**Learnt Sparsity for Effective and Interpretable Document Ranking**

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**ABSTRACT**

Machine learning models for the ad-hoc retrieval of documents and passages have recently shown impressive improvements due to better language understanding using large pre-trained language models. However, these over-parameterized models are inherently non-interpretable and do not provide any information on the parts of the documents that were used to arrive at a certain prediction.

In this paper we introduce the **select and rank** paradigm for document ranking, where interpretability is explicitly ensured when scoring longer documents. Specifically, we first select sentences in a document based on the input query and then predict the query-document score based only on the selected sentences, acting as an **explanation**. We treat sentence selection as a latent variable trained jointly with the ranker from the final output. We conduct extensive experiments to demonstrate that our **inherently interpretable** select-and-rank approach is competitive in comparison to other state-of-the-art methods and sometimes even outperforms them. This is due to our novel end-to-end training approach based on weighted reservoir sampling that manages to train the selector despite the stochastic sentence selection. We also show that our sentence selection approach can be used to provide explanations for models that operate on only parts of the document, such as BERT.

**1 INTRODUCTION**

Document ranking is a central task in web search and information retrieval, where the objective is to rank documents relevant to a user-specified keyword query. Recent advances in retrieval models have been dominated by over-parameterized contextual models that are based on tuning pre-trained contextual models like BERT [1, 8, 36], indicating that better language understanding [64] leads to better document understanding. However, such over-parameterized models are inherently non-interpretable as they automatically extract latent and complex query document features from large training sets. This leads to opaque decision-making that limits understanding in case of failures or undesirable results.

Although interpretability of machine learning models has been a popular topic in the past years, there is a limited number of approaches for ad-hoc document retrieval. Existing approaches focus on post-hoc interpretability of document rankers [54, 55]. However, a fundamental limitation of such post-hoc approaches is that explanations might not necessarily be accurate reflections of the model decisions [49]. Second, and more worrisome, is the problem of the evaluation of interpretability techniques due to the difficulty in gathering ground truth for evaluating an explanation due to human bias [29].

**Result Document**

*What makes Bikram yoga unique is its focus on practicing yoga in a room heated to 105 degrees Fahrenheit with 40 percent humidity. In Bikram yoga, be prepared to sweat profusely and come armed with a towel and lots of water. To practice Bikram at home, you’ll need a space heater and access to the pose sequence. On a general basis, you need to hold the yoga poses for about 10-12 breaths. With practice, you can also go up to 36 breaths. We chatted for a few moments, and found that we came to completely different conclusions. She finds Bikram more difficult because of the intense heat (about 5-10 degrees hotter than a hot vinyasa class) and lack of breaks in the standing series. That is why Bikram is easier for me. It will help you hold the pose for around 3 minutes. It is best to count the time in breaths (one breath cycle is one deep inhalation followed by complete exhalation).*

**Table 1:** Two sample sentences for the query "how long to hold bow in yoga" taken from the document marked as relevant by human annotators.

| Sentence 1 | Sentence 2 |
|------------|------------|
| "hold bow in yoga" taken from the document marked as relevant by human annotators. | "What makes Bikram yoga unique is its focus on practicing yoga in a room heated to 105 degrees Fahrenheit with 40 percent humidity."

**Figure 1:** The **Select-And-Rank** approach. The document is split into sentences $s_i$. The **selector** assigns a score to each sentence. The scores determine which of the sentences are selected as input for the **ranker**.

Unlike post-hoc approaches, we are specifically interested in document ranking models that are interpretable by design. We argue that an interpretable ranking model should help us understand which sentences or passages in the document are used for the relevance estimation. In this paper, we present a document ranking model where explanations are first-class citizens and are generated along with the prediction. Each prediction from our model can be unambiguously attributed to a reason or rationale that is both accurate and human-understandable. We define explanations as extractive pieces of text from the input document. An example explanation is shown in Table 1, where the highlighted sentences serve as an explanation for the relevance of the document.

**Our Approach – Select-And-Rank.** This paper proposes an approach, which we refer to as **Select-And-Rank**, for modeling long documents that address the above limitations. **Select-And-Rank**
consists of two phases. In the **select phase**, we use a light-weight selection model to extract potentially relevant sentences given a query. In the **rank phase**, we perform the relevance estimation just on the extracted evidence using a more involved ranker. Our idea is based on the observation that not all sentences in a document are relevant; instead, the document’s relevance signals are typically sparse. The selection phase essentially acts as a noise removal mechanism that eliminates most irrelevant sentences resulting in a high-signal succinct and query-based document representation (refer to Figure 1). Since the ranking is performed just on the selected sentence evidence, we are more interpretable than other models. That is, we can unambiguously attribute the reason behind ranking predictions to the selected sentences. As an added advantage, our sentence selection procedure is a principled manner of choosing a concise query-based document representation as input into size limited models like BERT. This is in contrast to other heuristic truncation approaches [8].

Within our modular framework, we consider two approaches for learning the model parameters: (1) a **pipeline model**, where we use distant supervision to train a sentence selection model independently from a downstream ranking model and (2) a **joint model** that is fully differentiable and is trained end-to-end with gradient descent. Specifically, we allow the user to regulate the model’s sparsity during training and inference by allowing up to \( k \) sentences to be chosen. Choosing \( k \) sentences is akin to sampling from a latent distribution over sentences in a document. We use a parameterized model to output such a distribution and apply the now famous gambel-softmax trick to approximate hard masking. Finally, we use relaxed subset sampling to enforce the user-specified sparsity \( k \). Similar approaches have been used in computer vision [37], NLP [4, 32] and for feature selection [74].

**Key Findings.** We conduct extensive empirical evaluation over three TREC datasets – TREC-DL, CORE17 and CLUEWEB09. Our intention is not to achieve the best performance in document ranking model. Instead, we aim to present a ranking model that is fully interpretable without compromising ranking performance. Firstly, we find that query-specific sparse document representation by sentence selection can improve the task performance over heuristic sentence selection approaches [8] by up to 20%. Secondly and more strikingly, our **SELECT-AND-RANK** models (with 20 selected sentences) perform on par with and sometimes outperform other document modeling approaches that model the entire document as a sequence of passages or sentences. Finally, we show how **SELECT-AND-RANK** can be used to even explain BERT rankers that operate only on parts of the input document.

## 2 RELATED WORK

Ad-hoc retrieval is a classical task in information retrieval where there is precedence of probabilistic models based on query likelihood [30] and BM25, proving to be hard to beat [48]. In the last five years, neural models have been proposed to model semantic representations of the text [22, 52, 53], positional information [23, 24, 39], local query-document interactions [14, 42, 43, 45, 71] or a combination of both [40]. Recently, contextual models, using BERT, have proven to be superior to the above neural models. The first to use BERT were MacAvaney et al. [36], who used the contextualized embeddings of BERT as a replacement for word embeddings in existing document retrieval models (PACRR and KNRM). Closest to our work are models that try to address the variable-length limitation due to BERT’s fixed input restriction either by passage-level [8, 50, 68] or sentence-wise [1] labeling. Dai and Callan [8] proposed an approach to split documents into passages and then fine-tune BERT to obtain passage level relevance score (Doc-Labeled). Such a document-labeling approach suffers from label noise because it assumes all passages of a relevant document are also relevant. On the other hand, Akkalyoncu Yilmaz et al. [1] scored documents aggregating per-sentence relevance BERT scores using a cross-domain transfer model. This approach has an unacceptably large inference time due to its sentence-level knowledge transfer. We use it as a useful upper bound of the performance benefits due to contextual modelling of the entire document. In this paper, our objective is to learn a selector and ranker in a joint manner to obviate heuristic design decisions relating to choice of passages for realizing a more effective and concise document representation.

Another line of work proposes weak supervision methods for training neural ranking architectures to learn from large-scale weak or noisy labels [10, 11, 75]. Other approaches inspired by the teacher-student paradigm [16, 69] attempt to infer better labels from noisy labels and use them to supervise the training of the network [62, 65]. Although similar in spirit to our approach, our work judiciously selects evidence from the original training document and not creating more training labels using a selector model.

**Select-and-Predict Models.** Training models based on a subset of the input is broadly studied under feature selection in machine learning. Different from classical feature selection, our aim is to select features from a document given a query, that is, we want to dynamically select features (words, phrases and sentences) from a document based on the input query. Such instance-wise feature selection has been explored in the machine learning literature [74], however their applicability to modeling documents is limiting. In computer vision, the selection phase is akin to using hard-attention models [37], where a sub-image of an input image is chosen for downstream classification. In NLP, similar models are studied for ensuring interpretability by design [31, 32]. Li et al. [34] use sentence selection to mimic human reading behavior to estimate the relevance of a document to a query. These works mainly differ in how they perform end-to-end training due to the explanation sampling step have been proposed subsequently. Common proposals for training include using REINFORCE [32, 34], actor-critic methods [74], pipelined approaches Zhang et al. [76] or re-parameterization tricks [4]. Lehman et al. [31] use a similar philosophy of decoupling rationale generator and predictor, albeit a slightly different architecture. Zhong et al. [77] additionally use human annotations while learning from task supervision. However, we do not have any explicit training data to train the selector network and rather use the task supervision signal to update the parameters of the selector network.

**Interpretable Models.** For language tasks, there has been work on post-hoc analysis of already learned neural models by analyzing state activation [15, 28, 33], attention weights [3, 6, 7, 38, 72, 73] or using probing tasks [59]. The attention weights learned as weights
assigned to token representation are intended to describe rationales. However, recently the faithfulness of interpreting model prediction with soft attention weights has been called into question [26, 67]. Specifically, contextual entanglement of inputs is non-trivial. The prediction model can still perform well even if the attention weights don’t correlate with the (sub-)token weight as desired by humans. Finally, there has been recent work on devising decoy datasets to measure utility of explanations methods for NLP models [25]. Our approach for rationale based explanations differs in the type of architectures, objectives, and general nature of its utility.

Interpretable Models for Ranking. For the ranking task, most of the work has focused on post-hoc interpretability of text rankers [12, 55, 56, 66] and learning-to-rank models [54, 60]. In contrast, our SELECT-AND-RANK models are interpretable by design. The closest to our work, and a parallel discovery, is [17], where the authors try to use cascading rankers after retrieval. However, cascading rankers differ from us in the style of optimization and the type of interpretability they provide.

3 SELECT AND RANK

In this section, we formally define the problem of document ranking (cf. Section 3.1). We then give a high level overview of our SELECT-AND-RANK framework that aims to generate an extractive sentence-level summary from the document prior to ranking (cf. Section 1). Finally, we present our algorithmic contribution that aims to train the parametric selector and ranker models using gradient-based optimization both in a pipelined and in a joint manner (cf. Sections 3.2 and 3.3).

3.1 Problem Statement

The usual ranking pipeline consists of two stages: First, given a query, an inexpensive term-frequency based retriever retrieves a set of documents from the complete, usually very large, collection. Afterwards, a more involved, expensive model re-ranks the result of the first-stage retrieval.

Our objective is to learn a parameterized model for document reranking. Specifically, given a training set of triples \( \{ (q^{(i)}, d^{(i)}, y^{(i)}) \}^N_{i=1} \), where \( q^{(i)} \) is a query, \( d^{(i)} \) is a document and \( y^{(i)} \) is a relevance label, our goal is to learn a model that predicts relevance scores \( \hat{y} \in \mathbb{R} \) for query-document pairs \( (q, d) \) and thus classifies the pair as relevant or irrelevant. We denote the set of documents retrieved in the first stage for the query \( q \) as \( D_q \). The resulting predictions are then used to obtain a ranking of all documents \( d \in D_q \). Finally, the rankings of all queries are evaluated using appropriate ranking metrics.

We model each document as a sequence of sentences, i.e.,

\[
\hat{d} = \{ s_1, s_2, \ldots, s_{|d|} \}. \tag{1}
\]

Our SELECT-AND-RANK approach assumes that only a subset of the constituent sentences actually contribute towards the relevance estimation. Based on this assumption, the model consists of two components – a selector and a ranker:

1. The selector or sentence-selection model \( \Psi (q, \hat{d}) \) defines a distribution \( \Pr(s_i | q, \hat{d}) \) over sentences in \( \hat{d} \) given the input query \( q \), encoding the relevance of the sentence given the query. This distribution is used to select an extractive, query-dependent summary \( \hat{d} \subseteq d \).

2. The ranker is a relatively involved relevance estimation or ranking model \( \Phi (q, \hat{d}) \) that generates a relevance label \( \hat{y} \) given the query and an extractive document summary \( \hat{d} \), thus focusing only on the relevant parts of the document.

The selector \( \Psi \) is a parameterized model that takes the query and sentences as input and outputs a score or weight \( w_i \) for each sentence, representing its relevance to the query:

\[
w_i = \Psi (q, s_i) \tag{2}
\]

The logit weights \( w_i \) are normalized using the softmax function, defining a distribution over the sentences:

\[
\Pr(s_i | q, \hat{d}) = \frac{\exp(w_i)}{\sum_{j=1}^{|\hat{d}|} \exp(w_j)} \tag{3}
\]

Using this distribution, a document summary \( \hat{d} \subseteq d \) is created as a subset of the document’s sentences by selecting sentences based on the selector’s scores, i.e. dropping some of the lower scoring sentences. The ranker takes as input the query and the document summary in order to compute the query-document relevance \( \hat{y} \):

\[
\hat{y} = \Phi (q, \hat{d}) \tag{4}
\]

Since the selector and ranker are in principle independent models, it is possible to train them in one of two ways:

1. Both models are trained separately; the selector is trained to extract a relevant summary from a document given a query, while the ranker is trained on a ranking dataset. The models are then applied consecutively to a query-document pair. We refer to this family of approaches as pipeline approaches.

2. The models are trained jointly in an end-to-end fashion, where the gradients are propagated directly from the final outputs back to the selector network. Since this approach includes a non-differentiable selection operation (arg max), it requires approximated differentiable subset sampling.

In this paper we analyze and compare the approaches above; furthermore, we implement a number of different selector models and compare them. Section 3.2 describes the pipeline approach, Section 3.3 describes the end-to-end approach.

3.2 Pipeline Approach

In this section we apply the SELECT-AND-RANK framework in the aforementioned pipeline setting. Concretely, this means that the selector and ranker are trained independently of each other. For sentence selection, we consider multiple approaches from simple term matching to rather complex auto-regressive language models:

1. Term-matching based selectors: We use tf-idf scores between the query \( q \) and sentences \( s_i \) to determine the best sentences.

2. Embedding based selectors: We use semantic similarity scores between the query \( q \) and sentences \( s_i \) to determine the best sentences. Both the query and sentence are represented as average over the constituent word embeddings.

3. Neural non-contextual selectors: We build a neural network to define a distribution over the sentences \( s_i \).
(4) **Contextual selectors**: We use BERT to define a distribution over the sentences \( s_i \).

Term and embedding based selections are non-parameterized in nature. However, some of the selectors (neural and contextualized models) are parameterized and need to be trained. We follow a transfer learning approach and use the MS MARCO passage re-ranking dataset [41] to train each selector on a passage ranking task. Specifically, the models learn to predict a relevance score given a query and a passage (or sentence). This task in itself is very similar to document summarization, supported by the fact that the passages in this particular dataset were created by splitting documents.

To ensure a fair comparison with other approaches, we do not consider summarized documents in the training phase of the ranker. During inference, the pipeline approach may be described as follows: The selector is applied to the query and document, outputting a score for each sentence in the document. Along with the query, the \( k \) highest scoring sentences then form the input to the ranker, maintaining their original order in the source document. The ranker outputs the final score \( \hat{y} \) that is used to rank the document.

### 3.3 End-to-End Approach

Existing approaches rely on sampling from a stochastic distribution using the REINFORCE algorithm, resulting in a boolean mask over the sentences. An alternative way to achieve end-to-end training instead is by allowing a continuous mask over the sentences. This is akin to using a soft-attention mechanism that is arguably easier to train. However, this approach does not allow for a reduction of the input sequence length, which can be problematic, especially with Transformer-based rankers. Additionally, during inference, one would still need a selection of \( k \) sentences given a soft-selection model. This in particular is ineffective, given that soft-selection models still rely on all sentences for more effective predictions. We therefore propose an approach based on the Gumbel-softmax trick [27], that enables gradient flow in models where discrete variables must be sampled.

#### 3.3.1 The Gumbel-Max Trick

The Gumbel-max trick provides a simple and efficient way to parameterize a discrete distribution and draw samples from it. Let \( X \) be a random variable. We wish to parameterize a categorical distribution such that \( P(X = i) \propto w_i \), where \( w_i \) is a weight associated to the \( i \)-th category. Using the Gumbel-max trick, we can simply draw a sample as

\[
X = \arg \max_i (\log w_i + g_i)
\]

where \( g_i = -\log(-\log u_i) \) is called Gumbel random variable and \( u_i \sim \text{Uniform}(0,1) \). The resulting sample is parameterized by the weights \( w \).

In order to completely relax the sampling process and allow for the propagation of gradients (i.e. end-to-end training), the trick is commonly extended, replacing arg max with softmax (Gumbel-softmax trick). In detail, the Gumbel-softmax estimator gives an approximate one-hot sample \( y \) with

\[
y_i = \frac{\exp \left( \frac{(\log w_i + g_i)}{t} \right)}{\sum_{j=1}^{k} \exp \left( \frac{(\log w_j + g_j)}{t} \right)} \quad \text{for } i = 1, ..., k
\]

where \( t \) is a temperature. By using the Gumbel-softmax estimator, one can generate samples \( y = (y_1, ..., y_k) \) to approximate the categorical distribution. Furthermore, as the randomness \( g \) is independent of \( w \), which is usually defined by a set of parameters, the reparameterization trick can be used to optimize the model’s parameters using standard backpropagation algorithms.

#### 3.3.2 Relaxed Subset Sampling

Since we are interested in sampling a subset, i.e. drawing a number of samples (in our case sentences) without replacement, we employ a relaxed subset sampling algorithm proposed by Xie and Ermon [70] that makes use of the aforementioned Gumbel-max trick. Let a set of items \( x_1, ..., x_n \) have associated weights \( w_i \) and Gumbel variables \( g_i \) as above. In order to sample a subset, a Gumbel-max key \( r_i = \log w_i + g_i \) is computed for each item. Since \( r_i \) is a monotonic transformation of \( w_i \) (fixing \( u_i \)), a relaxed subset sample of the items can be drawn by applying a relaxed top-\( k \) procedure directly on \( r \). The procedure proposed by Plötz and Roth [47] defines

\[
\alpha^+_i := r_i + \log(1 - p(a_i^+ = 1))
\]

(7)

and \( p(a_i^+ = 1) \) is the expectation of the distribution

\[
p(a_i^+ = 1) = \frac{\exp\left(\frac{\alpha_i^+/t}{\sum_{m=1}^{n}\exp\left(\alpha_m^+/t\right)}\right)}{\sum_{m=1}^{n}\exp\left(\alpha_m^+/t\right)}
\]

(8)

and \( t \) is a temperature. Finally, a relaxed \( k \)-hot vector is computed as \( \hat{v} = (v_1, ..., v_n) \) with \( v_i = \sum_{j=1}^{k} p(a_i^+ = 1) \).

#### 3.3.3 End-to-End Training

In order to train both selector and ranker jointly, we make use of the relaxed subset sampling as described in Section 3.3.2. We start by obtaining query and document representations \( q^\text{emb} \) and \( d^\text{emb} \) from a shared embedding \( E \):

\[
q^\text{emb} = E(q) \quad d^\text{emb} = E(d)
\]

(9)

The selector then operates on these representations and computes a weight \( w_i \) for each sentence \( s_i \), i.e.

\[
\{w_1, ..., w_{|d|}\} = \Psi(q^\text{emb}, d^\text{emb})
\]

(10)

We now draw a relaxed \( k \)-hot sample \( \hat{w} \) (cf. Section 3.3.2) from the set of sentences using the weights \( w \) and a temperature \( t \):

\[
\{\hat{w}_1, ..., \hat{w}_{|d|}\} = \text{SubsetSample}(w, k, t)
\]

(11)

Finally, the document summary \( \hat{d} \) is selected as the \( k \) highest scoring sentences according to \( \hat{w} \). The ranker only operates on the document summary \( \hat{d} \) and discards all other sentences. This means that the ranker needs to assemble its new inputs during the training process. The ordering of the sentences is maintained irrespectively of their scores. Since our goal is to train both models jointly, we have to preserve the gradients of the selector (i.e. \( \hat{w} \)) by combining them with the ranker inputs in a differentiable way. Let \( t_1, ..., t_n \) denote the embedded tokens corresponding to some sentence \( s_i \in \hat{d} \). We compute the actual input tokens for the ranker as

\[
\hat{t}_j = t_j \odot \hat{w}_j
\]

(12)

Note that \( t_j \) is a vector and \( \hat{w}_j \) is a scalar. We use \( \odot \) to denote the multiplication of each element in the vector with the scalar. Since \( \hat{w}_j \in [0,1] \), the multiplication in (12) actually changes the input representations, which is undesirable. We mitigate this by making use of the straight-through estimator [5]. The idea is to use \( \hat{t}_j \) as in
3.3.4 Inference. Since the relaxed subset sampling we use for the training is only necessary for the backward pass, we do not use it during inference. Instead, we simply select the $k$ highest scoring sentences. Thus, the inference is identical to that of the pipeline models.

3.4 Selectors

In this section, we show the selector networks we use in the end-to-end approach. Figure 2 illustrates the two selectors. In the following, we describe them in detail.

3.4.1 Linear Selector. The linear selector (Figure 2a) simply represents a sequence as the average of its token embeddings. Query and sentence representation are fed through a single feed-forward layer. The score is computed as the dot product.

3.4.2 Attentive LSTM Selector. The attentive LSTM selector (Figure 2b) is inspired by the QA-LSTM model proposed by Tan et al. [63]. Query and document are passed through a shared, bidirectional many-to-many LSTM. On the query side, we obtain the representation $\hat{q}$ by max-pooling over all LSTM outputs. On the document side, we split the LSTM outputs into sequences that correspond to the sentences. Let $h^i_j$ denote the LSTM output corresponding to the $j$-th token of the $i$-th sentence. Prior to max-pooling, we apply a simple token-level attention mechanism as

$$m^i_j = W_1 h^i_j + W_2 \hat{q}$$  \hspace{1cm} (13)

$$\hat{h}^i_j = h^i_j \exp \left( W_3 \tanh \left( m^i_j \right) \right)$$  \hspace{1cm} (14)

where $W_1$, $W_2$ and $W_3$ are trainable parameters. We finally compute the sentence representation $\hat{s}_i$ by max-pooling over all $\hat{h}^i_j$. The score of each sentence is the cosine similarity of its representation to the query representation.

3.5 Ranker

Throughout all of our experiments, we use a BERT$_{base}$ model as the ranker. The model is fine-tuned for ranking according to [44]: For a query $q = (q_1, ..., q_n)$ and a document $d = (d_1, ..., d_m)$, where $q_i$ and $d_i$ denote input tokens, the input is constructed as

$$[CLS], q_1, ..., q_n, [SEP], d_1, ..., d_m, [SEP]. \hspace{1cm} (15)$$

We impose a limit of a maximum of 512 input tokens, i.e. $n + m + 3 \leq 512$. Consequently, long documents are truncated to fit within this limit. We take the output $o$ of BERT, which corresponds to the [CLS] input token, and discard the rest. It is fed through dropout and a single feed-forward layer that outputs the final score:

$$\hat{y} = \sigma (Wo + b) \hspace{1cm} (16)$$

$W$ and $b$ denote the trainable parameters of the feed-forward layer and $\sigma$ is the sigmoid function.

4 EXPERIMENTAL SETUP

Our experiments aim to answer the following questions:

1. How do SELECT-AND-RANK models (in both pipeline and end-to-end setting) perform in the document re-ranking task (Sections 5.1 and 5.2)?
2. Does sentence selection lead to sparsification of the input documents, resulting in more interpretable ranking decisions (Sections 5.3 and 5.4)?
3. Can SELECT-AND-RANK models be used to explain rankers that focus only on the head of the documents due to limitations, such as BERT (Section 5.4)?

In this section, we begin by describing our baselines, experimental setup and evaluation procedure.

4.1 Datasets

We consider the following diverse TREC datasets with varying degrees of label properties:

1. TREC-DL: The TREC-DL document ranking dataset is divided into training, development and test set. We use the test set from 2019 for our experiments, the labels of which were made public recently. For each of the 200 queries in the test set, we re-rank the top-100 retrieved documents.
2. ClueWeb09: We consider the ClueWeb09 dataset shared in Dai and Callan [8]. The dataset contains 200 queries distributed uniformly in five folds and top-100 documents for each query is retrieved using QL [61].
3. Core17: The Core17 dataset contains 50 queries with subtopics and descriptions. Queries are accompanied by a 1.8M
document collection. We retrieve the top-1000 documents for each query using QL.

We analyzed the datasets in terms of the number of tokens per sentence and observed that the distribution of the number of tokens per sentence is almost identical among all three datasets. In particular, approximately 50% of all sentences have less than 25 tokens, and 90% of all sentences have less than 50 tokens. We use these findings to choose \( k = 20 \) for our experiments, based on the rough estimation that in this way, all 512 available input tokens of the BERT ranker will be used in most cases, while in the remaining cases, the number of inputs does not exceed the limit by a lot.

### 4.2 Baselines and Competitors

Since prior studies [1, 36] already established the effectiveness of contextual neural rankers over non-contextual ones, we consider the following three recent contextual language model based rankers as our baselines:

- **Doc-Labeled** [8] splits the documents into passages of 150 words with an overlap of 75 words between consecutive passages and considers 30 passages (first, last and 28 random passages). The relevance label of a query-document pair is then transferred to each of its query-passage pairs. This setup is used to train the models with passage-level annotation, and finally, passage level scores are aggregated to come up with document level score during inference.

- **BERT-3S** [1] is a BERT based transfer model trained on MS MARCO and Microblog\(^1\) to compute the scores of query-sentence pairs. The query-document level score and the top-three query-sentences score are taken into account to compute the final relevance score of that query-document pair.

- **BERT-CLS** [44] uses a vanilla BERT model to rank the documents, which are truncated beyond 512 tokens.

Additionally, the first-stage retrieval model, the query likelihood model [30], is also considered a ranking baseline.

### 4.3 Training Details

We train and validate using consistent and common experimental design. The neural models are trained using a pairwise max-margin loss; we consider triples \((q, d^+, d^-)\) of a query and two documents, where \(d^+\) is more relevant to \(q\) than \(d^-\). The loss is computed as

\[
\mathcal{L} = \max \left\{ 0, m - R(q, d^+) + R(q, d^-) \right\} \tag{17}
\]

where \(m\) is the margin and \(R\) is the model. Training triples are sampled in a balanced way such that each query is represented evenly in the training set. We train the models using the AdamW optimizer [35] with linear warmup during the first 1000 batches (10000 on TREC-DL). Validation is performed using MAP over the TREC-DL validation set to choose the best model. We fix a single random seed and use it for all of our experiments.

#### 4.3.1 Hyperparameters

In our experiments, we use hyperparameters commonly found in earlier works; the ranker is an uncased 768-dimensional BERT\(_{base}\) model with a maximum sequence length of 512. We use a learning rate of \(3 \times 10^{-5}\), dropout of 0.1 and a batch size of 32. The selectors (cf. Section 3.4) use 256-dimensional hidden representations throughout.

For performance reasons, we restrict the maximum number of query tokens to 50 and the maximum number of document tokens to 5000. Similarly, no more than the first 500 sentences in a single document are considered by the selector. We set the loss margin to \( m = 0.2 \) and the temperature to \( t = 1.0 \). As described in Section 4.1, we set \( k = 20 \) for training and inference.

### 5 RESULTS

In this section we analyze the effectiveness and interpretability of our approaches. We first conduct extensive evaluation of the different selectors, including both pipeline and end-to-end models. Next, we highlight the benefits of our proposed end-to-end modeling scheme (S&R-LIN and S&R-ATT).

#### 5.1 Variation of Selectors

In this section, we first briefly describe four different hard selection strategies used by the pipeline models. Next, we compare the four pipeline strategies as well as the two proposed end-to-end variants (cf. Section 3.4) of our approach. The hard selection approaches are described as follows:

1. **PL-BERT**: The similarity or relevance between a query and a sentence is computed using the approach proposed by Akkalyoncu Yilmaz et al. [1]. The model is trained on the MS MARCO passage re-ranking dataset according to Nogueira and Cho [44]. Finally, it is used to infer query-sentence level relevance score for each query-document pair.

2. **PL-LSTM**: It is similar to PL-BERT, but uses an LSTM instead of BERT. We limit the input to 1000 words for this configuration, similar to BERT’s limit of 512 tokens. The model is trained on the MS MARCO passage re-ranking dataset and the trained model is used to infer the relevance score of query-sentence pairs.

3. **PL-BM25**: We use a simple BM25 based term matching function\(^2\) to obtain the score between the query and the sentence.

4. **PL-SEM**: Semantic similarity score between query and sentence is computed using standard 300-dimensional GloVe embeddings.

To analyze the efficacy of the above-mentioned selection approaches, we also measure the performance of a simple strategy, **Random**, where we randomly select \(k\) sentences from the document. Table 2 shows the results of pipeline and **SELECT-AND-RANK** models for different selection strategies at \(k = 20\) and highlights the efficacy of the proposed approaches over Random. We also tried other values, but \(k = 20\) gives consistent performance for all three datasets. This may be attributed to the token limitation of the ranker. As mentioned earlier, the pipeline models apply the selection strategy only during the inference phase, i.e. trained models are used to predict the relevance of pairs of queries and summarized documents. The ranker itself is simply trained without any selection, i.e. documents are truncated to fit.

It is interesting to note that our lightweight selection strategies such as PL-BM25 and PL-SEM perform better than heavy parameterized and time-consuming neural selection models such as PL-BERT and PL-LSTM. PL-SEM shows best or comparable performance

\(^1\)We only consider MS MARCO to ensure a fair comparison.

\(^2\)https://pypi.org/project/rank-bm25/
for all three datasets. PL-BM25, while slightly worse, also shows promising performance. This compact representation of documents also helps in developing computationally efficient ranking models and reducing noise.

Our end-to-end models, S&R-LIN and S&R-ATT, show improvements over the pipeline models in most cases. Surprisingly, the linear, more lightweight selector often matches or exceeds the performance of the attention-based one.

### 5.2 Performance of Select-And-Rank

In this section we compare the performance of our proposed models to state-of-the-art models. For the pipeline approach, we choose the best selector (cf. Section 5.1). We further compare our end-to-end approaches, S&R-LIN and S&R-ATT, to a simple BERT baseline, denoted by BERT-CLS, which uses truncation of the document instead of sentence selection. First, each model is trained (fine-tuned) and evaluated on TREC-DL, as it offers an abundance of training data. For Core17 and ClueWeb09, we use the model from the TREC-DL experiment as initialization. This helps us to properly train the selector, as, unlike the BERT ranker, it does not start from a pre-trained model.

The results are illustrated in Table 3. Table 4 shows additional neural baselines [9, 18, 24, 46] evaluated on TREC-DL. The pipeline model works quite well on the Core17 dataset, but falls short on TREC-DL and ClueWeb09 compared to the end-to-end models. In the pipeline model, the selection phase is independent of the ranking phase; hence, the selection strategy does not receive any feedback from the ranking phase. It is evident from Table 3 that the end-to-end approach improves the ranking process.

Overall, we conclude that, by selecting sentences from the complete document, our approaches perform similarly to stand-alone rankers that operate only on the head of the documents, specifically BERT-CLS. This indicates that most documents contain redundant information (likely in the form of summaries) near the beginning that BERT-CLS is able to exploit. We confirm this in Section 5.3 by showing that there is little overlap between the document head and the sentences selected by S&R-LIN. Further, in Section 5.4 we use a Select-And-Rank model to explain the predictions of BERT-CLS by specifically selecting sentences from just the head of the documents.

### 5.3 The Effect of Token Limitation

In this part, we analyze the the token limitation that is inherent to the BERT ranker and further the role the selection strategy has in mitigating that limitation. In other words, we answer the following question: How many input tokens of the selected sentences would not have been seen by BERT without selection due to length restrictions? In general, existing research assumes that most of the information relevant to the query is present in the head part of the document [44]. The BERT-CLS baseline also works based on that assumption. However, recent strategies [19] showed that some information also exists beyond this token limit. Dai and Callan [8] tried to handle this by selecting first, last and 28 random passages in their DocLabeled approach, but this heuristic does not always work.

To that end, we choose the top-20 sentences based on PL-SEM and S&R-LIN and measure what fraction of these tokens exceeds the usable BERT input, i.e. is lost if we only consider the head part of a document. Figure 3 shows the cumulative distribution of the percentage of missing tokens for TREC-DL. The distribution pattern is similar for both methods: Less than 10% of the query-document pairs do not miss any of the selected tokens. Given the performance of the models shown in Section 5.2, this suggests that relevant information is repeated within the documents, such that multiple selections exists which result in similar performance.

### Table 2: Retrieval performance with $k = 20$

| Model   | MAP | nDCG@20 | MRR  | MAP | nDCG@20 | MRR  | MAP | nDCG@20 | MRR  |
|---------|-----|---------|------|-----|---------|------|-----|---------|------|
| Random  | 0.231 | 0.492 | 0.754 | 0.173 | 0.345 | 0.649 | 0.138 | 0.236 | 0.495 |
| PL-BERT | 0.237 | 0.501 | 0.822 | 0.200 | 0.399 | 0.759 | 0.169 | 0.294 | 0.529 |
| PL-LSTM | 0.257 | 0.558 | 0.827 | 0.194 | 0.399 | 0.788 | 0.166 | 0.289 | 0.552 |
| PL-BM25 | 0.264 | 0.568 | 0.893 | 0.196 | 0.412 | 0.727 | 0.171 | 0.297 | 0.555 |
| PL-SEM  | 0.265 | 0.571 | 0.920 | 0.207 | 0.414 | 0.768 | 0.167 | 0.286 | 0.534 |
| S&R-LIN | 0.269 | 0.597 | 0.946 | 0.203 | 0.411 | 0.710 | 0.174 | 0.303 | 0.535 |
| S&R-ATT | 0.271 | 0.590 | 0.924 | 0.205 | 0.403 | 0.714 | 0.168 | 0.292 | 0.518 |

*Random refers to the selection of $k$ random sentences.*
Table 3: Retrieval performance of baselines and Select-And-Rank methods. For Doc-Labeled, we report the performance of the best aggregation strategy (FirstP, MaxP, AvgP for TREC-DL, Core17 and ClueWeb09 respectively). Statistically significant improvements at a level of 95% are indicated by * (S&R-LIN) and # (S&R-ATT).

Table 4: The performance of Select-And-Rank models compared to a number of neural baselines on the TREC-DL dataset. The baseline results are taken from [18]. TKL-2k refers to the TKL model operating on 2000 tokens.

Figure 4: The performance of S&R-LIN applied only to the first 20 sentences of each document, which approximates selecting sentences from the input of BERT-CLS.

5.4 Explaining BERT-CLS
In Section 5.3 we showed that S&R-LIN and the standard BERT-CLS model operate on different parts of the input documents, yet they achieve comparable performance (cf. Table 3). In this section we explore whether Select-And-Rank models can be used to further sparsify the head part of a document and thus explain the predictions of BERT-CLS.

5.5 The Effect of First-Stage Retrieval
From Sections 5.2 and 5.4, it is evident that the performance of S&R-LIN is on par with the baselines, while maintaining the interpretability aspect of the approach. However, the re-ranking performance of the models is computed over the top-100 documents per query, retrieved using a QL model. One obvious question is, whether this performance is lost with a better first stage retrieval system. To answer this question, we re-retrieve the top-100 documents with QL and RM3 and apply the models over that set. Table 5 shows the results on TREC-DL. Note that the models are not re-trained, i.e. the models from previous experiments are used. There is no significant influence of RM3 on the performance of baselines; rather, performance drops to some extent in terms of nDCG. We assume that the reason for this is the fact that the models were not re-trained using the documents retrieved by QL and RM3.

5.6 Anecdotal Examples
In Table 6 we present an anecdotal example of the top sentence for each document, selected by our Select-And-Rank approaches in both pipeline and end-to-end variants. The documents in blue are the ground-truth documents as assessed by TREC evaluators. We see that the selected sentences already provide an insight into the evidence is considered important by the overall ranking model. Specifically, the rank 5 prediction by S&R-ATT happens because it mistakes bow pose in yoga with bows and arrows. It is clear from the selected sentence of PL-SEM that it does not consider...
the duration aspect of the query. A key aspect of Select-And-Rank is that the decision of the final ranker can be unambiguously attributed to these extracted sentences, providing interpretability to the model decision. Note that we cannot completely explain the decision making of the final ranker, since it could select a further subset of the selected sentences.

6 CONCLUSION

In this paper we proposed Select-And-Rank, a ranking framework that is interpretable by design. Our selection and ranking models are trainable end-to-end by gradient-based optimization using a combination of the gumbel-softmax trick and weighted reservoir sampling. In our experiments we found that, by enforcing sparsity in document representations by selecting a subset of sentences, we still perform on par with state-of-the-art models, while being interpretable. We also showed that there is no considerable performance difference in case of complex selectors, indicating that simple and fast selectors can be used instead. Finally, we showed that there seems to be a sweet spot in the choice of sparsity that varies depending on the dataset. We believe that the applicability of a sparsity-inducing component can extend beyond document ranking to other ranking tasks [2, 51, 57].

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Table 5: Performance over two first stage retrieval models, QL and QL+RM3 at depth 100 on the TREC-DL testset.

| Model   | MAP   | nDCG@20 | MAP   | nDCG@20 |
|---------|-------|---------|-------|---------|
| QL      | 0.237 | 0.487   | 0.271 | 0.512   |
| QL+RM3  | 0.204 | 0.452   | 0.219 | 0.425   |
| Doc-Labeled BERT-3S | 0.242 | 0.512 | 0.277 | 0.529 |
| BERT-CLS | 0.260 | 0.581 | 0.279 | 0.559 |
| PL-BERT | 0.237 | 0.501 | 0.247 | 0.480 |
| PL-SEM  | 0.265 | 0.571 | 0.268 | 0.536 |
| S&R-LIN | 0.269 | 0.597 | 0.286 | 0.568 |
| S&R-ATT | 0.271 | 0.590 | 0.284 | 0.563 |

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| S&R-ATT | 0.271 | 0.590 | 0.284 | 0.563 |

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System: S&R-ATT  Query: 1132213 "how long to hold bow in yoga"

| Rank | DocID  | Selected Sentence                                                                 |
|------|--------|-----------------------------------------------------------------------------------|
| 1    | D907461 | How long do I hold yoga poses?...                                                   |
| 2    | D907461 | How Long To Hold Bikram Yoga Poses...                                              |
| 3    | D907460 | How Long You Should Hold A Yoga Posture...                                         |
| 4    | D1211050| How Long To Hold Yoga Pose To Gain All The Benefits?...                            |
| 5    | D337672 | One way to build strength and endurance is to pull your hunting bow to full draw and... |
| 6    | D337672 | +                                                                                 |
| 7    | D970458 | -                                                                                 |
| 8    | D520508 | -                                                                                 |

Table 6: Example rankings with most relevant selected sentences. Document IDs from TREC-DL have a suffix (+/-) for (non-)relevant TREC judgments.

System: PL-SEM  Query: 1132213 "how long to hold bow in yoga"

| Rank | DocID  | Selected Sentence                                                                 |
|------|--------|-----------------------------------------------------------------------------------|
| 1    | D3378725| Bow Pose is an intermediate yoga backbend that deeply opens the chest and the front of the body.... |
| 2    | D907458 | In the style of hatha yoga I teach there are longer holds in the poses....          |
| 3    | D3378725| After a brief break, you move into the last eight standing exercises that make up the first half of the Bikram yoga sequence... |
| 4    | D907461 | How long do I hold yoga poses?...                                                   |
| 5    | D337672 | There is no better way to isolate the muscles needed to pull the bow back and hold the bow up than pulling the bow back and holding the bow up |
| 6    | D285734 | Straighten your legs, so that your body makes a ‘V’ shape and hold this position for 2 to 5 breaths.... |
| 7    | D190297 | if you are a beginner, you ought to bend your knees slightly to accomplish this.... |
| 8    | D520508 | Iyengar yoga can be good for physical therapy because... to make it easier for some people to get into the yoga postures.... |
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