup
- Support for splitting



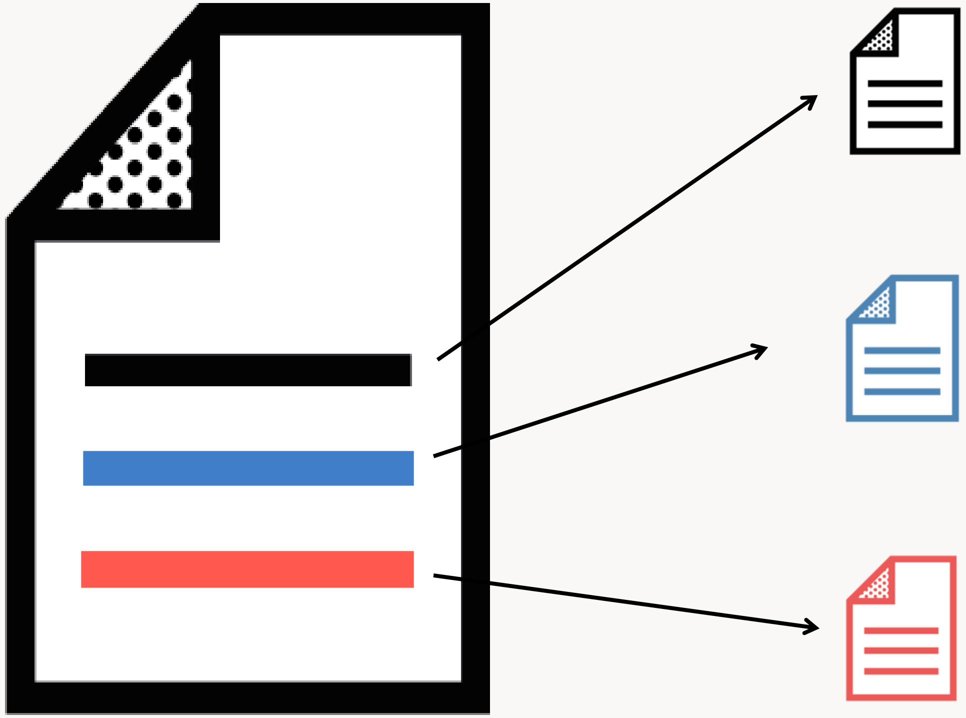
https://python.langchain.com/docs/integrations/document_loaders

Clean-up

- HTML Tags
- Formatting information
- Normalization
  - lowercasing
  - stemming, lemmatization
  - remove punctuation & stop words
- Enrichment
  - tagging
  - keywords, categories
  - metadata

Splitting (Text Segmentation)

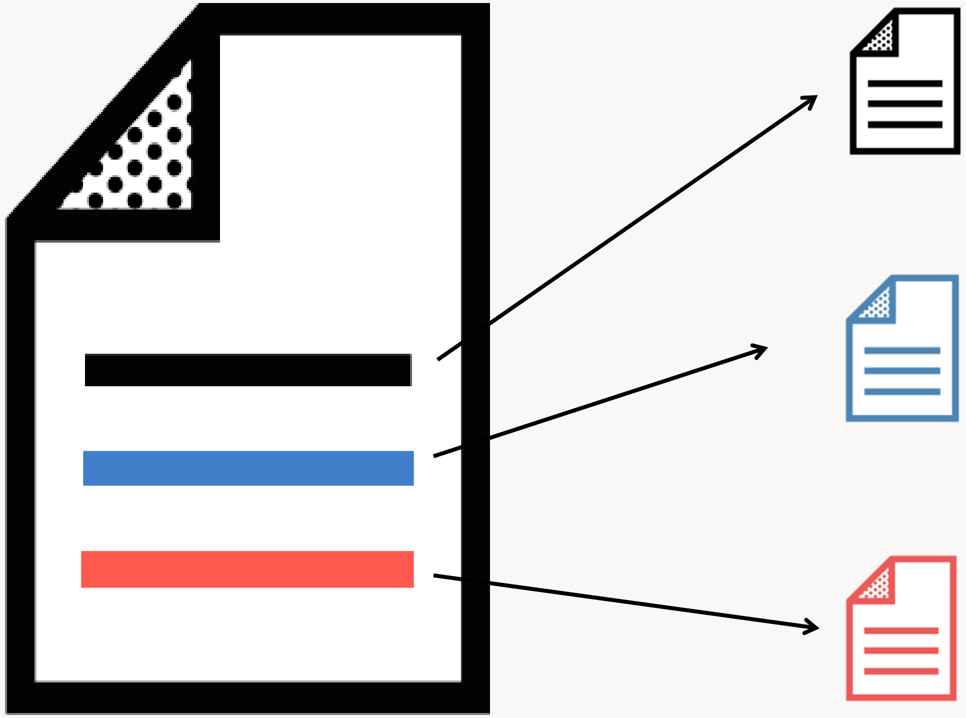
- Document is too large / too much content / not concise enough



- by size (text length)
- by character (\n\n)
- by paragraph, sentence, words (until small enough)
- by size (tokens)
- overlapping chunks (token-wise)

Splitting / Chunking (Text Segmentation)

- Document is too large / too much content / not concise enough



- by size (text length)
- by character (\n\n)
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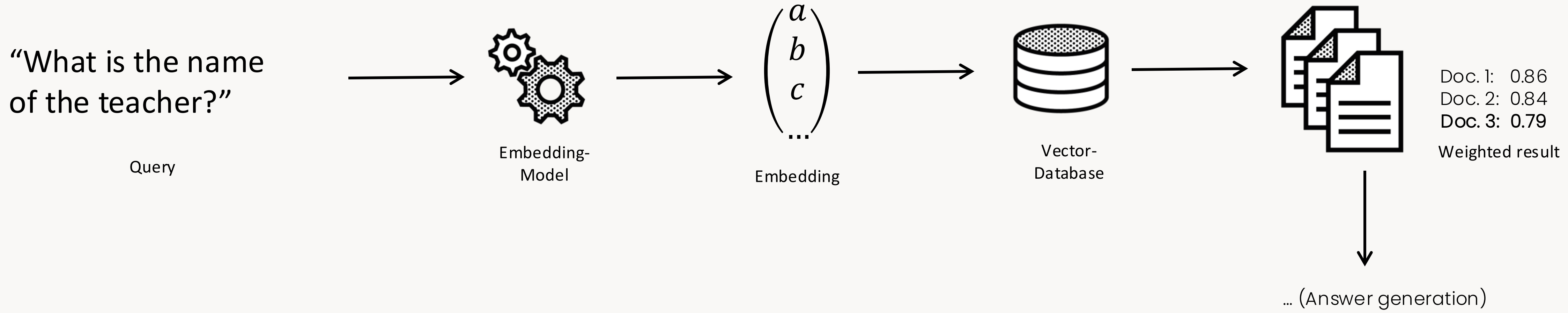
Semantic Chunking

- Every sentence gets an embedding
- Embeddings for each sentence are compared with each other
- When deviation is too large, we assume a meaning (topic) change
- At this border chunks are separated

- Needs a lot of vectors and comparisons
    - Indexing gets slow & expensive

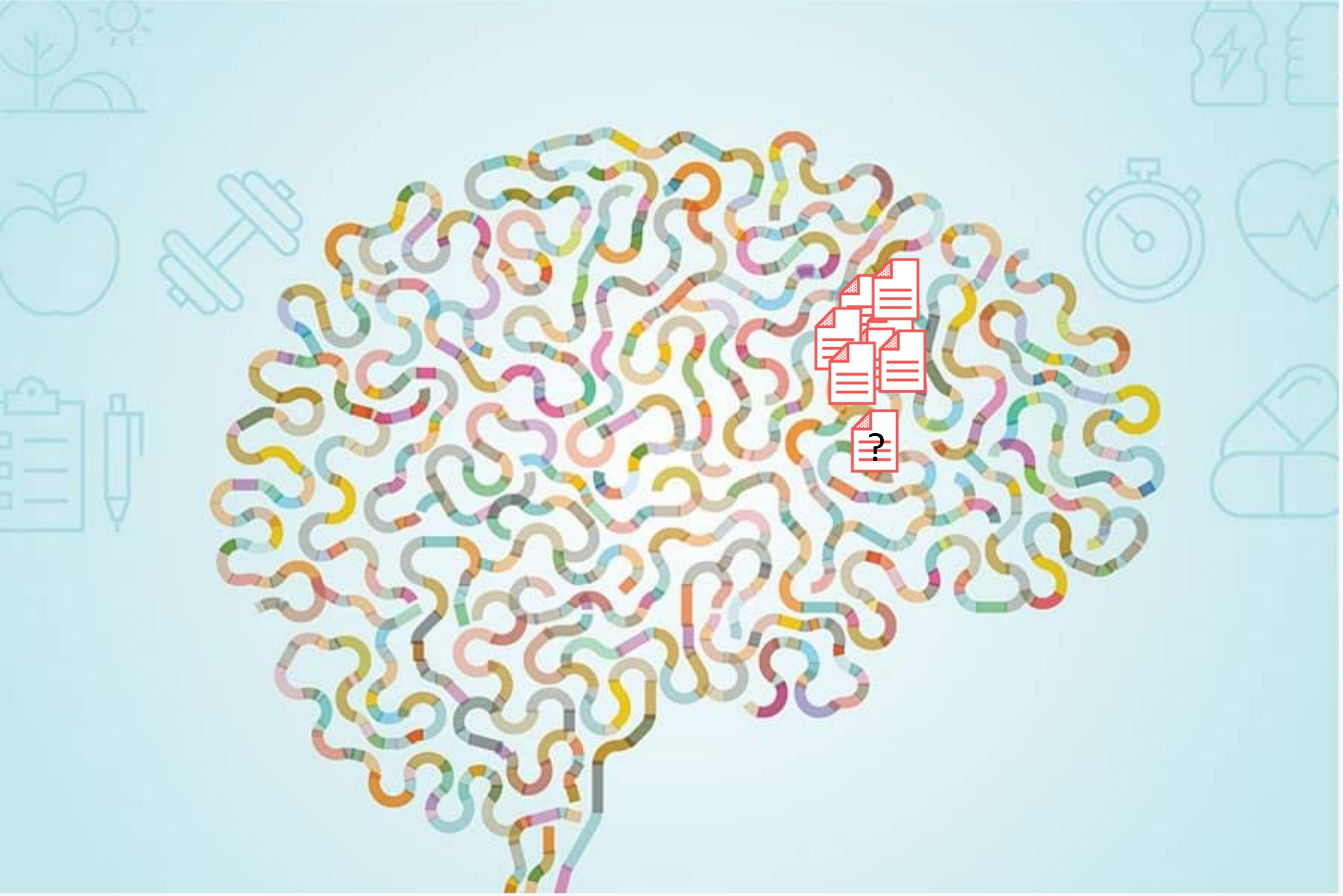
Retrieval (Search)

Retrieval


"What is the name of the teacher?"
Query
Embedding-Model
a
b
c
…
Embedding
Vector-Database
Doc. 1: 0.86
Doc. 2: 0.84
Doc. 3: 0.79
Weighted result
… (Answer generation)

Indexing II
Not good enough?

Not good enough?

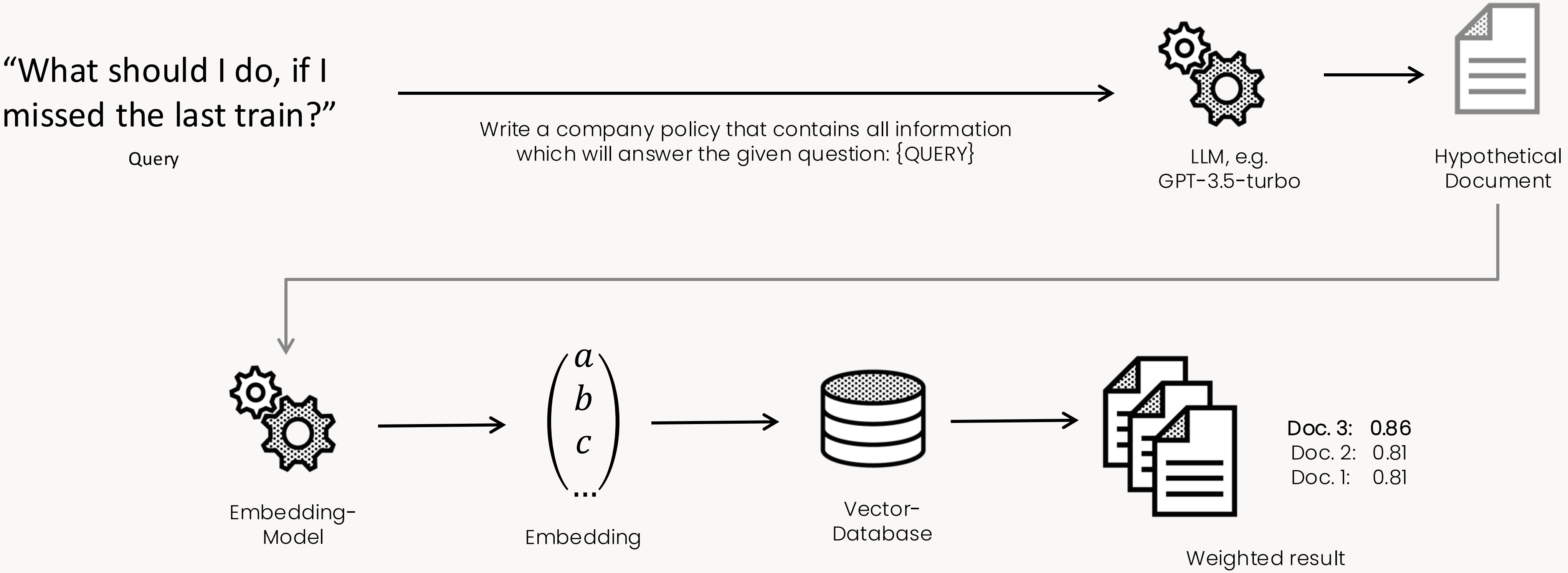


Not good enough?

- Semantic search still only uses your data
- It’s just as good as your embeddings
  - All chunks need to be sized correctly and distinguishable enough
- Garbage in, garbage out

HyDE (Hypothetical Document Embedddings)

- Search for a hypothetical Document



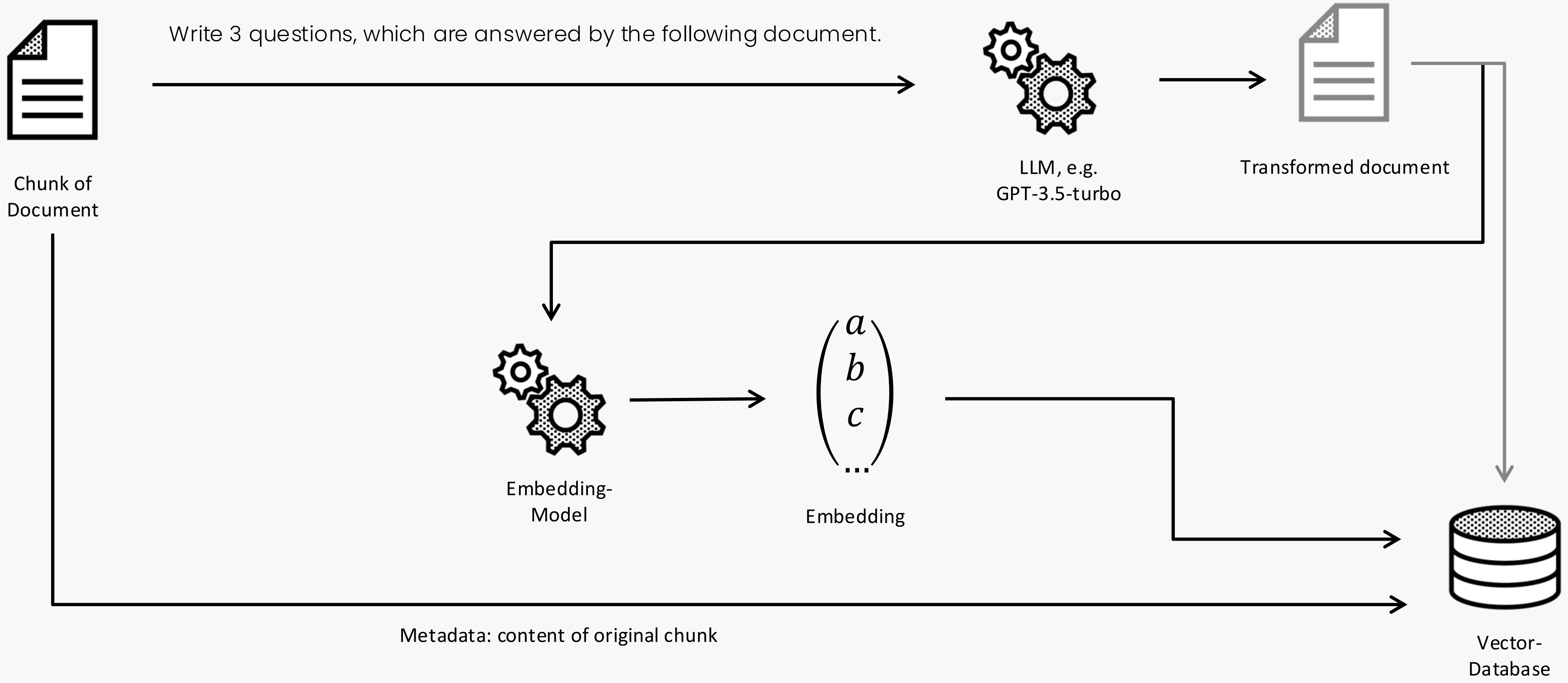
https://arxiv.org/abs/2212.10496

What else?

- Downside of HyDE:
  - Each request needs to be transformed through an LLM (slow & expensive)
  - A lot of requests will probably be very similar to each other
  - Each time a different hypothetical document is generated, even for an extremely similar request
    - Leads to very different results each time
- Idea: Alternative indexing
  - Transform the document, not the query

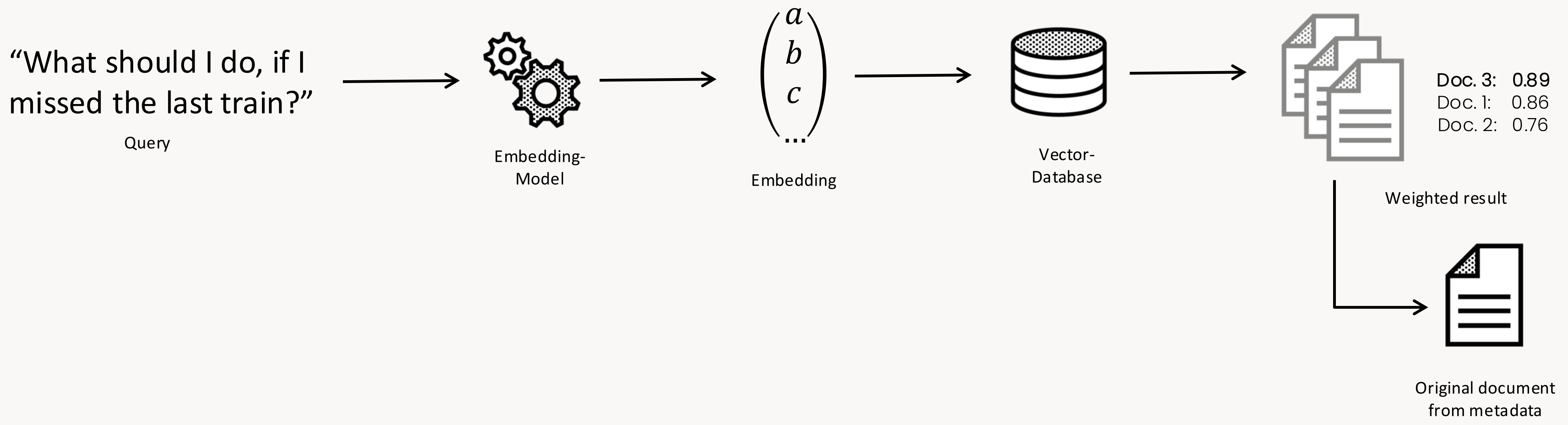
Alternative Indexing

HyQE: Hypothetical Question Embedding



Alternative Indexing

- Retrieval



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Demo

Compare embeddings

LangChain, Qdrant, OpenAI GPT

Additional strategies

Additional strategies

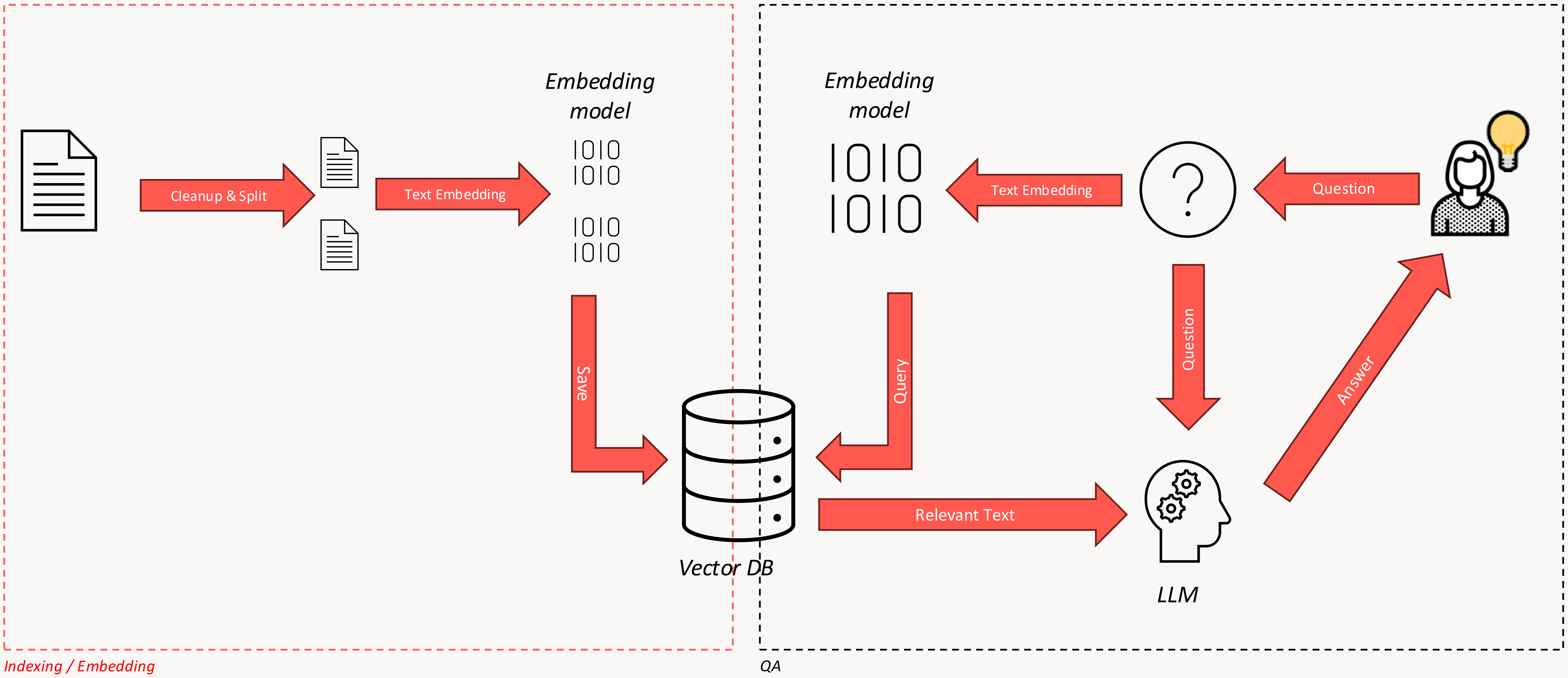
- Reranking (after retrieval): Retrieve with much higher n, rerank, then pick new top n
- Agentic RAG: Provide search as tool to LLM and let LLM determine what to search for, potentially refining search terms
- Add additional data sources, e.g. knowledge graphs

Additional strategies

- Index different document depths (via LLM calls) in addition to detailed chunks
  - Create a summary of the complete document
  - Create a summary of each chapter
  - Create a summary of each paragraph
- Allows for more general queries instead of nitty gritty detail questions only

Conclusion

Retrieval-augmented generation (RAG)
Indexing & (Semantic) search

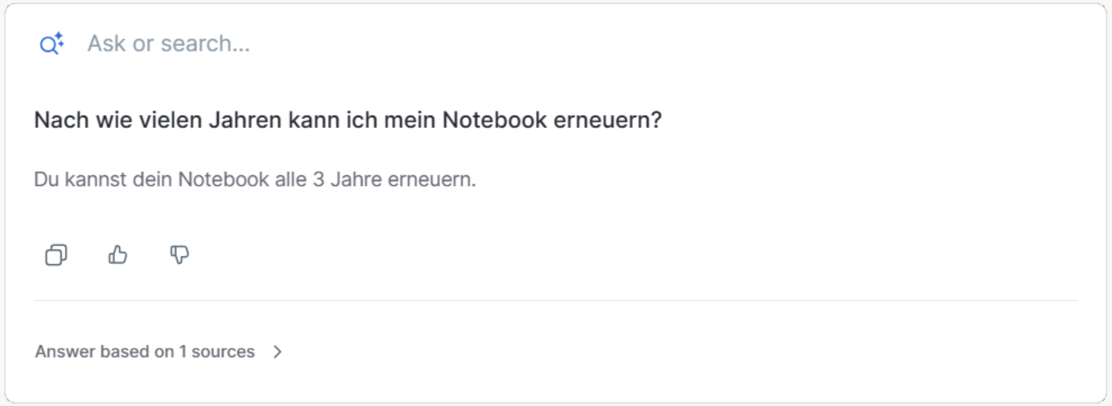


Recap: Not good enough?

- Tune text cleanup, segmentation, splitting
- HyDE or HyQE or alternative indexing
  - How many questions?
  - With or without summary
- Other approaches
  - Only generate summary
  - Extract "Intent" from user input and search by that
  - Transform document and query to a common search embedding
  - HyKSS: Hybrid Keyword and Semantic Search
    https://www.deg.byu.edu/papers/HyKSS.pdf
- Always evaluate approaches with your own data & queries
- The actual / final approach is more involved
  as it seems on the first glance

Conclusion

- Semantic search is a first and fast Generative AI business use-case
- Quality of results depend heavily on data quality and preparation pipeline
- RAG pattern can produce breathtaking good results without the need for user training



Thank you!

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Demos:

https://github.com/thinktecture-labs/dwx-2025-talk-to-your-data

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https://thinktecture.com/sebastian-gingter

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Slides & Code

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