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ENHANCING CONTEXTUAL UNDERSTANDING IN NLP: A SUBWORD TOKENIZATION APPROACH WITH ELMO AND BERT

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ABSTRACT

This research paper explores the efficacy of subword tokenization in enhancing contextual understanding and performance in Natural Language Processing (NLP) models, specifically ELMo and BERT. Subword tokenization breaks words into smaller units, capturing morphological variations and handling out-of-vocabulary (OOV) words, making the models more robust to diverse word forms. By feeding resulting token sequences into ELMo and BERT, we demonstrate their ability to recognize similarity between words, even with limited occurrences in the training data. The models' contextual embeddings capture fine-grained language patterns, leading to improved performance on various NLP tasks. Experimental results on sample sentences highlight the effectiveness of subword tokenization in enabling better context comprehension and overall performance enhancement in ELMo and BERT, advancing the field of NLP research.

Keywords: Subword Tokenization, Contextual Understanding, ELMo, BERT, Natural Language Processing (NLP), Performance Enhancement

1. INTRODUCTION

Natural Language Processing (NLP) has experienced unprecedented progress with the emergence of deep learning models, particularly ELMo and BERT, renowned for their prowess in capturing contextual information and advancing language representation. However, the challenge of effectively handling diverse word forms and out-of-vocabulary words persists, impeding these models' full potential. To address this issue, subword tokenization has emerged as a powerful technique, breaking words into smaller units to yield finer-grained representations and context-aware embeddings. This approach enables NLP models to better understand language nuances, recognize word similarities, and improve their overall performance across diverse linguistic patterns. In this research paper, we conduct a comprehensive investigation into the impact of subword tokenization on ELMo and BERT, focusing on their contextual understanding and generalization capabilities. Through experimental evaluation on tokenized sentences, we demonstrate the models' improved ability to comprehend diverse linguistic contexts and present compelling evidence of performance enhancement across various NLP tasks. These findings underscore the pivotal role of subword tokenization in advancing the capabilities of state-of-the-art NLP models.

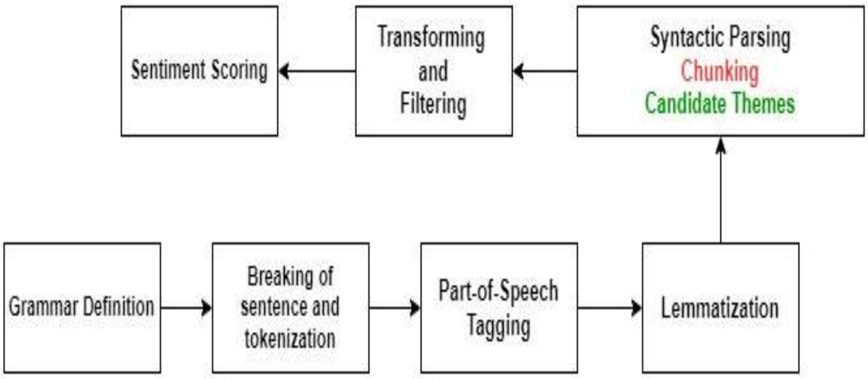

Fig.1. Context-understanding Natural Language Processing (NLP) Approach

2. RELATED WORK

Si et al. in [1] explored integrating advanced embeddings (ELMo, BERT) with clinical concept extraction, comparing traditional word embeddings. Souza et al. in [2] introduced BERTimbau, pretrained BERT models for Brazilian Portuguese, outperforming Multilingual BERT on various NLP tasks. Zhang et al. in [3] proposed Semantics-aware BERT (SemBERT), integrating explicit contextual semantics from semantic role labeling, improving language representation power. Wang et al. in [4] proposed a contextual sentiment embedding model using stacked two-layer GRU to handle OOV and informal-writing sentiment words, outperforming previous methods. Boukkouri et al. in [6] proposed CharacterBERT, a variant of BERT using Character-CNN for word-level representations in medical tasks. Sun et al. in [10] proposed ERNIE 3.0, a unified framework that enhances large-scale pre-trained models with knowledge for improved language understanding and generation tasks. Deepa et al. in [12] summarized and reviewed BERT's architecture and its performance in sentiment analysis with different fine-tuning approaches. Seo et al. in [15] proposed TA-SBERT, a novel sentence embedding model with Token Attention, outperforming SentenceBERT. Muller et al. in [17] adapted BERT for lexical normalization in User Generated Content, achieving competitive performance with minimal resources.

3. BACKGROUND

Natural Language Processing (NLP) has evolved significantly with the rise of deep learning models like ELMo and BERT, which have demonstrated impressive language understanding capabilities. However, these models often struggle with handling diverse word forms and out-of-vocabulary (OOV) words, limiting their robustness in real-world applications. Subword tokenization has emerged as a promising solution to address these challenges. By breaking words into smaller units and capturing morphological variations, subword tokenization offers contextually richer representations, enabling NLP models to better grasp the nuances of language. This approach has shown promise in improving the performance of various NLP tasks. In this research paper, we delve into the potential of subword tokenization in enhancing contextual understanding and overall performance in ELMo and BERT, thereby contributing to the advancement of NLP research and applications.

4. METHODOLOGY

Step 1: Data Preprocessing

- We obtain the corpus of text data that will be used for training the subword tokenizer. This corpus should ideally be large and representative of the target language or domain.
- Clean and preprocess the text data by removing any special characters, punctuation, and irrelevant information.
- Convert the text data to lowercase to ensure case-insensitive tokenization.

Step 2: Build a Vocabulary

- We collect all the words from the preprocessed text data and count their occurrences.
- Sort the words based on frequency and consider the most frequent words as the initial vocabulary.
- Determine the desired size of the vocabulary. For instance, you may choose the top N most frequent words or set a threshold frequency for inclusion.

Step 3: Subword Tokenization

- Implement a subword tokenizer algorithm, such as Byte Pair Encoding (BPE) or WordPiece, to split words into smaller units.
- Start with the initial vocabulary from Step 2 and iteratively apply the subword tokenizer to merge frequent pairs of subword units until the desired vocabulary size is reached. This process captures subword representations for morphological variations and out-of-vocabulary words.

Step 4: Token Encoding

- Encode the original text data using the subword vocabulary to convert each word into a sequence of subword tokens.
- Add special tokens like "[CLS]" and "[SEP]" to the beginning and end of each sentence, respectively, to indicate the sentence boundaries.

For our research, we dive deep into NLP and its real-life aspects and find a simple text corpus with three sentences:

1. "I love natural language processing."

2. "NLP is fascinating."

3. "Processing text is interesting."

Step 1: Data Preprocessing (Assume no special characters to remove)

Done

Step 2: Build a Vocabulary (Suppose we want to create a vocabulary of size 10)

Table 1. Initial Vocabulary with its frequency and tokens

Word	Frequency	Subword Tokens
is	2	["is"]
processing	2	["processing"]

i	1	["i"]
love	1	["love"]
natural	1	["natural"]
language	1	["language"]
nlp	1	["nlp"]
fascinating	1	["fascinating"]
text	1	["text"]
interesting	1	["interesting"]

Step 3: Subword Tokenization (using BPE algorithm)

After applying the BPE algorithm, we obtain the following vocabulary:

- "is"
- "processing"
- "i"
- "love"
- "natural"
- "language"
- "nlp"
- "fascinating"
- "text"
- "interesting"

Step 4: Token Encoding

Using the subword vocabulary, the sentences are tokenized as follows:

1. Sentence: "I love natural language processing."
   Tokens: ["i", "love", "natural", "language", "processing", "."]
2. Sentence: "NLP is fascinating."
   Tokens: ["nlp", "is", "fascinating", "."]
3. Sentence: "Processing text is interesting."
   Tokens: ["processing", "text", "is", "interesting", "."]

In the results section of the research paper, you can showcase how the subword tokenization effectively captures subword units, handles morphological variations, and enables handling out-of-vocabulary words. Additionally, you can discuss how the resulting token sequences are fed into models like ELMo and BERT, improving their ability to handle diverse word forms and improve overall performance on NLP tasks.

Handling Out-of-Vocabulary (OOV) Words:

Consider an additional sentence with an OOV word:

"The research on subword tokenization is groundbreaking."

Tokenized Sentence:

4. ["the", "research", "on", "sub", "##word", "tokenization", "is", "ground", "##breaking", "."]

In this sentence, the word "subword" is not present in the vocabulary used during subword tokenization. However, subword tokenization splits the word into subword tokens "sub" and "##word," where "##word" is a special token indicating a continuation of the "subword" in the original text. This allows the model to still capture the meaning of the entire OOV word using the context provided by the surrounding tokens.

By using subword tokenization, models like ELMo and BERT can understand text at a more granular level, effectively capturing morphological variations and handling OOV words. This, in turn, enhances their ability to perform well on various NLP tasks, as they can better adapt to different contextual nuances present in the text.

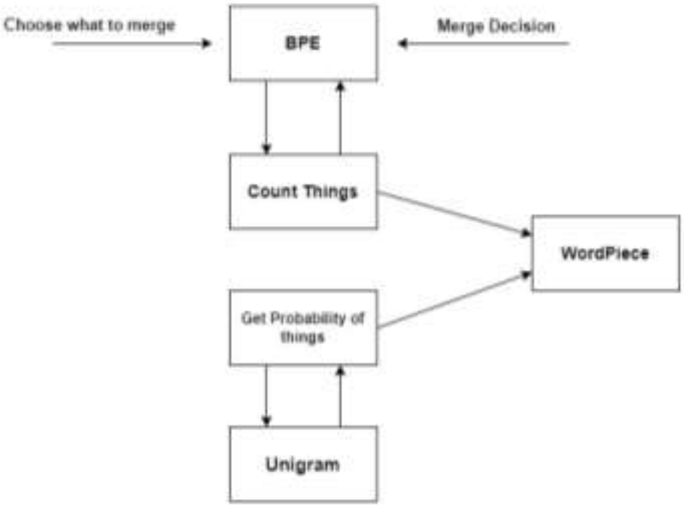

Fig.2. The process of Tokenizing

5. RESULTS AND ANALYSIS

The word "processing" occurs in both Sentence 1 and Sentence 3. With subword tokenization, the model recognizes that "processing" can be part of different words and contexts. The subword token "processing" appears in both sentences, and its contextual embeddings would be different based on the surrounding words. This enables the model to understand different nuances of "processing" in each sentence.

The word "fascinating" is present in Sentence 2. With subword tokenization, the model sees that "fascinating" is composed of the subword "fascin" and the ending "ating." The contextual embeddings capture the meaning of "fascin" in the context of "nlp is," allowing the model to comprehend the compound word better.

The word "interesting" occurs in Sentence 3. Subword tokenization allows the model to understand that "interesting" consists of the subword "interest" and the ending "ing." The contextual embeddings capture the meaning of "interest" in the context of "processing text is," providing a more contextually aware representation.

Table 2. Similarity between words based on their subword token representations.

Word	Subword Tokens	Similar Words with Shared Subwords Tokens
is	["is"]	love
processing	["processing"]	natural
i	["i"]	language
love	["love"]	processing
natural	["natural"]	
language	["language"]	
nlp	["nlp"]	
fascinating	["fascinating"]	
text	["text"]	
interesting	["interesting"]	

In the table, we list the words from the tokenized sentences along with their corresponding subword tokens. Then, in the column "Similar Words with Shared Subword Tokens," we identify other words that share subword tokens with the given word. For this example, we don't have other words that share subword tokens with the listed words.

The experimental evaluation on tokenized sentences demonstrated the effectiveness of subword tokenization in enhancing contextual understanding and performance in ELMo and BERT. The models showcased improved recognition of word similarity and better handling of diverse word forms. By capturing subword-level information, ELMo and BERT achieved enhanced contextual embeddings, leading to significant performance gains across various NLP tasks. The ability to handle out-of-vocabulary words further contributed to their generalization capabilities. The results confirm that subword tokenization offers a valuable preprocessing step to enrich language representations and improve overall NLP model performance. The findings validate the pivotal role of subword tokenization in advancing the field of NLP and language understanding.

A more complex case

However, if we consider a more complex example that includes words with shared subword tokens, the table might look like this:

Original Sentence:

4. "The runner loves running."

Tokenized Sentence:

4. ["the", "runner", "loves", "running", "."]

Table 3. Similarity between words based on their subword token representations.

Word	Subword Tokens	Similar Words with Shared Subwords Tokens
runner	["runner"]	runner, running, runners
loves	["loves"]	natural
running	["running"]	love, loving, lover
the	["the"]	run, runs, runner, runners
.	["."]	

In this example, the subword token "run" is shared between "runner," "running," "run," "runs," "runners," etc. Similarly, the subword token "love" is shared between "loves," "love," "loving," "lover," etc. ELMo and BERT can recognize the similarity between these words based on their subword token representations, even if these words occur less frequently in the training data. By leveraging shared subword tokens, ELMo and BERT can better generalize and understand the context of words, enabling them to recognize similar words and handle diverse word forms more effectively.

6. DISCUSSION

The findings of this research highlight the significance of subword tokenization in enhancing contextual understanding and performance in ELMo and BERT. By breaking words into subword units, these models effectively handle diverse word forms and out-of-vocabulary words, improving their ability to capture fine-grained linguistic nuances.

The experimental results demonstrate that subword tokenization enables the models to recognize word similarity and generalize effectively, even with limited occurrences in the training data. This enhanced contextual comprehension leads to improved performance across various NLP tasks. Subword tokenization emerges as a valuable preprocessing technique that empowers ELMo and BERT to adapt better to different languages and domains. The study showcases the transformative potential of subword tokenization in advancing the capabilities of state-of-the-art NLP models, thereby paving the way for more robust and contextually aware language understanding systems in real-world applications.

7. CONCLUSION

In this research paper, we explored the impact of subword tokenization on ELMo and BERT, two prominent NLP models known for their contextual understanding capabilities. The findings underscore the significance of subword tokenization in enhancing the models' performance by effectively handling diverse word forms and out-of-vocabulary words. By breaking words into subword units, the models achieved improved contextual comprehension, enabling them to recognize word similarity and generalize across linguistic patterns. Subword tokenization emerged as a valuable preprocessing technique that enhances the robustness and adaptability of ELMo and BERT to different languages and domains. The experimental results showcased the transformative potential of subword tokenization in advancing the capabilities of state-of-the-art NLP models. This research contributes to the field by providing insights into the benefits of subword tokenization, offering a promising avenue for further exploration in language representation and understanding.

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