Text Embedding. Text Retrieval & Ranking. Retrieval-Augmented Generation.

Alekseev Ilya, AIMasters, Fall 2024.

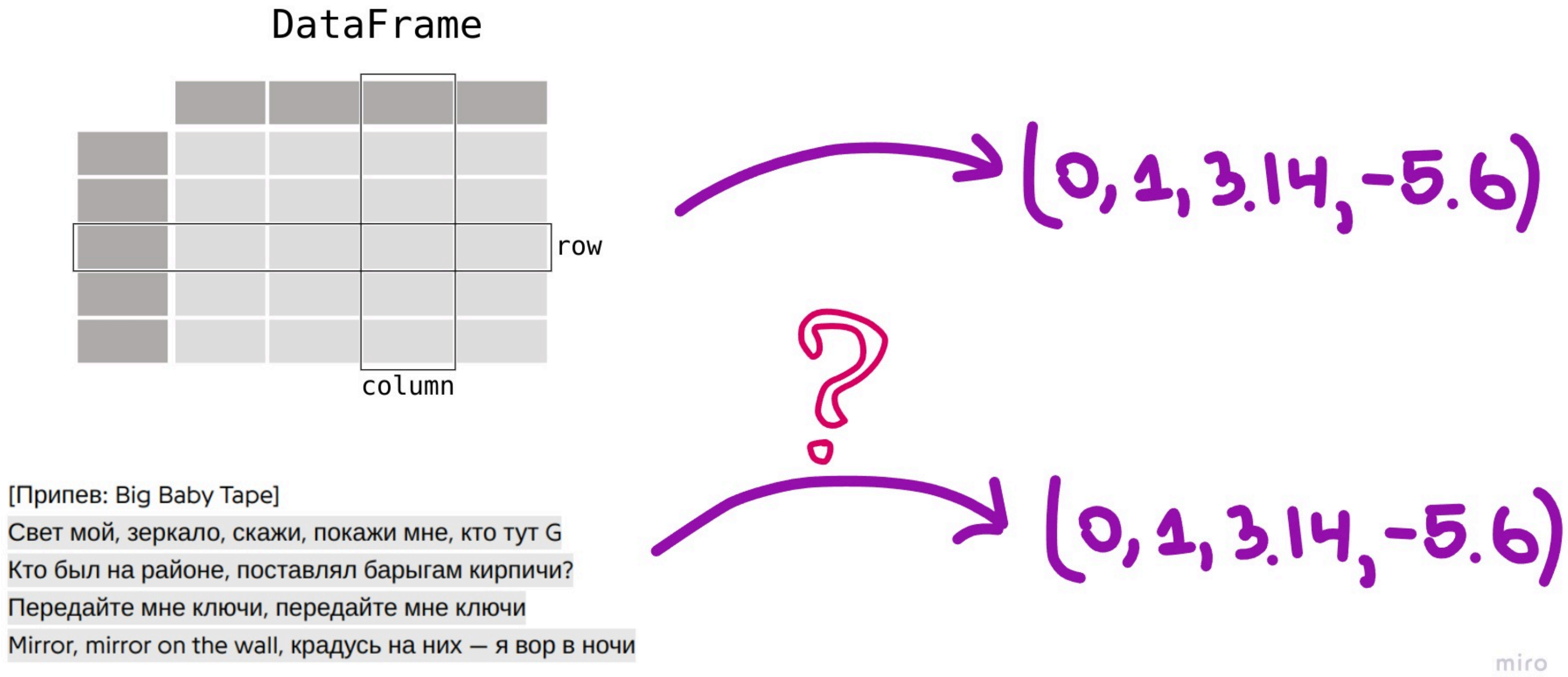
Text Embedding

Outline

- Text Embedding & Sequence-level Tasks
- BERT Embedding
- SBERT
- Contrastive Learning: Loss, Positives, Negatives

Text Embedding

*Embedding must be useful as **feature representation** and for **vector search**.*



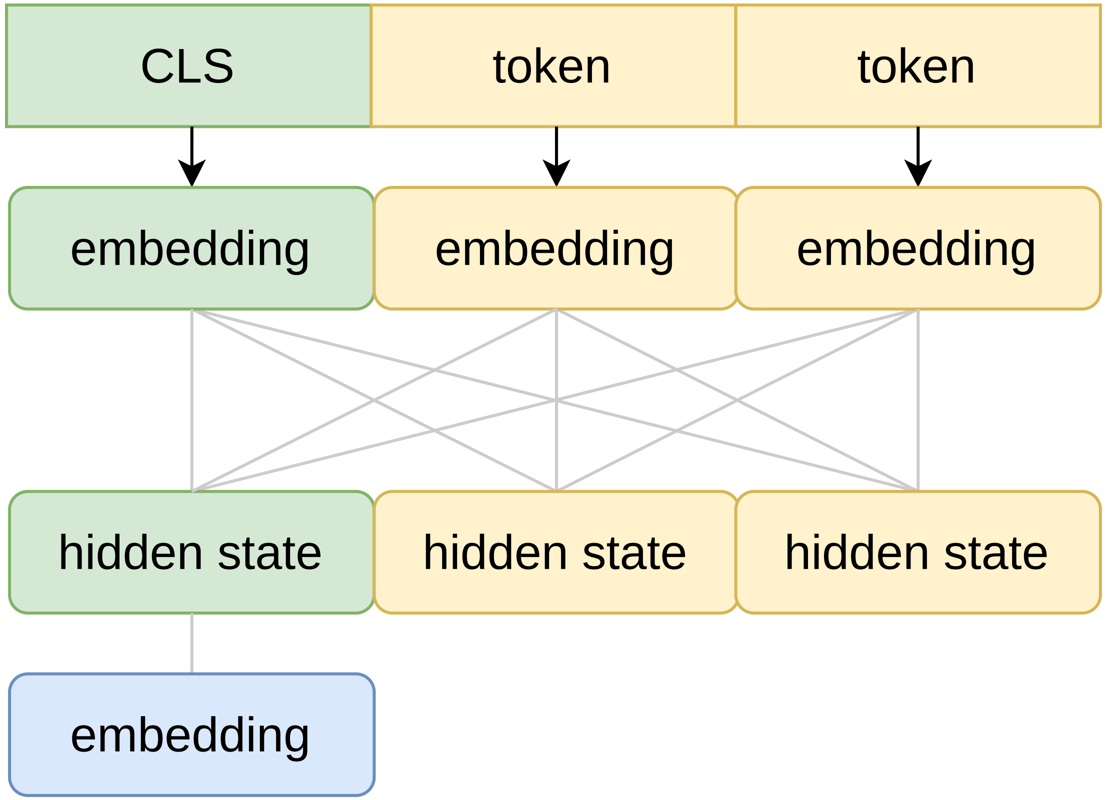
Sequence-level Tasks

- **Natural Language Inference (NLI)**: contradiction, eintailment, and neutral (pair classification)
- **Bitext Mining**: mine closest translation pairs from parallel corpus (knn)
- **Semantic Textual Similarity (STS)**: estimate the similarity of two texts (pair regression)
- **Retrieval**: find relevant documents for query text (knn)
- **Parahpase detection** (pair classification)
- Classification, clustering, reranking, summarization

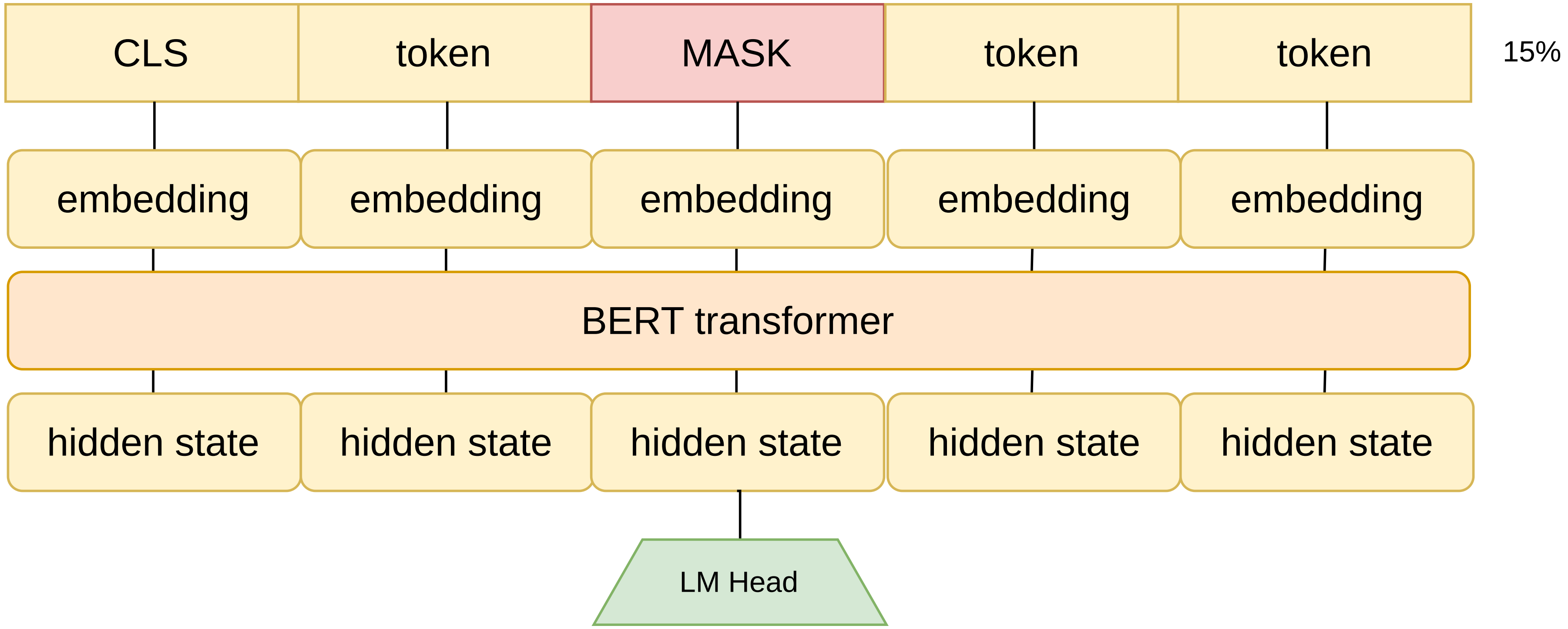
BERT Embedding

Feed to BERT and pool last hidden states:

- CLS
- Average
- Attention



BERT is not trained to produce good embeddings!

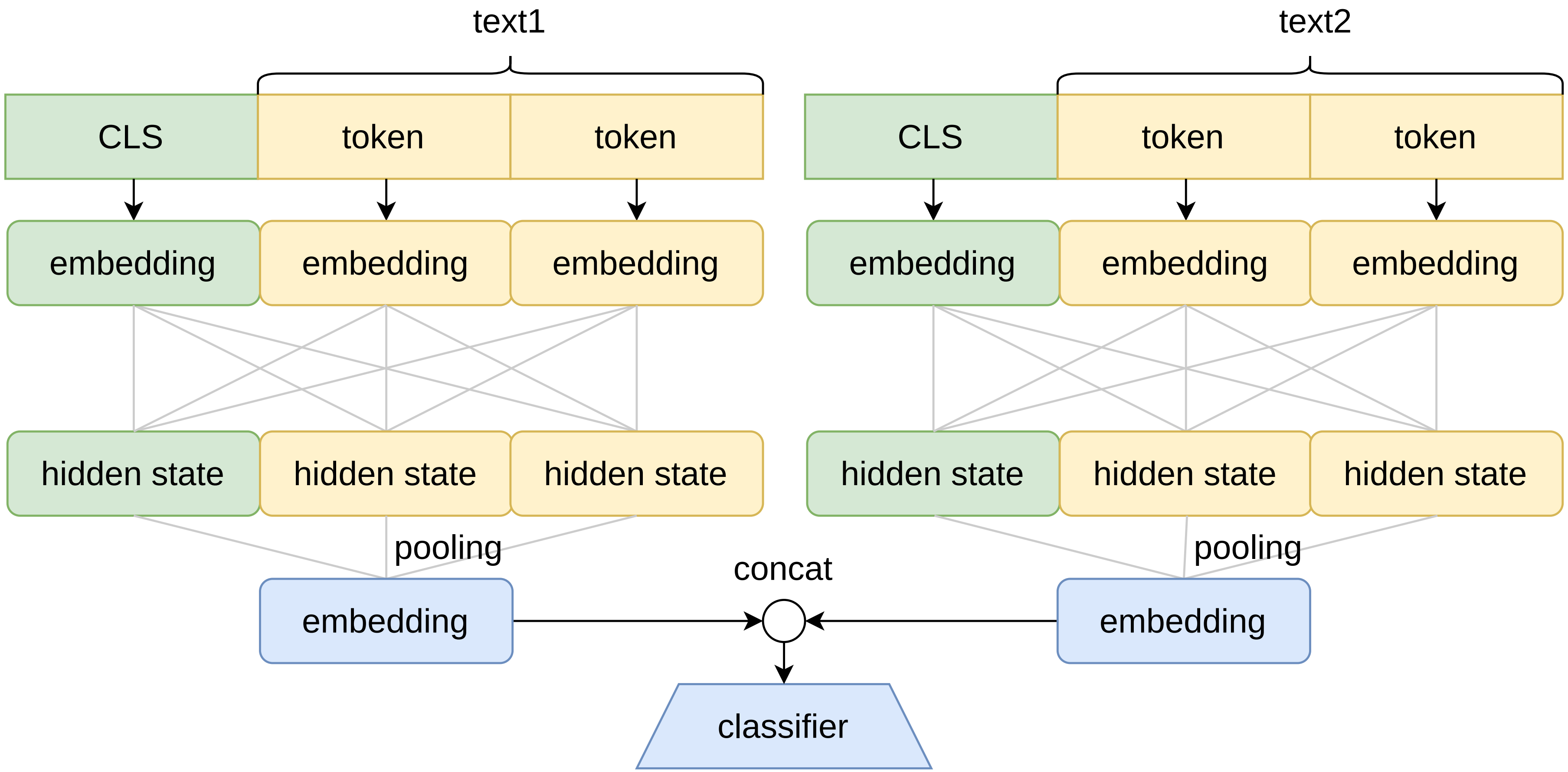


We need sentence-level task to encourage model to aggregate info effectively

Reimers & Gurevych, "Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks", EMNLP 2019 (citations: 12866)

Sequence-level task: *train BERT on NLI data*.

SBERT

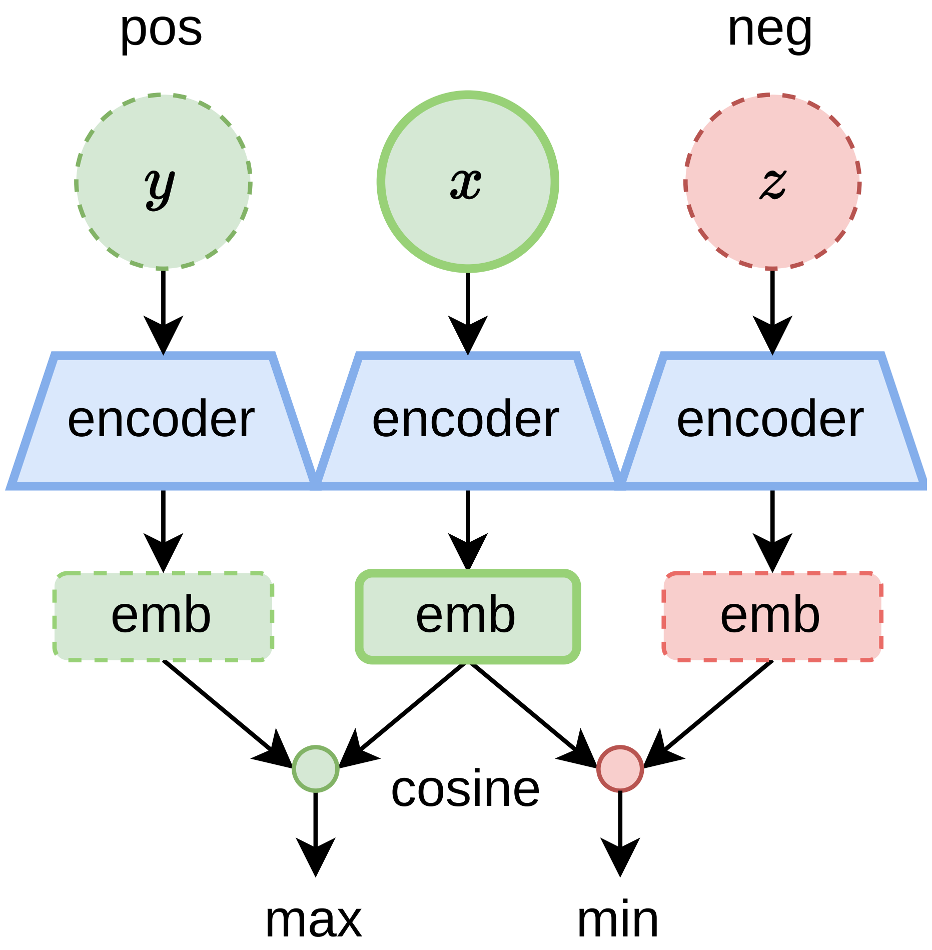

text1
text2
CLS
token
token
CLS
token
token
embedding
embedding
embedding
embedding
embedding
embedding
hidden state
hidden state
hidden state
hidden state
hidden state
hidden state
pooling
pooling
concat
embedding
embedding
classifier

SBERT: pros and cons

- \+ sequence-level task
- \+ bottleneck trick
- − supervised data
- − only features but not a vector search

Contrastive Learning

$$\mathcal{L} = -\log \frac{\exp(\cos(x, y))}{\sum_{z \in Z} \exp\left(\cos(x, z)\right)}$$



How to Mine Positives

- supervised datasets (NLI, STS, summarization, retrieval)
- scrapped data (QA forums, Reddit threads, web articles, news)
- augmentations (synonyms, paraphasing, dropout, token shuffling)

How to Mine Negatives

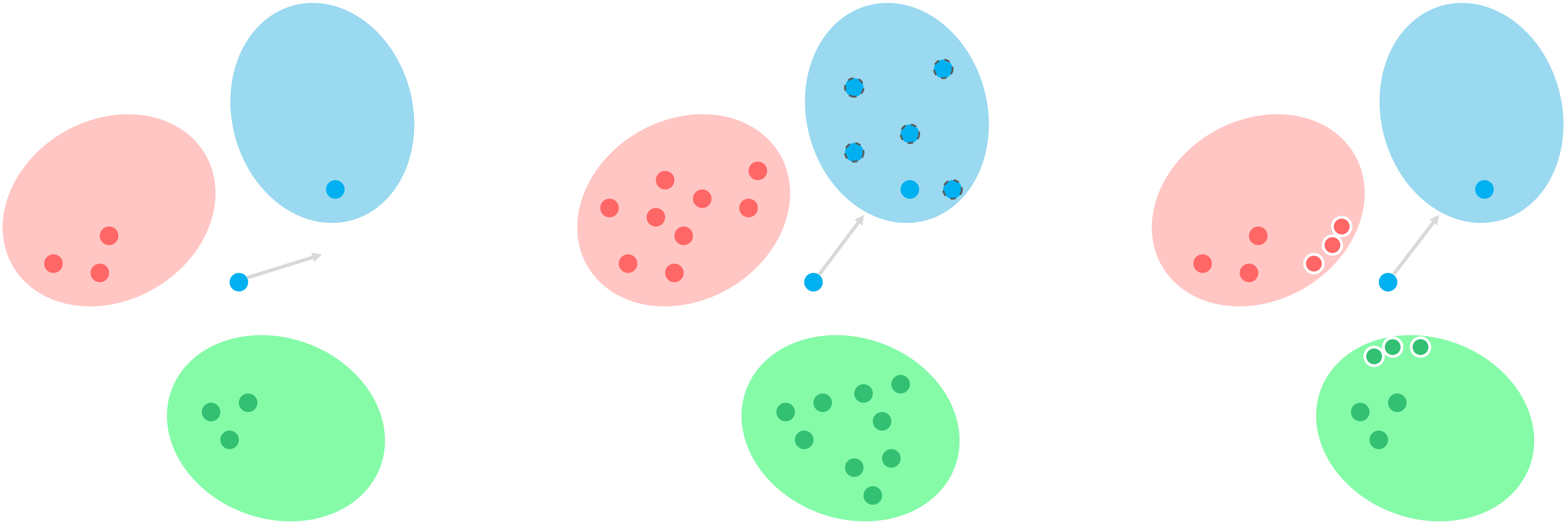
- in-batch negative sampling
- queue
- memory bank
- momentum contrast (MoCo)

In-batch Negative Sampling

```
# joint embedding
x_emb = encoder(x_txt)  # [B, d]
y_emb = encoder(y_txt)  # [B, d]

# pairwise cosine similarities
x_emb = F.normalize(x_emb, dim=1)
y_emb = F.normalize(y_emb, dim=1)
similarities = x_emb @ y_emb.T  # [B, B]

# symmetric loss
labels = torch.arange(len(x_emb))
loss_r = F.cross_entropy(similarities, labels, reduction='mean')
loss_c = F.cross_entropy(similarities.T, labels, reduction='mean')
loss = (loss_c + loss_r) / 2
```



SOTA Embedding Models

https://huggingface.co/spaces/mteb/leaderboard

Text Embedding: Summary

- Text Embedding & Sequence-level Tasks
- BERT Embedding
- SBERT
- Contrastive Learning: Loss, Positives, Negatives

Text Retrieval & Ranking

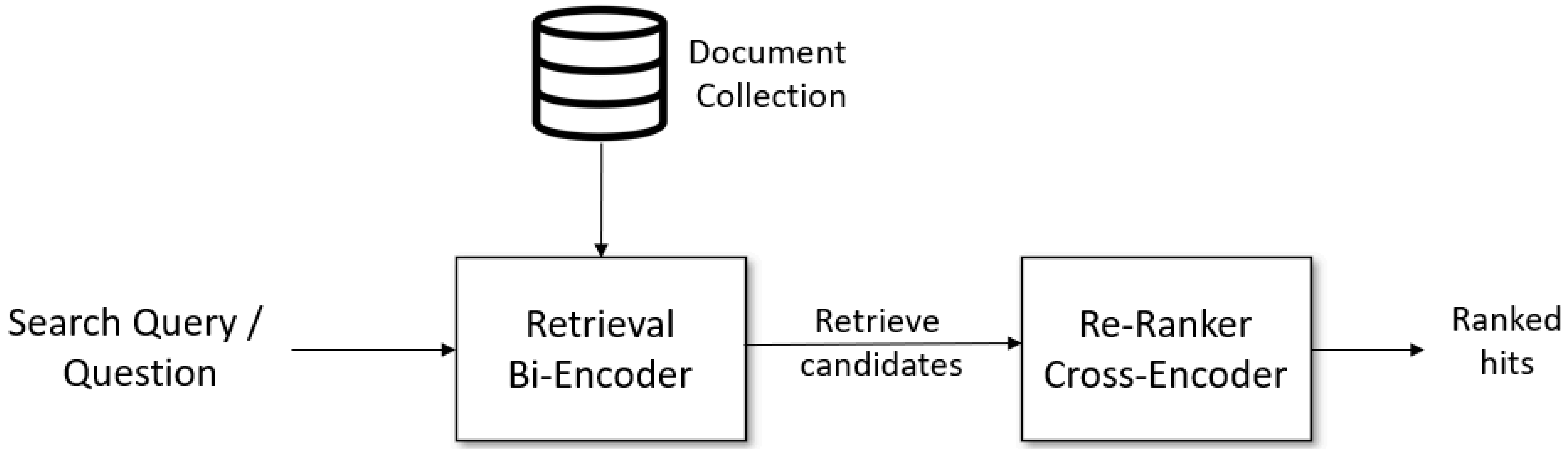
Outline

- Symmetric vs Asymmetric Search
- Bi-encoder vs Cross-encoder
- Sparse Text Embedding: BM25

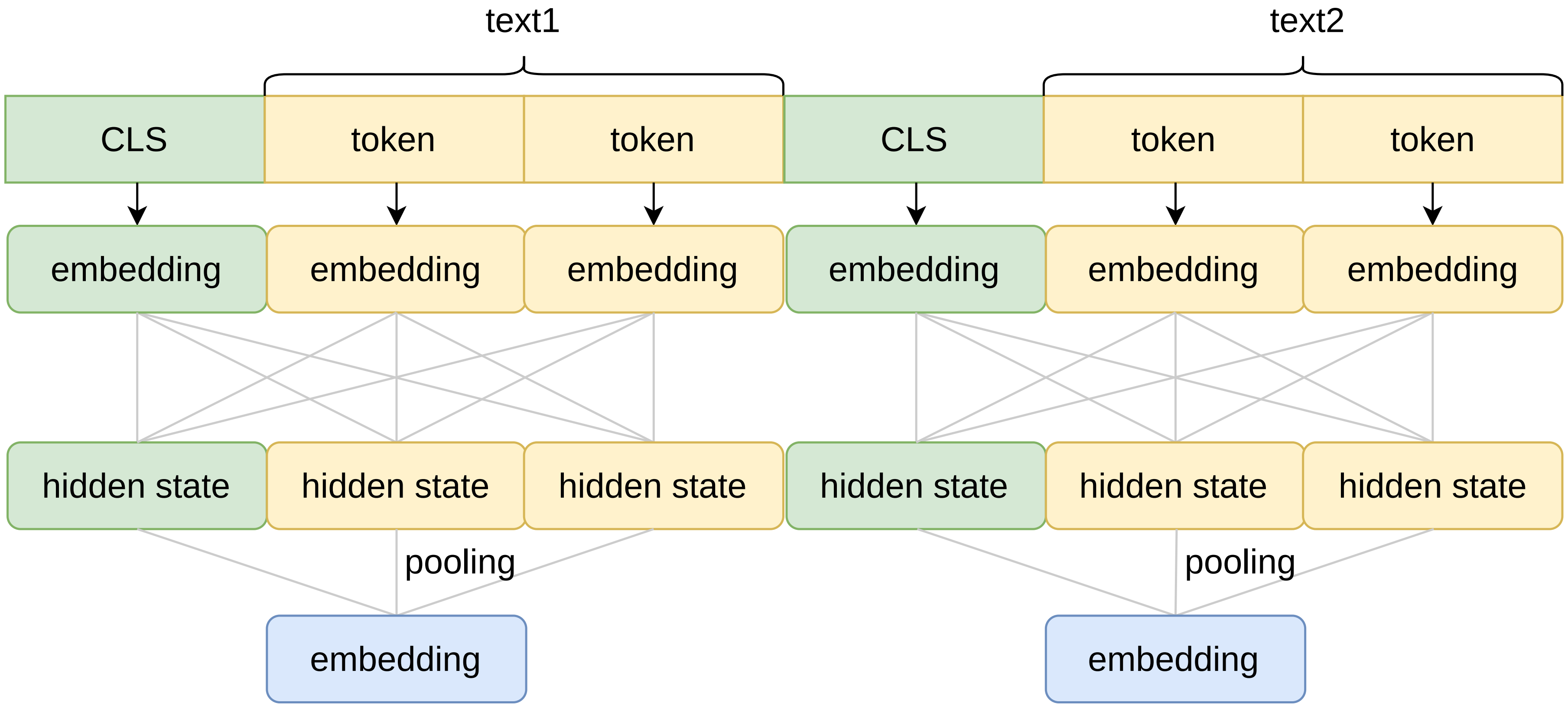
Retrieval Types

- **symmetric** search (clustering, knn, bitext mining)
  - query $\sim$ document
  - `q="The last time the survey was conducted, in 1995, those numbers matched."`
  - `d="In 1978, the paper's numbers weren't believed to be true."`
- **asymmetric** search (web search, QA)
  - query $\nsim$ document
  - `q="What is Python"`
  - `d="Python is an interpreted, high-level and general-purpose programming language."`

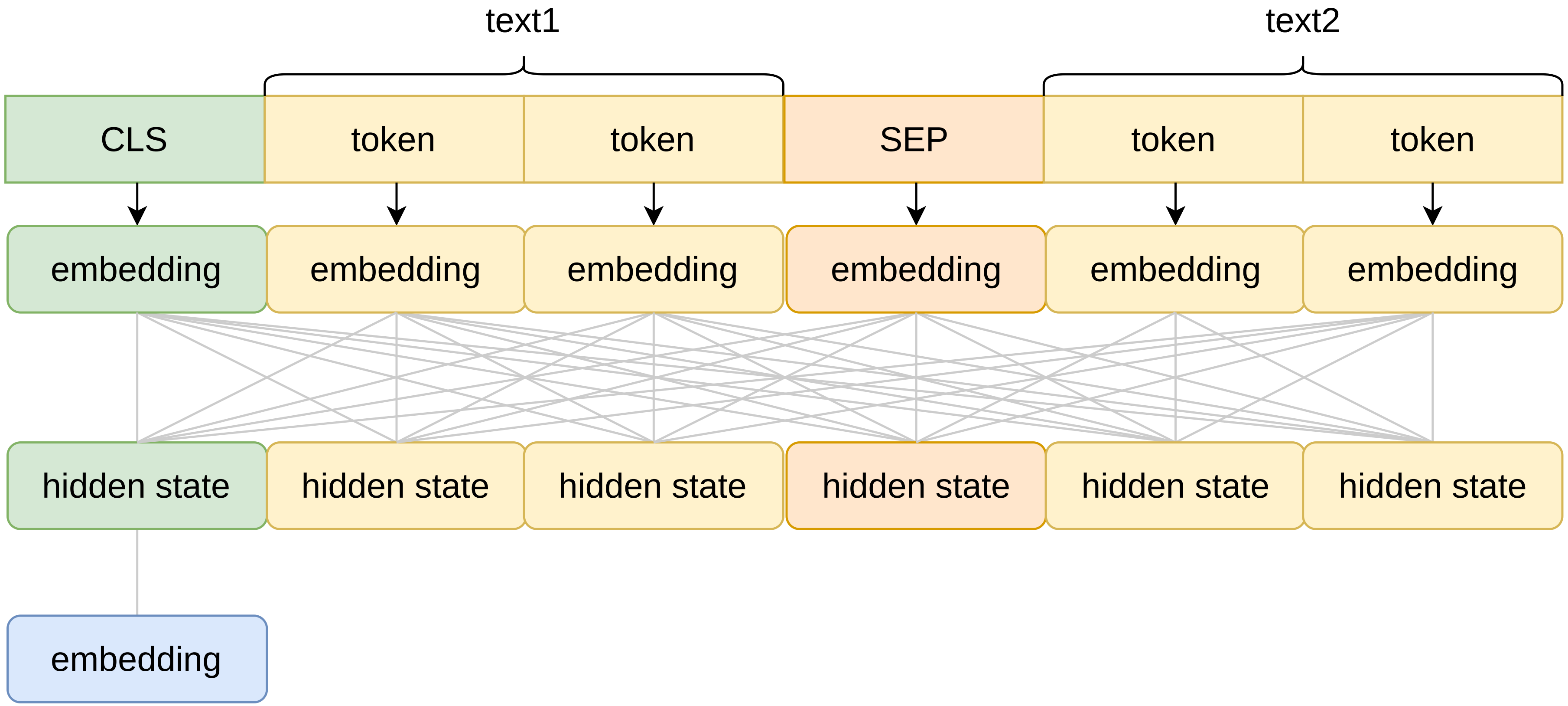
Search Engine



Bi-encoder


text1
text2
CLS
token
token
CLS
token
token
embedding
embedding
embedding
embedding
embedding
embedding
hidden state
hidden state
hidden state
hidden state
hidden state
hidden state
pooling
pooling
embedding
embedding

Cross-encoder



Sparse Text Embedding

Вектор $e(d)$ размера $|V|$:

- BoW:

$$[e(d)]_i = \mathrm{tf}(w_i, d)$$

- TF-IDF

$$[e(d)]_i = \mathrm{tf}(w_i, d) \cdot \mathrm{idf}(w_i)$$

- BM25

$$[e(d)]_i = \widetilde{\mathrm{tf}}(w_i, d) \cdot \widetilde{\mathrm{idf}}(w_i)$$

TF-IDF

- term frequency $\operatorname{tf}(w, d)$ есть число вхождений токена w_i в документ d
- document frequency $\operatorname{df}(w)$ есть число документов, в которых встречается w
- inverse document frequency есть мера редкости токена:

$$\operatorname{idf}(w) = 1 + \log \frac{1 + |D|}{1 + \operatorname{df}(w)}$$

- вместе дает число токенов с учётом редкости каждого токена:

$$[e(d)]_i = \operatorname{tf}(w_i, d) \cdot \operatorname{idf}(w_i)$$

BM25

- пусть $\ell(d)$ это отношение длины d к средней длине документов в датасете
- term frequency с поправкой на длину документа:

$$\widetilde{\mathrm{tf}}(w, d) = \frac{3 \cdot \mathrm{tf}(w)}{3(0.25 + 0.75 \cdot \ell(d)) + \mathrm{tf}(w)}$$

- inverse document frequency

$$\widetilde{\mathrm{idf}}(w_i) = \log \frac{|D| - \mathrm{df}(w) + 0.5}{\mathrm{df}(w) + 0.5}$$

- вместе это дает число токенов с учетом редкости, длины текста, числа повторений этого токена

$$[e(d)]_i = \widetilde{\mathrm{tf}}(w_i, d) \cdot \widetilde{\mathrm{idf}}(w_i)$$

Text Retrieval & Ranking: Summary

- Symmetric vs Asymmetric Search
- Search Engine Pipeline
- Bi-encoder vs Cross-encoder
- Sparse Text Embedding: BM25

Retrieval Augmented Generation

Outline

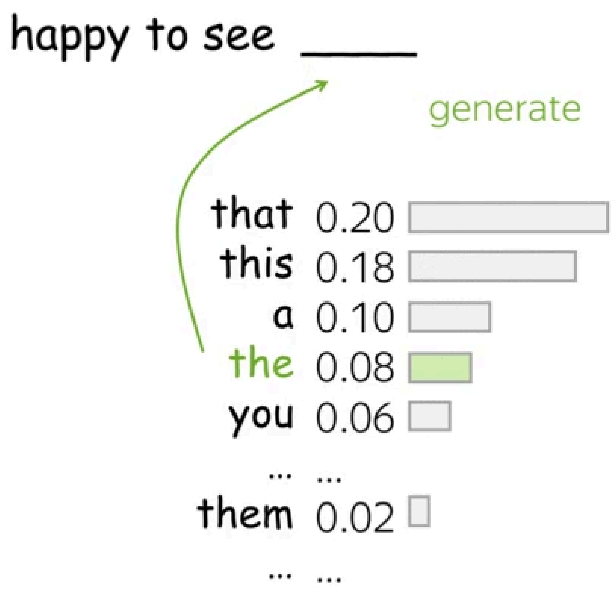
- Introduction. Naive RAG
- Evaluation
- Improve RAG. Prompting Techniques
- Improve RAG. Retriever and LLM Joint Training

Introduction. Naive RAG

Language Models are Few-Shot Learners

GPT-3 [Brown et al., 2020]

> …tasks which require using the information stored in the model's parameters to answer general knowledge questions.

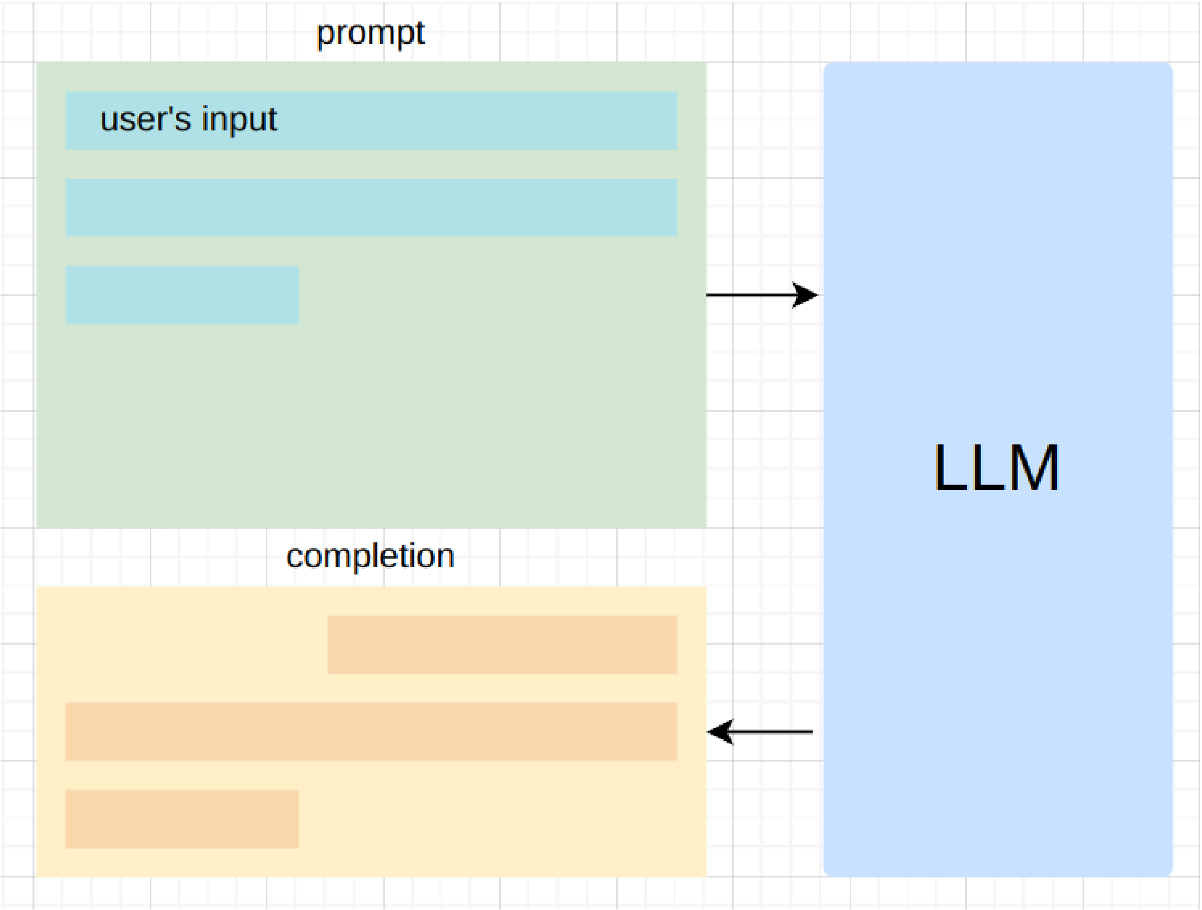


QA via Prompt Completion

Problems of simple generation:

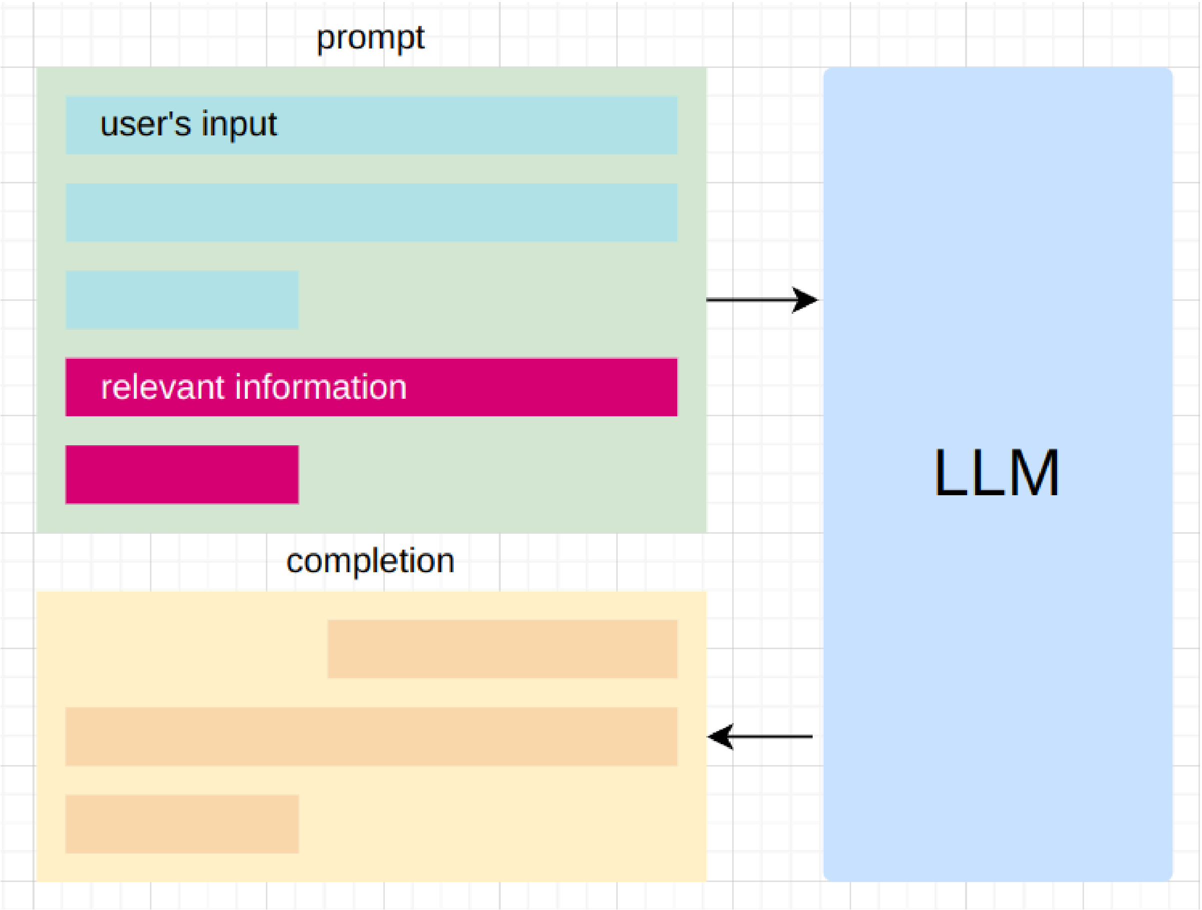
- hallucinations, missing references
- hard to update

Solution: **retrieval-augmented generation (RAG)**



Naive RAG

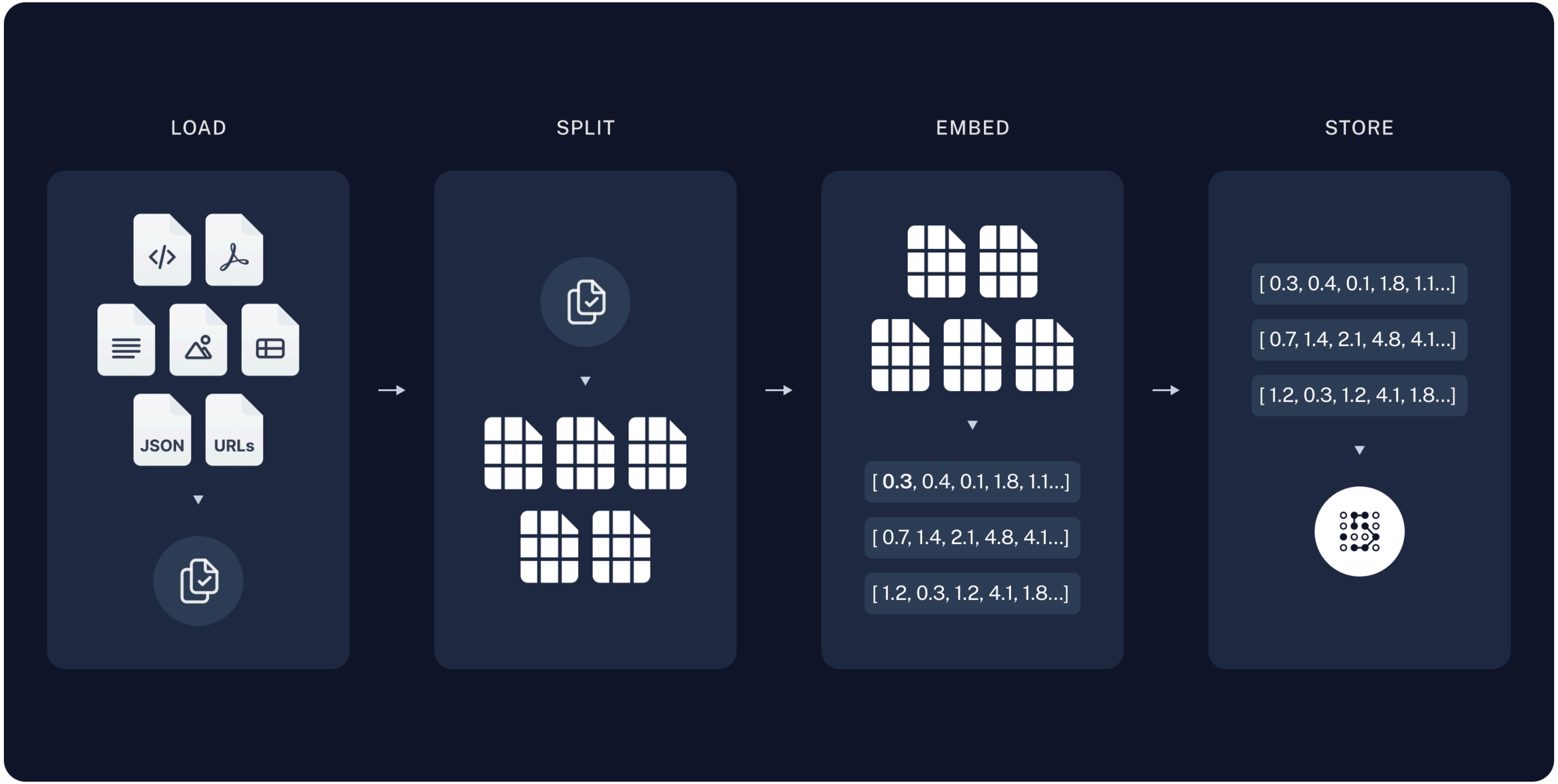
- retrieve documents relevant to query (user's input)
- insert top-k documents into prompt
- feed as prompt



Knowledge Stores

- web pages
- PDF, word, markdown (closed-book)
- wikipedia dump
- search engines

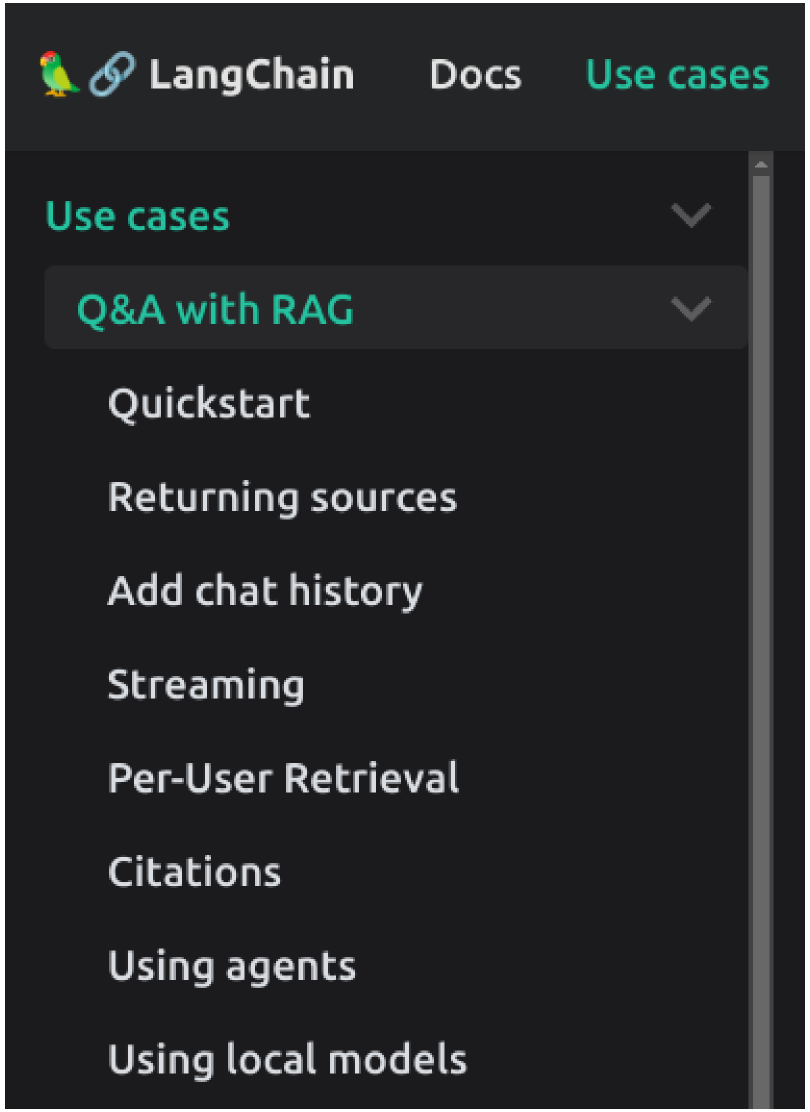
Implementation: LangChain



Implementation: LangChain

- choose SOTA LLM (Chatbot Arena)
- choose SOTA embedder (MTEB)

See also: LlamaIndex.

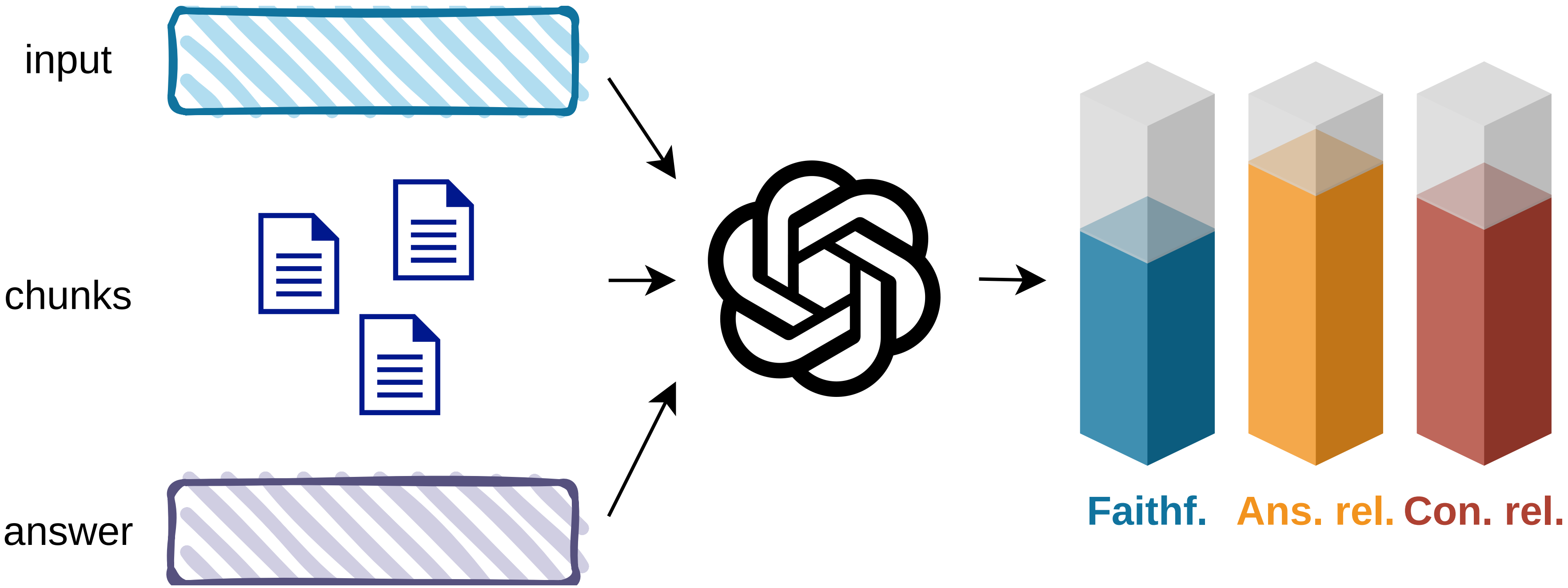


Evaluation

- Knowledge-intensive tasks
- RAG-specific benchmarks

RAGAs [Es et al., 2023]

Automated evaluation with LLM as assesor.



RAGAs [Es et al., 2023]

	Faith.	Ans. Rel.	Cont. Rel.
RAGAs	**0.95**	**0.78**	**0.70**
GPT Score	0.72	0.52	0.63
GPT Ranking	0.54	0.40	0.52

Table 1: Agreement with human annotators in pairwise comparisons of faithfulness, answer relevance and context relevance, using the WikEval dataset (accuracy).

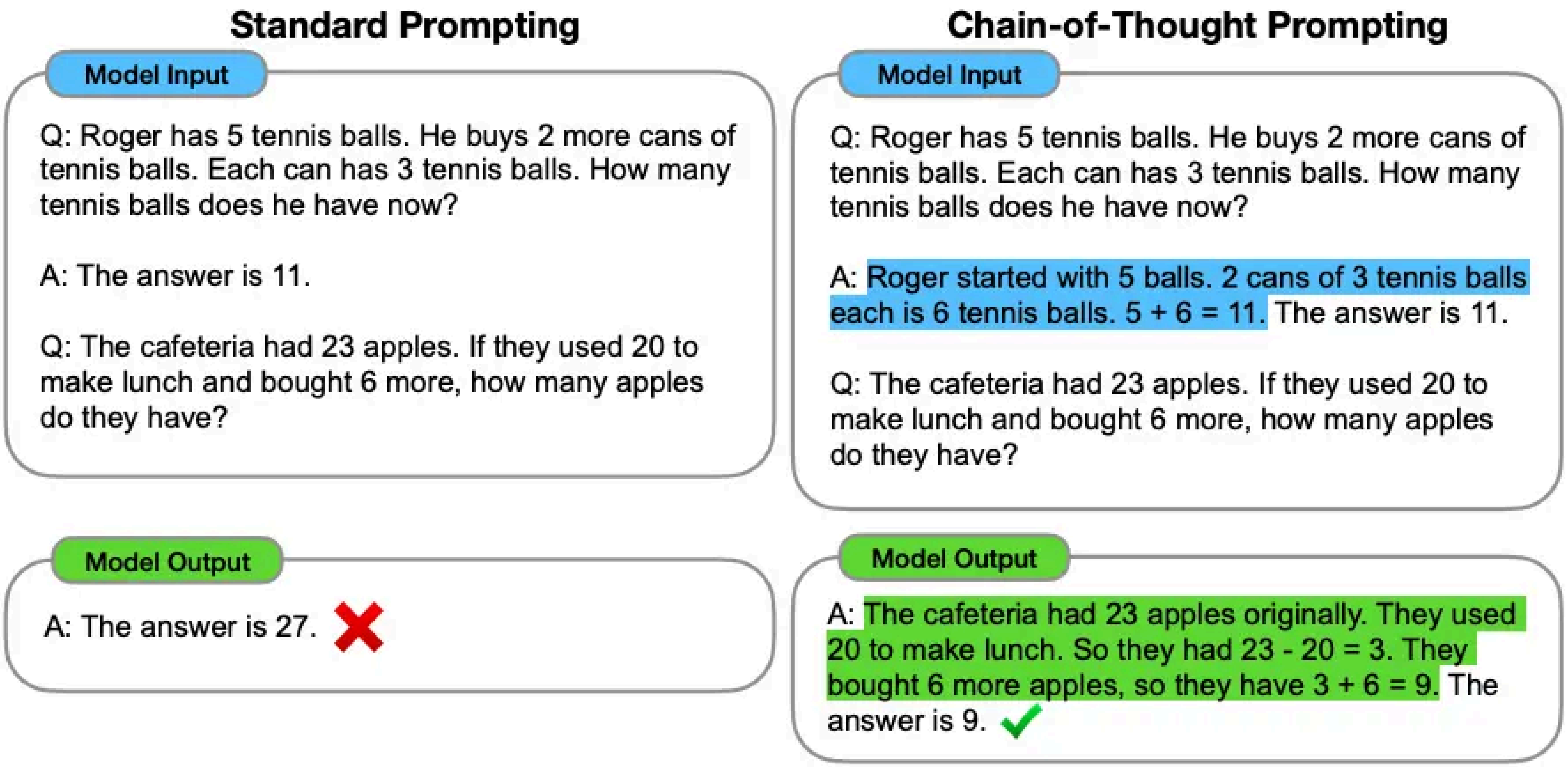
Improve Your RAG

- choose SOTA embedder and LLM according to public leaderboards
- prompting techniques
- train retriever and generator jointly

Prompting Techniques

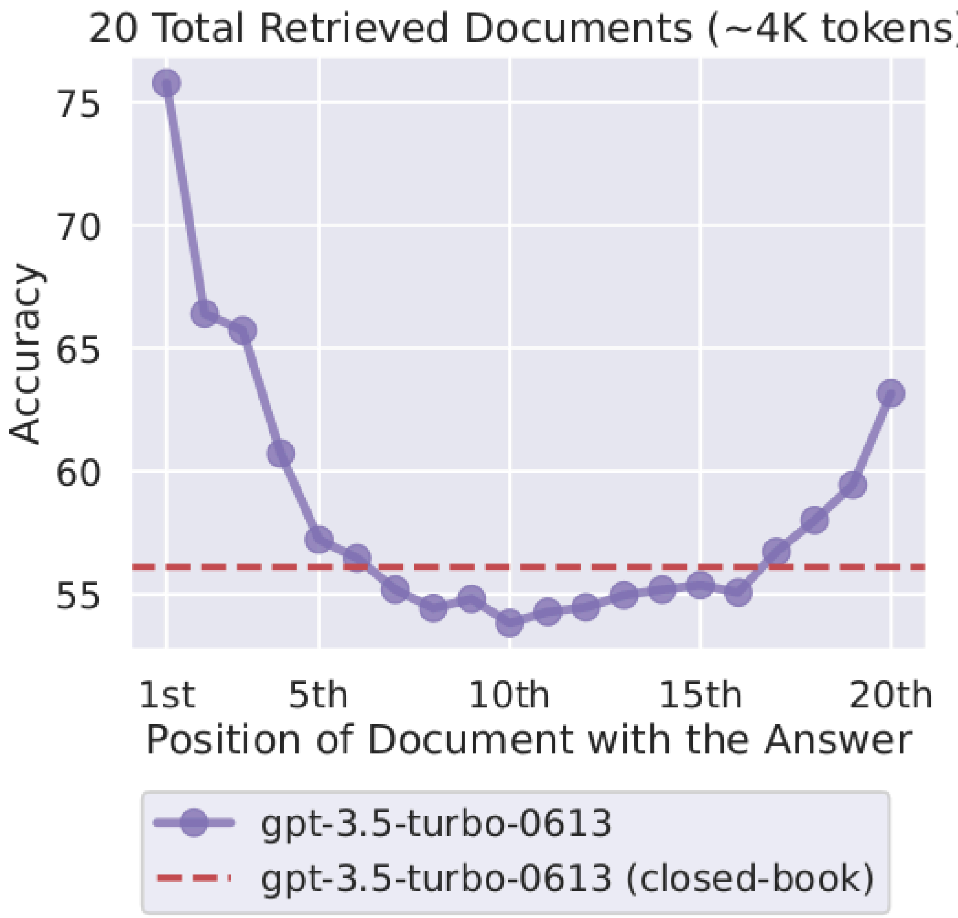
- query summarization / paraphrasing
- decompose into multiple questions (Chain-of-Thought)
- reranking chunks

Prompting Techniques: Chain-of-Thought



Prompting Techniques: Rerank Chunks

Lost in the middle [Liu et al., 2023]



Train Retriever and Generator Jointly

- RAG [Piktus et al., 2020], BART + DPR
- Hindsight [Paranjape et al., 2022], BART + Colbert
- Atlas [Izacard et al., 2022], T5 + Contriever
- Replug [Shi et al., 2023], GPT-3 + Contriever
- RA-DIT [Lin et al, 2023], Llama 2 + DRAGON

Meta AI almost everywhere!

RAG: Summary

- Introduction. Naive RAG
- Evaluation
- Improve RAG. Prompting Techniques
- Improve RAG. Retriever and LLM Joint Training