

University of Waterloo E-Thesis Template for L^AT_EX

by

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Abstract

Standard bag-of-words term-matching techniques in document retrieval fail to exploit rich semantic information embedded in the document texts. One promising recent trend in facilitating context-aware semantic matching has been the development of massively pre-trained language models, culminating in BERT as its most popular example today. In this work, we propose adapting BERT as a neural reranker for document retrieval with large improvements on news articles. Two fundamental issues arise in applying BERT to “ad hoc” document retrieval on newswire collections: relevance judgements in existing test collections are provided only at the document level, and documents often exceed the length that BERT was designed to handle. To overcome these challenges, we compute and aggregate sentence-level relevance scores to rank documents. We solve the problem of lack of appropriate relevance judgements by leveraging sentence-level and passage-level relevance judgements available in collections from other domains to capture cross-domain notions of relevance. We demonstrate that models of relevance can be transferred across domains. By leveraging semantic cues learned across various domains, we propose a model that achieves state-of-the-art results across three standard TREC newswire collections. We explore the effects of cross-domain relevance transfer, and trade-offs between using document and sentence scores for document ranking. We also present an end-to-end document retrieval system that incorporates the open-source Anserini information retrieval toolkit, discussing the related technical challenges and design decisions.

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Chapter 1

Introduction

Document retrieval refers to the task of generating a ranking of documents from a large corpus D in response to a query Q . In a typical document retrieval pipeline, an inverted index is constructed in advance from the collection, which often comprises unstructured text documents, for fast access during retrieval. When the user issues a query, the query representation is matched against the index, computing a similarity score for each document. The top most relevant documents based on their closeness to the query are returned to the user in order of relevance. This procedure may be followed by a subsequent re-ranking stage where the candidate documents outputted by the previous step are further re-ranked in a way that maximizes some retrieval metric such as average precision (AP).

Document retrieval systems traditionally rely on term-matching techniques, such as BM25, to judge the relevance of documents in a corpus. More specifically, the more common terms a document shares with the query, the more relevant it is considered. As a result, these systems may fail to detect documents that do not contain exact query terms, but are nonetheless relevant. For example, consider a document that expresses relevant information in a way that cannot be resolved without external semantic analysis. Figure 1 displays

<p>Query: international art crime</p> <p>Text: The thieves demand a ransom of \$2.2 million for the works and return one of them.</p>

Figure 1.1: An example of a query-text pair from the TREC Robust04 collection where a relevant piece of text does not contain direct query matches.

one such query-text pair where words semantically close to the query need to be identified to establish relevance. This “vocabulary mismatch” problem represents a long-standing challenge in information retrieval. To put its significance into context, Zhao et al. [57] show in their paper on term necessity prediction that, statistically, the average query terms do not appear in as many as 30% of relevant documents in TREC 3 to 8 “ad hoc” retrieval datasets.

Clearly, the classic exact matching approach to document retrieval neglects to exploit rich semantic information embedded in the document texts. To overcome this shortcoming, a number of models such as Latent Semantic Analysis [11], which map both queries and documents into high-dimensional vectors, and measure closeness between the two based on vector similarity, has been proposed. This innovation has enabled semantic matching to improve document retrieval by extracting useful semantic signals. With the advent of neural networks, it has become possible to learn better distributed representations of words that capture more fine-grained semantic and syntactic information [28], [34]. More recently, massively unsupervised language models that learn context-specific semantic information from copious amounts of data have changed the tide in NLP research (e.g: ELMo [35], GPT-2 [38]). These models can be applied to various downstream tasks with minimal task-specific fine-tuning, highlighting the power of transfer learning from large pre-trained models. Arguably the most popular example of these deep language representation models is the Bidirectional Encoder Representations from Transformers (BERT) [12]. BERT has achieved state-of-the-art results across a broad range of NLP tasks from question answering to machine translation.

While BERT has enjoyed widespread adoption across the NLP community, its application in information retrieval research has been limited in comparison. Guo et al. [16] suggest that the lackluster success of deep neural networks in information retrieval may be owing to the fact that they often do not properly address crucial characteristics of the “ad hoc” document retrieval task. Specifically, the relevance matching problem in information retrieval and semantic matching problem in natural language processing are fundamentally different in that the former depends heavily on exact matching signals, query term importance and diverse matching requirements. In other words, it is crucial to strike a good balance between exact and semantic matching in document retrieval. For this reason, we employ both document scores based on term-matching and semantic relevance scores to determine the relevance of documents.

In this thesis, we extend the work of Yang et al. [53] by presenting a novel way to apply BERT to “ad hoc” document retrieval on long documents – particularly, newswire articles – with significant improvements. Following Nogueira et al. [31], we adapt BERT for binary relevance classification over text to capture notions of relevance. We then deploy

the BERT-based re-ranker as part of a multi-stage architecture where an initial list of candidate documents is retrieved with a standard bag-of-words term matching technique. The BERT model is used to compute a relevance score for each constituent sentence, and the candidate documents are re-ranked by combining sentence scores with the original document score.

We emphasize that applying BERT to document retrieval on newswire documents is not trivial due to two main challenges: First of all, BERT has a maximum input length of 512 tokens, which is insufficient to accommodate the overall length of most news articles. To put this into perspective, a typical TREC Robust04 document has a median length of 679 tokens, and in fact, 66% of all documents are longer than 512 tokens. Secondly, most collections provide relevance judgements only at the document level. Therefore, we only know what documents are relevant for a given query, but not the specific spans within the document. To further aggravate this issue, a document is considered relevant as long as some part of it is relevant, and most of the document often has nothing to do with the query.

We address the abovementioned challenges by proposing two effective innovations: First, instead of relying solely on document-level relevance judgements, we aggregate sentence-level evidence to rank documents. As mentioned before, since standard newswire collections lack sentence level judgements to facilitate this approach, we instead explore leveraging sentence-level or passage-level judgements already available in collections in other domains, such as tweets and reading comprehension. To this end, we fine-tune BERT models on these out-of-domain collections to learn models of relevance. Surprisingly, we demonstrate that models of relevance can indeed be successfully transferred across domains. It is important to note that the representational power of neural networks come at the cost of challenges in interpretability. For this reason, we dedicate a portion of this thesis to error analysis experiments in an attempt to qualify and better understand the cross-domain transfer effects. We also elaborate on our engineering efforts to ensure reproducibility and replicability, and the technical challenges involved in bridging the worlds of natural language processing and information retrieval from a software engineering perspective.

1.1 Contributions

The main contributions of this thesis can be summarized as follows:

- We present two innovations to successfully apply BERT to *ad hoc* document retrieval with large improvements: integrating sentence-level evidence to address the fact that BERT cannot process long spans posed by newswire documents, and exploiting cross-domain models of relevance for collections without sentence- or passage-level annotations. With the proposed model, we establish state-of-the-art effectiveness on three standard TREC newswire collections at the time of writing. Our results on Robust04 exceed the previous highest known score of 0.3686 [9] with a non-neural method based on ensembles, which has stood unchallenged for ten years.
- We explore through various error analysis experiments the effects of cross-domain relevance transfer with BERT as well as the contributions of BM25 and sentence scores to the final document ranking. [Elaborate](#)
- We release an end-to-end pipeline, Birch¹, that applies BERT to document retrieval over large document collections via integration with the open-source Anserini information retrieval toolkit. An accompanying Docker image is also included to ensure that anyone can easily deploy and test our system. We elaborate on the technical challenges in the integration of NLP and IR capabilities, and the rationale behind design decisions.

1.2 Thesis Organization

[Add link to actual chapters](#) The remainder of this thesis is organized in the following order: Chapter 2 reviews related work in neural document retrieval and transfer learning, particularly applications of BERT to document retrieval. Chapter 3 motivates the approach with some background information on the task, and introduces the datasets used for both training and evaluation as well as metrics. Chapter 4 proposes an end-to-end pipeline for document retrieval with BERT by elaborating on the design decisions and challenges. Chapter 5 describes the experimental setup, and presents the results on three newswire collections – Robust04, Core17 and Core18. Chapter 6 concludes the thesis by summarizing the contributions and discussing future work.

¹<https://github.com/castorini/birch>

Chapter 2

Background and Related Work

2.1 Pretrained Language Models

Natural language processing tasks have traditionally been addressed with supervised learning on task-specific datasets. Due to the relatively small size of these datasets, training deep neural networks in this manner introduces the risk of overfitting on the training data, and lack of generalization across different datasets. With the increasing availability of large corpora, pretrained deep language models have been rapidly gaining traction among NLP researchers. Language model pretraining has proven extremely effective on many natural language processing tasks ranging from machine translation to reading comprehension. The underlying assumption in applying pretrained language models to downstream NLP tasks is that language modeling inherently captures many facets of language such as resolving long-term dependencies [23] and hierarchical patterns [15]. In general, pretrained language models can be applied to downstream tasks in one of two ways: feature-based and fine-tuning.

2.1.1 Feature-based Approaches

The feature-based approach, such as ELMo [35], employs deep pretrained representations learned with language modeling as additional features in task-specific architectures. This approach has the advantage of being easily incorporated into existing models with significant improvements in performance. ELMo [35] extends traditional word embeddings to learn context-sensitive features with a deep language model. Therefore, instead of taking the final layer of a deep LSTM (Long Short-Term Memory) as a word embedding,

ELMo embeddings are learned as a function of *all* the internal states of a bidirectional deep LSTM language model. This method is motivated by a thread of work in NLP that suggests that the higher levels of a deep LSTM capture context [27] and meaning while the lower levels learn syntactic features well [5]. While traditional pretrained word embeddings like GloVe [34] cannot differentiate between homonyms, ELMo can as it generates different embeddings for them depending on their context. ELMo embeddings are constructed as a shallow concatenation of independently trained left-to-right and right-to-left LSTMs. Peters et al. [35] show that integrating deep contextualized embeddings learned with ELMo into task-specific architectures significantly improves over the original performance in six NLP tasks, including question answering on SQuAD [39] and sentiment analysis on the Stanford Sentiment Treebank (SST-5) [43].

2.1.2 Fine-tuning Approaches

The fine-tuning approach is inspired by the growing trend in transfer learning. These models are first pretrained with respect to a language modeling objective, and then applied to downstream NLP tasks by “freezing” their last layer, and “fine-tuning” on external data for the specific task with minimal task-specific parameters. This approach has been shown to greatly boost the performance of many NLP tasks.

Radford et al. [38] claim that this phenomenon occurs because language models inherently capture many NLP tasks without explicit supervision. Therefore, they propose Generative Pretrained Transformers (GPT-2) to perform zero-shot task transfer on multiple sentence-level tasks from the GLUE benchmark [47] with impressive results. At the core of GPT-2 lies a multi-layer left-to-right transformer [45] decoder, with each layer consisting of a multi-head self-attention mechanism and fully connected feed-forward network [37]. The large capacity of the transformer is exploited by pretraining it on Google BookCorpus dataset [58] (800M words) where long contiguous spans of text allow the transformer to condition on long-range information.

To address the limitation of the unidirectional nature of GPT-2 [38], Bidirectional Encoder Representations from Transformers (BERT) [12] has introduced a novel way to pretrain bidirectional language models, and has since enjoyed widespread popularity across the NLP community. Standard language models cannot be conditioned on bidirectional context as this would cause the model to apply self-attention on the current token in a multi-layered context. However, BERT enables bidirectional language modeling by conditioning on both left and right context in all layers by employing a new pretraining objective called “masked language model” (MLM). Conceptually, MLM randomly masks some of the

input tokens, i.e: 15% of tokens in each sequence, at random with the goal of predicting the masked tokens based only on their left and right context. The final hidden vectors corresponding to the masked tokens are then fed into a softmax layer over the vocabulary as in a standard language model. This objective allows the representation to fuse both left and right context, which is indispensable for token-level tasks such as question answering, according to the authors. Ablation studies confirm that the bidirectional nature of BERT is the single most important factor in BERT’s performance. In addition to the novel language modeling approach, Devlin et al. [12] also propose a “next sentence prediction” task for applications that require an understanding of the relationship between two sentences, such as question answering or language language inference. Essentially, this trains a binary classifier to determine whether or not one sentence follows another sentence.

The underlying model architecture of BERT is a multi-layer bidirectional transformer [45]: The larger BERT model has 24 layers each with 1024 hidden nodes, and 16 self-attention heads in total. It is pretrained on the union of Google BookCorpus [58] (800M words) and English Wikipedia (2,500M words). The input representation for BERT is formed by concatenating the token with segment and position embeddings. Furthermore, the input may contain a single sentence or a sentence pair separated by the meta-token [SEP], i.e: separator. Each sequence is prepended with [CLS], corresponding to the “class” meta-token, whose final hidden state can be used for classification tasks. The words are represented

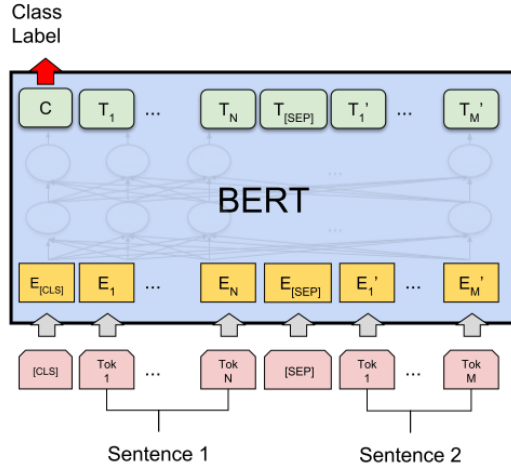


Figure 2.1: The architecture combining BERT an additional output layer for the sentence pair classification task, where E represents the input embedding for each sentence and T_i the contextual representation of token i . Adapted from Delvin et al. [12].

with WordPiece embeddings [48] with a vocabulary of 30,000 tokens. Originally proposed for segmentation problem in Japanese and Korean, the WordPiece model is used to divide words into small sub-word units in order to handle rare or out-of-vocabulary words more effectively. Positional embeddings are learned – not hard-coded – for up to 512, which is the maximum input size allowed by BERT.

To fine-tune BERT for classification tasks, a single-layer neural network is added on top of BERT with the class label as the input, and label probabilities are computed with softmax. The parameters of the additional layer and BERT are fine-tuned jointly to maximize the log-probability of the correct label. For span-level and token-level prediction tasks, the final step needs to be modified to account for multiple tokens. Figure 2.1 visualizes the model for fine-tuning BERT for the “sentence pair classification” task that takes two sentences separated by a [SEP] token as the input.

BERT has been applied to a broad range of NLP tasks from sentence classification to sequence labeling with impressive results. Most relevant to the task of document retrieval, applications of BERT include BERTserini by Yang et al. [52] which integrated BERT with Anserini for question answering over Wikipedia by fine-tuning BERT on SQuAD, and Nogueira et al. [31] who adopted BERT for passage reranking over MS MARCO.

2.2 Document Retrieval

2.2.1 Non-neural Document Retrieval

Traditional document retrieval techniques have evolved from the simple Boolean model to probabilistic models such as the Binary Independence Model over time to increase matching effectiveness. While these methods perform reasonably well for consistently short text like titles or abstracts, they have fallen short with the development of modern text collections with highly variable lengths. To this end, Okapi BM25 (commonly dubbed BM25) was developed as a bag-of-words ranking function that is sensitive to both term frequency and document length without introducing too many additional parameters [21]. Intuitively, BM25 pays more attention to the rarer terms in a query by increasing their term weight while dampening the matching signal for words that occur too frequently in a document with a term saturation mechanism. Term weights are also normalized with respect to the document length.

In addition to a term weighting scheme, query expansion has also been found to improve retrieval effectiveness by increasing recall. Unlike manual relevance feedback, pseudo

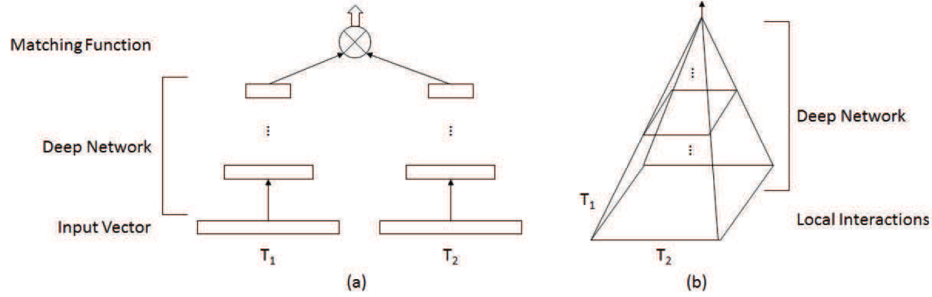


Figure 2.2: The two types of deep matching architectures: representation-focused (a) and interaction-focused (b). Adapted from Guo et al. [17].

relevance feedback allows for automatic local analysis without extended interaction with the user. RM3 is one such pseudo-relevance feedback mechanism where the original query is expanded by adding the top terms that appear in the contents of top k most relevant BM25 documents. While this method still relies on exact matching of query terms, it partly relieves the problem of synonymy. For instance, a query that contains the term “assistance” may be augmented with another high-frequency term “support” in relevant documents, therefore extending the range of matching. One obvious danger, however, is that retrieval may be incorrectly biased towards certain terms that occur frequently in the most relevant documents, but are not directly relevant to the query. Despite their simplicity, well-tuned BM25+RM3 baselines achieve competitive effectiveness on TREC collections [22].

2.2.2 Neural Document Retrieval

With the impressive results achieved by neural networks in many areas such as computer vision and natural language processing, document retrieval, too, has witnessed a shift from non-neural methods to neural methods over the last few years. Neural models have especially been instrumental in facilitating semantic matching in document retrieval. Neural models developed to address the deep matching problem in document retrieval can be divided into two broad categories based on their underlying architecture: representation-based and interaction-based. The high-level differences between these architectures can be observed in Figure 2.2.

Representation-based Models

Representation-based approaches first construct a representation from the input vectors for the query and document with a deep neural network, and then perform matching between these representations (see Figure 2.2). One set of such models loans the concept of word embeddings from natural language processing to represent query and documents. This paradigm represents words as low-dimensional continuous feature vectors that embody hidden semantic or syntactic dependencies. Some of the most popular pretrained English word embeddings include word2vec [28] trained on Google News, GloVe [34] on Common Crawl, Wikipedia and Twitter, and fastText [8] on English webcrawl and Wikipedia. These word embeddings can be learned from scratch for a specific corpus or pretrained over large corpora and reused with significant improvements over the former option [44]. There has also been some effort in learning word embeddings to directly capture relevance matching [54, 14] rather than linguistic features as in word2vec [28] or GloVe [34]. Word embeddings are commonly used as input to many representation-based retrieval models.

Other representation-based architectures explore alternative ways to represent text for effective retrieval. DSSM (short for Deep Structured Semantic Models) [19] extends previously dominant latent semantic models to deep semantic matching for web search by projecting query and documents into a common low-dimensional space. In order to accommodate a large vocabulary required by the task, the text sequences are mapped into character-level trigrams with a word hashing layer before computing a similarity matrix through dot product and softmax layers. While shown effective on a private dataset comprised of log files of a commercial search engine, DSSM requires too much training data to be effective. Moreover, DSSM cannot match synonyms because it is based on the specific composition of words and not semantic proximity. C-DSSM [42] was proposed as an extension to DSSM by replacing the multi-layer perceptron with a convolutional layer to devise semantic vectors for search queries and Web document. By performing a max pooling operation to extract local contextual information at the n-gram level, a global vector representation is formed from the local features. Shen et al. [42] demonstrate that both local and global contextual features are necessary for semantic matching for Web search. While C-DSSM improves over DSSM by exploiting the context of each trigram, it still suffers from most of the same issues listed above.

Interaction-based Models

Interaction-based approaches capture local matching signals, and directly compute word-word similarity between query and document representations. In contrast to more shallow representation-based approaches, this setup allows the deep neural network to learn more complex hierarchical matching patterns across multiple layers. Some notable examples of these architectures include DRMM [17], KNRM [49] and DUET [30].

DRMM [17], which stands for Deep Relevance Matching Model, maps variable-length local interactions of query and document into a fixed-length matching histogram. A feed forward matching network is used to learn hierarchical matching patterns from the histogram representation, and a matching score is computed for each term. An overall matching score is obtained by aggregating the scores from each query term with a term gating network. KNRM [49] similarly calculates the word-word similarities between query and document embeddings, but converts word-level interactions into ranking features with a novel kernel pooling technique. Specifically, a feature vector for each word in the query is constructed from the similarity matrix with k-max pooling. Ranking features are combined to form a final ranking score through a learning-to-rank layer. Unlike DRMM and KNRM, the goal of DUET [30] is to employ both local and distributed representations, therefore leveraging both exact matching and semantic matching signals. DUET is composed of two separate deep neural networks, one to match the query and the document using a one-hot representation, and another using learned distributed representations, which are trained jointly. The former estimates document relevance based on exact matches of the query terms in the document by computing an interaction matrix from one-hot encodings. The latter instead performs semantic matching by computing the element-wise product between the query and document embeddings. Their approach significantly outperform traditional baselines for web search with lots of clickthrough logs.

Contextualized Language Models

While the models introduced in Section 2.2.2 successfully leverage semantic information to varying degrees, they are limited by the size and variability of available training data. Ideally, these models would be trained on a large number of semantically and syntactically varied labeled query-document pairs; however, it is impractical to automatically gather a sufficient number of such training samples at scale. Instead massively pretrained unsupervised language models hold promises for obtaining better query and document representations, and therefore, achieving unprecedented effectiveness at semantic matching without the need for more relevance information. Section 2.1 outlines some of the most popular

unsupervised language models that form the basis of effective retrieval architectures. In general, these language models are deployed as re-rankers over an initial list of candidate documents retrieved with traditional term-matching techniques in Section 2.2.1.

Modeling relevance requires an understanding of the relationship between two text sequences, e.g: the query and the document. Clearly, traditionally language modeling does not suffice to capture such a relationship. Fortunately, BERT facilitates such relevance classification by pre-training a binary next sentence prediction task based on its masking language model approach as discussed in Section 2.1. However, it is still not trivial to apply BERT to document retrieval because BERT was not designed to handle long spans of text, such as documents, given a maximum input length of 512 tokens. Partly because of this inherent challenge, the majority of work on re-ranking with BERT has focused on passage re-ranking instead of document re-ranking.

Notably, Nogueira et al. [31] proposed to re-rank MS MARCO passages based on a simple re-implementation of BERT to learn a model of relevance, outperforming the previous state of the art by 27% in MRR@10 and replacing the previous top entry in the leaderboard of the MS MARCO passage retrieval task. Our neural model is inspired by the BERT re-implementation described in their paper. Padigela et al. [32] prioritize studying the reasons behind the gains that come with re-ranking MS MARCO passages with BERT. To put re-ranking with BERT into perspective, they compare their BERT-based reranker to feature based learning to rank models such as RankSVM [20] and a number of neural kernel matching models such as KNRM [49] and Conv-KNRM [10], and conclude that fine-tuning BERT is substantially more effective than either neural model. They also test four hypotheses regarding the behavior of matching with BERT compared to BM25; specifically, with respect to term frequency and document length.

To our knowledge, Yang et al. [53] are the first to successfully apply BERT to “ad hoc” document retrieval. They demonstrate that BERT can be fine-tuned to capture relevance matching by following the “next sentence classification” task of BERT on the TREC Microblog Tracks where document length does not pose an issue. They further propose overcoming the challenge of long documents by applying inference on each individual sentence and combining the top scores to compute a final document score. Their approach is motivated by user studies by Zhang et al. [56] which suggest that the most relevant sentence or paragraph in a document provides a good proxy for overall document relevance. The work of Yang et al. [53] pave the way for future work that culminated in this thesis.

More recently, MacAvaney et al. [25] shifted focus from incorporating BERT as a reranker to using its representation capabilities to improve existing neural architectures. By computing a relevance matrix between the query and each candidate document at each

layer of a contextualized language model – in particular, ELMo or BERT – they report a high score of NDCG@20 0.5381 on Robust04 by combining CEDR (Contextualized Embeddings for Document Ranking) [25] with KNRM [49]. They also propose a joint model that combines the classification mechanism of BERT into existing neural architectures to help benefit from both deep semantic matching with BERT *and* relevance matching with traditional ranking architectures.

A recent arXiv preprint by Qiao et al. [36] also examines the performance and behavior of BERT when used as a reranker for passage ranking on MS MARCO and for document ranking on the TREC Web Track. Their findings are consistent with those of Nogueira et al. [31] in that BERT outperforms previous neural models on the passage reranking task on MS MARCO. For ad hoc document ranking, they explore using BERT both as representation-based and interaction-based rankers and in combination with KNRM [49] and Conv-KNRM [10]. However, they find that their reranking TREC Web Track documents with BERT performs worse than Conv-KNRM and feature-based learning-to-rank models trained on user clicks in Bing’s search log.

2.2.3 Comparison of Non-neural and Neural Methods

Despite growing interest in neural models for document ranking, researchers have recently voiced concern as to whether or not they have truly contributed to progress [22], at least in the absence of large amounts of behavioral log data only available to search engine companies. Some of the models discussed in this section are designed for the web search task where a variety of other signals are available, such as large amounts of log data and the webgraph. However, this is not the case for “ad hoc” document retrieval where the only available data is the document text, which is the main focus of this thesis. The SIGIR Forum piece by Lin [22] also echoes the general skepticism concerning the empirical rigor and contributions of machine learning applications in Lipton et al. [24] and Sculley et al. [41]. In particular, Lin et al. [22] lament that comparisons to weak baselines sometimes inflate the merits of certain neural information retrieval methods.

To rigorously study the current state of document retrieval literature, Yang et al. [51] recently conducted a thorough meta-analysis of over 100 papers that report results on the TREC Robust 2004 Track. Their findings are illustrated in Figure 2.3 where the empty circles correspond to the baselines and filled circles to the best AP scores of each paper. The solid black line represents the best submitted run at AP 0.333, and the dotted black line the median TREC run at AP 0.258. The other line is a RM3 baseline run with default parameters from the Anserini open-source information retrieval toolkit [50] at AP 0.3903.

The untuned RM3 baseline is more effective than 60% of all studied papers, and 20% of them report results below the TREC median. More surprisingly, only six of the papers report AP scores higher than the TREC best, with the highest being by Cormack et al. [9] in 2009 at AP 0.3686. Their approach is based on building an ensemble of multiple TREC runs with reciprocal rank fusion. Among the neural models, the highest encountered score is by Zamani et al. [55] in 2018 at AP 0.2971. Deviating from the dominant approach of deploying neural models as rerankers, Zamani et al. [55] propose a standalone neural ranking model to learn a latent representation for each query and document, which is sparse enough to construct an inverted index for the entire collection. However, their reported result is still much lower than the TREC best and far below the best reported result of Cormack et al. [9]. Moreover, about half of the neural papers compare their results to a baseline *below* the TREC median, which is consistent with the claims of Lin et al. [22]. Overall, Figure 2.3 exhibits no clear upward trend in terms of AP on Robust04 from 2005 to 2018.

TREC Common Core 2017 (Core17) [1] and 2018 (Core18) [2] are two of the more recent document collections that we evaluate our models on, which are not nearly as well-studied as Robust04 yet. Excluding runs that make use of past labels or require human intervention, the TREC best run on Core17 is **umass baselnrm** at AP 0.275 and on Core18 **uwmrg** at AP 0.276. To our knowledge, Neural Vector Spaces for Unsupervised Information Retrieval by Van Gysel et al. [18] represents the only major neural model evaluated on Core17. While their approach has the advantage of not requiring supervised relevance judgements, their reported results are quite low. Otherwise, evaluation of neural retrieval

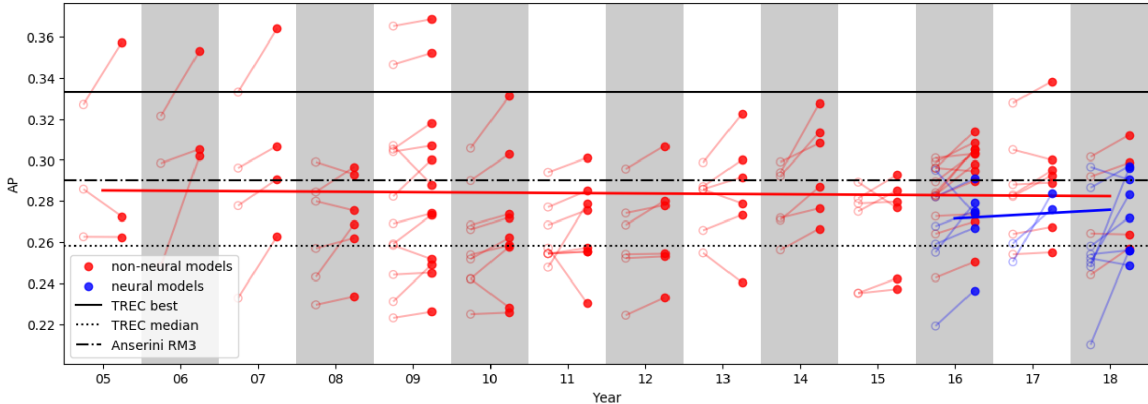


Figure 2.3: Visualization of best AP scores on Robust04 for 108 papers based on non-neural and neural approaches. Adapted from Yang et al. [51].

methods on both Core17 and Core18 has been limited.

2.3 Evaluation Metrics

Evaluation in information retrieval relies on the distinction between “relevant” and “irrelevant” documents with respect to an information need as expressed by a query. A number of automatic evaluation metrics has been formalized specifically for ranking tasks, some of which are described below.

2.3.1 Mean Average Precision (MAP)

Precision specifies what fraction of a set of retrieved documents is in fact relevant for a given query q . By extension, average precision (AP) expresses the average of the precision values obtained for the set of top k documents for the query. Suppose that $D = \{d_1, \dots, d_{m_j}\}$ is the set of all relevant documents for a query q_j , then AP can be formulated as:

$$AP = \frac{1}{m_j} \sum_{k=1}^{m_j} P(R_{jk}) \quad (2.1)$$

where R_{jk} represents the set of top k ranked retrieval results.

The respective AP for each query $q_j \in Q$ can be aggregated to obtain mean average precision (MAP) for the overall retrieval effectiveness in the form of a single-figure measure of quality across various recall levels:

$$MAP = \frac{\sum_{j=1}^{|Q|} AP}{Q} = \frac{1}{Q} \sum_{j=1}^{|Q|} \frac{1}{m_j} \sum_{k=1}^{m_j} P(R_{jk}) \quad (2.2)$$

MAP is known to have especially good discrimination and stability compared to other evaluation metrics, which makes it the ideal choice for large text collections [26]. It is hence one of the standard metrics among the TREC community.

2.3.2 Precision at k (P@k)

While MAP factors in precision at all recall levels, certain applications may have a distinctly different notion for ranking quality. Particularly in the case of web search, the user often only cares about the results on the first page or two. This restriction essentially requires measuring precision at fixed low levels of retrieved results, i.e: top k documents – hence the name for the metric “precision at k ”. On the one hand, it eliminates the need for any estimate of the size of the set of relevant documents because it is only concerned with the top documents. However, it also produces the least stable results out of all evaluation metrics. Moreover, precision at k does not average well because it is too sensitive to the total number of relevant documents for a query.

2.3.3 Normalized Discounted Cumulative Gain (NDCG@k)

Cumulative gain (CG) simply computes the sum of relevance labels for all the retrieved documents, treating the search results as an unordered set. However, since a highly relevant document is inherently more useful when it appears higher up in the search results, CG has been extended to discounted cumulative gain (DCG). DCG estimates the relevance of a document based on its rank among the retrieved documents. The relevance measure is accumulated from top to bottom, discounting the value of documents at lower ranks. NDCG at k measures DCG for the top k documents, normalizing by the highest possible value for a query; therefore, a perfect ranking yields NDCG equals 1.

NDCG is uniquely useful in applications with a non-binary notion of relevance, e.g: a spectrum of relevance. This makes NDCG comparable across different queries: The NDCG values for all queries can be averaged to reliably evaluate the effectiveness of a ranking algorithm for various information needs across a collection. Given a set of queries $q_j \in Q$ and relevance judgements R_{dj} for a document d :

$$NDCG(Q, k) = \frac{1}{|Q|} \sum_{j=1}^{|Q|} Z_{kj} \sum_{m=1}^k \frac{2^{R_{jm}} - 1}{\log_2(1 + m)^c} \quad (2.3)$$

where Z_{kj} is the normalization factor.

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