ECIR 2024, 24-28 March, Glasgow, Scotland





Ferdinand Schlatt Maik Fröbe

Matthias

Hagen



webis.de









- Query and document processed separately
- + Documents can be processed and indexed offline
- No interaction between queries and documents



- Query and document processed separately
- + Documents can be processed and indexed offline
- No interaction between queries and documents





- Query and document processed jointly
- Document must be processed at query time
- + Interaction between queries and documents

Bi-Encoder Cosine-Similarity BERT t Query Document

- Query and document processed separately
- + Documents can be processed and indexed offline
- No interaction between queries and documents





- Query and document processed jointly
 - Document must be processed at query time
- + Interaction between queries and documents

Cross-encoders are effective but slow and expensive to run. [Scells et al., SIGIR'22]

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

Query: python

Document: Python is a great programming language to learn.

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Full Attention



Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Longformer [Beltagy et al., arXiv'20]



Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Longformer [Beltagy et al., arXiv'20]

Attention to



Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Longformer [Beltagy et al., arXiv'20]



Attention to

- Document tokens' attention restricted to context window of length w
- Semantic "gist" suffices to determine the relevance of a document token
- □ Previous work used w = 64 to save memory and re-rank longer documents

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Longformer [Beltagy et al., arXiv'20]



Attention to

- Document tokens' attention restricted to context window of length w
- Semantic "gist" suffices to determine the relevance of a document token

Hypothesis: Very small window sizes are as effective as full attention.

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Query Independent Attention



Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Query Independent Attention



Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Query Independent Attention



- A document is relevant to a query and not vice versa
- The query–document relevance relationship is asymmetric

Making cross-encoders more efficient

One paradigm that improves cross-encoder efficiency is reducing the number of tokens that interact with each other. [Sekulic et al., TREC'20; Jiang et al., EMNLP'20]

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Query Independent Attention



Attention to

- A document is relevant to a query and not vice versa
- The query–document relevance relationship is asymmetric
- Hypothesis: Deactivating attention from query tokens to other tokens is as effective as full attention.

Sparse cross-encoder architecture

Our sparse cross-encoder architecture combines windowed self-attention and asymmetric cross-attention between sub-sequences.

Sparse cross-encoder architecture

Our sparse cross-encoder architecture combines windowed self-attention and asymmetric cross-attention between sub-sequences.

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Sparse Cross-Encoder



Sparse cross-encoder architecture

Our sparse cross-encoder architecture combines windowed self-attention and asymmetric cross-attention between sub-sequences.

[CLS] python [SEP] Python is a great programming language to learn . [SEP]

Sparse Cross-Encoder

Attention to



 Asymmetric attention not supported by standard transformer architectures

Sparse cross-encoder architecture

Our sparse cross-encoder architecture combines windowed self-attention and asymmetric cross-attention between sub-sequences.

[CLS] python [SEP] Python is a great programming language to learn . [SEP]





- Asymmetric attention not supported by standard transformer architectures
- Custom architecture with cross-attention between sub-sequences

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ntion	/ Lon	gform	ner		Spars	e Cro	ss-En	coder	
w =	∞	64	16	4	1	0	∞	64	16	4	1	0
Passage	0.62	0.62 [†]										
Document	0.58	0.58										

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ntion	/ Lon	gforn	ner		Spars	e Cro	ss-En	coder	
w =	∞	64	16	4	1	0	∞	64	16	4	1	0
Passage	0.62	0.62 [†]					0.62					
Document	0.58	0.58					0.57					

[†] denotes significant equivalence within ± 0.02 (paired TOST) with underlined score per row. MaxP results are grayed out.

1. Asymmetric query attention does not impact effectiveness ...

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ntion	/ Lon	gforn	ner		Spars	e Cro	ss-En	codei	r
w =	∞	64	16	4	1	0	∞	64	16	4	1	0
Passage	0.62	0.62 [†]					0.62	0.62				
Document	0.58	0.58					0.57	0.59				

[†] denotes significant equivalence within ± 0.02 (paired TOST) with underlined score per row. MaxP results are grayed out.

1. Asymmetric query attention does not impact effectiveness even combined with windowed self-attention

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ention ,	/ Lon	gform	ner	Sparse Cross-Encoder					
w =	∞	64	16	4	1	0	∞	64	16	4	1	0
Passage	0.62	0.62 [†]	0.62 [†]				0.62	0.62	0.61			
Document	0.58	0.58	0.59^{\dagger}				0.57	0.59	0.59			

- 1. Asymmetric query attention does not impact effectiveness even combined with windowed self-attention
- 2. Window size of w = 16 is on par with full attention

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ntion	/ Long	gforn	ner		Spars	e Cro	ss-Enc	oder	
w =	∞	64	16	4	1	0	∞	64	16	4	1	0
Passage	0.62	0.62 [†]	0.62 [†]	0.62 [†]			0.62†	0.62 [†]	0.61	0.61†		
Document	0.58	0.58	0.59^{\dagger}	0.59			0.57	0.59	0.59	0.58		

- 1. Asymmetric query attention does not impact effectiveness even combined with windowed self-attention
- 2. Window size of w = 4 is on par with full attention

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ention	/ Lon	gforme	er		Spars	e Cro	ss-En	Encoder		
w =	∞	64	16	4	1	0	∞	64	16	4	1	0	
Passage	0.62	0.62 [†]	0.62 [†]	0.62 [†]	0.61		0.62†	0.62†	0.61	0.61†	0.60		
Document	0.58	0.58	0.59^{\dagger}	0.59	0.58^{\dagger}		0.57	0.59	0.59	0.58	0.59		

- 1. Asymmetric query attention does not impact effectiveness even combined with windowed self-attention
- 2. Window size of w = 4 is on par with full attention
- 3. Window size of w = 1 still competitive

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ention	/ Lon	gform	er	ę	Spars	e Cro	ss-En	coder	•
w =	∞	64	16	4	1	0	∞	64	16	4	1	0
Passage	0.62	0.62 [†]	0.62 [†]	0.62 [†]	0.61	0.57	0.62 [†]	0.62 [†]	0.61	0.61 [†]	0.60	0.56
Document	0.58	0.58	0.59^{\dagger}	0.59	0.58 [†]	0.56	0.57	0.59	0.59	0.58	0.59	0.56

- 1. Asymmetric query attention does not impact effectiveness even combined with windowed self-attention
- 2. Window size of w = 4 is on par with full attention
- 3. Window size of w = 1 still competitive
- 4. Window size of w = 0 slightly less effective

Sparse cross-encoder effectiveness

nDCG@10 on TREC Deep Learning 2019–2022 passage and document

Task	Fu	II Atte	ention	/ Lon	gform	er		Spars	e Cro	ss-En	coder	
w =	∞	64	16	4	1	0	∞	64	16	4	1	0
Passage	0.62	0.62 [†]	0.62 [†]	0.62 [†]	0.61	0.57	0.62 [†]	0.62 [†]	0.61	0.61 [†]	0.60	0.56
Document	0.58	0.58	0.59^{\dagger}	0.59	0.58 [†]	0.56	0.57	0.59	0.59	0.58	0.59	0.56

- 1. Asymmetric query attention does not impact effectiveness even combined with windowed self-attention
- 2. Window size of w = 4 is on par with full attention
- 3. Window size of w = 1 still competitive
- 4. Window size of w = 0 slightly less effective
- → Also translates to out-of-domain effectiveness on TIREx [Fröbe et al. SIGIR'23]

Sparse cross-encoder efficiency

Latency and memory consumption on synthetic query document pairs

Unit	Full Attention	Longformer	Sparse CE	Sparse CE
w =	∞	64	64	4
Query	/ length 10, Pass	age length 164		
μs	368	980 (+166%)		
MB	9	15 (+67%)		
Query	/ length 10, Docu	ment length 40	86	
ms	49 (+250%)	14		
MB	1608 (+905%)	160		

Sparse cross-encoder efficiency

Latency and memory consumption on synthetic query document pairs

Unit	Full Attention	Longformer	Sparse CE	Sparse CE
w =	∞	64	64	4
Query	/ length 10, Pass	age length 164		
μs	368	980 (+166%)	527 (+43%)	
MB	9	15 (+67%)	9 (+0%)	
Query	y length 10, Docu	ment length 40	86	
ms	49 (+250%)	14	12 (-14%)	
MB	$1608 \ (+905\%)$	160	111 (-31%)	

1. Sparse cross-encoder with w = 64 is more efficient than the Longformer

Sparse cross-encoder efficiency

Latency and memory consumption on synthetic query document pairs

Unit	Full Attention	Longformer	Sparse CE	Sparse CE
w =	∞	64	64	4
Query	/ length 10, Pass	age length 164		
μs	368	980 (+166%)	527 (+43%)	364 (-1%)
MB	9	15 (+67%)	9 (+0%)	7 (-22%)
Query	/ length 10, Docu	ment length 40	86	
ms	49(+250%)	14	12 (-14%)	8 (-43%)
MB	$1608 \ (+905\%)$	160	111 (-31%)	66 (-59%)

- 1. Sparse cross-encoder with w = 64 is more efficient than the Longformer
- 2. Window size w = 4 is more efficient than full attention on passages

We introduced a sparse cross-encoder architecture that combines windowed self-attention and asymmetric cross-attention between sub-sequences.

- Attention from query tokens to other tokens can be deactivated without losing effectiveness.
- □ Very small window sizes are still effective for re-ranking with cross-encoders.
- Our sparse cross-encoder reduces memory consumption and runtime.

We introduced a sparse cross-encoder architecture that combines windowed self-attention and asymmetric cross-attention between sub-sequences.

- Attention from query tokens to other tokens can be deactivated without losing effectiveness.
- □ Very small window sizes are still effective for re-ranking with cross-encoders.
- Our sparse cross-encoder reduces memory consumption and runtime.

Renaur Thank you!

Code and models @ https://github.com/webis-de/ECIR-24

Investigating the Effects of Sparse Attention on Cross-Encoders Full TREC DL Table

Т	ask		Full A	Att. / L	ongfo	rmer			Spars	e Cro	ss-En	coder		QDS
	w =	∞	64	16	4	1	0	∞	64	16	4	1	0	64
	2019	.724	.719 [†]	.725†	.719	.714	.694	.722	.717	.724	.728	.715	.696	.720
ge	2020	.674	.681†	.680	.684	.676	.632	.666	.672	.661	.665	.649	.605	.682
ssa	2021	.656	.653	.650	.645	.629	.602	.656	.650	.639	.647	.625	.593	.656 [†]
Pas	2022	.496	.494†	.487	.486	.481	.441	.490	.492 [†]	.479	.484	.471	.427	.495 [†]
	Avg.	.619	.619 [†]	.616 [†]	.615 [†]	.607	.572	.615 [†]	.615 [†]	.607	.612†	.596	.560	.620
	2019	.658	.683	.678	.667	.689	.663	.638	.672	.685	.669	.692	.646	.697
ent	2020	.622	.640	.639	.661	.655	.644	.636	.638	.650	.642	.657	.638	.639
Ē	2021	.678	.671	.681	.683	.683	.629	.677	.681	.681	.670	.679	.644	.676
000	2022	.424	.425	.431	.425	.409	.389	.421	.446	.443	.417	.424	.405	.428
	Avg.	.575	.582	.586†	.587	.584†	.556	.573	.590	.594	.577	.589	.561	.587

Corpus	Doc. Len.	First Stage	monoT5			monoBERT		Sparse CE	
			Base	Large	3b	Base	Large	512	4096
Antique	49.9	.510	.505	.527	.537	.507	.484	.540	.174
Args.me	435.5	.405	.305	.338	.392	.314	.371	.313	.180
CW09	1132.6	.178	.186	.182	.201	.192	.134	.198	.212
CW12	5641.7	.364	.260	.266	.279	.263	.251	.312	.338
CORD-19	3647.7	.586	.688	.636	.603	.690	.625	.673	.642
Cranfield	234.8	.008	.006	.007	.007	.006	.006	.009	.003
Disks4+5	749.3	.429	.516	.548	.555	.514	.494	.487	.293
GOV	2700.5	.266	.320	.327	.351	.318	.292	.316	.292
GOV2	2410.3	.467	.486	.513	.514	.489	.474	.503	.460
MED.	309.1	.366	.264	.318	.350	.267	.298	.237	.180
NFCorpus	364.6	.268	.295	.296	.308	.295	.288	.284	.151
Vaswani	51.3	.447	.306	.414	.458	.321	.476	.436	.163
WaPo	713.0	.364	.451	.492	.476	.449	.438	.434	.296
Average	_	.358	.353	.374	.387	.356	.356	.365	.260

Investigating the Effects of Sparse Attention on Cross-Encoders Efficiency Graphs

