Crowdsourced Phrase-Based Tokenization for Low-Resourced Neural Machine Translation: The Case of Fon Language

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Abstract
Building effective neural machine translation (NMT) models for very low-resourced and morphologically rich African indigenous languages is an open challenge. Besides the issue of finding available resources for them, a lot of work is put into preprocessing and tokenization. Recent studies have shown that standard tokenization methods do not always adequately deal with the grammatical, diacritical, and tonal properties of some African languages. That, coupled with the extremely low availability of training samples, hinders the production of reliable NMT models. In this paper, using Fon language as a case study, we revisit standard tokenization methods and introduce Word-Expressions-Based (WEB) tokenization, a human-involved super-words tokenization strategy to create a better representative vocabulary for training. Furthermore, we compare our tokenization strategy to others on the Fon-French and French-Fon translation tasks.

1 Introduction
Motivation: In this work, when we say translation, we actually focus on transcreation, which is a form of translation that takes the cultural attributes of the language into consideration. In fact, while translation focuses on replacing the words in a source language with corresponding words in a target language, transcreation focuses on conveying the same message and concept in a target language while keeping the style, intent, and context of the target language.

Transcreation is of utmost importance in African languages because the way ideas are conveyed in African languages is entirely different from English or other non-African languages. For example, Igbo language at its core does not have a literal translation for "Good morning", but rather has its way of expressing something similar to it: "I boọla chi". In Fon language as well, there is no literal translation for "Thank you", and they say "Enan tchè numi" as a way of expressing gratitude. While most languages of the world have a few of these "expressions" that are not translated literally, they (word expressions with non-literal meanings) are abound in most African languages. This underlies the importance of revisiting translation of African languages, with an emphasis on relaying the message in its original form, as opposed to word-for-word translation.

Tokenization issue with transcreation: Here, we try to demonstrate the effect of tokenization on transcreation and the importance of prior knowledge of the language for tokenization of resource-constrained African languages like Fon.

Considering the following Fon sentence: «mètà mètà we zinwó hen wa aligbo me», how would you best tokenize it? What happens if we implement the standard method of splitting the sentence into its word elements: either using the space delimiter or using subword units?

This has been done (see Figure 1) and we discovered that a translation (to French) model, trained on sentences split this way, gave a literal translation of «chaque singe est entré dans la vie avec sa tête, son destin (English: each monkey entered the stage of life with its head, its destiny)» for the above Fon sentence. But we are not talking about a monkey here 🦍.

It is a metaphor and so the meaning of some of the words should be considered collectively as
phrases.

Using a phrase-based tokenizer, we got the grouping showed in Figure 2. A native speaker

Figure 2: Tokenization of «mètā mètā wè zinwò hèn wa aligbo mè» using a phrase-based tokenizer

A, looking at some of these grouped phrases will quickly point out the issue with the grouped phrases. Probably the phrase-based model could not effectively learn the phrases due to the low data it was trained on? Also, we got a translation of «singe chaque vient au monde dans vie avec tête et destin (English: monkey each comes into world in life with head and fate)». However this does not fully capture the intended idea and meaning of the message in Fon.

Now with the help of A, for this particular example, we get a surprising grouping as shown in Figure 3: When we train a model based on the

Figure 3: Tokenization using prior knowledge from A words and expressions grouping provided by A, we get a translation which is closest to the actual expression: «Every human being is born with his chances» ☺. Another interpretation would be that we must be open to changes, and constantly be learning to take advantages of each situation in life

Tokenization is generally viewed as a solved problem. Yet, in practice, we often encounter difficulties in using standard tokenizers for NMT tasks, as shown above with Fon. This may be because of special tokenization needs for particular domains (like medicine (He and Kayaalp, 2006; Cruz Díaz and Maña López, 2015)), or languages. Fon, one of the five classes of the Gbe language clusters (Aja, Ewe, Fon, Gen, and Phla-Phera according to (Capo, 2010)), is spoken by approximately 1.7 million people located in southwestern Nigeria, Benin, Togo, and southeastern Ghana. There exists approximately 53 different dialects of Fon spoken throughout Benin. Fon has complex grammar and syntax, is very tonal with highly influential diacritics (Dossou and Emezue, 2020). Despite being spoken by 1.7 million speakers, Joshi et al. (2020) have categorized Fon as «left behind» or «under-studied» in NLP. This poses a challenge when using standard tokenization methods.

Given that most Fon sentences (and by extension most African languages) are like the sentence in Figure 1 (or the combination of such expressions), there is a need to re-visit tokenization of such languages. In this paper, using Fon in our experiment, we examine standard tokenization methods, and introduce the Word-Expressions-Based (WEB) tokenization. Furthermore, we test our tokenization strategy on the Fon-French and French-Fon translation tasks. Our main contributions are the dataset, our analysis and the proposal of WEB for extremely low-resourced African languages (ALRLs). The dataset, models and codes will be open-sourced on our Github page.

2 Background and Related Works

Modern NMT models usually require large amount of parallel data in order to effectively learn the representations of morphologically rich source and target languages. While proposed solutions, such as transfer-learning from a high-resource language (HRL) to the low-resource language (LRL) (Gu et al., 2018; Renduchintala et al., 2018; Karakanta et al., 2018), and using monolingual data (Sennrich et al., 2016a; Zhang and Zong, 2016; Burlot and Yvon, 2018; Hoang et al., 2018), have proved effective, they are still not able to produce better translation results for most ALRLs. Standard tokenization methods, like Subword Units (SU) (Sennrich et al., 2015), inspired by the byte-pair-encoding (BPE) (Gage, 1994), have greatly improved current NMT systems. However, studies have shown that BPE does not always boost performance of NMT systems for analytical languages (Abbott and Martinus, 2018). Ngo et al. (2019) show that when morphological differences exist between source and target languages, SU does not significantly improve results. Therefore, there is a great need to revisit NMT with a focus on low-resourced, morphologically complex languages like Fon. This may involve taking a look at how to adapt standard NMT strategies to these languages.
3 Tokenization Strategies and their Challenges for Fon

In this section, we briefly discuss the standard tokenization strategies employed in NMT, as well as challenges faced while applying them to Fon. Word-Based tokenization (WB) consists of splitting sentences into words, according to a delimiter. We’ll show the limits of this method using this Fon expression: "un d’o ganji". "un" on its own is an interjection, to express an emotion of surprise or astonishment. But "un d’o" already means "I am", "I am at", or "I have", depending on the context in which it is used. The whole expression, "un d’o ganji", could mean "I am fine" or "I am okay".

Phrase-Based tokenization (PhB) encodes phrases (group of words) as atomic units, instead of words. As a result, models trained on PhB have the ability to learn and interpret language-specific phrases (noun, verbal and prepositional phrases), making it better than WB for Fon language. However, due to the low-resourcefulness of the language and the randomness of PhB alignments, some extracted pairs are not always contextually faultless. For example, the computer alignment gave respectively [zén, une (a, an, one)] and [azón, la (the)], instead of [zén, une marmite (a pot)] and [azón, la maladie (the disease)].

Encoding with SU has made great headway in NMT, especially due to its ability to effectively encode rare out-of-vocabulary words (Sennrich et al., 2016b). Machácek et al. (2018), in analyzing the word segmentation for NMT, reported that the common property of BPE and SU relies on the distribution of character sequences, but disregards any morphological properties of the languages in question. Apart from rule-based tokenization, there are machine learning approaches to tokenization as well, which unfortunately require a substantial amount of training samples (both original and tokenized versions of the same texts) (Riley, 1989; Mikheev, 2000; Jurish and Würzner, 2013). To the best of our knowledge, there is no known language-specific tokenization proposed for Fon in particular, and ALRLs in general, although there have been a number of works on adapting NMT specifically to them (like (Orife et al., 2020; van Biljon et al., 2020; Vaswani et al., 2017), to mention but a few).

4 Word-Expressions-Based tokenization (WEB)

WEB involves aligning and extracting meaningful expressions based on linguistic components of Fon (phonemes, morphemes, lexemes, syntax, and context). This requires the assistance of Fon-French native speakers. Some examples of good alignments are:

| Expression               | Translation                   |
|--------------------------|-------------------------------|
| nancé                   | maman (mum)                   |
| ku’d o jibèzân           | joyeux anniversaire (Happy Birthday) |
| nancé vivè              | maman chérie (dear mum)       |
| af’d o jid’è d’o wutu cè à | as-tu confiance en moi ? (do you have faith in me ?) |
| nанvi cè                | mon frère / ma soeur (my brother / my sister) |

It is important to note that WEB is not a human-in-the-loop process, because it doesn’t require human intervention to run. The human intervention occurs while cleaning and preprocessing the dataset. We describe our algorithm as a recursive search algorithm which finds the optimal combination of words and expressions that will produce a better translation for a source sentence. The following algorithm was designed to encode input sentences using the established vocabularies:

1. Run through the vocabulary and output a list $L$ of all possible word combinations for the words and expressions appearing in the sentence $S$.

2. Important principle in Fon: higher word orders $\Rightarrow$ more precise and meaningful expressions. Using this principle, for each element (word or expression), $w \in L$,

   (a) Check if there exists a higher word order, $v \in L$, such that $w \subseteq v$.

   (b) If 2a is true, discard $w$, else keep $w$.

3. The output is a list $\hat{L}$ of optimal expressions from the initial $L$, making up the initial sentence $S$.

4. Add $<\text{start}>$ and $<\text{end}>$ taggers respectively at the beginning and the end of every element $\hat{w}$ (word or expression) $\in \hat{L}$.

5. Encode every $\hat{w}$ (word or expression) $\in \hat{L}$.

We argue that WEB scales well because it does require only knowledge and intuitions from bilinguals, meaning that we can crowdsourse those phrases. We want to state clearly, in order to avoid any confusion, that WEB could be interpreted as another version of PhB, involving human evaluation.
For our study, it took a group of 8 people, all bilinguals speaking Fon and French, and approximately 350 hours in total to align and extract meaningful sentences manually. No preliminary trainings have been done with the annotators, given the fact that they are in majority linguists and natives of the Fon language. This made the step of sentences splitting into expressions, more natural, reliable and faster.

5 The Fon-French Dataset: Data Collection, Cleaning and expansion processes

As our goal is to create a reliable translation system to be used by the modern Fon-speaking community, we set out to gather more data on daily conversations domain for this study. Thanks to many collaborations with Fon-French bilinguals, journalists and linguists, we gathered daily citations, proverbs and sentences with their French translations. After the collection’s stage, we obtained a dataset of 8074 pairs of Fon-French sentences.

The cleaning process, which involved the Fon-French bilinguals, mainly consisted of analyzing the contextual meanings of the Fon sentences, and checking the quality of the French translations. In many cases, where the French translations were really bad, we made significant corrections.

Another major observation was the presence of many long and complex sentences. That’s where the idea of expanding the dataset came from: we proceeded to split, when possible, Fon sentences into short, independent, and meaningful expressions (expression of 1-6 words), and accordingly add their respective French translations. At the end of these processes, we obtained our final dataset of 25,383 pairs of Fon-French sentences.

6 Methodology, Results and Conclusion

In this section, we describe the implementation of WB, PhB, SU, WEB and we compare the results of our NMT model trained on them for our analysis.

6.1 Creation of vocabularies for WB, PhB, SU and WEB

For WB, we split the sentences according to the standard ‘space’ delimiter, using the TensorFlow-Keras text tokenizer, getting a vocabulary of 7,845 and 8,756 Fon and French tokens (words) respectively.

For PhB, we used the IBM1 model from nltk.translate.api module to align and extract all possible pairs of sentences. Our main observation was that, some pairs generated were either not meaningful or not matching, but we didn’t try to rearrange them in order to see how well the generated pairs, without human intervention, would affect the translation quality. In so doing, we got a vocabulary of 10,576 and 11,724 Fon and French tokens respectively (word and expressions).

For SU we used the TensorFlow’s SubwordTextEncoder with a target vocabulary size of 8500, leading to a vocabulary size of 7,952 and 8,116 for Fon and French respectively. There has been research that suggests that there is need to tune the only hyperparameter in BPE – the target vocabulary size – because although the effect of vocabulary size on translation quality is relatively small for high-resource languages (Haddow et al., 2018), large vocabularies in low-resource languages often result in low-frequency subwords being represented as atomic units at training time, thereby impeding the ability to learn good high-dimensional representations (Sennrich and Zhang, 2019a). For our pilot study, we however did not perform any tuning.

To implement WEB, we considered unique expressions as atomic units. Using the steps highlighted for WEB in section 4, we encoded those atomic units and obtained a vocabulary of 18,759 and 19,785 Fon and French tokens (word and expressions) used for the model training.

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1 https://www.nltk.org/
Table 1: Experimental results of our model trained on WB, SU, PhB and WEB.

| Translation | Tokenization | SacreBleu ↑ tokenize="null" | METEOR ↑ | TER ↓ tokenize="intl" | SacreBleu↑ chrF (*100) |
|-------------|--------------|-----------------------------|----------|------------------------|------------------------|
| Fon → Fr    | WB           | 6.80                        | 12.20    | 86.20                  | 17.64                  |
| Fon → Fr    | SU           | 7.60                        | 13.60    | 87.40                  | 19.01                  |
| Fon → Fr    | PhB          | 38.90                       | 53.70    | 43.90                  | 58.65                  |
| Fon → Fr    | WEB          | **66.60**                   | **77.77**| **24.20**              | **68.24**              |
| Fr → Fon    | WB           | 15.65                       | -        | -                      | -                      |
| Fr → Fon    | SU           | 25.68                       | -        | -                      | -                      |
| Fr → Fon    | PhB          | 38.74                       | -        | -                      | -                      |
| Fr → Fon    | WEB          | **49.37**                   | -        | -                      | **52.71**              |

Table 2: Model translations with WB, PhB, SU and WEB.

6.2 Dataset splitting, model’s architecture and training.

From the dataset, and because of the the amount of data to be used for the training, we carefully selected 155 mixed (short, long and complex) representative sentences i.e. sentences made of 2 or more expressions (or words), as test data; sentences that we believe, would test the model’s ability to correctly translate higher word order expressions in Fon. 10% of the training data, was set aside for validation.

For training, we used an encoder-decoder-based architecture (Sutskever et al., 2014), made up of 128-dimensional gated rectified units (GRUs) recurrent layers (Cho et al., 2014), with a word embedding layer of dimension 256 and a 10-dimensional attention model (Bahdanau et al., 2015).

We trained with a batch size of 100, learning rate of 0.001 and 500 epochs, using validation loss to track model performance. The training took all the 500 epochs, with the loss reducing from one epoch to another. We would like to emphasize that up only at 500 epochs, with the given hyperparameters, we obtained significant and meaningful translations.

All training processes took 14 days on a 16GB Tesla K80 GPU. We evaluated our NMT models performances using SacreBleu (Post, 2018), METEOR (Banerjee and Lavie, 2005), CharacTER (TER) (Wang et al., 2016), and chrF (Popović, 2015) metrics.

6.3 Results and Conclusion

Table 1 and Table 2 show that our baseline model performs better with PhB, and best with WEB, in terms of metric and translation quality. It is important to note that while BLEU scores of PhB and WEB, reduced on the Fr→Fon task, BLEU scores of WB and SU improved on it. We speculate
that this might be because WB and SU enhanced the model’s understanding of French expressions over Fon, confirming the findings of (Abbott and Martinus, 2018), and (Ngo et al., 2019). This corroborates our argument that in order to help NMT systems to translate ALRLs better, it is paramount to create adequate tokenization processes that can better represent and encode their structure and morphology.

This is a pilot project and there is headroom to be explored with improving WEB. We are also working on combining WEB with optimized SU, to get the best of both worlds. For example, Sennrich and Zhang (2019b) and Sennrich et al. (2017) have highlighted the importance of tuning the BPE vocabulary size especially in a low-resource setting. Since no tuning was done in our experiment, it is not clear if SU could be run in such a way to lead to better performance. Secondly, we are working on releasing platforms for the translation service to be used. We believe that it would be a good way to gather more data and keep constantly improving the model’s performance.

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References

Jade Z. Abbott and Laura Martinus. 2018. Towards neural machine translation for african languages. CoRR, abs/1811.05467.

Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. 2015. Neural machine translation by jointly learning to align and translate. In 3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings.

Satanjeev Banerjee and Alon Lavie. 2005. METEOR: An automatic metric for MT evaluation with improved correlation with human judgments. In Proceedings of the ACL Workshop on Intrinsic and Extrinsic Evaluation Measures for Machine Translation and/or Summarization, pages 65–72, Ann Arbor, Michigan. Association for Computational Linguistics.

Elan van Biljon, Arnu Pretorius, and Julia Kreutzer. 2020. On optimal transformer depth for low-resource language translation. In Proceedings of the International Conference on Learning Representations, https://arxiv.org/abs/2004.04418.

Franck Burlot and François Yvon. 2018. Using monolingual data in neural machine translation: a systematic study. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 144–155, Belgium, Brussels. Association for Computational Linguistics.

Hounkpati B.C. Capo. 2010. A Comparative Phonology of Gbe. De Gruyter Mouton, Berlin, Boston.

Kyunghyun Cho, Bart van Merrienboer, Çaglar Gülçehre, Fethi Bougares, Holger Schwenk, and Yoshua Bengio. 2014. Learning phrase representations using RNN encoder-decoder for statistical machine translation. CoRR, abs/1406.1078.

Noa P. Cruz Díaz and Manuel Maña López. 2015. An analysis of biomedical tokenization: Problems and strategies. In Proceedings of the Sixth International Workshop on Health Text Mining and Information Analysis, pages 40–49, Lisbon, Portugal. Association for Computational Linguistics.

Bonaventure F. P. Dossou and Chris C. Emezue. 2020. Ffr v1.0: Fon-french neural machine translation. In Proceedings of the AfricanNLP Workshop, International Conference on Learning Representations, arXiv:arXiv:2003.12111.

Bonaventure F. P. Dossou, Fabroni Yoclounon, Ricardo Ahounvlamè, and Chris Emezue. 2021. Fon french daily dialogues parallel data.

Philip Gage. 1994. A new algorithm for data compression. C Users J., 12(2):23–38.

Jiatao Gu, Hany Hassan, Jacob Devlin, and Victor O.K. Li. 2018. Universal neural machine translation for extremely low resource languages. In Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers), pages 344–354, New Orleans, Louisiana. Association for Computational Linguistics.

Barry Haddow, Nikolay Bogoychev, Denis Emelin, Ulrich Germann, Roman Grundkiewicz, Kenneth Heafield, Antonio Valerio Miceli Barone, and Rico Sennrich. 2018. The university of Edinburgh’s submissions to the WMT18 news translation task. In Proceedings of the Third Conference on Machine Translation: Shared Task Papers, pages 399–409, Belgium, Brussels. Association for Computational Linguistics.

Ying He and Mehmet Kayaalp. 2006. A Comparison of 13 Tokenizers on MEDLINE.

Vu Cong Duy Hoang, Philipp Koehn, Gholamreza Haffari, and Trevor Cohn. 2018. Iterative back-translation for neural machine translation. In Proceedings of the 2nd Workshop on Neural Machine
Translation and Generation, pages 18–24, Melbourne, Australia. Association for Computational Linguistics.

Pratik M. Joshi, Sebastin Santy, Amar Budhiraja, Kallika Bali, and Monojit Choudhury. 2020. The state and fate of linguistic diversity and inclusion in the nlp world. ArXiv; abs/2004.09095.

Bryan Jurish and Kay-Michael Würzner. 2013. Word and sentence tokenization with hidden markov models. J. Lang. Technol. Comput. Linguistics, 28:61–83.

Alina Karakanta, Jon Dehdari, and Josef Genabith. 2018. Neural machine translation for low-resource languages without parallel corpora. Machine Translation, 32(1–2):167–189.

Dominik Machácek, Jonás Vidra, and Ondrej Bojar. 2018. Morphological and language-agnostic word segmentation for NMT. CoRR; abs/1806.05482.

Andrei Mikheev. 2000. Tagging sentence boundaries. In Proceedings of the 1st North American Chapter of the Association for Computational Linguistics Conference, NAACL 2000, page 264–271, USA. Association for Computational Linguistics.

Thi-Vinh Ngo, Thanh-Le Ha, Phuong-Thai Nguyen, and Le-Minh Nguyen. 2019. Overcoming the rare word problem for low-resource language pairs in neural machine translation. In Proceedings of the 6th Workshop on Asian Translation, pages 207–214, Hong Kong, China. Association for Computational Linguistics.

Iroko Orife, Julia Kreutzer, Blessing Sibanda, Daniel Whitenack, Kathleen Siminyu, Laura Martinus, Jamiiil Toure Ali, Jade Abbott, Vukosi Marivate, Salomon Kabongo, Musie Meressa, Espoir Murhabazi, Orevaoghene Ahia, Elan van Biljon, Arshath Ramkilowan, Adewale Akinfaderin, Wole Akin, Ghollah Kioko, Kevin Degila, Herman Kämper, Bonaventure Dossou, Chris Emezue, Kelechi Ogueji, and Abdallah Bashir. 2020. Masakhane – machine translation for africa.

Maja Popović. 2015. chrF: character n-gram F-score for automatic MT evaluation. In Proceedings of the Tenth Workshop on Statistical Machine Translation, pages 392–395, Lisbon, Portugal. Association for Computational Linguistics.

Matt Post. 2018. A call for clarity in reporting BLEU scores. In Proceedings of the Third Conference on Machine Translation: Research Papers, pages 186–191, Belgium, Brussels. Association for Computational Linguistics.

Adithya Renduchintala, Pamela Shapiro, Kevin Duh, and Philipp Koehn. 2018. Character-aware decoder for neural machine translation. CoRR; abs/1809.02223.

Michael D. Riley. 1989. Some applications of tree-based modelling to speech and language. In Proceedings of the Workshop on Speech and Natural Language, HLT ’89, page 339–352, USA. Association for Computational Linguistics.

Rico Sennrich, Alexandra Birch, Anna Currey, Ulrich Germann, Barry Haddow, Kenneth Heafield, Antonio Valerio Miceli Barone, and Philip Williams. 2017. The university of Edinburgh’s neural MT systems for WMT17. In Proceedings of the Second Conference on Machine Translation, pages 389–399, Copenhagen, Denmark. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2015. Neural machine translation of rare words with subword units. CoRR; abs/1508.07909.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016a. Improving neural machine translation models with monolingual data. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 86–96, Berlin, Germany. Association for Computational Linguistics.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016b. Neural machine translation of rare words with subword units. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers), pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.

Rico Sennrich and Biao Zhang. 2019a. Revisiting low-resource neural machine translation: A case study. In Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics, pages 211–221, Florence, Italy. Association for Computational Linguistics.

Rico Sennrich and Biao Zhang. 2019b. Revisiting low-resource neural machine translation: A case study. CoRR; abs/1905.11901.

Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. 2014. Sequence to sequence learning with neural networks. CoRR; abs/1409.3215.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. CoRR; abs/1706.03762.

Weiyyue Wang, Jan-Thorsten Peter, Hendrik Rosendahl, and Hermann Ney. 2016. CharacTer: Translation edit rate on character level. In Proceedings of the First Conference on Machine Translation: Volume 2, Shared Task Papers, pages 505–510, Berlin, Germany. Association for Computational Linguistics.

Jiajun Zhang and Chengqing Zong. 2016. Exploiting source-side monolingual data in neural machine translation. In Proceedings of the 2016 Conference
on Empirical Methods in Natural Language Processing, page 1535. Austin, Texas. Association for Computational Linguistics.