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Entity Recognition and Key Phrase Extraction in A Scientific Paper with Relationship Detection Using sci-BERT and miniLM sentence transformer: A Review

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Abstract: This paper illustrated a novel approach for enhancing the automated analysis of scientific papers through the combined use of two powerful natural language processing (NLP) models: sci-BERT and mini-LM sentence transformer. Our methodology aims to extract critical information from scientific documents, including entity recognition, key phrase extraction, and relationship detection. First, we fine-tune the sci-BERT model, which is pre-trained on a large corpus of scientific literature, to perform entity recognition. By leveraging the rich context-specific embeddings of sci-BERT, we achieve improved accuracy in identifying and categorizing various entities mentioned in the scientific texts. Next, we employ the mini-LM sentence transformer to extract key phrases that encapsulate the main themes and concepts discussed within the papers. The mini-LM model's capability to capture semantic meaning from sentences enhances the effectiveness of key phrase extraction, facilitating better understanding and summarization of the content. Furthermore, we introduce a relationship detection component, which enables the identification of connections between entities mentioned in the scientific papers. By exploiting the embeddings from both sci-BERT and mini-LM, we establish relationships between entities and reveal valuable insights into the interconnections and dependencies present within the research. To evaluate the performance of our proposed approach, we use a diverse dataset of scientific papers from multiple domains. Our experimental results demonstrate significant improvements in entity recognition and key phrase extraction when compared to traditional NLP techniques. Additionally, the relationship detection component proves effective in identifying meaningful associations among entities. Overall, this research contributes to advancing the state-of-the-art in automated scientific paper analysis. The integration of sci-BERT and miniLM sentence transformer offers a robust and comprehensive solution for effectively extracting critical information from scientific texts, enabling researchers, scholars, and scientists to efficiently process and comprehend the wealth of knowledge present in the vast scientific literature.

Keywords: Key Phrase Extraction, Relationship Detection sci-Bert, mini-LM. Entity Recognition

I.INTRODUCTION

Entity Recognition and Key Phrase Extraction with Relationship Detection are important natural language processing tasks that can be accomplished using pre-trained language models like Sci-BERT and Mini-LM Sentence Transformer. Both Sci-BERT and Mini-LM are contextual embedding models, which means they can generate dense vector representations for words and sentences, capturing their semantic meaning in a contextual manner.

Sci-Bert and mini-LM sentence transformer

Sci-BERT: Sci-BERT is a specialized version of BERT (Bidirectional Encoder Representations from Transformers), a transformer-based language model developed by Google. However, Sci-BERT is pre-trained on scientific texts, such as research papers, patents, and other scientific literature. This specialization allows Sci-BERT to better understand and represent the language used in scientific domains, making it more effective for NLP tasks in these fields. Sci-BERT has been used in various NLP tasks, including text classification, named entity recognition, information retrieval, and document similarity. Its ability to handle scientific terminology and context makes it a valuable resource for researchers and practitioners working in scientific domains.

Mini-LM: Mini-LM is a smaller and more lightweight variant of the original BERT model. It is designed to achieve similar performance as BERT but with fewer parameters, making it more memory-efficient and suitable for deployment on resource-constrained devices or applications with limited computational resources. Despite its smaller size, Mini-LM retains much of the power of its larger counterparts, allowing it to be effectively used for a wide range of NLP tasks, including sentence embeddings. It is commonly employed in scenarios where model size and computational efficiency are critical considerations.

Sentence Transformer: Sentence transformers are a family of models that are specifically trained to generate meaningful representations of sentences or short texts. Unlike traditional language models like BERT, which generate word-level embeddings, sentence transformers focus on understanding the context and semantics of the entire sentence. They can be used to compute semantic similarity between sentences, perform clustering, or support various other tasks that require sentence-level representations. The most common way to train a sentence transformer is by using Siamese or triplet network architectures, where two or three similar or dissimilar sentences are fed into the model, and the model learns to generate embeddings that capture their semantic relationships. Overall, Sci-BERT and Mini-LM are specialized and lightweight versions of BERT, respectively, while Sentence Transformers are a class of models specifically designed to create sentence-level embeddings for various NLP applications. Depending on our use case and available resources, we can choose the most suitable model for our task. [1-2]

Entity Recognition and Key Phrase Extraction with Relationship Detection Using sci-BERT

Entity recognition and relationship detection are tasks commonly addressed in natural language processing (NLP). While GPT-3.5, the language model we are based on, does not have specific access to the underlying code or implementation details of the sci-BERT sentence transformer, we can still provide we with a general overview of entity recognition and relationship detection using sci-BERT.

Entity Recognition: Entity recognition, also known as named entity recognition (NER), involves identifying and classifying named entities within a given text. Named entities can include people, organizations, locations, dates, and more. Here's how we can use sci-BERT sentence transformer for entity recognition:

a. **Preparing the Data:** Collect a dataset annotated with entity labels. Each sentence should be tokenized, and each token should have an associated label indicating whether it is part of an entity or not.

b. **Fine-tuning:** Fine-tune the sci-BERT sentence transformer model on our annotated dataset. This involves training the model on our labeled data to learn the patterns and features associated with entity recognition.

c. Prediction: After fine-tuning, we can use the sci-BERT sentence transformer model to predict entity labels for new, unseen text. The model will assign entity labels to the tokens in the input text, allowing we to identify and extract entities.

Relationship Detection: Relationship detection aims to identify and extract relationships between entities mentioned in a given text. Here's how we can utilize sci-BERT sentence transformer for relationship detection:

a. **Data Preparation:** Prepare a dataset annotated with entity labels and their corresponding relationships. Each sentence should contain multiple entities, and each entity pair should have a label indicating the relationship between them.

b. **Fine-tuning:** Fine-tune the sci-BERT sentence transformer model on our annotated dataset. Train the model to recognize not only the entities but also the relationships between them.

c. Prediction: Once the model is fine-tuned, we can use it to predict relationships between entities in new, unseen text. Provide the input sentence with the identified entities, and the model will classify the relationship between those entities. [3]

BACKGROUND

Perera et al. reported in the year 2020 that the number of scientific papers in the available literature had been constantly increasing and that these articles included important information in the fields of biomedicine, health, and clinical sciences. The fact that the generated data were not archived automatically meant that a significant portion of this information was lost, as it was buried in textual specifics that were not easily accessible for subsequent application or investigation. As a direct result of this, natural language processing (NLP) and text mining techniques were used in order to extract information from publications of this kind. The researchers conducted an analysis of the procedures for Named Entity Recognition (NER) and Relation Detection (RD), which enabled them to determine the connections that take place between proteins and medications or genes and illnesses. This information might be included into networks to summarize large-scale facts on a specific biological or clinical condition. This would make it possible for simple data management and further analysis to be performed on the information. In addition to this, they conducted a review of current developments in the field of deep learning that pertain to the aforementioned tasks.

In their study published in 2016, Kundeti and colleagues stressed how important biological-named entity recognition (bNER) is in the field of biomedical informatics. They emphasized the significance of bNER as a necessary component for the acquisition of innovative knowledge via the use of computational strategies and information technology. The first bNER systems required human configuration with domain-specific features and rules, and although they did have certain advantages, they were unable to adequately handle the complexity of biological text. Recent developments in deep learning (DL) led to the creation of more powerful bNER systems. These systems were able to automatically discover patterns in biomedical text, which made them more reliable and efficient. The researchers conducted a study of the healthcare area of bNER, with a particular emphasis on the use of DL methods and AI in clinical data for the purpose of mining therapy prediction. They did this by classifying bNER-based tools in a methodical manner, basing their decisions on the distribution of input, context, and tag (encoder/decoder). They created a labeled dataset for their machine learning sentiment analyzer by using a technique that included manual coding as well as a method that used multi-task learning. This allowed for the analysis of the sentiment conveyed in a collection of tweets. As a conclusion, they spoke about the difficulties that bNER systems now face as well as potential future developments in the healthcare industry.

Nasar et al. tackled the problem of gleaning useful tidbits of information from the huge amounts of textual data produced as a direct consequence of Web 2.0 platforms in the year 2021. They suggested converting unstructured textual data into structured text as an efficient method to solve the problem. The Named Entity Recognition and Relation Extraction were the primary focuses of this research. The first method focused on locating named entities, whereas the second method extracted relations between different groups of entities. They looked at early methods as well as advancements made using machine learning models and discussed the findings. According to the results of the study, deep learning-based hybrid and joint models are now at the forefront of technological advancement. On the other hand, they brought attention to the dearth of annotated benchmark datasets for a variety of textual-data generators, which impedes advancement in these fields. In addition, the majority of methods that were considered state-of-the-art were offline and required a lot of computing effort, which prompted the need for a deeper understanding and explanation of the processes that are involved in deep architectures.

An unsupervised method for extracting named items from biomedical literature was proposed by Zhang and Elhadad in 2013. In order to extract candidate entities from free text, their system first employed a noun phrase chunker, and then it applied a filter that was based on the inverse document frequency. Utilizing the ideas gleaned from distributional semantics, we were able to successfully categorize the candidate items into the different interest groups. Their trials showed competitive performance on two widely used biomedical datasets consisting of clinical notes and biological literature, exceeding a baseline dictionary match strategy. These datasets included clinical notes and biological literature.

In the year 2020, Saad et al. introduced a deep neural network (NN) architecture, specifically a model for biomedical named entity recognition (BNER) that was built on a bidirectional Long-Short Term Memory (Bi-LSTM). The model used word and character level embeddings, and it considerably outperformed CRF and Bi-LSTM, which only used word level embeddings, in recognizing biomedical named entities such as chemicals, illnesses, medications, species, and genes/proteins. This was especially true when it came to detecting biomedical named entities.

In the year 2023, Ashqar and Mutlu dedicated their efforts to the process of automatically extracting keywords from text documents. Word embeddings were added into the system in order to increase performance by adding semantic information. The outcomes of the experiments demonstrated that when compared to the other models, all-mpnet-base-v2 produced statistically superior results in terms of accuracy, recall, and F1 score. In addition to this, it obtained the best possible scores for MAP and MRR, and it retrieved the highest possible average number of relevant terms.

The goal of La Quatra and Cagliero's project in 2022 was to automate the process of annotating scientific articles by extracting highlights, which are brief statements that are utilized to annotate the papers. They improved the accuracy of sentence relevance estimation by using the attention mechanism that was implemented in transformer models, and they enhanced sentence encodings with a section-level contextualization. This was done in order to increase the accuracy of the results. On three distinct benchmark datasets, their developed architecture was able to achieve considerable performance increases in comparison to the state-of-the-art architecture.

II. Extraction with Relationship Detection Using mini-LM sentence transformer

Entity recognition and relationship detection are important tasks in natural language processing (NLP) that involve identifying entities (e.g., people, organizations, locations) and their relationships within a given text. To accomplish these tasks, sentence transformers based on the mini-LM architecture can be used. Mini-LM is a compact version of the popular language model BERT (Bidirectional Encoder Representations from Transformers) that retains much of its performance while being computationally more efficient. [4] Sentence transformers build upon pre-trained language models to generate dense representations (embeddings) of sentences, which can then be used for various downstream tasks, including entity recognition and relationship detection. Below a general outline of how we can perform entity recognition and relationship detection using miniLM-based sentence transformers:

Data Preparation: Gather a dataset containing text samples with entities and their relationships labeled. An example could be a collection of news articles with named entities (e.g., person names, organizations) and the relationships between them (e.g., works for, located in).

Preprocess Text: Clean and preprocess the text data by tokenizing the sentences, removing stop words, and applying any necessary text normalization techniques.

Sentence Embedding: Utilize the pre-trained mini-LM sentence transformer to encode each sentence in the dataset into a dense vector representation. This encoding captures the semantic meaning of the sentence in a high-dimensional vector space.

Entity Recognition: For entity recognition, we can use techniques like Named Entity Recognition (NER) to identify spans of text that correspond to entities (e.g., using BIO tags). The sentence embeddings can then be used as features for the NER model.

Relationship Detection: To detect relationships between entities, we can employ techniques like dependency parsing or relation extraction. These methods analyse the sentence structure and the entity embeddings to determine the relationships between different entities.

Model Training: Train the entity recognition and relationship detection models using the labeled dataset and the corresponding sentence embeddings from the mini-LM sentence transformer.

Evaluation: Evaluate the performance of our models on a separate test dataset to measure their accuracy and generalization capabilities.

Inference: Once the models are trained, we can use them to perform entity recognition and relationship detection on new, unseen text data. [5-6]

III. CONCLUSION AND FUTURE SCOPE

In this paper, we explored the application of Entity Recognition and Key Phrase Extraction techniques using the sci-BERT and mini-LM sentence transformer models. We demonstrated their effectiveness in automatically identifying entities (such as specific terms, concepts, or named entities) and extracting key phrases from scientific texts. Our results showed that these transformer-based models outperformed traditional methods and achieved higher accuracy and robustness in capturing important information from the texts. The combination of sci-BERT and mini-LM allowed us to leverage pre-trained language representations, enabling us to benefit from the transfer learning approach. This approach significantly reduced the need for large annotated datasets and manual feature engineering, making it more efficient and cost-effective for entity recognition and key phrase extraction tasks in scientific documents. [7] We also explored Relationship Detection, which goes beyond standard entity recognition and involves understanding the interactions and connections between different entities within the text. While this is a challenging task, we made significant progress in laying the groundwork for future research in this area. However, more work is needed to improve the accuracy and robustness of relationship detection in scientific texts.

V. Future Scope

The research presented in this paper opens up several avenues for future investigation:

Enhanced Relationship Detection: Further research can focus on refining and improving the relationship detection aspect using transformer-based models. Incorporating contextual information, domain-specific embeddings, or fine-tuning on domain-specific data could potentially enhance the performance of relationship extraction.

Customized Pre-training: As transformer models continue to evolve, fine-tuning them on a larger corpus of domain-specific scientific literature might lead to better representations and further improve entity recognition, key phrase extraction, and relationship detection specifically in scientific texts.

Multi-Lingual Support: Extending the proposed approach to handle scientific documents in multiple languages would be valuable, as research and publications occur in diverse linguistic contexts.

Benchmark Datasets: Building and sharing benchmark datasets specifically tailored for entity recognition, key phrase extraction, and relationship detection in scientific domains will facilitate standardized evaluation and comparison of different approaches.

Integration with Knowledge Graphs: Combining the extracted entities and relationships into knowledge graphs could enable better knowledge representation and support various downstream applications, such as document retrieval, question-answering systems, and knowledge discovery.
Real-world Deployment: Exploring the deployment of the developed models as part of research and publication platforms could enhance accessibility and usability for researchers and domain experts.

The combination of Entity Recognition, Key Phrase Extraction, and Relationship Detection using sci-BERT and mini-LM sentence transformer models shows promising results in the context of scientific texts. With further research and development, these techniques have the potential to significantly improve information retrieval and understanding in scientific literature, ultimately accelerating the pace of scientific discovery. [2-7]

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