Neural Token Segmentation for High Token-Internal Complexity

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Abstract

Tokenizing raw texts into word units is an essential pre-processing step for critical tasks in the NLP pipeline such as tagging, parsing, named entity recognition, and more. For most languages, this tokenization step straightforward. However, for languages with high token-internal complexity, further token-to-word segmentation is required. Previous canonical segmentation studies were based on character-level frameworks, with no contextualised representation involved. Contextualized vectors à la BERT show remarkable results in many applications, but were not shown to improve performance on linguistic segmentation per se. Here we propose a novel neural segmentation model which combines the best of both worlds, contextualised token representation and character-level decoding, which is particularly effective for languages with high token-internal complexity and extreme morphological ambiguity. Our model shows substantial improvements in segmentation accuracy on Hebrew and Arabic compared to the state-of-the-art, and leads to further improvements on downstream tasks such as Part-of-Speech Tagging, Dependency Parsing and Named-Entity Recognition, over existing pipelines. When comparing our segmentation-first pipeline with joint segmentation and labeling in the same settings, we show that, contrary to pre-neural studies, the pipeline performance is superior.

1 Introduction

Tokenization refers to the process of splitting raw, space-delimited, tokens into distinct meaning-bearing units. A case in point is universal dependencies (UD) (Nivre et al., 2020) which adopt a two-level scheme, where tokens are first split into basic word-units, and only then further analyses (POS, dependencies) of these units is provided.

Specifically, in UD and many other NLP tasks the assumption is that a single word-unit needs to correspond to a single Part-of-Speech tag. In most languages, the process of extracting such word-units from space-delimited tokens is straightforward. In English, for instance, this involves splitting ‘isn’t’ into ‘is’ + ‘n’t’ or ‘John’s’ into ‘John’ + ‘’s’, which is a deterministic and unambiguous process for the most part. But for languages with high token-internal complexity and ambiguity, such as Hebrew and Arabic, this is not quite so. The rich orthographic and morpho-phonological processes that form tokens in these languages, as well as the lack of vocalization (a.k.a. diacritics, nikkud) in their texts, leads to extreme token-level ambiguity that poses particular challenges to segmentation. Consider, for instance, the Hebrew token בצל. It could map to: בצל (literally: in-shadow-of-them, meaning: in their shadow), בצל (literally: onion-of-them, meaning: their onion), בצל (literally: in-the-image, meaning: in the image) and more. Out of context, all of these analyses are equally likely. The correct segmentation becomes available only in the greater context of the global interpretation of the sentence.

Because segmentation for these languages is critical, many previous efforts on segmentation were language-specific (Monroe et al., 2014; Goldberg and Elhadad, 2013; Zalmout and Habash, 2017; Samih et al., 2017; Almuhareb et al., 2019; Sajjad et al., 2017; Tawfik et al., 2019). Other efforts such as UDPipe (Straka and Straková, 2017), Stanza (Qi et al., 2020), Shao et al. (2017) or Morfessor (Creutz and Lagus, 2002), aimed at universal segmentation models which are language agnostic. However, on widely accepted cross-lingual benchmarks as UD, their performance on languages with

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1 See the UD guidelines: universaldependencies.org/u/overview/tokenization.html.
complex ambiguous tokens (see §4) lags behind. On top of that, recent prominent works on canonical segmentation of morphologically-complex languages (Kann et al., 2016; Qi et al., 2020; Shao et al., 2018) utilized character-level sequence to sequence frameworks, yet lacked the critical disambiguating context of the tokens, as required by cases of extreme token-internal ambiguity.

In this paper, we propose to bridge this critical gap by devising a char-token segmentation (CATS) model3 where a character-based encoder-decoder network with attention is designed to take advantage of both the token’s surface form via character representations, and the full token’s contextualized embedding. The model is trained end-to-end, is completely language-agnostic, and does not require any external symbolic resources (contrary to Zalmout and Habash (2017); Seker and Tsarfaty (2020); Seeker and Çetinoglu (2015), and others).

We applied our model to a set of languages of high token-internal complexity from the Universal Dependencies 2.5 (UD) project (Nivre et al., 2020), outperforming state-of-the-art segmentation results on Hebrew, Arabic and Turkish. We confirm the utility of our segmentation on three downstream tasks: Part-Of-Speech (POS) tagging, dependency parsing and Named-Entity Recognition (NER), with substantial improvements over existing pipelines. Furthermore, we observed that, contrary to pre-neural studies (Cohen and Smith, 2007; Adler and Elhadad, 2006; Seker and Tsarfaty, 2020; Bareket and Tsarfaty, 2021) we see no particular advantage for joint modeling of segmentation and labeling over the pipeline in these settings.

2 Models

Let us begin by defining the contextualized segmentation task we are interested in. Formally, let \( \mathcal{V} \) be the token vocabulary of a given language and \( \mathcal{V}_w \) be the word vocabulary. We aim to induce a function \( f(v, c) = W \) that finds for every token \( t \in \mathcal{V} \) in a given context \( c \in \mathcal{C} \) the list of words \( W = (w_1, ..., w_n \mid w_i \in \mathcal{V}_w) \) composing this token. In practice, this means that the model’s input consists of the character-sequence of the current surface token, and a contextualized representation of this token within the sentence. The output is a character sequence where the space symbol indicates separation between words.

3All of our code and models will be made publicly available upon acceptance at anonymous.com.
3 Experiments

Goal We set out to empirically evaluate the proposed model on languages of high token-internal complexity from the UD 2.5 datasets (Nivre et al., 2020). We use the standard train/dev/test split of the UD corpora and report results on the test set of each language.

Segmentation Settings In our experiments we use two different types of contextualized token embeddings (i) RNN-based: applying a single-layer BiLSTM, and using the BiLSTM outputs as contextualized representations. The token embeddings are frozen, and the BiLSTM is trained as part of the model. (ii) Transformer-based: We use multilingual BERT (Devlin et al., 2019) hosted by Wolf et al. (2019) to extract contextualized embeddings for all tokens. In order to obtain the token’s contextualized vector, we average the vectors of all word pieces of that token.

All Models were trained with an Adam Optimizer with learning rate of $1e^{-3}$, and batch size of 128. Each dataset was trained for a different amount of epochs, depending on its size (20 to 40).

Pipeline Settings We evaluate our segmentation on three downstream tasks: POS tagging, dependency parsing and NER. We experimented with four types of segmentations in our pipeline setup: (i) Oracle: The gold segmentation given by UD. (ii) UDPipe: The predicted segmentation by UDPipe. (iii) Stanza: A multi-word segmentation tool by Stanza (Qi et al., 2020). (iv) CATS: our proposed segmentation model. For all languages, we rely on mBERT embeddings (Devlin et al., 2019).

Next, for the POS and NER tasks, the segmented text is followed by a BERT-based token classification model (Wolf et al., 2019). The classification model consists of a single classification head on top of a BERT model, fine-tuned on train for 3 epochs with batch size of 8. For dependency parsing we used the parsing capability of Stanza.

For the POS tagging and dependency parsing tasks, the same 4 datasets of UD 2.5 are used, using the UPOS column as gold for the POS task. For NER, a gold pre-segmented NER dataset is required for training and evaluation, so we resorted to a Hebrew dataset which consists BIOSE NE labels on top of the segmented raw tokens.

Joint Settings We evaluated our joint model on both POS and NER tasks, with loss weight of $\lambda = 0.2$. Since NER is a task that requires more semantic information (as opposed to syntactic POS tags) we experimented with a model variant (nicknamed JS-CATS) concatenating the BERT sentence embedding (i.e., the <CLS> token representation) on top of the token vector.

Baselines We use three kinds of baselines:

(i) No-Contextualization Baselines: To examine the contribution of the pre-trained token embeddings, we test our model with non-contextualized token embeddings (initialized either by Zeros or using FastText (FT)) trained with the main task (essentially falling back on standard canonical segmentation architecture as in (Kann et al., 2016)).

(ii) No-Char Baselines: We test the multi-lingual BERT (Devlin et al., 2019) segmentation capabilities by, first, testing its internal word-piece tokenizer, and also using simple LSTM character decoder with only the BERT vector as its input encoding, trained with the main task. In addition we compare our models to current state-of-the-art:

(iii) Language-Agnostic SOTA: We compare our models to the language-agnostic segmentation models of UDPipe (Straka and Straková, 2017) and Stanza (Qi et al., 2020).

Evaluation To evaluate segmentation, we adopt the precision, recall and F1-score, defined by Shao et al. (2018). We compute the metrics on the set of predicted surface segments, compared to the gold surface segments. We evaluate POS tagging by redefining the segments to include their POS labels and calculate F1-scores as usual. For NER we use the standard method of calculating F1-scores over entity spans, respecting both their surface form and label, as explained in ?. For dependency parsing, standard UAS/LAS scores do not fit the task since predicted segmentation may differ from the gold sequence, leading to indices mismatch. We thus use the aligned multi-set F1-score on Form-Head-Relation triplets.

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6The model of Shao et al. (2018) fit this criteria, however, the code is obsolete and not reproducible.

5For completeness, in the supplementary material we added (iv) Language-specific SOTA: comparing our model to the state-of-the-art language-specific model of Hebrew segmentation, YAP (More et al., 2019), which is known to be state-of-the-art on the Hebrew section of the SPMRL shared task (Seddah et al., 2014) and is the de-facto standard for segmentation work on Hebrew, in both academia and the industry.

6Using the evaluation code of Shao et al. (2018).
Table 1 presents the segmentation F1-scores on all models: Mean and Standard Deviation over 5 runs.

Table 2: POS tagging and Dependency Parsing Results. SEG, POS, and DEP stands for segmentation, POS tagging and Dependency Parsing F1-scores.

### Table 3: Hebrew SEG and NER F1-Scores.

| Model          | Test 1 | Test 2 | Test 3 | Test 4 | Test 5 |
|----------------|--------|--------|--------|--------|--------|
| BERT Tokens    | 98.3σ  | 98.31  | 97.9σ  | 98.07  | 94.58  |
| BERT decode    | 65.88±0.76 | 74.46±0.1 | 55.52±0.83 | 74.02±0.36 | 74.36±0.23 |
| UDPipe         | 85.22  | 94.58  | 98.31  | 97.9σ  | 98.07  |
| Stanza         | 93.19  | 97.88  | 98.07  | 94.58±0.15 | 98.3±0.13 |
| CATS: Zeros    | 94.03σ±0.15 | 98.3±0.13 | 97.9±0.29 | 74.46±0.1 | 98.69±0.15 |
| CATS: FT       | 95.76±0.18 | 98.3±0.03 | 97.72±0.2 | 74.46±0.1 | 98.69±0.15 |
| CATS: RNN      | 95.59±0.2 | 98.69±0.15 | 97.9±0.29 | 74.46±0.1 | 98.69±0.15 |
| CAST: BERT     | 98.84±0.29 | 98.3±0.13 | 98.43±0.19 | 74.46±0.1 | 98.69±0.15 |

Table 4: Error analysis of 100 predicted sentence analyses (number of errors in brackets). We provide further breakdown in the supplementary material.

| Oracle          | UDPipe | Stanza | CATS | JS |
|-----------------|--------|--------|------|----|
| Test            | SEG    | NER    | CATS | JS |
| BERT Token Clas. | 99.00  | 99.00  | 99.00 | 99.00 |
| Under-segment   | 75.4%  | 54.99% | 54.99 | 54.99 |
| Over-segment    | 1.96%  | 1.67%  | 1.67 | 1.67 |
| Model artifacts | 1.9%   | 1.67%  | 1.67 | 1.67 |
| Total errors    | 100%   | 100%   | 100% | 100% |

Table 4: Error analysis of 100 predicted sentence analyses (number of errors in brackets). We provide further breakdown in the supplementary material.

### 4 Results

Table 1 presents the segmentation F1-scores on all models for the UD languages we experiment with. First, we observe that BERT alone cannot cope with the complex segmentation of multi-word tokens – neither using its internal tokenizer, nor via its token-based vector embeddings. Further, our contextualized models show substantial improvements in segmentation scores on Hebrew, Arabic and Turkish, compared to all baselines and previous SOTA. Contextualized token embeddings exceed the performance of non-contextualized ones, highlighting the importance of context for diambiguation. All in all, both the token’s form and the context contribute to segmentation accuracy.

Tables 2 and 3 present our pipeline results on POS. Dependency parsing and NER labeling respectively, for the various segmentation possibilities. On any language that our model achieved a meaningful segmentation improvement (e.g., Hebrew, Arabic), an increase in downstream task results was also obtained. These results confirm the claim that segmentation mistakes indeed severely contaminate the downstream tasks.

In our joint model results in Tables 2 and 3, we observe that, contrary to previous studies, the joint model did not improve the segmentation accuracy, nor the labeling score over the pipeline (yet the sentence embeddings in JS-CATS improved labeling results substantially compared to J-CATS). The results observed here bring up again the question of ‘joint versus pipeline’ in the neural era, and present an opportunity to investigate more sophisticated joint segmentation-and-labeling models that extend the proposed architecture in new ways.

A manual error analysis we performed on 100 segmented sentences is presented in Table 4. We see that UDPipe has a higher tendency towards under-segmentation both on prefixes and suffixes. Secondly, though CATS BERT resulted in far fewer errors, the model presents unnecessary artifacts (10.2%) which are caused by the generative nature of our model. Further study on avoiding such artifacts might increase results further.

### 5 Conclusion

We present a simple, effective and accurate neural segmentation model that by combining character-level sequence-to-sequence modeling with pre-trained contextualized representations can effectively cope with complex and ambiguous segmentation of multi-word tokens. The model achieves state-of-the-art segmentation results on various languages, and leads to substantial improvements on key tasks down the pipeline. These results opens the door for (pre-)training large language models on (pre-)segmented data rather than on raw tokens, to yield even further improvements on natural language understanding on such languages.
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