Adapting the Transformer Attention Mechanism for Efficient and Effective Information Retrieval

Tübingen, 06.06.2025

Ferdinand Schlatt

ferdinand.schlatt@uni-jena.de

Friedrich-Schiller-Universität Jena

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UNIVERSITÄT
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Adapting Attention

Standard Encoder Models for NLP

Transformer-based models are designed be as flexible as possible.

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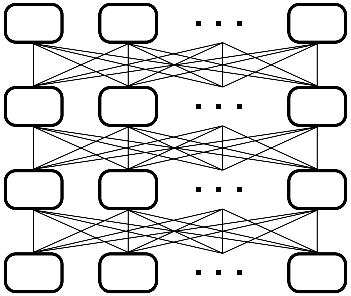

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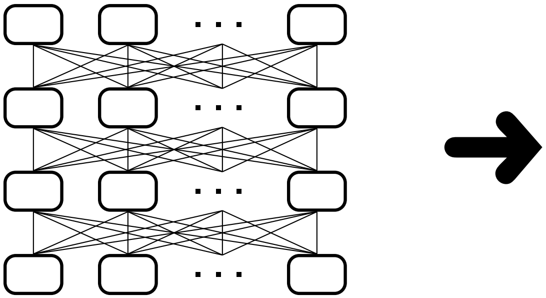

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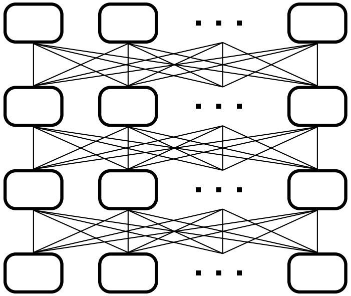

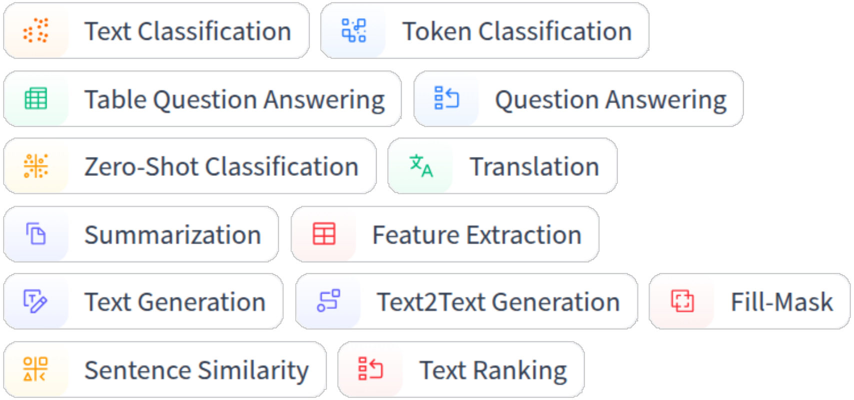

Text Classification
Token Classification
Table Question Answering
Question Answering
Zero-Shot Classification
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Summarization
Feature Extraction
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https://huggingface.co/models

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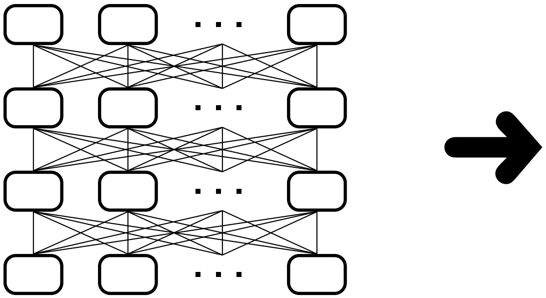

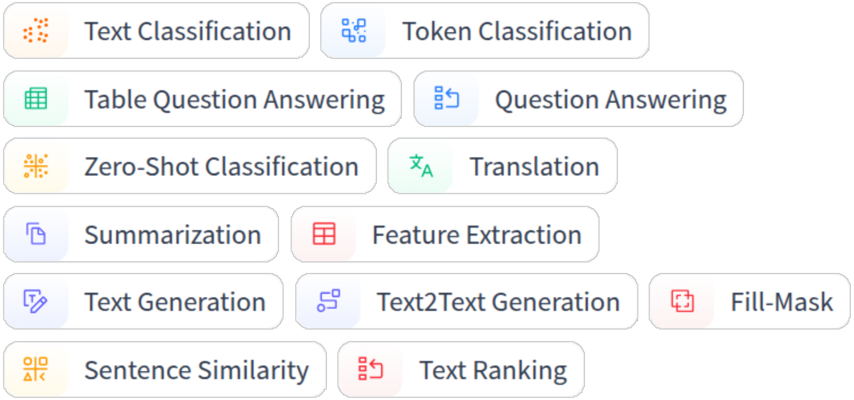

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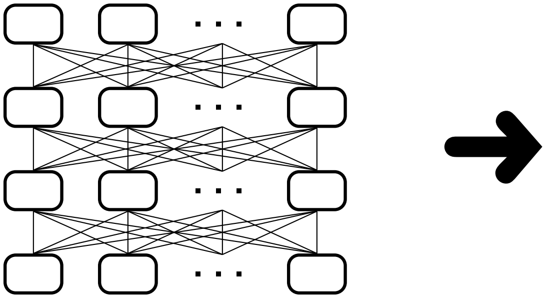

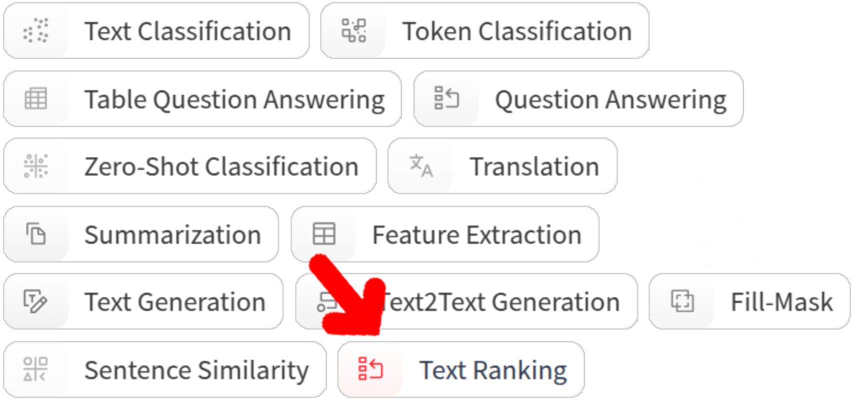

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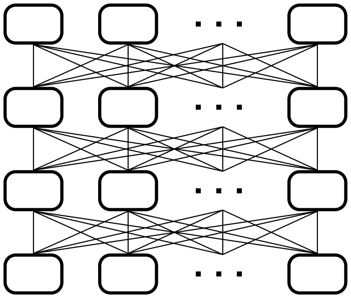

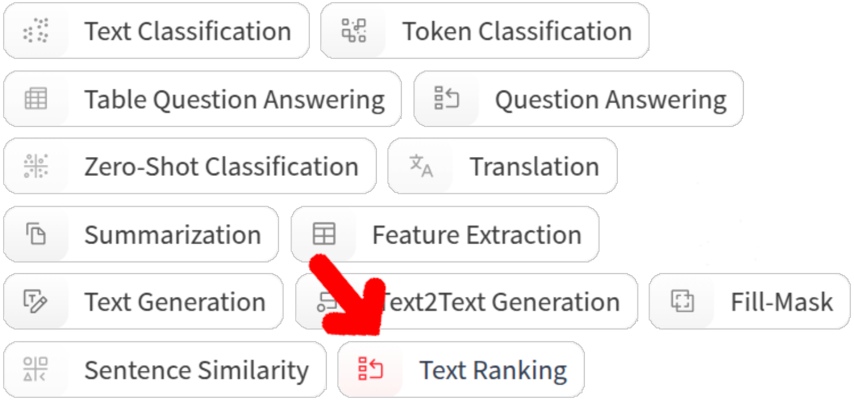

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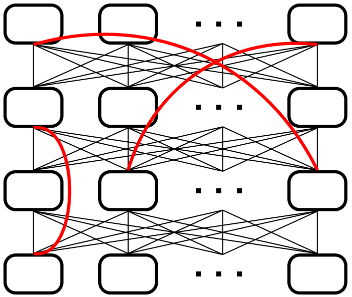

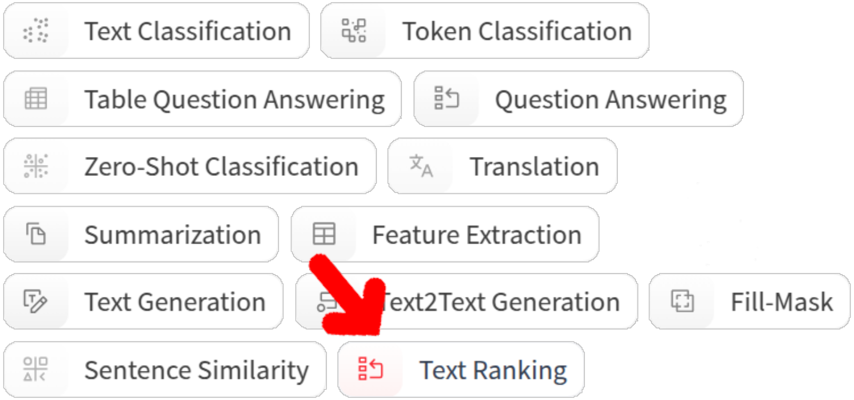

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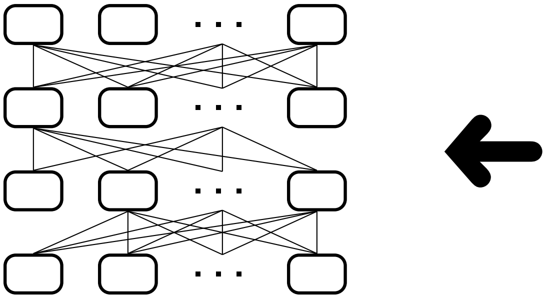

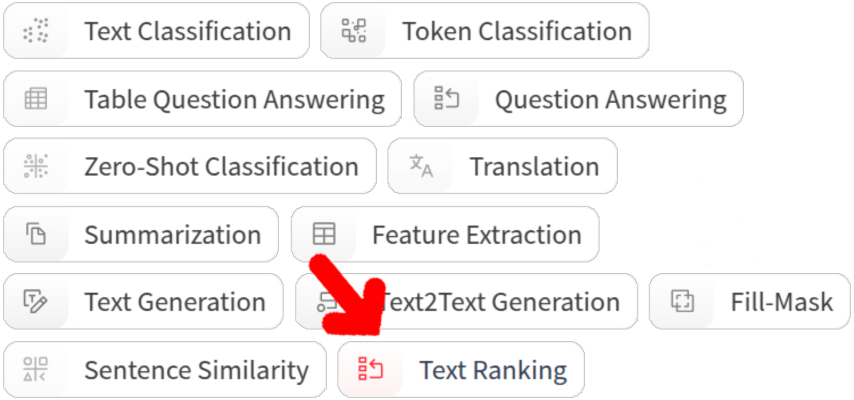

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Can we improve performance by “fine-tuning” the attention mechanism?

- We could add attention to make the model more effective . . .
- . . . or remove attention to make the model more efficient

Set-Encoder

Comparing Pointwise, Pairwise, and Listwise Cross-Encoders

Query 🔍 learn python

Documents 🗎 Python is a great language to learn.
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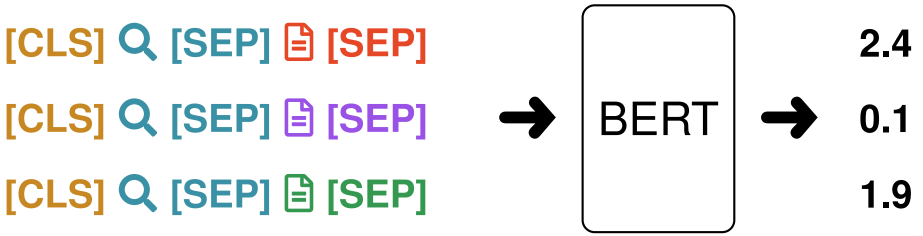

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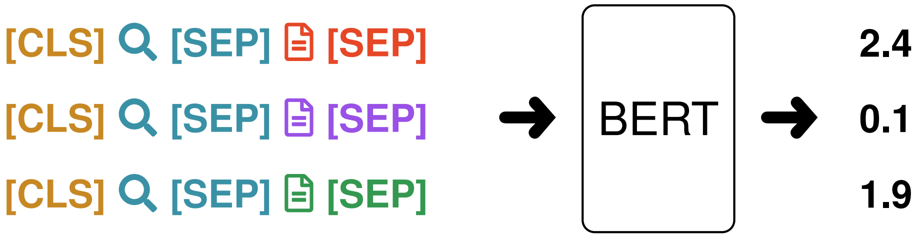
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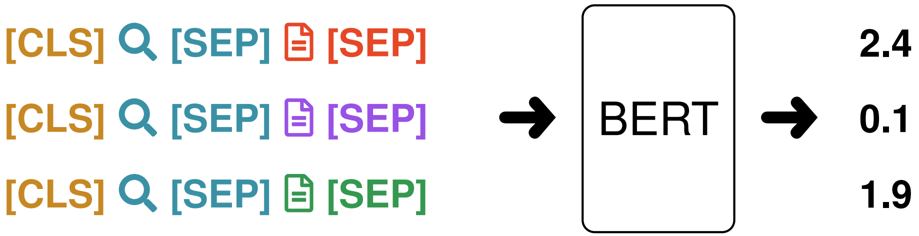

[CLS] 🔍 [SEP] 🗎 [SEP]
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→ BERT →

2.4
0.1
1.9

Issue: The model scores each document independently.

➜ Listwise (and pairwise) models enable interactions between documents.

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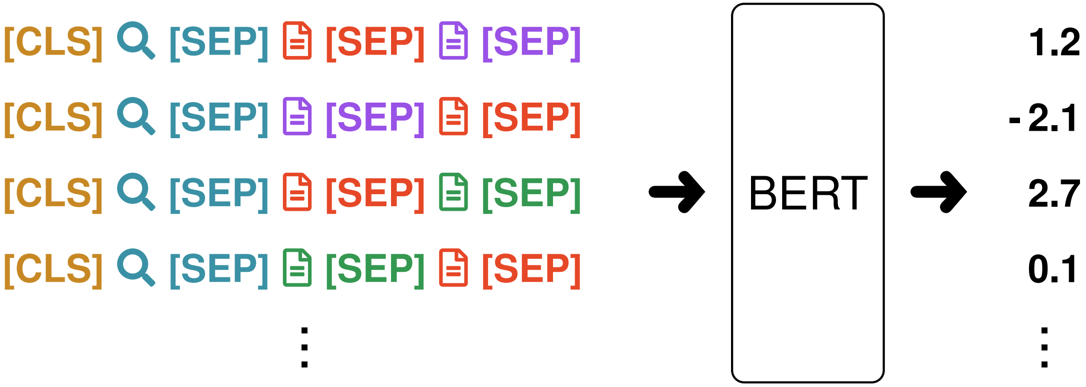

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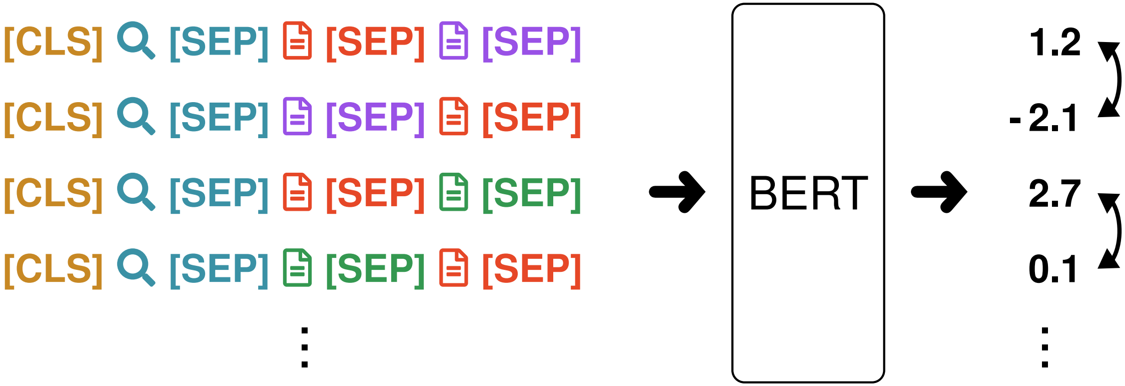

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Issue: Relevance scores are not symmetric.

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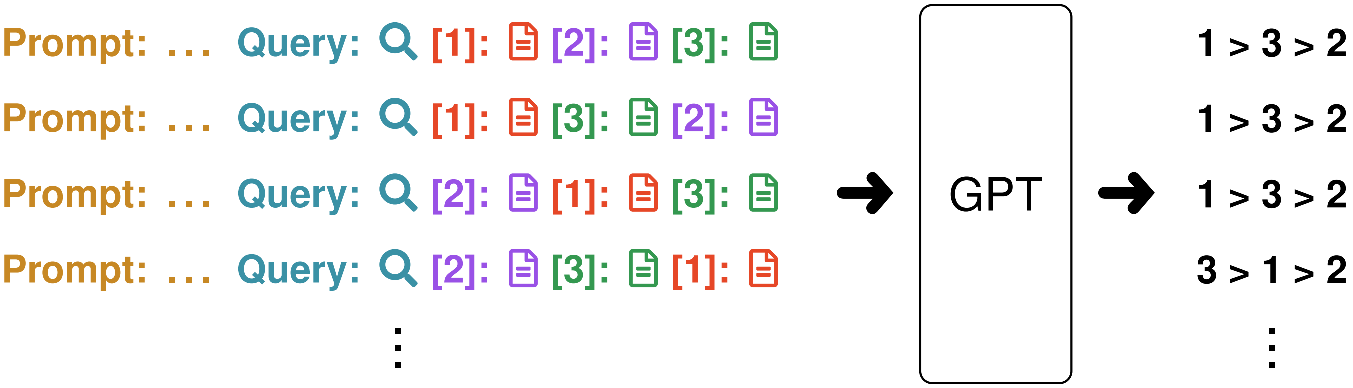

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⋮

→ GPT →

1 > 3 > 2
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3 > 1 > 2
⋮

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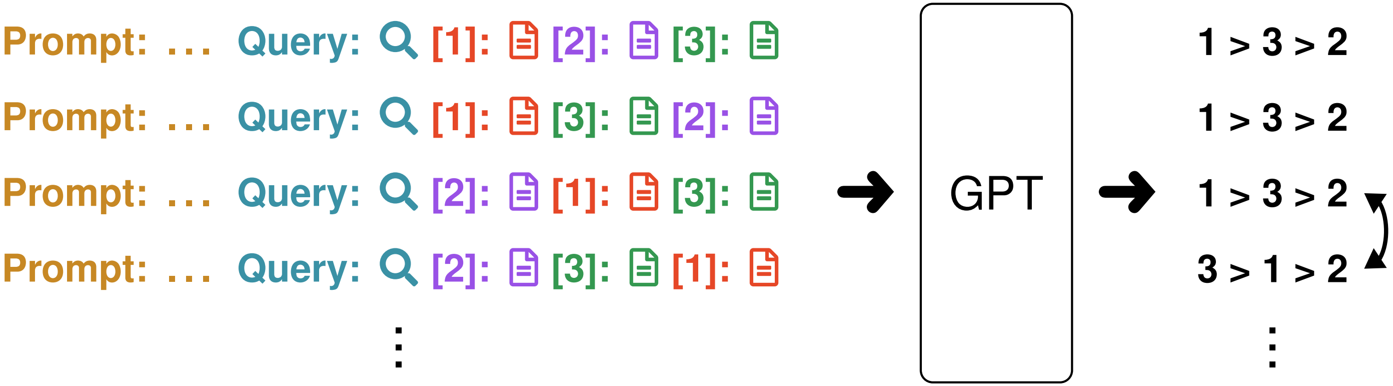

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Issue: Relevance preference order is not consistent.

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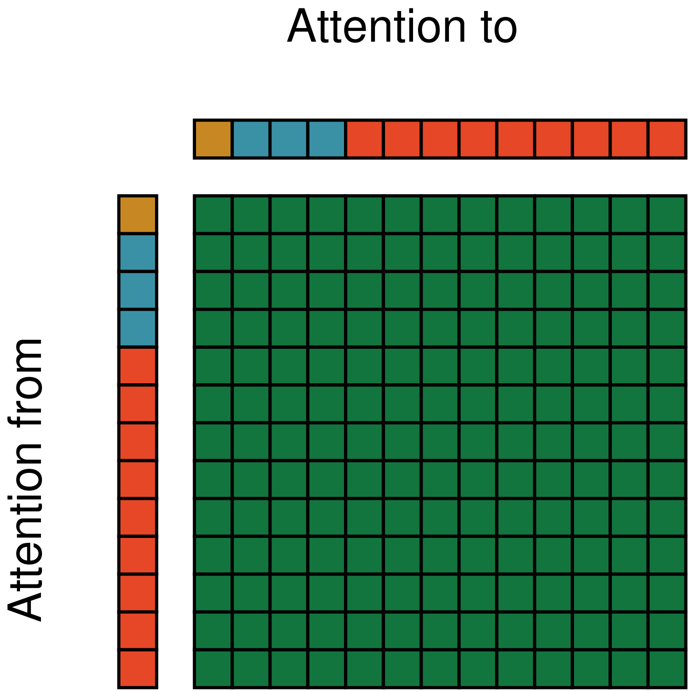

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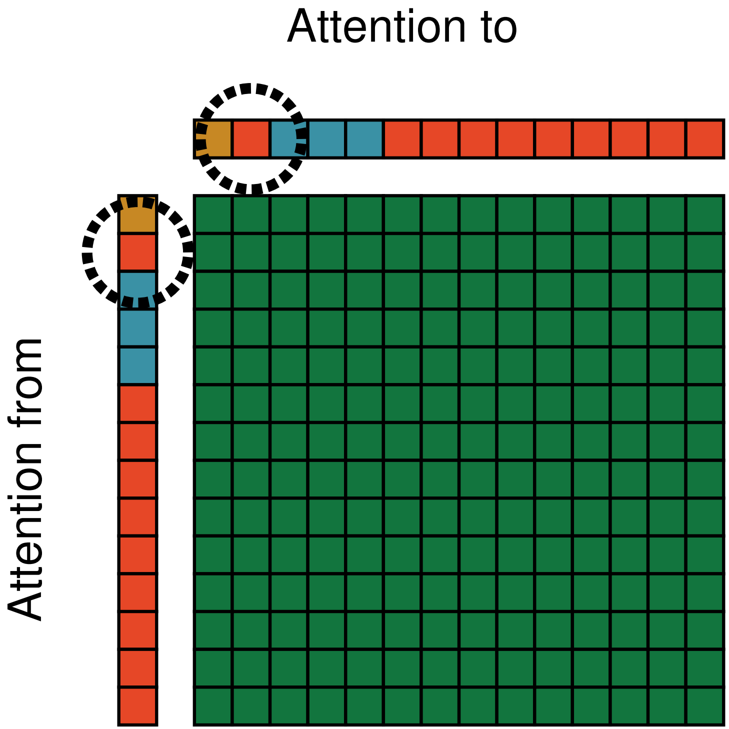

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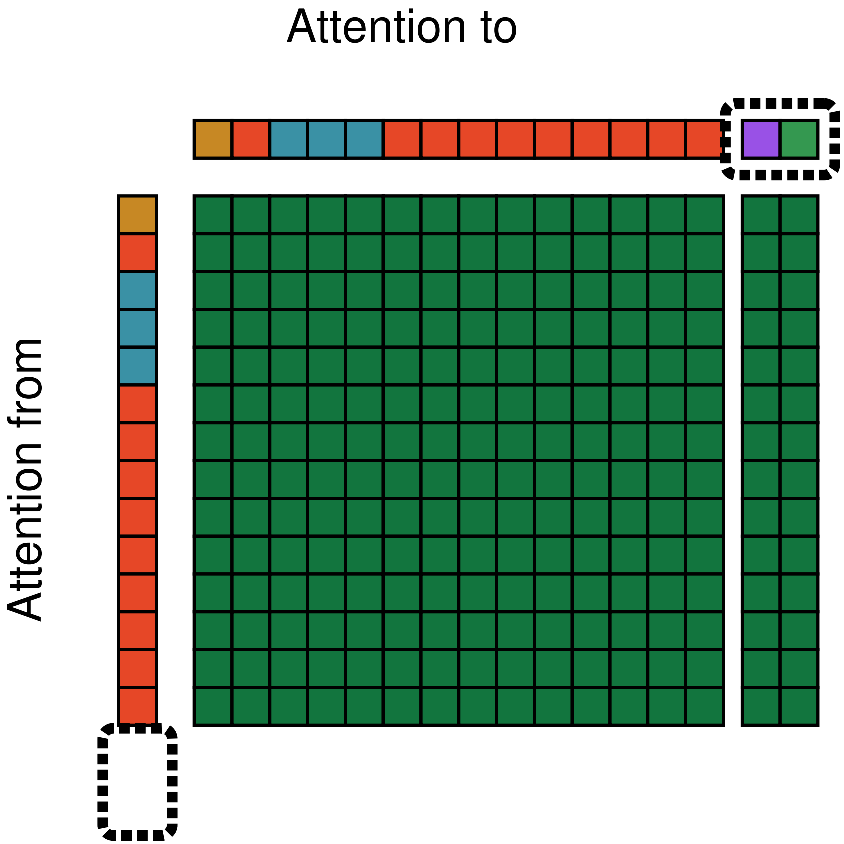

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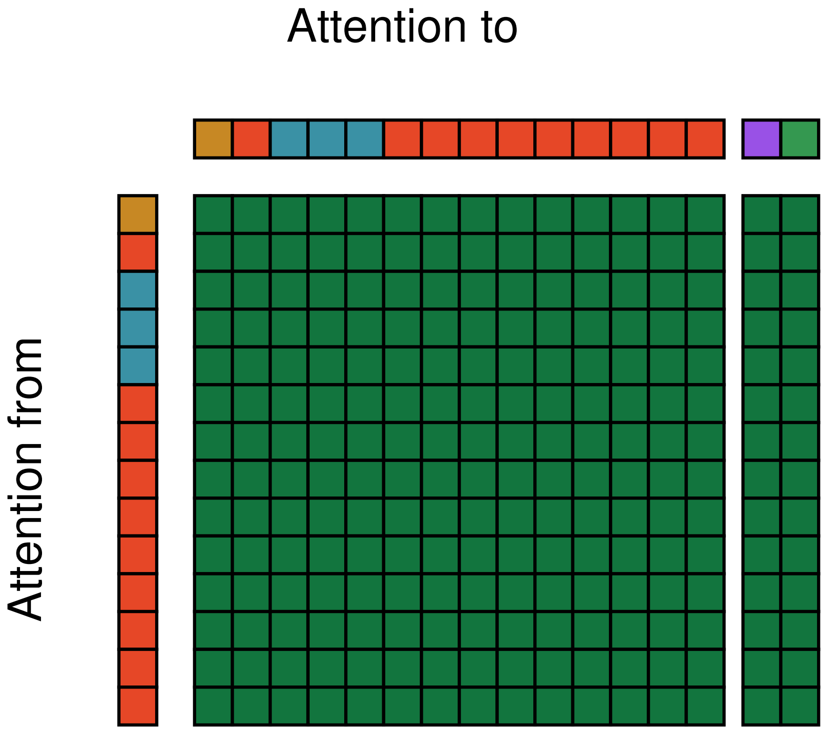

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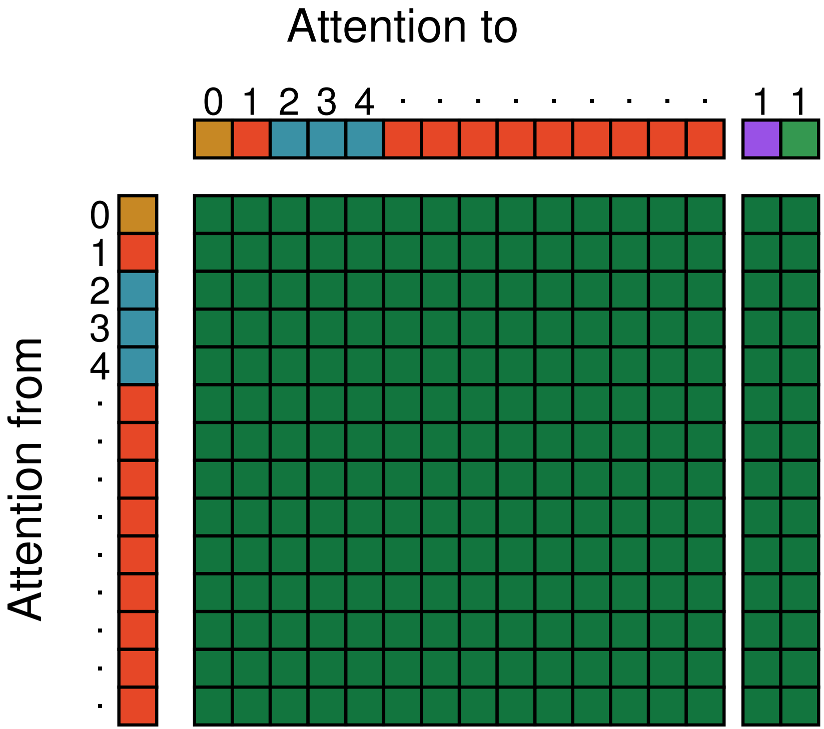

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- ❑ [INT] tokens aggregate semantic information and shares information with other documents
- ❑ Permutation-invariant because all [INT] tokens share the same positional encoding

Set-Encoder

Effectiveness

nDCG@10 on TREC Deep Learning 2019 and 2020 passage and TIREx

Model	**DL’19**	**DL’20**	**TIREx**
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➜ LLM-rankers are not permutation-invariant and affected by the first-stage

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Permutation Invariance

Re-ordering input documents affects previous listwise model’s ranking preferences.

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We create corrupted BM25 rankings to test a model’s robustness to permutations.

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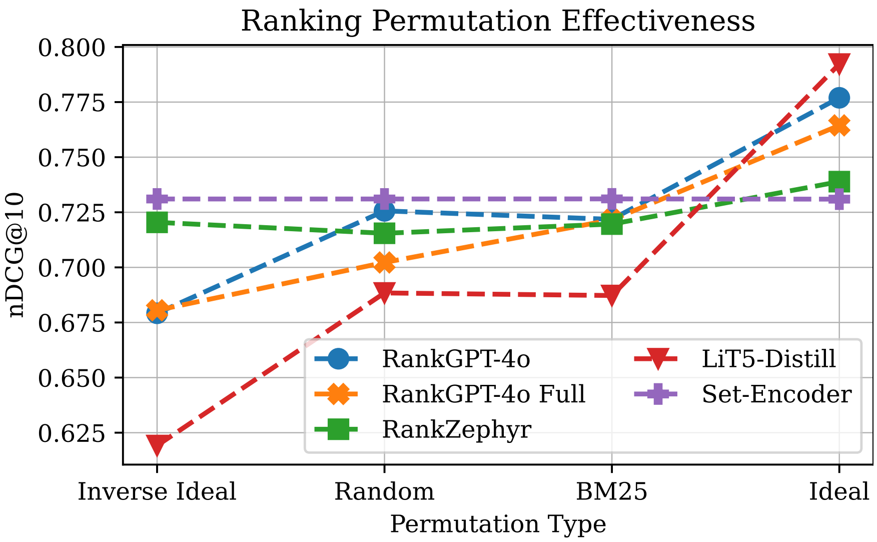

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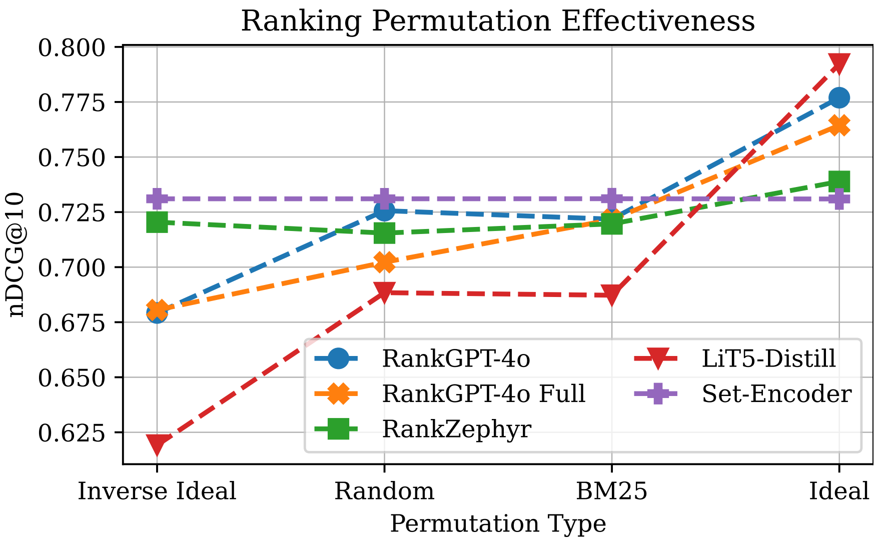

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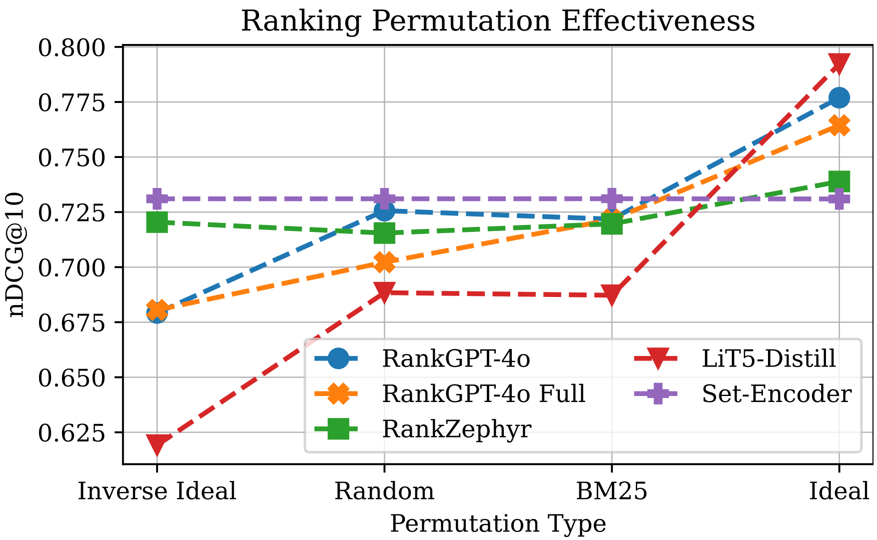

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- ❑ Set-Encoder is invariant to the order of the input documents

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Set-Encoder

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- Are document interactions necessary for independent relevance judgements?

Set-Encoder

Listwise Re-Ranking

We build a synthetic task which requires document interactions.

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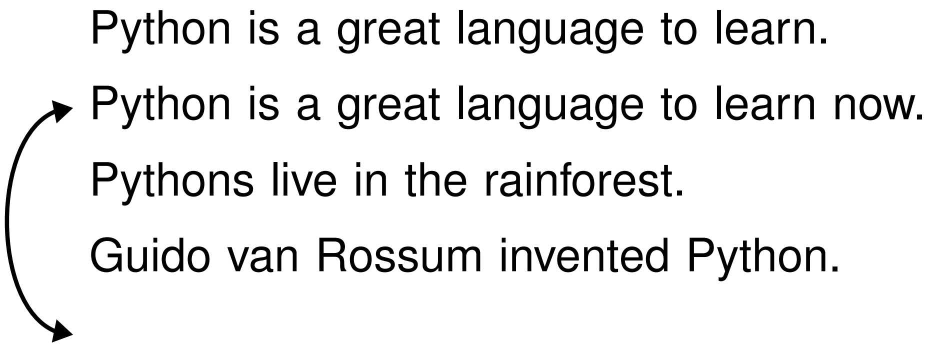

Python is a great language to learn.

Python is a great language to learn now.

Pythons live in the rainforest.

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Fine-tune models to rank according to relevance and put duplicates at the end.

Set-Encoder

Listwise Re-Ranking

We build a synthetic task which requires document interactions.

α-nDCG@10 ($\alpha = 0.99$) on the synthetic task

Model	**TREC DL 19**	**TREC DL 20**
First Stage	0.700	0.722
RankGPT-4o	0.741	0.773
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- ❑ Set-Encoder improves over baselines in novelty-aware re-ranking
- ❑ Without the interaction token, the Set-Encoder is less effective

Set-Encoder

Intermediate Conclusion

The Set-Encoder enables permutation-invariant inter-document interactions.

Set-Encoder

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Checkpoints are released on HF and can be used with our Lightning IR framework.

Lightning IR

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Code and paper @
webis-de/set-encoder

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Questions?

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Token-Independent Text Encoder (TITE)

Standard Bi-Encoder Model

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Standard Bi-Encoder Model

Query learn python

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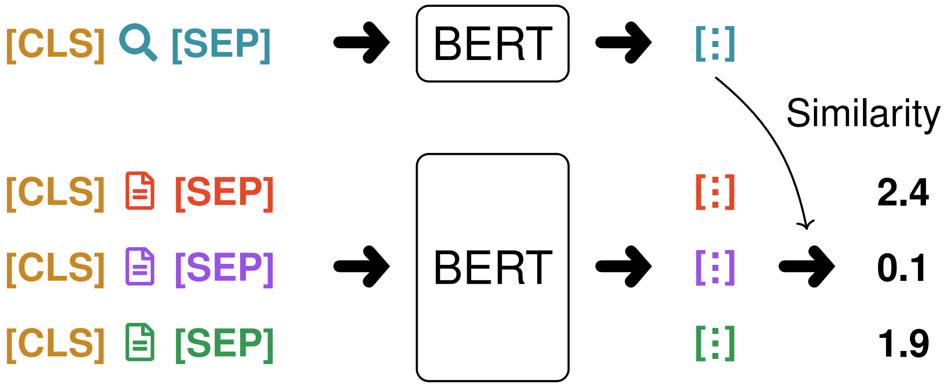
Sentence-BERT [Reimers and Gurevych, EMNLP’19]



[CLS] 🔍 [SEP] → BERT → [⋮]

Similarity

[CLS] 📄 [SEP]
[CLS] 📄 [SEP] → BERT → [⋮] → 2.4
[CLS] 📄 [SEP]

[⋮] 0.1
[⋮] 1.9

Token-Independent Text Encoder (TITE)

Pooling in Bi-Encoder Models

To obtain a single vector, bi-encoder models pool the token representations.

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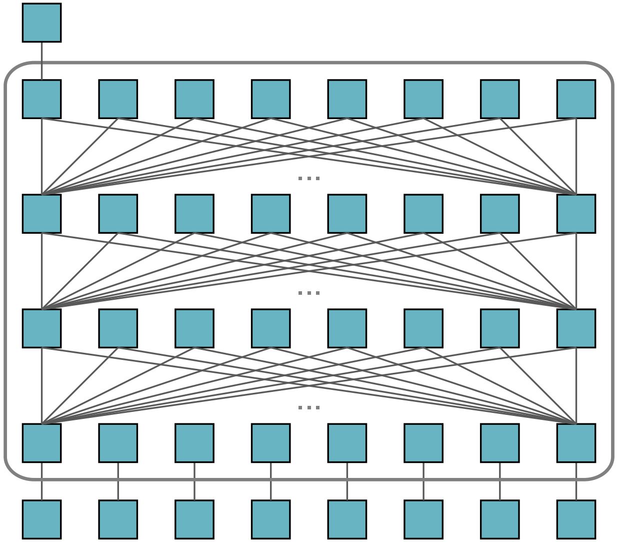

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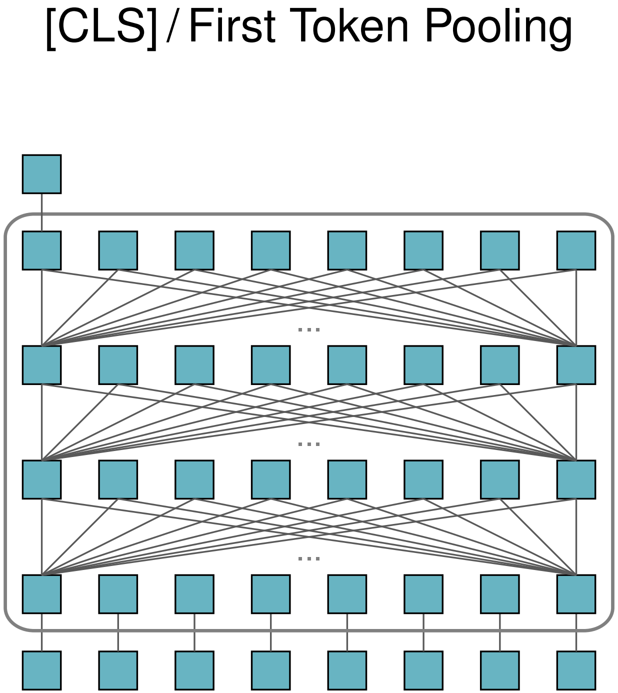

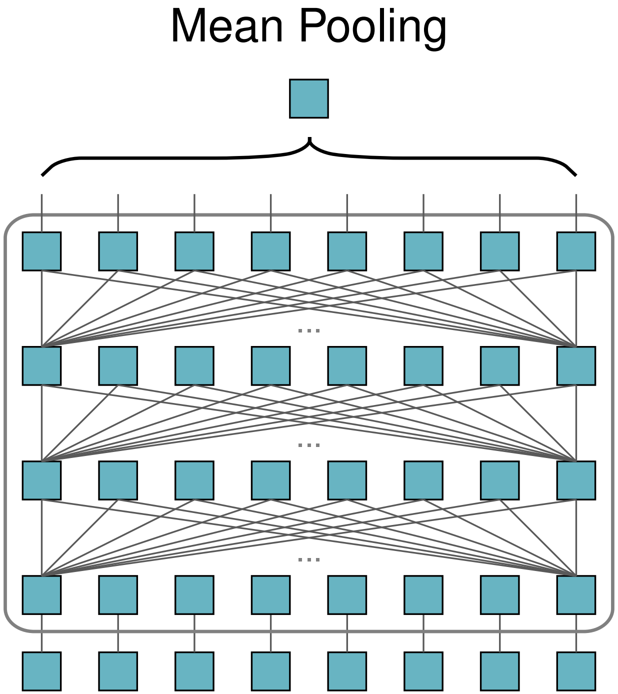

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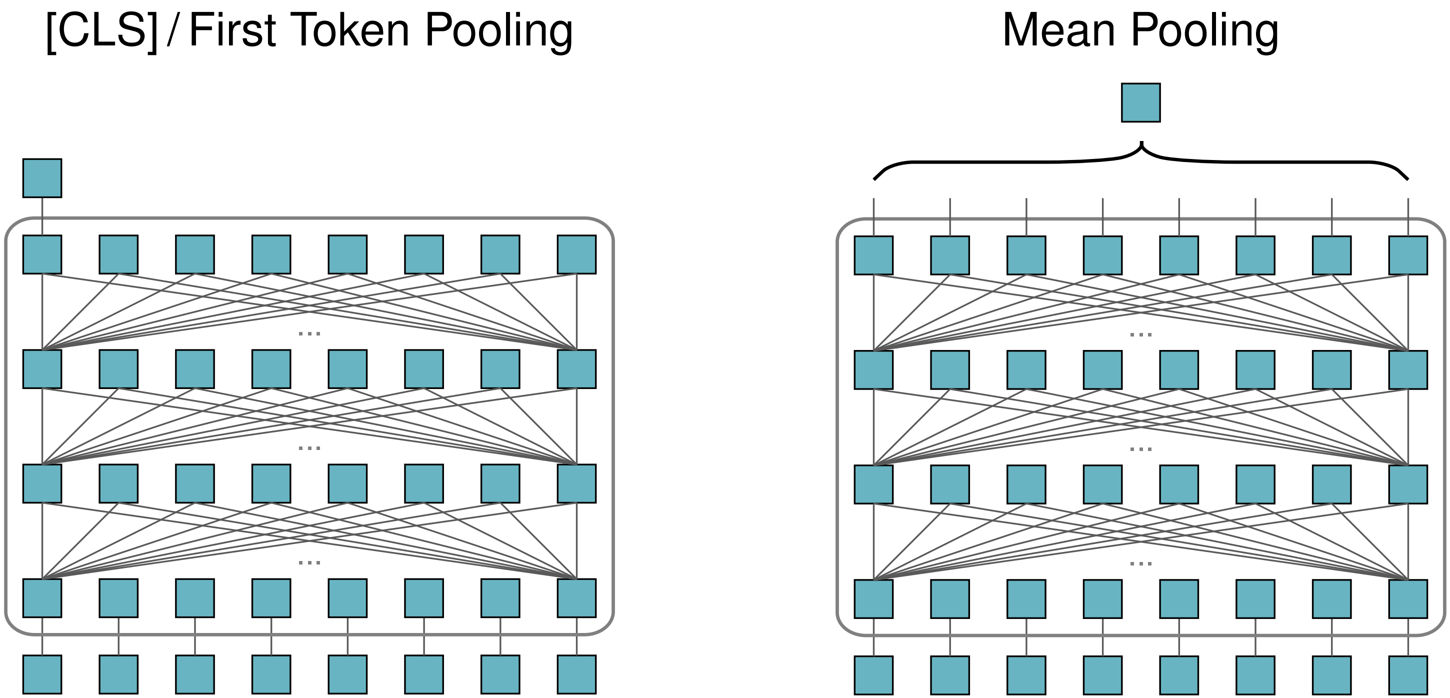

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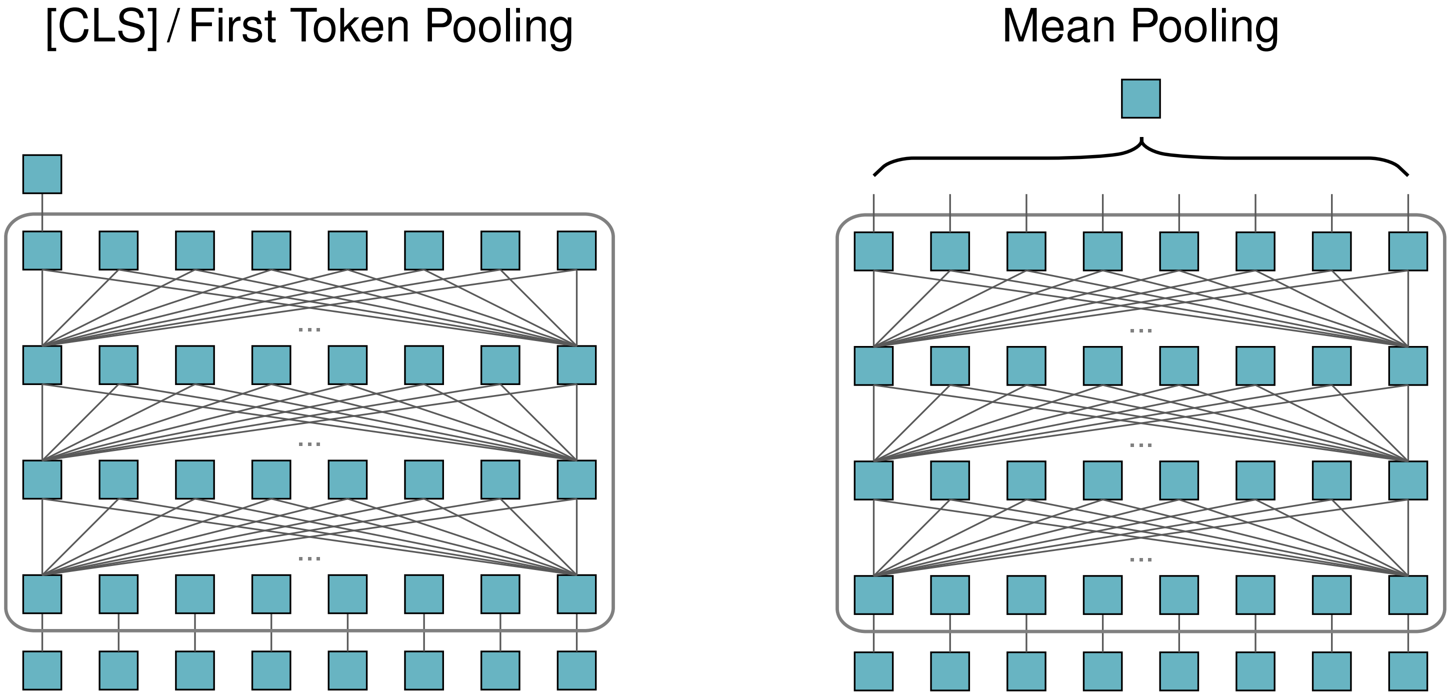

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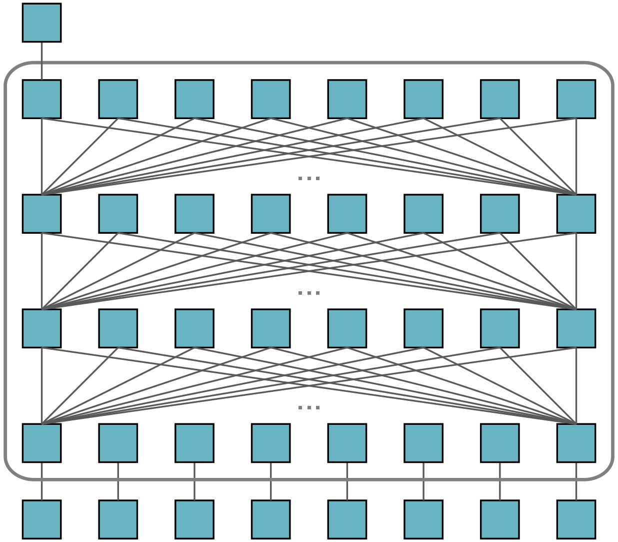
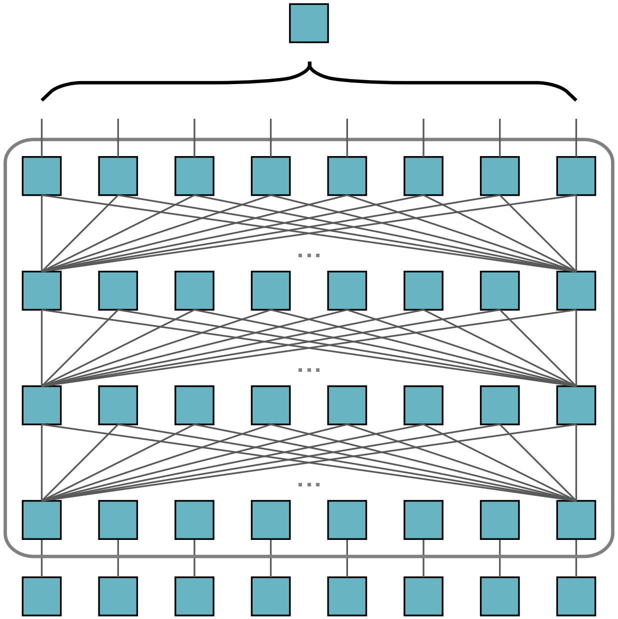


Mean Pooling



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➜ Combine both approaches by pooling within the transformer layers

Token-Independent Text Encoder (TITE)

Encoder Model with Single Vector Output

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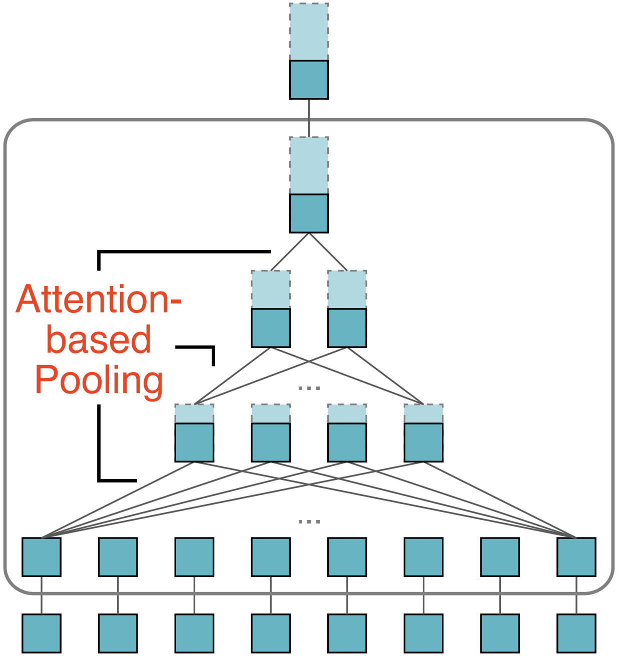

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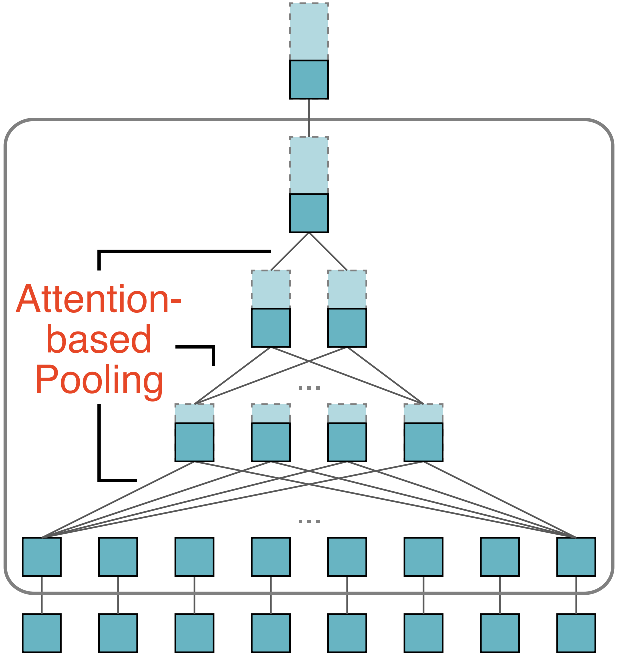

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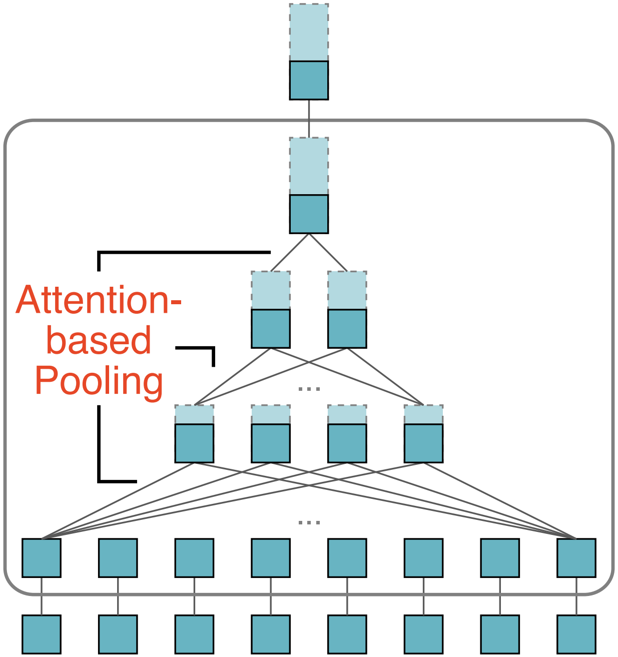

- ❑ TITE outputs a single sequence-level vector for an input sequence
- ❑ Optionally, the dimensionality of vectors can be increased

Token-Independent Text Encoder (TITE)

Attention-based Pooling

Attention-based pooling builds on the Funnel Transformer. [Dai et al., NeurIPS'20]

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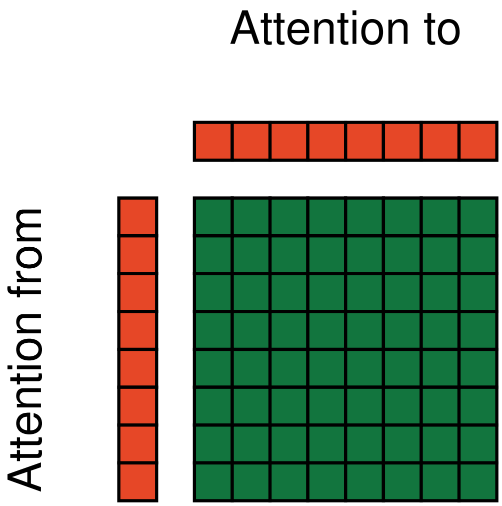

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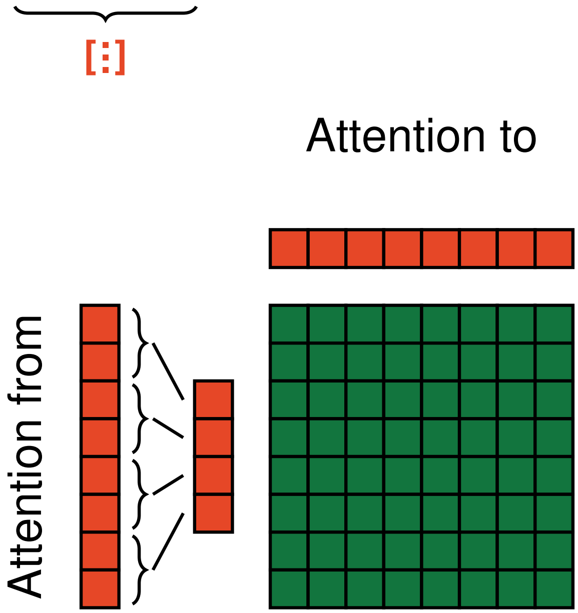

1. Pool the representations of neighboring tokens

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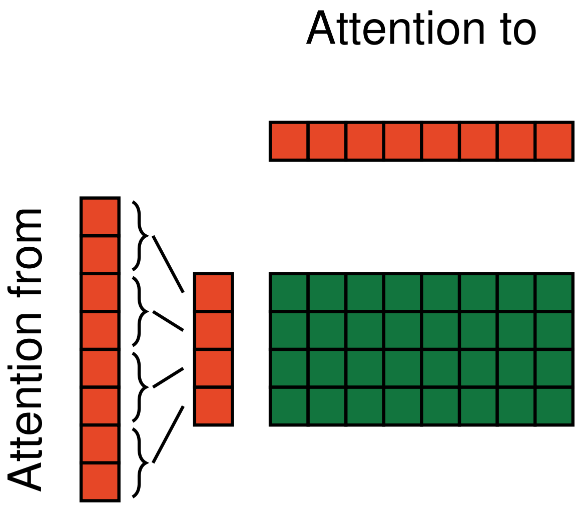

1. Pool the representations of neighboring tokens
2. Allow a pooled "meta-token" to attend to all tokens of the previous layer

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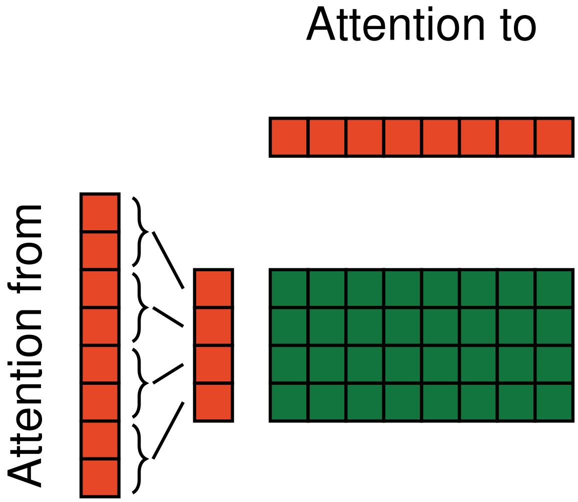

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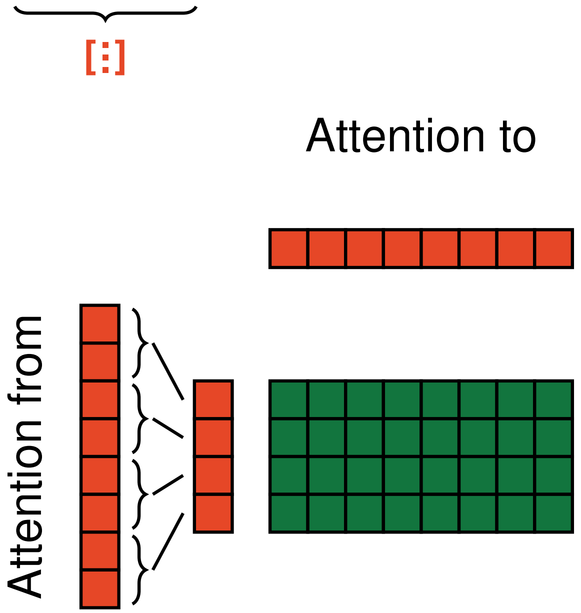

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- Fine-grained attention across “meta-tokens”

Token-Independent Text Encoder (TITE)

Efficiency and Effectiveness

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Efficiency and Effectiveness

Efficiency

Model	**Queries**	**Docs**
BERT	48.0	8.7
ModernBERT		
TITE (Base)		
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Queries and documents per second (×1,000)

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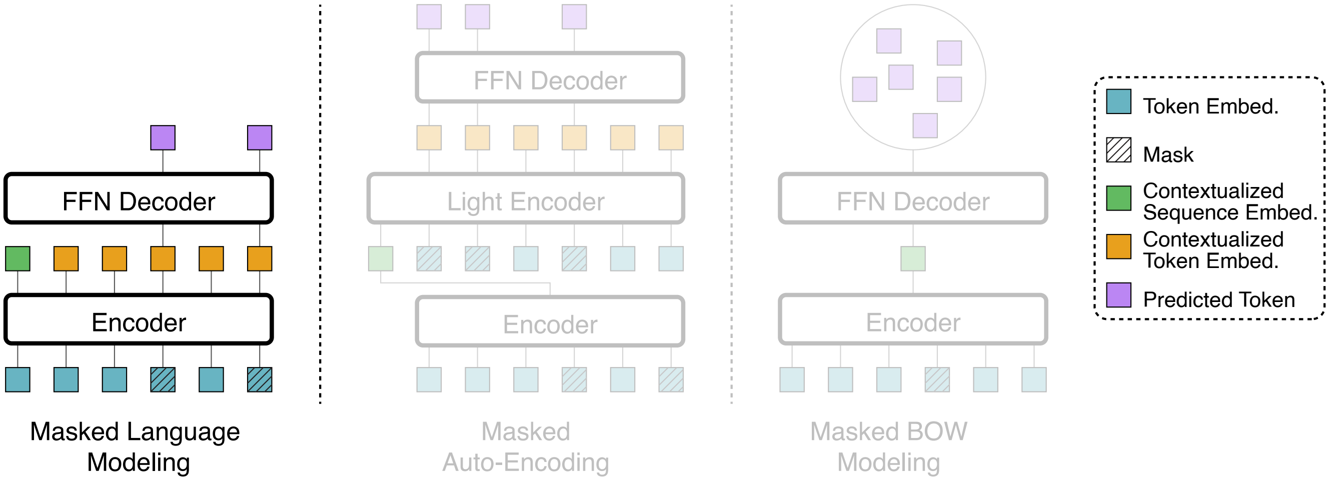
Is TITE less effective than RetroMAE due to the architecture or pre-training?

Token-Independent Text Encoder (TITE)

Sequence-Level Pre-Training

Token-Independent Text Encoder (TITE)

Sequence-Level Pre-Training



FFN Decoder

Encoder

Masked Language Modeling

FFN Decoder

Light Encoder

Encoder

Masked Auto-Encoding

FFN Decoder

Encoder

Masked BOW Modeling

🟦 Token Embed.

▨ Mask

🟩 Contextualized Sequence Embed.

🟧 Contextualized Token Embed.

🟪 Predicted Token

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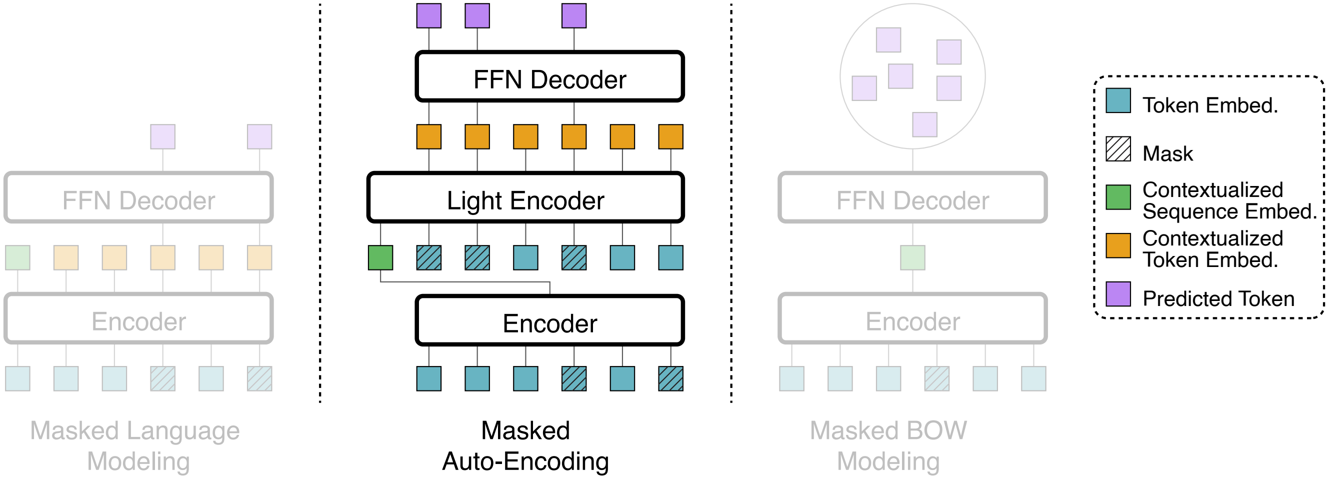

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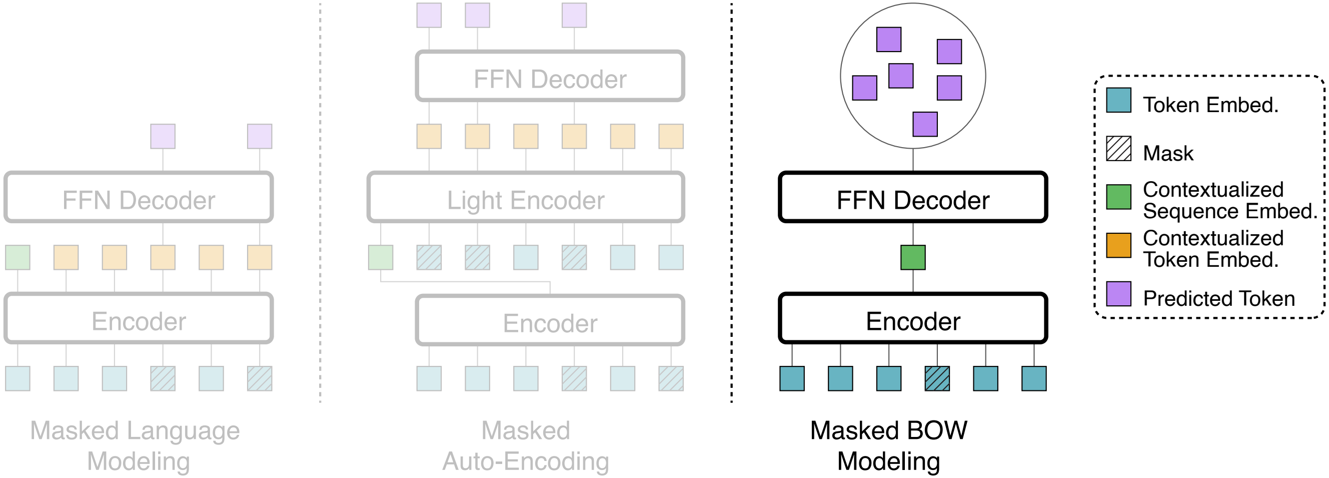

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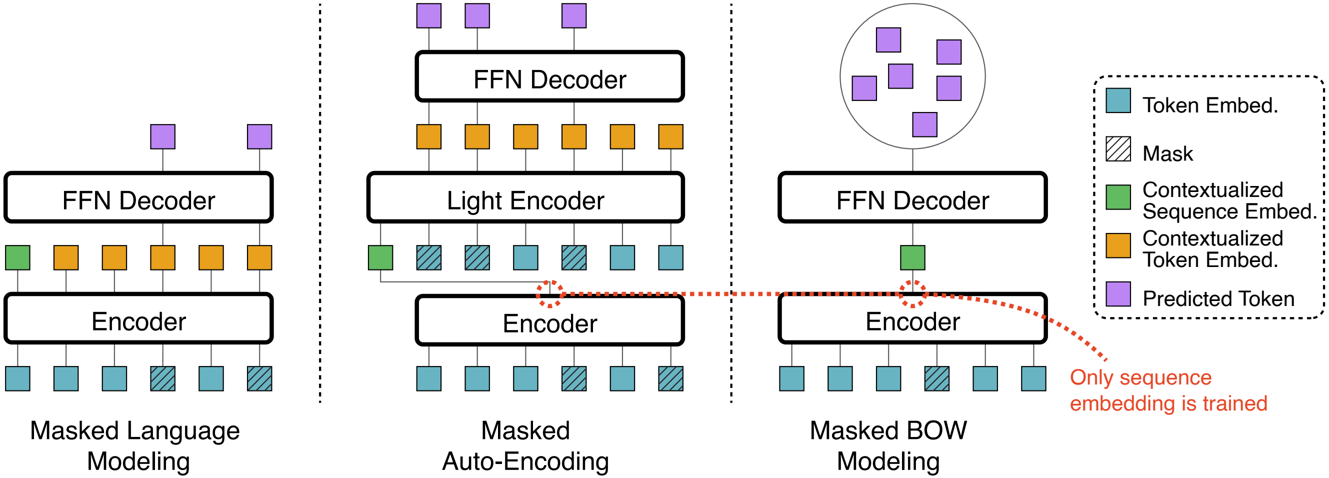

Only sequence embedding is trained

Token-Independent Text Encoder (TITE)

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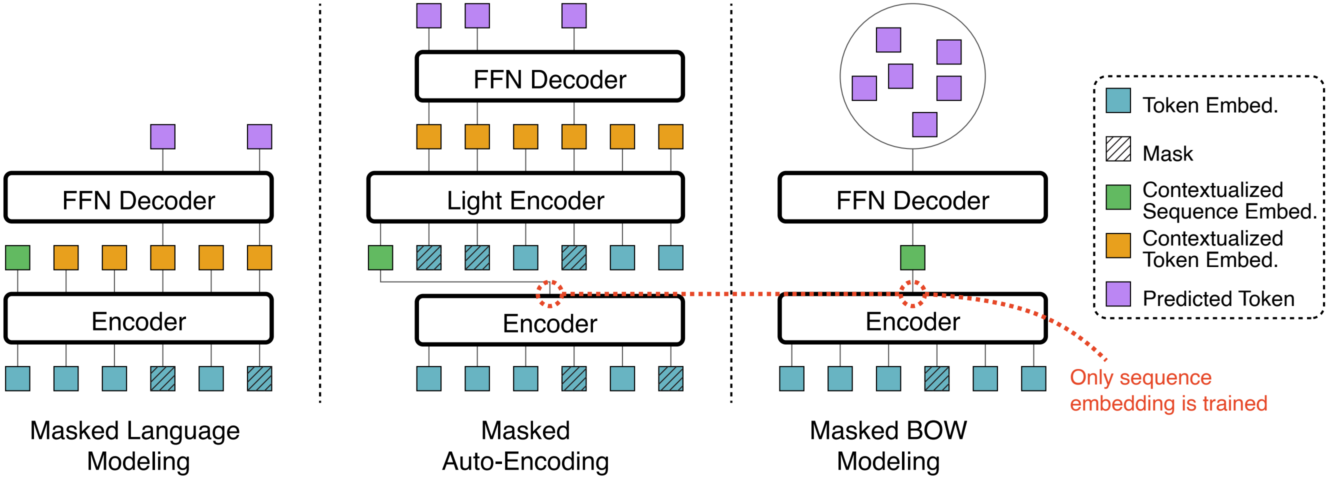

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CLS-BERT	✗	✓	✓			
TITE	✗	✓	✓			
TITE	✗	✓	✗			
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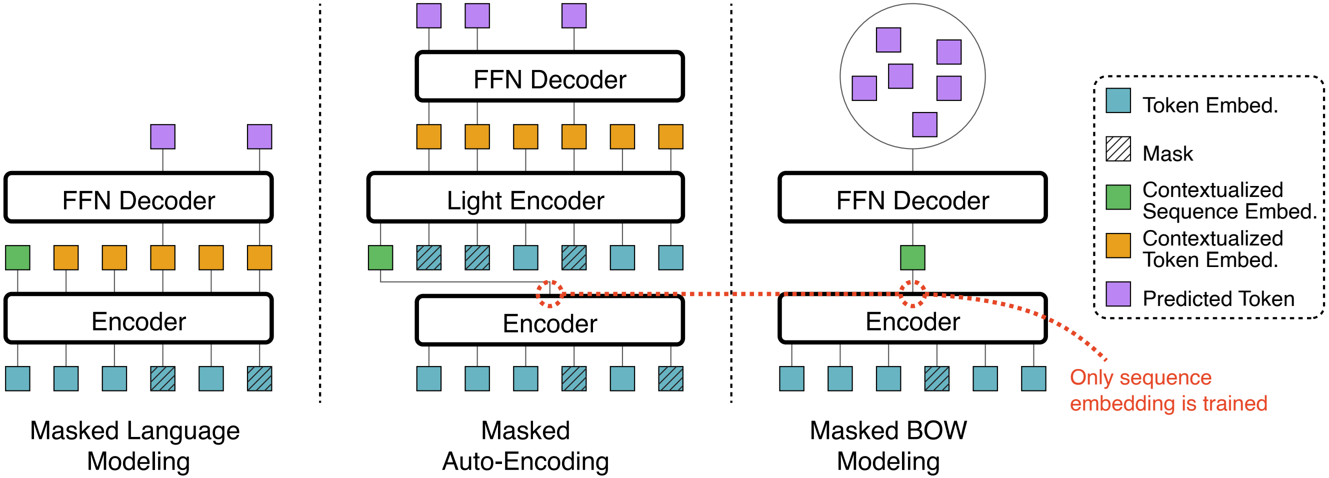

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TITE	✗	✓	✓			
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❑ MLM + MAE > MLM

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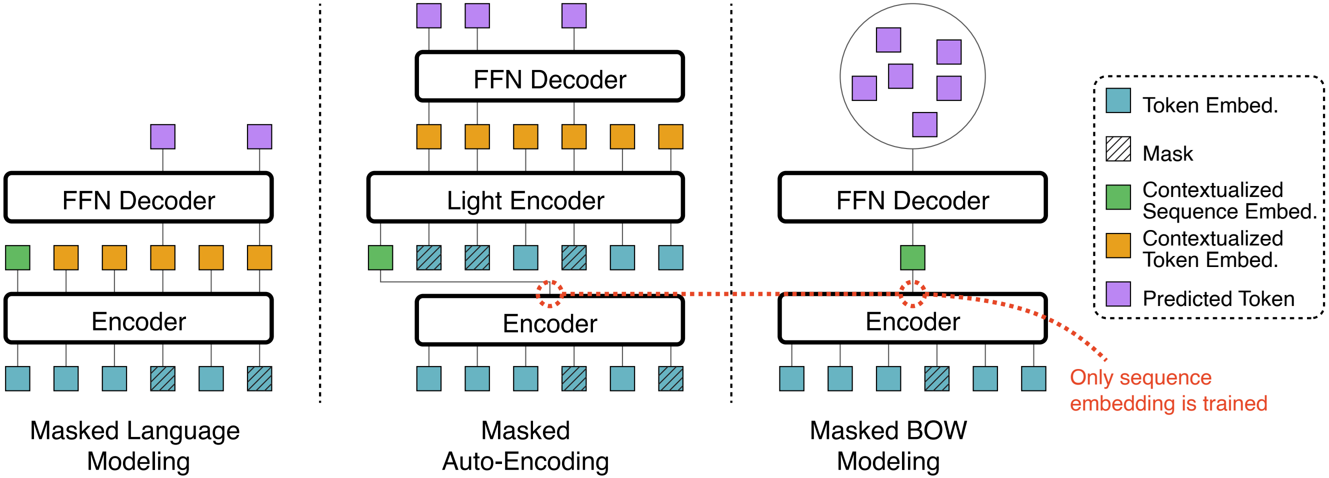

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Model	$\mathcal{L}$			**DL'19**	**DL'20**	**BEIR**
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S-BERT	✓	✗	✗	.700	.688	.449
RetroMAE	✓	✓	✗	.723	.711	.476
CLS-BERT	✗	✓	✓	.704	.674	.444
TITE	✗	✓	✓	.705	.670	.449
TITE	✗	✓	✗			
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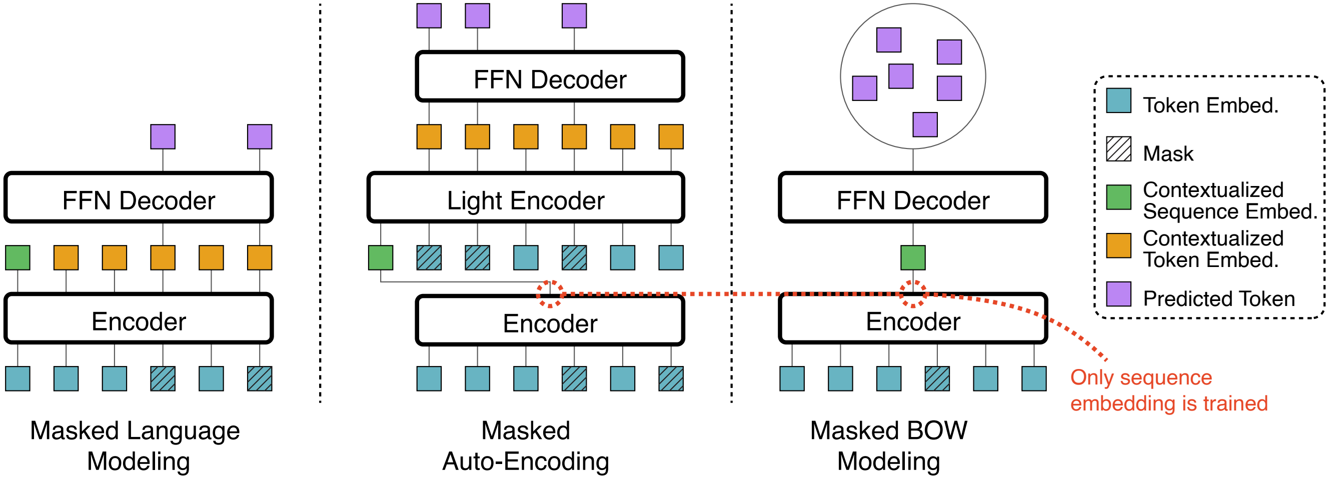
- ❑ $\text{MLM} + \text{MAE} > \text{MLM}$
- ❑ $\text{MLM} \approx \text{MAE} + \text{BOW}$

Token-Independent Text Encoder (TITE)

Sequence-Level Pre-Training



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TITE	✗	✓	✗	.657	.657	.400
TITE	✗	✗	✓	.660	.676	.426

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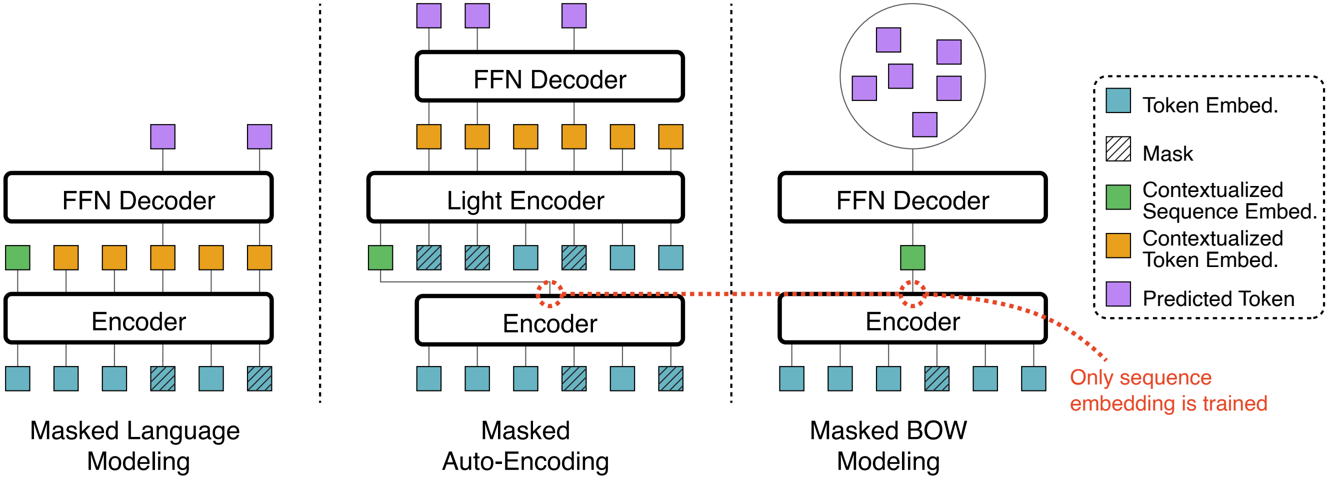

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➜ Gap caused by pre-training and not architecture

Token-Independent Text Encoder (TITE)

Conclusion

TITE outputs a single sequence-level vector for an input sequence.

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webis-de/tite

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Coding Tutorial
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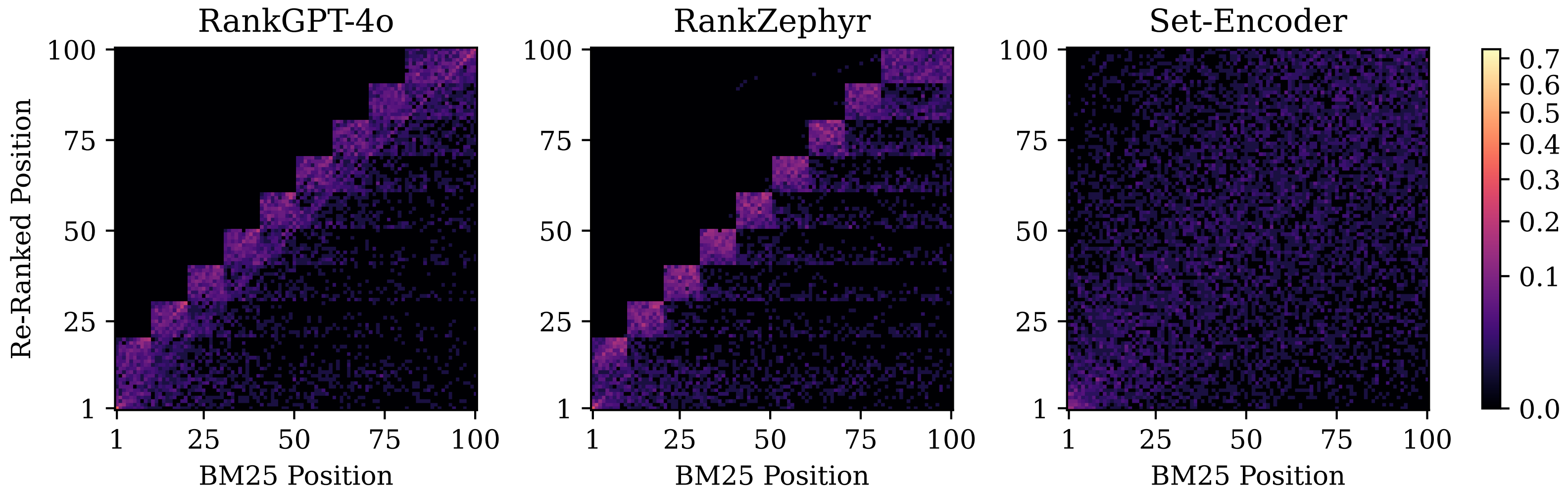
Thanks!

Set-Encoder

Rank Changes

Previous listwise re-rankers are biased by the order of the input documents.

What do these biases look like? ➜ Plot the original vs re-ranked position.



A substantial number of previous works attempt to mitigate these positional biases.
[Zhuang et al., SIGIR’24; Parry et al., arXiv’24]

➜ Making the model permutation-invariant is a more principled approach.

Set-Encoder

TREC DL

Model	Size	TREC DL 19		TREC DL 20	
		BM25	CBv2	BM25	CBv2
First Stage	–	0.480†	0.732†	0.494†	0.724†
RankGPT-4o	N/A	0.725	0.784	0.719	0.793
RankGPT-4o Full	N/A	0.732	0.781	0.711	0.796
RankZephyr	7B	0.719	0.749	0.720	0.798
LiT5-Distill	220M	0.696	0.753	0.679†	0.744†
monoT5 3B	3B	0.705	0.745	0.715	0.757
RankT5 3B	3B	0.710	0.752	0.711	0.772
monoELECTRA	110M	0.720	0.768	0.711†	0.770
	330M	**0.733**	0.765	0.727	**0.799**
Set-Encoder	110M	0.724	0.788	0.710†	0.777
	330M	0.727	**0.789**	**0.735**	0.790

Set-Encoder

TREC DL Novelty

	Model	Prompt / Loss		nDCG		α-nDCG	
				2019	2020	2019	2020
(1)	First Stage	–		0.732	0.724	$0.700^{\dagger}$	$0.722^{\dagger}$
(2)	RankGPT-4o	Relevance		$0.784^{\dagger}$	$0.793^{\dagger}$	0.750	0.759
(3)		Novelty		$0.778^{\dagger}$	**0.806**†	0.741	0.773
(4)	RankGPT-4o Full	Relevance		$0.781^{\dagger}$	$0.796^{\dagger}$	0.738	0.763
(5)		Novelty		$0.785^{\dagger}$	$0.803^{\dagger}$	0.750	0.771
(6)	RankZephyr	Relevance		0.749	$0.798^{\dagger}$	$0.699^{\dagger}$	0.765
(7)		Novelty		0.753	$0.800^{\dagger}$	$0.700^{\dagger}$	0.760
(8)	**Model**	**1st $\mathcal{L}$**	**2nd $\mathcal{L}$**				
(9)	monoELECTRA	$\mathcal{L}_{\text{InfoNCE}}$	$\mathcal{L}_{\text{RankNet}}$	$0.768^{\dagger}$	$0.770^{\dagger}$	$0.718^{\dagger}$	$0.745^{\dagger}$
(10)			$\mathcal{L}_{\text{NA-RankNet}}$	0.704	0.675	0.785	0.753
(11)	Set-Encoder	$\mathcal{L}_{\text{InfoNCE}}$	$\mathcal{L}_{\text{RankNet}}$	$0.780^{\dagger}$	$0.757^{\dagger}$	$0.733^{\dagger}$	$0.747^{\dagger}$
(12)			$\mathcal{L}_{\text{NA-RankNet}}$	0.714	0.651	0.779	$0.743^{\dagger}$
(13)		$\mathcal{L}_{\text{DA-InfoNCE}}$	$\mathcal{L}_{\text{RankNet}}$	**0.788**†	$0.777^{\dagger}$	$0.740^{\dagger}$	$0.752^{\dagger}$
(14)			$\mathcal{L}_{\text{NA-RankNet}}$	0.710	0.690	**0.821**	**0.803**
(15)	Set-Enc. ~~[INT]~~	$\mathcal{L}_{\text{DA-InfoNCE}}$	$\mathcal{L}_{\text{NA-RankNet}}$	0.707	0.670	0.773	$0.748^{\dagger}$

Set-Encoder

Out-of-Domain Re-Ranking

Model	**Size**	**Antique**	**Args.me**	**ClueWeb09**	**ClueWeb12**	**CORD-19**	**Cranfield**	**Disks4+5**	**GOV**	**GOV2**	**MEDLINE**	**NFCorpus**	**Vaswani**	**WaPo**	**G. Mean**
First Stage	–	.516†	.405	.177†	**.364**†	.586†	**.012**	.424†	.259†	.467†	.385	.281†	.447†	.364†	.286
RankZephyr	7B	.534†	.364†	.213	.303	**.767**†	.009	.542	.349	.560	**.460**†	.314	.512	**.508**	.320
LiT5-Distill	220M	.576†	.395	.214	.275†	.686	.011	.495†	.304†	.534†	.354†	.293†	.429†	.470	.302
monoT5 3B	3B	.590	.415	.188†	.323	.649†	.011	.526	.345	.529†	.395	.319	.474†	.469	.313
RankT5 3B	3B	.598	**.421**	**.227**	.336	.713	.010	.538	**.353**	.528†	.406	**.323**	.459†	.468†	**.322**
m.ELECTRA	110M	.593	.375†	.209	.295	.692	.010	.507†	.305†	.541†	.399	.306	.522	.458†	.309
	330M	.575†	.369†	.221	.313	.716	.008	**.546**	.344	.572	.419	.316	.526	.504	.318
Set-Encoder	110M	.594	.375†	.216	.299	.683	.010	.513†	.306†	.543†	.396	.306	.523	.461†	.311
	330M	**.606**	.409	.226	.310	.702	.009	.534	.334	**.573**	.405	.313	**.530**	**.508**	.321

Set-Encoder

Efficiency

Model	**Size**	**Time**	**Memory**
RankGPT-4o	N/A	18.773	N/A
RankGPT-4o Full	N/A	7.362	N/A
RankZephyr	7B	24.047	15.48
LiT5-Distill	220M	2.054	2.69
monoT5$_{3B}$	3B	0.998	29.36
RankT5$_{3B}$	3B	0.942	29.04
monoELECTRA	110M	0.139	1.18
	330M	0.215	2.69
Set-Encoder	110M	0.147	1.25
	330M	0.219	2.60

TITE

Efficiency

Model						**Kernel**	**Queries**	**Documents**
BERT						Eager	24.0 (0.5×)	2.0 (0.2×)
DistilBERT						Eager	47.1 (1.0×)	3.7 (0.4×)
Funnel Transformer						Eager	14.2 (0.3×)	1.3 (0.1×)
TITE (Pool Param.: ①)						Eager	69.8 (1.5×)	6.7 (0.8×)
BERT						SDPA	28.9 (0.6×)	3.2 (0.4×)
DistilBERT						SDPA	57.9 (1.2×)	6.4 (0.7×)
TITE (Pool Param.: ①)						SDPA	81.2 (1.7×)	13.4 (1.5×)
BERT						Flash	48.0	8.7
ModernBERT						Flash	41.1 (0.9×)	8.3 (1.0×)
		k,s	Arr.	Loc.	Dim.			
TITE	①	2	L	Intra	768	Flash	89.0 (1.9×)	20.8 (2.4×)
	②	2	S	Intra	768	Flash	96.0 (2.0×)	28.5 (3.3×)
	③	3	L	Intra	768	Flash	68.1 (1.4×)	14.5 (1.7×)
	④	3	S	Intra	768	Flash	94.6 (2.0×)	30.8 (3.5×)
	⑤	2	L	Pre	768	Flash	89.6 (1.9×)	21.2 (2.4×)
	⑥	2	L	Post	768	Flash	89.0 (1.9×)	20.3 (2.3×)
	⑦	2	L	Intra	1536	Flash	70.1 (1.5×)	16.3 (1.9×)

TITE

Effectiveness

Model	TREC DL		BEIR															
	2019	2020	ArguAna	Climate-FEVER	CQADupStack	DBPedia	FEVER	FiQA	HotpotQA	NFCorpus	NQ	Quora	SCIDOCS	SciFact	TREC-COVID	Touché	Arith. Mean	Geom. Mean
BM25	.506†	.480†	.397†	.165†	.302	.318†	.651†	.236†	.633†	.322	.305†	.789†	.149	.679†	.595†	**.442**†	.427	.379
S-BERT (Repro.)	.700	.688	.336	.224	.319	.369	.727	.317	.574	.303	.510	.844	.146	.603	.756	.256	.449	.399
S-BERT	.705	.726	.384†	.221	.337	.385	.762†	.323	.585†	.315	.522†	.844	.146	.606	.744	.237	.458	.407
S-DistilBERT	.705	.699	.355†	.233	.322	.375	.774†	.286†	.571	.298	.497†	.833†	.140	.596	.666†	.224	.441	.391
S-ModernBERT	–	–	.357	.236	.331	.238	.599	.288	.461	.237	.395	.859	.125	.570	.721	.208	.402	.352
RetroMAE (Repro.)	.723	.711	.375†	**.242**†	.340	.406†	.737†	.340†	.624†	.336†	.539†	.844	**.163**†	.663†	**.780**	.273	.476	.428
RetroMAE	.712	**.730**	.367†	.240†	.342	.428†	.777†	.343†	.668†	.325†	**.573**†	**.853**†	.160†	.638	.759	.280	.482	.432
ColBERTv2	**.732**	.724	.453†	.176†	**.359**	**.441**†	.774†	.346†	.665†	.330†	.547†	.851†	.150	.691†	.732	.257	.484	.427
SPLADE++	.731	.720	**.520**†	.230	.334	.437†	**.788**†	**.347**†	**.687**†	**.347**†	.538†	.834†	.159†	**.704**†	.727	.247	**.493**	**.440**
TITE (Base)	.705	.670	.391†	.204†	.312	.376	.699†	.302	.604†	.334†	.484†	.818†	.156	.647†	.691	.271	.449	.403
TITE (Upscale)	.724	.686	.373†	.209†	.323	.374	.704†	.298	.616†	.328†	.490†	.827†	.155	.632	.715	.275	.451	.404

Model Parameters						TREC DL		BEIR	
		k,s	Arr.	Loc.	Dim.	2019	2020	Arith.	Geom.
TITE	①	2	L	Intra	768	.705	.670	.449	.403
	②	2	S	Intra	768	.675	.663	.443	.397
	③	3	L	Intra	768	.683	.672	.445	.400
	④	3	S	Intra	768	.673	.669	.443	.399
	⑤	2	L	Pre	768	.686	.682	.445	.400
	⑥	2	L	Post	768	.670	.683	.446	.399
	⑦	2	L	Intra	1536	.724	.686	.451	.404