BERT(s) to Detect Multiword Expressions

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Abstract. Multiword expressions (MWEs) present groups of words in which the meaning of the whole is not derived from the meaning of its parts. The task of processing MWEs is crucial in many natural language processing (NLP) applications, including machine translation and terminology extraction. Therefore, detecting MWEs is a popular research theme. In this paper, we explore state-of-the-art neural transformers in the task of detecting MWEs. We empirically evaluate several transformer models in the dataset for SemEval-2016 Task 10: Detecting Minimal Semantic Units and their Meanings (DiMSUM). We show that transformer models outperform the previous neural models based on long short-term memory (LSTM). The code and pre-trained model will be made freely available to the community.

Keywords: Multiword Expressions · Transformers · Deep Learning.

1 Introduction

The term “multiword expressions” (MWEs) denotes a group of words that act as a morphologic, syntactic and semantic unit in linguistic analysis; however, their meaning cannot be inferred from the meaning of their components [4]. For example, the MWE "by and large" have a meaning equivalent to "on the whole". But none of the words in the MWE imply this [3]. MWEs can be categorised in to different categories such as lexicalised phrases and institutionalised phrases; however the basic definition remains same in all the categories. MWEs appear in almost all languages and is a common method of expressing ideas.

Apart from the difficulty of deriving meaning from individual components, which is known as non-compositionality in phraseology, MWEs have several challenges when processing them computationally [8]. 1. MWEs are non-substitutable, which means that the components of MWE cannot be replaced by synonyms (e.g., by and big). 2. MWEs and non-MWEs can be ambiguous (e.g., by and large, we agree vs he walked by and large tractors passed him). These unique challenges in MWEs raise several fundamental problems with many NLP applications. For example, parsing and machine translation (MT) [17][10], which depends on a clear distinction between word tokens and phrases, has to be rethought to accommodate MWEs [8][29]. The usual approach in these applications is to identify MWEs first, and then treat them accordingly. Therefore, detecting MWEs is a key research area in NLP.
In recent years, the identification of MWEs has been modelled as a supervised machine learning task where the machine learning models are trained on an annotated dataset. As we explain in Section 2, several datasets have been released to train these machine learning models. Furthermore, shared tasks such as SemEval-2016 Task 10 [28] and PARSEME [27] have contributed to develop datasets. In recent years, neural network-based models, and in particular architectures incorporating Recurrent Neural Networks (RNNs) such as Long Short Term Memory (LSTM) and Convolutional Neural Networks (CNNs) have achieved state-of-the-art performance in MWE identification tasks [27]. Usually, these models utilise pre-trained word embedding models such as word2vec [15] and glove [22]. We describe these models in Section 2. However, these traditional word embeddings provide the same embedding for polysemous words [21] [20]. Therefore, non-substitutability and the ambiguous nature of the MWEs can cause complications with traditional word embeddings.

A possible solution is to utilise neural architectures such as transformers that incorporate context more into the learning process. However, as far as we know, there has not been any research done to compare the performance of different transformer models in the MWE identification task. In this research, we empirically evaluate several transformer models in detecting MWEs to fill this gap. The findings of this research can be beneficial for many NLP applications that require detecting MWEs.

The main contributions of this study are,

1. We empirically evaluate eight different transformer models in the task of detecting multiword expressions using a recent dataset released for SemEval-2016 Task 10 [28].
2. We show that transformer-based models to identify multiword expressions outperform previous neural models based on LSTMs.
3. We provide important resources to the community: the code as an open-source framework, as well as the pre-trained models will be freely available to the community on HuggingFace [30] model hub. Furthermore, we have created a docker image of the experiments adhering to the ACL reproducibility criteria.

2 Related Work

As mentioned before, a clear majority of the recent research to detect MWEs are neural based models. Usually the MWE detection is modelled as a token classification task where the model predicts whether a certain token belongs to a MWE or not. Therefore this task is similar to a named entity recognition

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1 The public GitHub repository is available on [https://github.com/DamithDR/MultiwordExpressions](https://github.com/DamithDR/MultiwordExpressions) and the pre-trained models are available on [https://huggingface.co/Damith/mwe-xlm-roberta-base](https://huggingface.co/Damith/mwe-xlm-roberta-base)

2 The docker image is available on [https://hub.docker.com/r/damithpremasiri/transformer-based-mwe](https://hub.docker.com/r/damithpremasiri/transformer-based-mwe)
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The most popular method to detect MWEs are based on recurrent neural network variants such as LSTMs and gated recurrent units (GRUs) \cite{25}. \cite{18} use a LSTM model with Conditional random field (CRF) to detect MWEs. Furthermore, they incorporate dependency parse information to improve the results. Graph convolutional neural networks (GCNs) \cite{13} have also been applied to MWE identification. \cite{25} incorporate multi-head self-attention to improve the performance of GCN in MWE detection. Transformers have also been used to detect MWEs\cite{5,12}; however, the research has been limited to a few transformer models. Therefore, in this research, we fill this gap by empirically evaluating multiple transformers in the task of MWE identification.

3 Data

The dataset we used was from the 2016 SemEval shared task \cite{28}. The shared task was designed to predict both minimal semantic units and semantic classes (supersenses). The training data combines and harmonises three data-sets, the STREUSLE 2.1 corpus of web reviews, as well as the Ritter and Lowlands Twitter datasets. The Ritter and Lowlands datasets have been reannotated for MWEs and supersenses to improve their quality and to more closely follow the conventions used in the STREUSLE annotations. The DiMSUM data files have tab-separated columns in the spirit of CoNLL, with blank lines to separate sentences. Each row contained nine columns: token offset, word, lowercase lemma, POS, MWE tag, offset of parent token (i.e. previous token in the same MWE), strength level encoded in the tag, supersense label and sentence ID. In this research we used only the word and the MWE tag. There are multiple MWE tagging formats such as IOB and IOB2. The dataset contains the IOB format where I - Inside, O - Outside, B - Beginning of a MWE. The I- prefix indicates that the tag is inside a chunk. An O indicates that a token belongs to no chunk. The B- prefix indicates that the tag is the beginning of a chunk that immediately follows another chunk without O tags between them.

The data composition is shown in the table 1. In the initial test dataset, there were 16500 words with 1000 sentences, however we had to remove one sentence from the test set due to encoding issues faced with the Python libraries.

4 Methodology

The main motivation behind the methodology is the state-of-art results produced by transformers in multiple different NLP tasks such as question answering \cite{23},

\begin{itemize}
  \item \textsuperscript{3} SemEval 2016 shared task description: \url{http://dimsum16.github.io/}
  \item \textsuperscript{4} The STREUSLE 2.1 is available on: \url{http://www.cs.cmu.edu/~ark/LexSem/}
  \item \textsuperscript{5} Twitter dataset is available on: \url{https://github.com/coastalcph/supersense-data-twitter}
\end{itemize}
Table 1. Datasets composition

| Dataset | No of Words | No of Sentences |
|---------|-------------|-----------------|
| Train   | 73826       | 4800            |
| Test    | 16400       | 999             |

machine translation quality estimation [24], cyber bullying [19] [26], language identification [11] and named entity recognition [2]. We experiment with two types of models, which we explain in the following sections.

Transformer models such as BERT [9] have been trained using masked language modelling objective and then can be fine-tuned for multiple different tasks [1]. This research uses the pre-trained transformer models for a token classification task. As shown in Figure 1, we added a token level classifier on top of the transformer model. The token-level classifier is a linear layer that takes the last hidden state of the sequence as the input and produces a label for each token as the output. In this case, each token can have three labels; B, I and O.

We experimented with several popular, widely used transformer models to detect MWEs. Namely they are BERT [9], RoBERTa [32], XLNet [31], XLM-RoBERTa [7] and Electra [6]. For BERT we used several variations such as bert-base-cased, bert-base-uncased, bert-base-multilingual-cased and bert-base-multilingual-uncased while for other transformer model we only used the avail-
able base model. All the transformer-based methods were experimented using batch size 32, Adam optimiser with learning rate 4e-5. They were trained for 3 epochs with linear learning rate warm-up over 10% of the training data. These experiments were done in an NVIDIA GeForce RTX 2070 GPU.

*BILSTM-CRF* is another token classification architecture which provided state-of-the-art results before transformers \([10]\). Bidirectional LSTM (BiLSTM) is capable of learning contextual information both forwards and backwards in time compared to conventional LSTMs. In this study, we used the Bi-LSTM architecture given this bidirectional ability to model temporal dependencies. CRFs \([14]\) are a statistical model that are capable of incorporating context information and are highly used for sequence labeling tasks. A CRF connected to the top of the Bi-LSTM model provides a powerful way to model relationships between consecutive outputs (across time) and provides a means to efficiently utilise past and future tag information to predict the current tag of word. For the experiments, we used a learning rate 1.5e-1 and the model was trained for 50 epochs. BiLSTM-CRF experiments were conducted on a CPU.

### 5 Results

In this section, we report and compare the results of our experiments using standard evaluation metrics Weighted Recall, Weighted Precision, Weighted F1 and Macro F1 for the MWEs detection task. As shown in the Table 2, it is clear that the transformer-based models outperform the BiLSTM-CRF method with clear margins. The BiLSTM-CRF could achieve only 0.8253 and 0.3135 for Weighted F1 and Macro F1 scores, respectively, while all the transformer models we experimented outperform that. A clear observation is that even though BiLSTM-CRF has a fairly high Weighted F1 score, the Macro F1 score is very low. Since the Macro F1 score is sensitive to class imbalance, we hypothesise that this model is struggling to predict some specific label(s). On the other hand, transformer models achieve a high Macro F1 score suggesting that they can predict all the classes equally.

Results of transformers based neural methods have similar performance with slight differences from one model to another. It is clear that the best performer is the xlm-roberta-base model, which could achieve the best performance for both Weighted F1 and Macro F1 over all other models by achieving scores of 0.9169, 0.7366 accordingly. This is followed by the xlnet-base-cased model with a Macro F1 score of 0.7317, showing the competitiveness of the transformer models in MWE detection tasks. Interestingly, a multilingual model such as xlm-roberta-base could outperform language-specific transformer models on MWEs detecting task on this dataset.

Another interesting observation is that the cased models outperform the uncased models. This is similar in both bert and bert-multilingual models, where the cased models slightly outperform the uncased models. We believe that cased models can perform better in detecting MWEs than uncased models according to this dataset.
Overall, transformers based neural methods perform higher than BiLSTM-CRF. It is clear that the results of all the transformer-based methods varied between 0.6863 - 0.7366 of Macro F1, showing their strong and competitive performance in MWE detection tasks.

6 Conclusion

MWE detection is an important research area for many NLP applications. In this paper, we empirically evaluate several neural transformer models in the MWE detection task using a recent dataset released for SemEval-2016 Task 10 and show that all the transformer models outperform the LSTM based method. From the experimented transformer models, xlm-roberta-base provided the best results outperforming other transformer models. We can conclude that transformer models can handle the challenges presented by MWEs better than the previous LSTM based methods.

In the future, we would like to explore the cross-lingual capabilities of the transformer models in the MWE detection task. Cross-lingual transformer models such as xlm-roberta can be used to transfer knowledge between languages so that a model can be trained only on English data but can be used to predict on other languages. Since the xlm-roberta-based performed best in this study, we believe that this model can be further explored to detect MWEs in different languages.

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