**ABSTRACT**

In this paper, we propose a novel method for the prior-art search task. We fine-tune SciBERT transformer model using Triplet Network approach, allowing us to represent each patent with a fixed-size vector. This also enables us to conduct efficient vector similarity computations to rank patents in query time. In our experiments, we show that our proposed method outperforms baseline methods.

**CCS CONCEPTS**

- Information systems → Information retrieval
- Applied computing → Document searching

**KEYWORDS**

patent search, transformer models, information retrieval

## 1 INTRODUCTION

The number of patents is increasing rapidly with the incredible advances in scientific knowledge and technology. This brings many challenges for patent examiners as they have to compare each patent application against prior ones and determine whether it is novel. Therefore, we need effective search engines that can find relevant patents for a given patent application.

Prior-art search has particular challenges compared to typical search operations [5]. Firstly, the patent documents are generally long and use very technical language. Secondly, the documents are prepared to show the novelty of the application, instead of focusing on the similarities with the existing ones. Thirdly, it is a recall-oriented retrieval task as we have to find all relevant patents to detect the novelty of a patent application.

Prior work shows that BERT [2] based models achieve state-of-the-art results in various Natural Language Processing (NLP) tasks. Therefore, in order to find relevant patents for a given patent, we can fine-tune a BERT [2] model to directly predict the pairwise similarity between patents. However, this approach has two main shortcomings. Firstly, BERT models are capable of processing only 512 “tokens”, which corresponds to roughly 400 words on an average text. However, patents are generally much longer than 400 words and we have to provide two patent documents to calculate their similarity, reducing the number of tokens we can use for each patent. Therefore, this approach would force us to ignore many parts of patent documents. Secondly, given that we have millions of patents, predicting similarity scores using a fine-tuned BERT model for all patents for a given query patent would be excessively slow.

In this paper, we develop a novel method for overcoming the shortcomings discussed above. In particular, we represent each patent using SciBERT [1] allowing us to capture technical language used in patent documents. Next, we fine-tune SciBERT model based on Triplet Networks approach [3]. This allows us to derive a fixed vector for each patent document and apply efficient vector computations. In query time, we rank patents based on their cosine similarity to the query patent. In our experiments with 1.8M patents, we show that our proposed method outperforms baseline methods.

## 2 PROPOSED APPROACH

In this section, we explain the details of representing patents with SciBERT and Triplet Network based fine-tuning.

### 2.1 Patent Representation

BERT models are successful at catching the semantics of texts. However, the language of patent documents might include many technical terminologies while BERT is pre-trained using Wikipedia articles and BooksCorpus. Therefore, we exploit SciBERT [1], which is pre-trained on large multi-domain corpus of scientific publications, instead of using the original BERT.

Patent documents are generally much longer than BERT based models can process. We could truncate patent documents to meet the limits of BERT. However, it would mean ignoring many parts of the patent documents that might be useful for our search task. Therefore, in order to capture the semantics of patent documents, we create separate embeddings for the description ($d_j$) and claims ($c_j$) part of each patent. For descriptions longer than 400 words, we use TextRank [4] automatic summarization tool to reduce the text length to 400 words. However, for the claims part of patents, we do not use the text summarization but truncate the parts that exceed BERT’s token limit. This is because the first claim of patents is generally the main innovative part of the patents while the other claims are less important ones. Subsequently, we concatenate the vectors for the description and claim parts to form a single embedding for each patent and normalize them to have a unit norm. In order to give more emphasis to the description part of the patents than their claims, we multiply each element of $d_j$ by $\sqrt{0.8}$ and multiply each element of $c_j$ with $\sqrt{0.2}$. The parameters are selected arbitrarily. Note that because of the vector multiplication in cosine similarity calculation, the relative weights used for description and claims parts will be 8:2.

### 2.2 Fine-Tuning via Triplet Networks

We fine-tune SciBERT using Triplet Networks approach [3] which allows us to derive fixed-size embeddings for each patent, and thereby, apply efficient vector operations to calculate the similarity between patents. In the Triplet Network approach, we have to provide positive and negative samples for each patent such that the model can learn the semantic differences between relevant and not relevant
In particular, we construct 3 embeddings for each patent based on i) an anchor (i.e., the patent itself) patent \( (a) \), ii) a positive (i.e., relevant) patent \( (p) \), and iii) a negative (i.e., not relevant) patent \( (n) \). We calculate triplet objective loss as follows:

\[
\text{max}(\text{CosineDistance}(v_a, v_p) - \text{CosineDistance}(v_a, v_n) + \epsilon, 0)
\]

where \( v_a \), \( v_p \), and \( v_n \) are the embeddings for \( a \), \( p \), and \( n \), respectively. \( \epsilon \) is a margin ensuring that \( v_p \) is at least \( \epsilon \) closer to \( v_a \) than \( v_n \).

Obviously, the training data and the label distribution directly affect supervised models’ performance. Therefore, we take the following steps to select the patents given as positive and negative samples:

- We select ‘positive’ texts from the cited patents which have a similarity score of higher than 0.6 according to vectors provided by Google\(^1\).
- We select 20% of the negatives from the not-cited patents which are from the Cooperative Patent Classification (CPC) group of the anchor patent. Therefore, the model can learn textual properties of patents that are on a similar topic but not as close as the positive ones.
- We select 20% of the negatives from the patents which are not cited by the anchor patent but cited by the patents that it cites. This process allows us to train the models with negative samples that are not semantically far from the anchor patent.
- The remaining 60% of the negatives are randomly selected from the patents which are not cited by the anchor patent but have a similarity score of less than 0.6 based on Google’s vectors. Therefore, the model can learn the textual properties of patents that are distinctively different from the anchor.

### 3 EXPERIMENTS

We randomly select 2 million patents granted after 1980. Among these patents, 1,817,504 of them have a title, abstract, description, and claims sections. From this sample, we randomly select 5,000 patents for testing, and others are used in training. Following prior work \[5\], we consider cited patents as relevant ones and not-cited ones as not-relevant.

We train the model with four million examples (i.e., patent triplets). We use patents which have at least five backward and forward citations in total, as anchors in the training set. We train the model using 4 Nvidia Titan RTX GPUs with a batch size of 8, using Adam optimizer with a learning rate of \( 3e^{-6} \) with linear learning rate warm-up over 10% of the training data for 1 epoch.

We compare our model against BM25 and ‘TF-IDF ranking functions that Lucene\(^2\) provides. The results are shown in Table 1. We observe that our approach outperforms Lucene’s methods based on all four metrics, suggesting that our proposed method can be an effective solution for the prior-art search problem.

### 4 CONCLUSION

In this paper, we propose a novel method to represent patent documents by fine-tuning SciBERT with Triple Network approach. We show that our proposed method outperforms baseline methods in our experiments. In the future, we plan to extend our work in several directions. Firstly, we plan to use other variants of BERT pre-trained with different types of documents, e.g., PatentBERT. In addition, we plan to investigate which parts of patent documents are more important for the prior-art search task and how to best summarize them. Furthermore, we will investigate using BERT variants that have higher token limits. Finally, we believe that our model should be evaluated in various test collections and compared against other baseline methods.

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\(^1\)https://console.cloud.google.com/marketplace/details/google_patents_public_datasets/google-patents-research-data

\(^2\)https://lucene.apache.org/core/