UniCase - Rethinking Casing in Language Models

Rafał Powalski
Applica.ai
rafal.powalski@applica.ai

Tomasz Stanisławek
Applica.ai
Warsaw University of Technology
tomasz.stanislawek@applica.ai

Abstract

In this paper, we introduce a new approach to dealing with the problem of case-sensitiveness in Language Modelling (LM). We propose simple architecture modification to the RoBERTa language model, accompanied by a new tokenization strategy, which we named Unified Case LM (UniCase). We tested our solution on the GLUE benchmark, which led to increased performance by 0.42 points. Moreover, we prove that the UniCase model works much better when we have to deal with text data, where all tokens are uppercased (+5.88 point).1

1 Introduction

Many natural languages in their written form encode some information in the case of the letter: the beginning of the sentence, proper nouns, headings of publication titles, to name a few. People can process that kind of information in a special way, learning word semantics separately from the case information. However, state-of-the-art (SOTA) approaches for building Language Models do not use this property (Devlin et al., 2019; Liu et al., 2019; Raffel et al., 2020; Brown et al., 2020). As an example, consider RoBERTa language model, where we have different tokenizer outputs for each word case type (lower, title, upper) and multiple vocabulary entries for the same word but different cases (see Table 1).

Whereas different approaches to dealing with case-sensitivity issues were proposed and tested on Machine Translation systems (Etchegoyhen and Gete, 2020; Shi et al., 2020) where the impact of the casing can be significant, there are no similar studies in the context of building Language Models. In fact, most of LMs use cased (with the original text) and uncased (with lowercased text) version of the model (Devlin et al., 2019; Liu et al., 2019; Conneau et al., 2020).

In this paper, we present a model that resolves the problems presented in Table 1. Particularly, we provide two main contributions. Firstly, we propose UniCase: a new language model based on transformer architecture with novel tokenization strategy. Our method improves RoBERTa scores by 0.42 on the GLUE benchmark (Wang et al., 2018). Secondly, we test our new UniCase model on noisy texts, where true case is unknown (all texts were converted to uppercase or lowercase). We will release all pretrained models in an open, public repository.

2 Related work

2.1 Language Modelling

State-of-the-art approaches (Devlin et al., 2019; Liu et al., 2019; Raffel et al., 2020; Brown et al., 2020) for building Language Models use Transformer architecture (Vaswani et al., 2017) with BPE (Sennrich et al., 2016) or Unigram LM-based tokenization methods (Kudo, 2018), where each subtoken from the vocabulary has only one semantic embedding in the model. With that architecture there are two common approaches for dealing with the problem of case-sensitiveness in Language Modelling: cased (with original text) (Liu et al., 2019; Conneau et al., 2020; Raffel et al., 2020; Sun et al.,...
and uncased (with lowercased text) (Devlin et al., 2019; Iandola et al., 2020; Sanh et al., 2020), where cased models proved to be more suitable for majority of NLP tasks (Wang et al., 2018, 2020; Devlin et al., 2019).

2.2 Tokenization

Tokenization is a way of splitting a text into tokens, which NLP models use as smallest piece of information. Over the years researchers have been introducing different approaches to tokenization with three types of tokens as bases: words, characters and subwords. Subwords are considered to be the most effective one (Rai and Borah, 2021).

Byte-Pair-Encoding (BPE) (Sennrich et al., 2016) segmentation balances vocabulary size and the length of a sequence processed by the model in the single pass. The general idea behind BPE is to create the vocabulary by iteratively merging the most frequent pair of characters or subtokens into a new one. Thus, words with low frequencies in the corpus will be represented as combinations of multiple subtokens or characters. It turns out, that this solution has its own drawbacks, such as lack of multiple segmentations endowed with probabilities, and regularization techniques. These two issues were fixed by introducing tokenization based on unigram language model, which can produce multiple subword segmentations endowed with probabilities (Kudo, 2018). It has been proved that language models based on Unigram LM tokenizer work better (Bostrom and Durrett, 2020).

2.3 Neural Machine Translation

Neural Machine Translation (NMT) has recently been the subfield of NLP where many new tokenization techniques were introduced, before being more widely adopted by the whole NLP community (Sennrich et al., 2016; Kudo, 2018). This is also true when it comes to the new approaches to encoding case information into the neural models (Bérard et al., 2019; Etchegoyhen and Gete, 2020; Shi et al., 2020). The following methods are commonly used in NMT: Truecasing, Recasing, Case Factors (CF) and Inline Casing (IC). Two of them can be naturally adopted to the problem of language modelling: CF (subtoken embedding is the concatenation of lowercased base-token embedding and the case embedding for each variant i.e. title, uppercase, mixed) and IC (working on lowercased text but adding extra tags before words which indicate case variants). In this paper we propose a solution which is similar to the Case Factors method with some modifications.

3 Method

In this section we describe our approach to dealing with casing in language models. It can be decomposed into two main parts: tokenization and model architecture.

3.1 Tokenization

As described in Section 2.2 Unigram tokenizer outperforms BPE on Language Model pretraining (Bostrom and Durrett, 2020), therefore we are basing our solution on this method. In addition, we want to create a tokenizer which is able to fulfil the following conditions:

- tokenization should be the same for texts regardless of different casing, with the exception of the next point
- the above condition can be violated for words written with mixed casing (e.g. camelCasing), such words could be split in places where letter casing changes (e.g. word RoBERTa could be splitted into _Ro/BERT/a, even though word Roberta could be represented as a single token).

In order to do that, we trained the Unigram Sentencepiece tokenizer (Kudo and Richardson, 2018) in a way, where word tokens are kept in various case variants. We obtained that, in order to satisfy above conditions, we need only 3 case variants (shapes) i.e. lowercase (aaa), uppercase (AAA) and titlecase (Aaa). Other shapes are only needed in mixed case variants which we decided to split. It is worth mentioning, that such token multiplication by its shape variants is valid only for word tokens. For tokens which contain numbers, punctuation marks, etc. we kept only the original.

3.2 Model

Model architecture is modified in order to utilize the information, that some word tokens in the dictionary, are linked with the same base (lowercase) form. To this end, we decompose the token embedding into base-token embedding and case embedding (Figure 1). These embeddings are trainable and added to each other in the same fashion as positional embeddings are added in the original Transformer architecture (Vaswani et al., 2017). In the consequence of such decomposition, models
with the same number of parameters, can utilize much bigger vocabularies.

During the pretraining phase, we are also decomposing the original masked token prediction task into base-token prediction and case prediction tasks. Final loss is computed as a weighted sum of two tasks’ losses (1). By using weights, we are forcing the model to focus more on base-token prediction. On the initial setting we chose $\alpha = 0.1$.

$$L = L_{\text{base token}} + \alpha L_{\text{case}}$$ (1)

4 Experiments
4.1 Implementation
We are basing our UniCase architecture on RoBERTa code implemented in FAIRSEQ (Ott et al., 2019). Code and pretrained models will be publicly released.

4.2 Unsupervised training

4.2.1 Models
We have trained two versions of UniCase model corresponding to different tokenizer settings.

- UniCase model based on UniCase Tokenizer with $20k$ base tokens, which correspond to $\text{base_token_embedding_size} = 20k$ and $\text{vocab_size} \approx 57k$
- UniCase model based on UniCase Tokenizer with $32k$ base tokens, which correspond to $\text{base_token_embedding_size} = 32k$ and $\text{vocab_size} \approx 90k$

Both models correspond to RoBERTa-base in terms of size.

As a baseline model we chose RoBERTa-base architecture and trained it from scratch. We modified original setup and used a Unigram tokenizer ($\text{vocab_size} = 32k$) to be sure that potential performance deterioration is not caused by the BPE tokenizer, which was proved to be not an optimal choice for tokenization (Bostrum and Durrett, 2020).

We have trained all models on DGX-2 server using the setting recommended by RoBERTa authors with $\text{batch_size} = 2048$ for $100k$ update steps.

4.2.2 Data
The size and quality of pretraining data was proved to play important role for achieving state-of-the-art results (Liu et al., 2019; Brown et al., 2020). Thus, all our models were pretrained on the CCNet dataset (Wenzek et al., 2019), which contains about 700 millions of documents for English language, corresponding to 330 GB of uncompressed text.

4.3 Experiments
4.3.1 Data
We conducted all our experiments on the GLUE benchmark (Wang et al., 2018), which is a collection of well known datasets for testing natural language understanding systems. The original benchmark contains 9 tasks, from which we skip the problematic WNLI set. All our results were based on development sets.

4.3.2 Settings
We have trained all models separately for each of the GLUE tasks, using only the training data for the corresponding task. For finetuning on each task we have used parameters recommended by RoBERTa authors (Liu et al., 2019). All results presented in tables are medians over four random initializations.

4.3.3 Results on original texts
At the beginning, we evaluated all pretrained models (described in section 4.2.1) by using text in original casing (see Table 2. We observed that both UniCase models variants perform better than baseline model. Only on SST dataset RoBERTa model is better. Interestingly, this is the only task in GLUE
Table 2: Results on GLUE. The “Average” column is slightly different than the official GLUE score, since we exclude the problematic WNLI set. F1 scores are reported for QQP and MRPC, Spearman correlations are reported for STS-B, and accuracy scores are reported for the other tasks. All task results are median over four runs.

5 Conclusion

We have presented and tested new UniCase architecture dealing with case-sensitivity in Language Modelling by decomposing information about casing into a separate component. Consequently, we were able to build models with the same number of parameters utilizing larger vocabularies. In contrast to classic Language Models, UniCase does not have to build a semantic understanding of words or sentences in all case variants, potentially leading to more effective training.

We showed that our method outperforms the RoBERTa baseline on almost all tested tasks. Notably, results reported on uppercased GLUE tasks show that models trained with our method understand uppercased documents much better. That shows a promising application of UniCase models in understanding documents where uppercased letters or words are more common, i.e., business documents, forms, invoices.

Acknowledgments

We thank Filip Graliński, Łukasz Gancarek, Michał Pietruszka, Łukasz Borochmann and Dawid Jurkiewicz for their discussion about the paper and ours managing directors at Applica.ai: Adam Dancewicz and Piotr Surma.

The authors would like to acknowledge the support the Applica.ai project has received as being co-financed by the European Regional Development Fund (POIR.01.01.00- 0144/17-00).
References

Kaj Bostrom and Greg Durrett. 2020. Byte pair encoding is suboptimal for language model pretraining.

Tom B. Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel M. Ziegler, Jeffrey Wu, Clemens Winter, Christopher Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language models are few-shot learners.

Alexandre Bérard, Ioan Calapodescu, and Claude Roux. 2019. Naver labs europe’s systems for the wmt19 machine translation robustness task.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. Bert: Pre-training of deep bidirectional transformers for language understanding.

Thierry Etchegoyhen and Harritxu Gete. 2020. To case or not to case: Evaluating casing methods for neural machine translation. In Proceedings of the 12th Language Resources and Evaluation Conference, pages 3752–3760, Marseille, France. European Language Resources Association.

Forrest N. Iandola, Albert E. Shaw, Ravi Krishna, and Kurt W. Keutzer. 2020. SqueezeBert: What can computer vision teach nlp about efficient neural networks?

Taku Kudo. 2018. Subword regularization: Improving neural network translation models with multiple subword candidates.

Taku Kudo and John Richardson. 2018. SentencePiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations, pages 66–71, Brussels, Belgium. Association for Computational Linguistics.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach.

Myle Ott, Sergey Edunov, Alexei Baevski, Angela Fan, Sam Gross, Nathan Ng, David Grangier, and Michael Auli. 2019. fairseq: A fast, extensible toolkit for sequence modeling. In Proceedings of NAACL-HLT 2019: Demonstrations.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J. Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer.

Abigail Rai and Samarjeet Borah. 2021. Study of various methods for tokenization. In Applications of Internet of Things, pages 193–200, Singapore. Springer Singapore.

Victor Sanh, Lysandre Debut, Julien Chaumond, and Thomas Wolf. 2020. Distilbert, a distilled version of bert: smaller, faster, cheaper and lighter.

Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. 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.

Xuewen Shi, Heyan Huang, Ping Jian, and Yi-Kun Tang. 2020. Case-sensitive neural machine translation. In Advances in Knowledge Discovery and Data Mining, pages 662–674, Cham. Springer International Publishing.

Yu Sun, Shuohuan Wang, Yukun Li, Shikun Feng, Hao Tian, Hua Wu, and Haifeng Wang. 2019. Ernie 2.0: A continual pre-training framework for language understanding. arXiv preprint arXiv:1907.12412.

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

Alex Wang, Yada Pruksachatkun, Nikita Nangia, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel R. Bowman. 2020. SuperGlue: A stickier benchmark for general-purpose language understanding systems.

Alex Wang, Amanpreet Singh, Julian Michael, Felix Hill, Omer Levy, and Samuel Bowman. 2018. GLUE: A multi-task benchmark and analysis platform for natural language understanding. In Proceedings of the 2018 EMNLP Workshop BlackboxNLP: Analyzing and Interpreting Neural Networks for NLP, pages 353–355, Brussels, Belgium. Association for Computational Linguistics.

Guillaume Wenzek, Marie-Anne Lachaux, Alexis Conneau, Vishrav Chaudhary, Francisco Guzmán, Armand Joulin, and Edouard Grave. 2019. Ccnet: Extracting high quality monolingual datasets from web crawl data.