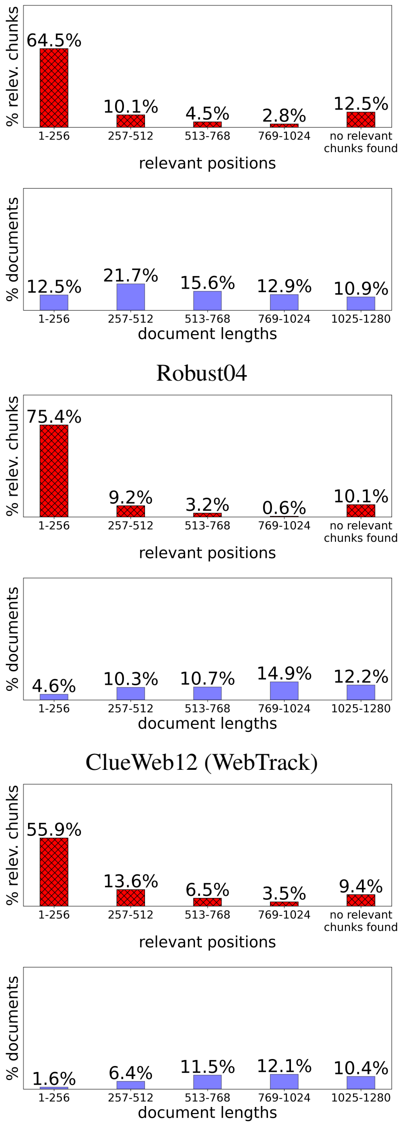
Positional Bias in Long-Document Ranking: Impact, Assessment, and Mitigation

Anonymous ACL submission

Abstract

We tested over 20 Transformer models for ranking of long documents (including recent *LongP* models trained with FlashAttention and RankGPT models "powered" by OpenAI and Anthropic cloud APIs). We compared them with a simple *FirstP* baselines, which applied the *same* model to the truncated input (at most 512 tokens). On MS MARCO, TREC DL, and Robust04 no long-document model outperformed *FirstP* by more than 5% (on average). We hypothesized that the lack of improvement by long-context models is not due to inherent model limitations, but due to benchmark positional bias (most relevant passages tend to occur early in documents). To further confirm this we analyzed positional relevance distributions across five corpora and six query sets and observed the same early-position bias. We then introduced a new diagnostic dataset, MS MARCO FarRelevant, where relevant spans were deliberately placed beyond the first 512 tokens. On this dataset, many long-context models—including RankGPT—failed to generalize and performed near the random baseline, suggesting overfitting to positional bias. Finally, we experimented with de-biasing the training data, but the success of this approach was mixed. Our findings (1) highlight the need for careful benchmark design in evaluating long-context models for document ranking, (2) identify model types that are more robust to positional bias, and (3) motivate further work on approaches to de-bias training data. We release our code and data to support further research.[1]



Robust04

ClueWeb12 (WebTrack)

TREC DL 2019-2021 (combined)

Figure 1: Illustration of relevant passage bias for three document collections: A distribution of first relevant passage positions (red bars) vs. relevant document lengths (blue bars). Lengths and offsets are measured in the number of subword tokens (BERT-base tokenizer). Best viewed in color. See more results in Table 7 in § B.1)

1 Introduction

Various advances in Transformer architectures—including sparse attention (Zaheer et al., 2020; Beltagy et al., 2020) and FlashAttention (Dao et al., 2022)—have motivated a growing interest in long-

[1] https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/.

document ranking and retrieval. However, despite the ability of these models to process substantially more text, on *popular retrieval benchmarks*, the improvements of these models over simpler truncation-based approaches remain surprisingly modest (Dai and Callan, 2019; Gao and Callan, 2022; Coelho et al., 2024). A widely used truncation-based *FirstP* baseline (Dai and Callan, 2019)—where models score only the first 512 tokens of each document—often performs competitively, or sometimes even better, than long-context counterparts (see, e.g., Table 1).

Despite anecdotal knowledge about the presence of this phenomenon in the MS MARCO document-retrieval collection among TREC Deep Learning track participants and some early reports (Hofstätter et al., 2020b, 2021a) the available evidence has been scattered and incomplete. In particular, despite the track's five-year history, none of the track's overview papers mentioned this issue (Craswell et al., 2020, 2021a,b, 2022, 2023).

Moreover, it remains unclear whether these limitations stem from model deficiencies or from characteristics of the benchmarks themselves. In this paper, we initially hypothesized that both factors—model robustness and benchmark design—may be responsible for the limited gains of long-document models over *FirstP* baselines. However, our findings suggest that benchmark design, particularly positional relevance bias, is the dominating factor.

To verify our research hypotheses, we first conducted a large-scale, systematic study of over 20 Transformer-based ranking models (Devlin et al., 2019; Vaswani et al., 2017) for long-document retrieval. This was done using three popular document collections—MS MARCO Documents v1/v2 (Craswell et al., 2021a) and Robust04 (Clarke et al., 2004)—along with diverse query sets (both large and small) several Transformer backbones and multiple training seeds. In addition to locally trained models, we also assessed a listwise LLM ranker RankGPT (Sun et al., 2023) "powered" by OpenAI (OpenAI, 2023) and Anthropic (Anthropic, 2024) cloud APIs. Despite the increased context capacity of long-document models, we found that none of them consistently outperformed their *FirstP* baselines by more than 5% on average.

Next, we estimated positional relevance bias across five document collections (including MS MARCO v2) and more than six query sets. As can be seen in Fig. 1, in the vast majority of cases the first relevant passage occurred within the initial 512 tokens. In contrast, the distribution of passage positions is more uniform and has a long tail. This confirms the presence of positional bias not only in MS MARCO, but also in other TREC collections (a complete set of plots is provided in Fig. 7 of Appendix § B.4).

Our initial exploration prompted two *broad* research questions:

- **RQ1:** How robust are long-document models to the positional-bias of relevant passages?
- **RQ2:** How much progress has the community made in improving long-document ranking models? Do we really improve upon *FirstP* baselines? Given that all long-document models are at least 2× slower than respective *FirstP* baselines (see Figure 3, § A.4), one could question practicality of such models and suggest using *FirstP* variants instead.

To answer these questions, we constructed a new *diagnostic* synthetic collection MS MARCO Far-Relevant where relevant passages were not present among the first 512 tokens. On this dataset, many long-context models—including RankGPT (Sun et al., 2023)—failed to generalize and performed at a random baseline level, suggesting overfitting to positional bias. Poor performance of models on our new synthetic collection prompted another important question **RQ3:** Can de-biasing training data mitigate model overfitting to positional bias?

In summary our paper makes the following contributions:

- We re-examined the issue of positional relevance bias, gathered extensive evidence confirming its presence, and evaluated the robustness of ranking models against this bias;
- Our work highlights the need for careful benchmark design in evaluating long-context models for document ranking, which do not mask the benefits of long-context models and identifies model types that are more robust to positional bias;
- We perform an extensive reproduction study of over 20 ranking models using two established benchmark collections for long-document retrieval and ranking;

- We experiment with de-biasing training data and motivate further research in this area.

We release our code and data to support further research.[2]

2 Related Work

Neural Ranking models have been a widely studied topic in recent years (Guo et al., 2019), though the success of early approaches was debated (Lin, 2019). This changed with the introduction of BERT, a bi-directional encoder-only Transformer model (Devlin et al., 2019), which significantly outperformed previous methods in both NLP (Devlin et al., 2019) and information retrieval (IR) tasks (Nogueira et al., 2019; Craswell et al., 2021a).

Several Transformer-based models, such as ELECTRA (Clark et al., 2020) and DEBERTA (He et al., 2021), have improved upon BERT through different training strategies and datasets. However, due to their architectural similarities, we—following Lin et al. (2021)—refer to these collectively as BERT models.

Despite their strong performance, neural models are vulnerable to distribution shifts, often relying on superficial features and exhibiting various *biases*. They do not consistently outperform BM25 on out-of-domain data (Thakur et al., 2021; Mokrii et al., 2021), can be misled by minor text modifications and distractor sentences (MacAvaney et al., 2022), or reformulated queries (Penha et al., 2022). They also struggle to effectively utilize information located in the middle of long input contexts (Liu et al., 2024).

A seemingly similar yet distinct issue of positional relevance bias has been identified in information retrieval settings, particularly within the MS MARCO document-retrieval collection (Hofstätter et al., 2020b; Coelho et al., 2024). Some studies have reported strong performance of *FirstP* baselines on long-document retrieval collections, interpreting this as evidence of benchmark-induced positional bias (Zhu et al., 2024). However, strong performance of *FirstP* baseline is only indirect evidence, potentially resulting from implementation bugs, suboptimal training methods, or model-inherent biases. (Coelho et al., 2024) found that embedding models trained on MS MARCO "dwell" in the beginning and are somewhat less effective when relevant information is present elsewhere in a document. The study used only two embedding models and has additional limitations: (1) it is unclear if the bias is fully attributable to data (2) the models were not tested under conditions of extreme positional bias, (3) no mitigation strategy was evaluated.

To address the issue with existing benchmarks, (Zhu et al., 2024) proposed a *LongEmbed* benchmark with two synthetic tasks where relevant mini-passages were scattered uniformly across documents whose lengths varied from 256 to 32768 tokens. However, as discussed in §B.3 of the Appendix, these synthetic sets are quite unnatural and lack diversity. Furthermore, Zhu et al. (2024) provide only small query sets and no in-domain training data, making it difficult to assess the upper performance bound that models can achieve on this dataset. As another important limitation Zhu et al. (2024), only explored training-free extensions of positional encoding and did not investigate methods to de-bias training data. In contrast, Hofstätter et al. (2021a) proposed to de-bias training data using a simple-yet-effective approach. However, they did *not* evaluate it on *challenging* long-document datasets.

Due to the quadratic complexity of the Transformer's attention mechanism (Vaswani et al., 2017; Bahdanau et al., 2015), early Transformer models restricted input length to a maximum of 512 (subword) tokens. Until around 2022, two main strategies were used to process long documents: (1) localizing attention and (2) splitting documents into smaller, independently processed chunks. Attention-localization methods apply a limited-span (sliding window) attention with selective global attention. Given the vast number of such approaches (see Tay et al. 2020), evaluating all of them is impractical. Therefore, we focus on two popular models: Longformer (Beltagy et al., 2020) and BigBird (Zaheer et al., 2020). More recently, it has also become feasible to train long-context models with (an IO-efficient) FlashAttention algorithm without sparsifying attention (Dao et al., 2022). In our work we use two such models: JINA (Günther et al., 2023) and MOSAIC (Portes et al., 2023).

In summary, the methods to tackle longer documents are divided into *LongP* methods—where longer document lengths are "natively" supported and *SplitP* methods—where the longer document cannot be processed as a whole and needs to be processed in chunks. The results of each chunk

[2] https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/.

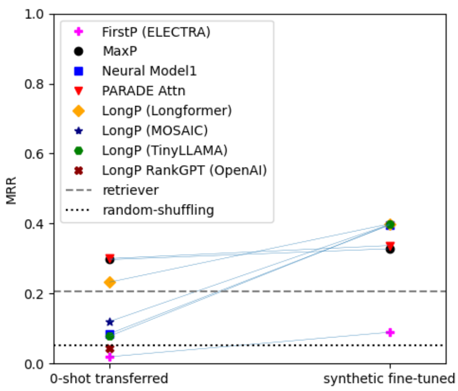


Figure 2: Zero-shot vs. fine-tuned performance on MS MARCO FarRelevant for a representative set of models.

are aggregated together using various aggregation techniques, including a computation of a maximum or a weighted-sum prediction score (Yilmaz et al., 2019; Dai and Callan, 2019; MacAvaney et al., 2019). This includes MaxP (Dai and Callan, 2019), AvgP, SumP (MacAvaney et al., 2019), as well as PARADE Avg and PARADE Max models (MacAvaney et al., 2019). Some *SplitP* approaches aggregate using simple neural networks. This includes all CEDR (MacAvaney et al., 2019) models, the Neural Model 1 (Boytsov and Kolter, 2021), and the PARADE Attention model (Li et al., 2024). In contrast, PARADE Transformer (Li et al., 2024) models' aggregator network is an additional Transformer model. Due to space constraints, a detailed description of document-splitting (*SplitP*) approaches is provided in the Appendix § C.

The recent success of decoder-only models—commonly known as LLMs—has led to a new generation of cross-encoding *LongP* models that natively support longer contexts. First, a pre-trained cross-encoding decoder-only model can be directly fine-tuned in a ranking or embedding task (Ma et al., 2023). Second, the RankGPT approach (Sun et al., 2023) formulates document ranking as a generation task: The model is prompted with a list of documents and an instruction to generate their ranking—an ability made possible through instruction-tuning and/or alignment (Wei et al., 2022; Ouyang et al., 2022). When the combined length of concatenated documents exceeds the input context size, RankGPT employs an overlapping sliding window strategy, followed by aggregation of the results.

3 Experiments

3.1 Data

Our primary datasets, used for both training and evaluation, consist of several realistic collections (along with their respective query sets) and synthetic data. All datasets are in *English*. Document and query statistics are provided in Appendix § B.1 Tables 9 and 10.

The realistic datasets include two versions of the MS MARCO Documents collection (v1 and v2), MS MARCO Passages collection (v1), (Bajaj et al., 2016; Craswell et al., 2020, 2021b), Robust04 (Voorhees, 2004), and the NQ BEIR, which is a Natural Question (Kwiatkowski et al., 2019) subset incorporated into the BEIR benchmark (Thakur et al., 2021).

Following Hofstätter et al. (2021a), we created a de-biased version of MS MARCO by randomly splitting documents at word boundaries and then concatenating the shuffled segments. This de-biasing process is only partial, as shorter documents remain more frequent. To address this imbalance, we experimented with oversampling longer documents, but this approach did not yield improvements.

Our synthetic data consists of two subsets from LongEmbed (Zhu et al., 2024) and our newly created MS MARCO FarRelevant collection. All these can be considered a variant of the needle-in-the-haystack tests, where an informational "nugget" is randomly embedded within unrelated text (Saad-Falcon et al., 2024; Zhu et al., 2024; Liu et al., 2024). We use two LongEmbed subsets: Needle and Passkey: Each has 800 question-document pairs with document lengths varying from (approximately) 256 to 32768 tokens.

MS MARCO FarRelevant was created by randomly mixing relevant and non-relevant passages from the MS MARCO *Passage* collection (Craswell et al., 2020) in such a way that (1) each document contained exactly one relevant passage, (2) this passage did not start before token 512, and (3) the document length was at most 1431 tokens with (see an algorithm in the Appendix § B.2). It has about 0.5 million documents with an average length of 1.1K tokens. Due to MS MARCO datasets having a **non-commercial license**, MS MARCO FarRelevant has the same licensing restriction. In Appendix § B.3, we present dataset examples and argue that—while all these collections share the limitation of not resembling natu-

Retriever / Ranker	MS MARCO	TREC DL	Robust04		Avg. gain
	dev	(2019-2021)	title	description	over FirstP
	MRR	**NDCG@10**	**NDCG@20**		
retriever	0.312	0.629	0.428	0.402	–
FirstP (BERT)	0.394	0.632	0.475	0.527	–
FirstP (Longformer)	0.404	0.643	0.483	0.540	–
FirstP (ELECTRA)	0.417	0.662	0.492	0.552	–
FirstP (DEBERTA)	0.415	0.672	0.534	0.596	–
FirstP (Big-Bird)	0.408	0.656	0.507	0.560	–
FirstP (JINA)	0.422	0.654	0.488	0.532	–
FirstP (MOSAIC)	0.423	0.643	0.453	0.538	–
FirstP (TinyLLAMA)	0.395	0.615	0.431	0.473	–
FirstP (E5-4K) **zero-shot**	0.380	0.641	0.438	0.429	–
FirstP RankGPT (GPT-4o-mini)	–	**0.708**	–	0.562	
AvgP	0.389 (−1.3%)	0.642 (+1.5%)	0.478 (+0.5%)	0.531 (+0.9%)	+0.4%
MaxP	0.392 (−0.4%)	0.644^{a} (+1.9%)	0.488^{a} (+2.6%)	0.544^{a} (+3.3%)	+1.9%
MaxP (ELECTRA)	0.414 (−0.6%)	0.659 (−0.5%)	0.502 (+2.0%)	0.563 (+2.1%)	+0.8%
MaxP (DEBERTA)	0.402^{a} (−3.2%)	0.671 (−0.1%)	0.535 (+0.2%)	0.609^{a} (+2.2%)	-0.2%
SumP	0.390 (−1.0%)	0.639 (+1.0%)	0.486 (+2.2%)	0.538 (+2.1%)	+1.1%
CEDR-DRMM	0.385^{a} (−2.3%)	0.629 (−0.5%)	0.466 (−2.0%)	0.533 (+1.3%)	-0.9%
CEDR-KNRM	0.379^{a} (−3.8%)	0.630 (−0.3%)	0.483 (+1.7%)	0.535 (+1.7%)	-0.2%
CEDR-PACRR	0.395 (+0.3%)	0.643^{a} (+1.6%)	0.496^{a} (+4.3%)	0.549^{a} (+4.2%)	+2.6%
Neural Model1	0.398 (+0.9%)	0.650^{a} (+2.8%)	0.484 (+1.8%)	0.537 (+1.9%)	+1.8%
PARADE Attn	0.416^{a} (+5.5%)	0.652^{a} (+3.1%)	0.503^{a} (+5.7%)	0.556^{a} (+5.6%)	**+5.0%**
PARADE Attn (ELECTRA)	0.431^{a} (+3.3%)	0.680^{a} (+2.7%)	0.523^{a} (+6.4%)	0.581^{a} (+5.3%)	+4.4%
PARADE Attn (DEBERTA)	0.422^{a} (+1.6%)	0.688^{a} (+2.4%)	$\mathbf{0.549}^{a}$ (+2.9%)	$\mathbf{0.615}^{a}$ (+3.2%)	+2.5%
PARADE Avg	0.392 (−0.6%)	0.646^{a} (+2.1%)	0.483 (+1.5%)	0.534 (+1.5%)	+1.1%
PARADE Max	0.405^{a} (+2.7%)	0.655^{a} (+3.5%)	0.489^{a} (+2.8%)	0.548^{a} (+4.0%)	+3.3%
PARADE Transf-RAND-L2	0.419^{a} (+6.3%)	0.655^{a} (+3.6%)	0.488^{a} (+2.8%)	0.548^{a} (+4.1%)	+4.2%
PARADE Transf-RAND-L2 (ELECTRA)	$\mathbf{0.433}^{a}$ (+3.9%)	0.670 (+1.2%)	0.523^{a} (+6.3%)	0.574^{a} (+3.9%)	+3.8%
PARADE Transf-PRETR-L6	0.402^{a} (+1.9%)	0.643 (+1.6%)	0.494^{a} (+4.0%)	0.554^{a} (+5.1%)	+3.2%
LongP (Longformer)	0.412^{a} (+1.9%)	0.668^{a} (+3.9%)	0.500^{a} (+3.6%)	0.568^{a} (+5.1%)	+3.6%
LongP (Big-Bird)	0.397^{a} (−2.9%)	0.651 (−0.7%)	0.452^{a} (−10.9%)	0.477^{a} (−14.9%)	-7.3%
LongP (JINA)	0.416^{a} (−1.5%)	0.665^{a} (+1.7%)	0.503^{a} (+2.9%)	0.558^{a} (+4.9%)	+2.0%
LongP (MOSAIC)	0.421 (−0.4%)	0.664^{a} (+3.3%)	0.456 (+0.6%)	0.570^{a} (+6.0%)	+2.4%
LongP (TinyLLAMA)	0.402^{a} (+1.7%)	0.608 (−1.1%)	0.452^{a} (+4.8%)	0.505^{a} (+6.7%)	+3.0%
LongP (E5-4K) **zero-shot**	0.353^{a} (−7.1%)	0.649 (+1.3%)	0.439 (+0.1%)	0.434 (+1.1%)	-1.1%
LongP RankGPT (GPT-4o-mini)	–	0.706 (−0.3%)	–	0.562 (+0.0%)	-0.1%

In each column we show a relative gain with respect model's respective *FirstP* baseline: The last column shows the average relative gain over *FirstP* baselines. Best numbers are in **bold**: Results are averaged over three seeds. Unless specified explicitly, the backbone is **BERT-base**. Statistical significant differences with respect to this baseline are denoted using the superscript **a**. p-value threshold is 0.01 for an MS MARCO development collection and 0.05 otherwise.

Table 1: Ranking Performance on MS MARCO, TREC DL, and Robust04.

ral documents—MS MARCO FarRelevant offers greater diversity and serves as a more suitable benchmark for evaluating text retrieval systems.

Robust04 is another relatively small dataset containing 0.5 million documents, comprising a mix of news articles and government records, some of which are quite lengthy. However, it includes only a limited number of queries (250), making it a challenging benchmark for training models in low-data scenarios. Each query consists of a title and description: the title expresses a concise information need, while the description provides a more detailed request, often written in proper English prose. We use Robust04 in a cross-validation setting with folds created by Huston and Croft (2014) provided via IR-datasets (MacAvaney et al., 2021).[3]

MS MARCO v1 was created from the MS MARCO reading comprehension dataset (Bajaj et al., 2016) and consist of two *related* collections: MS MARCO Passages and MS MARCO Documents. MS MARCO v1 comes with *large* query sets, which is particularly useful for training and testing models in the big-data regime. These query sets consist of question-like queries sampled from the Bing search engine log with subsequent filtering (Craswell et al., 2021b). Note that queries are not necessarily proper English questions, e.g., "lyme disease symptoms mood", but they are answerable by a short passage retrieved from a set of about 3.6M Web documents (Bajaj et al., 2016). MS MARCO v1 test sets were created in two stages, where initially relevance judgments

[3] In that we do not train Robust04 models from scratch, but rather fine-tune models trained on MS MARCO Documents.

Ranker	**MS MARCO**	**TREC DL**	**FarRelevant**		**LongEmbed**	
	dev	(2019-2021)	zero-shot transf.	fine-tuned	Needle	Passkey
	MRR	**NDCG@10**	**MRR**	**MRR**	**MRR**	**MRR**
			Original MS MARCO training set			
FirstP (ELECTRA)	0.417	0.662	0.019	0.089	0.205	0.235
MaxP (ELECTRA)	0.414	0.659	0.328	0.349	**0.331**	**0.338**
PARADE Attn (ELECTRA)	0.431	**0.680**	**0.338**	0.354	0.270	0.334
PARADE Transf-RAND-L2 (ELECTRA)	**0.433**	0.670	0.229	**0.432**	0.321	0.333
CEDR-KNRM	0.379	0.630	0.055	0.382	0.129	0.166
			De-biased MS MARCO (Hofstätter et al., 2021a)			
MaxP (ELECTRA)	0.377^a (-9.1%)	0.665 $(+0.8\%)$	0.321 (-2.1%)	0.349	0.316 (-4.6%)	0.325 (-3.9%)
PARADE Attn (ELECTRA)	0.390^a (-9.4%)	0.653^a (-3.9%)	0.326 (-3.6%)	0.354	0.251 (-7.1%)	0.330 (-1.0%)
PARADE Transf-RAND-L2 (ELECTRA)	0.410^a (-5.4%)	0.677 $(+1.0\%)$	0.328^a $(+43.5\%)$	**0.432**	0.259^a (-19.4%)	0.331 (-0.7%)
CEDR-KNRM	0.269^a (-29.0%)	0.503^a (-20.2%)	0.202^a $(+268.8\%)$	0.382	0.121 (-5.8%)	0.181 $(+8.6\%)$

Except *FirstP* we train each model using the original and the de-biased MS MARCO. For each model trained on the de-biased dataset, we compute a gain (or loss) compared to the same model trained on the original training set. Statistical significance of the differences are denoted using the superscript superscript **a** (p-value threshold is 0.05 for TREC DL and 0.01 for other collections). Best numbers are in **bold**: Results are averaged over three seeds.

Table 2: Performance of (Selected) Rankers Trained on Original and De-biased MS MARCO

were created for the passage variant of the dataset. Then, document-level relevance labels were created by transferring passage-level relevance to original documents from which passages were extracted.

Relevance labels in the training and development sets are "sparse": There is about one positive example per query without explicit negatives. In addition to sparse relevance judgments—separated into training and developments subsets—there is a small number (98) of queries that have "dense" judgments provided by NIST assessors for TREC 2019 and 2020 deep learning (DL) tracks (Craswell et al., 2021a).

The MS MARCO v2 collection was created for the TREC 2021 Deep Learning (DL) track (Craswell et al., 2021b). It is an expanded version of MS MARCO v1 and incorporates a subset of sparse relevance judgments from MS MARCO v1. In the training set, newly added documents lack both positive and negative judgments, introducing a bias where many relevant documents are mistakenly considered non-relevant. As a result, we do not train on v2 data and only use it for testing.

3.2 Setup

We focus cross-encoding rankers, which process queries concatenated with documents (Nogueira and Cho, 2019). This includes various *SplitP* and *LongP* models discussed in § 2 and in the Appendix § C. As a reference point we also tested a bi-encoder embedding E5-4K model, which had strong performance on LongEmbed benchmark with context sizes under 4K tokens (Zhu et al., 2024). E5-4K was tested as a ranking model and only in the zero-shot mode (without fine-tuning).

Nearly all rankers are based on BERT models (bidirectional encoder-only Transformer) with 100M–200M parameters (see Table 11). Additionally, we evaluated two types of LLM rankers: (1) a fine-tuned TinyLLAMA model which delivers strong performance relative to is compact size (Zhang et al., 2024) and (2) generative black-box LLMs. For (2), we used OpenAI's GPT-4o-mini (OpenAI, 2023) and Anthropic's Claude Haiku-3 (Anthropic, 2024), both of which support at least a 128K-token input context.

We trained each model using *three* seeds, except the bi-encoder model E5 (Zhu et al., 2024) and RankGPT (Sun et al., 2023), which were evaluated only in the zero-shot mode. Due to the high evaluation cost, we also did not test RankGPT on some query sets, in particular, excluding MS MARCO dev set, as it is quite large.

To compute statistical significance, we averaged query-specific metric values over these seeds. Due to space constraints, additional experimental details are provided in the Appendix § A.1. Moreover, in the main part of the paper we only show results for the mean reciprocal rank (MRR) and the non-discounted cumulative gain at rank k (NDCG@K). Additional precision-based metrics are presented in the Appendix (see § A.5).

3.3 Results

Realistic Datasets. Our main experimental results for MS MARCO, TREC DL 2019-2021, and Robust04 are presented in Table 1. Fig. 2 and Table 4 (in the Appendix § A.5) show results for MS

MARCO FarRelevant. In the Appendix (see A.3) we also show that we can match or outperform key prior results, which, we believe, boosts the trustworthiness of our experiments.

We abbreviate names of several PARADE models: Note that PARADE ATTN denotes a PARADE Attention model. The PARADE TRANSF or P. TRANSF prefix denotes PARADE Transformer models where an aggregator Transformer can be either trained from scratch (TRANSF-RAND-L2) or initialized with a pretrained model (TRANSF-PRETR-L6). L2 and L6 denote the number of aggregating layers (two and six, respectively).[4]

Unless explicitly specified, the backbone Transformer model for *SplitP* methods is BERT-base (Devlin et al., 2019). Although using other backbones such as ELECTRA (Clark et al., 2020) and DEBERTA (He et al., 2021) can improve an overall accuracy, we observe a bigger gain compared to a *FirstP* baseline when we use BERT-base (see § A.3 in the Appendix).

To ease understanding and simplify presentation, we display key results for a representative sample of models in Fig. 3 and Fig. 2 (in § 1). Moreover, in Table 1 we present only a single aggregate number for all TREC DL query sets, which is obtained by combining all the queries and respective relevance judgments (i.e., we post an overall average rather than an average over the mean values for 2019, 2020, and 2020). More detailed results, including both OpenAI and Anthropic RankGPT, are available in Appendix A.5, specifically in Tables 7 and 8.

From Fig. 3 and Table 1 we learn that the maximum average gain over respective *FirstP* baselines is only 5% (when measured using MRR or NDCG@K). Gains are much smaller for a number of models, which sometimes match or underperform their *FirstP* baselines on one or more dataset and some of these differences are statistically significant. In particular, this is true for RankGPT (Sun et al., 2023), CEDR-DRMM, CEDR-KNRM (MacAvaney et al., 2019), JINA (Günther et al., 2023) and MOSAIC (Portes et al., 2023).

We can also see that the *LongP* variant of the Longformer model appears to have a relatively strong performance, but so does the *FirstP* version of Longformer. Thus, we think that a good performance of Longformer on MS MARCO and Robust04 collections can be largely explained by better pretraining compared to the original BERT-base model rather than to its ability to ability to process long contexts. Moreover, FirstP (ELECTRA) and FirstP (DEBERTA) are even more accurate than FirstP (Longformer) and perform comparably well (or better) with chunk-and-aggregate document models that uses BERT-base as the backbone model. This is a fair comparison aiming to demonstrate that on a typical test collection the benefits of long-context models are so small that comparable benefits can be obtained by finding or training a more effective *FirstP* model. *FirstP* models are more efficient during inference and they can be pretrained using a larger number of tokens for the same cost (so they could perform better).

Based on our analysis of positions of first relevance passages, we hypothesize that limited benefits of long-context models are not due inability to process long context, but rather due to a positional bias of relevant passages, which tended to be among the first 512 document tokens (see Figure 1 and Figure 7 in Appendix B.4).

Synthetic Data. To further support this hypothesis, we carried out two sets of experiments using our new MS MARCO FarRelevant collection, where a relevant passage did not start until token 512. We carried out both the zero-shot experiment (evaluation of the model trained on MS MARCO) as well fine-tuning experiment using 50K in-domain queries (from the MS MARCO FarRelevant).

Because *FirstP* models perform poorly in this setting our main baselines here are Longformer and *MaxP* models. For models with ELECTRA and DEBERTA backbones we compare with MaxP (ELECTRA) and MaxP (DEBERTA), respectively. Otherwise, the baseline is MaxP (BERT). Results for key models are shown in Fig. 2 and more detailed results can be found in Table 4 of the Appendix § A.5. We make the following key observations:

- The *FirstP* models performed roughly at the random-baseline level in both zero-shot and fine-tuning modes (**RQ1**). Surprisingly, E5-4K performance is also at a random-baseline level despite its competitive performance on LongEmbed benchmark (Zhu et al., 2024), MS MARCO, and Robust04 (see Table 1);
- Both GPT-4o-mini and Claude Haiku-3

[4] Note, however, that TRANSF-PRETR-L2 has only four attention heads.

RankGPT perform at the random-baseline level as well! As a sanity check, and to verify if more accurate and expensive LLMs could do better, we assessed performance of GPT-4o for a sample of 100 queries. The respective RankGPT (Sun et al., 2023) ranker was still not better than a random baseline (**RQ1**).

- Simple aggregation models including MaxP and PARADE Attention had good zero-shot accuracy, but benefited little from fine-tuning on MS MARCO FarRelevant (**RQ1**);
- In contrast, other long-document models had poor zero-shot performance (sometimes at a a random baseline level), but outstripped *respective* MaxP baselines by as much as 13.3%-27.7% after finetuning (**RQ1** and **RQ2**);
- Not only positional bias diminished benefits of supporting longer document contexts, but it also lead to model overfitting to the bias and performing poorly in a zero-shot setting when the distribution of relevant passages changed substantially;
- With exception of RankGPT (Sun et al., 2023) on TREC DL 2019-2021, PARADE Transformer models were more effective than other models on standard collections, their advantage was small (a few %). In contrast, on MS MARCO FarRelevant, PARADE Transformer (ELECTRA) outperformed the next competitor Longformer by 8% and PARADE Max (ELECTRA)—an early chunk-and-aggregate approach—by as much as 23.8% (**RQ2**).
- It is also worth highlighting the consistently strong performance of PARADE models on both standard long-document collections and MS MARCO FarRelevant. The best PARADE models substantially outperformed the best *LongP* models in both zero-shot and fine-tuning settings, although the specific models leading in each setting may differ.

Bias Mitigation. To address **RQ3**, we trained four representative models on a de-biased version of MS MARCO (see Appendix § A.1.3 for selection rationale), using the de-biasing approach by Hofstätter et al. (2021a), and tested them on MS MARCO FarRelevant as well as on Needle/Passkey subsets of LongEmbed (Zhu et al., 2024). We also evaluated four models fine-tuned on MS MARCO FarRelevant on TREC DL 2019-2020 query sets. Due to the substantial NDCG@10 drop (0.1–0.15) observed for PARADE Transformer and CEDR-KNRM, we concluded that fine-tuning on purely synthetic data is not viable and did not pursue it further.

According to Table 2, de-biasing improved performance of CEDR-KNRM and PARADE Transformer on MS MARCO FarRelevant. Yet, it mostly caused performance degradation on the original MS MARCO dataset and on LongEmbed subsets. It did not benefit the MaxP and PARADE Attention models, which were the most robust to positional bias. We further tested de-biased models on two short-document collections and achieved more favorable outcomes. According to Table 3 in Appendix A, for three out of four models (except PARADE Attention) de-biasing has either a neutral or slightly positive effect, especially on BEIR NQ. These results are promising, but they also suggest that mitigating positional bias remains a challenging problem (**RQ3**).

4 Conclusion

In this work, we revisited the problem of positional relevance bias in long-document retrieval and presented extensive evidence of its widespread impact across existing benchmarks. Using both real and synthetic datasets—including our new *diagnostic* dataset, MS MARCO FarRelevant—we evaluated the robustness and effectiveness of over 20 ranking models.

Our findings highlight the importance of benchmark design that does not obscure the benefits of long-context modeling. We identified model families (e.g., PARADE Attention and MaxP) that are more robust to positional bias, and confirmed the strong performance of PARADE models (Li et al., 2024), which remain competitive even against recent long-context architectures.

Finally, our de-biasing experiments yielded only limited gains, motivating further research into more effective mitigation strategies, including combining de-biasing with training on well-designed synthetic data.

5 Limitations

Our paper has several limitations related primarily to the choice of datasets, models, and the strength of evidence for the positional bias of relevant passages.

First of all, our evaluation uses only cross-encoding ranking models. With an exception of E5-4K model, which is used in the zero-shot ranking mode, we do not train or evaluate bi-encoding models (typically used to create query and document embeddings for the first-stage retrieval). We nonetheless believe that—given a large number of proposals for long-document ranking—a reproduction and evaluation of cross-encoding long-document rankers is a sufficiently important topic that alone warrants a publication.

Moreover, as we explain below, we also use cross-encoding rankers as a tool to detect and expose bias in the position of relevant information. In that, cross-encoders are easier to train using standard (rather than high-memory) GPUs with mini-batch size one and gradient accumulation. They also typically require only one epoch to converge (only a few models need two or three epochs). In contrast, bi-encoders are trained using large batches with in-batch negatives for multiple epochs (e.g., Karpukhin et al. (2020) report using at least 40 epochs).

Second, a bulk of our ranking experiments uses only two *English* document collections: MS MARCO Documents v1 and v2 (Craswell et al., 2021b) and Robust04 (Clarke et al., 2004). However, we have to restrict the choice of datasets to make multi-seed evaluations of 20+ models feasible. Yet, to corroborate existence of positional bias we used two additional popular long-document collections: Gov2 (Allan et al., 2008) and ClueWeb12 (Collins-Thompson et al., 2013a). For the study on robustness of model to positional bias and its mitigation, we used two additional synthetic collections: MS MARCO FarRelevant and two subsets from LongEmbed (Zhu et al., 2024) together with short-document collections MS MARCO Passages (v1) (Craswell et al., 2020) and BEIR NQ (Kwiatkowski et al., 2019; Thakur et al., 2021).

One could argue that the limited improvements over *FirstP* baselines result from the models' inability to handle long contexts. To address this concern, we trained and evaluated a diverse set of cross-encoding ranking models, including both split-and-aggregate models and models explicitly designed for long input sequences. Additionally, we assessed cloud-based RankGPT rankers, which have shown strong performance in recent research (Sun et al., 2023).

However, we can still test only a limited number of models: One might always argue that there are untested architectures that would outperform *FirstP* baselines by a much larger margin. To demonstrate that selected models can, in principle, benefit from long contexts and decisively outperform simple baselines such as *FirstP* and even *MaxP* models we trained and/or evaluated them on a synthetic collection MS MARCO FarRelevant, which can be seen as a challenging version of a needle-in-the-haystack test. This is still a limiting experiment, because synthetic collections—with documents composed from randomly selected passages—are imperfect proxies for real-life datasets. In Appendix § B.3 we discuss limitation in detail and argue that MS MARCO FarRelevant is a more suitable synthetic benchmark for evaluating text retrieval systems compared to LongEmbed subsets Needle and Passkey (Zhu et al., 2024).

In summary, we provided three types of evidence for positional bias of relevant passages: strong performance of *FirstP* models on standard collections, direct estimation of the distribution of relevant passages using substring matching and LLM relevance judges (Upadhyay et al., 2024), as well as experimentation with the synthetic collection MS MARCO FarRelevant where relevant passages distribution was not skewed towards the beginning of a document. Each experiment provided imperfect/limited evidence on its own, but together they strongly supported the existence of relevance position bias.

While our analysis confirms a strong early-position relevance bias across multiple retrieval benchmarks, we acknowledge that this pattern may not generalize to all domains. For example, prior work has shown that in scientific abstracts, both the first and last sentences tend to be crucial (Ruch et al., 2006). Investigating positional relevance patterns in such domains is an important direction for future work.

In our experiments with Robust04 and MS MARCO, we truncated documents to a maximum of 1431 BERT tokens. However, this constraint did not hinder our ability to address key research questions. As detailed in Appendix § A.2, using larger inputs led to only marginal improvements.

Notably, when models trained on MS MARCO were applied to MS MARCO FarRelevant in a zero-shot setting, we observed a significant drop in

MRR (at least 17%) across many models. Several models—including RankGPT (Sun et al., 2023)—even failed to outperform a random-shuffling baseline, despite MS MARCO FarRelevant documents containing fewer than 1500 tokens.

Interestingly, despite this token limitation, several long-context models significantly outperformed both *FirstP* and *MaxP* baselines by over 20%. This suggests that even short-document collections can serve as a meaningful benchmark for distinguishing strong and weak long-context models—unlike the original MS MARCO, where all models have close accuracy.

6 Ethics Statement

We believe our study does not pose any ethical concerns. We do not collect any new data with the help of human annotators and we do not use human or animal subjects in our study. Although we do discover a positional bias in existing retrieval collections, we are not aware of any potential risks or harms that can be caused by the exposure of this bias.

In terms of the environmental impact, our computational requirements are rather modest, because we only fine-tuned our models rather than trained them from scratch. These models were also rather small by modern standards. Except 1B-parameter TinyLLAMA (Zhang et al., 2024), each model has about 100M parameters (see Table 11 for details). Despite training and testing 20+ models with three seeds, we estimate to have spent only about 6400 GPU hours for our main experiments. 96% of the time we used NVIDIA A10 (or similarly-powerful) RTX 3090 GPUs and 4% of the time we used NVIDIA A6000.

We believe this is roughly equivalent to training a single 1B-parameter TinyLLAMA model, which required about 3400 GPU hours using a more powerful NVIDIA A100. This, in turn, this is only a tiny fraction of compute required to train LLAMA2 models (2% compared to a 7B LLAMA2 smodel).[5]

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[5] https://github.com/microsoft/Llama-2-Onnx/blob/main/MODEL-CARD-META-LLAMA-2.md

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A Experiments: Additional Information, Ablations, and Detailed Results

A.1 Detailed Training and Evaluation Setup

A.1.1 General Setup

In our work, a ranker is applied to the output of the first-stage retrieval model, also known as a candidate-generator. Depending on the experiment and the dataset we use different candidate generators: for MS MARCO v1 and Robust04 we used a BM25 ranker (Robertson, 2004). In that, for MS MARCO v1 it was applied to documents expanded using the doc2query approach (Nogueira and Lin, 2019). For MS MARCO v2, we used a hybrid retriever where candidate records are first produced using a k-NN search and subsequently re-ranked using a linear fusion of BM25 scores and the cosine similarity between query and document embeddings. Embeddings were generated using ANCE (Xiong et al., 2021).

Ranker	**TREC DL (2019-2020)**	**NQ BEIR**
	NDCG@10	**NDCG@10**
Original MS MARCO training set		
MaxP (ELECTRA)	0.715	0.514
PARADE Attn (ELECTRA)	0.710	0.496
PARADE Transf-RAND-L2 (ELECTR.)	0.703	0.474
CEDR-KNRM	0.599	0.318
De-biased MS MARCO (Hofstätter et al., 2021a)		
MaxP (ELECTRA)	**0.716** $(+0.1\%)$	**0.516** $(+0.6\%)$
PARADE Attn (ELECTRA)	0.675^a (-4.9%)	0.427^a (-14.0%)
PARADE Transf-RAND-L2 (ELECTR.)	0.706 $(+0.4\%)$	0.485^a $(+2.5\%)$
CEDR-KNRM	0.604 $(+0.7\%)$	0.353^a $(+11.0\%)$

We train each model using the original and the de-biased MS MARCO. For each model trained on the de-biased dataset, we compute a gain (or loss) compared to the same model trained on the original training set. Statistical significance of the differences are denoted using the superscript superscript **a** (p-value threshold is 0.05 for TREC DL and 0.01 for NQ BEIR). Best numbers are in **bold**: Results are averaged over three seeds.

Table 3: Performance of (Selected) Rankers Trained on Original and De-biased MS MARCO and Tested on Short-Document Collections.

Depending on the collection we computed a subset of the following metrics: the mean reciprocal rank (MRR), the non-discounted cumulative gain at rank k (NDCG@K) (Järvelin and Kekäläinen, 2002), the mean average precision (MAP), and precision at rank (P@K), $k \in \{10, 20\}$. Due to space constraints, we included results with MAP and P@K only in the Appendix (see § A.5). Note that for test sets with sparse labels (MS MARCO development set and MS MARCO FarRelevant) we computed only MRR.

All experiments were carried out using the an **anonymous** retrieval toolkit framework, which employed Lucene and an **anonymous** toolkit for k-NN search to provide retrieval capabilities. Deep learning support was provided via PyTorch (Paszke et al., 2019) and HuggingFace Transformers library (Wolf et al., 2019). The instructions to reproduce our key results are publicly available in the on-line appendix.[6]

A.1.2 Model Training

A ranker was trained to distinguish between positive examples (known relevant documents) and hard negative examples (documents not marked as relevant) sampled from the set of top-k candidates returned by the candidate generator. We used $k = 100$ for MS MARCO and MS MARCO FarRelevant and $k = 1000$ for Robust04 (based on preliminary experiments).

Retriever / Ranker	zero-shot transferred		fine-tuned	
Random shuffling of top-100	0.052		0.052	
Retriever	0.207		0.207	
FirstP (BERT)	0.016^{b}		0.090^{b}	
FirstP (Longformer)	0.017^{b}		0.091^{b}	
FirstP (ELECTRA)	0.019^{b}		0.089^{b}	
FirstP (Big-Bird)	0.021^{b}		0.089^{b}	
FirstP (JINA)	0.018^{b}		0.088^{b}	
FirstP (MOSAIC)	0.018^{b}		0.089^{b}	
FirstP (TinyLLAMA)	0.020^{b}		0.079^{b}	
FirstP (E5-4K)	0.015^{ab}		–	
AvgP	0.154^{ab}	(-48.1%)	0.365^{ab}	$(+11.4\%)$
MaxP	0.297^{b}		0.328^{b}	
MaxP (ELECTRA)	0.328^{b}		0.349^{b}	
MaxP (DEBERTA)	0.298^{b}		0.332^{b}	
SumP	0.211^{ab}	(-28.8%)	0.327^{b}	(-0.4%)
CEDR-DRMM	0.157^{ab}	(-47.3%)	0.372^{ab}	$(+13.3\%)$
CEDR-KNRM	0.055^{ab}	(-81.5%)	0.382^{a}	$(+16.4\%)$
CEDR-PACRR	0.209^{ab}	(-29.6%)	0.393^{a}	$(+19.9\%)$
Neural Model1	0.085^{ab}	(-71.3%)	0.396^{a}	$(+20.6\%)$
PARADE Attn	0.300^{b}	$(+1.0\%)$	0.337^{b}	$(+2.8\%)$
PARADE Attn (ELECTRA)	**0.338**^{b}	$(+3.3\%)$	0.354^{b}	$(+1.6\%)$
PARADE Attn (DEBERTA)	0.307^{b}	$(+3.2\%)$	0.343^{b}	$(+3.4\%)$
PARADE Avg	0.274^{ab}	(-7.6%)	0.322^{b}	(-1.7%)
PARADE Max	0.291^{b}	(-2.1%)	0.330^{b}	$(+0.6\%)$
PARADE Transf-RAND-L2	0.243^{a}	(-18.2%)	0.419^{ab}	$(+27.7\%)$
P. Transf-RAND-L2 (ELECTRA)	0.229^{a}	(-30.2%)	**0.432**^{ab}	$(+23.8\%)$
PARADE Transf-PRETR-L6	0.267^{ab}	(-10.0%)	0.413^{a}	$(+26.0\%)$
P. Transf-PRETR-LATEIR-L6	0.244^{a}	(-18.0%)	0.358^{ab}	$(+9.2\%)$
LongP (Longformer)	0.233^{a}	(-21.7%)	0.399^{a}	$(+21.7\%)$
LongP (Big-Bird)	0.126^{ab}	(-57.4%)	0.401^{a}	$(+22.1\%)$
LongP (JINA)	0.069^{ab}	(-76.9%)	0.372^{ab}	$(+13.4\%)$
LongP (MOSAIC)	0.120^{ab}	(-59.6%)	0.397^{a}	$(+21.2\%)$
LongP (TinyLLAMA)	0.078^{ab}	(-73.6%)	0.397^{a}	$(+21.1\%)$
LongP (E5-4K)	0.057^{ab}	(-80.7%)	N/A (zero-shot only)	
LongP RankGPT (GPT-4o-mini)	0.043^{b}		N/A (zero-shot only)	
LongP RankGPT (Claude-3-haiku)	0.051^{b}		N/A (zero-shot only)	

In each column we show a relative gain over models' respective *MaxP* baseline. For *LongP* models, the gain is over *MaxP* (BERT). Statistically significant differences from a respective *MaxP* baseline are denoted with the superscript **a**. Statistical significant differences with respect to *Longformer* are denoted with the superscript **b** (p-value < 0.01).

Table 4: Model Ranking Performance on MS MARCO FarRelevant.

Each model was trained using *three* seeds. All models except MOSAIC were trained using half-precision. MOSAIC models were trained using full-precision. MOSAIC training was unstable (even though we used the full precision) and often resulted in close-to-zero performance. For this reason we continued training with *more* seeds until we obtained three models with reasonable performance. This seed selection strategy could potentially have biased (up) MOSAIC results. To compute statistical significance, we averaged query-specific metric values over these seeds.

All MS MARCO models were trained from scratch. Then these models were fine-tuned on Robust04. Note that except for the aggregation Transformers and TinyLLAMA, we use a *base*, i.e., a 12-layer Transformer (Vaswani et al., 2017) models. TinyLLAMA has 22 layers and about 1B parameters. BERT-base is more practical then a 24-layer BERT-large and performs at par with BERT-large on MS MARCO and Robust04 (Hofstätter et al., 2020a; Li et al., 2024). In our own experiments, we see that large (24 and more layers) model perform much better on the MS MARCO Passage collection, but we were not able to outperform 12-layer models on the MS MARCO Documents collection. Note that Longformer (Beltagy et al., 2020), Big-Bird (Zaheer et al., 2020), and DEBERTA base (He et al., 2021), JINA (Günther et al., 2023), and MOSAIC (Portes et al., 2023) all have 12 layers, but a larger embedding matrix.

One training epoch consisted in iterating over all queries and sampling one positive and one negative example with a subsequent computation of a pairwise margin loss. We used the minibatch size one with gradient accumulation over 16 steps. The learning rates are provided in the model configuration files (in the on-line repository).[7] We used the AdamW optimizer (Loshchilov and Hutter, 2017) and a constant learning rate with a 20% linear warm-up (Mosbach et al., 2020).

We have learned that—unlike neural *retrievers*—cross-encoding rankers (Nogueira and Cho, 2019) are relatively insensitive to learning rates, their schedules, and the choice of loss functions. We were sometimes able to achieve better results using multiple negatives per query and a listwise margin loss (or cross-entropy). However, the gains were small and not consistent compared to a simple pairwise margin loss used in our work (in fact, using a listwise loss function sometimes lead to overfit-

[6] https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/

[7] https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/.

Model	MS MARCO	TREC DL			Robust04	
	dev	2019	2020	2021	title	description
	MRR	**NDCG@10**			**NDCG@20**	
Prior work (FirstP, MaxP), Zhang et al. (Zhang et al., 2021)						
FirstP (BERT)	–	–	–	–	0.449	0.510
MaxP (BERT)	–	–	–	–	0.477 (+6.2%)	0.530 (+3.9%)
MaxP (ELECTRA)	–	–	–	–	0.523	0.574
Prior work (PARADE) Li et al. (Li et al., 2024)						
PARADE Attn (ELECTRA)	–	–	–	–	0.527	0.587
PARADE Max (ELECTRA)	–	0.679	0.613	–	0.544	0.602
PARADE Transf-RAND (ELECTRA)	–	0.650	0.601	–	**0.566**	0.613
Our results						
FirstP (BERT)	0.394	0.631	0.598	0.660	0.475	0.527
MaxP (BERT)	0.392 (−0.4%)	0.648 (+2.6%)	0.615 (+2.8%)	0.665 (+0.8%)	0.488^a (+2.6%)	0.544^a (+3.3%)
PARADE Attn	0.416^a (+5.5%)	0.647 (+2.5%)	0.626^a (+4.6%)	0.677 (+2.5%)	0.503^a (+5.7%)	0.556^a (+5.6%)
FirstP (ELECTRA)	0.417	0.652	0.642	0.686	0.492	0.552
MaxP (ELECTRA)	0.414 (−0.6%)	0.659 (+1.0%)	0.630 (−1.9%)	0.683 (−0.5%)	0.502 (+2.0%)	0.563 (+2.1%)
PARADE Attn (ELECTRA)	**0.431**^{a} (+3.3%)	0.675^a (+3.5%)	0.653 (+1.8%)	0.705 (+2.8%)	0.523^a (+6.4%)	0.581^a (+5.3%)
FirstP (DEBERTA)	0.415	0.675	0.629	0.702	0.534	0.596
MaxP (DEBERTA)	0.402 (−3.2%)	0.679 (+0.6%)	0.620 (−1.4%)	0.705 (+0.4%)	0.535 (+0.2%)	0.609 (+2.2%)
PARADE Attn (DEBERTA)	0.422^a (+1.6%)	**0.685** (+1.4%)	**0.659**^{a} (+4.8%)	**0.713** (+1.4%)	0.549^a (+2.9%)	**0.615**^{a} (+3.2%)
FirstP (Longformer)	0.404	0.657	0.616	0.654	0.483	0.540
LongP (Longformer)	0.412^a (+1.9%)	0.676^a (+2.9%)	0.628 (+2.0%)	0.693^a (+6.0%)	0.500^a (+3.6%)	0.568^a (+5.1%)
FirstP (Big-Bird)	0.408	0.663	0.620	0.679	0.507	0.560
LongP (Big-Bird)	0.397^a (−2.9%)	0.655 (−1.1%)	0.618 (−0.3%)	0.675 (−0.5%)	0.452^a (−10.9%)	0.477^a (−14.9%)
FirstP (JINA)	0.422	0.658	0.618	0.679	0.488	0.532
LongP (JINA)	0.416^a (−1.5%)	0.670^a (+1.8%)	0.632 (+2.1%)	0.689 (+1.4%)	0.503^a (+2.9%)	0.558^a (+4.9%)
FirstP (MOSAIC)	0.423	0.654	0.607	0.662	0.453	0.538
LongP (MOSAIC)	0.421 (−0.4%)	0.660 (+0.9%)	0.630^a (+3.7%)	0.694^a (+4.9%)	0.456 (+0.6%)	0.570^a (+6.0%)

In each column we show a relative gain over model's respective *FirstP* baseline: The last column shows the average relative gain over *FirstP*. Best numbers are in **bold**: Our results are averaged over three seeds (but not necessarily prior art).
Statistical significant differences with respect to this baseline are denoted using the superscript superscript **a**. p-value threshold is 0.01 for an MS MARCO development collection and 0.05 otherwise.

Table 5: Comparison of long-context models to respective FirstP baselines and prior art.

ting). Note again that this is different from neural *retrievers* where training is difficult without using a listwise loss and/or batch-negatives (Karpukhin et al., 2020; Xiong et al., 2021; Qu et al., 2021; Zerveas et al., 2021; Formal et al., 2021).

For MS MARCO, all models except PARADE-Transf-Pretr-LATEIR-L6 and PARADE-Transf-RAND-L2 were trained for one epoch: Further training did not improve (and sometimes degraded) accuracy. However, PARADE-Transf-RAND-L2 and PARADE-Transf-Pretr-LATEIR-L6 required two-to-three epochs to reach the maximum accuracy. For training using de-biased MS MARCO, we used only one epoch. In the case of Robust04, each model was finetuned for 100 epochs, but all epochs were short, so the overall training and evaluation time was comparable to that of fine-tuning on MS MARCO for a single epoch.

To reproduce our main results, we estimate that one needs about 6400 GPU hours: 6000 hours using NVIDIA A10 (or RTX 3090) with 24 GB of memory and 400 hours using NVIDIA A6000 with 48 GB of memory. A6000 was required only for TinyLLAMA.

From our experience models trained on MS MARCO v2 performed worse on TREC 2021 queries compared to models trained on MS MARCO v1. This may indicate that models somehow learn to distinguish between original MS MARCO v1 documents and newly added ones (which did not have positive judgements in the training sets). As a result, these models are biased and tend to not rank these new documents well even when they are considered to be relevant by NIST assessors. For this reason, we used MS MARCO v2 data in a zero-shot transfer mode where ranking models trained on MS MARCO v1 are evaluated on TREC DL 2021 queries.

A.1.3 Miscellaneous Notes

To enable efficient training and evaluation of the large number of models, for Robust04 and original MS MARCO documents were truncated to have at most 1431 BERT tokens. In § A.2 (see Table 6) we show that for our top-performing model PA-

Retriever / Ranker	MS MARCO dev	TREC DL (2019-2021)	Robust04 title	 description	Avg. gain Over FirstP
	MRR	**NDCG@10**	**NDCG@20**		
Retriever	0.312	0.629	0.428	0.402	–
PARADE Attn (1 chunk)	0.401	0.637	0.476	0.527	–
PARADE Attn (2 chunks)	0.408^a (+1.8%)	0.653^a (+2.7%)	0.499^a (+4.9%)	0.544^a (+3.3%)	+3.2%
PARADE Attn (3 chunks)	0.406^a (+1.3%)	0.648^a (+1.7%)	**0.505**^{a} (+6.1%)	0.557^a (+5.7%)	+3.7%
PARADE Attn (4 chunks)	**0.412**^{a} (+2.9%)	**0.654**^{a} (+2.7%)	0.504^a (+5.9%)	**0.558**^{a} (+5.9%)	**+4.3%**
PARADE Attn (5 chunks)	0.409^a (+2.0%)	0.652^a (+2.4%)	0.502^a (+5.6%)	0.556^a (+5.5%)	+3.9%
PARADE Attn (6 chunks)	0.411^a (+2.4%)	0.653^a (+2.6%)	0.504^a (+5.9%)	0.554^a (+5.2%)	+4.0%

Table 6: Effectiveness of the PARADE Attention model for different input truncation thresholds

RADE Attention (Li et al., 2024) using a larger number of chunks only marginally improves outcomes. Depending on a dataset, the highest accuracy is achieved using either three or four chunks. However, for training on de-biased MS MARCO, the truncation threshold is much higher: 8109 tokens.

For *SplitP* approaches, queries were padded to 32 BERT tokens with padding being masked out during training (longer queries were truncated). For *SplitP* models with greedy partitioning into disjoint chunks, long document were split into at most three chunks containing 477 document tokens (each concatenated with up to 32 query tokens plus three special tokens).

We evaluated 20+ models, but we had to exclude two LongT5 variants (Guo et al., 2022) and RoFormer (with ROPE embeddings) (Su et al., 2024) due to poor convergence and/or crashes. Specifically, even after 10 epochs of training LongT5 models were $\approx 10\%$ less accurate than BERT-base *FirstP* trained for one epoch. Given the uncertainty regarding the possible convergence of models as well as the need to train these for three epochs, we have to abandon this experiment as overly expensive. RoFormer models were failing due to CUDA errors when the context length exceeded 512: We were not able to resolve this issue.

For bias-mitigation experiments, for several reasons, we us ed only a subset of models. First, we had to exclude all *LongP* models since none of them supported a context longer than 8192 tokens. In contrast, in this experiment we trained our chunk-and-aggregate tokens up to the length of 8109 and then extrapolated to rank documents up to 32768 tokens long. Second, we chose representative models with vastly different generalization properties. MaxP and PARADE Attention models performed well on MS MARCO FarRelevant in the zero-shot setting, but did not benefit much from in-domain fine-tuning. PARADE Transformer MRR dropped from 0.433 to 0.229 in the zero-shot setting, but increased up to 0.432 after in-domain fine-tuning. CEDR-KNRM also benefited a lot from fine-tuning on MS MARCO FarRelevant, but its zero-shot performance was at the level of random-baseline.

A.2 Varying the Number of Chunks

To understand if truncating input to have at most 1431 BERT tokens negatively affected model performance, we carried out an ablation study where one of the top-performing models was trained and evaluated using inputs of varying maximum lengths. To this end we used PARADE Attention with the number of input chunks varying from one to six. In that the same number of chunks was used during training and evaluation, i.e., we had to carry out six experiments. Similar to our main experiments, we trained each model using three seeds. We carried out this ablation experiment using our MS MARCO and Robust04 datasets.

The results are presented in Table 6: We can see that—depending on the dataset—three or four input chunks are optimal. However, the additional gains over the *FirstP* baseline are at most 0.6% when averaged over all test sets.

Gao and Callan 2022 carried out a similar ablation using ClueWeb09: Increasing the number of input chunks from three to six lead to only about 2.3% relative improvement in NDCG@20. However, even this modest gain could have been slightly inflated due to model not being trained *directly* on shorter inputs. Indeed, truncation of an input for a six-chunk model to one chunk is potentially less effective than training and evaluating the model using one-chunk data.

Model	MS MARCO dev	TREC DL 2019-2021		
	MRR	NDCG@10	P@10	MAP
Retriever	0.312	0.629	0.720	0.321
FirstP (BERT)	0.394	0.632	0.712	0.311
FirstP (Longformer)	0.404	0.643	0.722	0.317
FirstP (ELECTRA)	0.417	0.662	0.734	0.320
FirstP (DEBERTA)	0.415	0.672	0.741	0.327
FirstP (Big-Bird)	0.408	0.656	0.727	0.321
FirstP (JINA)	0.422	0.654	0.728	0.320
FirstP (MOSAIC)	0.423	0.643	0.726	0.316
FirstP (TinyLLAMA)	0.395	0.615	0.692	0.301
FirstP (E5)	0.380	0.641	0.722	0.317
FirstP RankGPT (OpenAI)	–	**0.708**	**0.790**	**0.352**
FirstP RankGPT (Anthropic)	–	0.703	0.776	0.347
AvgP	0.389 (−1.3%)	0.642 (+1.5%)	0.717 (+0.7%)	0.317^a (+2.0%)
MaxP	0.392 (−0.4%)	0.644^a (+1.9%)	0.723 (+1.5%)	0.322^a (+3.7%)
MaxP (ELECTRA)	0.414 (−0.6%)	0.659 (−0.5%)	0.745 (+1.5%)	0.326 (+2.1%)
MaxP (DEBERTA)	0.402^a (−3.2%)	0.671 (−0.1%)	0.746 (+0.7%)	0.335^a (+2.5%)
SumP	0.390 (−1.0%)	0.639 (+1.0%)	0.715 (+0.4%)	0.319^a (+2.6%)
CEDR-DRMM	0.385^a (−2.3%)	0.629 (−0.5%)	0.708 (−0.5%)	0.313 (+0.6%)
CEDR-KNRM	0.379^a (−3.8%)	0.630 (−0.3%)	0.711 (−0.1%)	0.313 (+0.8%)
CEDR-PACRR	0.395 (+0.3%)	0.643^a (+1.6%)	0.719 (+0.9%)	0.320^a (+2.9%)
Neural Model1	0.398 (+0.9%)	0.650^a (+2.8%)	0.723^a (+1.5%)	0.323^a (+3.9%)
PARADE Attn	0.416^a (+5.5%)	0.652^a (+3.1%)	0.728^a (+2.2%)	0.324^a (+4.2%)
PARADE Attn (ELECTRA)	0.431^a (+3.3%)	0.680^a (+2.7%)	0.763^a (+3.9%)	0.335^a (+4.9%)
PARADE Attn (DEBERTA)	0.422^a (+1.6%)	0.688^a (+2.4%)	0.763^a (+3.0%)	0.339^a (+3.9%)
PARADE Avg	0.392 (−0.6%)	0.646^a (+2.1%)	0.715 (+0.4%)	0.317^a (+2.1%)
PARADE Max	0.405^a (+2.7%)	0.655^a (+3.5%)	0.733^a (+2.9%)	0.324^a (+4.1%)
PARADE Transf-RAND-L2	0.419^a (+6.3%)	0.655^a (+3.6%)	0.734^a (+3.1%)	0.326^a (+5.0%)
PARADE Transf-RAND-L2 (ELECTRA)	**0.433**^{a} (+3.9%)	0.670 (+1.2%)	0.747 (+1.8%)	0.327 (+2.2%)
PARADE Transf-PRETR-L6	0.402^a (+1.9%)	0.643 (+1.6%)	0.717 (+0.8%)	0.322^a (+3.6%)
PARADE Transf-PRETR-LATEIR-L6	0.398 (+1.1%)	0.626 (−0.9%)	0.707 (−0.7%)	0.307 (−1.1%)
LongP (Longformer)	0.412^a (+1.9%)	0.668^a (+3.9%)	0.752^a (+4.1%)	0.333^a (+5.1%)
LongP (Big-Bird)	0.397^a (−2.9%)	0.651 (−0.7%)	0.726 (−0.2%)	0.322 (+0.3%)
LongP (JINA)	0.416^a (−1.5%)	0.665^a (+1.7%)	0.742^a (+2.0%)	0.328^a (+2.4%)
LongP (MOSAIC)	0.421 (−0.4%)	0.664^a (+3.3%)	0.740^a (+1.9%)	0.327^a (+3.7%)
LongP (TinyLLAMA)	0.402^a (+1.7%)	0.608 (−1.1%)	0.692 (+0.0%)	0.306 (+1.6%)
LongP (E5)	0.353^a (−7.1%)	0.649 (+1.3%)	0.724 (+0.3%)	0.323 (+1.8%)
LongP RankGPT (OpenAI)	–	0.706 (−0.3%)	0.783 (−1.0%)	0.350 (−0.7%)
LongP RankGPT (Anthropic)	–	0.707 (+0.5%)	0.780 (+0.5%)	0.348 (+0.4%)

In each column we show a relative gain with respect model's respective *FirstP* baseline: The last column shows the average relative gain of *FirstP*. Best numbers are in **bold**: Results are averaged over three seeds. Unless specified explicitly, the backbone is **BERT-base**.

Statistical significant differences with respect to this baseline are denoted using the superscript superscript **a**. p-value threshold is 0.01 for an MS MARCO development collection and 0.05 otherwise.

E5-models were used only in the zero-shot model, i.e., without fine-tuning.

Table 7: Ranking performance on MS MARCO and TREC DL.

A.3 Backbone Selection for *SplitP* Models and Prior Art Comparison

A.3.1 Choice of a Backbone

To understand if using BERT-base as backbone model for various *SplitP* (i.e., chunk-and-aggregate) approaches diminished models' ability to process and understand long contexts, we carried out a focused comparison of several backbone models, including ELECTRA (Clark et al., 2020) and DEBERTA (He et al., 2021). To this end, we used two methods: PARADE (Li et al., 2024) Attention and *MaxP*. PARADE Attention model achieved the largest average gain over *FirstP* in our main experiments (see Table 1), whereas *MaxP* models were extensively benchmarked in the past (Li et al., 2024; Dai and Callan, 2019; Zhang et al., 2021). Although prior work found ELECTRA to be a better backbone model in terms of *absolute* accuracy (Li et al., 2024; Zhang et al., 2021), we found no systematic evaluation of the relationship between a backbone model and achievable *FirstP* gains.

Results in Tables 5 and 1 confirm overall superiority of both ELECTRA and DEBERTA over BERT-base. In that, DEBERTA models are nearly always more effective compared to ELECTRA models with biggest differences on Robust04. However, their *relative* effectiveness with respect to their respective *FirstP* baselines does not exceed that of BERT-base. The same is true for *LongP* models. Except Longformer they performed equally or worse compared to *FirstP* on 8 test sets out of 18. Moreover, all *LongP* models achieved lower average gains over *FirstP* (see the last column in Table 1). We conclude that to measure capabilities of chunk-and-aggregate model to understand and incorporate long context, it appears to be *beneficial* to use BERT-base instead of ELECTRA or DEBERTA.

Finally, we would like to note that on standard benchmarks Big-Bird's (Zaheer et al., 2020) *FirstP* version *always* outperforms its *LongP* version (sometimes by as much as 10-15%), which seems to be puzzling. We noticed, however, that for shorter inputs, the model turns off sparse attention and prints the respective warning. Thus, we hypothesize that it is the use of sparse attention that causes this degradation. In contrast, the sparse attention implementation of the Longformer (Beltagy et al., 2020) does not exhibit such a degradation (although with Longformer, not all attention is sparse: query-to-document attention is full). Despite BigBird underperforms on standard benchmarks, it still does well on MS MARCO FarRelevant after fine-tuning (see Table 4).

A.4 Efficiency Evaluation

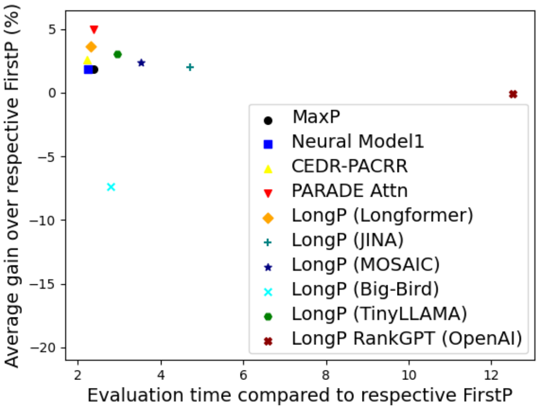


Figure 3: Average relative gain (in %) vs. relative increase in run-time compared to *respective FirstP* baselines on MS MARCO, TREC DL 2019-2021, and Robust04 (for a representative subset of models). Except LongP RankGPT, *LongP* models truncate documents to be at most 1431 tokens. There is no truncation for RankGPT.

From the efficiency-effectiveness plot in Fig. 3, we can see that all long-document models are at least 2× slower than respective *FirstP* baselines. The biggest average gain of merely 5% is achieved by the PARADE Attn model (with a BERT-base backbone) at the cost of being 2.5× slower than its *FirstP* baseline. All *LongP* models are even slower and show less improvement. Given such small benefits at the cost of a substantial slow-down, one could question practicality of such models and suggest using *FirstP* variants instead.

A.4.1 Comparison to Prior Art

We also use Table 5 to compare with prior art. We generally reproduce prior art, in particular, experiments by Li et al. 2024, who invented PARADE models. Our ELECTRA-based models achieve higher NDCG@10 on TREC DL 2019-2020 and PARADE Attention models come very close, but they are about 3-5% worse compared to their PARADE Transformer on Robust04. At the same time, our DEBERTA-based PARADE Attention model achieves similar NDCG@20 scores.

Note that one should not expect identical results due to differences in training regimes and candidate

Model	NDCG@20	P@20	MAP	NDCG@20	P@20	MAP
Retriever	0.428	0.365	0.255	0.402	0.334	0.240
FirstP (BERT)	0.475	0.405	0.277	0.527	0.447	0.303
FirstP (Longformer)	0.483	0.413	0.277	0.540	0.454	0.307
FirstP (ELECTRA)	0.492	0.424	0.294	0.552	0.465	0.320
FirstP (DEBERTA)	0.534	0.459	0.319	0.596	0.503	0.350
FirstP (Big-Bird)	0.507	0.435	0.300	0.560	0.473	0.325
FirstP (JINA)	0.488	0.421	0.287	0.532	0.450	0.305
FirstP (MOSAIC)	0.453	0.390	0.266	0.538	0.455	0.310
FirstP (TinyLLAMA)	0.431	0.370	0.246	0.473	0.398	0.262
FirstP (E5-4K)	0.438	0.371	0.247	0.429	0.355	0.234
FirstP RankGPT (OpenAI)	–	–	–	0.562	0.456	0.280
FirstP RankGPT (Anthropic)	–	–	–	0.541	0.446	0.268
AvgP	0.478 (+0.5%)	0.411 (+1.6%)	0.292^a (+5.4%)	0.531 (+0.9%)	0.451 (+1.0%)	0.324^a (+6.7%)
MaxP	0.488^a (+2.6%)	0.425^a (+5.1%)	0.306^a (+10.6%)	0.544^a (+3.3%)	0.467^a (+4.5%)	0.338^a (+11.5%)
MaxP (ELECTRA)	0.502 (+2.0%)	0.441^a (+3.9%)	0.319^a (+8.3%)	0.563 (+2.1%)	0.483^a (+4.0%)	0.350^a (+9.3%)
MaxP (DEBERTA)	0.535 (+0.2%)	0.464 (+1.2%)	0.340^a (+6.7%)	0.609^a (+2.2%)	0.519^a (+3.2%)	0.378^a (+7.9%)
SumP	0.486 (+2.2%)	0.418^a (+3.4%)	0.305^a (+10.2%)	0.538 (+2.1%)	0.461^a (+3.1%)	0.337^a (+11.1%)
CEDR-DRMM	0.466 (−2.0%)	0.403 (−0.4%)	0.287^a (+3.8%)	0.533 (+1.3%)	0.458^a (+2.5%)	0.326^a (+7.6%)
CEDR-KNRM	0.483 (+1.7%)	0.413 (+1.9%)	0.291^a (+5.1%)	0.535 (+1.7%)	0.456 (+2.0%)	0.324^a (+6.8%)
CEDR-PACRR	0.496^a (+4.3%)	0.426^a (+5.3%)	0.307^a (+11.0%)	0.549^a (+4.2%)	0.466^a (+4.4%)	0.337^a (+11.2%)
Neural Model1	0.484 (+1.8%)	0.417^a (+3.1%)	0.298^a (+7.7%)	0.537 (+1.9%)	0.459^a (+2.6%)	0.330^a (+8.8%)
PARADE Attn	0.503^a (+5.7%)	0.433^a (+6.9%)	0.311^a (+12.4%)	0.556^a (+5.6%)	0.476^a (+6.5%)	0.344^a (+13.3%)
PARADE Attn (ELECTRA)	0.523^a (+6.4%)	0.456^a (+7.4%)	0.329^a (+11.7%)	0.581^a (+5.3%)	0.495^a (+6.5%)	0.358^a (+11.9%)
PARADE Attn (DEBERTA)	**0.549**^{a} (+2.9%)	**0.475**^{a} (+3.6%)	**0.346**^{a} (+8.7%)	**0.615**^{a} (+3.2%)	**0.522**^{a} (+3.8%)	**0.383**^{a} (+9.4%)
PARADE Avg	0.483 (+1.5%)	0.412 (+1.8%)	0.291^a (+5.2%)	0.534 (+1.5%)	0.457 (+2.4%)	0.318^a (+4.7%)
PARADE Max	0.489^a (+2.8%)	0.420^a (+3.8%)	0.306^a (+10.8%)	0.548^a (+4.0%)	0.470^a (+5.3%)	0.337^a (+11.0%)
PARADE Transf-RAND-L2	0.488^a (+2.8%)	0.423^a (+4.6%)	0.303^a (+9.7%)	0.548^a (+4.1%)	0.469^a (+5.0%)	0.338^a (+11.6%)
PAR. Transf-RAND-L2 (ELECTRA)	0.523^a (+6.3%)	0.454^a (+6.9%)	0.330^a (+12.2%)	0.574^a (+3.9%)	0.488^a (+5.0%)	0.354^a (+10.6%)
PARADE Transf-PRETR-L6	0.494^a (+4.0%)	0.426^a (+5.3%)	0.308^a (+11.5%)	0.554^a (+5.1%)	0.474^a (+6.1%)	0.346^a (+14.1%)
PAR. Transf-PRETR-LATEIR-L6	0.450^a (−5.2%)	0.389^a (−3.9%)	0.277 (+0.3%)	0.501^a (−4.9%)	0.423^a (−5.3%)	0.302 (−0.5%)
LongP (Longformer)	0.500^a (+3.6%)	0.435^a (+5.3%)	0.309^a (+11.5%)	0.568^a (+5.1%)	0.482^a (+6.1%)	0.347^a (+12.9%)
LongP (Big-Bird)	0.452^a (−10.9%)	0.389^a (−10.7%)	0.274^a (−8.8%)	0.477^a (−14.9%)	0.400^a (−15.5%)	0.279^a (−14.2%)
LongP (JINA)	0.503^a (+2.9%)	0.434^a (+3.1%)	0.309^a (+7.5%)	0.558^a (+4.9%)	0.473^a (+5.2%)	0.335^a (+9.7%)
LongP (MOSAIC)	0.456 (+0.6%)	0.393 (+0.8%)	0.280^a (+5.3%)	0.570^a (+6.0%)	0.484^a (+6.3%)	0.350^a (+13.0%)
LongP (TinyLLAMA)	0.452^a (+4.8%)	0.396^a (+6.9%)	0.267^a (+8.7%)	0.505^a (+6.7%)	0.428^a (+7.6%)	0.297^a (+13.3%)
LongP (E5-4K)	0.439 (+0.1%)	0.375 (+1.0%)	0.250 (+1.3%)	0.434 (+1.1%)	0.360 (+1.6%)	0.241^a (+2.9%)
LongP RankGPT (OpenAI)	–	–	–	0.562 (+0.0%)	0.456 (−0.0%)	0.281 (+0.3%)
LongP RankGPT (Anthropic)	–	–	–	0.538 (−0.6%)	0.445 (−0.2%)	0.268 (−0.0%)

In each column we show a relative gain with respect model's respective *FirstP* baseline: The last column shows the average relative gain of *FirstP*. Best numbers are in **bold**: Results are averaged over three seeds. Unless specified explicitly, the backbone is **BERT-base**. Statistical significant differences with respect to this baseline are denoted using the superscript superscript **a**. p-value threshold is 0.05. E5-models were used only in the zero-shot model, i.e., without fine-tuning.

Table 8: Ranking performance on Robust04.

generators. In particular, in the case of Robust04, Li et al. 2024 use RM3 (BM25 with a pseudo-relevance feedback (Jaleel et al., 2004)), which is more effective than BM25 (Robertson, 2004) (which we use on Robust04).

Another important comparison point is Robust04 results by Zhang et al. 2021 who were able to reproduce original *MaxP* results by Dai and Callan 2019, which used BERT-base as a backbone. In addition, they experimented with ELECTRA models "pre-finetuned" on MS MARCO. When comparing BERT-base results, Zhang et al. 2021 have the maximum relative gain of 6.6% compared to ours 3.3%. However, in absolute terms we got higher NDCG@20 for both *FirstP* and *MaxP*. Their MaxP (ELECTRA) has comparable performance to ours on TREC DL 2019-2020, but it is 2-4% better on Robust04. In turn, our MaxP (DEBERTA) is better by 2-6%. Although we do not always match prior art using the same backbone models, we generally match or outperform prior results, which, we believe, boosts the trustworthiness of our experiments.

A.5 Additional Experimental Results

In this section we provide links for additional experimental results. In particular, we compute additional effectiveness metrics for MS MARCO, TREC DL, and Robust04. MS MARCO and TREC DL results are shown in Table 7. Robust04 datasets are presented and Table 8. Furthermore, we provide detailed results for MS MARCO FarRelevant in Table 4. Evaluation results of rankers trained on de-biased data and tested on short-document collections can be found in Table 3.

B Additional Dataset Details

B.1 Summary Dataset Statistics

Summary query and dataset statistics is given in Tables 9 and 10. Please, note that in the case of MS MARCO FarRelevant, we created about 500K training and 7K testing queries, but to reduce experimentation cost we ended up using only 50K and 1K, respectively.

B.2 MS MARCO FarRelevant Creation Algorithm

The MS MARCO FarRelevant dataset was created as follows: Assume that C_t is the number of tokens in the passage:

data set	# of documents	average # of BERT tokens per document
Long-document collections		
MS MARCO doc. v1	3.2M	1.4K
MS MARCO doc. v2	12M	2K
Robust04	0.5M	0.6K
MS MARCO FarRelevant	0.53M	1.1K
Needle (LongEmbed)	0.8K	variable-length
Passkey (LongEmbed)	0.8K	variable-length
Short-document collections		
MS MARCO pass. v1	8.8M	75
Natural Questions (BEIR)	2.7M	107

LongEmbed subsets each have 16 subsets of documents whose lengths vary from (approximately) 256 to 32768 tokens.

Table 9: Document Statistics

	# of queries	avg. # of BERT tokens	avg. # of pos. judgements
MS MARCO doc. v1			
MS MARCO doc. train	352K	7	1
MS MARCO doc. dev	5193	7	1
TREC DL 2019	43	7	153.4
TREC DL 2020	45	7.4	39.3
MS MARCO v2			
TREC DL 2021	57	9.8	143.9
Robust04			
title	250	3.6	69.6
description	250	18.7	69.6
MS MARCO FarRelevant			
train	50K	7.0	1
test	1K	7.0	1
LongEmbed			
Needle	800	13.0	1
Passkey	800	9.7	1
Natural Questions (BEIR)			
all queries	3452	9.9	1.2
MS MARCO pass. v1			
TREC DL 2019	43	7	95.4
TREC DL 2020	54	7.2	66.8

Table 10: Query Statistics

- Select randomly a document length between $512 + C_t$ and 1431;

- Using rejection sampling, obtain K_1 non-relevant samples such that their *total* length exceeds 512, but the length of $K_1 - 1$ first samples is at most 512.

- Using the same approach, sample another $K_2 + 1$ samples such that the total length of K_2 samples is at most $1431 - C_t$, but the total length of $K_2 + 1$ samples exceeds this value.

- Discard the last sampled passage and randomly mix the remaining K_2 non-relevant passages with a single relevant passage.

- Finally, append the resulting string to the concatenation of the first K_1 non-relevant passages.

B.3 Comparison of FarRelevant and Synthetic Data from LongEmbed

Our synthetic data consists of two subsets Needle and Passkey from LongEmbed collection (Zhu et al., 2024) and our newly created MS MARCO FarRelevant dataset. The datasets can be seen a variant of a needle-in-the-haystack benchmark (Saad-Falcon et al., 2024; Zhu et al., 2024) and they share a common limitation: the resulting documents are constructed by combining pieces of text in a purely mechanical fashion and do not represent natural documents. In this section, we describe Needle and Passkey in more detail and compare them to our proposed collection MS MARCO FarRelevant, which—we believe—offers several practical advantages despite also being synthetic.

The needle subset is created by taking a single document (a Paul Graham essay on taste[8]), truncating it to generate 16 buckets of varying lengths (from 256 to 32,768 tokens), and inserting a single answer-bearing sentence at a random location. An example query-document pair can be found in Figure 4. While this design ensures precise control over document length (doubling per bucket), it introduces several problems:

1. **Extremely low document diversity**: All examples are truncated variants of the same original text, which severely limits the variability in document style and content.
2. **Artificial signal separation**: The inserted answer sentence differs substantially from the background text, making it easy for models to identify it.

The Passkey subset is similar in structure and also uses length-bucketed documents, but instead of a single sentence, it inserts a three-sentence passkey definition into a synthetic background context (see Figure 5). However, the background is even less natural than Needle's subset background, being composed of unrelated or nonsensical declarative statements (e.g., "The sky is blue. The sun is yellow. Here we go. There and back again."). This leads to even greater distributional mismatch between signal and context.

Critically, both Needle and Passkey were designed primarily to test *answer extraction* or retrieval of small, highly localized answer-bearing spans. They are not well suited to studying retrieval or ranking of entire passages or documents, especially when relevance is more distributed or contextual.

Our MS MARCO FarRelevant (see Figure 6 for an example) is designed to be textually similar to MS MARCO Documents but with different positional biases for relevant passages. We believe it offers a more robust testbed for long-context *document ranking*. While it is also synthetic in construction, it avoids many of the pitfalls noted above. Each document is created by concatenating multiple passages, which are typically *meaningful* and *complete*, only one of which is relevant to the query. The remaining passages serve as distractors but are independently coherent. Although these documents do not exist in the wild, they are much more diverse in content and style than those in Needle or Passkey despite being typically much shorter. Furthermore, each individual passage is semantically complete and belongs to a real corpus, namely, MS MARCO Passages.

B.4 Positional Bias Identification

To assess positional bias, we we used a combination of approximate string matching and LLM-based judging, which was recently shown to highly correlate with human judgments (Upadhyay et al., 2024; Arabzadeh and Clarke, 2025). The resulting distributions can be found in Figure 7.

Approximate string matching was used for MS MARCO training and development (*dev*) sets, both of which have sparse labels. Although initially MS

[8] https://www.paulgraham.com/goodtaste.html

> Aaron Swartz created a scraped feed of the essays page. November 2021(This essay is derived from a talk at the Cambridge Union.)When I was a kid, I'd have said there wasn't. My father told me so. Some people like some things, and other people like other things, and who's to say who's right?It seemed so obvious that there was no such thing as good taste that it was only through indirect evidence that I realized my father was wrong.
> **The novel "The Lord of the Rings" was written by Tolkien and published in the mid-20th century.**
> And that's what I'm going to give you here: a proof by reductio ad absurdum. If we start from the premise that there's no such thing as good taste, we end up with conclusions that are obviously false, and therefore the premise must be wrong. We'd better start by saying what good taste is. There's a narrow sense in which it refers to aesthetic judgements and a broader one in which it refers to preferences of any kind. The strongest proof would be to show that taste exists in the

Figure 4: A sample relevant document for the Needle collection. The query/question is: "Who wrote the novel "The Lord of the Rings" and when was it published?". The answer-bearing sentence is marked by bold font.

> The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. **Joyce Jenkins's pass key is 44349. Remember it. 44349 is the pass key for Joyce Jenkins.** The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. The grass is green. The sky is blue. The sun is yellow. Here we go. There and back again. The grass is green. The sky is blue. The sun is yellow. Here we go.

Figure 5: A sample relevant document for the Passkey collection. The query/question is: "what is the passkey for Joyce Jenkins?". The answer-bearing sentence is marked by bold font.

Andhra Pradesh Airports make an easy access for tourists visiting the state. This huge state has many airports, which serves the needs of both tourists and residents commuting to different parts in its large expanse. However, Hyderabad Airport is the major as well as the only international airport of Andhra Pradesh. Hyderabad, a major IT hub of India, boasts of the sixth busiest airport in India. Keeping the rush of passengers in mind, the Government is planning to establish another airport in Hyderabad.

In contrast, traditional English Longbow shooters step into the bow, exerting force with both the bow arm and the string hand arm simultaneously, especially when using bows having draw weights from 100 lbs to over 175 lbs. Heavily stacked traditional bows (recurves, long bows, and the like) are released immediately upon reaching full draw at maximum weight, whereas compound bows reach their maximum weight around the last inch and a half, dropping holding weight significantly at full draw. The Oreo Biscuit was first developed and produced by the National Biscuit Company (today known as Nabisco) in 1912 at its Chelsea, Manhattan factory in the current-day Chelsea Market complex, located on Ninth Avenue between 15th and 16th Streets. Today, this same block of Ninth Avenue is known as Oreo Way..

It's possible to take a day trip to the Bahamas by ferry. In some cases, less than it would cost to fly. The high-speed Balearia Bahamas Express travels from Fort Lauderdale to the city of Freeport on Grand Bahama, one of many Bahamian islands with British roots.It's roughly the distance from Philadelphia to New York.Prepare for a long day.n some cases, less than it would cost to fly. The high-speed Balearia Bahamas Express travels from Fort Lauderdale to the city of Freeport on Grand Bahama, one of many Bahamian islands with British roots. It's roughly the distance from Philadelphia to New York.

I was 17 when I took Bactrim for a UTI, I was a month away from turning 18 and was given this because another antibiotic would have more side effects I was told. I took it for 5 days and became horribly sick from a nasty cold and was told to stop Bactrim and to take Z Pac instead for 5 days.

Cases When Medicare Does NOT Automatically Start for You Medicare will NOT automatically start when you turn 65 if you're not receiving Social Security Benefits or Railroad Retirement Benefits for at least 4 months prior to your 65th birthday. You wanted to know how you can feel on your belly that you're pregnant. And actually this a pretty hard thing to do.There are better ways to find out if you're pregnant or not. For example, if you ever miss a period, the best thing to do is to take a home pregnancy test, because that's the first sign of pregnancy.And if it's positive, ...here are better ways to find out if you're pregnant or not. For example, if you ever miss a period, the best thing to do is to take a home pregnancy test, because that's the first sign of pregnancy.

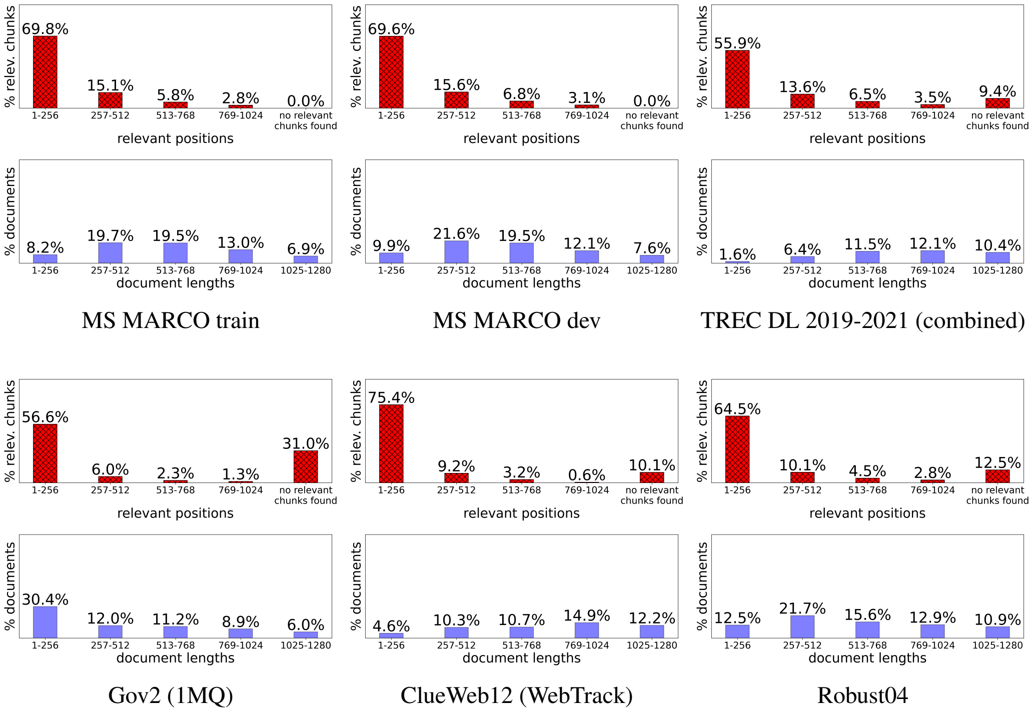
1 Whisk light soy sauce, dark soy sauce, red wine vinegar, chili oil, ginger, sugar, garlic, and green onion together in a bowl; pour into a sealable container, seal, and refrigerate 1 hour. See how to make a simple sweet-and-sour peach sauce. See how easy and delicious it is to make horseradish sauce from scratch.

Here you'll find a number of Kentucky facts including the state history at a glance; Kentucky state facts such as the location of the state capital, city populations, geography and natural resources; Information on Kentucky' government, symbols and traditions; and even a list of famous Kentuckians.

Confidence votes 193. Replacing a car window usually cost around $300 give or take based upon where you live, what options your car glass needs and what type of car you drive. Additionally, you can save money if you can repair your car glass instead of completely replacing it. However, if the window is completely shattered this will not be an option.

Flying time from Chicago, IL to Cairo, Egypt. The total flight duration from Chicago, IL to Cairo, Egypt is 12 hours, 47 minutes. This assumes an average flight speed for a commercial airliner of 500 mph, which is equivalent to 805 km/h or 434 knots. It also adds an extra 30 minutes for take-off and landing. Your exact time may vary depending on wind speeds.

Figure 6: A sample relevant document for the MS MARCO FarRelevant collection. The query/question is: "how long is the flight from chicago to cairo". The answer-bearing passage is marked by bold font.



MS MARCO train

MS MARCO dev

TREC DL 2019-2021 (combined)

Gov2 (1MQ)

ClueWeb12 (WebTrack)

Robust04

Figure 7: Illustration of relevant passage bias for five document collections (including MS MARCO v2) and 6+ query sets. A distribution of first relevant passage positions (red bars) vs. relevant document lengths (blue bars). Positions and lengths are measured in the number of subword tokens (BERT-base tokenizer). Best viewed in color.

MARCO passages were exact substrings of MS MARCO documents, document and passage texts were collected at different times this lead to some content divergence (Craswell et al., 2021a) that made exact mapping virtually impossible. There have been prior and contemporaneous attempts to recover initial positions, but only with a limited success. In particular, (Coelho et al., 2024) used exact matching and found only about one thousand matching passages. Hofstätter et al. (2020b) used matching of answer words—rather than passage text itself—and were able to match only 32% of the passages. Both of these attempts match only a small-to-modest fraction of passages while being a subject to biases.

Our approximate string matching combines approximate substring matching with longest-substring matching and incorporates efficiency heuristics to identify initial candidate sets. Candidate sets were constructed using two approaches: selecting all relevant passages and documents (for a given query) and retrieving top-5 documents using relevant passages as queries. To assess reliability, we manually inspected a subset of the matched passages and found the procedure to be sufficiently accurate. We then applied this approach to two sets of queries:

- A set of all 5193 queries from the *dev* set;
- A (random and uniform) sample of 5000 training queries.

In both cases, we were able to find matches for about 85% of the queries.

For queries sets with "dense" relevance judgments produced by TREC NIST assessors we used an LLM judge. This included TREC 2019, 2020, 2021 TREC DL queries (Craswell et al., 2021b), Robust04 (Clarke et al., 2004), Gov2 with 2007, 2008 Million Query Track queries (Allan et al., 2008), and ClueWeb12 with 2012 and 2013 Web Track queries (Collins-Thompson et al., 2013b). It is noteworthy that Hofstätter et al. (2020b) employed crowd-workers to identify the distribution of relevance chunks. They found similar evidence of the relevance position bias, but their study was limited only to TREC DL 2019 query set.

To avoid potential positional biases in LLM-judging, we divided each document into non-overlapping chunks and judged each chunk separately. Chunking was preserving sentence boundary while ensuring each chunk size was close to having 256 tokens. For efficiency reasons, we only considered at most 36 chunks (about 9K tokens) and 500-2000 positive query-document pairs per query set. A chunk was considered to be relevant if it received a positive grade from the LLM-judge. The LLM-judge model was GPT4-mini (OpenAI, 2023).

For most collections, there was only a small fraction of documents where the LLM-judge found no relevant query-document pairs. One exception is the Gov2 collection with 2007, 2008 Million Query Track queries where this happened in about 30% of the cases. Despite this gap, Gov2 still had a substantial positional bias with about 57% of the cases where the first chunk was deemed to be relevant.

Model family	# of params.
PARADE Transformer	132-148M
Longformer	149M
BigBird	127M
JINA	137M
MOSAIC	137M
DEBERTA-based models	184M
TinyLLAMA-based models	1034M
Other BERT- and ELECTRA-based models	≈110 M

Table 11: Number of Model Parameters

C Ranking with Cross-Encoding Long-Document Models

In this section, we describe long-document cross-encoding models in more details. With an exception of TinyLLAMA (Zhang et al., 2024) all models use only smallish bi-directional encoder-only Transformers (Vaswani et al., 2017) with 100-200M parameters in total (see Table 11). TinyLLAMA is a so-called LLM-ranker: a “causal” decoder-only Transformer that has about 1B parameters. Moreover, we focus only on the pure-Transformer architectures leaving hybrid architectures such as RankMamba for future work (Xu, 2024).

We assume that an input text is split into small chunks of texts called *tokens*. Although tokens can be complete English words, Transformer models usually split text into sub-word units (Wu et al., 2016).

The length of a document d—denoted as $|d|$—is measured in the number of tokens. Because neural networks cannot operate directly on text, a sequence of tokens $t_1 t_2 \ldots t_n$ is first converted to a sequences of d-dimensional embedding vectors $w_1 w_2 \ldots w_n$ by an *embedding* network. These embeddings are context-independent, i.e., each token is always mapped to the same vector (Collobert et al., 2011; Mikolov et al., 2013).

For a detailed description of Transformer models, please see the annotated Transformer guide (Rush, 2018) as well as the recent survey by Lin et al. (Lin, 2019), which focuses on the use of BERT-style cross-encoding models for ranking and retrieval. For this paper, it is necessary to know only the following basic facts:

- BERT is an encoder-only model, which converts a sequence of tokens $t_1 t_2 \ldots t_n$ to a sequence of d-dimensional vectors $w_1 w_2 \ldots w_n$. These vectors—which are token representations from the *last* model layer—are commonly referred to as contextualized token embeddings (Peters et al., 2018);

- BERT operates on word pieces (Wu et al., 2016) rather than on complete words;

- The vocabulary includes two special tokens: `[CLS]` (an aggregator) and `[SEP]` (a separator);

- Using a *pooled* representation of token vectors $w_1 w_2 \ldots w_n$, a linear layer is used to produce a ranking score. A nearly universal pooling approach in cross-encoding rankers is to use the vector of the `[CLS]` token, i.e., w_1. However, we learned that some models (e.g., JINA (Günther et al., 2023)) converge well *only* with mean pooling, i.e., they use $\frac{1}{n}\sum_{i=1}^{n} w_i$.

A “vanilla” BERT ranker (dubbed as monoBERT by Lin et al. (Lin, 2019)) uses a single fully-connect layer F as a prediction head, which converts the last-layer representation of the `[CLS]` token (i.e., a contextualized embedding of `[CLS]`) into a scalar (Nogueira and Cho, 2019). It makes a prediction based on the following sequence of tokens: `[CLS]` q `[SEP]` d `[SEP]`, where q is a query and d is a document.

An alternative approach is to aggregate contextualized embeddings of regular tokens using a shallow neural network (MacAvaney et al., 2019; Boytsov and Kolter, 2021; Khattab and Zaharia, 2020) (possibly together with the contextualized embedding of `[CLS]`) . This was first proposed by MacAvaney et al. (MacAvaney et al., 2019) who also found that incorporating `[CLS]` improves performance. However, Boytsov and Kolter proposed a shallow aggregating network that does not use the output of the [CLS] token and achieved the same accuracy on MS MARCO datasets (Boytsov and Kolter, 2021).

Replacing the standard BERT model in the vanilla BERT ranker with a BERT variant that "natively" supports longer documents (e.g., Big-Bird (Zaheer et al., 2020)) is, perhaps, the simplest way to deal with long documents. We collectively call these models as LongP models. For a typical BERT model, however, long documents and queries need to be split or truncated so that the overall number of tokens does not exceed 512. In the *FirstP* mode, we process only the first chunk and ignore the truncated text. In the *SplitP* mode, each chunk is processed separately and the results are aggregated. In the remaining of this section, we discuss these approaches in detail.

C.1 LongP models

In our work, we benchmark both sparse-attention and full-attention models. Sparse attention LongP models include two popular options: Longformer (Beltagy et al., 2020) and Big-Bird (Zaheer et al., 2020). In that, we use the same approach to score documents as with the vanilla BERT ranker, namely, concatenating queries with documents and making a prediction based on the contextualized embedding of the [CLS] token (Nogueira and Cho, 2019). Both Big-Bird and Longformer use a combination of the local, "scattered" (our terminology), and global attention. The local attention utilizes a sliding window of a constant length where each token attends to each other token within this window. In the case of the global attention, certain tokens can attend to *all* other tokens and vice-versa, In Big-Bird, only special tokens such as [CLS] can attend globally. In Longformer, the user have to select such tokens explicitly. Following Beltagy et al. (Beltagy et al., 2020), who applied this technique to question-answering, we "place" global attention only on query tokens. Unlike the global attention, the scattered attention is limited to restricted sub-sets of tokens, but these subsets do not necessarily have locality. In Big-Bird the scattered attention relies on random tokens, whereas Longformer uses a dilated sliding-window attention with layer- and head-specific dilation.

Full-attention models include JINABert (Günther et al., 2023), TinyLLAMA (Zhang et al., 2024), and MosaicBERT (Portes et al., 2023), henceforth, simply JINA, TinyLLAMA and MOSAIC. All these models use a recently proposed FlashAttention (Dao et al., 2022) to efficiently process long-contexts as well as special positional embeddings that can generalize to document lengths not seen during training. In that, JINA and MOSAIC use AliBi (Press et al., 2022), while TinyLLAM uses ROPE embeddings (Su et al., 2023). JINA and MOSAIC are bi-directional encoder-only Transformer model whereas TinyLLAMA is a unidirectional (sometimes called causal) decoder-only Transformer model (Vaswani et al., 2017).

In addition architectural difference, models differ in pretraining strategies. MOSAIC relies primarily on the masked language (MLM) objective without next sentence prediction (NSP). JINA uses this approach as a first step, following a RoBERTa pretraining strategy (Liu et al., 2019) and fine-tuning on retrieval and classification tasks with mean-pooled representations. TinyLLAMA was trained using an autoregressive language modeling objective (Zhang et al., 2024). We found that JINA lost an ability to effectively pool on the [CLS] token and we used mean-pooling instead. We also use mean pooling for TinyLLAMA. For MOSAIC we used pooling on [CLS].

C.2 SplitP models

SplitP models differ in partitioning and aggregation approaches. Documents can be split into either disjoint or overlapping chunks. In the first case, documents are split in a greedy fashion so that each document chunk except possibly the last one is exactly 512 tokens long after being concatenated with a (padded) query and three special tokens. In the second case, we use a sliding window approach with a window size and stride that are not tied to the maximum length of BERT input. Because our primary focus is accuracy and we aim to understand the limits of long-document models, we exclude from evaluation several *SplitP* models, e.g., by Hofstätter et al. (2021b); Zou et al. (2021), which achieve better efficiency-effectiveness tradeoffs by pre-selecting certain document parts and feeding only selected parts into a BERT ranker.

Greedy partitioning into disjoint chunks CEDR models (MacAvaney et al., 2019) and the Neural Model 1 (Boytsov and Kolter, 2021) use the first method, which involves:

- tokenizing the document d;
- greedily splitting a tokenized document d into

m disjoint chunks: $d = d_1 d_2 \ldots d_m$;

- generating m token sequences `[CLS]` q `[SEP]` d_i `[SEP]` by concatenating the query with document chunks;

- processing each sequence with a BERT model to generate contextualized embeddings for regular tokens as well as for `[CLS]`.

The outcome of this procedure is m `[CLS]`-vectors cls_i and n contextualized vectors $w_1 w_2 \ldots w_n$ (one for *each* document token t_i) that are aggregated in a model-specific ways.

MacAvaney et al. (MacAvaney et al., 2019) use contextualized embeddings as a direct replacement of context-free embeddings in the following neural architectures: KNRM (Xiong et al., 2017), PACRR (Hui et al., 2018), and DRMM (Guo et al., 2016). To boost performance, they incorporate `[CLS]`-vectors in a model-specific way. We call the respective models as *CEDR-KNRM*, *CEDR-PACRR*, and *CEDR-DRMM*.

They also proposed an extension of the vanilla BERT ranker that makes a prediction using the average `[CLS]` token: $\frac{1}{m}\sum_{i=1}^{m} cls_i$ by passing it through a linear projection layer. We call this method *AvgP*.

The Neural Model 1 (Boytsov and Kolter, 2021) uses the same greedy partitioning approach as CEDR, but a different aggregator network, which does not use the embeddings of the `[CLS]` token. This network is a neural parametrization of the classic Model 1 (Berger and Lafferty, 1999; Brown et al., 1993).

Sliding window approach The BERT MaxP/SumP (Dai and Callan, 2019) and PARADE (Li et al., 2024) models use a sliding window approach. Assume w is the size of the window and s is the stride. Then the processing can be summarized as follows:

- tokenizing, the document d into sub-words $t_1 t_2 \ldots t_n$;

- splitting a tokenized document d into m possibly overlapping chunks $d_i = t_{i \cdot s} t_{i \cdot s+1} \ldots t_{i \cdot s+w-1}$: Trailing chunks may have fewer than w tokens.

- generating m token sequences `[CLS]` q `[SEP]` d_i `[SEP]` by concatenating the query with document chunks;

- processing each sequence with a BERT model to generate a last-layer output for each sequence `[CLS]` token.

The outcome of this procedure is m `[CLS]`-vectors cls_i, which are subsequently aggregated in a model-specific ways. Note that PARADE and MaxP/SumP models do not use contextualized embeddings of regular tokens.

BERT MaxP/SumP These models (Dai and Callan, 2019) use a linear layer F to produce m relevance scores $F(cls_i)$. Then complete document scores are computed as $\max_{i=1}^{m} F(cls_i)$ and $\sum_{i=1}^{m} F(cls_i)$ for the MaxP and SumP models, respectively.

PARADE These models (Li et al., 2024) can be divided into two groups. The first group includes PARADE average, PARADE max, and PARADE attention, which all use simple approaches to produce an aggregated representation of m `[CLS]`-vectors cls_i. To compute a relevance score these aggregated representations are passed through a linear layer F.

In particular, PARADE average and PARADE max combine cls_i using averaging and the element-wise maximum operation, respectively to generate aggregated representation of m `[CLS]` tokens cls_i.[9] The PARADE attention model uses a learnable attention (Bahdanau et al., 2015) vector C to compute a scalar weight w_i of each i as follows: $w_1 w_2 \ldots w_m = softmax(C \cdot cls_1, C \cdot cls_2, \ldots, C \cdot cls_m)$. These weights are used to compute the aggregated representation as $\sum_{i=1}^{m} w_i cls_i$

PARADE Transformer models combine `[CLS]`-vectors cls_i with an additional *aggregator* transformer model $AggregTransf()$. The input of the aggregator Transformer is sequence of cls_i vectors prepended with a learnable vector C, which plays a role of a `[CLS]` embedding for $AggregTransf()$. The last-layer representation of the first vector is passed through a linear layer F to produce a relevance score:

$$F(AggregTransf(C, cls_1, cls_2, \ldots, cls_m)[0]) \quad (1)$$

[9] Note that both PARADE average and AvgP vanilla ranker use the same approach to aggregate contextualized embeddings of `[CLS]` tokens, but they differ in their approach to select document chunks. In particular, AvgP uses non-overlapping chunks while PARADE average relies on the sliding window approach.

An aggregator Transformer can be either pretrained or randomly initialized. In the case of a pretrained transformer, we completely discard the embedding layer. Furthermore, if the dimensionality of cls_i vectors is different from the dimensionality of input embeddings in $AggregTransf$, we project cls_i using a linear transformation.

Miscellaneous models We attempted to implement additional state-of-the-art models (Gao and Callan, 2022; Fu et al., 2022). Gao and Callan (Gao and Callan, 2022) introduced a late-interaction model MORES+, which is a modular long document reranker that uses a sequence-to-sequence transformer in a non-auto-regressive mode. In MORES+ document chunks are first encoded using the encoder-only Transformer model. Then they use a modified decoder Transformer for joint query-to-all-document-chunk cross-attention: This modification changes a causal Transformer into an encoder-only bi-directional Transformer model. As of the moment of writing, the MORES+ model holds the first position on a competitive MS MARCO document leaderboard.[10]. However, the authors provide only incomplete implementation which does not fully match the description in the paper (i.e., crucial details are missing). We reimplemented this model to the best of our understanding, but our implementation failed to outperform even BM25.

Inspired by this approach, we managed to implement a late-interaction variant of the PARADE model, which we denoted as PARADE-LATEIR. Similar to the original PARADE model, it splits documents into overlapping chunks. However, it then encodes chunks and queries independently. Next, it uses an interaction Transformer to (1) mix these representations, and (2) combine output using an aggregator Transformer. In total, the model uses three backbone encoder-only Transformers: All of these Transformers are initialized using pretrained models.

Fu et al. (2022) proposed a multi-view interactions-based ranking model (MIR). They implement inter-passage interactions via a multi-view attention mechanism, which enables information propagation at token, sentence, and passage levels. Due to the computational complexity, they restrict these interactions to a set of salient/pivot tokens. However, the paper does not provide enough details regarding the choices of these tokens. There is no software available and authors did not respond to our clarification requests. Thus, this model is also excluded from our evaluation.

[10] https://microsoft.github.io/MSMARCO-Document-Ranking-Submissions/leaderboard/