Multi-Stage Document Ranking with BERT

Rodrigo Nogueira, 1 Wei Yang, 2 Kyunghyun Cho, 3,4,5,6 and Jimmy Lin 2

1 Tandon School of Engineering, New York University
2 David R. Cheriton School of Computer Science, University of Waterloo
3 Courant Institute of Mathematical Sciences, New York University
4 Center for Data Science, New York University
5 Facebook AI Research 6 CIFAR Azrieli Global Scholar

Abstract

The advent of deep neural networks pre-trained via language modeling tasks has spurred a number of successful applications in natural language processing. This work explores one such popular model, BERT, in the context of document ranking. We propose two variants, called monoBERT and duoBERT, that formulate the ranking problem as pointwise and pairwise classification, respectively. These two models are arranged in a multi-stage ranking architecture to form an end-to-end search system. One major advantage of this design is the ability to trade off quality against latency by controlling the admission of candidates into each pipeline stage, and by doing so, we are able to find operating points that offer a good balance between these two competing metrics. On two large-scale datasets, MS MARCO and TREC CAR, experiments show that our model produces results that are either at or comparable to the state of the art. Ablation studies show the contributions of each component and characterize the latency/quality tradeoff space.

1 Introduction

Neural models pre-trained on language modeling tasks such as ELMo (Peters et al., 2017), OpenAI GPT (Radford et al., 2018), and BERT (Devlin et al., 2019) have achieved impressive results on NLP tasks ranging from natural language inference to question answering. One such popular model, BERT, has recently been applied to search-related tasks, retrieval-based question answering (Yang et al., 2019b), as well as document ranking (Yang et al., 2019c; MacAvaney et al., 2019; Yilmaz et al., 2019).

This paper builds on previous initial work (Nogueira and Cho, 2019) to tackle the document ranking problem with a multi-stage ranking architecture. We introduce two BERT variants, called monoBERT and duoBERT. The monoBERT model treats document ranking as a binary classification problem over individual candidate documents, while the duoBERT model adopts a pairwise classification approach that considers pairs of candidate documents. For end-to-end document ranking, we arrange these models as stages in a pipeline where each balances the size of the candidate set against the inherent complexity of the model. This design allows us to obtain the benefits of richer models while controlling the increased inference latencies that come with these richer models.

Our work makes the following contributions: We start by describing monoBERT, a pointwise classification model of document relevance that was introduced in Nogueira and Cho (2019). Second, we propose a novel extension of monoBERT, called duoBERT, that adopts a pairwise classification approach to document relevance. Third, we integrate monoBERT and duoBERT in a multi-stage ranking architecture that allows us to reap the benefits of our richer duoBERT model with only a modest increase in inference latency. The architecture adopts an innovation from the information retrieval (IR) community that to our knowledge has not been explored by NLP researchers. Fourth, perhaps unsurprising, we show that pre-training on the corpus of the target task improves effectiveness over pre-training on out-of-domain corpora.

We evaluate our models on two large-scale document retrieval datasets that are conducive to deep learning experiments: the MS MARCO dataset and the Complex Answer Retrieval (CAR) Task at TREC. On both datasets, our results are either at or comparable to the state of the art. As we show through component-level ablation studies, both monoBERT and duoBERT contribute significantly to overall effectiveness. Additionally,
within the framework of multi-stage ranking, we characterize the latency vs. effectiveness tradeoff space of each model.

2 Background and Related Work

In this paper, we tackle the document ranking problem (also known as ad hoc retrieval), following the widely-accepted standard formulation: Given a user’s information need expressed as a query \( q \) and a (potentially large) corpus of documents, the system’s task is to produce a ranking of \( k \) documents that maximizes some metric, such as mean average precision (MAP) or mean reciprocal rank (MRR). Throughout this paper, per standard parlance in IR, document is used generically to refer to a unit of text being retrieved, when in actuality it may be a passage, a sentence, etc.

The basic idea behind multi-stage ranking is to break document ranking down into a series of pipeline stages. Following an initial retrieval stage, which typically issues a “bag of words” query against an inverted index, each subsequent stage re-ranks the set of candidates passed along from the previous stage until the final output is returned to the user. This basic approach has received much interest in academia (Matveeva et al., 2006; Wang et al., 2011; Asadi and Lin, 2013; Chen et al., 2017; Mackenzie et al., 2018) as well as industry. Known production deployments include the Bing web search engine (Pedersen, 2010) as well as Alibaba’s e-commerce search engine (Liu et al., 2017).

Multi-stage ranking architectures have evolved to strike a balance between model complexity and search latency by controlling the size of the candidate set at each stage. Increasingly richer models can be made practical by considering successively smaller candidate sets. For certain (easy) queries, stages of the pipeline can be skipped entirely, known as “early exits” (Cambazoglu et al., 2010). Viewed in this manner, multi-stage ranking captures the same intuition as progressive refinement in classifier cascades (Viola and Jones, 2004). For example, an early stage might consider only term statistics of single terms, whereas later stages might consider bigrams, phrases, or even apply lightweight NLP techniques. Given this setup, a number of researchers have proposed techniques based, for example, on boosting for composing these stages in an end-to-end manner (Wang et al., 2011; Xu et al., 2012). In our work, we make the connection between BERT-based models and multi-stage ranking, which allows us to trade off the quality of the results with inference latency.

The advent of deep learning has brought tremendous excitement into the information retrieval community. Although machine-learned ranking models have been well studied since the mid-2000s under the banner of “learning to rank”, the paradigm is heavily driven by manual feature engineering (Liu, 2009; Li, 2011); commercial web search engines are known to incorporate thousands of features (or more) in their models. Continuous vector space representations coupled with neural models promise to obviate the need for handcrafted features and have attracted the attention of many researchers. Well-known neural ranking models include DRMM (Guo et al., 2016), DUET (Mitra et al., 2017), KNRM (Xiong et al., 2017), and Co-PACRR (Hui et al., 2018); the literature is too vast for an exhaustive review here, and thus we refer readers to recent overviews (Onal et al., 2018; Mitra and Craswell, 2019).

Although often glossed over, most neural ranking models today (including all the models referenced above) are actually re-ranking models, in the sense that they operate over the output of a list of candidate documents, typically produced by a “bag of words” query. Thus, document retrieval with neural models today already uses multi-stage ranking, albeit an impoverished form with only a single re-ranking stage. This recognition provides a starting point of our work, from which we build BERT-based multi-stage ranking.

3 Multi-Stage Ranking with BERT

In our formulation, a multi-stage ranking architecture comprises a number of stages, denoted \( H_0 \) to \( H_N \). Except for \( H_0 \), which retrieves \( k_0 \) candidates from an inverted index, each stage \( H_n \) receives a ranked list \( R_{n-1} \) comprising \( k_{n-1} \) candidates from the previous stage. Each stage, in turn, provides a ranked list \( R_n \) comprising \( k_n \) candidates to the subsequent stage, with the obvious requirement that \( k_n \leq k_{n-1} \). The ranked list generated by the final stage \( H_N \) is designated for consumption by the (human) searcher.

For expository purposes, we consider stages to receive and produce candidates even though they may in fact be documents, passages, etc. Within this general framework, we instantiate a specific
design composed of three stages ($H_0$, $H_1$, and $H_2$), as shown in Figure 1.

In our approach, each stage is unconstrained in its implementation other than the input–output specifications outlined above. For example, a pipeline stage is not obligated to consider all candidates provided to it, and in fact, latency introduced by each stage can be controlled by truncating the number of input candidates. Furthermore, each stage can choose to pay attention or ignore scores of the candidates it receives; in the latter case, the ranked list devolves into a set of unranked candidates. In our experiments, we explore the latency–quality tradeoff space that is induced by this design flexibility (see Section 5).

3.1 $H_0$: “Bag of Words” BM25

The first stage $H_0$ receives as input the user query $q$ and produces top-$k_0$ candidates $R_0$. In our implementation, the query is treated as a “bag of words” for ranking documents from the corpus using a standard inverted index based on the BM25 scoring function (Robertson et al., 1994). We use the Anserini IR toolkit (Yang et al., 2017, 2018), which is built on the popular open-source Lucene search engine.

BM25 is based on exact term matches, and all candidates must contain at least one term from the user’s query. However, since later BERT stages operate in continuous vector spaces, they have the ability to identify relevant candidates that do not have many matching terms. Thus, it is critical in $H_0$ to optimize for recall to provide subsequent stages a diverse set of documents to work with. On the other hand, precision is less of a concern because non-relevant documents can be discarded by later stages.

3.2 $H_1$: monoBERT

In general, the task of a re-ranking stage $H_n$ is to estimate a score $s_i$ quantifying how relevant a candidate $d_i \in R_{n-1}$ is to a query $q$. Naturally, we expect that the ranking induced by these scores yields a higher metric (e.g., MAP or MRR) than the scores from the previous stage.

In stage $H_1$, we call monoBERT our pointwise re-ranker, which is a BERT model used as a binary relevance classifier. Using the same notation as Devlin et al. (2019), we feed the query $q$ as sentence A and the text of candidate $d_i$ as sentence B. We truncate the query to have at most 64 tokens. We also truncate the candidate text such that the concatenation of query, candidate, and separator tokens have a maximum length of 512 tokens. Given these limits, we observe that none of the queries or documents of the datasets used in our experiments (TREC CAR and MS MARCO) have to be truncated.

Once the segment is passed through the model, we use the [CLS] vector as input to a single layer neural network to obtain a probability $s_i$ of the candidate $d_i$ being relevant to $q$. We obtain a score $s_i$ for each candidate independently and generate a new list of candidates $R_1$ by keeping only the top-$k_1$ candidates based on these scores.

---

Figure 1: Illustration of our multi-stage ranking architecture. In the first stage $H_0$, given a query $q$, the top-$k_0$ ($k_0 = 5$ in the figure) candidate documents $R_0$ are retrieved using BM25. In the second stage $H_1$, monoBERT produces a relevance score $s_i$ for each pair of query $q$ and candidate $d_i \in R_0$. The top-$k_1$ ($k_1 = 3$ in the figure) candidates with respect to these relevance scores are passed to the last stage $H_2$, in which duoBERT computes a relevance score $p_{i,j}$ for each triple $(q, d_i, d_j)$. The final list of candidates $R_2$ is formed by re-ranking the candidates according to these scores (see Section 3.3 for a description of how these pairwise scores are aggregated).

---

\[ s_i = \text{score based on } q \text{ and } d_i \]

\[ p_{i,j} = \text{score based on } q, d_i, d_j \]

---

\[ \text{http://anserini.io/} \]
We train the model for re-ranking using cross-entropy loss:

\[ L_{\text{mono}} = - \sum_{j \in J_{\text{pos}}} \log(s_j) - \sum_{j \in J_{\text{neg}}} \log(1 - s_j), \]

where \( J_{\text{pos}} \) is the set of indexes of the relevant candidates and \( J_{\text{neg}} \) is the set of indexes of the non-relevant candidates in \( R_0 \).

### 3.3 \( H_2 \): duoBERT

The output \( R_1 \) from the previous stage is used as input to the pairwise re-ranker we call duoBERT. Within the framework of “learning to rank”, duoBERT can be characterized as a “pairwise” approach, while monoBERT can be characterized as a “pointwise” approach (Liu, 2009). In this pairwise approach, the re-ranker estimates the probability \( p_{i,j} \) of the candidate \( d_i \) being more relevant than \( d_j \).

This re-ranker is also a BERT model that takes as input the query as sentence A, candidate \( d_i \) as sentence B, and candidate \( d_j \) as sentence C. Similar to the original implementation, each sentence type (A, B, and C) has its own embedding that is summed to the token and positional embeddings. We truncate the query, candidates \( d_i \) and \( d_j \) to 62, 223, and 223 tokens, respectively, so the entire sequence will have at most 512 tokens when concatenated with the [CLS] token and the three separator tokens. Using the above truncation limits, in the datasets used in this work none of the queries are truncated, and less than 1% of the documents are truncated.

We use the [CLS] vector as input to a single layer neural network to obtain the probability \( p_{i,j} \). Since there are \( k_1 \) candidates, \( k_1 (k_1 - 1) \) probabilities are computed. We then train the model with the following loss:

\[ L_{\text{dao}} = - \sum_{i \in J_{\text{pos}}, j \in J_{\text{neg}}} \log(p_{i,j}) - \sum_{i \in J_{\text{neg}}, j \in J_{\text{pos}}} \log(1 - p_{i,j}), \]

Note in the equation above that candidates \( d_i \) and \( d_j \) are never both relevant or not relevant.

At inference time, we aggregate the pairwise scores \( p_{i,j} \) so that each document receives a single score \( s_i \). We investigate five different aggregation methods (SUM, BINARY, MIN, MAX, and SAMPLE):

\[ \text{SUM} : s_i = \sum_{j \in J_i} p_{i,j}, \]

\[ \text{BINARY} : s_i = \sum_{j \in J_i, p_{i,j} > 0.5} 1, \]

\[ \text{MIN} : s_i = \min_{j \in J_i} p_{i,j}, \]

\[ \text{MAX} : s_i = \max_{j \in J_i} p_{i,j}, \]

\[ \text{SAMPLE} : s_i = \sum_{j \in J_i(m)} p_{i,j}, \]

where \( J_i = \{0 \leq j < |R_1|, j \neq i \} \) and \( m \) is the number of samples drawn without replacement from the set \( J_i \).

The SUM method measures the pairwise agreement that candidate \( d_i \) is more relevant than the rest of the candidates \( \{d_j\}_{j \neq i} \). The BINARY method is inspired by the Condorcet method (Montague and Aslam, 2002), which is a strong aggregation baseline (Cormack et al., 2009). The MIN (MAX) method measures the relevance of \( d_i \) only against its strongest (weakest) competitor. The SAMPLE method aims to decrease the high inference costs of pairwise computations via sampling.

The final list of candidates \( R_2 \) is obtained by re-ranking the candidates in \( R_1 \) according to their scores \( s_i \). In our current design, the output \( R_2 \) is provided for human consumption, and serves as the input to computing the final evaluation metrics (e.g., MAP).

### 4 Experimental Setup

A fortunate confluence of events has enabled the multi-stage ranking architecture we propose in this paper. First, of course, is the innovation captured in BERT, as the latest refinement in a long stream of neural models that make heavy use of pre-training. Second, and just as important, is the availability of data. For document retrieval, most IR researchers have not had access to sufficient training data until recently.

As demonstrated by Lin (2019), in a limited data regime, it is not entirely clear that neural techniques actually perform better than well-tuned “classic” IR techniques; subsequent work by Yang et al. (2019a) show that the gains are modest at best. Until recently, research in neural ranking models mostly took advantage of proprietary datasets derived from user behavior logs (which large organizations can gather in abundance). Since these datasets cannot be shared,
only a small set of researchers could productively work on neural ranking models and different models could not be easily compared; the combination of both factors hamper rapid progress.

Fortunately, the field has seen the release of two large-scale datasets for powering data-hungry neural models: MS MARCO (Bajaj et al., 2018) and TREC CAR (Dietz et al., 2017). We take advantage of both datasets to train our models, which we detail below.

4.1 MS MARCO

The Microsoft MAchine Reading COMprehension dataset (MS MARCO) is a large-scale resource created from approximately half a million anonymized questions sampled from Bing’s search query logs. We focus on the passage ranking task, where given a corpus of 8.8M passages extracted from 3.6M web documents, the system’s goal is to retrieve passages that answer the question. Each passage contains an average of 55 words (or 340 characters), and hence is relatively short—however, in order to maintain consistent terminology throughout this paper, we refer to these basic units of retrieval as “documents.”

The training set (for the passage ranking task) comprises approximately 500k pairs of query and relevant document, and another 400M pairs of query and non-relevant documents. The relevance judgments are provided by humans. The development set contains 6,980 queries, with, on average, one relevant document per query. Thus, a noteworthy property of this dataset is the sparsity of relevance judgments—as opposed to typical TREC test collections built using pooling (Voorhees, 2002), which have far fewer topics (usually around 50) but many more judgments per topic (typically, hundreds). A blind, held-out evaluation set with 6,837 queries is also available, but without relevance judgments. Evaluation on these queries is provided by the Microsoft organizers upon submission to the online leaderboard. The official metric for this dataset is MRR@10.

Target Corpus Pre-training (TCP). Before training our models on the re-ranking task, we apply a two-phase pre-training. In the first phase, the model is pre-trained using Wikipedia (2.5B words) and the Toronto Book corpus (0.8B words) for one million iterations, as described by Devlin et al. (2019). In the second phase, we further pre-train the model on the MS MARCO corpus (0.5B words) for 100k iterations with a maximum sequence length of 512 tokens, batches of size 128, and learning rate of $5 \times 10^{-5}$. This second pre-training phase takes approximately 24 hours on a TPU v3.2

Training. We fine-tune both monoBERT and duoBERT using a TPU v3 with a batch size of 128 (128 sequences × 512 tokens = 63,384 tokens/batch) for 100k iterations, which takes approximately 24 hours. This corresponds to training on 12.8M (100k × 128) query–document pairs. We could not see any improvement on the dev set when training for another three days, which is equivalent to seeing 50M query–document pairs in total. To avoid biasing our model towards predicting non-relevant labels, which are approximately 1000 times more frequent in the training set, we build each batch by sampling an equal amount of relevant and non-relevant passages.

For both models, we use Adam (Kingma and Ba, 2014) with the initial learning rate set to $3 \times 10^{-6}$, $\beta_1 = 0.9$, $\beta_2 = 0.999$, L2 weight decay of 0.01, learning rate warmup over the first 10,000 steps, and linear decay of the learning rate. Dropout probability is set to 0.1 in all layers.

Inference. In our base configuration, we use top-$k_0 = 1000$ and top-$k_1 = 50$ candidates as input to monoBERT and duoBERT, respectively. Our experiments, however, include ablation settings as well as different parameterizations to characterize the contributions of each component as well as the latency–quality tradeoff space.

4.2 TREC CAR

Our second dataset is from the Complex Answer Retrieval (CAR) Track at the 2017 Text Retrieval Conference (TREC), whose aim is to explore passage-level retrieval techniques for simple fact and entity-centric needs (Dietz et al., 2017). The primary dataset is synthetically constructed by exploiting the hierarchical structure of Wikipedia: “queries” are constructed by concatenating a Wikipedia article title with the title of one of its sections. The relevant documents are the paragraphs within that section. The corpus consists of cleaned paragraphs from English Wikipedia, except for the abstracts, totaling 29M documents, with an average of 60 words (or 380

2https://cloud.google.com/tpu/
characters) per document. The released dataset has five predefined folds, and we use the first four as a training set (approximately 3M queries), and the remaining as a validation set (approximately 700k queries). The test set is the same one used to evaluate the submissions to TREC 2017 CAR (2,254 queries).

Although the TREC 2017 CAR organizers provide manual annotations for the test set, only the top five documents retrieved by systems that submitted to the official evaluation have manual annotations. The sparsity of these judgments means that it is difficult to fairly evaluate runs that did not participate in the original evaluation. Hence, in this paper we evaluate using the automatic annotations, which provide a richer set of judgments. Per the official TREC CAR evaluation, we use Mean Average Precision (MAP) as the evaluation metric.

**Training.** Both monoBERT and duoBERT are trained in the same manner as for MS MARCO, with the same hyperparameter settings. However, there is an important difference. The official pre-trained BERT models are pre-trained on the full Wikipedia, and therefore they have seen, although in an unsupervised way, Wikipedia documents that are used in the test set of TREC CAR. Thus, to avoid this leak of test data into training, we pre-train the BERT re-ranker only on the half of Wikipedia used by TREC CAR’s training set, which contains 1.1B words.

For fine-tuning, we generate our query-document pairs by retrieving the top ten documents from the entire TREC CAR corpus using BM25. This means that we end up with 30M example pairs (3M queries $\times$ 10 candidates/query) to train our model. We train it for 100k iterations, or 12.8M examples (100k iterations $\times$ 128 pairs/batch). Similar to the MS MARCO experiments, we did not see any gain on the dev set by training the model longer.

### 5 Results

Results on the MS MARCO dataset are shown in Table 1. The first row shows the BM25 baseline provided by Microsoft. Our initial application of BERT to the MS MARCO dataset, denoted by the entry monoBERT (Jan 2019), was published in January 2019 (Nogueira and Cho, 2019). On the evaluation data, it surpassed the previous best entry IRNet (submitted just five days earlier) by nearly eight points. This entry implements what we refer to as monoBERT here, albeit with a few minor differences, explained below.

We are, based on official leaderboard records, the first to adapt BERT to the MS MARCO dataset, and to our knowledge, our model represents the first application of BERT to any retrieval task. We further note that every subsequent submission on the MS MARCO leaderboard (as of October 2019) exploits BERT in some capacity (evidenced by “BERT” appearing in every submission name). Given the availability of our source code on GitHub, it is likely that many of these entries are derived from or build on monoBERT, or are at least inspired by our innovation.

Our BM25 baseline with Anserini is shown in the first row of the second block of Table 1; in our multi-stage ranking architecture, this is $R_0$, the output of $H_0$. Although both runs purport to implement BM25, Anserini is two points better than the Microsoft baseline. Our recall at 1000 hits is 85.7%, compared to only 81.5% from Microsoft’s baseline. It is a well-known fact in IR that different systems implementing the same scoring function might report very different results (Mihalcea et al., 2014; Lin et al., 2016), owing to details such as tokenization, stopword selection, stemming, and parameter tuning. Thus, the differences between Anserini and the Microsoft baseline are not surprising.

By applying the monoBERT stage $H_1$ to the top 1000 ranked list from Anserini ($H_0$) with $k_0 = 4$.

### Table 1: MS MARCO Results.

| Method | Dev   | Eval  |
|--------|-------|-------|
| BM25 (Microsoft Baseline) | 16.7  | 16.5  |
| IRNet  | 27.8  | 28.1  |
| monoBERT (Jan 2019)       | 36.5  | 35.9  |
| Anserini (BM25)           | 18.7  | 19.0  |
| + monoBERT                 | 37.2  | 36.5  |
| + monoBERT + duoBERTMAX    | 32.6  | -     |
| + monoBERT + duoBERTSUM    | 37.9  | -     |
| + monoBERT + duoBERTSUM + TCP | 38.2 | 37.0  |
| + monoBERT + duoBERTSUM + TCP | 38.3 | -     |
| + monoBERT + duoBERTSUM + TCP | 39.0 | 37.9  |
| Leaderboard best           | 39.7  | 38.3  |
Table 2: Main Result on TREC 2017 CAR.

| Method                     | MAP  |
|---------------------------|------|
| BM25 (Kashyapi et al., 2018) | 13.0 |
| Co-PACRR (MacAvaney et al., 2017) | 14.8 |
| BM25 (Anserini)            | 15.3 |
| + monoBERT                 | 34.8 |
| + monoBERT + duoBERT\textsubscript{MAX} | 32.6 |
| + monoBERT + duoBERT\textsubscript{SUM} | 36.9 |
| + monoBERT + duoBERT\textsubscript{BINARY} | 36.9 |

(1000), we observe a gain of 17.5 points. This result is slightly better than the monoBERT entry from January 2019 because that submission re-ranked the Microsoft baseline (a slightly worse $H_0$, in essence). Other minor differences include a refactored codebase to improve reusability and readability.

Adding the duoBERT stage $H_2$ with the $\text{SUM}$ aggregation method (Equation 3), denoted $\text{duoBERT}_{\text{SUM}}$, improves over monoBERT alone by 0.5 points on the held-out evaluation set. In this setting, duoBERT considers the top 50 candidates from $H_1$, and thus requires an additional $50 \times 49$ BERT inferences to compute the final ranking (the time required for aggregation is negligible). This improvement in MRR, of course, comes at a cost in increased latency, an issue we explore in more detail below. The entry marked $\text{duoBERT}_{\text{MAX}}$ shows that the MAX aggregation method (Equation 6) performs quite poorly, and in fact makes monoBERT results worse. We find that the BINARY method (Equation 4) performs slightly better (0.1 points) than SUM on the development set. Given these results, we abandon the MAX aggregation method in subsequent experiments.

Note that official figures from the held-out evaluation set are not available for all conditions because obtaining those values requires formal submission of runs to the MS MARCO organizers. As good experimental practice, in order to avoid too much “unnecessary probing” of the held-out test data, we only submitted what we felt to be the most promising conditions.

Finally, pre-training on the target corpus (monoBERT + duoBERT\textsubscript{SUM} + TCP) improves MRR@10 by another 0.8 points. This result is in line with recent work that shows improvements with target corpus pre-training over out-of-domain corpus pre-training (Beltagy et al., 2019; Raffel et al., 2019).

Results for TREC CAR are presented in Table 2, organized in a similar manner as Table 1. We see similar trends on this dataset. Again, Anserini’s implementation of BM25 leads to 2.3 MAP points improvement over another Lucene-based implementation from Kashyapi et al. (2018). It is also 0.5 MAP points higher than the best entry from TREC 2017 CAR (MacAvaney et al., 2017). The monoBERT model gives an impressive jump of 19.5 MAP points over the BM25 baseline and duoBERT\textsubscript{SUM} or duoBERT\textsubscript{BINARY} provides another improvement of 2.1 points. To our knowledge, this is the best-known result on this dataset. Note that we do not report target corpus pre-training results on TREC CAR because its target corpus is the same as the original BERT pre-training corpus, i.e., English Wikipedia.

In general, we notice that improvements from our BERT models are larger on TREC CAR than they are on MS MARCO. We believe this is primarily due to the evaluation metric: improvements in MRR@10 are much harder to achieve, since only the first correct answer contributes to the score, while better rankings of all relevant documents improve the MAP score. Additionally, MRR@10 is a highly discrete metric (there are only 11 possible values), and these values are arranged such that large gains in effectiveness are only possible in the early ranks (thus increasing the level of task difficulty).

5.1 Tradeoffs with monoBERT

The experimental results presented above capture monoBERT and duoBERT settings that focus on obtaining the best output quality. Our next set of experiments explore different parameterizations of the multi-stage ranking architecture that realizes different quality–latency tradeoffs.

For monoBERT, the number of candidates $k_0$ is the control “knob”: latency increases linearly as we consider more candidates, but effectiveness increases as well. This relationship is shown in Figure 2 for MS MARCO on the left and TREC CAR on the right. To aid in comparisons with duoBERT experiments below, the $x$-axis shows the number of inferences performed per query, which is exactly the same as $k_0$, since each query–candidate pair from $R_1$ serves as an input to monoBERT.

As expected, we see diminishing returns with larger $k_0$ values on both datasets. For example, compared to $k_0 = 1000$, on both datasets we can
achieve more than half the gain in effectiveness with only around a fifth of the number of inferences. These curves also highlight the inadequacy of BM25 scores alone, since with a deep candidate list $R_0$, monoBERT is considering documents that have quite low BM25 scores.

5.2 Tradeoffs with duoBERT

Similar to monoBERT, we can control the latency–quality tradeoff of duoBERT by considering different $k_1$ values. In these experiments, $k_0$ is fixed at 1000, and in Figure 3 we plot changes in effectiveness (MRR@10 for MS MARCO on the left, MAP for TREC CAR on the right) as a function of latency (inferences/query) for different values of $k_1$. We find that actual inference latencies (measured in milliseconds) for duoBERT and monoBERT are comparable, and so the number of inferences per query provides a natural abstract time unit to support meaningful comparisons.

In the figure, each curve represents an aggregation technique and contains six points that correspond to $k_1 = \{0, 10, 20, 30, 40, 50\}$, where $k_1 = 0$ corresponds to monoBERT. The values for the SAMPLE method represent the average of ten trials. Of the four aggregation methods compared, BINARY yields the highest effectiveness on the MS MARCO dataset, albeit by a small margin over SUM. On TREC CAR, BINARY and SUM are very close, although SUM appears to be slightly better, especially at lower cutoffs. The SAMPLE
method has a lower effectiveness than BINARY and SUM for any fixed number of inferences per query. This result shows that the top-$k_1$ candidates from monoBERT are a closer approximation of the true relevance ranking than uniformly sampling from a larger candidate set. This is an interesting result: given the choice of sampling from a larger candidate set or exhaustively enumerating all pairs from a smaller candidate set, the latter option always seems to yield better answers.

Considering these results, it seems that a good operating point is $k_1 = 20$ with BINARY aggregation on MS MARCO and SUM aggregation on TREC CAR. In both cases, we obtain close to the maximum achievable score, with only a 40% increase in latency compared to monoBERT only (whereas $k_1 = 50$, SUM or BINARY, more than doubles the number of inferences required over monoBERT).

### 5.3 Multi-Stage Tradeoffs

Our next set of experiments quantify the tradeoffs when changing both $k_0$ and $k_1$; results are shown in Figure 4. Since inference times are approximately the same between monoBERT and duoBERT, we can quantify latency by the number of inferences.

On both datasets, the most computationally expensive point in the blue curve ($k_0 = 1000$ and $k_1 = 50$) has a much higher effectiveness than the least expensive point in the red curve ($k_0 = 50$ and $k_1 = 50$). This provides an example that analyzing multiple cutoffs jointly can improve our understanding of the tradeoff space.

### 5.4 Qualitative Analyses

Finally, we conduct qualitative analyses by sampling retrieved passages from three methods: BM25, monoBERT, and duoBERT. A few examples are shown in Table 3. From the first two examples, we can see that BM25 tries to maximize unigram matches between queries and passages, and thus often neglects $n$-grams, while monoBERT learns to assign a high matching score to $n$-grams. This also shows an example where a high BM25 score—that comes from repeated instances of query terms—can be misleading. Our monoBERT model, at least in this example, does not appear to be fooled.

From the last two samples in Table 3, we can see that duoBERT matches the synonyms between “low” in the query and “reduced” in the passage, while monoBERT fails to distinguish “low” in the query and “elevated” in the passage.

### 6 Future Work and Conclusions

While our work is firmly situated in the context of multi-stage ranking architectures, it makes sense to discuss the broader landscape of applying neural models to document ranking. Search-related tasks, almost by definition, need to consider a large corpus, and thus it is impractical to apply inference over all documents for a given query. This simple fact necessitates reliance on standard “bag of words” techniques to reduce the “working set” that is presented to neural models.

Such a design, however, is inelegant, which has led researchers to explore alternatives that are able to directly perform ranking. The most promising
| Query | Sample Passage | Label | Rank  |
|-------|----------------|-------|-------|
| who wrote song killing the blues | Killing The Blues by Robert Plant and Alison Krauss. This was written by Chris Isaak’s bass guitarist Roly Salley, and was originally the title track of Salley’s 2005 solo album. This song was used in an advertising campaign for the chain store JC Penney, which features sentimental images of heartland Americana, such as family reunions and Fourth of July celebrations. | R | BM25: 621, monoBERT: 1 |
| who wrote the blues song Crossroads | Blues singer Robert Johnson’s most famous songs. Who wrote the song ‘Blue Shades’. It is a concert piece with allusions... | N | BM25: 1, monoBERT: 9 |
| what causes low liver enzymes | Reduced production of liver enzymes may indicate dysfunction of the liver. This article explains the causes and symptoms of low liver enzymes. Scroll down to know how the production of the enzymes can be accelerated. | R | monoBERT: 47, duoBERT: 1 |
| Other causes of elevated liver enzymes may include: Alcoholic hepatitis (severe liver inflammation caused by excessive alcohol consumption) Autoimmune hepatitis (liver inflammation caused by an autoimmune disorder) Celiac disease (small intestine damage caused by gluten) Cytomegalovirus (CMV) infection. | N | monoBERT: 1, duoBERT: 7 |

Table 3: Comparison of BM25 vs. monoBERT, and monoBERT vs. duoBERT, showing result ranks of answers. (N: not relevant, R: relevant)

The approach is formulated as a representational learning problem, where the task is to learn some nonlinear transformation of queries and documents (i.e., using a neural network) such that documents relevant to a query have high similarities in terms of a simple metric such as cosine similarity (Henderson et al., 2017; Zamani et al., 2018; Ji et al., 2019). This, in essence, transforms neural ranking into approximate nearest-neighbor search once queries and documents have been mapped into the learned representational space.

While this is indeed a promising approach, and has seen production deployment in limited contexts (Henderson et al., 2017), this thread of research is better characterized as exploratory. It is unclear whether representational learning is sufficient to boil the complex notion of relevance down to simple similarity computations—and if it isn’t, the complete end-to-end retrieval architecture will need to involve multiple stages anyway. In contrast, multi-stage ranking architectures are mature, well understood, easy to deploy, and proven in production.

Our future work aims to build the stages of the pipeline jointly, in which hyperparameters are automatically tuned for end-to-end performance. Also, explicitly using scoring signals from previous stages of the pipeline in later stages has the potential to increase overall effectiveness as more information is shared among stages. Lastly, current BERT-based models can only handle documents that are a few sentences long (at the most). Models that can handle longer documents without truncation, such as Yilmaz et al. (2019), should be evaluated on datasets such as the MS MARCO document ranking task. Overall, we believe that multi-stage ranking architectures pave the way to practical deployment of complex and computationally-intensive neural models.

**Acknowledgments**

RN and KC thank support by NVIDIA and CIFAR and were partly supported by Samsung Advanced Institute of Technology (Next Generation Deep Learning: from pattern recognition to AI) and Samsung Electronics (Improving Deep Learning using Latent Structure). WY and JL thank support by the Natural Sciences and Engineering Research Council (NSERC) of Canada, with additional computational resources provided by Compute Ontario and Compute Canada.

**References**

Nima Asadi and Jimmy Lin. 2013. Effectiveness/efficiency tradeoffs for candidate generation in multi-stage retrieval architectures. In *Proceedings of the 36th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2013)*, pages 997–1000, Dublin, Ireland.

Payal Bajaj, Daniel Campos, Nick Craswell, Li Deng, Jianfeng Gao, Xiaodong Liu, Rangan Majumder, Andrew McNamara, Bhaskar Mitra, Tri Nguyen, Mir Rosenberg, Xia Song, Alina Stoica, Saurabh Tiwary, and Tong Wang. 2018. MS MARCO: A human generated MACHine Reading COMprehension dataset. arXiv:1611.09268v3.

Iz Beltagy, Arman Cohan, and Kyle Lo. 2019. SciBERT: Pretrained contextualized embeddings for scientific text. arXiv:1903.10676.
Ruey-Cheng Chen, Luke Gallagher, Roi Blanco, and B. Barla Cambazoglu, Hugo Zaragoza, Olivier Chapelle, Jiang Chen, Ciyu Liao, Zhaohui Zheng, and Jon Degenhardt. 2010. Early exit optimizations for additive machine learned ranking systems. In Proceedings of the Third ACM International Conference on Web Search and Data Mining (WSDM 2010), pages 411–420, New York, New York.

Ruey-Cheng Chen, Luke Gallagher, Roi Blanco, and J. Shane Culpepper. 2017. Efficient cost-awal, cascaded ranking in multi-stage retrieval. In Proceedings of the 40th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2017), pages 445–454, Tokyo, Japan.

Gordon V. Cormack, Charles L. A. Clarke, and Stefan Büttcher. 2009. Reciprocal rank fusion outperforms Condorcet and individual rank learning methods. In Proceedings of the 32nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2009), pages 758–759, Boston, Massachusetts.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pages 4171–4186, Minneapolis, Minnesota.

Laura Dietz, Manisha Verma, Filip Radlinski, and Nick Craswell. 2017. TREC complex answer retrieval overview. In Proceedings of the Twenty-Sixth Text REtrieval Conference (TREC 2017).

Jiafeng Guo, Yixing Fan, Qingyao Ai, and W. Bruce Croft. 2016. A deep relevance matching model for ad-hoc retrieval. In Proceedings of the 25th ACM International on Conference on Information and Knowledge Management, pages 55–64, Indianapolis, Indiana.

Matthew Henderson, Rami Al-Rfou, Brian Strope, Yunhsuan Sung, Laszlo Lukacs, Ruqi Guo, Sanjiv Kumar, Balint Miklos, and Ray Kurzweil. 2017. Efficient natural language response suggestion for Smart Reply. arXiv:1705.00652.

Kai Hui, Andrew Yates, Klaus Berberich, and Gerard de Melo. 2018. Co-PACRR: A context-aware neural IR model for ad-hoc retrieval. In Proceedings of the Eleventh ACM International Conference on Web Search and Data Mining (WSDM 2018), pages 279–287, Marina Del Rey, California.

Shiyu Ji, Jinxin Shao, and Tao Yang. 2019. Efficient interaction-based neural ranking with locality sensitive hashing. In Proceedings of the 2019 World Wide Web Conference (WWW 2019), pages 2858–2864, San Francisco, California.

Sumanta Kashyapi, Shubham Chatterjee, Jordan Ramsdell, and Laura Dietz. 2018. TREMA-UNH at TREC 2018: Complex answer retrieval and news track. In Proceedings of the Twenty-Seventh Text REtrieval Conference (TREC 2018).

Diederik P. Kingma and Jimmy Ba. 2014. Adam: A method for stochastic optimization. arXiv:1412.6980.

Hang Li. 2011. Learning to Rank for Information Retrieval and Natural Language Processing. Morgan & Claypool Publishers.

Jimmy Lin. 2019. The neural hype and comparisons against weak baselines. In SIGIR Forum, volume 52, pages 40–51.

Jimmy Lin, Matt Crane, Andrew Trotman, Jamie Callan, Ishan Chattopadhayaya, John Foley, Grant Ingersoll, Craig Macdonald, and Sebastiano Vigna. 2016. Toward reproducible baselines: The open-source IR reproducibility challenge. In Proceedings of the 38th European Conference on Information Retrieval (ECIR 2016), pages 408–420, Padua, Italy.

Shichen Liu, Fei Xiao, Wenhui Ou, and Luo Si. 2017. Cascade ranking for operational e-commerce search. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (SIGKDD 2017), pages 1557–1565, Halifax, Nova Scotia, Canada.

Tie-Yan Liu. 2009. Learning to rank for information retrieval. Foundations and Trends in Information Retrieval, 5(3):225–331.

Sean MacAvaney, Andrew Yates, Arman Cohan, and Nazli Goharian. 2019. CEDR: Contextualized embeddings for document ranking. In Proceedings of the 42nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2019), pages 1101–1104, Paris, France.

Sean MacAvaney, Andrew Yates, and Kai Hui. 2017. Contextualized PACRR for complex answer retrieval. In Proceedings of the Twenty-Sixth Text REtrieval Conference (TREC 2017).

Joel Mackenzie, Shane Culpepper, Roi Blanco, Matt Crane, Charles Clarke, and Jimmy Lin. 2018. Query driven algorithm selection in early stage retrieval. In Proceedings of the 11th ACM International Conference on Web Search and Data Mining (WSDM 2018), pages 396–404, Marina Del Rey, California.

Irina Matveeva, Chris Burges, Timo Burkard, Andy Laucius, and Leon Wong. 2006. High accuracy retrieval with multiple nested ranker. In Proceedings of the 29th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2006), pages 437–444, Seattle, Washington.
Bhaskar Mitra and Nick Craswell. 2019. An introduction to neural information retrieval. *Foundations and Trends in Information Retrieval*, 13(1):1–126.

Bhaskar Mitra, Fernando Diaz, and Nick Craswell. 2017. Learning to match using local and distributed representations of text for web search. In *Proceedings of the 26th International Conference on World Wide Web (WWW 2017)*, pages 1291–1299, Perth, Australia.

Mark Montague and Javed A. Aslam. 2002. Condorcet fusion for improved retrieval. In *Proceedings of the Eleventh International Conference on Information and Knowledge Management (CIKM 2002)*, pages 538–548, McLean, Virginia.

Hannes Mühleisen, Thaer Samar, Jimmy Lin, and Arjen de Vries. 2014. Old dogs are great at new tricks: Column stores for IR prototyping. In *Proceedings of the 37th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2014)*, pages 863–866, Gold Coast, Australia.

Rodrigo Nogueira and Kyunghyun Cho. 2019. Passage re-ranking with BERT. *arXiv:1901.04085*.

Kezban Dilek Onal, Ye Zhang, Ismail Sengor Altingovde, Md Mustafizur Rahman, Pinar Karagoz, Alex Braylan, Brandon Dung, Heng-Lu Chang, Henna Kim, Quinten McNamara, Aaron Angert, Edward Banner, Vivek Khetan, Tyler McDonnell, An Thanh Nguyen, Dan Xu, Byron C. Wallace, Maarten de Rijke, and Matthew Lease. 2018. Neural information retrieval: At the end of the early years. *Information Retrieval*, 21(2–3):111–182.

Jan Pedersen. 2010. Query understanding at Bing. In *Industry Track Keynote at the 33rd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2010)*, Geneva, Switzerland.

Matthew E. Peters, Waleed Ammar, Chandra Bhagavatula, and Russell Power. 2017. Semi-supervised sequence tagging with bidirectional language models. *arXiv:1705.00108*.

Alec Radford, Karthik Narasimhan, Tim Salimans, and Ilya Sutskever. 2018. Improving language understanding by generative pre-training.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2019. Exploring the limits of transfer learning with a unified text-to-text transformer. *arXiv:1910.10683*.

Stephen E. Robertson, Steve Walker, Susan Jones, Micheline Hancock-Beaulieu, and Mike Gatford. 1994. Okapi at TREC-3. In *Proceedings of the 3rd Text REtrieval Conference (TREC-3)*, pages 109–126, Gaithersburg, Maryland.

Paul Viola and Michael J. Jones. 2004. Robust real-time face detection. *International Journal of Computer Vision*, 57:137–154.

Ellen M. Voorhees. 2002. The philosophy of information retrieval evaluation. In *Evaluation of Cross-Language Information Retrieval Systems: Second Workshop of the Cross-Language Evaluation Forum, Lecture Notes in Computer Science Volume 2406*, pages 355–370.

Lidan Wang, Jimmy Lin, and Donald Metzler. 2011. A cascade ranking model for efficient ranked retrieval. In *Proceedings of the 34th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2011)*, pages 105–114, Beijing, China.

Chenyang Xiong, Zhuyun Dai, Jamie Callan, Zhiyuan Liu, and Russell Power. 2017. End-to-end neural ad-hoc ranking with kernel pooling. In *Proceedings of the 40th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2017)*, pages 55–64, Tokyo, Japan.

Zhixiang Eddie Xu, Kilian Q. Weinberger, and Olivier Chapelle. 2012. The greedy miser: Learning under test-time budgets. In *Proceedings of the 29th International Conference on Machine Learning (ICML 2012)*, Edinburgh, Scotland.

Peilin Yang, Hui Fang, and Jimmy Lin. 2017. Anserini: Enabling the use of Lucene for information retrieval research. In *Proceedings of the 40th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2017)*, pages 1253–1256, Tokyo, Japan.

Peilin Yang, Hui Fang, and Jimmy Lin. 2018. Anserini: Reproducible ranking baselines using Lucene. *Journal of Data and Information Quality*, 10(4):Article 16.

Wei Yang, Kuang Lu, Peilin Yang, and Jimmy Lin. 2019a. Critically examining the “neural hype”: weak baselines and the additivity of effectiveness gains from neural ranking models. In *Proceedings of the 42nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR 2019)*, pages 1129–1132, Paris, France.

Wei Yang, Yuqing Xie, Aileen Lin, Xingyu Li, Luchen Tan, Kun Xiong, Ming Li, and Jimmy Lin. 2019b. End-to-end open-domain question answering with BERTserini. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics (Demonstrations)*, pages 72–77, Minneapolis, Minnesota.

Wei Yang, Haotian Zhang, and Jimmy Lin. 2019c. Simple applications of BERT for ad-hoc document retrieval. *arXiv:1903.10972*. 
Zeynep Akkalyoncu Yilmaz, Wei Yang, Haotian Zhang, and Jimmy Lin. 2019. Cross-domain modeling of sentence-level evidence for document retrieval. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing.

Hamed Zamani, Mostafa Dehghani, W. Bruce Croft, Erik Learned-Miller, and Jaap Kamps. 2018. From neural re-ranking to neural ranking: Learning a sparse representation for inverted indexing. In Proceedings of the 27th ACM International Conference on Information and Knowledge Management (CIKM 2018), pages 497–506, Torino, Italy.