Understanding Performance of Long-Document Ranking Models through Comprehensive Evaluation and Leaderboarding

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Abstract

We evaluated 20+ Transformer models for ranking of long documents (including recent LongP models trained with FlashAttention) and compared them with a simple FirstP baseline, which applies the same model to the truncated input (at most 512 tokens). We used MS MARCO Documents v1 as a primary training set and evaluated both zero-shot transferred and fine-tuned models.

On MS MARCO, TREC DLs, and Robust04 no long-document model outperformed FirstP by more than 5% in NDCG and MRR (when averaged over all test sets). We conjectured this was not due to models’ inability to process long context, but due to a positional bias of relevant passages, whose distribution was skewed towards the beginning of documents. We found direct evidence of this bias in some test sets, which motivated us to create MS MARCO FarRelevant (based on MS MARCO Passages) where the relevant passages were not present among the first 512 tokens.

Unlike standard collections where we saw both little benefit from incorporating longer contexts and limited variability in model performance (within a few %), experiments on MS MARCO FarRelevant uncovered dramatic differences among models. The FirstP models performed roughly at the random-baseline level in both zero-shot and fine-tuning scenarios. Simple aggregation models including MaxP and PARADE Attention had good zero-shot accuracy, but benefited little from fine-tuning. Most other models had poor zero-shot performance (sometimes at a random baseline level), but outstripped MaxP by as much as 13-28% after finetuning. Thus, the positional bias not only diminishes benefits of processing longer document contexts, but also leads to model overfitting to positional bias and performing poorly in a zero-shot setting when the distribution of relevant passages changes substantially. We make our software and data available.

1 Introduction

Transformer models (Vaswani et al., 2017)—such as BERT (Devlin et al., 2019)—pretrained in a self-supervised manner considerably advanced state-of-the-art of core natural language processing (NLP) (Devlin et al., 2019; Radford et al., 2018) and information retrieval (Nogueira and Cho, 2019). However, due to quadratic cost of the self-attention with respect to an input sequence length, a number of “chunk-and-aggregate” approaches were proposed.

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

and evaluated (Dai and Callan, 2019; MacAvaney et al., 2019; Boytsov and Kolter, 2021; Li et al., 2024), but existing studies typically have at least one of the following shortcomings:

- Reliance only on small-scale query collections such as TREC DL (Craswell et al., 2020, 2022), Robust04 (Voorhees, 2004), and Gov2 Terabyte (Clark et al., 2005);

- Lacking systematic comparison with respective FirstP baselines, which consists in applying the same model to input truncated to the first 512 tokens,

- Lacking comparison with LongP models—directly supporting long inputs—such as sparse-attention models Longformer and BigBird (Beltagy et al., 2020; Zaheer et al., 2020), or more recent full-attention models trained with FlashAttention (Dao et al., 2022);

- Using undisclosed seed-selection strategies, which can restrict reproducibility since there can be substantial (in the order of few %) differences due to using different seeds.

To fill this gap we evaluated over 20 recent models for ranking of long documents and carried out their systematic comparison using two popular document collections: MS MARCO Documents v1/v2 (Craswell et al., 2020) and Robust04 (Clarke et al., 2004), diverse query sets (both large and small) and multiple training seeds. We found that ranking models capable of processing long documents—including LongP models with sparse or full attention—showed little to no improvement compared to their respective FirstP baselines (which truncated documents to satisfy the input-sequence constraint of most off-the-shelf Transformer models, i.e., 512 tokens).

This finding is generally in line with previously reported results (see § B.4) and an ablation experiment showed that limited improvement over FirstP was not related to the choice of the backbone Transformer model (see Table 7). Furthermore, we used our best models to produce several high-ranking runs on a competitive leaderboard. This, in our view, strengthens the credibility of our evaluation.

From the efficiency-effectiveness plot in Fig. 1, 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.

Our initial exploration prompted two broad research questions:

- RQ1: What is the reason for the lackluster performance of long-document models?
- RQ2: How much progress has the community made in improving long-document ranking models?

To answer these questions, we started with analyzing a distribution of relevant passages in the MS MARCO document collection and found evidence of a substantial positional bias, namely, relevant passages tended to appear in the beginning of documents. This finding—which partially answers RQ1—prompted an additional research question:

- RQ3: How robust are long-document models to the positional-bias of relevant passages?

To further support the relevance-bias hypothesis and answer RQ3, we constructed a new synthetic collection MS MARCO FarRelevant where relevant passages were not present among the first 512 tokens. Using MS MARCO FarRelevant, we evaluated zero-shot transferred as well as fine-tuned models and found the following (see Fig. 2):

- The FirstP models performed roughly at the random-baseline level in both zero-shot and fine-tuning modes (RQ3):
• Simple aggregation models including MaxP and PARADE Attention had good zero-shot accuracy, but benefited little from fine-tuning on MS MARCO FarRelevant (RQ3);

• In contrast, other long-document models had poor zero-shot performance (sometimes at a random baseline level), but outstripped respective MaxP baselines by as much as 13.3%-27.7% after finetuning (RQ3);

• Not only positional bias diminished benefits of processing longer document contexts, but it also lead to models’ overfitting to the bias and performing poorly in a zero-shot setting when the distribution of relevant passages changed substantially (RQ3);

• Although 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).

Our key contributions are as follows:

• We carried a comprehensive evaluation of 20+ long-document ranking models, which included both the chunk-and-aggregate models as well as the models that directly supported long inputs (using both the standard collections MS MARCO Documents v1/v2 and Robust04 as well as the new synthetic collection MS MARCO FarRelevant);

• We contributed to the nascent field of analytical experimentation with a full control of outcomes by creating a new dataset MS MARCO FarRelevant, which we made available together with code.²

• Our study confirmed superiority of PARADE (Li et al., 2024) models, but also showed their limited benefits on standard collections, which we attributed to the existence of positional bias of relevant passages (in such collections);

• We used MS MARCO FarRelevant to support the positional-bias hypothesis as well as to demonstrate that best long-document ranking models substantially (by up to 27.7%) outperform simpler baselines (such as MaxP) when training/fine-tuning data is available. However, they can also suffer more from the distribution shift and perform much worse in the zero-shot scenario.

2 Methods

2.1 Related Work

Neural Ranking models have been a popular topic in recent years (Guo et al., 2019), but the success of early approaches was controversial (Lin, 2019). This changed with an introduction of a bi-directional encoder-only Transformer model BERT (Devlin et al., 2019), which was a successor of GPT (Radford et al., 2018) and ELMO (Peters et al., 2018). BERT was hugely successful and its resounding success can be attributed to a combination of the large model size and massive pre-training using self-supervision. A number of different Transformer models such as ELECTRA (Clark et al., 2020), and DEBERTA (He et al., 2021) improve upon BERT using different training strategies and/or datasets. However, due to their architectural similarities we—following Lin et al (Lin et al., 2021)—collectively call them as BERT models.

Nogueira and Cho were first to apply BERT to ranking of text documents (Nogueira and Cho, 2019). In the big-data regime—most notably in the TREC deep learning track (Craswell et al., 2020)—BERT models outperformed prior neural and non-neural approaches by a large margin. They were also quite successful for several small-scale query collections outperforming previous neural and traditional approaches (Li et al., 2024; MacAvaney et al., 2019; Dai and Callan, 2019).

Despite their impressive performance, neural models are susceptible to the distribution shift and learning superficial features. Several authors found that neural rankers applied to out-of-domain data do not always outperform BM25 (Thakur et al., 2021; Mokrii et al., 2021). They can also be confused by superficial text modifications such as adding distractor sentences (MacAvaney et al., 2022). Likewise, ranking performance can decrease if a query is reformulated (Penha et al., 2022). Weller et al. (Weller et al., 2023) showed that neural models are not effective to “spot” negation and often perform at random level in this respect. However, we are not aware of the prior work

²https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/.
systematically studying robustness to positional biases of relevant passages.

The Transformer model (Vaswani et al., 2017) uses an attention mechanism (Bahdanau et al., 2015) where each sequence position can attend to all the positions in the previous layer. Because self-attention complexity is quadratic with respect to a sequence length, direct processing of long documents is not always practical. Thus, a vast majority of existing Transformer models limit the input length to be at most 512 (subword) tokens.

Until recently, there have been two general approaches to handling long documents: localization of attention and splitting documents into chunks each of which is processed separately. Attention-localization approaches combine a limited-span (i.e., a sliding window) attention with some form of a selective global attention. There are many such approaches proposed (see, e.g., a survey by Tay et al. 2020) and it would be infeasible to evaluate them all. Instead we consider two popular models: Longformer (Beltagy et al., 2020) and Big-Bird (Zaheer et al., 2020).

With a document-splitting approach, one has to split documents into several chunks, process each chunk separately, and aggregate results, e.g., by computing a maximum or a weighted prediction score (Yilmaz et al., 2019; Dai and Callan, 2019). With respect to training approaches, the MaxP and SumP models by Dai and Callan (Dai and Callan, 2019) assume that each chunk in a relevant document is relevant. However, this assumption is problematic as the degree of relevance varies from passage to passage. Yilmaz et al. (Yilmaz et al., 2019) work around this problem by training a MaxP BERT model on short documents and zero-transfer it to long documents. In this study we work around this problem by training all document-splitting approaches including MaxP (Dai and Callan, 2019) in the end-to-end fashion, i.e., by plugging aggregated document-level scores directly into a loss function (analogous to training of CEDR (MacAvaney et al., 2019) and PARADE (Li et al., 2024) models).

More recently, it has also become possible to train longer-context models using FlashAttention (Dao et al., 2022). FlashAttention computes attention exactly and it does not eliminate quadratic complexity. However, it dramatically speeds up training while reducing memory requirements by using an IO-efficient computation approach.

Because our primary focus is accuracy and we aim to understand the limits of long-document models, we exclude from evaluation several recent models (e.g., (Hofstätter et al., 2021; Zou et al., 2021)) that achieve better efficiency-effectiveness trade-offs by pre-selecting certain document parts and feeding only selected parts into a BERT ranker.

Recently, several teams have focused on creating challenging benchmarks for long-document retrieval. A recent LoCo v1 (Saad-Falcon et al., 2024) benchmark has 12 datasets. Despite 11 out of 12 collections has average document lengths in the order of dozens of thousands tokens, the E5 model with a 512 token input limit achieves high NDCG@10 scores (in the range of 0.4-0.85) for seven out of 12 LoCo v1 datasets. This prompted Zhu et al., 2024 to propose a more challenging LongEmbed benchmark containing a mix of real and synthetic datasets (Zhu et al., 2024).

### 2.2 Data

Our primary datasets include two MS MARCO Documents collections (v1 and v2) (Bajaj et al., 2016; Craswell et al., 2020, 2022), Robust04 (Voorhees, 2004), and associated query sets. In addition, we created a collection MS MARCO FarRelevant by using passages and relevance judgments from the MS MARCO Passages collection.

Robust04 is a small collection of 0.5M documents that has a mixture of news articles and government documents some of which are quite long. Yet it has only a small number of queries (250),

| Table 1: Distribution of Start/End Positions of Relevant Passages Inside Documents |
|---------------------------------|-----------------|-----------------|
| input chunk # | MS MARCO dev (estimated) | FIRA (Hofstätter et al., 2020b) (crowd-sourced) |
| start | end | start | end |
| 1 | 85.9% | 71.0% | 83.8% | 76.4% |
| 2 | 9.1% | 14.9% | 9.9% | 15.3% |
| 3 | 2.6% | 6.1% | 2.3% | 3.9% |
| 4 | 1.2% | 3.0% | 2.2% | 2.2% |
| 5 | 0.6% | 1.4% | 0.7% | 0.9% |
| 6 | 0.6% | 1.2% | 0.4% | 0.5% |
| 6+ | 0.1% | 2.5% | 0.7% | 0.7% |

Chunk size is 477 BERT tokens.

| Table 2: Document Statistics |
|-----------------------------|------------------|
| data set | # of documents | average # of BERT tokens per document |
| MS MARCO v1 | 3.2M | 1.4K |
| MS MARCO v2 | 12M | 2K |
| Robust04 | 0.5M | 0.6K |
| MS MARCO FarRelevant | 0.53M | 1.1K |
Table 3: Query Statistics

|                      | # of queries | avg. # of BERT tokens | avg. # of pos. judgements |
|----------------------|--------------|------------------------|---------------------------|
| **MS MARCO v1**      |              |                        |                           |
| MS MARCO train       | 352K         | 7                      | 1                         |
| MS MARCO 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                         |

which makes it a challenging benchmark for training models in a low-data regime. Each query has a title and a description, which represent a brief information need and a more elaborate request (often a proper English prose), respectively. We use Robust04 in a cross-validation settings with folds established by Huston and Croft (Huston and Croft, 2014) provided via IR-datasets (MacAvaney et al., 2021). All datasets are in English. Document and query statistics are summarized in Tables 2 and 3.

MS MARCO v1 was created from the MS MARCO reading comprehension dataset (Bajaj et al., 2016) and it has two related collections: passages and 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., 2020). 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 judgements 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. To assess positional bias, we mapped relevant passages (from the MS MARCO Passage collection) to their positions in documents. Because document and passage texts were collected at different times this lead to some content divergence (Craswell et al., 2020) and made exact mapping impossible: In particular, Hofstätter et al. 2020b were able to match only 32% of the passages.

We deemed such mapping insufficient: To obtain a more comprehensive mapping we resorted to approximate matching and were able to match about 85% of the passages. We manually inspected a sample of matched passages to ensure that the matching procedure was reliable. Moreover, the distribution of positions of relevant passages matched that of a related FIRA dataset (Hofstätter et al., 2020b), where such information was collected by crowdsourcing. Positional bias information is summarized in Table 1.

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 judgements—separated into training and developments subsets—there is a small number (98) of queries that have “dense” judgements provided by NIST assessors for TREC 2019 and 2020 deep learning (DL) tracks (Craswell et al., 2020).

MS MARCO v2 collections was created for TREC 2021 DL track. It is an expanded version of MS MARCO v1 and uses a subset of sparse relevance judgements from MS MARCO v1. In the training set, newly added documents do not have any (positive or negative) judgments, which created a bias and made MS MARCO v2 training set less useful than that of MS MARCO v1.

The MS MARCO FarRelevant collection was created from the MS MARCO passage collection in such a way that each document contained exactly one relevant passage and this passage did not start before token 512 (see algorithm in the Appendix § B.1). Moreover, we created just a single relevant document for each training or testing query. MS MARCO FarRelevant is a variant of a the needle-in-the-haystack test (Saad-Falcon et al., 2024; Zhu et al., 2024). It is designed to be textually similar to MS MARCO Documents but with different positional biases for relevant passages. Due MS MARCO having a non-commercial license, MS MARCO FarRelevant has the same licensing restriction.

Although we generated about 7K test queries and about 500K training queries, we used only 50K and 1K queries for fine-tuning and testing, respectively. On one hand, this was sufficient for accurate training and testing and, on the other hand, it reduced experimentation time and cost.
2.3 Overview of Selected Methods

Due to space constraints, a detailed description is given in the Appendix § A. In summary, all methods can be divided into split-and-aggregate (SplitP) methods and LongP methods that “natively” support longer documents inputs. SplitP use either simple aggregating operations (averaging, summing, taking the maximum) or an aggregator neural network. CEDR (MacAvaney et al., 2019), PARADE Attention (Li et al., 2024), and Neural Model 1 (Boytsov and Kolter, 2021) aggregate using simple neural networks, whereas PARADE Transformer models aggregator is a smaller Transformer (Li et al., 2024).

We focused on cross-encoding rankers, which process queries concatenated with documents (Nogueira and Cho, 2019). As a reference point we also tested a bi-encoding 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 use only BERT models (i.e., bi-directional encoder-only Transformers) and have in total 100M-200M parameters (see Table 6). In addition, inspired by a recent success of LLM-rankers (Pradeep et al., 2023; Ma et al., 2023), we tested a much larger cross-encoding decoder-only (“causal”) Transformer model. Specifically we chose a 1B-parameter TinyLLAMA model due to its impressive performance for its relatively small size (Zhang et al., 2024).

3 Experiments

3.1 Setup

We trained each cross-encoding ranking model using three seeds, except the bi-encoder model E5 (Zhu et al., 2024), which was evaluated only in the zero-shot mode. 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 § B.2. 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-related metrics are computed in the Appendix (see § B.5).

3.2 Results

Our main experimental results for MS MARCO, TREC DL 2019-2021, and Robust04 are presented in Table 4. Table 5 and Fig. 2 show results for MS MARCO FarRelevant. In the Appendix (see B.4) we 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).3

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 § B.4 in the Appendix).

To ease understanding and simplify presentation, we display key results for a representative sample of models in Fig. 1 and Fig. 2 (in § 1). Moreover, in Table 4 we present only a single aggregate number for all TREC DL query sets, which is obtained by combining all the queries and respective relevance judgements (i.e., we post an overall average rather than an average over the mean values for 2019, 2020, and 2020).

From Fig. 1 and Table 4 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 even underperform their FirstP baselines on one or more dataset and some of these differences are statistically significant. In particular, this is true for CEDR-DRMM, CEDR-KNRM (MacAvaney et al., 2019), JINA ( Günther et al., 2023) and MOSAIC (Portes et al., 2023) on the MS MARCO development set.

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

3Note, however, that Transf-PRETR-L2 has only four attention heads.
| Retriever / Ranker | MS MARCO | TREC DL (2019-2021) | Robust04 | Avg. gain over FirstP |
|-------------------|----------|---------------------|----------|-----------------------|
|                   | MRR      | NDCG@10             | NDCG@20  |                       |
| retriever          |          |                     |          |                       |
| 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                 | -                     |
| 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 (+1.9%)     | 0.488 (+2.6%) | 0.544 (+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 (-3.2%) | 0.671 (-0.1%)    | 0.535 (+0.2%) | 0.609 (+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 (-2.3%) | 0.629 (-0.5%)     | 0.466 (-2.0%) | 0.533 (+1.3%) | -0.9% |
| CEDR-KNRM          | 0.379 (-3.8%) | 0.630 (-0.3%)     | 0.483 (+1.7%) | 0.535 (+1.7%) | -0.2% |
| CEDR-PACRR         | 0.395 (+0.3%) | 0.643 (+1.6%)     | 0.496 (+4.4%) | 0.549 (+4.2%) | +2.6% |
| Neural Model1      | 0.398 (+0.9%) | 0.650 (+2.8%)     | 0.484 (+1.8%) | 0.537 (+1.9%) | +1.8% |
| PARADE Attn        | 0.416 (+5.5%) | 0.652 (+3.1%)     | 0.503 (+5.7%) | 0.556 (+5.6%) | +5.0% |
| PARADE Attn (ELECTRA) | 0.431 (+6.3%) | 0.680 (+2.7%)     | 0.523 (+6.4%) | 0.581 (+5.3%) | +4.4% |
| PARADE Attn (DEBERTA) | 0.422 (+6.6%) | 0.688 (+2.4%)     | 0.549 (+2.9%) | 0.615 (+3.2%) | +2.5% |
| PARADE Avg         | 0.392 (-0.6%) | 0.646 (+2.1%)     | 0.483 (+1.5%) | 0.534 (+1.5%) | +1.1% |
| PARADE Max         | 0.405 (+2.7%) | 0.655 (+3.5%)     | 0.489 (+2.8%) | 0.548 (+4.0%) | +3.3% |
| PARADE Trans-RAND-L2 | 0.419 (+6.3%) | 0.655 (+3.6%)     | 0.488 (+2.8%) | 0.548 (+4.1%) | +4.2% |
| PARADE Trans-RAND-L2 (ELECTRA) | 0.433 (+3.9%) | 0.670 (+1.2%) | 0.523 (+6.3%) | 0.574 (+3.9%) | +3.8% |
| PARADE Trans-PRETR-L6 | 0.402 (+1.9%) | 0.643 (+1.6%)     | 0.494 (+4.0%) | 0.554 (+5.1%) | +3.2% |
| PARADE Trans-PRETR-LATEIR-L6 | 0.398 (+1.1%) | 0.626 (-0.9%)     | 0.450 (-5.2%) | 0.501 (-4.9%) | -2.5% |
| LongP (Longformer) | 0.412 (+1.9%) | 0.668 (+3.9%)     | 0.500 (+3.6%) | 0.568 (+5.1%) | +3.6% |
| LongP (Big-Bird)   | 0.397 (-2.9%) | 0.651 (-0.7%)     | 0.452 (-10.9%) | 0.477 (-14.9%) | -7.3% |
| LongP (JINA)       | 0.416 (-1.5%) | 0.665 (+1.7%)     | 0.503 (+2.9%) | 0.558 (+4.9%) | +2.0% |
| LongP (MOSAIC)     | 0.421 (-0.4%) | 0.664 (+3.3%)     | 0.456 (+6.0%) | 0.570 (+6.0%) | +2.4% |
| LongP (TinyLLAMA)  | 0.402 (+1.7%) | 0.608 (-1.1%)     | 0.452 (+4.8%) | 0.505 (+6.7%) | +3.0% |
| LongP (E5-4K) zero-shot | 0.353 (-7.1%) | 0.649 (+1.1%)     | 0.439 (+0.1%) | 0.434 (+1.1%) | -1.1% |

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.

The 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 use 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 potentially perform better).

Our analysis of position of relevance passages in MS MARCO as well as results by Hofstätter et al. 2020b provide strong evidence 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 Table 1).

To further support this hypothesis, we carried out two sets of experiments using the MS MARCO FarRelevant collection, where a relevant passage was never in the first chunk. We carried out both the zero-shot experiment (evaluation of the model trained on MS MARCO) as well fine-tuning experiment using 50K MS MARCO FarRelevant
Statistically significant differences from a respective MaxP baseline by as much as 13.3%-27.7% after finetuning (RQ3);

- 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;

- Although 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).

Note that no LongP model outperformed the best chunk-and-aggregate approaches (while being also slower). Compared to simple aggregation models such as MaxP (ELECTRA) and PARADE Attention (ELECTRA), LongP models have at least 1.4× lower MRR in the zero-shot setting. In fact, in this setting three out of four LongP models—except Longformer—have a very low MRR with JINA being at the random-baseline level. LongP models also do not outperform PARADE Transformer model in the zero-shot setting and are at least 8% worse after fine-tuning. In this setting, three out of four LongP models have MRR scores \( \approx 0.4 \) that are not statistically different from that of Longformer.

### 4 Conclusion

We carried a comprehensive evaluation of 20+ long-document ranking models, which included both chunk-and-aggregate approaches and LongP models that directly support long inputs, using standard IR collections as well as a synthetic new dataset MS MARCO FarRelevant. These experiments helped us expose the bias in the distribution of relevant queries. Because FirstP models perform poorly in this setting we use different baselines, namely, 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). From Fig. 2 and Table 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 (RQ3). 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 4);
information (a trend to appear in the beginning of documents) and to demonstrate that MS MARCO FarRelevant is a hard benchmark even for models that supported long inputs. We made our code and MS MARCO FarRelevant available.

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.

Second, we focus on popular English document collections: MS MARCO Documents v1/v2 (Craswell et al., 2020) and Robust04 (Clarke et al., 2004). However, we have to restrict the choice of datasets to make multi-seed evaluations of 20+ models feasible. Despite this limitation, identifying bias in commonly used collections is an important task on its own. Moreover, strong performance of FirstP baselines was also noticed in other collections: Gao and Callan 2022 showed this for ClueWeb09 (and Robust04). Zhu et al. 2024 noticed a strong E5 FirstP performance on many LoCo datasets (Saad-Falcon et al., 2024).

While good performance of FirstP models strongly suggests a positional bias in relevant passages, we believe this alone is not sufficient evidence. Additionally—using the structure of the MS MARCO datasets—we attempt to directly identify positions of relevant passages. In that we could not map about 15% of the passages to documents, because these documents were changed after the passages were extracted. Although the failure to map 15% of passages can potentially bias the estimates for the distribution of relevant passages, we think it is unlikely because document updates were likely affected by the same positional biases as their prior versions. Moreover, our results are also supported by the FIRA experiment (Hofstätter et al., 2020b), where relevant positions were identified manually for a sample of documents used in TREC Deep Learning track (Craswell et al., 2020, 2022).

One can also argue that limited gains over FirstP baselines can be attributed to models’ inability to process long contexts. To counter this argument, we trained and evaluated a large number of diverse cross-encoding ranking models, which included both split-and-aggregate models as well as models directly supporting long inputs. 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 needle-in-the-haystack collection MS MARCO FarRelevant. This is still a limiting experiment, because synthetic collections—with documents composed from randomly selected passages—are imperfect proxies for real-life datasets.

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, and 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 support the existence of relevance position bias.

Finally, in contrast to some recent studies extending input contexts with dozens of thousands of tokens (Zhu et al., 2024; Saad-Falcon et al.,

<https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/>.
we truncated documents to have at most 1431 BERT tokens. This limitation, however, did not prevent us from answering our key research questions. In particular, as we showed and explained in the Appendix § B.3, using larger inputs only marginally improved outcomes for popular IR collections such as MS MARCO, Robust04 or ClueWeb09. At the same time, when we trained models on MS MARCO and applied them to MS MARCO FarRelevant in a zero-shot mode, we observed a large (at least 17%) decrease in MRR with many models struggling to outperform a random-shuffling baseline. This indicates that even short-document collections can be quite challenging.

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 6 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, is only a tiny fraction of compute required to train LLAMA2 models (2% compared to a 7B LLAMA2 model).§

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A 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 6). TinyLLAMA is a so-called LLM-ranker: a “causal” decoder-only Transformer that has about 1B parameters.

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 sequence 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.

### A.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 (Gün-
ther 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 TinyLLAMA 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].

A.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.

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: $d = d_1d_2\ldots dm$;
- 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 $w_1w_2\ldots wn$ (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 $t_1t_2\ldots tn$;
- splitting a tokenized document $d$ into $m$ possibly overlapping chunks $d_i = t_is t_i+1\ldots t_i+s+w-1$: 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 $cls_i$. 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: $w_1w_2\ldots w_m = \text{softmax}(C \cdot cls_1, C \cdot cls_2, \ldots, C \cdot cls_m)$. 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:

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

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.

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. (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.

We additionally implemented both the encoder-only and the encoder-decoder variant of LongT5 (Guo et al., 2022) as well as RoFormer (with ROPE...
embeddings) (Su et al., 2024). We eventually had to abandon them due to poor convergence (LongT5) and/or CUDA crashes (RoFormer).

B Experiments: Additional Information, Ablations, and Detailed Results

B.1 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:

- 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.2 Detailed Training and Evaluation Setup

B.2.1 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).

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 § B.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 FlexNeuART (Boytsov and Nyberg, 2020) framework, which employed Lucene and NMSLIB (Boytsov and Naidan, 2013) 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.

B.2.2 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).

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

8https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/
Table 7: Comparison of Long-context Models to Respective FirstP baselines and Prior Art.

| Model                  | MS MARCO | TREC DL 2019 | TREC DL 2021 | Robust04 |
|------------------------|----------|--------------|--------------|----------|
|                        | MRR      | NDCG@10      | NDCG@20      |
|                        |          |              |              |          |
| Prior work (FirstP, MaxP), Zhang et al. (Zhang et al., 2021) |          |              |              |          |
| FirstP (BERT)          | 0.394    | 0.631        | 0.598        | 0.660    | 0.475    | 0.527    |
| MaxP (BERT)            | 0.392    | 0.648        | 0.615        | 0.665    | 0.677    | 0.515    |
| PARADE Attn (ELECTRA)  | 0.414    | 0.652        | 0.642        | 0.686    | 0.492    | 0.552    |
| PARADE Max (ELECTRA)   | 0.417    | 0.659        | 0.630        | 0.683    | 0.502    | 0.563    |
| PARADE Transf-RAND (ELECTRA) | 0.431a  | 0.675a       | 0.653        | 0.705    | 0.533    | 0.592    |
|                        | 0.415    | 0.675        | 0.629        | 0.702    | 0.534    | 0.596    |
| MaxP (DEBERTA)         | 0.402    | 0.679        | 0.620        | 0.705    | 0.535    | 0.609    |
| PARADE Attn (DEBERTA)  | 0.422a   | 0.685        | 0.659a       | 0.713    | 0.549a   | 0.615a   |
| FirstP (Longformer)    | 0.404    | 0.657        | 0.616        | 0.654    | 0.483    | 0.540    |
| LongP (Longformer)     | 0.412a   | 0.665        | 0.626        | 0.693    | 0.509a   | 0.568a   |
| FirstP (Big-Bird)      | 0.408    | 0.663        | 0.620        | 0.679    | 0.507    | 0.560    |
| LongP (Big-Bird)       | 0.397a   | 0.655        | 0.618        | 0.675    | 0.452a   | 0.477a   |
| FirstP (JINA)          | 0.422    | 0.658        | 0.618        | 0.679    | 0.488    | 0.532    |
| LongP (JINA)           | 0.416a   | 0.670a       | 0.632        | 0.689    | 0.503a   | 0.558a   |
| FirstP (MOSAIC)        | 0.423    | 0.654        | 0.607        | 0.662    | 0.453    | 0.538    |
| LongP (MOSAIC)         | 0.421    | 0.660        | 0.630a       | 0.694a   | 0.456    | 0.579a   |

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.

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), BigBird (Zaheer et al., 2020), and DEBERTA base (He et al., 2021), JINA (Güntner 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). 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 overfitting). 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. 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

9https://anonymous.4open.science/r/long_doc_rank_model_analysis_v2-78E9/
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.

### B.2.3 Miscellaneous Notes

To enable efficient training and evaluation of the large number of models, documents were truncated to have at most 1431 BERT tokens. In § B.3 (see Table 8) we show that for our top-performing model PARADE 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.

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.

### B.3 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 8: We can see that—depending on the dataset—three or four input 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 led 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.

### B.4 Reproducibility and Backbone Selection for SplitP Models

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 4), 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.
Table 8: Effectiveness of the PARADE Attention Model for Different Input Truncation Thresholds

| Retriever / Ranker | MS MARCO | TREC DL (2019-2021) | Robust04 | Avg. gain Over FirstP |
|-------------------|-----------|----------------------|----------|-----------------------|
|                   | MRR       | NDCG@10              | NDCG@20  |                       |
| Retrieval         | 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* (+1.8%) | 0.653* (+2.7%) | 0.499* (+4.9%) | 0.544* (+3.3%) | +3.2% |
| PARADE Attn (3 chunks) | 0.406* (+1.3%) | 0.648* (+1.7%) | 0.505* (+6.1%) | 0.557* (+5.7%) | +3.7% |
| PARADE Attn (4 chunks) | 0.412* (+2.9%) | 0.654* (+2.7%) | 0.504* (+5.9%) | 0.558* (+5.9%) | +3.3% |
| PARADE Attn (5 chunks) | 0.409* (+2.0%) | 0.652* (+2.4%) | 0.502* (+5.6%) | 0.556* (+5.5%) | +3.9% |
| PARADE Attn (6 chunks) | 0.411* (+2.4%) | 0.653* (+2.6%) | 0.504* (+5.9%) | 0.554* (+5.2%) | +4.0% |

Results in Tables 7 and 4 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 4). 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.

We also use Table 7 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 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) is 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.
| Model                  | MS MARCO                  | 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 (E5-4K) zero-shot | 0.380 | 0.641 | 0.722 | 0.317 |
| AvgP                   | 0.389 (-1.3%) | 0.642 (+1.5%) | 0.717 (+0.7%) | 0.317* (+2.0%) |
| MaxP                   | 0.392 (-0.4%) | 0.644* (+1.9%) | 0.723 (+1.5%) | 0.322* (+3.7%) |
| MaxP (ELECTRA)         | 0.414 (-0.6%) | 0.659 (-0.5%) | 0.745 (-1.5%) | 0.326 (+2.1%) |
| MaxP (DEBERTA)         | 0.402* (-3.2%) | 0.671 (-0.1%) | 0.746 (+0.7%) | 0.335* (+2.5%) |
| SumP                   | 0.390 (-1.0%) | 0.639 (-1.0%) | 0.715 (+0.4%) | 0.319* (+2.6%) |
| CEDR-DRMM              | 0.385* (-2.3%) | 0.629 (-0.5%) | 0.708 (-0.5%) | 0.313 (+0.6%) |
| CEDR-KNRM              | 0.379* (-3.8%) | 0.630 (-0.3%) | 0.711 (-0.1%) | 0.313 (+0.8%) |
| CEDR-PACRR             | 0.395 (+0.3%) | 0.643* (+1.6%) | 0.719 (-0.9%) | 0.320* (+2.9%) |
| Neural Model           | 0.398 (+0.9%) | 0.650* (+2.8%) | 0.723* (+1.5%) | 0.323* (+3.9%) |
| PARADE Attn            | 0.416* (+5.5%) | 0.652* (+3.1%) | 0.728* (+2.2%) | 0.324* (+4.2%) |
| PARADE Attn (ELECTRA)  | 0.431* (+3.3%) | 0.680* (+2.7%) | 0.763* (+3.9%) | 0.335* (+4.9%) |
| PARADE Attn (DEBERTA)  | 0.422* (+1.6%) | **0.688*** (+2.4%) | **0.763*** (+3.0%) | **0.339*** (+3.9%) |
| PARADE Avg             | 0.392 (-0.6%) | 0.646* (+2.1%) | 0.715 (+0.4%) | 0.317* (+2.1%) |
| PARADE Max             | 0.405* (+2.7%) | 0.655* (+3.5%) | 0.733* (+2.9%) | 0.324* (+4.1%) |
| PARADE Transf-RAND-L2  | 0.419* (+6.3%) | 0.655* (+3.6%) | 0.734* (+1.1%) | 0.326* (+5.0%) |
| PARADE Transf-RAND-L2 (ELECTRA) | **0.433*** (+3.9%) | 0.670 (+1.2%) | 0.747 (+1.8%) | 0.327* (+2.2%) |
| PARADE Transf-PRETR-L6  | 0.402* (+1.9%) | 0.643 (+1.6%) | 0.717 (+0.8%) | 0.322* (+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* (+1.9%) | 0.668* (+3.9%) | 0.752* (+4.1%) | 0.333* (+5.1%) |
| LongP (Big-Bird)       | 0.397* (+2.9%) | 0.651 (-0.7%) | 0.726 (-0.2%) | 0.322 (-0.3%) |
| LongP (JINA)           | 0.416* (-1.5%) | 0.665* (+1.7%) | 0.742* (+2.0%) | 0.328* (+2.4%) |
| LongP (MOSAIC)         | 0.421 (-0.4%) | 0.664* (+3.3%) | 0.740* (+1.9%) | 0.327* (+3.7%) |
| LongP (TinyLLAMA)      | 0.402* (+1.7%) | 0.608 (-1.1%) | 0.692 (+0.0%) | 0.306 (+1.6%) |
| LongP (E5-4K) zero-shot | 0.333* (-7.1%) | 0.649 (+3.3%) | 0.724 (+0.3%) | 0.323 (-1.8%) |

In each column we show a relative gain with respect to 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 `*`. `p`-value threshold is 0.01 for an MS MARCO development collection and 0.05 otherwise. ES-models were used only in the zero-shot model, i.e., without fine-tuning.
Table 10: Ranking Performance on Robust04.

| 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|
| AvgP                 | 0.478 (+0.5%) | 0.411 (+1.6%) | 0.292 (+5.4%) | 0.531 (+0.9%) | 0.451 (+1.6%) | 0.324 (+6.7%) |
| MaxP                 | 0.488 (+2.6%) | 0.425 (+5.1%) | 0.306 (+10.6%) | 0.544 (+3.3%) | 0.467 (+4.5%) | 0.338 (+11.5%) |
| MaxP (ELECTRA)       | 0.502 (+2.0%) | 0.441 (+3.9%) | 0.319 (+8.3%) | 0.563 (+2.1%) | 0.483 (+4.0%) | 0.350 (+9.3%) |
| MaxP (DEBERTA)       | 0.535 (+0.2%) | 0.464 (+1.2%) | 0.340 (+6.7%) | 0.609 (+2.2%) | 0.519 (+3.2%) | 0.378 (+7.9%) |
| SumP                 | 0.486 (+2.2%) | 0.418 (+3.4%) | 0.305 (+10.2%) | 0.538 (+2.1%) | 0.461 (+3.1%) | 0.337 (+11.1%) |
| CEDR-DRMM            | 0.466 (+2.0%) | 0.403 (+0.4%) | 0.287 (+3.8%) | 0.533 (+1.3%) | 0.458 (+2.5%) | 0.326 (+7.6%) |
| CEDR-KNRM            | 0.483 (+1.7%) | 0.413 (+1.9%) | 0.291 (+5.1%) | 0.535 (+1.7%) | 0.456 (+2.0%) | 0.324 (+6.8%) |
| CEDR-PANCRR          | 0.490 (+4.3%) | 0.426 (+5.3%) | 0.307 (+11.0%) | 0.549 (+4.2%) | 0.466 (+4.4%) | 0.337 (+11.2%) |
| Neural Modell        | 0.484 (+1.8%) | 0.417 (+3.1%) | 0.298 (+7.7%) | 0.537 (+1.9%) | 0.459 (+2.6%) | 0.330 (+8.8%) |
| PARADE Attn (ELECTRA) | 0.503 (+5.7%) | 0.433 (+6.9%) | 0.311 (+12.4%) | 0.556 (+5.6%) | 0.476 (+6.5%) | 0.344 (+13.3%) |
| PARADE Attn (DEBERTA) | 0.528 (+6.4%) | 0.456 (+7.4%) | 0.329 (+11.7%) | 0.581 (+5.3%) | 0.495 (+6.5%) | 0.358 (+11.9%) |
| PARADE Attn (MOSAIC) | 0.549 (+2.9%) | 0.472 (+6.8%) | 0.346 (+8.7%) | 0.615 (+3.2%) | 0.522 (+3.8%) | 0.383 (+9.4%) |
| PARADE Avg           | 0.483 (+1.5%) | 0.412 (+1.8%) | 0.291 (+5.2%) | 0.534 (+1.5%) | 0.457 (+2.4%) | 0.318 (+4.7%) |
| PARADE Max           | 0.489 (+2.8%) | 0.420 (+3.8%) | 0.306 (+10.8%) | 0.548 (+4.0%) | 0.470 (+5.3%) | 0.337 (+11.0%) |
| PARADE Transf-RAND-L2 | 0.488 (+2.8%) | 0.423 (+4.6%) | 0.303 (+7.7%) | 0.548 (+4.1%) | 0.469 (+5.0%) | 0.338 (+11.6%) |
| PAR. Transf-RAND-L2 (ELECTRA) | 0.523 (+6.3%) | 0.454 (+6.9%) | 0.380 (+12.2%) | 0.574 (+3.9%) | 0.488 (+5.0%) | 0.354 (+10.6%) |
| PARADE Transf-PRETR-L6 | 0.494 (+4.0%) | 0.426 (+5.3%) | 0.308 (+11.5%) | 0.554 (+5.1%) | 0.474 (+6.1%) | 0.346 (+14.1%) |
| PAR. Transf-PRETR-LATEIR-L6 | 0.450 (+5.2%) | 0.389 (+3.9%) | 0.277 (+0.3%) | 0.501 (+4.9%) | 0.423 (+5.3%) | 0.302 (−0.5%) |
| LongP (Longformer)   | 0.500 (+4.6%) | 0.435 (+5.3%) | 0.309 (+11.5%) | 0.568 (+5.1%) | 0.482 (+6.1%) | 0.347 (+12.9%) |
| LongP (Big-Bird)     | 0.452 (+10.9%) | 0.389 (−10.7%) | 0.274 (−8.8%) | 0.477 (−14.9%) | 0.400 (−15.5%) | 0.279 (−14.2%) |
| LongP (JINA)         | 0.503 (+2.9%) | 0.434 (−3.1%) | 0.309 (−7.5%) | 0.558 (+4.9%) | 0.473 (+5.2%) | 0.335 (+9.7%) |
| LongP (MOSAIC)       | 0.456 (−0.6%) | 0.393 (−0.8%) | 0.280 (−5.3%) | 0.570 (+6.0%) | 0.484 (−6.3%) | 0.350 (−11.0%) |
| LongP (TinyLLAMA)    | 0.452 (−4.8%) | 0.396 (−6.9%) | 0.267 (−8.7%) | 0.505 (−6.7%) | 0.428 (−7.6%) | 0.297 (−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 (−2.9%) |

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.
B.5 Additional Accuracy Metrics

In this section we show results for additional effectiveness metrics. MS MARCO and TREC DL results are shown in Table 9. Robust04 datasets are presented and Table 10.