Transformer-based Detection of Multiword Expressions in Flower and Plant Names

1Damith Premasiri, 2Amal Haddad Haddad, 1Tharindu Ranasinghe, and 1Ruslan Mitkov
1University of Wolverhampton, UK
2University of Granada, Spain
{damith.premasiri,tharindu.ranasinghe,R.Mitkov}@wlv.ac.uk
amalhaddad@ugr.es

Abstract. Multiword expression (MWE) is a sequence of words which collectively present a meaning which is not derived from its individual words. MWEs detection is an important topic in different natural language processing (NLP) applications, including machine translation. Therefore, detecting MWEs in different domains is an important research topic. With this study, we explore state-of-the-art neural transformers in the task of detecting MWEs in flower and plant names. We evaluate different transformer models on a dataset created from Encyclopedia of Plants and Flower. We empirically show that neural transformers could outperform previous neural models like long-short term memory (LSTM) even in specific domains such as flower and plant names.

Keywords: Multiword Expressions · Transformers · Deep Learning · Flowers · Plants

1 Introduction

The correct interpretation of Multiword Expressions (MWEs) is crucial to many natural language processing (NLP) applications but is challenging and complex. In recent years, the computational treatment of MWEs has received considerable attention, but there is much more to be done before one can claim that NLP and Machine Translation (MT) systems process MWEs successfully [12].

The study of multiword expressions in NLP has been gaining prominence, and in recent years the number of researchers and projects focusing on them has increased dramatically. The successful computational treatment of MWEs is essential for NLP, including MT and Translation Technology. The inability to detect MWEs automatically may result in incorrect (and even unfortunate) automatic translations and may jeopardise the performance of applications such as text summarisation and web search.

Multiword expressions do not only play a crucial role in the computational treatment of natural languages. Often terms are multiword expressions (and not single words), making them highly relevant to terminology. The requirement for correct rendering of MWEs in translation and interpretation highlights their
importance in these fields. Given the pervasive nature of MWEs, they play a crucial role in the work of lexicographers who study and describe both words and MWEs. Lastly, MWEs are vital in the study of language, which includes not only language learning, teaching and assessment but also more theoretical linguistic disciplines such as pragmatics, cognitive linguistics and construction grammar, which are nowadays aided by (and, in fact, often driven by) corpora. MWEs are very relevant for corpus linguists, too. As a result, MWEs provide an excellent basis for interdisciplinary research and for collaboration between researchers across different areas of study, which for the time being, is underexplored.

This study is concerned with developing and evaluating a methodology designed to identify multiword expressions among flower and plant names. Multiword expressions are common among the names of flowers and plants, as in the case of *Leontopodium alpinum*, *White Moonlight* or *Pink Shirley Alliance*. To the best of our knowledge, this is the first study covering this domain.

The rest of the paper is structured as follows. Section 2 outlines related work. Section 3 describes the dataset used for our experiments, while section 4 presents the methodology. Section 5 reports the evaluation results, and finally, section 6 summarises the conclusion of this study.

## 2 Related Work

Neural models are increasingly employed to detect MEWs. Since both MWEs detection and named entity recognition (NER) tasks are about token classification, they can be modelled using similar models. Therefore we are using a set of models which are used in NER for the MWE detection task, too [20].

LSTMs [9] and gated recurrent units (GRUs) [20] are the most popular deep learning methods which have been employed in MWEs detection task. There are methods where an LSTM network [9] is combined with a Conditional random field (CRF) for the same task. Furthermore, graph convolutional neural networks (GCNs) [10] have also been used for MWE identification. The performance of GCNs in MWEs detection has improved using multi-head self-attention [20]. Transformers have also been used in MWEs detection; [21,24]; however, the research has been minimal and has focussed only on general domains. More specifically, there is limited research on MWEs detection tasks in specific fields, such as MWEs detection in flower and plant names. This paper tries to understand how the state-of-the-art transformer models work in MWEs detection in flower and plant names by empirically evaluating several transformer models.

## 3 Data

The subject of flowers and plants is of great interest to both professionals and the general public and is relevant to professionals in botany, phytotherapy, plant pharmacology, designers, etc. In addition, there is a lot of interest among the general public as many people dedicate their time to planting plants and growing them in their gardens and homes. Apart from that, the identification of names of
flowers and plants as terms is also relevant to terminologists and translators. The study of the names of plants as terms helps in laying the basis of term coining processes and gives insights into the underlying mechanisms of term creation. Translators also benefit from this information for its transfer between languages. For this reason, the automatic identification of names of flowers and plants is relevant to meeting all those needs.

The Encyclopaedia of Plants and Flowers of The American Horticultural Society, edited by Christofer Brickel and published by Dorling Kindersley editorial, is used as the corpus for this study. This edition is available in a digitalised format in the online library of the Internet Archive. This encyclopaedia consists of 522,707 words. It contains a dictionary of names of flowers from around the world, with approximately 8000 terms referring to both scientific and common names and their origins, as well as 4000 images. It also contains descriptions of each flower, instructions on how to plant it and how to use the plants to design gardens. The dataset has been created by extracting the text from Encyclopedia of Plants and Flowers. This encyclopedia consists of two main parts: the plant catalogue and the plant dictionary. The book describes the origins of plant names and basic gardening concepts apart from its main concerns. The plant catalogue describes different categories such as Trees, Shrubs, Roses, Perennials etc. In the remaining parts, the plants are subdivided into large, medium and small subdivisions Ex: large trees, and small trees. The plant dictionary is a dictionary which seeks to cover all possible plant names along with a short description and references to different sections in the plant catalogue accordingly. The flower and plant names in the dictionary are abbreviated similarly to an ordinary dictionary. The data was pre-processed by annotating the terms of proper names. The training and test data were created by combining both the plant catalogue and plant dictionary and pre-processing them and tagging the MWE according to the IOB format. The I, O, and B tags stand for Inside, Outside and Beginning, respectively, based on the MWE tag position of the word. The training set consists of 38,985 sentences, whilst the test set consists of 14,234 sentences.

4 Methodology

Transformers based models have produced state-of-the-art art results in many NLP tasks such as text classification, sense disambiguation, question answering, machine translation and named entity recognition. Therefore, we employ transformers based models for MWEs detection task while comparing performance with Bidirectional LSTM model. We further discuss these models in the following sections.

Transformer models such as BERT have been trained using masked language modelling objective and they can be fine-tuned for multiple different tasks. Within this study we fine-tune number of transformer models for MWEs detection which is a token classification task. We modify the original BERT architecture by adding a token level classifier following the last hidden layer as shown...
in Figure 1 to achieve the architecture of the MWE detection model. This is a linear classification layer which uses the last hidden state as input and output the relevant token per word such as B,I and O.

![MWE token classification transformer architecture](image)

**Fig. 1.** MWEs token classification transformer architecture [14]

We conducted our experiments with many popular transformer models to detect MWEs such as BERT [6], RoBERTa [27], XLNet [26], XLM-RoBERTa [5] and Electra [1]. We evaluated several different BERT variations such as bert-base-cased, bert-base-uncased, bert-base-multilingual-cased, bert-base-multilingual-uncased. Furthermore we experimented sci-bert-cased[2] and sci-bert-uncased[2] which are pre-trained on scientific corpus as more specific variants of BERT[6]. The other transformer models are evaluated only on their base model. All the transformer-based methods made use of a 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 carried out in an NVIDIA GeForce RTX 2070 GPU and in Google colab GPU[1].

**BiLSTM-CRF** is another token classification architecture which provided state-of-the-art results before transformers [13]. Bidirectional LSTM (BiLSTM) is an improved version of conventional LSTMs which is capable of learning contextual information both forwards and backwards in time. Unlike standard LSTM, the input flows in both directions, and it’s capable of utilizing information from both sides. It utilises an additional LSTM layer which reverses direction of the

1 https://colab.research.google.com/
information flow. This study leverages the BiLSTM architecture given its’ bidirectional ability to model temporal dependencies. CRFs \cite{11} are a statistical model that are capable of incorporating context information and are highly used for sequence labelling tasks. The BiLSTM-CRF model provides a way of combining the relationships of consecutive outputs of the network and utilise both past and future tag information to for prediction. Since the BiLSTM has both of the past and future information, combining CRF on top of the BiLSTM provides powerful network for precisely predicting the tags. BiLSTM-CRF experiments were performed on a CPU with a learning rate of 1e-3 and the model was trained for 60 epochs.

5 Results

In this section, we report the results of conducted experiments using macro averaged F1 as it is widely used in classification tasks. As shown in Table 1 it is clear that the transformer-based models outperform the BiLSTM-CRF method with clear margins. The BiLSTM-CRF could achieve only 0.3320 Macro F1 score, while all the transformer models we experimented outperformed that. A noticeable observation is that best transformer model had nearly double the F1 score of BiLSTM-CRF model while all the other transformer models performed competitively.

| Model                                   | Macro F1 |
|-----------------------------------------|----------|
| roberta-base                            | 0.5039   |
| xlm-roberta-base                        | 0.5650   |
| xlnet-base-cased                        | 0.6312   |
| bert-base-multilingual-cased            | 0.6086   |
| bert-base-multilingual-uncased         | 0.6422   |
| bert-base-cased                         | 0.6393   |
| bert-base-uncased                       | 0.6227   |
| electra-base-discriminator              | 0.5753   |
| sci-bert-cased                          | 0.6214   |
| sci-bert-uncased                        | 0.6307   |
| BiLSTM-CRF                              | 0.3320   |

Table 1. Results for multiword expression detection in flower and plant names

The clear winner is the bert-base-multilingual-uncased model with a Macro F1 score of 0.6422. This is followed by bert-base-cased and xlnet-base-cased models with Macro F1 scores of 0.6393 and 0.6312, respectively. In general, transformer models have better performance with slight margins among them. An
interesting observation is that multilingual-bert model outperforms sci-bert models, which are trained on a corpus featuring a high frequency of scientific terms. We conjecture that this could be due to a lack of the flower names and plant names related data in the sci-bert training set. Nevertheless, sci-bert-uncased model competitively performed with 0.6307 Macro F1 score, which is only a 0.0115 difference from the best performing model.

Another interesting observation was while the multi-lingual bert model was the best performer, the cross-lingual model; xlm-roberta-base did not do well with a F1 score of 0.5650. This score is very close to the least successful model among transformers which was roberta-base with Macro F1 of 0.5039. Yet these values are outperforming the BiLSTM-CRF model, which shows the powerful nature of transformers based models in MWE tasks over the other neural methods like BiLSTM.

Overall, transformers-based neural methods clearly perform better than BiLSTM-CRF. All the transformer-based methods performed above 0.5000 of Macro F1, showing their strong performance in MWE detection tasks.

6 Conclusion

MWE detection has significant importance in many NLP applications, especially in translation and terminology studies. In this paper, we focus on an empirical analysis of multiple neural transformer models in the MWE detection task using a flowers and plants dataset. We show that all transformer models outperform the LSTM-based method. Of the transformer models we experimented with, bert-base-multilingual-uncased reported the best results doing better than other transformer models. We can conclude that transformer models can handle the challenges presented by MWEs in local domains like plant names and flower names better than the previous neural methods, such as LSTM.

In the future, we would like to explore more specific domains similar to flower and plant names. It would be interesting to study how MWEs detection works in different languages with different flower and plant names. We are encouraged to explore cross-lingual models more in this regard to understand how well these models perform across languages on the MWEs detection task for similar datasets.

References

1. Alloatti, F., Di Caro, L., Sportelli, G.: Real life application of a question answering system using BERT language model. In: Proceedings of the 20th Annual SIGdial Meeting on Discourse and Dialogue. pp. 250–253. Association for Computational Linguistics, Stockholm, Sweden (Sep 2019). https://doi.org/10.18653/v1/W19-5930
2. Beltagy, I., Lo, K., Cohan, A.: SciBERT: A pretrained language model for scientific text. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural
3. Brickell, C.: Encyclopedia of plants and flowers. In: Encyclopedia of plants and flowers. Dorling Kindersley, Santa Fe, New Mexico, USA (2012)

4. Clark, K., Luong, M.T., Le, Q.V., Manning, C.D.: ELECTRA: Pre-training text encoders as discriminators rather than generators. In: ICLR (2020), https://openreview.net/pdf?id=r1xMH1BtvB

5. Conneau, A., Khandelwal, K., Goyal, N., Chaudhary, V., Wenzek, G., Guzmán, F., Grave, E., Ott, M., Zettlemoyer, L., Stoyanov, V.: Unsupervised cross-lingual representation learning at scale. In: Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics, pp. 8440–8451. Association for Computational Linguistics, Online (Jul 2020), https://doi.org/10.18653/v1/2020.acl-main.747, https://aclanthology.org/2020.acl-main.747

6. Devlin, J., Chang, M.W., Lee, K., Toutanova, K.: BERT: Pre-training of deep bidirectional transformers for language understanding. In: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 4171–4186. Association for Computational Linguistics, Minneapolis, Minnesota (Jun 2019), https://doi.org/10.18653/v1/N19-1423, https://aclanthology.org/N19-1423

7. Hettiarachchi, H., Ranasinghe, T.: BRUMS at SemEval-2020 task 3: Contextualised embeddings for predicting the (graded) effect of context in word similarity. In: Proceedings of the Fourteenth Workshop on Semantic Evaluation. pp. 142–149. International Committee for Computational Linguistics, Barcelona (online) (Dec 2020), https://doi.org/10.18653/v1/2020.semeval-1.16, https://aclanthology.org/2020.semeval-1.16

8. Hettiarachchi, H., Ranasinghe, T.: TransWiC at SemEval-2021 task 2: Transformer-based multilingual and cross-lingual word-in-context disambiguation. In: Proceedings of the 15th International Workshop on Semantic Evaluation (SemEval-2021), pp. 771–779. Association for Computational Linguistics, Online (Aug 2021), https://doi.org/10.18653/v1/2021.semeval-1.102, https://aclanthology.org/2021.semeval-1.102

9. Hochreiter, S., Schmidhuber, J.: Long Short-Term Memory. Neural Computation 9(8), 1735–1780 (11 1997), https://doi.org/10.1162/neco.1997.9.8.1735

10. Kipf, T.N., Welling, M.: Semi-supervised classification with graph convolutional networks. arXiv preprint arXiv:1609.02907 (2016)

11. Lafferty, J.D., McCallum, A., Pereira, F.C.N.: Conditional random fields: Probabilistic models for segmenting and labeling sequence data. In: Proceedings of the Eighteenth International Conference on Machine Learning. p. 282–289. ICML ’01, Morgan Kaufmann Publishers Inc., San Francisco, CA, USA (2001)

12. Monti, J., Seretan, V., Pastor, G.C., Mitkov, R.: Multiword expressions in machine translation and translation technology. In: Multiword Expressions in Machine Translation and Translation Technology. pp. 1–37. John Benjamins Publishers (2018)

13. Panchendrarajan, R., Amaresan, A.: Bidirectional LSTM-CRF for named entity recognition. In: Proceedings of the 32nd Pacific Asia Conference on Language, Information and Computation. Association for Computational Linguistics, Hong Kong (1–3 Dec 2018), https://aclanthology.org/Y18-1061
14. Premasiri, D., Ranasinghe, T.: Bert (s) to detect multiword expressions. In: International Conference ‘Computational and Corpus-based Phraseology - Europhras 2022 (2022)

15. Premasiri, D., Ranasinghe, T., Zaghouani, W., Mitkov, R.: Dtw at Qur’ān qa 2022: Utilising transfer learning with transformers for question answering in a low-resource domain. In: Proceedings of the 5th Workshop on Open-Source Arabic Corpora and Processing Tools (OSACT5). (2022)

16. Ranasinghe, T., Orasan, C., Mitkov, R.: An exploratory analysis of multilingual word-level quality estimation with cross-lingual transformers. In: Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers), pp. 434–440. Association for Computational Linguistics, Online (Aug 2021). https://doi.org/10.18653/v1/2021.acl-short.55

17. Ranasinghe, T., Sarkar, D., Zampieri, M., Ororbia, A.: WLV-RIT at SemEval-2021 task 5: A neural transformer framework for detecting toxic spans. In: Proceedings of the 15th International Workshop on Semantic Evaluation (SemEval-2021), pp. 833–840. Association for Computational Linguistics, Online (Aug 2021). https://doi.org/10.18653/v1/2021.semeval-1.111

18. Ranasinghe, T., Zampieri, M.: Multilingual offensive language identification with cross-lingual embeddings. In: Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing (EMNLP). pp. 5838–5844. Association for Computational Linguistics, Online (Nov 2020). https://doi.org/10.18653/v1/2020.emnlp-main.470

19. Ranasinghe, T., Zampieri, M.: MUDES: Multilingual detection of offensive spans. In: Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies: Demonstrations. pp. 144–152. Association for Computational Linguistics, Online (Jun 2021). https://doi.org/10.18653/v1/2021.naacl-demos.17

20. Rohanian, O., Taslimipoor, S., Kouchaki, S., Ha, L.A., Mitkov, R.: Bridging the gap: Attending to discontinuity in identification of multiword expressions. In: Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers), pp. 2692–2698. Association for Computational Linguistics, Minneapolis, Minnesota (Jun 2019). https://doi.org/10.18653/v1/N19-1275

21. Taslimipoor, S., Bahauddini, S., Kochmar, E.: MTLB-STRUCT @parseme 2020: Capturing unseen multiword expressions using multi-task learning and pre-trained masked language models. In: Proceedings of the Joint Workshop on Multiword Expressions and Electronic Lexicons, pp. 142–148. Association for Computational Linguistics, online (Dec 2020). https://aclanthology.org/2020.mwe-1.19

22. Uyangodage, L., Ranasinghe, T., Hettiarachchi, H.: Can multilingual transformers fight the COVID-19 infodemic? In: Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2021), pp. 1432–1437. INCOMA Ltd., Held Online (Sep 2021). https://aclanthology.org/2021.ranlp-1.160

23. Uyangodage, L., Ranasinghe, T., Hettiarachchi, H.: Transformers to fight the COVID-19 infodemic. In: Proceedings of the Fourth Workshop on NLP for Internet
24. Walsh, A., Lynn, T., Foster, J.: A bert’s eye view: Identification of irish multiword expressions using pre-trained language models. In: Proceedings of the Thirteenth International Conference on Language Resources and Evaluation (LREC 2022). European Language Resources Association (ELRA), Marseille, France (Jun 2022)

25. Wang, Q., Li, B., Xiao, T., Zhu, J., Li, C., Wong, D.F., Chao, L.S.: Learning deep transformer models for machine translation. In: Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics. pp. 1810–1822. Association for Computational Linguistics, Florence, Italy (Jul 2019).

26. Yang, Z., Dai, Z., Yang, Y., Carbonell, J., Salakhutdinov, R.R., Le, Q.V.: Xlnet: Generalized autoregressive pretraining for language understanding. In: Wallach, H., Larochelle, H., Beygelzimer, A., d’Alché-Buc, F., Fox, E., Garnett, R. (eds.) Advances in Neural Information Processing Systems. vol. 32. Curran Associates, Inc. (2019).

27. Zhuang, L., Wayne, L., Ya, S., Jun, Z.: A robustly optimized BERT pre-training approach with post-training. In: Proceedings of the 20th Chinese National Conference on Computational Linguistics. pp. 1218–1227. Chinese Information Processing Society of China, Huhhot, China (Aug 2021).