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Open Source Large Language Models in 3 Weeks

Learn How to Answer Questions, Use
SBERT, Llama & Co and Tailor Them to
Your Needs





Learning Objectives

By the end of this course, you will understand:

- Text retrieval (extractive question answering)
- Working with Open Source LLMs
- Choosing the correct base LLM
- Text generation (generative question answering)
- Deployment in limited environment





Agenda

- Introduction
- Syntactic and Semantic Similarity
- From Word Embeddings to Sentence Embeddings
- SBERT for Calculating Similarity
- Retrieving Content
- Optimizing with Cross Encoders
- Dense Passage Retrieval



Introduction

- About me (Christian Winkler)
 - Programming for almost 40 years
 - PhD in physics, working as a professor at a university of applied science
- About the course
 - LLMs and the technology can be intimidating
 - Let's try to clarify the myths
 - Hands on experience



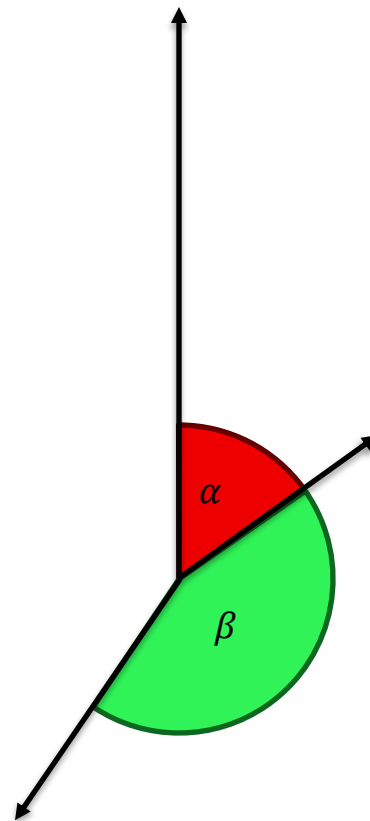


Recap: the document-term matrix

	looking	cheap	flight	where	should	stay	thanks	answer	nearest	train	station	car	airport
Looking for cheap flight?	1	1	1	0	0	0	0	0	0	0	0	0	0
Where should I stay?	0	0	0	1	1	1	0	0	0	0	0	0	0
Thanks for your answer	0	0	0	0	0	0	1	1	0	0	0	0	0
Nearest train station	0	0	0	0	0	0	0	0	1	1	1	0	0
Looking for a car	1	0	0	0	0	0	0	0	0	0	0	1	0
Train to airport	0	0	0	0	0	0	0	0	0	1	0	0	1

Syntactic vs. semantic similarity

- Similarity: measure between 0 and 1, often cosine similarity (angle between vectors)
- Syntactic similarity uses tokens (without flections)
 - Remove flections via lemmatization
 - Cannot capture synonyms etc.
- *Semantic* similarity uses concepts
 - More complex representation needed
- Solution: Word embeddings
 - Most prominent version: word2vec





Word embeddings

- "You shall know a word by the company it keeps."
- Example
 - What is "tezgüino"?
 - What is similar to "tezgüino"?

A bottle of _____ is on the table.
Everybody likes _____.
Don't have _____ before you drive.
We make _____ out of corn.



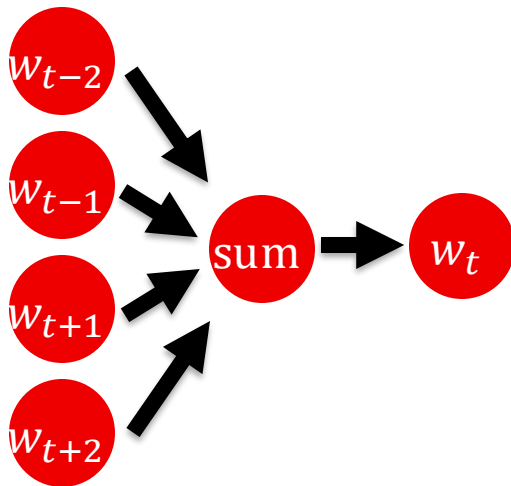
Schematic idea of word embeddings

"Royalty"
"Masculinity"
"Femininity"
"Age"

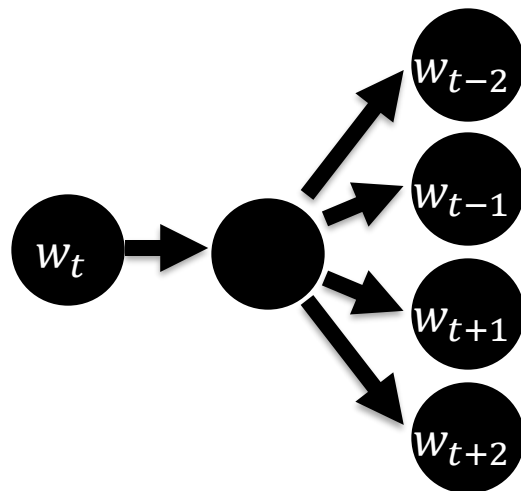
King	0,96	0,99	0,03	0,64
Queen	0,99	0,05	0,97	0,72
Woman	0,08	0,03	0,98	0,51
Princess	0,93	0,01	0,93	0,12



Construction

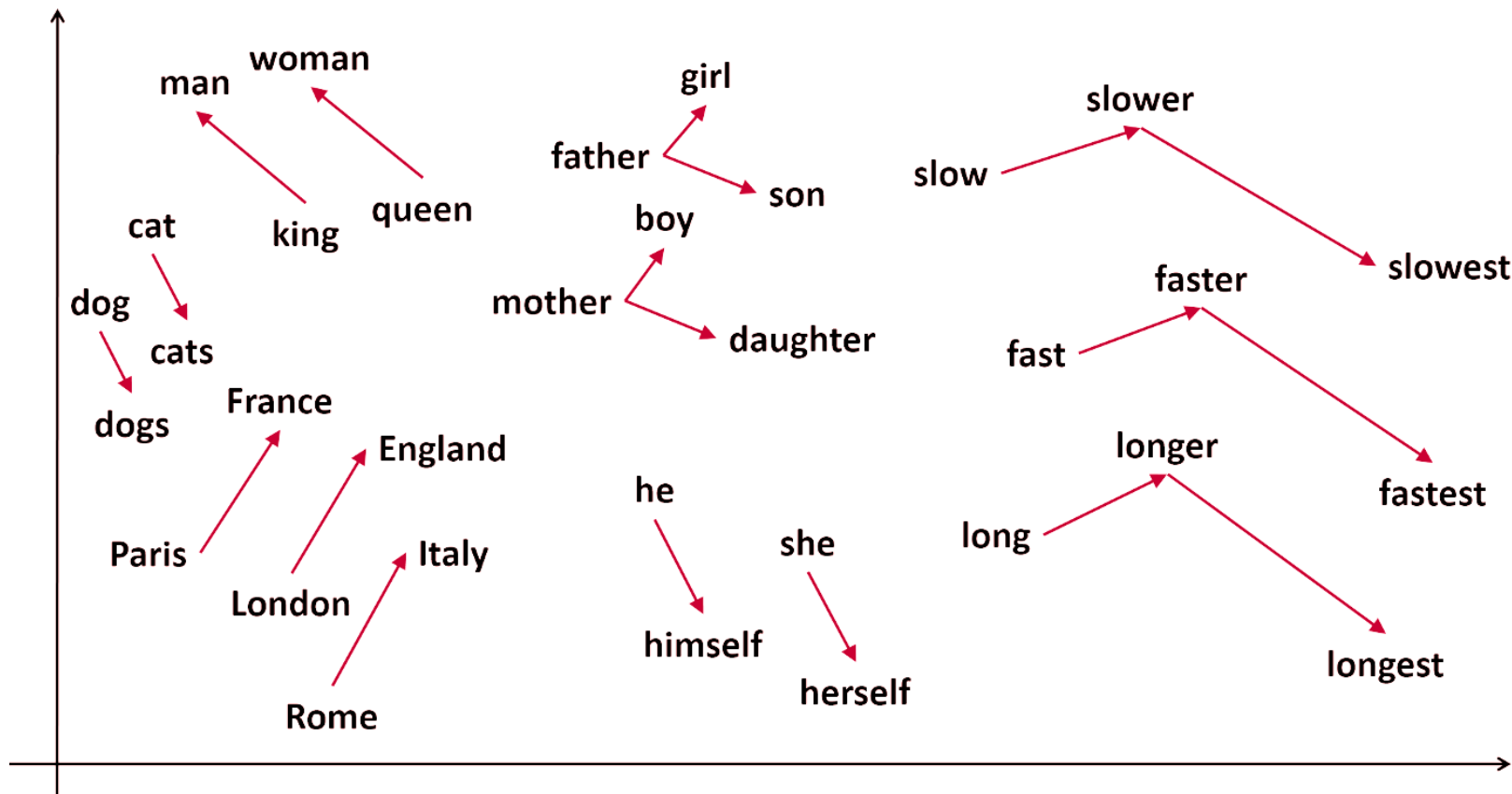


continuous bag-of-
words



Skip-gram

Similarities and relationships

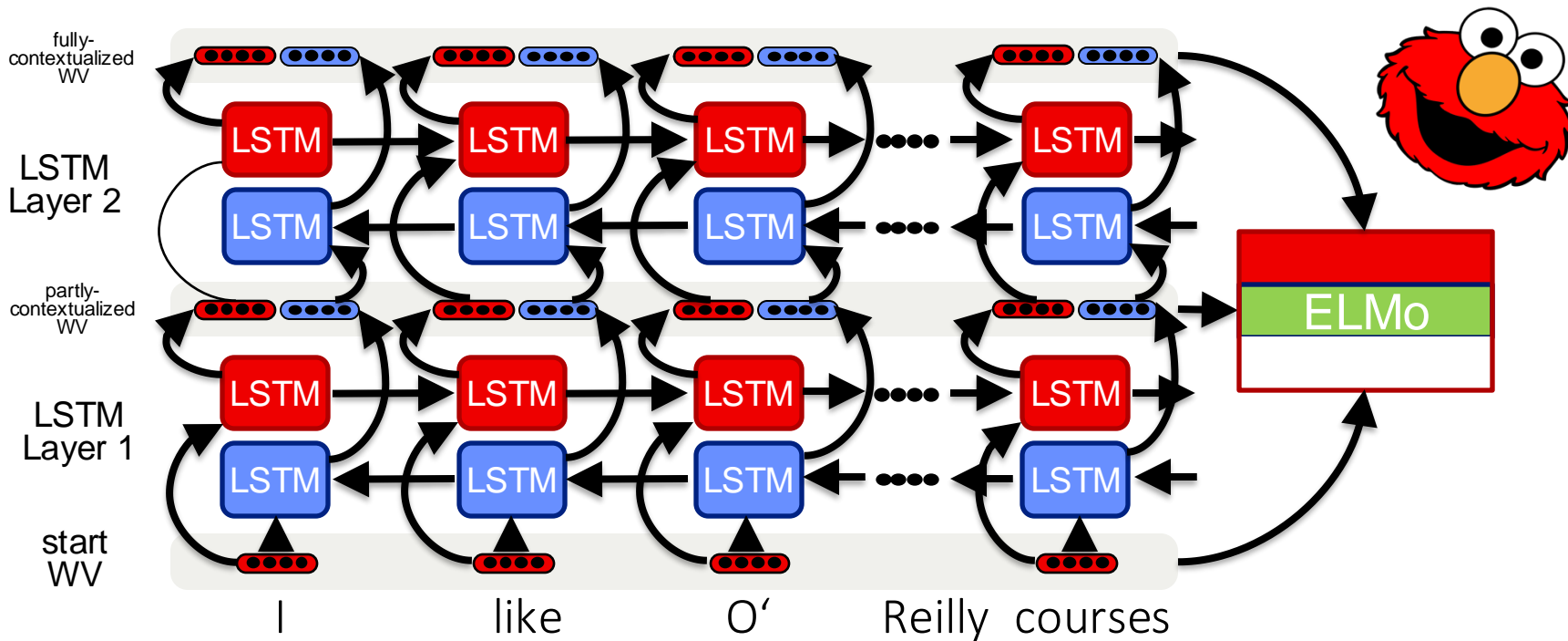




Shortcomings of word embeddings

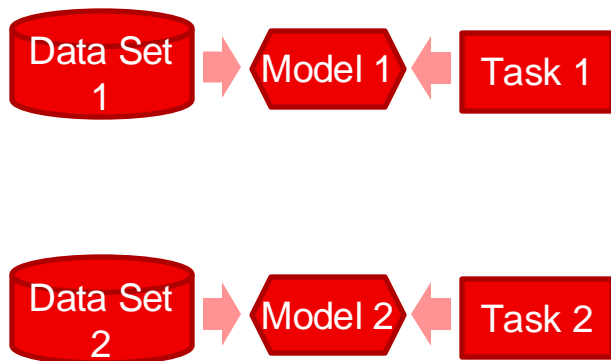
- Missing contextualization
 - Important for meaning
 - Irony and sarcasm
- Homonyms cannot be captured
 - Meaning of word depends on context
 - Read a *book* or *book* a flight
- Each model has to be trained separately
 - No transfer learning

Basic idea of contextualized language models



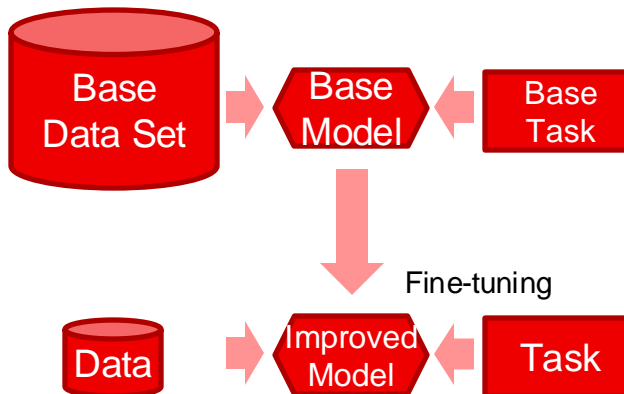
Transfer learning

Classical ML



Each model is trained for one specific task. Start without prior knowledge. Need large labeled training data set.

Transfer Learning



A base model is trained with a large unlabeled dataset. With much less data, it is finetuned for a specific task. Effort is almost negligible compared to base task.

Transformer architecture

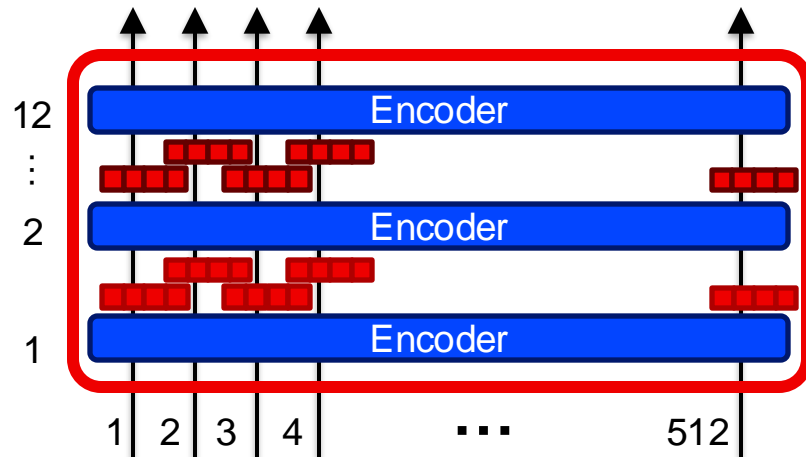
Language models are complex with billions of parameters

Base: Transformer architecture with self-attention

- Attention to which words?
- Many layers with contextualization
- Complex and a bit confusing

BERT: Training for *missing* words

GPT: Training for *next* word





Q&A





Challenge: find similar sentences



Is BERT already enough for this?

- Almost, but not completely
- Model is tuned for guessing missing words
- Model can be finetuned for similarity
 - Start with mean pooling: create averages of individual (contextualized) word embeddings
 - Use supervised learning with a pre-labeled dataset
 - → Optimized model understanding similarity
- Fortunately, this has already been completed
- Model is called SBERT (<https://sbert.org>)

Challenge

- Use existing corpus
 - UN general debates (free)
- 1. Prepare data
 - a) Segment sentences
 - b) Calculate SBERT encoding of each sentence (due to time only for 2022)
 - c) Save encoding
- 2. Encode statement
- 3. Find most similar vector



Recipe



Load data

Calculate sentence fragments

Calculate embeddings for each
sentence

Save embeddings



Work interactively in Jupyter notebook: Semantic retrieval



Q&A



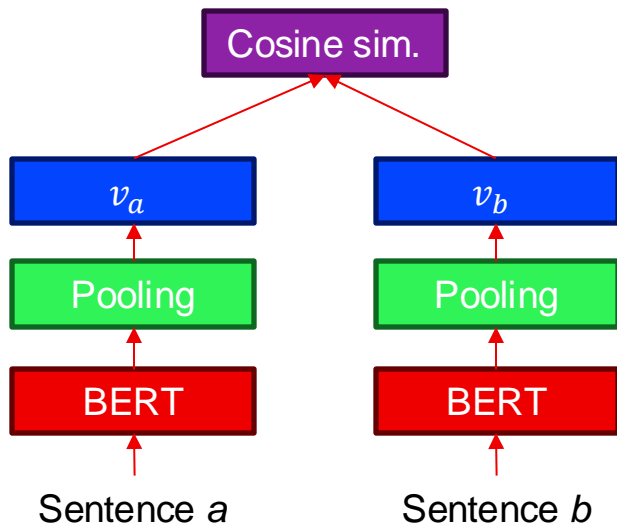


Cross encoders



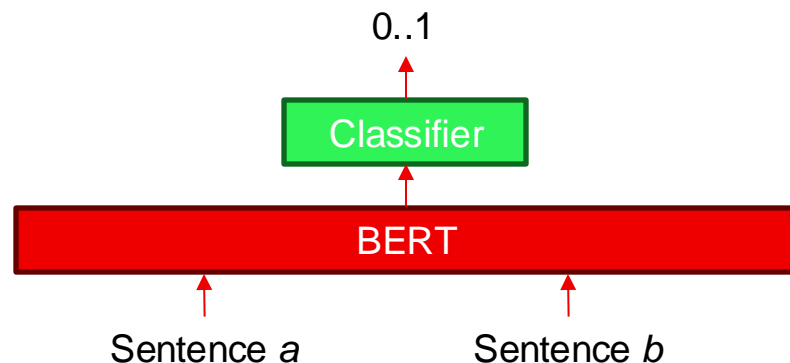
How do cross-encoders work

So far...



Bi-encoder

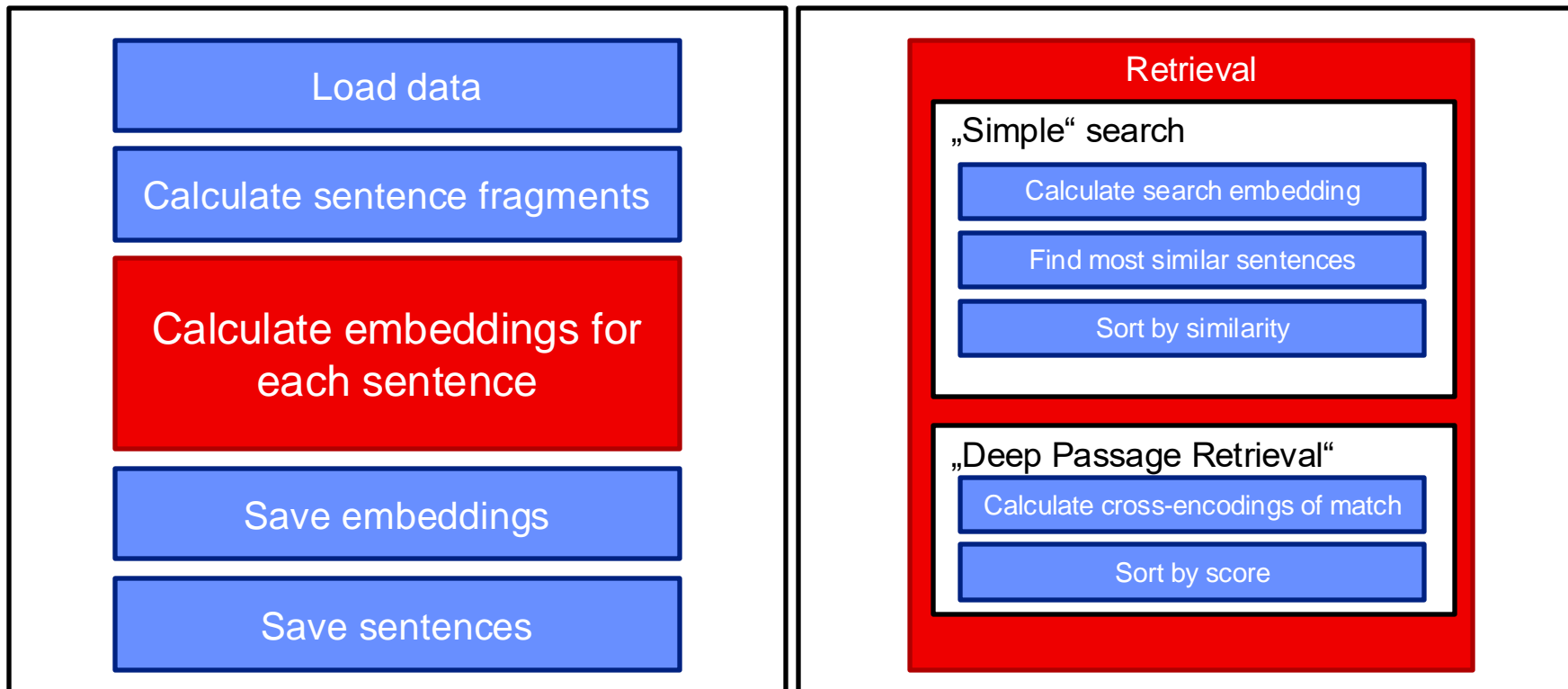
New



Cross-encoder



Improving the prior solution





Work interactively in Jupyter notebook: Dense passage retrieval



Q&A





Using existing software

LangChain

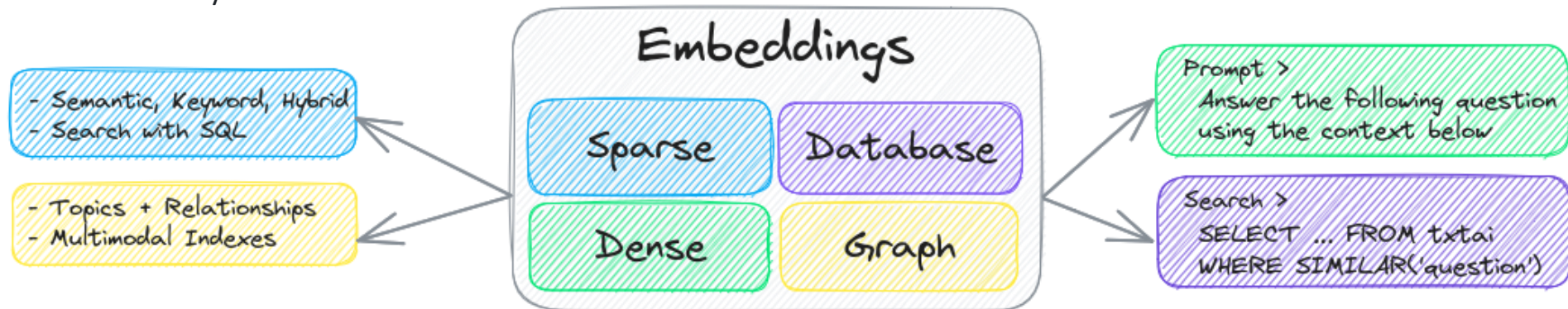


- Open source framework
- Tries to unify LLM handling via APIs
- Pros
 - Very easy to change backends etc.
 - Working with pipelines
 - Easier handling of “chained” method call
 - Very popular and many examples
- Cons
 - Code quality sometimes doubtful
 - Documentation hard to read





- “txtai is an all-in-one embeddings database for semantic search, LLM orchestration and language model workflows.”
- Everything is integrated
- Very nice API





LlamaIndex

- Open source framework
- Integrated cloud available
- Uses OpenAI as standard, but configurable
- Pros
 - Easy to change backends etc.
 - Very active and loved by developers
 - Good documentation
- Cons
 - Still a bit new
 - Extractive and generative models entangled



**Work interactively in Jupyter notebook:
use LangChain and txtai**

Summary & discussion





Group Discussion

- Any questions left?
- What would you like to achieve with this technology?



Review Course Outcomes

By the end of this course, you should be able to:

- Calculate sentence embeddings with SBERT
- Understand and use cross-encoders
- Use existing software like LangChain and txtai to build a semantic search engine



Resources

GitHub repository

- <https://github.com/datanizing/oreilly-open-source-llm>
- Continuously updated

Hugging Face Embedding Leaderboard

- <https://huggingface.co/spaces/mteb/leaderboard>

General Discussion

- <https://www.reddit.com/r/LocalLLaMA/>

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