NAVIGATION-BASED CANDIDATE EXPANSION AND PRETRAINED LANGUAGE MODELS FOR CITATION RECOMMENDATION

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ABSTRACT

Citation recommendation systems for the scientific literature, to help authors find papers that should be cited, have the potential to speed up discoveries and uncover new routes for scientific exploration. We treat this task as a ranking problem, which we tackle with a two-stage approach: candidate generation followed by re-ranking. Within this framework, we adapt to the scientific domain a proven combination based on “bag of words” retrieval followed by re-scoring with a BERT model. We experimentally show the effects of domain adaptation, both in terms of pretraining on in-domain data and exploiting in-domain vocabulary. In addition, we introduce a novel navigation-based document expansion strategy to enrich the candidate documents processed by our neural models. On three different collections from different scientific disciplines, we achieve the best-reported results in the citation recommendation task.

1 INTRODUCTION

The volume of scientific publications is growing at an incredible rate. For example, 800,000 papers are added per year to MEDLINE, a database of life sciences and biomedical literature.1 A recent study estimates that 3M papers are published annually in the English language, with a growth rate of 3–5% per year (Johnson et al., 2018). This flood of information has made it nearly impossible for researchers to keep abreast of discoveries and innovations, both in their specific sub-field as well as more broadly. Furthermore, there is an overwhelming amount of material that a scientist entering a new field of study needs to read before becoming familiarized with common concepts, methods, and other foundations.

A number of tools have come along to help researchers cope with this deluge. For example, keyword-based literature search engines (Google Scholar,2 Microsoft Academic,3 PubMed,4 and Semantic Scholar5) and citation recommendation tools (Bollacker et al., 1999; Basu et al., 2001; McNee et al., 2002; Kodakateri Pudhiyaveetil et al., 2009; He et al., 2010) help scientists find relevant articles, often exploiting citation networks to identify what’s important in a particular field. Methods to automatically populate scientific knowledge bases (Gao et al., 2006; Spangler et al., 2014; Sybrandt et al., 2017) form another broad approach to tackling this challenge.

In this work, we investigate the potential of deep language models such as BERT (Devlin et al., 2019) and large scientific datasets such as Open Research (Ammar et al., 2018) to improve scientific search tools. More concretely, we work on the task of scientific literature recommendation, where

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1https://www.nlm.nih.gov/bsd/stats/cit_added.html
2https://scholar.google.com/
3https://academic.microsoft.com/home
4https://www.ncbi.nlm.nih.gov/pubmed/
5https://www.semanticscholar.org/
a paper (title and abstract) is given as a query, and the system’s task is to find which papers should be cited. We use a standard keyword search engine (based on inverted indexes) with BM25 ranking (Robertson et al., 1994) to initially retrieve candidate documents and evaluate various pretrained language models as re-rankers.

In domain-specific tasks such as ours, one common issue is low recall in the initial retrieval due to the vocabulary mismatch between query and relevant documents. As a result, current tools often require from the user multiple rounds of interactions (e.g., query rewrites) where each step requires reading abstracts or passages, a cognitively-demanding task. We address this challenge by trying to automatically mimic this process to enrich the candidate documents that are fed into the re-ranker, based on the graph of citations.

We find that this simple pipeline comprising off-the-shelf keyword-based initial retrieval, local search in the graph of citations, and BERT re-ranking is more effective than cluster-based methods (Ren et al., 2014; Bhagavatula et al., 2018). To summarize, our contributions are the following:

- We introduce a novel method to combine keyword-based retrieval with navigation-based retrieval and obtain state-of-the-art results in three citation recommendation datasets.
- We evaluate eleven pretrained ranking models and find that pretraining on the target domain and using domain-specific vocabulary lead to large improvements over a general-purpose model.
- We find that despite the effectiveness of the pretrained language models as query–document relevance estimators, they perform poorly when the term overlap between query and candidate documents is low. To address this issue, we train with more query–candidate pairs that have low term overlap, but interestingly, such a model performs poorly, even on the training set (see Section 5.3).
- Contrary to our expectation that query and candidate terms have equal importance to the relevance estimator model, we find that query terms are more important (see Section 5.4).

2 RELATED WORK

Most of the early methods for scientific literature search and recommendation use keyword-based retrieval methods to provide access to the documents (Ginsparg, 1994; Lawrence et al., 1999). These methods suffer from the term mismatch problem, which is common in “bag-of-words” retrieval methods, but the issue is aggravated by the diversity of the scientific vocabulary (Jerome et al., 2001; Dinh & Tamine, 2011; Nabeel Asim et al., 2018). As the number of users grows, popular search engines can exploit interaction signals to learn better ranking models (Mohan et al., 2017; Fiorini et al., 2018b,a). However, the reported gains are relatively small compared to classic ranking methods such as BM25.

Another common approach in scientific recommendation systems is collaborative filtering (McNee et al., 2002; Liu et al., 2015; Chen & Lee, 2018). These methods typically suffer from the cold-start problem, in which there is not enough data about new items (or users) to make predictions accurately.

More recently, cluster-based methods have started to become competitive with traditional retrieval-based methods in this task. Kanakia et al. (2019) cluster papers based on their word embedding representation and use co-citations to alleviate the cold-start problem. However, they perform human evaluations on a private dataset, which excludes an empirical comparison to our approach.

Navigational methods for information retrieval have been less explored with somewhat limited success. For example, Nogueira & Cho (2016) present an artificial agent trained to navigate Wikipedia to find answers to Jeopardy/ questions. Similarly, Lao & Cohen (2010) use the literature graph and predictive models of proximity measures, such as Random Walk with Restart, to recommend papers. Likewise, navigation on knowledge graphs is extensively used in question-answering tasks (Bordes et al., 2014; Das et al., 2017; Guu et al., 2015; Lin et al., 2018).

Perhaps closest to our work is Eto (2019), who uses a combination of proximity measures from the graph of co-citations to score candidate documents. The edges in the graph are weighted by the distance in which two citations occur in the citing document. This method requires access to the full text of the citing document, which is often not available (for example, due to paywalled
content). Our method, on the other hand, predicts citations using only article abstracts, which are widely available in scientific corpora.

The methods described so far and the one proposed in this work fall in the category of global methods, which aim at recommending citations for the entire paper. Another category comprises local methods, which aim at recommending citations for a specific sentence or paragraph in the document (He et al., 2010; Lu et al., 2011; Huang et al., 2012; 2015). We do not compare our method with these as we do not assume access to the full text.

3 Method

In this work, we address the task of citation recommendation: given a partially written paper, the system’s task is to return all papers that should be cited in it. The input query \( q \) is the title and abstract of a paper, i.e., we do not have access to the full text. We argue that this assumption is crucial to building a useful tool as users might desire recommendations of related papers prior to writing most of the document.

Our method, illustrated in Figure 1, is a multi-stage ranking pipeline that comprises two main phases, Navigation and Ranking, which can be repeated for multiple iterations \( t < T, T \in \mathbb{N} \), where \( T \) is a hyperparameter.

In the first iteration \( (t = 0) \), the input to the method is the top-\( k_{t}^d \) papers \( D_t \) retrieved by a keyword search engine when queried with query \( q \). For \( t > 0 \), the input is the top-\( k_{t-1}^d \) papers \( D_{t-1} \) returned by the previous iteration.

**Navigation:** Given input \( D_t \), we collect papers \( C_t \) cited by \( D_t \). We limit the number of papers in \( C_t \) to \( k_{t}^c \) by incrementally removing citations from the lowest-ranked papers in \( D_t \). Both \( k_{t}^d, k_{t}^c \in \mathbb{N}^+ \) are hyperparameters of our method. The output of this phase is \( D_t \cup C_t \).

**Ranking:** We compute the probability \( p(d_t^i|q) \) for each paper \( d_t^i \in D_t \cup C_t \) being relevant to \( q \). For this, we use a BERT (Devlin et al., 2019) re-ranker model from Nogueira & Cho (2019). Using the same notation as Devlin et al., we feed the query tokens as sequence A and the candidate paper tokens as sequence B. In our task, both the query and the candidate paper are the concatenation of the title and abstract of each paper, resulting in an input that is often longer than the maximum tokens allowed by the model, which is typically 512 tokens. To circumvent this, we iteratively remove tokens from the largest sequence until the maximum number of tokens is reached. We use the model.

![Figure 1: Illustration of our proposed method. The goal of the task is to find papers that should be cited by a given paper \( q \), represented as the concatenation of its title and abstract. The input at iteration \( t = 0 \) is the top-\( k_{t}^d \) papers \( D_t \) retrieved by a keyword search engine when queried with \( q \) (in the figure, \( k_{t}^d = 2 \) and \( D_t = (d_1, d_2) \)). For \( t > 0 \), \( D_t \) is the output of the previous iteration. In the navigation phase, we collect papers \( C_t \) cited by \( D_t \) (in the figure, \( C_t = (d_3, d_4, d_5) \)). We limit the size of \( C_t \) to \( k_{t}^c \) by discarding the citations of the lowest-ranked papers in \( D_t \) (in the figure, \( k_{t}^c = 3 \) and \( d_6 \) is discarded). In the ranking phase, we use a trainable classifier to assign a relevance score with respect to \( q \) and each paper in \( D_t \cup C_t \) (in the figure). The output of an iteration of the method comprises the papers re-ranked according to these scores.](image-url)
as a binary classifier: we feed the [CLS] vector to a single layer neural network to obtain $p(d_i | q)$. The output of an iteration of our method is a list of papers $D_t \cup C_t$ ranked by $p(d_i | q)$. Training details are provided in Section 4.3.

Intuitively, our method tries to mimic a common user behavior: an initial set of candidate papers is refined by repeatedly gathering references from it and selecting the ones that deserve further reading. When multiple iterations are applied, the navigation phase allows exploration of distant literature while the ranking phase avoids an exponential growth of retrieved papers by keeping only the ones estimated as most relevant.

From another perspective, our method is similar to the beam search navigational algorithm proposed by Nogueira & Cho (2016). Ours, however, has broader applicability as we do not need a hierarchy of links (such as the ones in Wikipedia) to start navigating. Instead, we use keyword search to retrieve an initial set of candidate documents.

4 EXPERIMENTAL SETUP

4.1 DATASETS

Open Research. We train and evaluate our models on the Open Research corpus (Ammar et al., 2018). It comprises 7.2M computer science and biomedical paper abstracts and their references. We closely follow the data processing from Bhagavatula et al. (2018) to create the training, development, and test sets. That is, we sort papers by publication year and use the oldest 80% for training (1991–2014), the next 10% for development (2014–2015), and the most recent 10% for testing (2015–2016). Since the development and test sets are too large (400k+ papers), we randomly sample 20k examples from each set. We remove papers that do not cite any others or that have no year of publication. Finally, we remove citations of papers that are not in the corpus or whose publication year is less than that of the citing paper. Table 1 shows the statistics of the resulting dataset.

Note that our dataset statistics do not match the ones reported in Bhagavatula et al. (2018), but they match those output by the evaluation script provided by the authors. The difference is that the authors report in the paper statistics before the filtering steps (such as removing papers without references). Thus, our corpus and dataset splits match exactly the ones used by the authors to run their experiments.

DBLP and PubMed. The DBLP and PubMed datasets are introduced by Ren et al. (2014) and comprise papers from computer science and biomedicine, respectively. We apply the same data processing steps from Bhagavatula et al. (2018), and the resulting datasets are summarized in Table 1.

Table 1: Statistics of the datasets.

|                   | Open Research | DBLP | PubMed |
|-------------------|---------------|------|--------|
| Total # of docs   | 6,892,252     | 50,227 | 47,347 |
| Total # of citations | 44,400,729  | 156,807 | 825,371 |
| Avg. # citations per doc | 6.45         | 3.12  | 17.43 |
| Avg. len. per doc (char) | 1,391        | 1,193 | 1,504 |
| Queries - Train   | 3,343,809     | 27,322 | 26,793 |
| - Dev             | 487,582       | 8,324  | 2,768 |
| - Test            | 464,449       | 931    | 8,815 |
| q/rel. doc pairs - Train | 32,470,673  | 106,011 | 558,674 |
| - Dev             | 5,985,787     | 38,628 | 66,655 |
| - Test            | 5,944,269     | 12,168 | 200,042 |

4 https://s3-us-west-2.amazonaws.com/ai2-s2-research-public/open-corpus-archive/2017-02-21/papers-2017-02-21.zip
7 https://github.com/allenai/citeomatic/blob/master/citeomatic/scripts/evaluate.py
4.2 Duplication

When evaluating our method on DBLP and PubMed, we use models trained on Open Research’s training set as this yields better results than training on the much smaller DBLP and PubMed training sets. To avoid leaking training data into the evaluation sets, we use the following method to remove documents in Open Research’s training set that appear in the development and test sets of PubMed and DBLP. We remove special characters from the title and use Jaccard similarity to calculate the closeness of two documents. We set our shingles to a single word and our threshold to 0.7. This method results in approximately half of the papers in the development and test sets of PubMed and DBLP being removed from the training set of Open Research.

4.3 Re-Ranker Training

To obtain the positive and negative examples used to train our binary classification models, we retrieve the top 10 papers for a query using the Anserini IR toolkit\(^8\) (Yang et al., 2017; 2018) with BM25 ranking. Among these, less than 10% on average are relevant papers (positive examples). We do not balance positive and negative examples, and we discuss this decision in Section 5.2.

We start training from a pretrained BERT model and fine-tune it to our task using cross-entropy loss:

$$L = - \sum_{j \in J_{\text{pos}}} \log(p(d_j|q)) - \sum_{j \in J_{\text{neg}}} \log(1 - p(d_j|q)),$$

where \(J_{\text{pos}}\) and \(J_{\text{neg}}\) are the sets of indexes of the relevant and irrelevant papers, respectively, and \(p(d_j|q)\) is the relevance probability the model assigned to \(j\)-th paper.

We fine-tune the model using Google’s TPUs v3 with a batch size of 128 (128 sequences \times 512 tokens = 65,536 tokens/batch) for 300k iterations, which takes approximately three days. This corresponds to training on 38.4M (300k \times 128) query–candidate pairs, or 1.1 epochs. We do not see any improvements in the development set when training for another 700k iterations, which is equivalent to 3.8 epochs.

We use Adam (Kingma & 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. We use a dropout probability of 0.1 in all layers.

4.4 Inference and Metrics

At inference time, we first retrieve the top 1000 candidate documents with the title and abstract as the query using BM25 ranking in Anserini. These documents are optionally further expanded with the proposed navigation method and re-ranked with SciBERT-Large. Following Bhagavatula et al. (2018), we evaluate the models using \(F_1\) of the top 20 retrieved papers (\(F_1@20\)) and Mean Reciprocal Ranking (MRR) of top 1000 retrieved papers. We additionally report Recall@1000 to compare the effectiveness of our navigation phase with keyword-based search.

5 Results

Our main results are shown in Tables 2, 3, and 4. Our ranking model, SciBERT-Large, is selected based on the experiments in Section 5.1. On the Open Research dataset, our best configuration (BM25 + Navigation + ranking SciBERT-Large) improves upon the best previous result by more than 2 points on \(F_1@20\) and 11 points on MRR. On the smaller DBLP and PubMed datasets, our best method is on par with the state of the art. Note that our BERT-based models are trained only on Open Research as we achieve better results than training on the smaller datasets.

Our baseline BM25 implementation is 3–7 points higher in \(F_1@20\) than the implementation of Bhagavatula et al. This is due to the choice of query form, which is analyzed in Section 5.4, and perhaps a better implementation of BM25 in Anserini. Our method without the navigation component (BM25 + Ranking SciBERT-Large) is at least on par with the state-of-the-art method in this task (Citeomatic). By including documents from navigation (BM25 + Navigation + Ranking SciBERT-Large),

\(^8\)http://anserini.io/
we increase Recall@1000 by 10–20 points and $F_1@20$ by 1–2 points. The smaller improvement in $F_1@20$ compared to recall is unexpected, and we investigate this in Section 5.2.

Our method appears to be as effective and more scalable than a cluster-based approach. For example, Bhagavatula et al. (2018) requires at least 100 GB of RAM to search the 7M documents in the Open Research corpus,\footnote{https://github.com/allenai/citeomatic#citeomatic-evaluation} whereas keyword search has far more modest memory requirements.

In the next sections, we investigate the effectiveness of our method by evaluating various pretrained language models, as well as the effects of multiple iterations, class imbalance, and different queries.

### 5.1 IN- VS. OUT-DOMAIN PRETRAINING CORPUS

Here we investigate how different pretraining configurations change effectiveness in the target task. The results, shown in Table 5, are from fine-tuning the pretrained models on Open Research’s training set for 300k iterations with a batch of size 128, which corresponds to approximately 1.1 epochs. In the remainder of this paper, we call \textit{in-domain} corpus a collection whose majority of documents are of the same domains as those in Open Research (i.e., biomedicine and computer science), and we call \textit{out-domain} corpus a collection whose majority of papers are not from those domains.

The models pretrained on an in-domain corpus, i.e., BioBERT (Lee et al., 2019) (row 7) and SciBERT (Beltagy et al., 2019) (rows 8–11), give significant improvements in the target task.

|                      | $F_1@20$ Dev | $MRR$ Dev | $R@1000$ Dev |
|----------------------|--------------|-----------|--------------|
| BM25 (Bhagavatula et al., 2018) | -            | 0.058     | -            |
| BM25 (Anserini, Ours)          | 0.082        | 0.089     | 0.279        | 0.312        | 0.424        | 0.421        |
| Citeomatic (Bhagavatula et al., 2018) | -            | 0.125     | -            |
| BM25 + Ranking SciBERT-Large (Ours) | 0.136        | 0.132     | 0.430        | 0.431        | 0.424        | 0.421        |
| BM25 + Navigation + Ranking SciBERT-Large (Ours) | **0.154** | **0.148** | **0.451** | **0.445** | **0.658** | **0.624** |

Table 2: Main results on Open Research.

|                      | $F_1@20$ Dev | $MRR$ Dev | $R@1000$ Dev |
|----------------------|--------------|-----------|--------------|
| BM25 (Bhagavatula et al., 2018) | -            | 0.237     | -            |
| BM25 (Anserini, Ours)          | 0.105        | 0.194     | 0.352        | 0.585        | 0.669        | 0.691        |
| ClusCite (Ren et al., 2014)    | -            | 0.303     | -            |
| Citeomatic (Bhagavatula et al., 2018) | -            | 0.274     | -            |
| BM25 + Ranking SciBERT-Large (Ours) | 0.149        | 0.272     | 0.472        | **0.714**    | 0.669        | 0.691        |
| BM25 + Navigation + Ranking SciBERT-Large (Ours) | 0.148        | 0.277     | 0.469        | **0.714**    | **0.817**    | **0.862**    |

Table 3: Main results on DBLP.

|                      | $F_1@20$ Dev | $MRR$ Dev | $R@1000$ Dev |
|----------------------|--------------|-----------|--------------|
| BM25 (Bhagavatula et al., 2018) | -            | 0.209     | -            |
| BM25 (Anserini, Ours)          | 0.299        | 0.268     | 0.793        | 0.721        | 0.794        | 0.765        |
| ClusCite (Ren et al., 2014)    | -            | 0.274     | -            |
| Citeomatic (Bhagavatula et al., 2018) | -            | **0.329** | -            |
| BM25 + Ranking SciBERT-Large (Ours) | 0.326        | 0.304     | 0.835        | **0.792**    | 0.794        | 0.765        |
| BM25 + Navigation + Ranking SciBERT-Large (Ours) | 0.324        | 0.301     | 0.836        | **0.790**    | **0.903**    | **0.876**    |

Table 4: Main results on PubMed.
models pretrained on a corpus of a similar size but different domain (rows 3–5). Pretraining on an out-domain corpus ten times the size of the in-domain corpus results in lower effectiveness on the target task, RoBERTa (Liu et al., 2019) (row 6 vs. 10). We conclude that, at least for the task of citation recommendation, pretraining on a smaller in-domain corpus is more effective than pretraining on a larger but out-domain corpus.

When pretraining settings are kept the same except for the vocabulary, the use of in-domain vocabulary gives 5–10% improvement over out-domain vocabulary (row 8 vs. 9 and row 10 vs. 11). Beltagy et al. (2019) report a similar finding in other tasks.

NCBI models (Peng et al., 2019) (rows 1 and 2) are pretrained on an in-domain corpus but produce worse results than models pretrained on an out-domain corpus of a similar size (rows 3–5). They also underperform when compared to SciBERT-Base (row 8), which is pretrained on an in-domain corpus of a similar size but comprises full papers instead of abstracts. As noted by Beltagy et al. (2019), this result indicates that pretraining with longer documents improves the target task effectiveness.

We find that model size is even more important than document length; our SciBERT-Large models (rows 10 and 11) have higher effectiveness than the SciBERT-Base models (rows 8 and 9) despite being pretrained on a smaller corpus of 7M paper abstracts (1.4B tokens) as opposed to 1M full-text papers (3.2B tokens).

### 5.2 Multiple iterations

We evaluate our method with up to three iterations ($T = 3$) of navigation and ranking. The hyperparameters $k_d^2$ and $k_c^2$ are found by setting $k_d^2 + k_c^2 = 1000$, sweeping $k_d^2$ over \{0, 100, 200, ..., 1000\}, and using the values that yield the highest $R@1000$ on the development set of Open Research. These values are: $k_d^2 = 300$ ($k_c^2 = 700$), $k_d^2 = 700$ ($k_c^2 = 300$), and $k_d^2 = 900$ ($k_c^2 = 100$).

We show the development set results in Table 6. Although Recall@1000 increases with more iterations, $F_1@20$ and MRR reach their peak with one iteration. We conjecture that this is due to a
| Query Type              | Open Research | PubMed | DBLP |
|------------------------|---------------|--------|------|
|                        | F\textsubscript{1} @ 20 | MRR  | R\textsubscript{1000} | F\textsubscript{1} @ 20 | MRR  | R\textsubscript{1000} | F\textsubscript{1} @ 20 | MRR  | R\textsubscript{1000} |
| Key Terms (Whoosh)     | 0.065 0.251 0.282 | 0.201 0.595 0.604 | 0.130 0.425 0.510 |
| Title                  | 0.063 0.244 0.287 | 0.199 0.584 0.654 | 0.133 0.424 0.551 |
| Title and Abstract     | **0.095** 0.351 0.363 | **0.268** 0.720 0.765 | **0.194** 0.585 0.691 |

Table 7: BM25 results on Open Research’s development set when different query types are used. Navigation and BERT-based re-ranking are not applied.

limitation of our current re-ranker, whose effectiveness drops when candidate papers that have less lexical similarity (i.e., term overlap) with the query are presented at inference time. To support this claim, we empirically verify that the proportion of candidate document terms (excluding stopwords) that overlaps with the query (last column of Table 6) decreases by quite a bit as we go from one to two iterations, hence the drop in F\textsubscript{1} and MRR despite the increase in recall.

### 5.3 Class Imbalance

Because we only use the top 10 papers returned by BM25 as training examples, the BERT-based models in this work are trained with more negative examples than positive ones (94% vs. 6%). In a separate experiment, to balance these classes, we include in the training phase pairs of query and relevant papers not retrieved by BM25, but this results in F\textsubscript{1} and MRR close to zero in both training and development sets. We obtain a similar result when adding to the training set negative candidates randomly sampled from the corpus. We hypothesize that, although BERT is a strong model for the document ranking task, it partly relies on exact term match to learn relevance. Thus, when we sample training documents not using an exact term match method such as BM25, fewer terms between the query and the candidate paper match, making learning harder. Further studies should investigate if this limitation applies to other tasks as well.

### 5.4 Query Analysis

In the citation recommendation task, the query can take many forms, such as the title of the paper, the concatenation of title and abstract, or keywords extracted from the text. Here we investigate how these query types affect the effectiveness of a keyword-based retrieval method.

In Table 7, we show the effectiveness of BM25 on the Open Research development set. For **Key Terms**, we follow Bhagavatula et al. (2018) and use Whoosh\textsuperscript{10} to first create an index and then extract key terms from the title and abstract with Whoosh’s **key_terms_from_text** method. Despite being faster due to having fewer query terms, the results show that this method has lower effectiveness than simply concatenating the title and abstract of the paper.

One of the limitations of transformer-based models (including BERT) is that memory consumption increases quadratically with the number of tokens in the input sequence. On modern hardware such as TPUs v3 or GPU V100s, the maximum number of tokens that one can efficiently train a BERT-Large model is approximately 512. In our task, since the concatenation of query and candidate tokens is typically longer than this value, there is a trade-off between the number of tokens we allocate for each sequence type.

In Figure 2, we show how effectiveness changes as we allocate more tokens to the query than to the candidate document while limiting the sum of the two sequence types to 512 tokens. These results are obtained with BM25 + SciBERT-Base. The curve shows that query terms are more important to the re-ranker model, as increasing query tokens from 64 to 256 increases F\textsubscript{1} by 2 points. Decreasing candidate document tokens from 256 to 64 barely changes F\textsubscript{1}. This result is somewhat surprising as one expects the two sequences to have equal importance in the task of query–document relevance estimation. Note that in all previous experiments (Tables 2–6), we used 256 tokens for the query and 256 for the candidate; this suggests that our main results might be even higher had we tuned this hyperparameter as well. Future work should investigate if this is particular to citation recommendation, or if it also occurs in other retrieval tasks with lengthy queries.

\textsuperscript{10}https://whoosh.readthedocs.io/en/latest/
Figure 2: F$_1$ @ 20 on the development set when varying the number of tokens allocated to the input sequence (whose limit is 512 tokens) for the query (as opposed to the candidate document).

6 CONCLUSION

We provide an extensive evaluation of pretrained language models for the scientific literature recommendation task. We find that in-domain pretraining and domain-specific vocabulary greatly improve effectiveness. Local search in the graph of citations significantly mitigates the vocabulary mismatch problem due to “bag of word” initial retrieval: recall increases by 10–20 points in three datasets.

Additionally, we present two unexpected findings:

1. The effectiveness of BERT-based models degrades as the term overlap between query and candidate document decreases; increasing the number of training examples that have low query–candidate term overlap results in a poor model (i.e., does not fix this issue). This finding suggests that, despite the wealth of semantic knowledge captured by BERT-based models, they still rely to a large degree on exact term matches for this task.

2. Despite the symmetry of the two inputs when trying to estimate the relevance of a candidate article to a query article, we find that terms from the query article are more important than terms from the candidate article in allocating “space” for BERT input.

Future work should investigate these observations.

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REFERENCES

Waleed Ammar, Dirk Groeneveld, Chandra Bhagavatula, Iz Beltagy, Miles Crawford, Doug Downey, Jason Dzubelberger, Ahmed Elgohary, Sergey Feldman, Vu Ha, Rodney Kinney, Sebastian Kohlmeier, Kyle Lo, Tyler Murray, Hsu-Han Ooi, Matthew Peters, Joanna Power, Sam Skjonsberg, Lucy Wang, Chris Wilhelm, Zheng Yuan, Madeleine van Zuylen, and Oren Etzioni. Construction of the literature graph in Semantic Scholar. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 3 (Industry Papers), pp. 84–91, 2018.

Chumki Basu, Haym Hirsh, William W. Cohen, and Craig Nevill-Manning. Technical paper recommendation: A study in combining multiple information sources. Journal of Artificial Intelligence Research, 14:231–252, 2001.

Iz Beltagy, Arman Cohan, and Kyle Lo. SciBERT: Pretrained contextualized embeddings for scientific text. arXiv:1903.10676, 2019.
Chandra Bhagavatula, Sergey Feldman, Russell Power, and Waleed Ammar. Content-based citation recommendation. *arXiv:1802.08301*, 2018.

Kurt D. Bollacker, Steve Lawrence, and C. Lee Giles. A system for automatic personalized tracking of scientific literature on the web. In *Proceedings of the Fourth ACM conference on Digital Libraries (DL ’99)*, pp. 105–113, 1999.

Antoine Bordes, Sumit Chopra, and Jason Weston. Question answering with subgraph embeddings. *arXiv:1406.3676*, 2014.

Tsung Teng Chen and Maria Lee. Research paper recommender systems on big scholarly data. In *Pacific Rim Knowledge Acquisition Workshop*, pp. 251–260, 2018.

Rajarshi Das, Shehzad Dhuliawala, Manzil Zaheer, Luke Vilnis, Ishan Durugkar, Akshay Krishnamurthy, Alex Smola, and Andrew McCallum. Go for a walk and arrive at the answer: Reasoning over paths in knowledge bases using reinforcement learning. *arXiv:1711.05851*, 2017.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 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)*, pp. 4171–4186, 2019.

Duy Dinh and Lynda Tamine. Combining global and local semantic contexts for improving biomedical information retrieval. In *European Conference on Information Retrieval*, pp. 375–386, 2011.

Masaki Eto. Extended co-citation search: Graph-based document retrieval on a co-citation network containing citation context information. *Information Processing & Management*, 56(6):102046, 2019.

Nicolas Fiorini, Kathi Canese, Grisha Starchenko, Evgeny Kireev, Won Kim, Vadim Miller, Maxim Osipov, Michael Kholodov, Rafis Ismagilov, Sunil Mohan, James Ostell, and Zhiyong Lu. Best Match: New relevance search for PubMed. *PLoS Biology*, 16(8):e2005343, 2018a.

Nicolas Fiorini, Robert Leaman, David J. Lipman, and Zhiyong Lu. How user intelligence is improving PubMed. *Nature Biotechnology*, 36(10):937, 2018b.

Yong Gao, June Kinoshita, Elizabeth Wu, Eric Miller, Ryan Lee, Andy Seaborne, Steve Cayzer, and Tim Clark. Swan: A distributed knowledge infrastructure for Alzheimer disease research. *Web Semantics: Science, Services and Agents on the World Wide Web*, 4(3):222–228, 2006.

Paul Ginsparg. First steps towards electronic research communication. *Computers in Physics*, 8(4):390–396, 1994.

Kelvin Guu, John Miller, and Percy Liang. Traversing knowledge graphs in vector space. *arXiv:1506.01094*, 2015.

Qi He, Jian Pei, Daniel Kifer, Prasenjit Mitra, and C. Lee Giles. Context-aware citation recommendation. In *Proceedings of the 19th International Conference on World Wide Web*, pp. 421–430, 2010.

Wenyi Huang, Saurabh Kataria, Cornelia Caragea, Prasenjit Mitra, C. Lee Giles, and Lior Rokach. Recommending citations: Translating papers into references. In *Proceedings of the 21st ACM International Conference on Information and Knowledge Management (CIKM ’12)*, pp. 1910–1914, 2012.

Wenyi Huang, Zhaohui Wu, Chen Liang, Prasenjit Mitra, and C. Lee Giles. A neural probabilistic model for context based citation recommendation. In *Twenty-Ninth AAAI Conference on Artificial Intelligence*, 2015.

Rebecca N. Jerome, Nunzia B. Giuse, Kimbra Wilder Gish, Nila A. Sathe, and Mary S. Dietrich. Information needs of clinical teams: Analysis of questions received by the clinical informatics consult service. *Bulletin of the Medical Library Association*, 89(2):177, 2001.
Rob Johnson, Anthony Watkinson, and Michael Mabe. The STM report: An overview of scientific and scholarly publishing. *International Association of Scientific, Technical and Medical Publishers*, 2018.

Anshul Kanakia, Zhihong Shen, Darrin Eide, and Kuansan Wang. A scalable hybrid research paper recommender system for Microsoft Academic. In *The World Wide Web Conference*, pp. 2893–2899, 2019.

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

Ajith Kodakateri Pudhiyaveetil, Susan Gauch, Hiep Luong, and Josh Eno. Conceptual recommender system for CiteSeerX. In *Proceedings of the Third ACM Conference on Recommender Systems*, pp. 241–244, 2009.

Ni Lao and William W. Cohen. Relational retrieval using a combination of path-constrained random walks. *Machine Learning*, 81(1):53–67, 2010.

Steve Lawrence, Kurt Bollacker, and C. Lee Giles. Indexing and retrieval of scientific literature. In *Proceedings of the 8th ACM International Conference on Information and Knowledge Management (CIKM ’99)*, pp. 139–146, 1999.

Jinhyuk Lee, Wonjin Yoon, Sungdong Kim, Donghyeon Kim, Sunkyu Kim, Chan Ho So, and Jae-woo Kang. BioBERT: A pre-trained biomedical language representation model for biomedical text mining. *arXiv:1901.08746*, 2019.

Xi Victoria Lin, Richard Socher, and Caiming Xiong. Multi-hop knowledge graph reasoning with reward shaping. *arXiv:1808.10568*, 2018.

Haifeng Liu, Xiangjie Kong, Xiaomei Bai, Wei Wang, Teshome Megersa Bekele, and Feng Xia. Context-based collaborative filtering for citation recommendation. *IEEE Access*, 3:1695–1703, 2015.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. RoBERTa: A Robustly Optimized BERT Pre-training Approach. *arXiv:1907.11692*, 2019.

Yang Lu, Jing He, Dongdong Shan, and Hongfei Yan. Recommending citations with translation model. In *Proceedings of the 20th ACM International Conference on Information and Knowledge Management (CIKM ’11)*, pp. 2017–2020, 2011.

Sean M. McNee, Istvan Albert, Dan Cosley, Prateep Gopalkrishnan, Shyong K. Lam, Al Mamunur Rashid, Joseph A. Konstan, and John Riedl. On the recommending of citations for research papers. In *Proceedings of the 2002 ACM Conference on Computer Supported Cooperative Work*, pp. 116–125, 2002.

Sunil Mohan, Nicolas Fiorini, Sun Kim, and Zhiyong Lu. Deep learning for biomedical information retrieval: Learning textual relevance from click logs. In *BioNLP 2017*, pp. 222–231, 2017.

Muhammad Nabeel Asim, Muhammad Wasim, Muhammad Usman Ghani Khan, and Waqar Mahmood. Improved biomedical term selection in pseudo relevance feedback. *Database*, 2018, 2018.

Rodrigo Nogueira and Kyunghyun Cho. End-to-end goal-driven web navigation. In *Advances in Neural Information Processing Systems*, pp. 1903–1911, 2016.

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

Yifan Peng, Shangcai Yan, and Zhiyong Lu. Transfer learning in biomedical natural language processing: An evaluation of BERT and ELMo on ten benchmarking datasets. *arXiv:1906.05474*, 2019.

Xiang Ren, Jialu Liu, Xiao Yu, Urvashi Khandelwal, Quanquan Gu, Lidan Wang, and Jiawei Han. ClusCite: Effective citation recommendation by information network-based clustering. In *Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 821–830, 2014.
Stephen E. Robertson, Steve Walker, Susan Jones, Micheline Hancock-Beaulieu, and Mike Gatford. Okapi at TREC-3. In Proceedings of the 3rd Text REtrieval Conference (TREC-3), pp. 109–126, Gaithersburg, Maryland, 1994.

Scott Spangler, Angela D. Wilkins, Benjamin J. Bachman, Meenakshi Nagarajan, Tajhal Dayaram, Peter J. Haas, Sam Regenbogen, Curtis R. Pickering, Austin Comer, Jeffrey N. Myers, Ioana Roxana Stanoi, Linda Kato, Ana Lelescu, Jacques J. Labrie, Neha Parikh, Andreas Martin Lisewski, Lawrence Donehower, Ying Chen, and Olivier Lichtarge. Automated hypothesis generation based on mining scientific literature. In Proceedings of the 20th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1877–1886, 2014.

Justin Sybrandt, Michael Shtutman, and Ilya Safro. Moliere: Automatic biomedical hypothesis generation system. In Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, pp. 1633–1642, 2017.

Peilin Yang, Hui Fang, and Jimmy Lin. 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), pp. 1253–1256, 2017.

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