Denoising Dense Representations with Symbols for Robust Zero-Shot Retrieval

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Tutorial Timetable

1. Part 1: Knowledge Graphs and Entities
   1. Welcome & Latent Space Representations (Dietz)
   2. Knowledge Graphs and GPT (Bast)
   3. Entity Linking (Bast)
2. Part 2: Neuro-Symbolic Foundations
   1. Ranking Wikipedia Entities / Aspects (Chatterjee)
   2. Neural Text Representations and Semantic Annotations (Dietz)
   3. Infusion of Symbolic Knowledge into Text Representation (Nie)
3. Part 3: Reasoning, Robustness, and Relevance
   1. Denoising Dense Representations with Symbols (Nogueira) ← **We are here**
   2. Reasoning about Relevance (Dalton)
   3. From PRF to Retrieval Enhanced Generation (Dietz)
4. Part 4: Emerging Topics
   1. Conclusion and Outlook
   2. Panel Discussion

Agenda

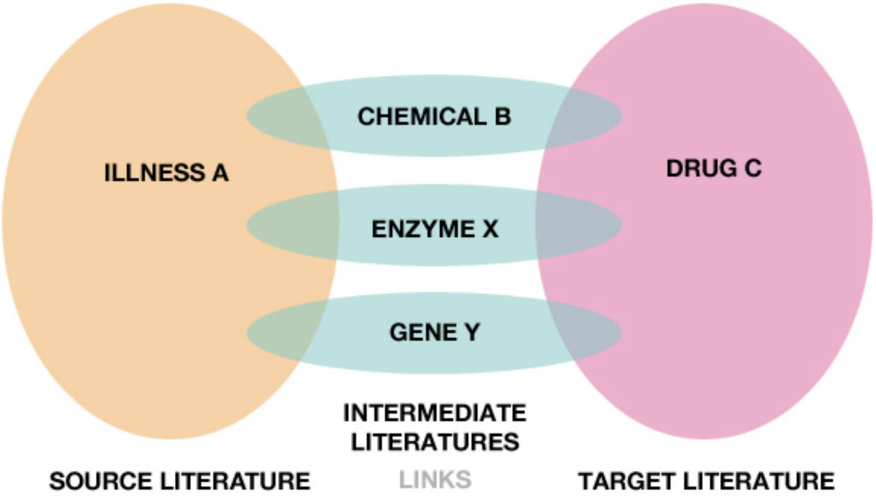
- The need for better search engines in the context of LLMs
- 3 ways of using transformers for search:
    - Dense Retrievers
    - Sparse Retrievers
    - Rerankers
- In-domain vs out-of-domain analysis

Why am I interested in information retrieval?

Automated **hypothesis generator** using **literature-based discovery**:

To connect pieces of knowledge previously thought to be unrelated

Example:
What are the best drugs for illness A?



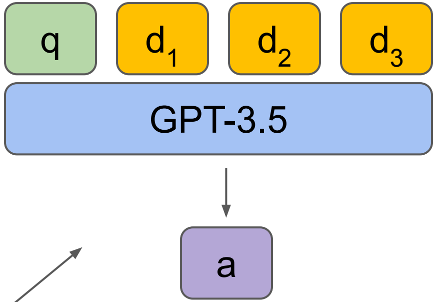
Swanson linking

Just ask GPT-4 to generate hypotheses?

Maybe, but it is yet to be shown that this works…

- LLM's can hardly remember facts about specialized domains, let alone connect them

Information given to LLMs needs to be carefully selected



A example from the IIRC dataset:

Wilhelm Müller was born on 7 October 1794 at **Dessau**, the son of a tailor. In 1813-1814 he took part, as a volunteer in the Prussian army, in the national rising against **Napoleon**. He participated in the battles of **Lützen**, **Bautzen**, **Hanau** and **Kulm**. In 1814 he returned to his studies at Berlin. Müller's son, **Friedrich Max Müller**, was an English orientalist who founded the comparative study of religions.

Which battle Wilhelm Müller fought in while in the Prussian army had the most casualties?

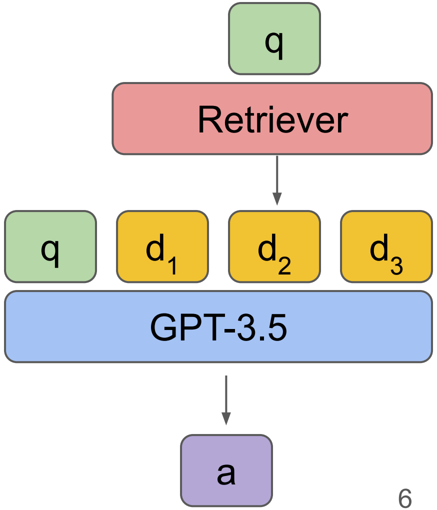
Battle of Lützen (1813)
Napoleon lost 19,655 men, while the Prussians lost 8,500 men and the Russians lost 3,500 men

Battle of Bautzen
Losses on both sides totaled around 20,000.

Battle of Hanau
Overall, 4,500 French soldiers and 9,000 allied soldiers were lost in the battle.

Battle of Kulm
The French lost more than half of the pursuing force of 34,000; The allies lost approximately 13,000 soldiers.

IIRC dataset	F1
Human	88.4
GPT-3.5 + Gold Evidence	84.2
GPT-3.5 + SOTA Retriever	50.6



[Visconde: Multi-document QA with GPT-3 and Neural Reranking, ECIR 2023]

Just train retrievers on more data?

- Many interesting problems do not have labelled datasets
- We need robust zero-shot retrievers!

A Simple Search Engine

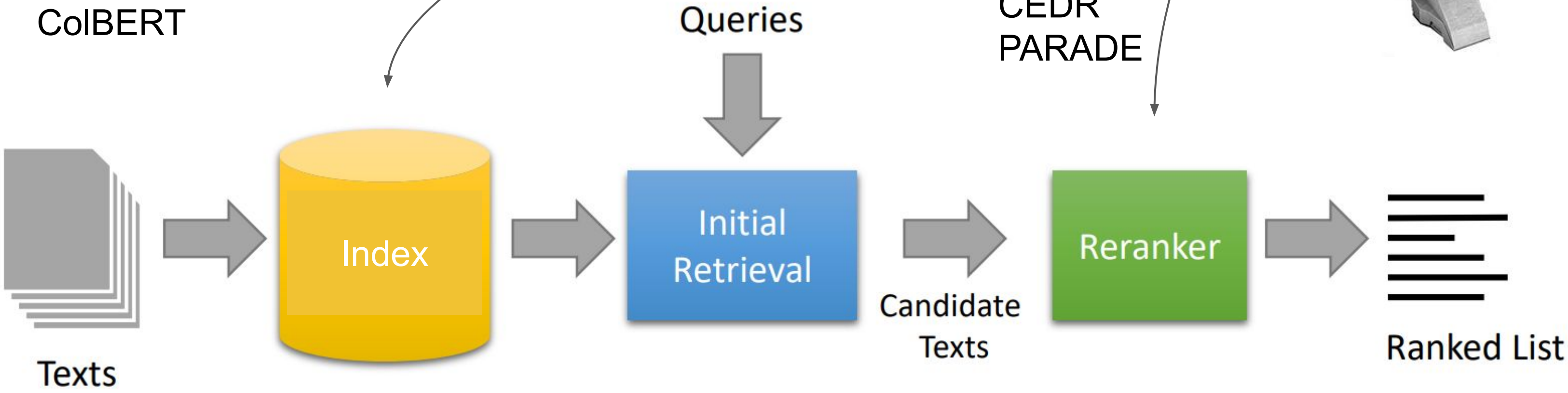
Where to use a Pretrained Transformer Model?

Dense:
DPR
ANCE
TAS-B
COIL
ColBERT

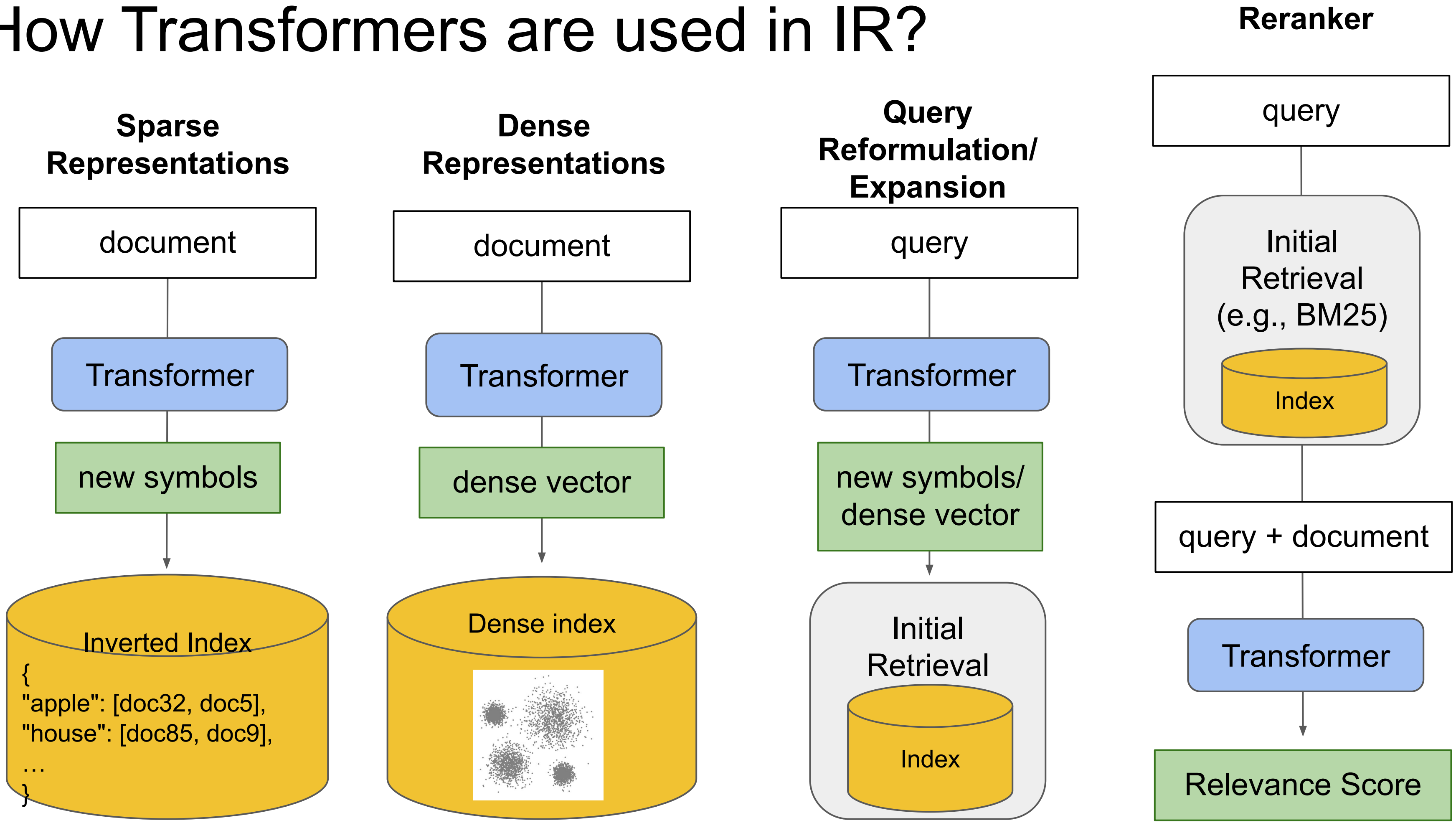
Sparse:
DeepCT
doc2query
DeepImpact
SPLADE

BERT-QE
CEQE
SQET

monoBERT
monoT5
duoT5
CEDR
PARADE

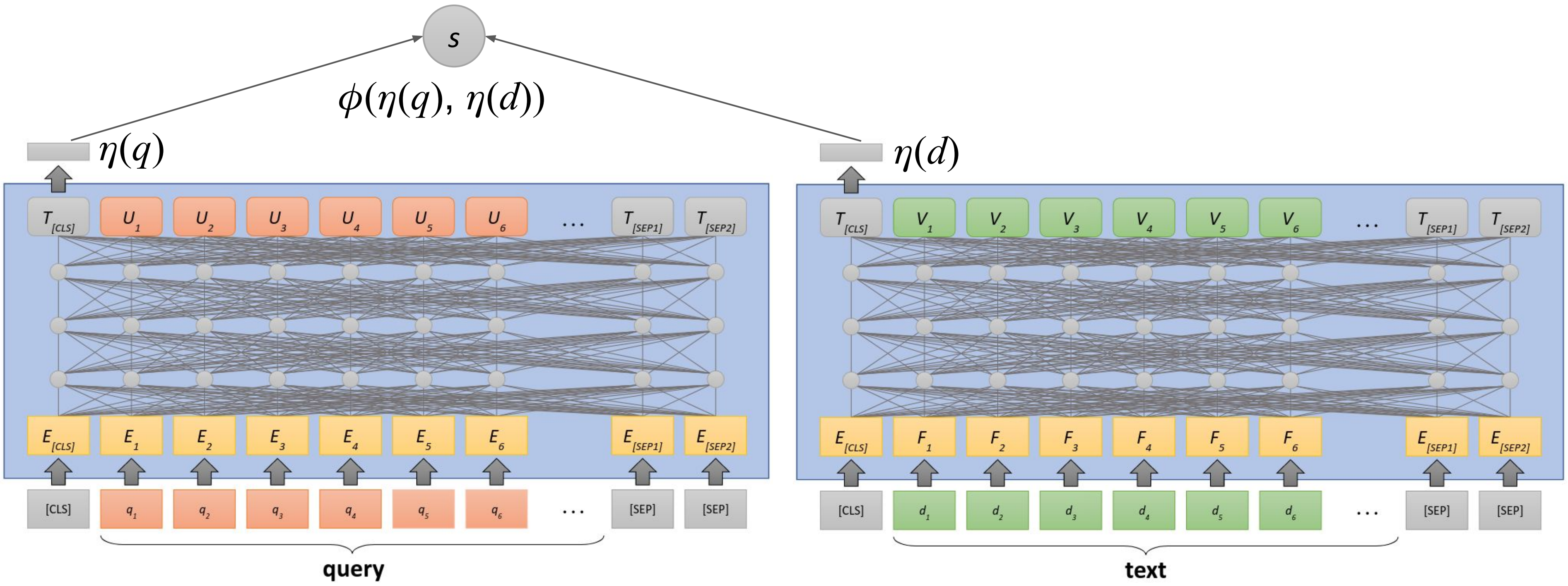


How Transformers are used in IR?



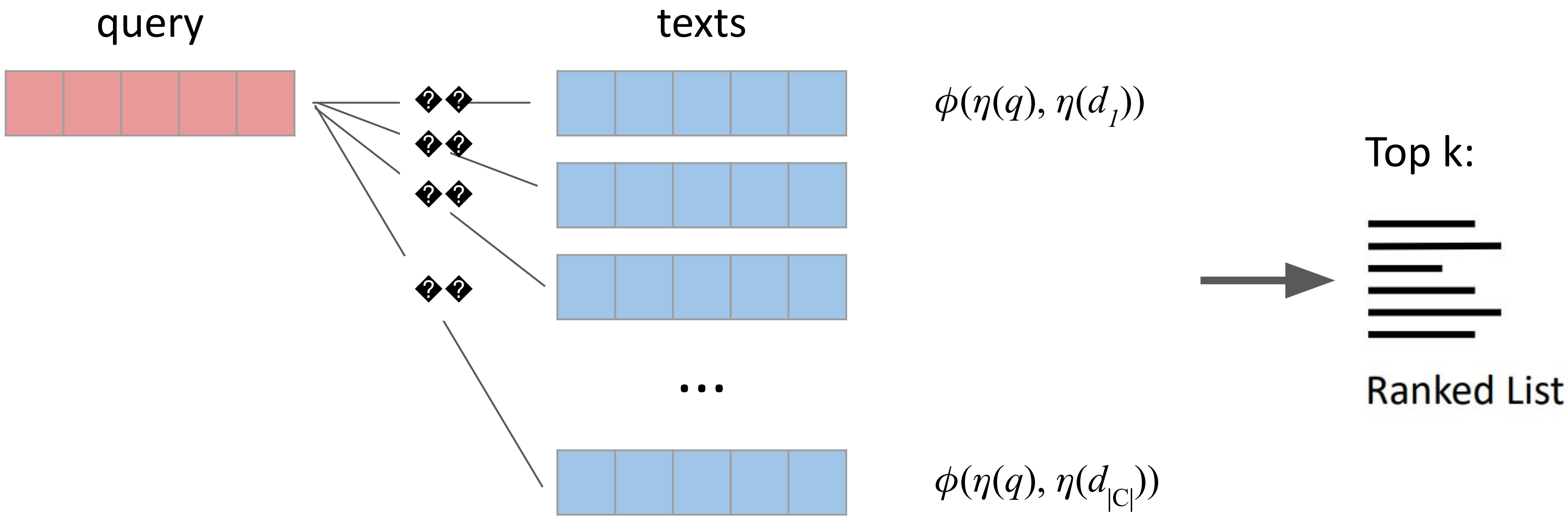
Dense representations

Single-vector dense retriever based on BERT



Retrieval: Find the top k most relevant texts to a query

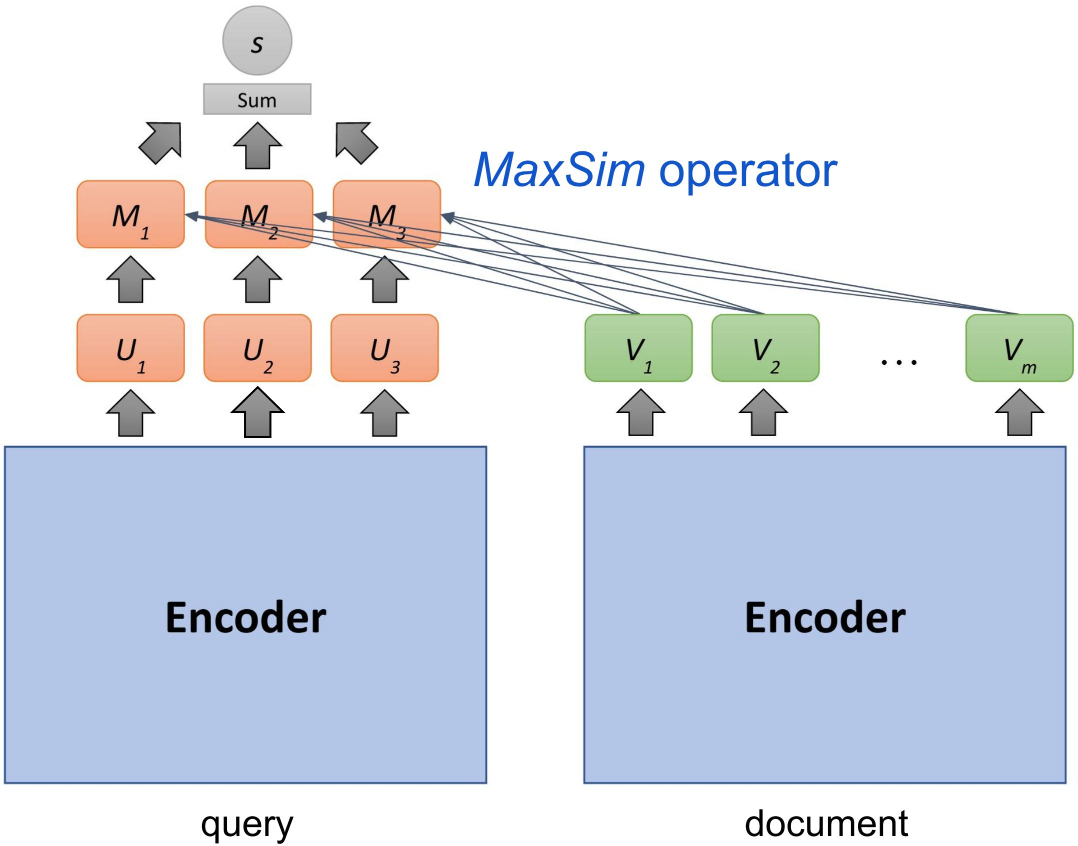
Brute-force search:



We often need to search many (e.g.: millions) of texts

- Brute-force won't scale

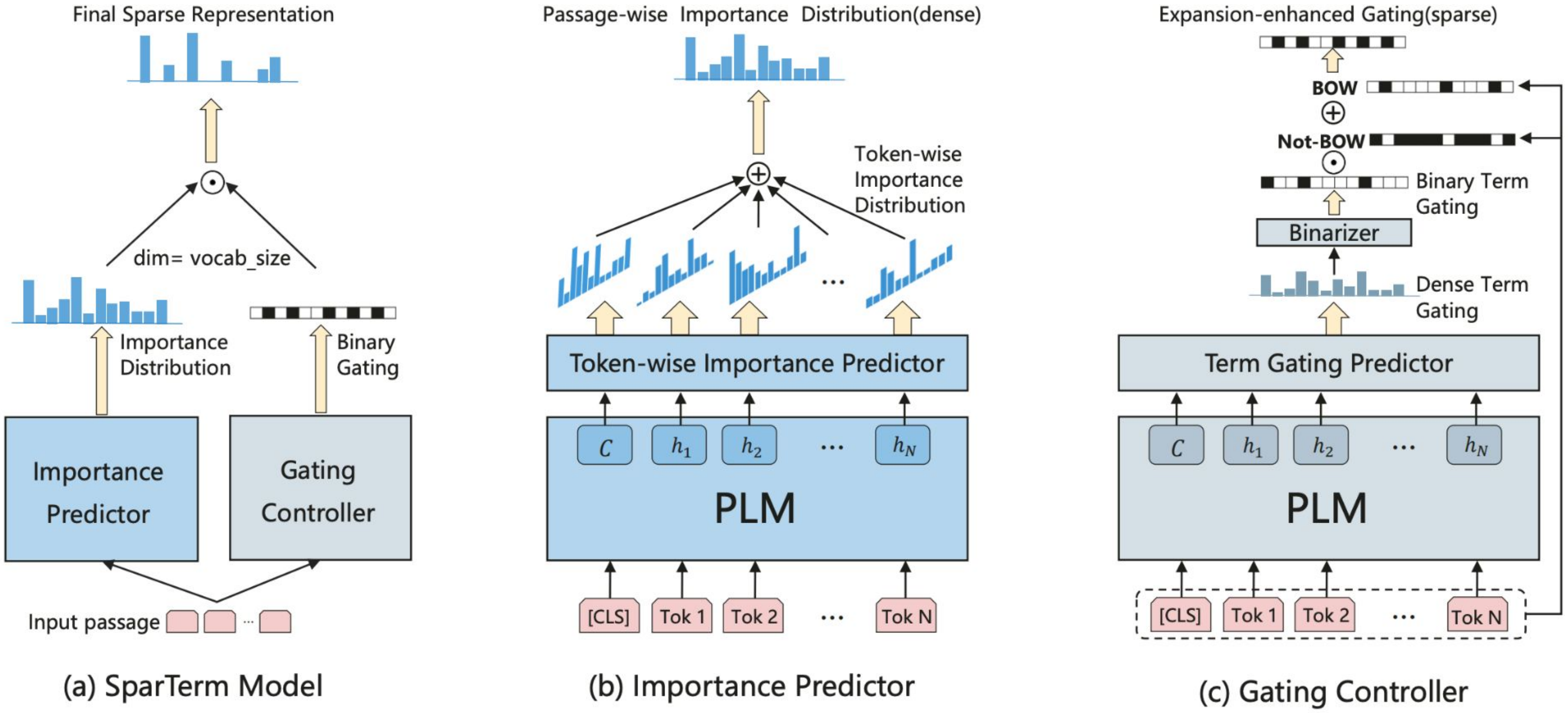
Multi-vector Dense Retriever: ColBERT



Khattab, Zaharia. ColBERT: Efficient and Effective Passage Search via Contextualized Late Interaction over BERT. SIGIR 2020.

Sparse representations

Learned Sparse Representations: SparTerm



Source: [SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval]

SPLADE: Learned Sparse Representations

State-of-art retriever on BEIR *without* a reranker

|embedding| = vocabulary size

log(1 + ReLU(logits) ensures sparsity (i.e., most elements are zeros)

Can be used with existing inverted index infrastructure (e.g., Lucene)

Training loss:

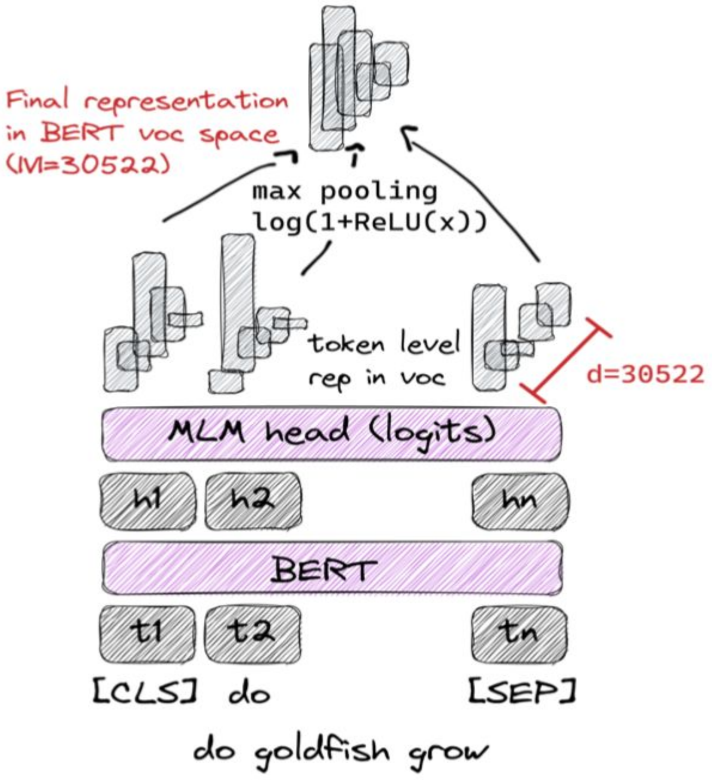
$$\mathcal{L} = \mathcal{L}_{rank-IBN} + \lambda_q \mathcal{L}^q_{\text{reg}} + \lambda_d \mathcal{L}^d_{\text{reg}}$$

$$\mathcal{L}_{rank-IBN} = -\log \frac{e^{s(q_i,d_i^+)}}{e^{s(q_i,d_i^+)} + e^{s(q_i,d_i^-)} + \sum_j e^{s(q_i,d_{i,j}^-)}}$$

high score for relevant query-doc pairs

$$\ell_{\text{FLOPS}} = \sum_{j \in V} \bar{a}_j^2 = \sum_{j \in V} \left(\frac{1}{N} \sum_{i=1}^{N} w_j^{(d_i)} \right)^2$$

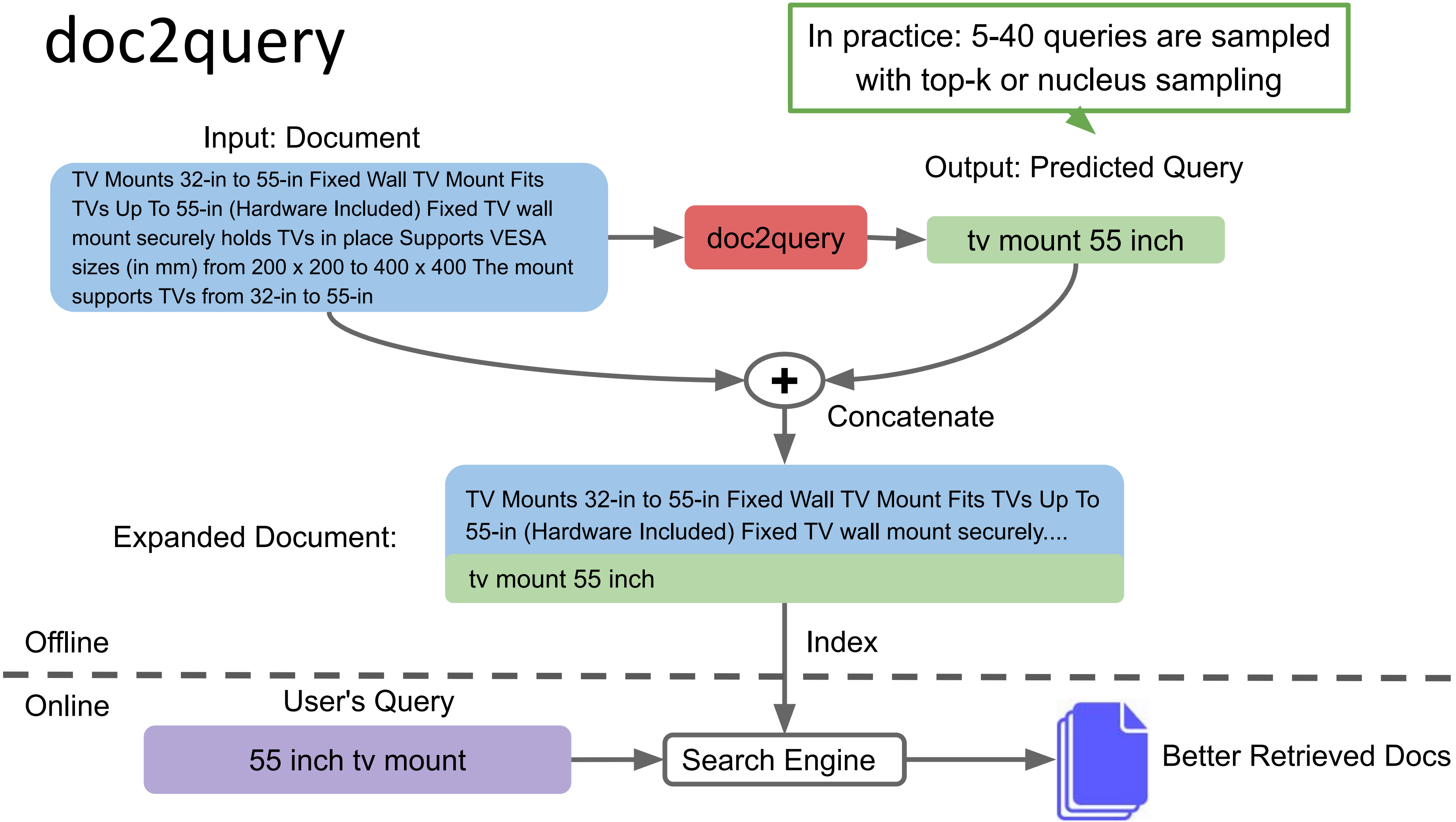
ensures low term weights



Formal et al. 2021

Augmenting Sparse Representations with doc2query

doc2query


In practice: 5-40 queries are sampled with top-k or nucleus sampling
Input: Document
TV Mounts 32-in to 55-in Fixed Wall TV Mount Fits TVs Up To 55-in (Hardware Included) Fixed TV wall mount securely holds TVs in place Supports VESA sizes (in mm) from 200 x 200 to 400 x 400 The mount supports TVs from 32-in to 55-in
doc2query
Output: Predicted Query
tv mount 55 inch
+
Concatenate
Expanded Document:
TV Mounts 32-in to 55-in Fixed Wall TV Mount Fits TVs Up To 55-in (Hardware Included) Fixed TV wall mount securely....
tv mount 55 inch
Offline
Index
Online
User's Query
55 inch tv mount
Search Engine
Better Retrieved Docs

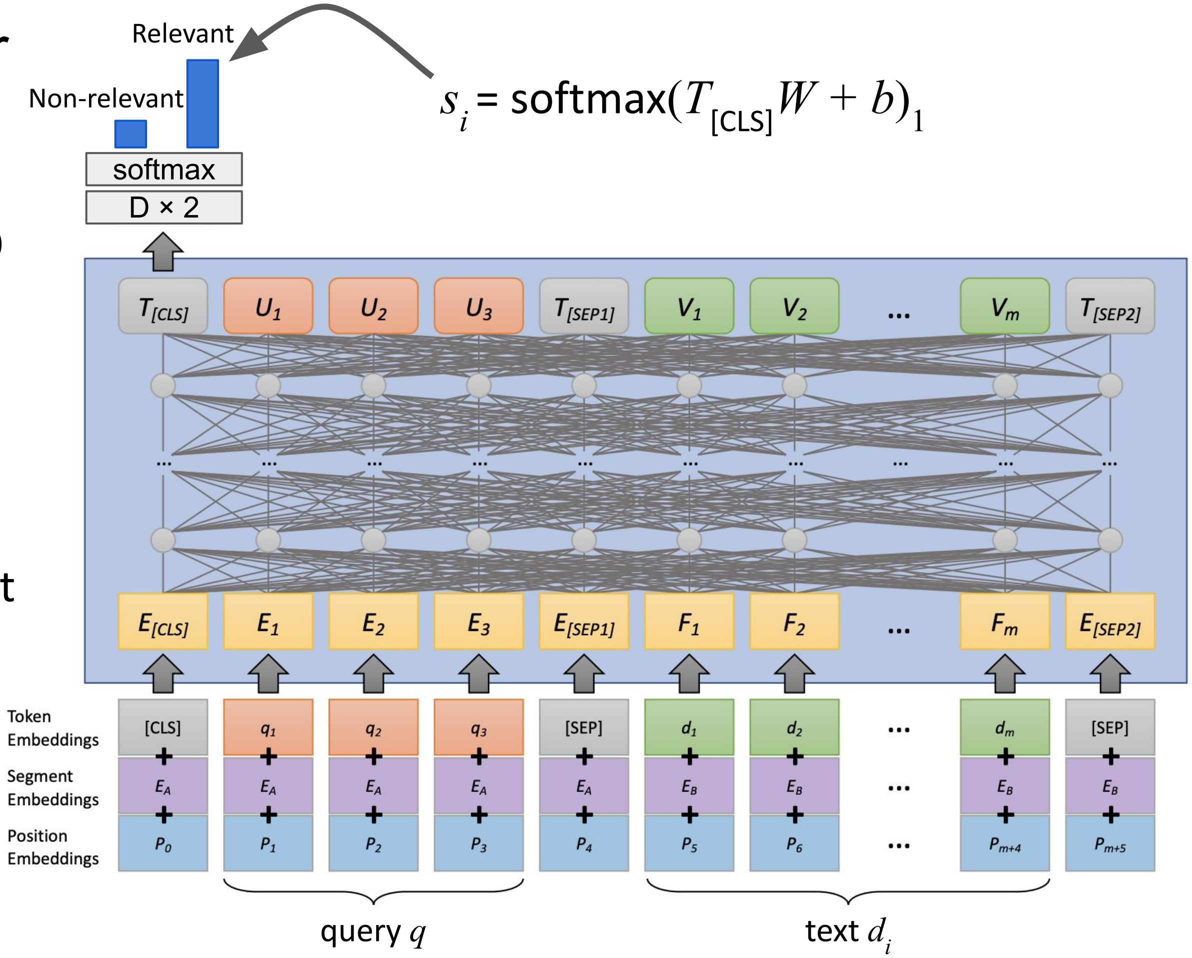
Rerankers

monoBERT:
BERT as a reranker

We want:

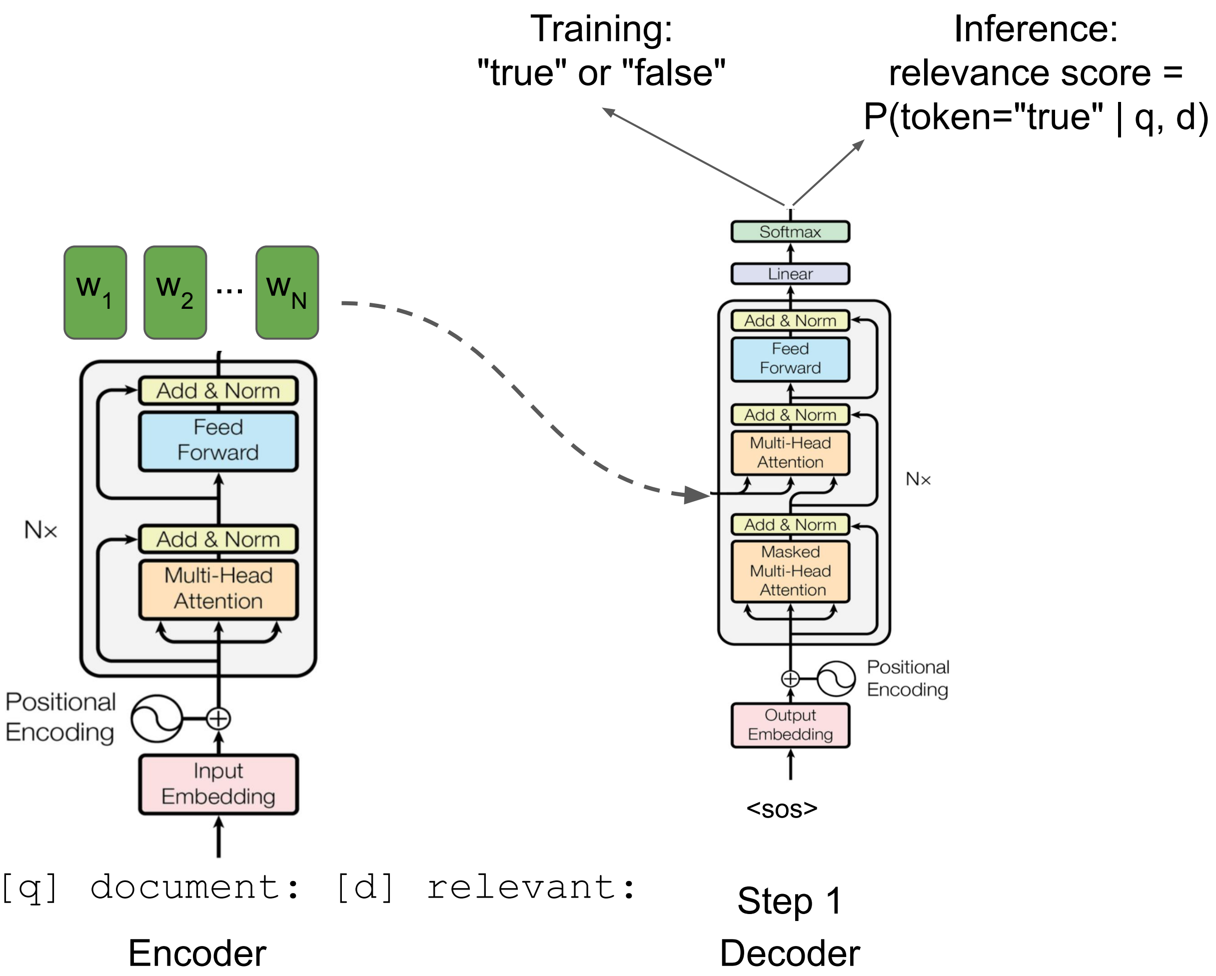
$s_i = P(\text{Relevant} = 1|q, d_i)$

A binary classifier finetuned on pairs of <query, relevant text> and <query, non-relevant text>



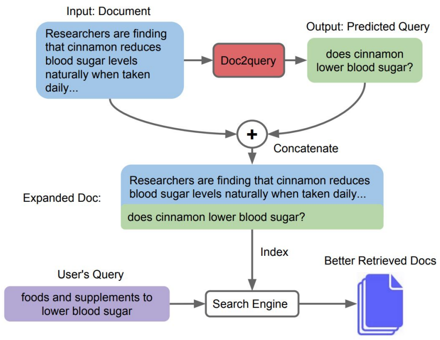
monoT5:
T5 as a reranker

Why use a sequence-to-sequence model if we don't need to generate text?

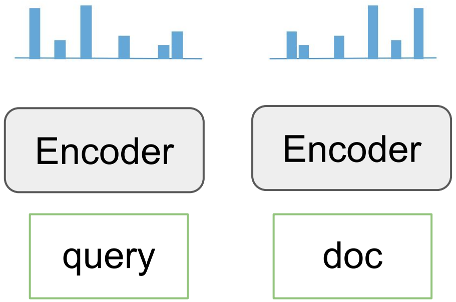


[Nogueira et al.,. "Document Ranking with a Pretrained Sequence-to-Sequence Model", 2020](#)

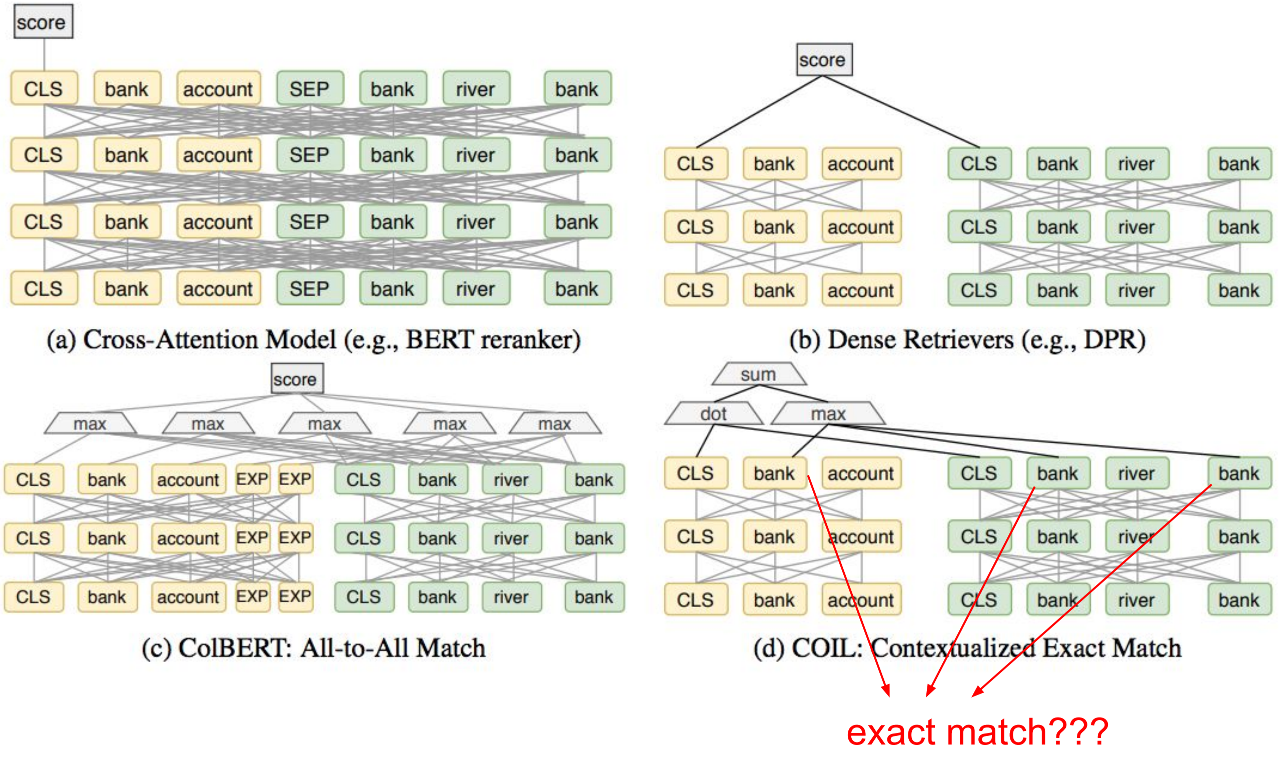
In summary



Document expansion (doc2query)



Learned Sparse (e.g., SPLADE)



Sources: Gao et al., "COIL: Revisit Exact Lexical Match in Information Retrieval with Contextualized Inverted List", 2021
Formal et al., "SPLADE: Sparse lexical and expansion model for first stage ranking", 2021
Nogueira et al., "Document expansion by query prediction", 2019

Which is better in in-domain vs out-of-domain?

What is in-domain vs out-domain?

It is a subjective definition!

In Domain:

- Training and test examples (queries/documents) are from the same domain (e.g., finance)

Out-of-domain:

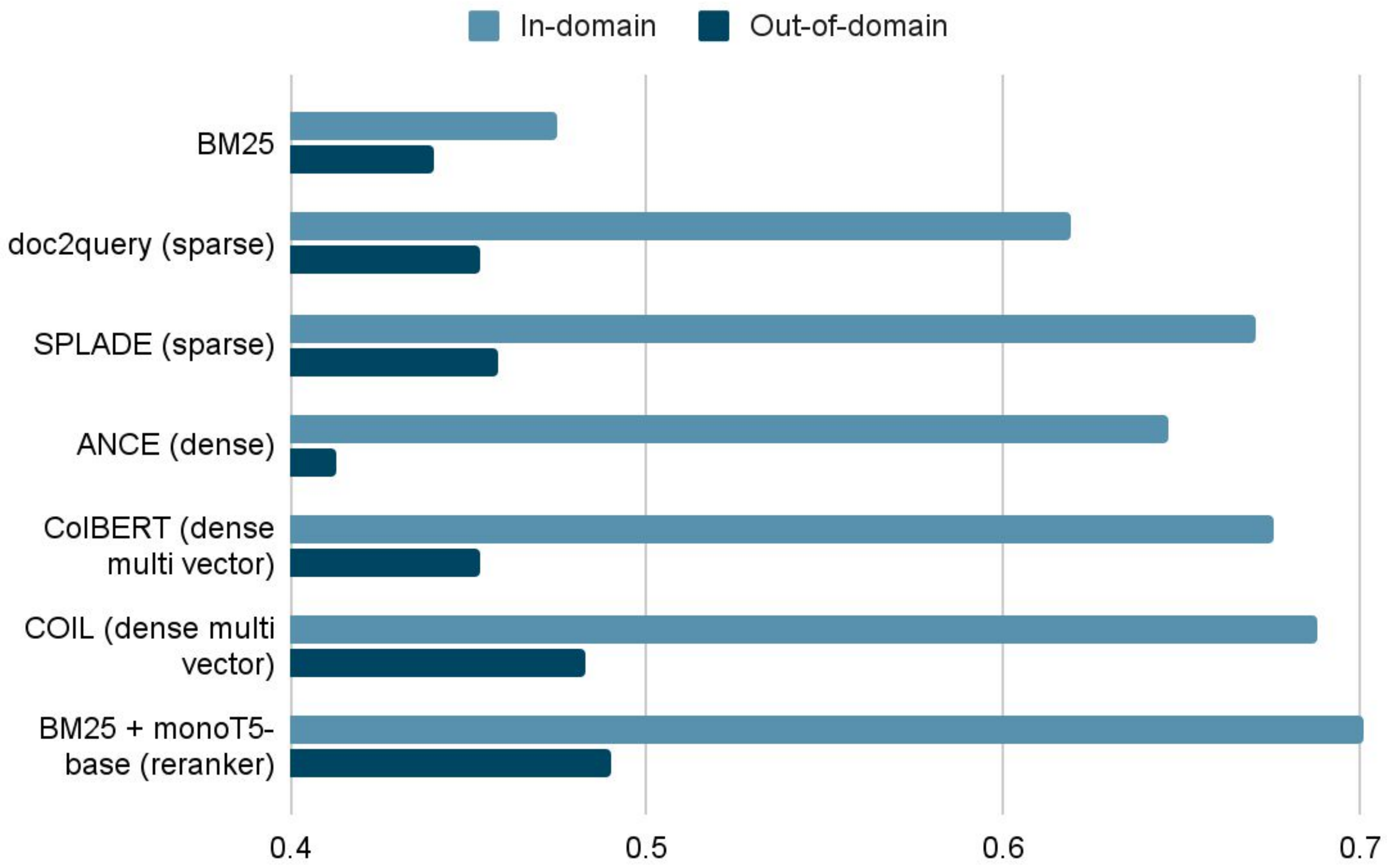
- Training and test examples (queries/documents) are from different domains (e.g., finance vs biomedicine)

In-domain vs Out-of-domain

No distillation (e.g., Splade v2, ColBERT v2)
No IR-specific pretraining (e.g. CoCondenser, Contriever)
No larger training dataset (e.g., GTR, E5)

Method	nDCG@10 In-domain TREC-DL 20	nDCG@10 Out-of-domain BEIR
BM25	0.475	0.440
doc2query (sparse)	0.619	0.453
SPLADE (sparse)	0.671	0.458
ANCE (dense)	0.646	0.413
ColBERT (dense multi vector)	0.676	0.453
COIL (dense multi vector)	0.688	0.483
BM25 + monoT5-base (reranker)	0.701	0.490

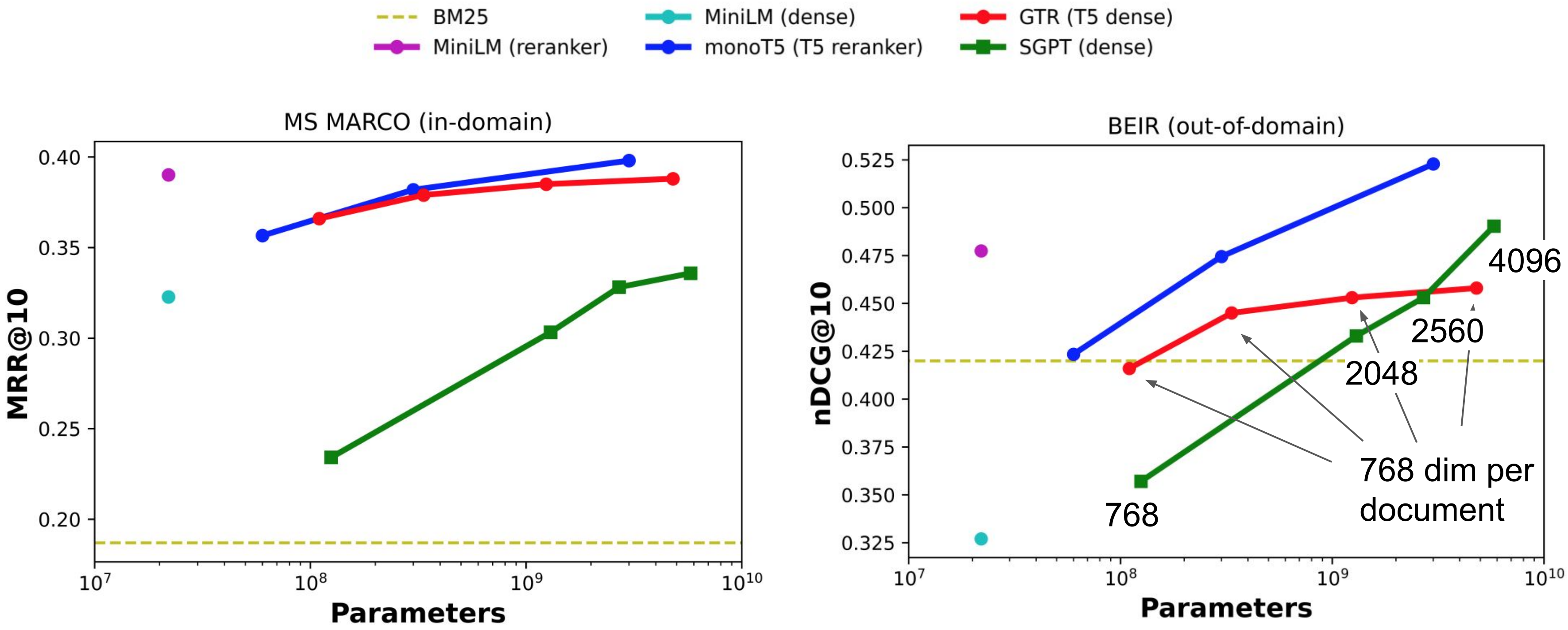
Source: [Lin SC, Lin J., "A Dense Representation Framework for Lexical and Semantic Matching", 2022]



In-domain
Out-of-domain
BM25
doc2query (sparse)
SPLADE (sparse)
ANCE (dense)
ColBERT (dense multi vector)
COIL (dense multi vector)
BM25 + monoT5-base (reranker)
0.4
0.5
0.6
0.7

2022

Scaling up model size



GTR is from Ni et al., "Large Dual Encoders Are Generalizable Retrievers", 2021
SGPT is from Muennighoff, "SGPT: GPT Sentence Embeddings for Semantic Search", 2022
Charts from Rosa et al., "No Parameter Left Behind: How Distillation and Model Size Affect Zero-Shot Retrieval", 2022

Conclusions

- Retrieval method: No clear winner if you have lots of query-relevant passages to train on;
- Fine-grained representations (i.e., symbols) are key for OOD effectiveness;
- Rerankers seem to have better OOD effectiveness than dense retrievers