SciEv: Finding Scientific Evidence Papers for Scientific News

A Preprint

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Abstract

In the past decade, many scientific news media that report scientific breakthroughs and discoveries emerged, bringing science and technology closer to the general public. However, not all scientific news article cites proper sources, such as original scientific papers. A portion of scientific news articles contain misinterpreted, exaggerated, or distorted information that deviates from facts asserted in the original papers. Manually identifying proper citations is laborious and costly. Therefore, it is necessary to automatically search for pertinent scientific papers that could be used as evidence for a given piece of scientific news. We propose a system called SciEv that searches for scientific evidence papers given a scientific news article. The system employs a 2-stage query paradigm with the first stage retrieving candidate papers and the second stage reranking them. The key feature of SciEv is it uses domain knowledge entities (DKEs) to find candidates in the first stage, which proved to be more effective than regular keyphrases. In the reranking stage, we explore different document representations for news articles and candidate papers. To evaluate our system, we compiled a pilot dataset consisting of 100 manually curated (news,paper) pairs from ScienceAlert and similar websites. To our best knowledge, this is the first dataset of this kind. Our experiments indicate that the transformer model performs the best for DKE extraction. The system achieves a P@1=50%, P@5=71%, and P@10=74% when it uses a TFIDF-based text representation. The transformer-based re-ranker achieves a comparable performance but costs twice as much time. We will collect more data and test the system for user experience.

Keywords  Scholarly papers, Fake news, Web api, Deep learning, Domain knowledge entity, Embedding, Transformer

1 Introduction

Scientific news articles report scientific and technological progresses, breakthroughs, discoveries, and innovations. Scientific news is important media to disseminate scientific knowledge to the general public. Different from other types of news, such as political news, scientific news is believed to be written in the way such that it faithfully presents facts from the source. However, this may not always be the case. For example, exaggerations in popular scientific writing could misinform the public and even researchers [West and Bergstrom [2021]]. Since the start of Covid-19, public support for policies to control the spread of this virus is being undercut by misinformation, leading to the World Health Organization’s “infodemic” declaration [Zarocostas [2020]]. Scientific misinformation could be spread orally or over social media, causing social problems and further damage the credibility of scientific news. Effectively curbing scientific misinformation is crucial to avoid these problems.

In the past years, many websites that report scientific results in form of news articles have been launched. Examples of these websites include [ScienceAlert.com](http://ScienceAlert.com) and [ScienceDaily.com](http://ScienceDaily.com). Many articles published on these websites contain references to source papers. These references provide scientific evidence to the news content and boost the
**News article:**
The star in question is called **AG Draconis**: a well-known binary star that's been observed by astronomers since the late 19th century.

**Research paper:**
**AG Draconis** is a strongly interacting binary system which manifests characteristic symbiotic activity of alternating quiescent and active stages.

Figure 1: An example of a DKE (underlined) appearing in both a news article and a research paper.
third type (news→paper), a news article cites a scientific paper. Citing a news article in a research paper is relatively uncommon and beyond the scope of our study.

The collaborative filtering (CF) method has been widely used for news recommender systems since it was proposed by Melville et al. [2002]. This method requires building the document and the user profiles. However, the reading history of news articles is usually unknown, making it difficult to build user profiles.

Many citation recommender systems were proposed using different text representation models. Early work used Synset Frequency-Inverse Document Frequency (SF-IDF) to represent the news text. SF-IDF was similar to TF-IDF except that it used WordNet synonym sets to expand the semantic representation of a given word. Other types of work leverage word embeddings. For example, Peng et al. (2016) developed a news citation recommendation system using a word-embedding based re-ranking and grounded entities (i.e., explicit semantics). Okura et al. (2017) proposed a model called embedding-based news recommendation (EBNR) using the denoising autoencoders variant for news representations. Wang et al. (2018) utilized news titles and entities to represent the news via a knowledge-aware convolutional neural network (CNN). Saskr et al. (2019) developed a news recommendation system that combines news titles and bodies using average embeddings.

Depending on the type of input, citation recommendation systems can be classified into local and global citation recommendations. Local citation recommendation systems are based on text snippets, such as a sentence or even several words. Global citation recommendation systems make recommendations based on the full text or the abstract of a document.

We propose the Scientific Evidence paper retrieval system called SciEv, which can be classified as a news→paper recommender system based on global text. To our best knowledge, few systems have been proposed with the same functionality. Recently, many pre-trained language models were proposed (e.g., BERT), and have shown efficacy in retrieval tasks by representing text with distributed vectors, e.g., [Zhang et al. 2020]. This motivates us to compare these language models in the news→paper recommender system.

### 3 System Overview

The architecture of the SciEv system adopted a two-stage retrieval model proposed, e.g., [Zhang et al. 2020]. The architecture of the system contains four modules (Figure 2) as described below.

#### Preprocessing

The input of this module is an HTML page of a scientific news article, downloaded from the Web. Only textual content is retained for further analysis. In the experiments below, we used a preprocessor that parses web pages downloaded from ScienceAlert.com. The parser could easily be customized to parse news body text from other websites. The text was then cleansed so square brackets, extra spaces, special characters (such as @, #), and numerical digits were removed. Finally, the cleansed news article was segmented into sentences. Each sentence was tokenized and each token is labeled with part-of-speech (POS) tags.

#### DKE Extraction

As mentioned above, DKEs will be used as queries to retrieve candidate papers, so the next step is to extract them from the news article body text. We use DKEs instead of keyphrases or general name entities because DKEs represent the scientific domain knowledge and certain DKEs in news articles also appear in the source papers.
This module is based on a transformer model trained on a multi-domain corpus. We elaborate the DKE extraction in Section 5.1.

**Candidate Paper Retrieval (CPR)** This module searches for the scientific paper candidates using extracted DKEs as queries. Here, we assume a frequency-based ranking algorithm such as BM25 [Robinson and Zaragoza, 2009], which is implemented in popular search platforms, e.g., Apache Solr and Elasticsearch. In our experiment, we use arXiv.org, a digital repository that hosts around 2 million pre-printed papers covering major fields in Computer Science, Mathematics, Physics, Astronomy, Statistics, Materials Science, and Social Science. The website offers a free search API.

To obtain a high recall in this stage, we perform a union of multiple query results. Each query contains a single or a combination of up to 3 DKEs (connected by “AND”). The final candidate result list is obtained by merging the top 10 results of all queries and removing duplicate papers in terms of titles and authors. This step is necessary for narrowing down the search space because constructing vector representations for millions of papers and ranking them by cosine similarity could take impractically long time. This module reduces the candidate pool down to thousands of articles, and boosts the efficiency of the overall retrieval model. Empirically, the system finds approximately 500-3000 candidate papers for each news article.

**Paper Re-ranking** This module reranks candidate documents based on the vector representations of news articles and paper abstracts. The purpose of this step is to increase the precision by promoting scientific papers that are highly topically relevant to the news article. Here we apply cosine similarity, which is a common practice in many vector search engines (e.g., Covidx [Zhang et al., 2020]). The key is to generate a high-quality vector representation. The vector representation of the scientific paper is constructed by encoding the abstracts into a fix-length vector using a pre-trained language model. The vector representations of the news articles are constructed in a similar way. We investigate the performances of state-of-the-art language models.

### 4 Datasets

As mentioned above, to our best knowledge, we are not aware of existing datasets containing scientific news and corresponding research papers. Our pilot ground truth dataset is obtained using 100 scientific news articles downloaded from ScienceAlert, ScienceNews, EurekAlert, and Forbes. The articles were manually curated so that at least one source scientific paper is provided as a hypertext link or a reference in the original news article. We found up to 5 papers linking to a news article. The average length of these news articles is approximately 900–1000 words. The news articles are from a variety of domains such as history, arts, astronomy, biology, environment, computer science, and medicine.

We use two datasets for training the DKE extractor: the SemEval 2017 Task 10 dataset [Augenstein et al., 2017] and the OA-STM dataset. Scientific news articles can be written in multiple domains. To train a robust DKE extractor for articles in various domains, we pre-train a model using the SemEval 2017 Task 10 dataset [Augenstein et al., 2017], consisting of 500 passages extracted from journal papers in Computer Science, Materials Science, and Physics. The dataset was double annotated and three types of entities were identified, namely, MATERIAL, METHOD, and PROCESS. There are in total more than 7000 entities manually annotated from the whole dataset. However, this dataset covers only three domains, so we fine-tune the pre-trained model on the OA-STM dataset, containing pre-processed abstracts from scientific papers in 10 domains, including agriculture, astronomy, biology, chemistry, computer science, earth science, engineering, materials science, math, and medicine. There are 11 abstracts in each domain. For each abstract, four core scientific concepts were annotated including PROCESS, METHOD, MATERIAL, and DATA. There are in total 5595 entities annotated. Existing studies indicated that a classifier trained on data from all 10 domains performs better than trained on data from a single domain [Brack et al., 2020]. When using these two datasets, we collapse all categories into one category called DKE.

### 5 Methods

#### 5.1 DKE Extraction

DKE extraction can be seen as a named entity recognition (NER) task. Although many NER models have been proposed, there is not a consensus that a certain model definitely beats the others in all scenarios. The performance of NER models...
usually depends on data properties Li et al. [2022]. Therefore, we compare the following models in the DKE extraction task.

**BiLSTM-CRF and Res-BiLSTM-CRF** In this model, we applied the bi-directional long short-term memory (BiLSTM) model to obtain the hidden representation of a word level token, followed by a conditional random field (CRF) layer. This model has been applied for many NER tasks Huang et al. [2015b] and achieved state-of-the-art performance on standard datasets, e.g., Luo et al. [2020]. We also considered an alternative model with two BiLSTM networks with a residual connection. In the residual unit, the output of a shallow layer is directly added to the output of a deeper layer Srivastava et al. [2015]. Either model uses random weights as input and learns the hidden representation of each token from the context.

**BiLSTM-W2Vec** In this model, the representation of each token is constructed by concatenation of the hidden representation output by a BiLSTM with the pre-trained word2vec model Mikolov et al. [2013]. A CRF layer is then applied to classify each token.

**BiLSTM-ChE** Character embedding can be used for capturing morphological information of words Santos and Guimaraes [2015] and mitigating the out-of-vocabulary problem Verwimp et al. [2017]. In this model, we combine character and word level encodings. The first layer uses a BiLSTM to encode each character and combine them into a word-level vector. The second BiLSTM layer encodes each word-level token into a new vector. These two vectors are concatenated to generate the final representation of each work-level token. A CRF classifier is then applied to tag each token.

**BiLSTM-ChE-Attention** In this model, a self-attention layer is added after combining the character and word embeddings in the BiLSTM-ChE model.

**Res-BiLSTM-ELMo** ELMo is a context-dependent language model trained on the 1 Billion Word Benchmark Peters et al. [2018], providing word representations with rich features. In this model, we initialize the Res-BiLSTM model using the pre-trained ELMo embedding.

**Transformer Models** The aggregation of self-attention and positional encoding has made transformer models successful for many tasks such as named entity recognition (NER) Vaswani et al. [2017]. One representative language model is Bidirectional Encoder Representations from Transformers (BERT) Devlin et al. [2018], which has been successfully applied for NER Liang et al. [2020] and other downstream tasks. We implemented two transformer models. One model was trained from scratch on the OA-STM dataset. The other model was developed by fine-tuning a pre-trained BERT model as a backbone encoder on the OA-STM dataset. Before the classification layer, the BERT encoder extracts high-quality language features from our text data. Based on these features, the classification layer classifies these entities into DKEs and non-DKEs (Figure 3).

**Text-Rank** Text-rank is an unsupervised graph-based model inspired by Google’s PageRank algorithm to extract keyphrases Mihalcea and Tarau [2004]. The algorithm builds an undirected graph for each target document, in which
the nodes correspond to words in the target document, and edges are drawn between two words that occur next to each other in the text.

**HESDK**  HESDK is a hybrid approach to extract DKEs [Wu et al. 2017]. In the first phase, candidate phrases are extracted by a grammar-based chunk parser which is then filtered by a linear support vector machine (SVM). In the second phase, a CRF model is used to predict the probabilities of tags for a given token based on lexical and morphological features. The results from both approaches are merged and further filtered by a rule-based filter.

**Stanford NER**  To demonstrate the advantage of using DKEs, we extract regular named entities using the Stanford CoreNLP [Manning et al. 2014]. We use 7-class Stanford NER model trained on the MUC6 and MUC7 datasets. The model extracts seven named entities, including LOCATION, PERSON, ORGANIZATION, MONEY, PERCENT, DATE, and TIME.

Depending on the length of the news article, the DKE extractors can extract 50-200 DKEs per article, resulting in 500-3000 candidate scientific papers. For all baseline methods, we use the term frequency-inverse document frequency (TFIDF, see below) to represent news articles and scientific papers.

### 5.2 Document Embedding

In the reranking phase, we represent a news article and scientific paper abstracts with fix-length feature vectors. We compare both local and distributed representation models. First, although pre-trained language models have generally exhibited advantages over local representation models on many tasks, the performance of document representation could be task-dependent. If the similarity of two documents is not on the semantic level but on the literal level, pre-trained language models may lose the advantage. Second, language models on document representation is usually data dependent. The case is more challenging in our task as there is a discrepancy between vocabularies of news articles and research papers. General-use language models, such as BERT [Devlin et al. 2018], usually well-represent text prevalent in news and Wikipedia articles. Scientific language models, such as SciBERT [Beltagy et al. 2019], on the other hand, usually well-represent text used in scientific papers.

**TFIDF weighted Bag-of-Words (BoW)**  BoW is a traditional text representation model [Shahmirzadi et al. 2019]. In this model, each news article or the scientific abstract is represented as a sparse vector containing $|V|$ elements, in which $|V|$ is the vocabulary size of a retrieval corpus. Each element is the TFIDF value of the corresponding term. The retrieval corpus is defined as the combination of the news article and its candidate papers. The IDF for each term is calculated based on the retrieval corpus it belongs to.

**d2vec**  In this model, for each given document, the vector representation of each word is aggregated in a certain way to represent the whole document. We use the pre-trained word2vec model to calculate a 300 dimensional vector representation of each word. The document vector is the average of vectors of all tokens.

**Doc2vec**  Doc2vec is a model to create a vector representation of a document [Le and Mikolov 2014] of various lengths. The d2vec model above does not count the word sequence information and does not incorporate the context into the embedded vectors. In doc2vec, when training the word vectors, the document vector $D$ is trained as well. When the document sequence is finished, the document vector $D$ holds a representation of the document. We use the model implemented by Python Gensim Doc2Vec.

**Weighted Doc2Vec**  After getting document representation using the Python Gensim Doc2Vec, we extract word representation for each of the words from the document. We then weighted that word using the TFIDF value. Eventually, we combine all the word representation followed by feature-wise averaging to create a new document representation.

**SciBERT**  SciBERT is a transformer-based encoder trained on a large corpus of scientific text [Beltagy et al. 2019]. Because this model is trained on scientific literature, it has shown advantages over BERT in scientific text classification and summarization tasks [Gu et al. 2020], partially because its relatively larger vocabulary overlaps with the given corpus. We perform a similar aggregation to the d2vec to obtain the document embedding by averaging the vector representation of each token in a document.

**SBERT**  Sentence transformer or sentence-BERT (SBERT) is a modified version of the pre-trained BERT model [Reimers and Gurevych 2019]. It uses a Siamese network with the triplet loss function to produce sentence embeddings. Each sentence in a document is encoded using SBERT. We then use the averaged embedding as the document embedding.
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SPECTER  SPECTER is a document embedding model trained on EMNLP scientific publications ranging from 2016 to 2018 [Cohan et al. 2020]. The SPECTER model was designed to overcome the limitations of SciBERT by leveraging inter-document relatedness. This model uses a pre-trained SciBERT transformer model as a backbone and incorporates inter-document context into the SciBERT model. SPECTER builds embeddings from the title and abstract of a paper.

6 Evaluation and Comparison

6.1 Metrics

We use precision, recall, and F1 score to evaluate the DKEs extractor models. Precision is calculated as the ratio of correctly extracted DKEs divided by the total number of DKEs extracted. The recall is calculated as the ratio of the correctly extracted DKEs divided by the total number of DKEs labeled. F1 score is the harmonic mean of precision and recall. We use the following metrics to evaluate the system.

Mean-reciprocal-recall (MRR)  MRR is defined as

\[
\text{MRR} = \frac{1}{|Q|} \sum_{i} \frac{1}{\text{rank}(i)}
\]

in which \( Q \) is the total number of queries, and \( \text{rank}(i) \) is the rank of a relevant scientific paper. MRR assumes there is only one relevant document in the search results of each query. When evaluating queries corresponding to multiple papers, we use the top-ranked paper to calculate MRR.

Normalized Discounted Cumulative Gain (NDCG)  We use NDCG with a binary relevance. The metric was used for evaluating cases in which one query returns multiple relevant papers.

\( P@K \)  We use the precision at rank \( K \) to measure the fraction of relevant scientific papers within certain top results. It can be used when there are multiple relevant papers. We evaluate \( P@K \) when \( K = 1, 5, 10, 20, \) and \( 50 \).

6.2 DKE Extraction

DKE extraction is the key step to generate queries to retrieve paper candidates. Each model was trained on 80% documents from all domains and tested on 20% of documents on individual domains. Figure 5 shows the comparison of performance of DKE extraction models. The results indicate that the fine-tuned BERT model outperforms all other models, achieving a nearly perfect performance for all domains, with F1 varying from 0.92 to 1.00 depending on the
domain (Table 5). Specifically, the model correctly extracted all DKEs in the math domain. The superior results are attributed to the BERT transformer encode, which was pre-trained on CoNLL-2003 [Devlin et al. 2018]. The other models underperformed most likely because they were trained from scratch on much smaller training datasets and did not generalize well. Among these models, the ELMo-BiLSTM performed relatively better than its peer models. Specifically, the model achieved an F1=52.8%, 53.5%, and 51.1% for materials science, biology, and chemistry, respectively. The results verified the advantage of initializing the BiLSTM encoder with pre-trained language models, e.g., [Wu et al. 2020]. One interesting phenomenon is that adding self-attention to the BiLSTM-ChE model boosts the performance on certain domains such as agriculture, engineering, math, and biology but decreases the F1 scores of other domains.

Table 1: A comparison of our system in different settings.

| System setting name | Query type | DKE model | Text representation | P@K | MRR | Average NDCG | TPRR (sec) | T_all (sec) |
|---------------------|------------|-----------|-------------------|-----|-----|--------------|-----------|-----------|
| Baseline1            | –          | –         | –                 | 14%| –   | –            | –         | –         |
| Baseline2            | KP         | TextRank  | TFIDF             | 18%| –   | –            | –         | –         |
| Baseline3            | NE         | CoreNLP   | TFIDF             | 38%| –   | –            | –         | –         |
| Baseline4            | DKE        | HESDK     | TFIDF             | 39%| –   | –            | –         | –         |
| BERT-TFIDF           | DKE        | BERT      | TFIDF             | 50%| 71% | 74%          | 80%       | 86%       |
| BERT-d2vec           | DKE        | BERT      | d2vec             | 26%| 31% | 41%          | 55%       | 60%       |
| BERT-Doc2vec         | DKE        | BERT      | Doc2Vec           | 36%| 51% | 54%          | 64%       | 71%       |
| BERT-WdDoc2vec       | DKE        | BERT      | Weighted Doc2Vec  | 35%| 55% | 60%          | 68%       | 84%       |
| BERT-SciBERT         | DKE        | BERT      | SciBERT           | 19%| 30% | 36%          | 43%       | 67%       |
| BERT-SBERT           | DKE        | BERT      | SBERT             | 47%| 69% | 74%          | 82%       | 90%       |
| BERT-SPECTER         | DKE        | BERT      | SPECTER           | 41%| 69% | 73%          | 84%       | 91%       |

1 Quoted from Harrison et al. [2019]. The specific corpus used is not available, making it impossible to make a fair comparison.
2 Keyphrases extracted using TextRank [Mihalcea and Tarau 2004].
3 Named entities extracted using Stanford CoreNLP [Manning et al. 2014].
4 HESDK [Wu et al. 2017].

6.2.1 System Performance

Table 1 shows the performance of the system on retrieving scientific evidence papers. For each system setting, we report the query type, the model used for DKE extraction, and document representation, P@K, MRR, and the average NDCG. We also measured the time it takes to finish ranking (the PRR module only), and the overall time for the entire system (Figure 2). The runtime information can be important to deploy an online system. For comparison, we add four baseline settings, all using TFIDF weighted BoW model to represent documents but use different query types.

The results indicate that the BERT-TFIDF and the BERT-SPECTER settings achieved the top performances. The BERT-TFIDF model achieves the best P@1/5/10, MRR, and average NDCG. The BERT-SPECTER model achieves the best P@20 and P@50. Specifically, the best baseline (Baseline4), which retrieves 60% scientific papers within the top 50th position, whereas the BERT-SPECTER model can retrieve 91%. The result first demonstrates the efficacy of querying DKEs, as opposed to general named entities. In particular, retrieval settings using DKEs as queries outperformed all the retrieval settings using general named entities or keyphrases. Second, the relatively high P@K when K is high (k=20, 50) can be attributed to the powerful capability of the language models to capture the semantic similarities between news articles and papers. On the other hand, the simple TFIDF document presentation coupled with BERT model outperforms all other models when K=1, 5, and 10. This result indicates that the TFIDF model can capture news article and scientific paper pairs that exhibit higher literal similarities. However, when we lower the selection threshold (by increasing k), the most relevant scientific papers to news articles are more semantically similar. We postulate this could be attributed to paraphrasing instead of using exactly the same terms.

Through error analysis, we found that the major reason that caused our retrieval models to fail was that the scientific news contain much less DKEs. One example is a news article called “How to spot deepfakes? Look at light reflection in the eyes” [Harrison et al. 2019]. Other types of news articles use more images, videos, and equations to convey scientific discoveries, rather than plain text. One example is a news article titled “Math Genius Has Come Up With a Wildly Simple New Way to Solve Quadratic Equations” [Wu et al. 2020].

Regarding runtime, Baseline3 using the Stanford CoreNLP takes the shortest overall time of 13.90 seconds. The top performing setting BERT-TFIDF takes the shortest PRR time of 0.8 second and a relatively short overall time of 66.70 seconds. The BERT-SPECTER setting takes much longer time, which almost doubles the BERT-TFIDF model. From
In this work, we proposed a system called SciEv, which automatically recommends scientific papers given a scientific news article. Although this can be broadly treated as a citation recommender system, we introduced a new scenario, in which the citing document is a news article and the cited document is one or several research papers. Our system consists of four modules: preprocessing, DKE extraction, candidate paper retrieval using DKEs, and paper reranking based on document embedding. We trained a multi-disciplinary transformer-based transfer-learning model that beats other heuristic and learning-based models, achieving an F1=0.93–1. We also compares the capabilities of different document embedding models in capturing the similarities between the news article and research papers. Our experiments on different system settings indicated that using DKEs was an effective and efficient way to retrieve research papers given a scientific news article. However, the TFIDF representation seems more powerful than the language model (e.g., SPECTER) to find our scientific papers when K is relatively low (K < 20). The language model starts to exhibit advantages over TFIDF when the search results are more inclusive with a higher K (K ≥ 20 in our case). The results indicate that an ensembled re-ranking model may achieve an higher performance, which we will pursue in future work.

The ultimate goal is to build a public application that is capable of automatically assessing the credibility of scientific news, based on pertinent scientific papers. To this end, we need to find effective and efficient ways to find the most relevant ones pertaining to a given scientific news report from the vast amount of scholarly papers and to evaluate the consistency of a scientific report against a list of relevant publications. The SciEv system we proposed here answers the first question. However, the overall runtime is still over 10 seconds. In the future, we will consider a more efficient method to further reduce the overall runtime to seconds by parallelizing queries and text embeddings.

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### Appendix: DKE Extraction Performance Comparison

Figure 5 shows the differential performance of the DKE extractor for 10 domains in the OA-STM dataset.
Figure 5: A comparison of performances of DKE extraction models. For comparison, we also show a “Transformer” model without initializing tokens using the pre-trained BERT model. Categories along x-axis are below. Arg: agriculture; Astr: astronomy; Bio: biology; Chem: chemistry; CS: computer science; Eng: engineering; ES: environmental science; Math: mathematics; Med: medical science; MS: materials science.