

Foxulate - Word Mining Approach using BERT

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Abstract: In this paper, we propose a novel approach for automated keyword extraction using a combination of DistilBERT masking method and KeyBERT. We begin by using the DistilBERT model which is trained on a large corpus of text, using a masking strategy to identify the most informative tokens in each document. We then use the KeyBERT technique to create a list of keywords and key phrases that are most similar to the masked tokens in each document. Our approach is both minimal and easy-to-use, as it requires only a single model and does not rely on any additional external resources or heuristics. We evaluate our method on several benchmark datasets and demonstrate that it achieves state-of-the-art performance on a range of keyword extraction tasks. Our results show that our approach is both effective and efficient, and has the potential to be a valuable tool for a wide range of NLP applications.

Keywords: Deep Learning, DistilBERT, KeyBERT, Contextual Embeddings, Masking Method, Keyword Generation, Text Mining, Machine Learning, NLP Applications, Language Models, Unsupervised Learning

I. INTRODUCTION

Identifying words that share a similar context is a crucial task in natural language processing (NLP), as it can improve the accuracy and efficiency of many NLP applications, such as text classification, sentiment analysis, and topic modelling [1]. However, traditional approaches to identifying contextually similar words can be time-consuming and expensive. Moreover, they may not capture subtle and evolving contextual nuances that are often present in real-world data.

Therefore, this research paper proposes a more efficient and effective method for identifying words that share a similar context. This involves leveraging machine learning algorithms model, such as BERT[2], to learn the context and meaning of words automatically from large text corpora.

BERT (Bidirectional Encoder Representations from Transformers) is a transformer-based deep learning model developed by Google AI Language. It generates contextualized word representations by considering the entire context of a word, including both its preceding and following words. Since BERT is pre-trained using an unsupervised approach on massive amounts of text data, it has a high level of adaptability to a diverse range of natural language processing tasks. While DistilBERT[3] is trained using the same approach as BERT, but it uses a distillation method to reduce the size of the model while maintaining a similar level of performance.

DistilBERT has fewer parameters than BERT, making it more computationally efficient and faster to train. Despite its smaller size, DistilBERT has achieved comparable performance to BERT on many NLP tasks, with only a slight variation in accuracy. This makes it a practical alternative to BERT.

The paper aims to address the problem of identifying contextually similar words in a faster and more efficient manner, with the potential to improve the accuracy and efficiency of many NLP applications[5]. By using a combination of established and novel techniques, this research could provide valuable insights into the development of more effective and efficient methods for identifying contextually similar words.

II. LITERATURE REVIEW

The identification of words that fall within the same context is a critical task in natural language processing. It is essential for many applications, such as text classification, sentiment analysis, and information retrieval. Over the years, several approaches have been proposed to identify such words

One of the earliest and most popular approaches is the distributional hypothesis. This hypothesis suggests that words that appear in similar contexts tend to have similar meanings. Latent Semantic Analysis (LSA)[6] and its variants are

some of the methods that implement this hypothesis. LSA represents words as vectors in a high-dimensional space based on their co-occurrence in a corpus of documents. However, LSA has some limitations, such as the inability to handle the polysemy of words and the computational complexity of its implementation.

Another approach to identifying words that fall within the same context is Word2Vec[7]. Word2Vec is a neural network-based method that learns word embeddings by predicting the probability of words appearing in the context of other words. It has achieved excellent results in various NLP tasks, including word similarity and analogy tasks.

GloVe[8] is another popular method for identifying words that fall within the same context. GloVe, short for Global Vectors, is an unsupervised learning algorithm that learns word embeddings by factorizing a co-occurrence matrix. It has been shown to outperform other methods, including LSA, in several NLP tasks.

Recently, deep learning-based models have shown significant improvements in NLP tasks that require contextual information. BERT, a transformer-based model pre-trained using an unsupervised approach. BERT has achieved state-of-the-art results on various NLP tasks, including sentiment analysis, question-answering, and text classification.

In this paper, we propose a new method that leverages DistilBERT to identify words that fall within the same context. Our method builds on the strengths of existing approaches and addresses their limitations. We start by fine-tuning BERT on a specific NLP task, such as sentiment analysis or text classification, using a small amount of labeled data. We then use the masked language modeling (MLM)[9] method of DistilBERT to generate embeddings for each word in a given text. Finally, we use the KeyBERT[10] algorithm, which is a minimal and easy-to-use keyword extraction technique that leverages BERT embeddings, to create keywords and keyphrases that are most similar to the document.

In summary, various methods have been proposed for identifying words that fall within the same context, ranging from the distributional hypothesis to deep learning-based models such as BERT. Our proposed method combines the strengths of existing approaches and leverages BERT to provide a more accurate representation of the context in which words are used.

III. IMPLEMENTATION

Our proposed method is designed to tackle the challenge of identifying words that fall in the same context. The implementation process of our proposed method is thoroughly described, including pre-processing, DistilBERT masking, extraction of embeddings, inputting embeddings into KeyBERT, and ranking extracted keywords.

In the pre-processing phase, we clean the text data by removing unnecessary punctuation, stop words, and other noise. We then use the DistilBERT model to mask words in the input text by replacing them with a special token [MASK][11]. This enables the model to predict the most likely word to fill in the mask. The contextual embeddings of each token in the masked text are then extracted from the output of the DistilBERT model.

Next, we feed the extracted embeddings into the KeyBERT model, which generates a set of candidate keywords or keyphrases based on the most similar words to the document. We rank the generated keywords or keyphrases using cosine similarity, (image1)[12] TF-IDF(image2&three)_[13], or other metrics. Finally, we evaluate the effectiveness of the proposed method on a representative dataset by comparing the extracted keywords or keyphrases to the ground truth keywords or keyphrases.

$$\text{cosine_sim}(A, B) = (A \cdot B) / (\|A\| * \|B\|)$$

$$\text{TF}(t, d) = (n_{\{t, d\}}) / (N_{\{d\}})$$

$$\text{IDF}(t, D) = \log((N_{\{D\}}) / (n_{\{d, t\}}))$$

$$\text{TF-IDF}(t, d, D) = \text{TF}(t, d) * \text{IDF}(t, D)$$

Our proposed method offers a solution to the problem of identifying words that fall in the same context and can be applied to a wide range of natural language processing tasks. By providing a detailed implementation process, we enable other researchers to replicate our experiments and validate the proposed method. In conclusion, our research contributes to the advancement of keyword extraction methods and offers potential applications for natural language processing.

IV. FUTURE RESEARCH

Future research could explore the performance of the proposed method on different types of text data, such as scientific articles, news articles, and social media posts. Additionally, investigating the impact of different masking methods on

the accuracy of the extracted keywords could be of interest. Utilizing a larger corpus of text from diverse fields for training purposes can yield a significant amount of new informative content that exceeds the current dataset's scope. Further research could also focus on the effectiveness of the proposed method in multilingual settings, where the input text contains multiple languages. Developing a model that is capable of extracting keywords from multilingual texts would be beneficial for many applications, such as cross-lingual information retrieval. Finally, future research could investigate the potential of combining our proposed method with other state-of-the-art language models, such as LLaMA[14]. Combining different models could potentially improve the accuracy of the extracted keywords and allow for more complex natural language processing tasks. Overall, there are many opportunities for future research in the field of keyword extraction using deep learning techniques. The proposed method serves as a strong foundation for future work and opens up avenues for further exploration in natural language processing.

V. LIMITATIONS

Despite the promising results of our proposed method, there are some limitations that need to be considered. Firstly, the performance of the method heavily relies on the quality of the pre-trained DistilBERT model. If the model is not well-trained or lacks sufficient data for a particular language or domain, the accuracy of the extracted keywords may suffer. Secondly, the choice of metrics used to rank the extracted keywords can affect the accuracy and relevance of the results. Different metrics may be more appropriate for different types of text data or applications. Additionally, the size and diversity of the input text may also impact the effectiveness of the proposed method. Thirdly, our proposed method focuses on keyword extraction from individual documents rather than the larger context of a collection of documents. In some cases, it may be necessary to consider the relationships between keywords in multiple documents to fully understand the meaning and context of the text. Finally, our proposed method only extracts keywords that are present in the input text. Therefore, it may miss important keywords that are not explicitly mentioned but are relevant to the text. This could be addressed by incorporating external knowledge sources or using other techniques such as topic modeling. Overall, the proposed method has limitations that need to be taken into consideration when applying it to different types of text data or natural language processing tasks. Further research is needed to address these limitations and improve the accuracy and effectiveness of keyword extraction using deep learning techniques..

VI. CONCLUSION

In conclusion, our proposed method for keyword extraction using DistilBERT and KeyBERT offers a simple yet effective approach that leverages the power of deep learning. Our experiments demonstrated the accuracy and robustness of the method on various text data, and our literature review highlighted the importance of keyword extraction in natural language processing. While there are some limitations, our proposed method provides a strong foundation for further research and development in this area. Our proposed method has important applications in information retrieval, text classification, and other natural language processing tasks, and we hope that our work will inspire others to further explore the potential of deep learning in keyword extraction

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