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

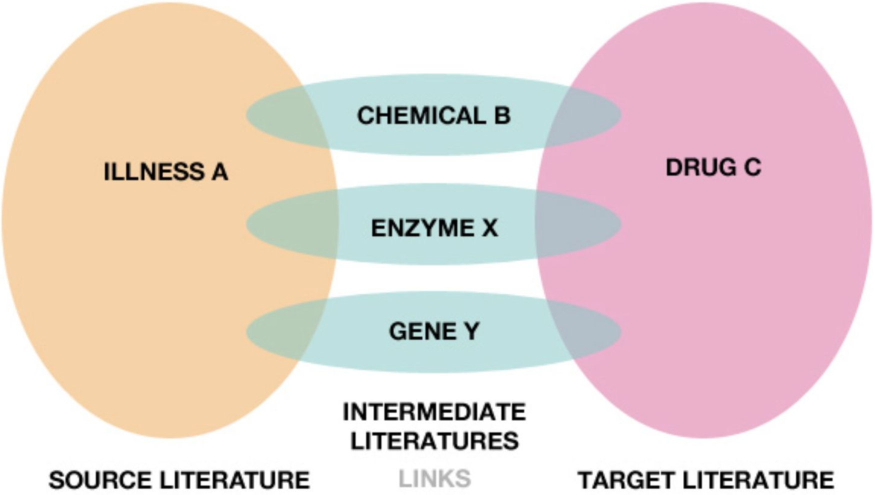
- Motivation: The need for better search engines in the context of LLMs
- 3 ways of using Transformers for search:
    - Dense Retrievers
    - Sparse Retrievers
    - Rerankers
- In-domain vs out-of-domain analysis
- Scaling up model size

Why am I interested in information retrieval?

To connect pieces of knowledge previously thought to be unrelated

E.g., to build an automated **hypothesis generator** using **literature-based discovery**

Example:
What are the best drugs for illness A?



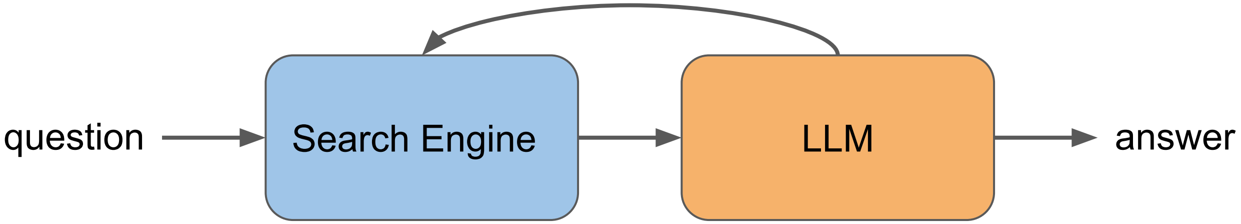
[Swanson linking]

Just ask GPT-4 to generate hypotheses?

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

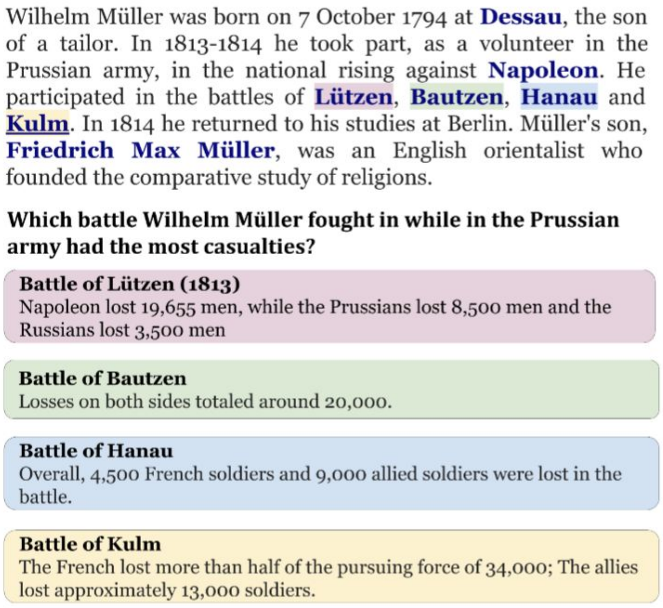
- Current LLM's can hardly remember facts about long-tail topics, let alone connect them

For now, we need to use a search engine to give a LLM the necessary information to link pieces of knowledge



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?

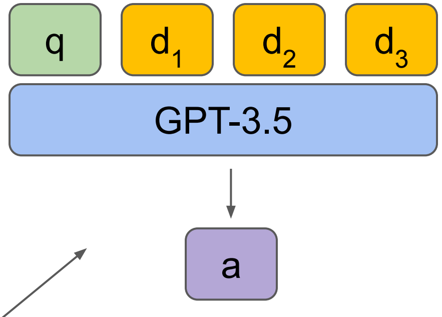
Battle of Lützen (1813)
Napoleon lost 19,655 men, while the Prussians lost 8,500 men and the Russians lost 3,500 men

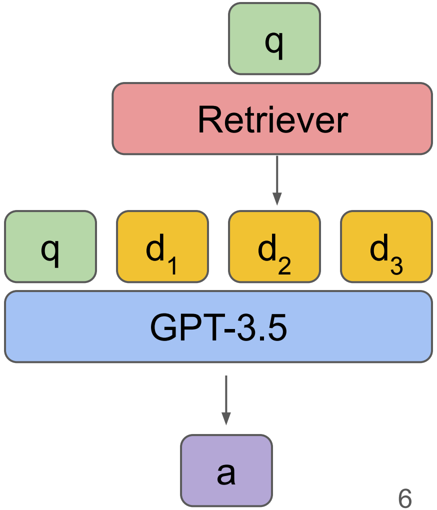
Battle of Bautzen
Losses on both sides totaled around 20,000.

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





Pereira et al., 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
  - Ex: domain-specific tasks, long-tail knowledge
- We need robust zero-shot retrievers!

A Simple Search Engine

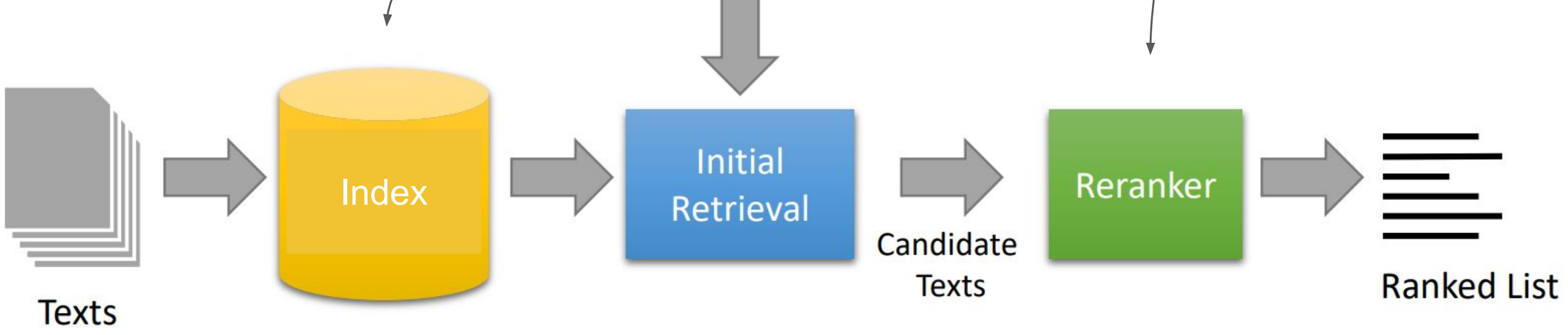
Where to use a Pretrained Transformer Model?

Dense:
DPR
ANCE
TAS-B
COIL
ColBERT

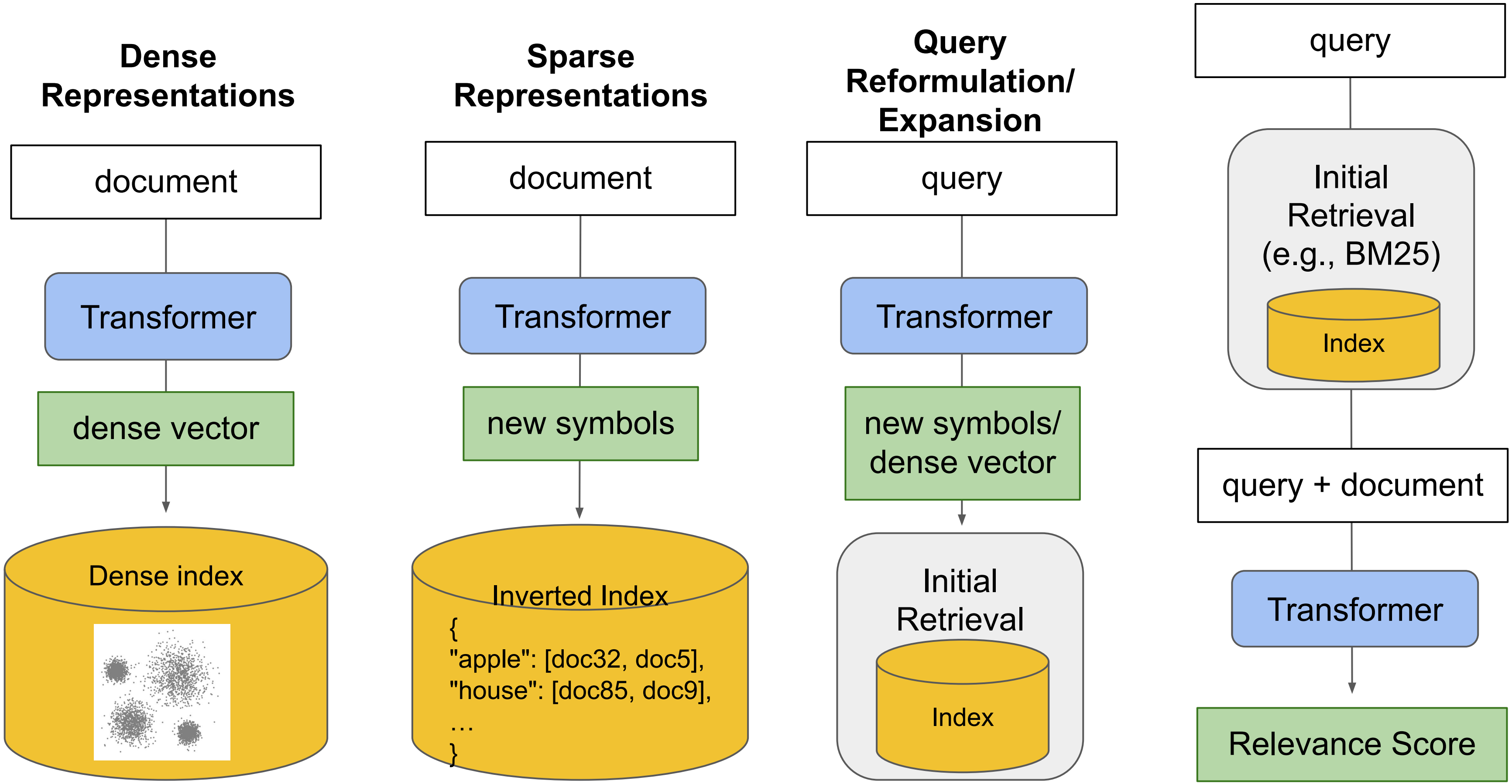
Sparse:
DeepCT
doc2query
DeepImpact
SPLADE

BERT-QE
CEQE
SQET

monoBERT
monoT5
duoT5
CEDR
PARADE



How Transformers are used in IR?



Dense Representations

document

Transformer

dense vector

Dense index

Sparse Representations

document

Transformer

new symbols

Inverted Index

```
{
"apple": [doc32, doc5],
"house": [doc85, doc9],
…
}
```

Query Reformulation/ Expansion

query

Transformer

new symbols/ dense vector

Initial Retrieval

Index

Reranker

query

Initial Retrieval (e.g., BM25)

Index

query + document

Transformer

Relevance Score

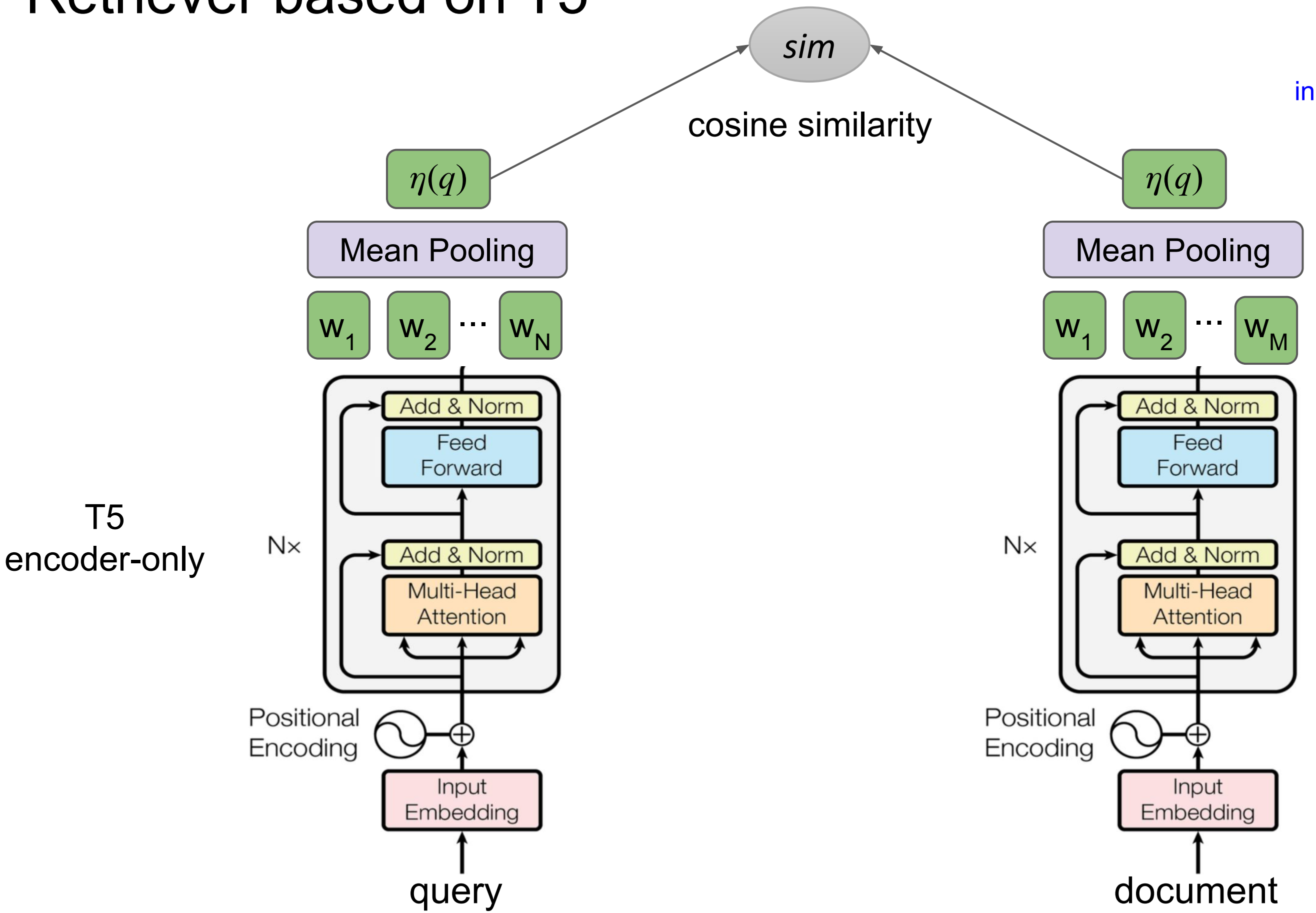
Dense representations

GTR: Single-vector Dense Retriever based on T5

$$\text{Loss} = \frac{e^{\mathrm{sim}(q_i,p_i^+)/\tau}}{\sum_{j\in\mathcal{B}} e^{\mathrm{sim}(q_i,p_j^+)/\tau} + e^{\mathrm{sim}(q_i,p_j^-)/\tau}}$$

in-batch negatives

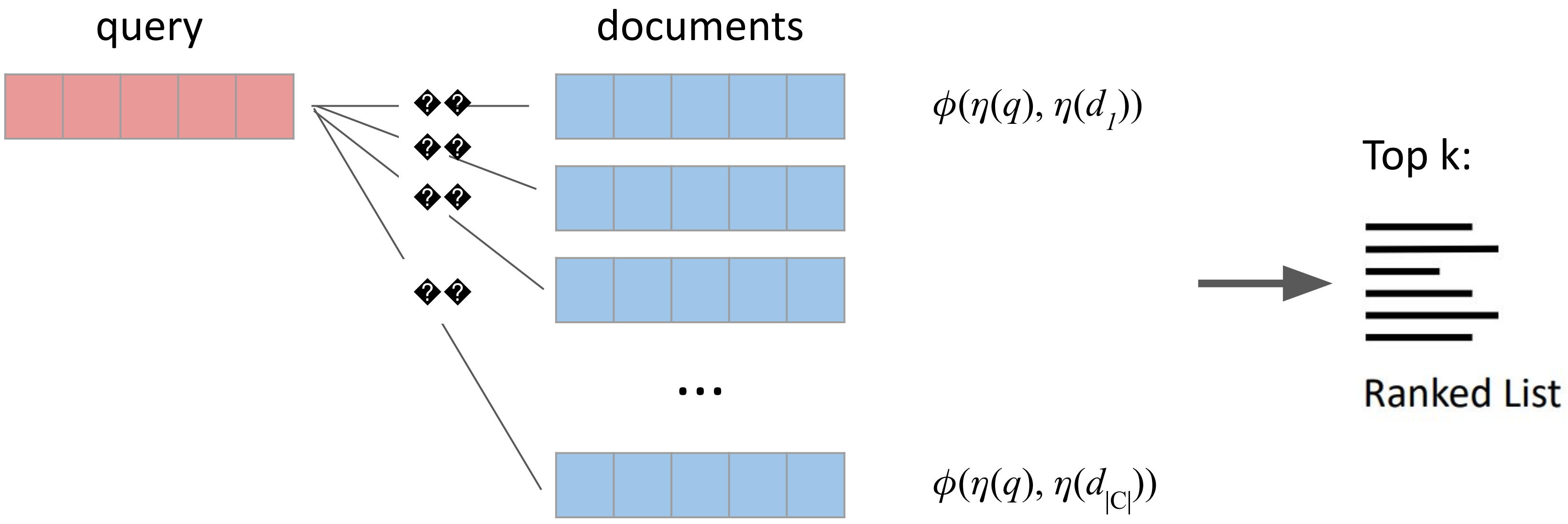
negatives from other retrievers



Ni et al., "Large Dual Encoders Are Generalizable Retrievers", ENMLP 2022

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

Brute-force search:



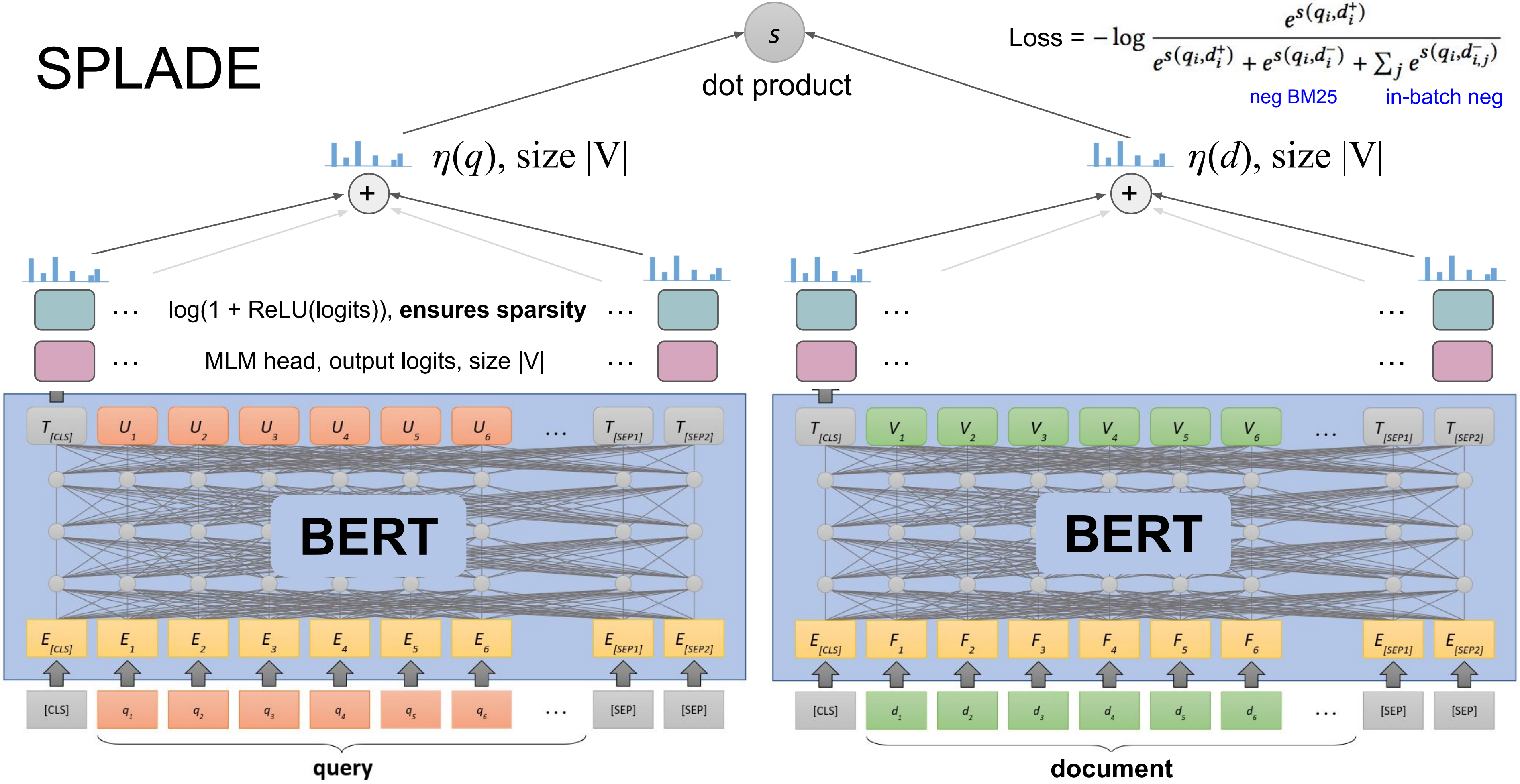
We often need to search many (e.g.: millions) of documents

- Brute-force won't scale, Approximate Nearest Neighbor methods are commonly used

Learned Sparse Representations

SPLADE

$$\text{Loss} = -\log \frac{e^{s(q_i,d_i^+)}}{e^{s(q_i,d_i^+)} + \underbrace{e^{s(q_i,d_i^-)}}_{\text{neg BM25}} + \underbrace{\sum_j e^{s(q_i,d_{i,j}^-)}}_{\text{in-batch neg}}}$$



s

dot product

$\eta(q)$, size |V|

$\eta(d)$, size |V|

log(1 + ReLU(logits)), **ensures sparsity**

MLM head, output logits, size |V|

query

document

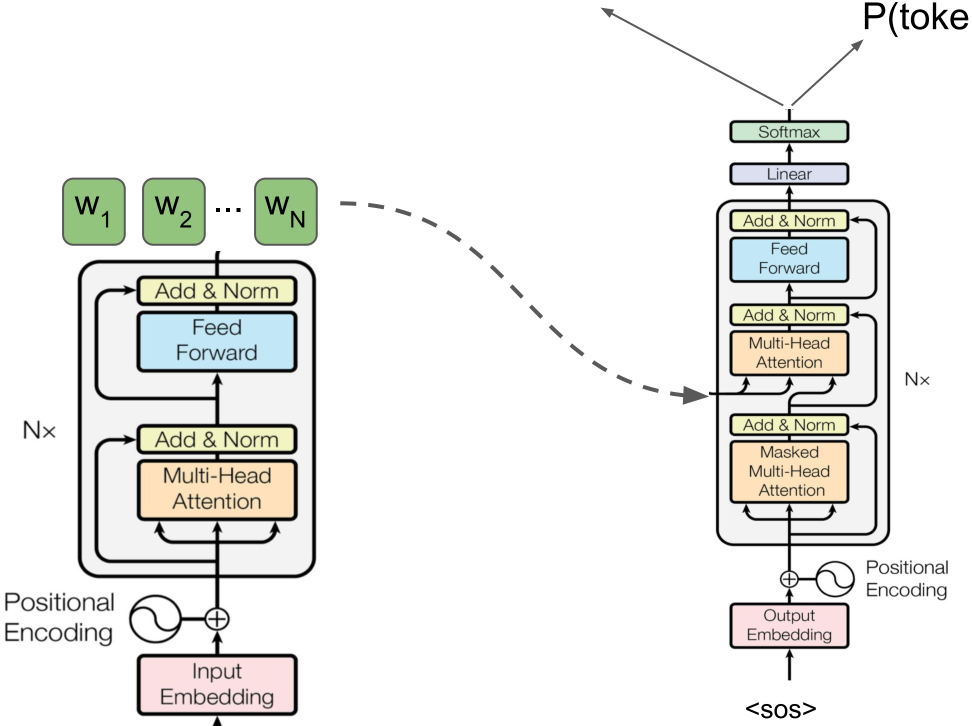
Formal et al. SPLADE: Sparse Lexical and Expansion Model for First Stage Ranking, 2021

Rerankers

monoT5:
T5 as a reranker

Training:
"true" or "false"

Inference:
relevance score =
P(token="true" | q, d)



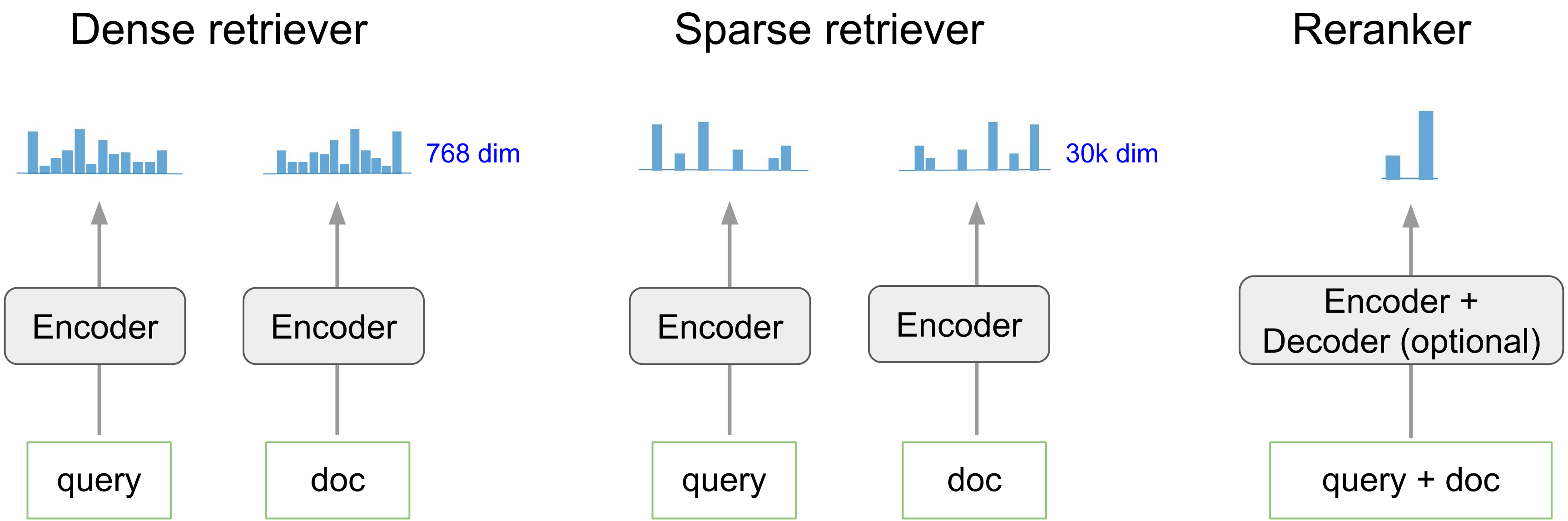
`query: {q} document: {d} relevant:`

Encoder

Step 1
Decoder

[Nogueira et al., "Document Ranking with a Pretrained Sequence-to-Sequence Model", Findings of EMNLP 2020]

In summary



Dense retriever

768 dim

Encoder

Encoder

query

doc

Sparse retriever

30k dim

Encoder

Encoder

query

doc

Reranker

Encoder + Decoder (optional)

query + doc

Which is better in in-domain and out-of-domain IR tasks?

What is in-domain and out-of-domain?

It is a subjective definition

"In-domain" refers to queries and documents used in evaluation being from the same domain as training examples

"Out-of-domain" refers to training and test examples being from different domains (e.g., train on finance examples and evaluate on biomedicine examples)

In-domain vs Out-of-domain

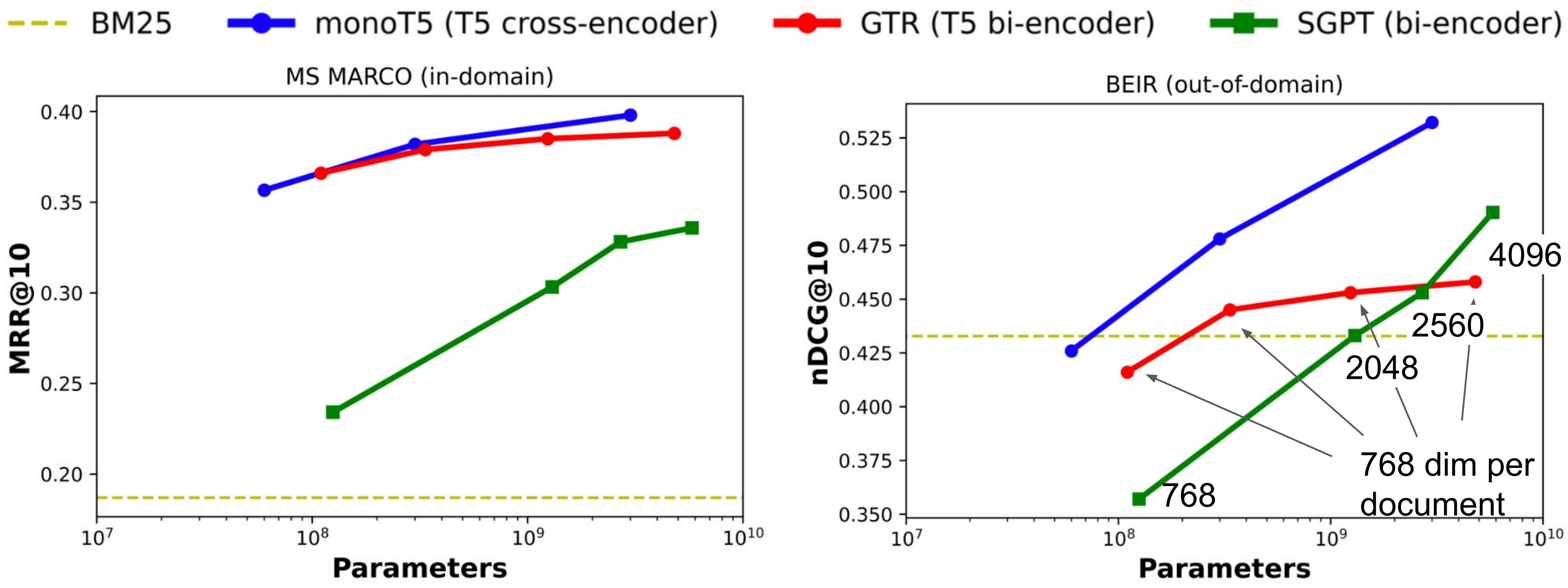
No distillation (e.g., Splade v2, ColBERT v2)
No IR-specific pretraining (e.g. CoCondenser, Contriever)

	nDCG@10	
Method	**In-domain TREC-DL 20**	**Out-of-domain BEIR (18 datasets)**
BM25	0.475	0.440
SPLADE (sparse)	0.671	0.458
GTR-base (T5 dense)	0.696	0.430
BM25 + monoT5-base (T5 reranker)	0.701	0.478

Models were trained on MS MARCO
(same distribution of TREC-DL 2020)

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

Scaling up model size



4096

2560

2048

768

768 dim per document

SGPT is from Muennighoff, "SGPT: GPT Sentence Embeddings for Semantic Search", 2022
Charts from Rosa et al., "In Defense of Cross-Encoders for 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 out-of-domain effectiveness;
- Cross-encoders in the form of rerankers show better OOD effectiveness than bi-encoders in the form of dense retrievers
- In fact, "simple" BM25 + monoT5-3B is close to SOTA on BEIR and "won" many other competitions

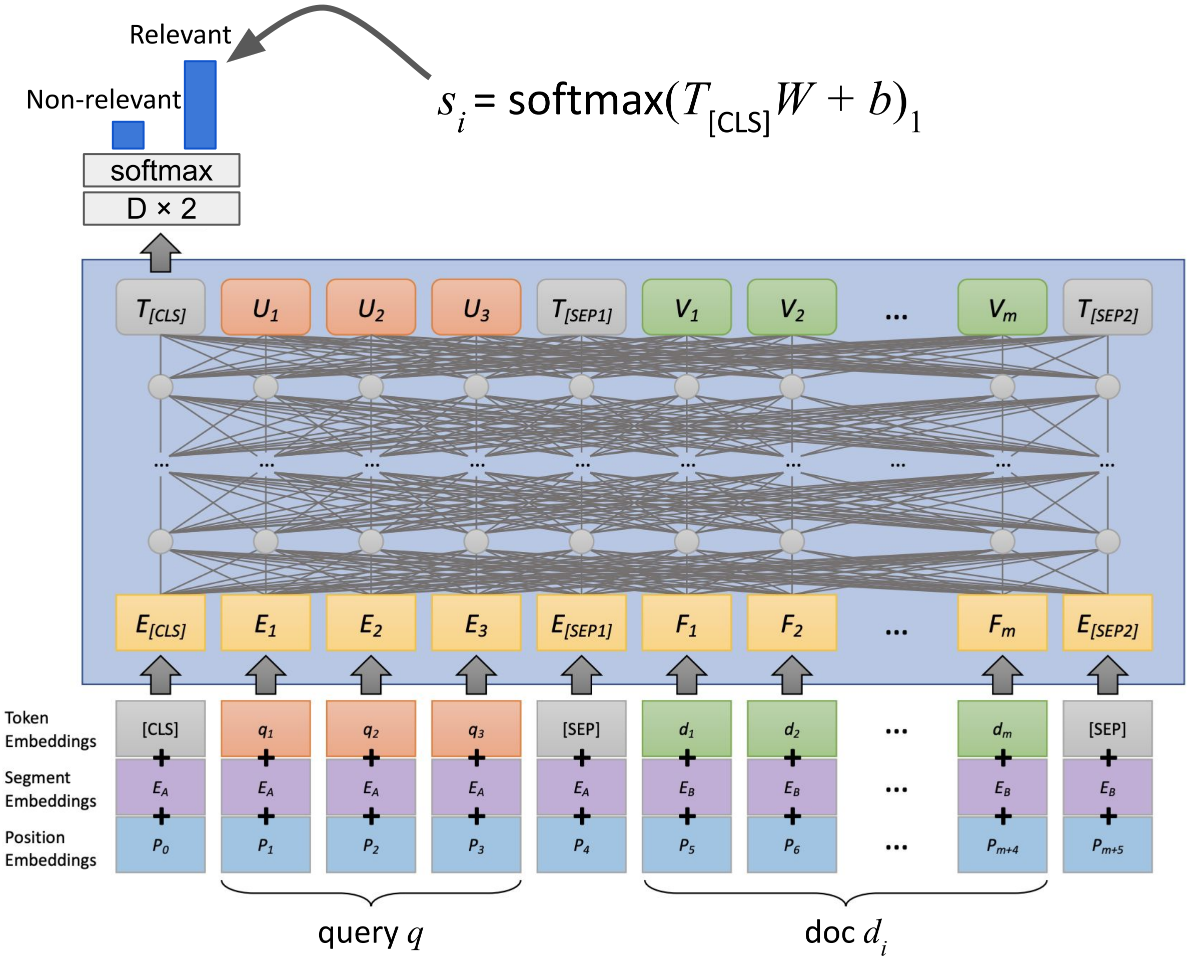
Extras

monoBERT:
BERT as a reranker

We want:

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

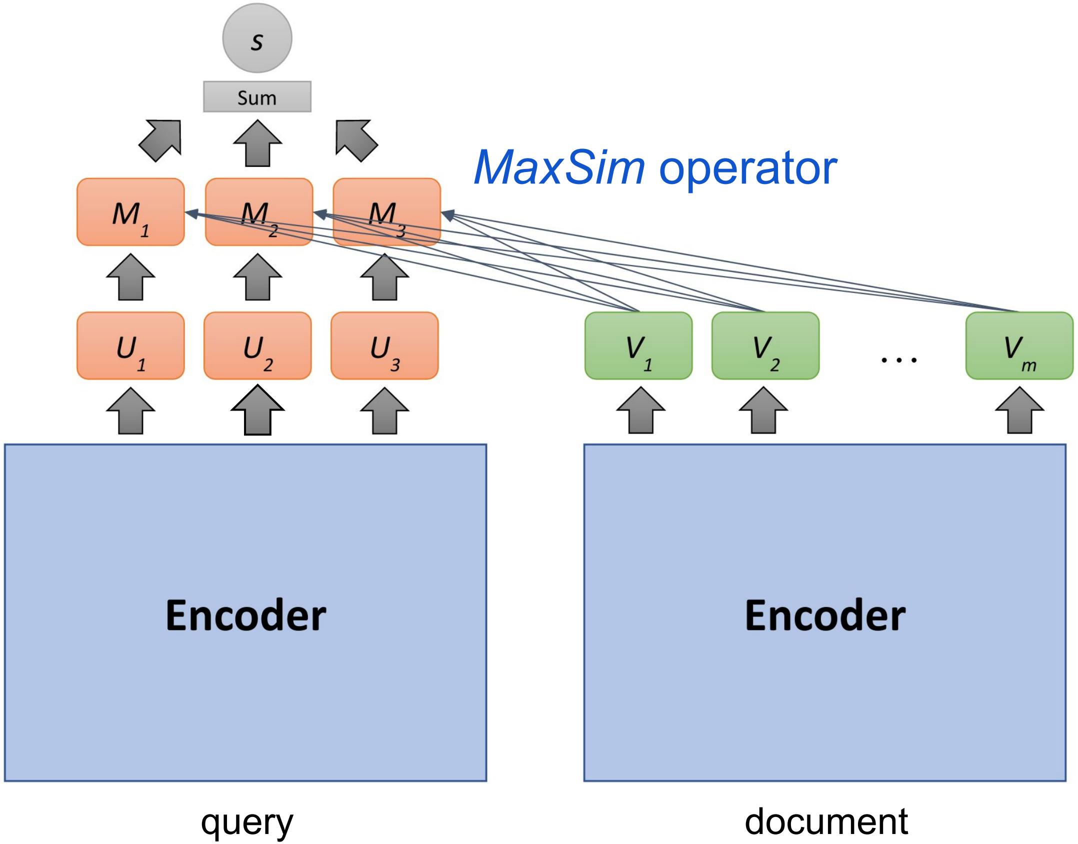
A binary classifier finetuned on pairs of <query, relevant doc> and <query, non-relevant doc>



$s_i = \text{softmax}(T_{\text{[CLS]}}W + b)_1$

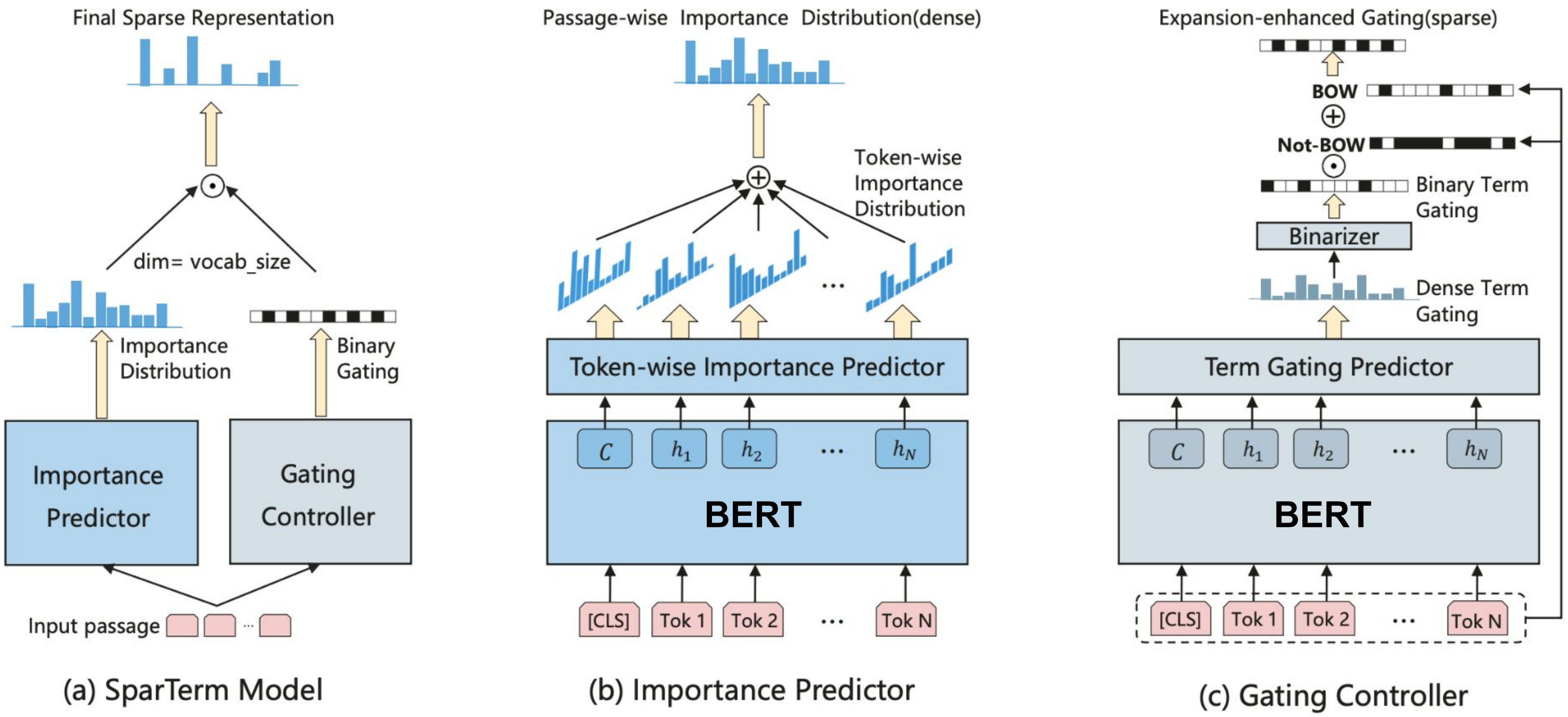
Nogueira and Cho, Passage Re-ranking with BERT, 2019

Multi-vector Dense Retriever: ColBERT



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

Learned Sparse Representations: SparTerm



Bai et al., SparTerm: Learning Term-based Sparse Representation for Fast Text Retrieval, 2020

SPLADE: Learned Sparse Representations

|w| = embedding dim = vocabulary size

w_j = 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:

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

dot product of q_i and d_i

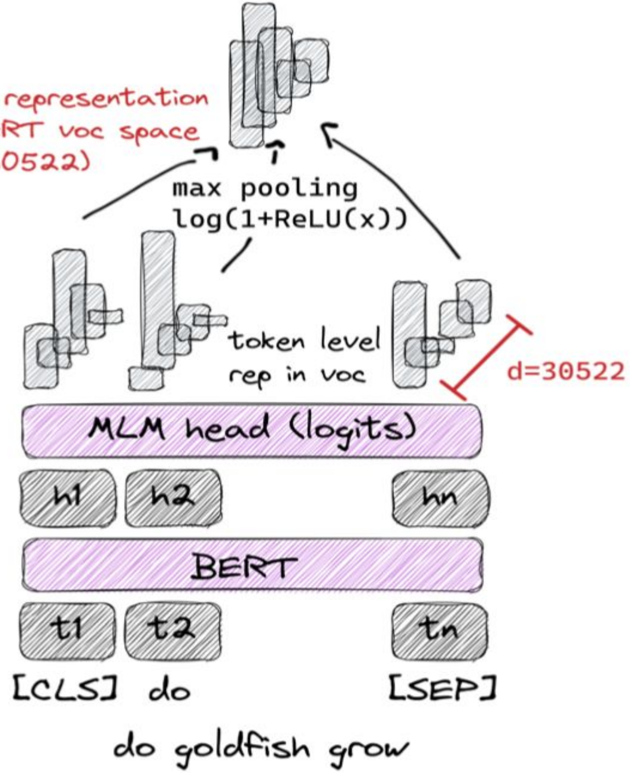
$$\mathcal{L}_{rank-IBN} = -\log \frac{e^{s(q_i,d_i^+)}}{e^{s(q_i,d_i^+)} + e^{s(q_i,d_i^-)} + \sum_j e^{s(q_i,d_{i,j}^-)}}$$

negative from BM25

in-batch negatives

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

ensures low term weights

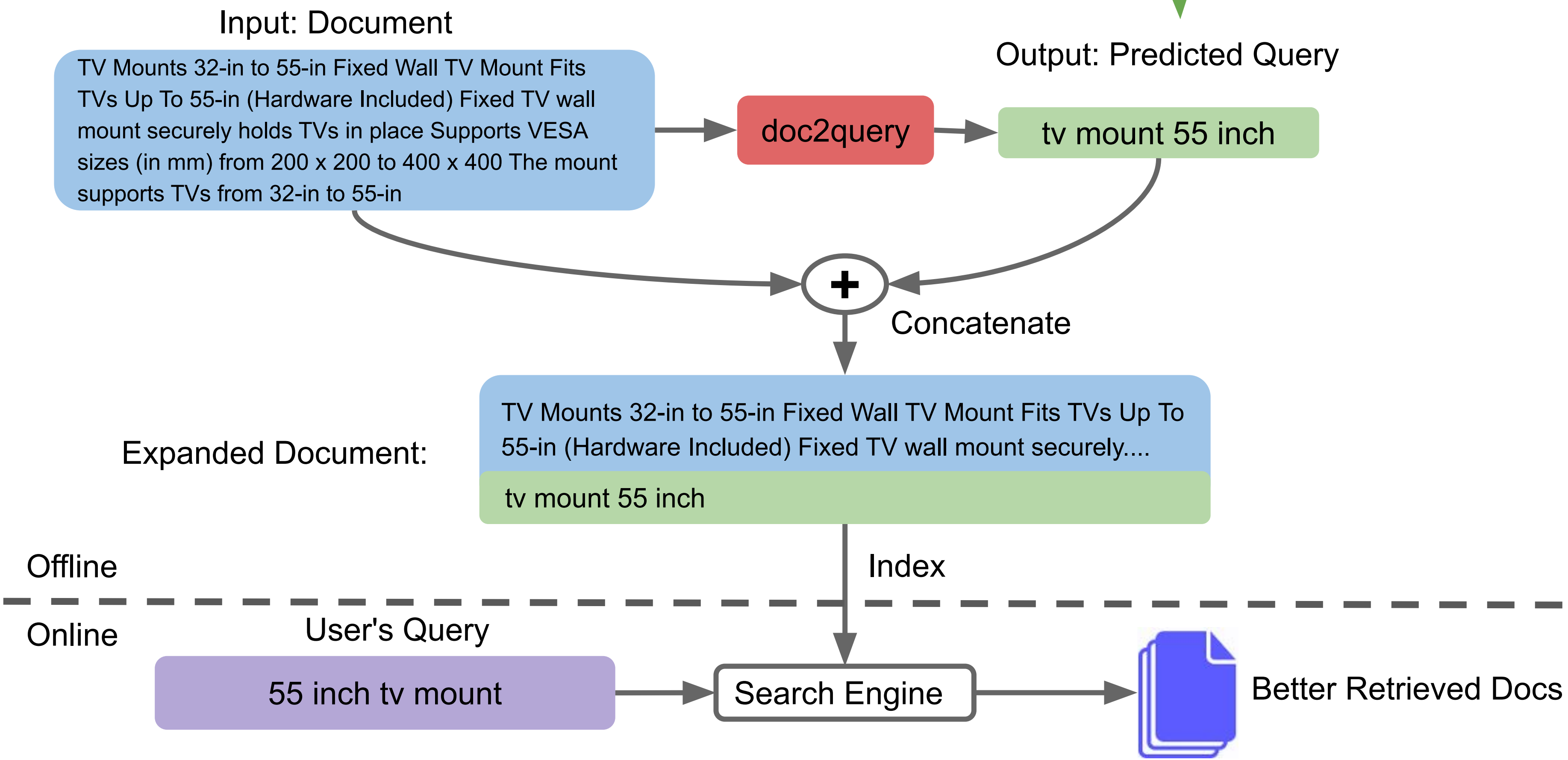


Formal et al. SPLADE: Sparse Lexical and Expansion Model for First Stage Ranking, 2021

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

Index

Offline

Online

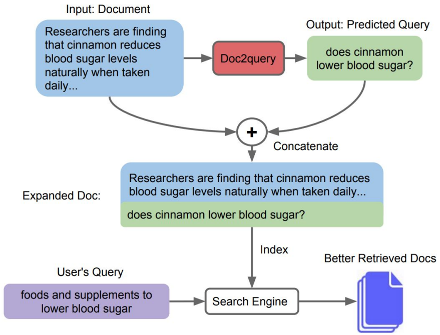
User's Query

55 inch tv mount

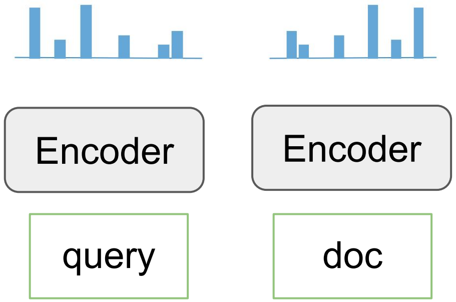
Search Engine

Better Retrieved Docs

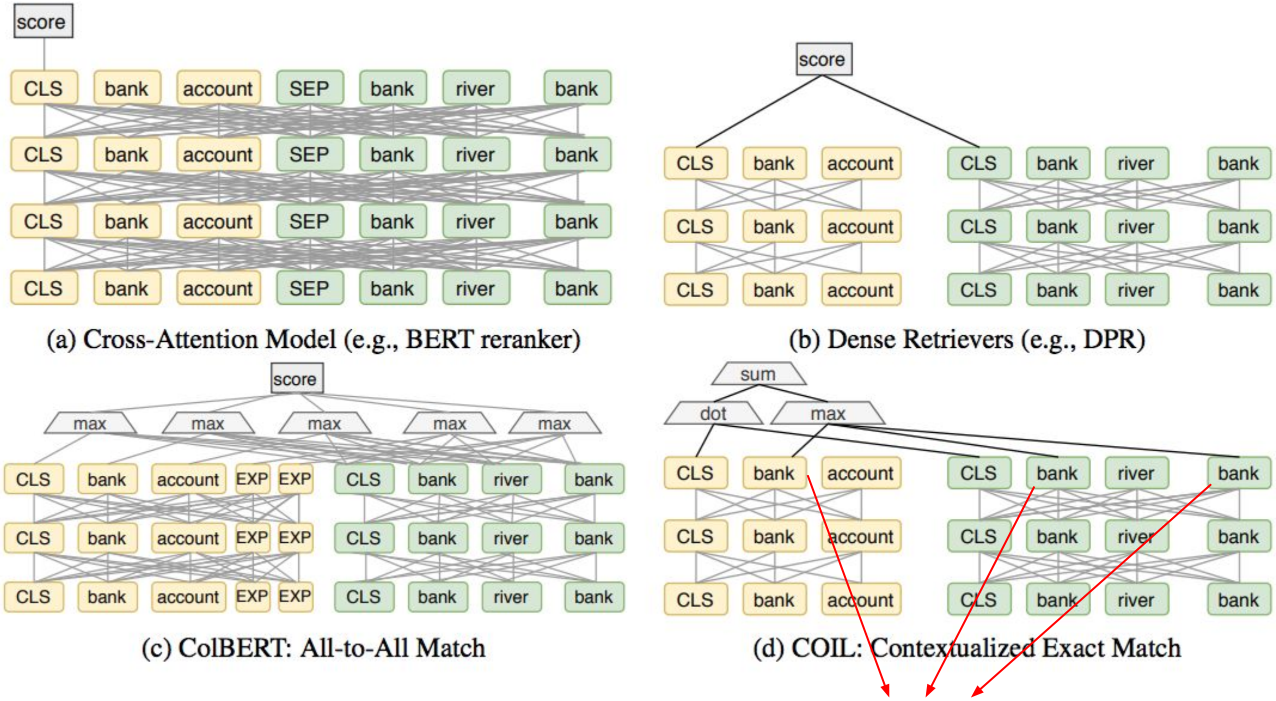
In summary


Input: Document
Researchers are finding that cinnamon reduces blood sugar levels naturally when taken daily...
Doc2query
Output: Predicted Query
does cinnamon lower blood sugar?
+
Concatenate
Expanded Doc:
Researchers are finding that cinnamon reduces blood sugar levels naturally when taken daily...
does cinnamon lower blood sugar?
Index
Better Retrieved Docs
User's Query
foods and supplements to lower blood sugar
Search Engine

Document expansion (doc2query)



Learned Sparse (e.g., SPLADE)



(a) Cross-Attention Model (e.g., BERT reranker)

(b) Dense Retrievers (e.g., DPR)

(c) ColBERT: All-to-All Match

(d) COIL: Contextualized Exact Match

exact match???

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

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	Out-of-domain BEIR
BM25	0.475	0.440
doc2query (sparse)	0.619	0.453
SPLADE (sparse)	0.671	0.458
GTR-base (T5, dense)	0.696	0.430
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