

Team Galápagos Tortoise at LongEval 2024: Neural Re-Ranking and Rank Fusion for Temporal Stability

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Motivation

- Modern retrieval systems use multi-stage re-ranking
- Static test collections prone to train-test leakage
 - Unrealistic scenario
- Models struggle with temporal changes
- Let's develop systems that maintain effectiveness over time



(How Stable Diffusion thinks BERT would explain multi-stage re-ranking.)

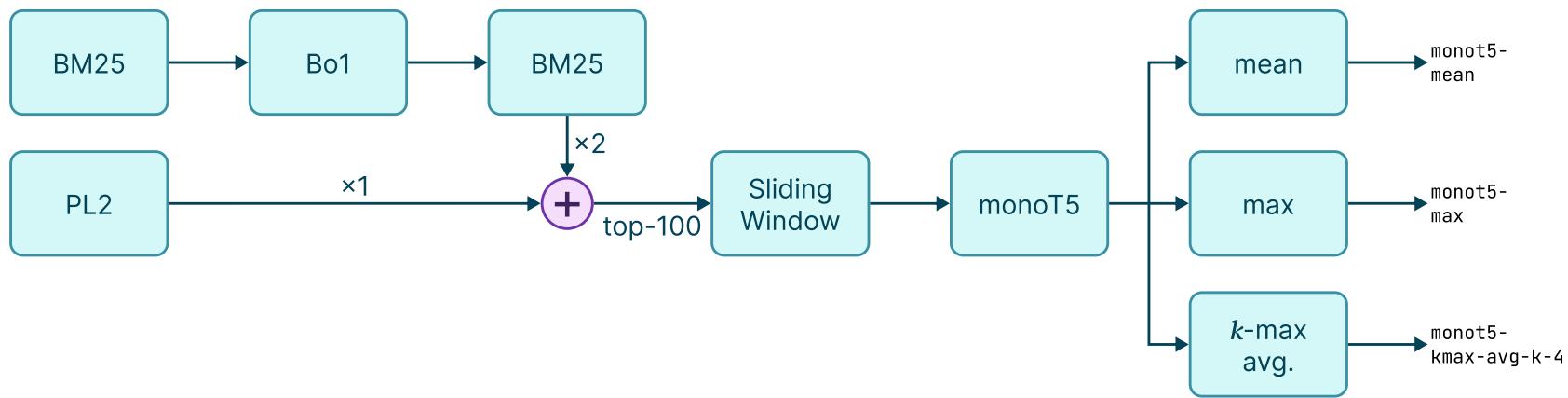
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Our Research

1. Explore passage score aggregations for monoT5 re-ranking
 - ❑ Standard bi-encoder re-ranking after lexical first-stage retrieval
 - ❑ Passage score aggregations: max, mean, k -max average
 2. Explore rank fusion of diverse retrieval models
 - ❑ LLM-based re-ranker after lexical first-stage retrieval
 - ❑ Fusion with cross-encoder, late-interaction, and lexical
- Evaluate effectiveness and temporal stability
- ❑ nDCG
 - ❑ Decline over time: Jan→Jun, Jun→Aug, Jan→Aug

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Approach: monoT5 Re-Ranking



- Initial retrieval: Weighted combination of BM25 and PL2
- Re-ranking top-50 results with monoT5
- Comparing passage score aggregation schemes:
 - Max passage
 - Mean passage
 - k -max average ($k = 4$, tuned on Jan. data)

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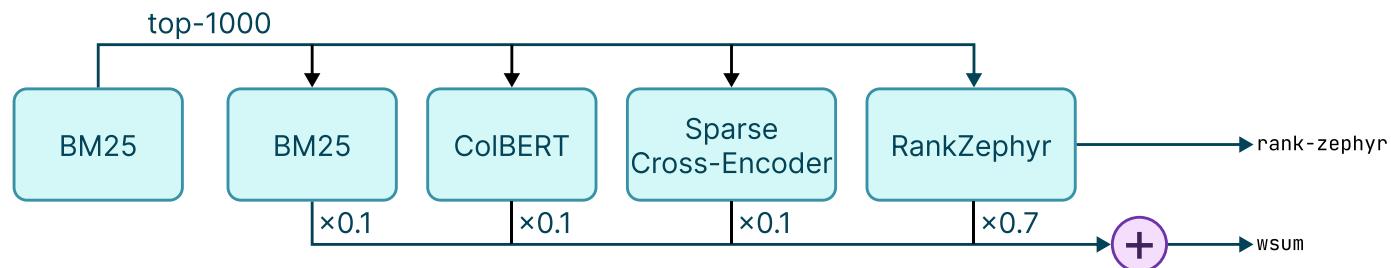
Results: monoT5 Re-Ranking

- Max passage aggregation outperforms mean passage
- Difference more significant on recent datasets
- k -max average worse than max passage
- All systems show temporal decline in effectiveness

System	nDCG@10		nDCG	
	value	p value	value	p value
<i>January 2023</i>				
max passage	0.209	—	0.307	—
4-max avg. passage	0.208	0.86	0.305	0.41
mean passage	0.209	0.93	0.307	0.82
<i>June 2023</i>				
max passage	0.196	—	0.260	—
4-max avg. passage	0.191	0.24	0.257	0.24
mean passage	0.184	0.02	0.253	0.02
<i>August 2023</i>				
max passage	0.159	—	0.198	—
4-max avg. passage	0.156	0.07	0.196	0.12
mean passage	0.150	<0.01	0.191	<0.01

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Approach: Rank Fusion



- Weighted rank fusion of:
 - RankZephyr (weight: 0.7)
 - Sparse Cross-Encoder (weight: 0.1)
 - ColBERT (weight: 0.1)
 - BM25 (weight: 0.1)
- Optimized for nDCG@10 on January 2023 dataset

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Results: Rank Fusion

- ❑ Rank fusion significantly outperforms most individual models
- ❑ No significant difference between fusion and just RankZephyr
- ❑ Highly effective systems (fusion, RankZephyr) show greater temporal decline

System name	nDCG@10		nDCG	
	value	p value	value	p value
<i>January 2023</i>				
rank fusion	0.251	—	0.355	—
RankZephyr	0.247	0.07	0.353	0.26
Sparse Cross-Enc.	0.221	<0.01	0.337	<0.01
CoBERT	0.216	<0.01	0.330	<0.01
<i>June 2023</i>				
rank fusion	0.228	—	0.293	—
RankZephyr	0.228	0.98	0.295	0.34
Sparse Cross-Enc.	0.202	<0.01	0.277	<0.01
CoBERT	0.183	<0.01	0.264	<0.01
<i>August 2023</i>				
rank fusion	0.180	—	0.220	—
RankZephyr	0.178	0.15	0.219	0.52
Sparse Cross-Enc.	0.169	<0.01	0.212	<0.01
CoBERT	0.161	<0.01	0.206	<0.01

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Summary

- Max passage aggregation most effective/stable for monoT5 re-ranking
- Rank fusion improves effectiveness but not temporal stability
- All systems, including BM25, show effectiveness decline over time
- Future work:
 - Investigate temporal decline in lexical models
 - Explore more fusion candidates

Code and Data

🔗 github.com/webis-de/CLEF-24



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Thank you & merci!