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# Is Typology-Based Adaptation Effective for Multilingual Sequence Labelling?

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## Abstract

Recent work has shown that a single multilingual model with typologically informed parameter sharing can improve the performance in dependency parsing on both high-resource and zero-shot conditions. In this work, we investigate whether such improvements are also observed in the POS, NER and morphological tagging tasks.

## 1 Introduction

Recent studies have shown that state-of-the-art neural models can successfully be trained on multiple languages simultaneously for various NLP tasks such as named-entity recognition (Mulcaire et al., 2019; Rahimi et al., 2019), morphosyntactic tagging (Tsai et al., 2019), dependency parsing (Ammar et al., 2016; Kondratyuk and Straka, 2019), and machine translation (Johnson et al., 2017; Aharoni et al., 2019). Multilingual approaches have the following benefits over monolingual counterparts: (1) Multilingual models learn better generalization by sharing model parameters among multiple source languages which enables cross-lingual transfer and zero-shot learning. (2) Maintaining a single multilingual model is easier than a large set of language-specific models which increase the total size and system complexity.

However, a multilingual model trained on a high number of languages can face the “transfer - interference trade-off” (Johnson et al., 2017; Arivazhagan et al., 2019; Conneau et al., 2020). This trade-off leads multilingual models to outperform monolingual baselines on low/zero-resource languages (*positive transfer*), but to underperform on high-resource languages due to the lack of language specific capacity (*negative interference*). Moreover, multilingual transfer could give mixed results when the model is trained on a diverse set of source languages in terms of script, phonology, morphology,

syntax, and semantics.

Early work on multilingual learning has been applied in POS and morphological tagging (Gillick et al., 2016; Tsai et al., 2019), NER (Mulcaire et al., 2019; Rahimi et al., 2019), and UD parsing (Ammar et al., 2016; Kondratyuk and Straka, 2019; Üstün et al., 2020). Gillick et al. (2016) showed that a compact multilingual model operating on bytes could reach similar or better performance in POS and NER. Mulcaire et al. (2019) and Wu and Dredze (2019) showed that multilingual language model pretraining based on ELMo (Peters et al., 2018) and BERT (Devlin et al., 2019), improves the performance on POS, NER and UD tasks, including zero-shot settings. More recently, Kondratyuk and Straka (2019) trained a massively multilingual UD parser, UDify, on 75 languages using multilingual BERT (mBERT), which shows competitive or improved performance, but mostly on low-resource languages.

Finally, Üstün et al. (2020) have proposed a multilingual dependency parser, UDapter, with language-specific and typologically informed parameter sharing. This parser learns task-specific adapters (Houlsby et al., 2019), which are inserted into mBERT, via language embeddings by using contextual parameter generation (Platanios et al., 2018) to balance maximum sharing and language-specific capacity in a single multilingual model. Furthermore, language embeddings are defined as a function of a large set of linguistically curated and predicted typological features obtained from the URIEL (Littell et al., 2017) database. While typology features had been used before (Ammar et al., 2016), this work was the first to report improvements on both high-resource and zero-shot results, while not using gold POS tags.

In this work, we extend UDapter to three other sequence labelling tasks, namely: POS tagging, NER and morphological (MORPH) tagging. We

	ar	eu	fi	he	hi	ko	ru	sv	tr	zh	be*	fo*	kk*	olo*	sa*	yue*	HR-AVG	LR-AVG
<i>POS tagging (Accuracy)</i>																		
UDify	96.3	94.5	96.4	96.5	96.7	95.3	98.5	97.6	93.4	93.8	94.6	80.0	85.0	74.5	41.4	68.1	95.9	58.0
UDapter	96.8	95.7	97.3	97.1	97.4	96.5	98.9	98.4	95.1	95.2	96.9	79.6	83.4	76.6	42.2	66.3	96.8	58.4
<i>Morphological Tagging (F1)</i>																		
UDify	95.7	92.0	94.7	94.9	97.0	99.6	97.6	97.6	90.9	98.9	92.3	58.4	52.2	59.9	40.7	-	95.9	44.4
UDapter	96.8	95.4	96.7	96.2	97.7	99.8	98.3	98.3	94.8	99.2	92.0	56.3	52.5	62.4	20.6	-	97.3	44.3
<i>Named Entity Recognition (F1)</i>																		
UDify	87.9	91.3	90.9	84.7	86.8	87.3	88.6	94.4	91.9	78.8	80.2	78.3	72.4	-	53.8	76.4	88.3	67.4
UDapter	89.4	92.7	92.4	86.7	89.5	88.8	89.8	95.8	93.1	81.3	80.4	81.0	65.4	-	45.6	75.2	89.9	65.6
<i>Dependency Parsing (LAS)</i>																		
UDify	80.12	76.4	85.1	84.4	89.3	78.0	89.0	86.2	62.7	77.8	80.1	68.6	61.9	42.1	19.4	30.5	83.0	50.4
UDapter	84.42	83.3	89.0	88.8	92.0	85.9	92.2	90.3	69.6	83.2	79.3	69.2	60.7	43.3	22.2	32.8	87.3	51.3

Table 1: Results of UDapter (Üstün et al., 2020) and UDify (Kondratyuk and Straka, 2019) trained per task on 13 languages. ‘\*’ indicates the zero-shot experiments. HR-AVG is calculated over all 13 training languages, and LR-AVG is calculated over all low-resource languages used in the evaluations.

present results on a large set of languages, including the zero-shot setting, and compare them to the parsing results presented in (Üstün et al., 2020).

## 2 Experiments

We modify UDapter (Üstün et al., 2020), by adding simple task-specific softmax layers for POS, MORPH tagging, and NER. Parameters of task-specific layers are modified by typologically informed language embeddings as in the original model. As a baseline, we use UDify (Kondratyuk and Straka, 2019) trained on our set of 13 languages (see below). Both UDapter and UDify are trained separately for each of the three tasks with the same hyper-parameter setting as in Üstün et al. (2020) for 30 epochs.

For training languages, following Kulmizev et al. (2019), we choose Arabic (ar), English (en), Basque (eu), Finnish (fi), Hebrew (he), Hindi (hi), Italian (it), Japanese (ja), Korean (ko), Russian (ru), Swedish (sv), Turkish (tr) and Chinese (zh). In the zero-shot setup, both models are evaluated on languages used in Üstün et al. (2020) if annotations exist in the datasets. Table 1 shows results on a subset of languages including Belarusian (be), Faroese (fo), Kazakh (kk), Livvi (olo), Sanskrit (sa) and Cantonese (yue). We selected this subset so that each language is from the same family as one of the high-resource languages. For POS and MORPH tagging, we use UD 2.3 (Nivre et al., 2018) and for NER, we use WikiANN (Pan et al., 2017) which was divided into train/dev/test by Rahimi et al. (2019).

## 3 Results and Conclusion

Results including dependency parsing scores from Üstün et al. (2020) are given in Table 1. Language-specific adaptation of a multilingual model with typological features increases the performance in all tasks for high-resource (HR) languages. The increase in MORPH tagging and parsing is larger than for POS and NE.

However, for low-resource (LR) languages, we find a mixed picture. In POS tagging and parsing, UDapter outperforms UDify but the improvements are rather small compared to HR. In MORPH tagging, we observed a very small decrease on average but a large variation, mostly due to the inconsistent annotations in LR languages. For UDapter, jointly predicting separate morphological attributes besides the unfactored tag string (Inoue et al., 2017), helps the model to learn infrequent tags, but overall performance is still below the baseline. Finally, in NER, unlike the other three tasks, UDapter has significantly lower performance. A possible explanation is that while POS tagging and parsing have more structured and universal representation which allows the model to exploit multilingual sharing even for unseen words, NER requires better word-level representations where typological features may not have benefits. Moreover, the low representation quality of LR languages in mBERT (Wu and Dredze, 2020) may have a stronger negative effect on these tasks.

This is work in progress. We are currently studying the reasons of the different trends and we plan to provide further analysis during the presentation.

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