Applying Occam's Razor to Transformer-Based Dependency Parsing: What Works, What Doesn't, and What is Really Necessary

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Abstract

The introduction of pre-trained transformer-based contextualized word embeddings has led to considerable improvements in the accuracy of graph-based parsers for frameworks such as Universal Dependencies (UD). However, previous works differ in various dimensions, including their choice of pre-trained language models and whether they use LSTM layers. With the aims of disentangling the effects of these choices and identifying a simple yet widely applicable architecture, we introduce STEPS, a new modular graph-based dependency parser. Using STEPS, we perform a series of analyses on the UD corpora of a diverse set of languages. We find that the choice of pre-trained embeddings has by far the greatest impact on parser performance and identify XLM-R as a robust choice across the languages in our study. Adding LSTM layers provides no benefits. A multi-task training setup outputting additional UD features may contort results. Taking these insights together, we propose a simple but widely applicable parser architecture and configuration, achieving new state-of-the-art results for 11 out of 12 diverse languages.[1]

1 Introduction

Recent years have seen considerable improvements in the performance of syntactic dependency parsers for frameworks such as Universal Dependencies (UD; de Marneffe et al., 2014). For graph-based parsers, these improvements can in large part be attributed to two developments: (1) the introduction of deep biaffine classifiers (Dozat and Manning, 2017), which now constitute the de-facto standard approach for graph-based dependency parsing, and (2) the rise of pre-trained distributed word representations, particularly transformer-based contextualized embeddings such as BERT (Devlin et al., 2019) or RoBERTa (Liu et al., 2019). Both characteristics are present in recent top-performing systems (Che et al., 2018; Straka et al., 2019; Kondratyuk and Straka, 2019; Kanerva et al., 2018, 2020; Che et al., 2018).

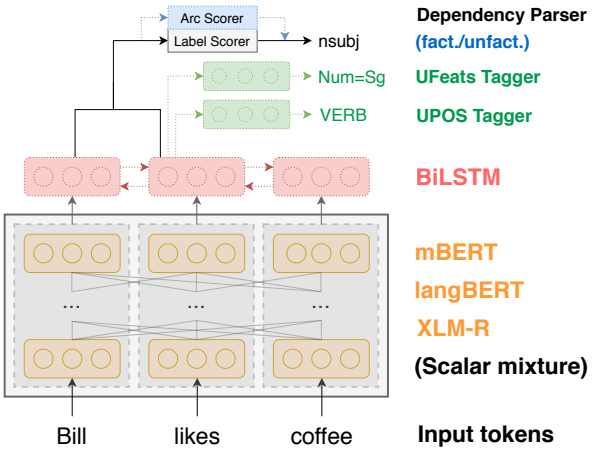

Figure 1: Modular architecture of the STEPS parser. Dotted lines denote optional components.

However, there remain a considerable number of implementation and configuration choices whose impact on parser performance is less well understood. This is evidenced by the many different model configurations (see Table 1) present in parsers that have achieved top results in recent shared tasks addressing UD parsing (Zeman et al., 2017, 2018; Bouma et al., 2020). The choices include (a) the particular pre-trained word embeddings or language model to use, (b) whether to utilize an LSTM in addition to (fine-tuned) contextualized word embeddings; and (c) whether to use a multi-task training setup simultaneously predicting additional UD features (such as morphology or parts of speech) during parsing.

The aim of this paper is to disentangle the effects of the above factors and determine their impact on parser performance. We appeal to the concept of Occam's razor by ways of avoiding architectural el-

[1]We will release our code and pre-trained models on github.com/boschresearch/steps-parser.

ements that do not bring about a testable advantage. With this idea in mind, we introduce STEPS (the **S**tuttgart **T**ransformer-based **E**xtensible **P**arsing **S**ystem), a modular graph-based dependency parser which implements commonly used modules such as biaffine scorers (Dozat et al., 2017; Kondratyuk and Straka, 2019) or LSTM layers (Straka, 2018) (see Figure 1). Using STEPS, we perform a series of experiments on the UD treebanks of a diverse set of languages. Our setup facilitates estimating the impact of the various architectures and configuration decisions in a comparable way.

Our most important insight is that a relatively simple architecture using biaffine heads on top of fine-tuned XLM-R (Conneau et al., 2019) leads to the highest parsing accuracy for almost all languages in our study, sometimes outperforming prior work by large margins. Our analysis indicates that LSTM layers do not lead to benefits. Simplifying the architecture even further by using a single scorer for edge and label prediction results in similar performance but on average leads to longer training times. Our contributions are as follows:

(1) We introduce STEPS, a new implementation of a graph-based dependency parser designed to be modular and easily extensible. STEPS achieves new state-of-the-art UD parsing performance for 11 out of the 12 typologically diverse languages in our study, and also outperforms the previous state-of-the-art for UD feature and POS tag prediction for 10 languages. We will make our code and pre-trained models for 12 languages publicly available.

(2) We conduct a detailed experimental study, identifying components of parser architecture that are really necessary to obtain a strongly performing system that is applicable across a wide range of languages. The final system uses XLM-R, no LSTM layer, and a factorized edge and label scoring architecture.

(3) We show that multi-task setups predicting additional features as commonly employed in UD parsing may confound results for parsing for individual languages; we hence propose to compare parsing accuracy in unified evaluation settings in future work.

(4) We show that our parser can be easily adapted to Enhanced UD parsing, also resulting in state-of-the-art performance for 5 out of 7 evaluated languages.

Parser	Pre-trained embed.	LSTM	MTL
StanfordNLP	word2vec, fastText	yes	no
UDPipe 2.0	word2vec, fastText	yes	yes
HIT-SCIR	fastText, ELMo	yes	no
UDify	mBERT	no	yes

Table 1: Settings for a number of previously state-of-the-art graph-based dependency parsers. "LSTM" states whether the parser makes use of an LSTM, and "MTL" states whether the parser is also trained to predict other UD properties such as POS tags or morphological features.

This paper is structured as follows. Sec. 2 gives the necessary background on relevant state-of-the-art neural graph-based dependency parsers as well as related work on analysing and comparing parsers. Sec. 3 describes the architecture and configuration options for our new STEPS parser, at the same time introducing the various factors studied in our experiments (Sec. 4). Sec. 5 presents the adaption of our system to Enhanced UD. Finally, we discuss implications for parser choice and future parser design (Sec. 6).

2 Related Work

This section provides an outline of the architectural details of recently developed graph-based dependency parsers. In addition, we briefly review related work on dependency parser analysis. Table 1 shows the configurations of four parsers that were among the best-performing systems in the CoNLL 2017 and CoNLL 2018 Shared Tasks on UD parsing. The parsers use a variety of pre-trained embeddings. Except for UDify, the systems do not fine-tune them, but additionally train their own tokens embeddings.

Recent Graph-based Parsers. **StanfordNLP** (Dozat et al., 2017) was one of the first systems to apply the biaffine graph-based parser architecture to Universal Dependency parsing. Its token representations make use of pre-trained word2vec (Mikolov et al., 2013) embeddings that are contextualized using a BiLSTM. **UDPipe 2.0** (Straka, 2018) uses a multi-task setup in which POS and feature tagging, lemmatization, and dependency parsing share layers. The system was later extended (Straka et al., 2019, henceforth **UDPipe+**) by incorporating multilingual BERT (mBERT; Devlin et al., 2019) in its token representations. **HIT-SCIR** (Che et al., 2018) was one of the first UD parsers to make use of contextualized pre-trained word embeddings

(in the form of ELMo; Peters et al., 2018). The model does not make use of a multi-task training setup. **UDify** (Kondratyuk and Straka, 2019) differs from previous UD parsers in two ways. First, it does not use an LSTM layer for token representation, instead using a learned scalar mixture of mBERT layers and fine-tuning mBERT during training. Different scalar mixture coefficients are learned for POS tagging, feature prediction, and lemmatization, which are trained jointly with dependency parsing in a multi-task setting. Second, UDify learns a single model for all languages, concatenating all UD 2.5 training sets.

Multi-Purpose Parsers. Other parsers with modular or extensible architectures include **Alto** (Gontrum et al., 2017), a prototyping tool for new grammar formalisms based on Interpreted Regular Tree Grammars (IRTGs), and **PanParser** (Aufrant and Wisniewski, 2018), a modular framework for transition-based dependency parsing. In contrast to these two, STEPS is a graph-based dependency parser that focuses on easy configuration of different transformer-based language models and neural architecture variants.

Parser Analyses and Comparisons. Recent years have seen a wide range of studies comparing different language models for dependency parsing (e.g., Kanerva et al., 2018; Pyysalo et al., 2020; Smith et al., 2018; Kulmizev et al., 2019). Additionally, several studies have investigated the amount of implicit syntactic information captured in pre-trained LMs such as ELMo and BERT (Tenney et al., 2019a,b; Hewitt and Manning, 2019). Conversely, several studies have investigated the utility of structural features for dependency parsing in the presence of LSTMs and/or contextualized word embeddings, generally finding that their impact is diminished in the presence of contextual information (Falenska and Kuhn, 2019; Fonseca and Martins, 2020).

Our work differs from these studies in that we evaluate several very different dimensions of parser architecture at the same time, utilizing the same underlying backbone and thus ensuring comparability across experiments.

3 STEPS: A Modular Graph-Based Dependency Parser

In this section, we describe our modular dependency parser STEPS (**S**tuttgart **T**ransformer-based **E**xtensible **P**arsing **S**ystem). Each subsection focuses on a particular aspect of the parser setup, providing background on its usage and its potential impact on parser performance.

3.1 Input Token Representation

STEPS provides a number of different options for input token representation. As Table 1 shows, parsers have made use of a variety of pre-trained embeddings, with transformer-based language models having become the predominant current approach. We hence focus on the latter and compare multilingual BERT (**mBERT**; Devlin et al., 2019), language-specific BERTs (**langBERT**), and the multilingual **XLM-R** model (Conneau et al., 2019). XLM-R utilizes the pre-training optimizations first proposed for RoBERTa (Liu et al., 2019), which includes training on a considerably larger amount of data. A detailed overview of all transformer models used in our experiments can be found in Appendix A.1.

STEPS represents each token i using a vector $\mathbf{r}_i$ corresponding to the embedding of its first word-piece token. Following Kondratyuk and Straka (2019), we compute token embeddings as weighted sums of the representations of the respective tokens given by the internal transformer encoder layers. Coefficients for this sum are learned during training, and layer dropout is applied in order to prevent the model from focusing on particular layers. Our model learns a different set of these coefficients of for each output task (see Sec. 3.2 and Sec. 3.3 below). In addition to the above described **transformer-only** setting, we also compute another version of token embeddings by feeding the embeddings computed by the sum operations into a multi-layer bidirectional **LSTM** (BiLSTM), whose per-token output then constitutes $\mathbf{r}_i$.

3.2 Biaffine Classifier Architecture

STEPS makes use of biaffine classifiers as proposed by Dozat and Manning (2017), which have become the de-facto standard method for graph-based dependency parsing. In a first step, a head representation $\mathbf{h}_i^{head}$ and a dependent representation $\mathbf{h}_i^{dep}$ are created for each input token i represented as embedding vector $\mathbf{r}_i$ via two single-layer feedforward neural networks:

$$\mathbf{h}_i^{head} = \text{FNN}^{head}(\mathbf{r}_i) \quad (1)$$

$$\mathbf{h}_i^{dep} = \text{FNN}^{dep}(\mathbf{r}_i) \quad (2)$$

These representations are then fed into the biaffine function, which maps head–dependent pairs (i, j) onto vectors $\mathbf{s}_{i,j}$ of arbitrary size:

$$\mathbf{s}_{i,j} = \text{Biaff}\big(\mathbf{h}_i^{head}, \mathbf{h}_j^{dep}\big) \quad (3)$$

$$\text{Biaff}(\mathbf{x}_1, \mathbf{x}_2) = \mathbf{x}_1^\top \mathbf{U}\mathbf{x}_2 + W(\mathbf{x}_1 \oplus \mathbf{x}_2) + \mathbf{b} \quad (4)$$

$\mathbf{U}$, W and $\mathbf{b}$ are learned parameters; $\oplus$ denotes the concatenation operation. The scores $s_{i,j}$ can now be leveraged in different ways to construct an output tree or graph; this will be described next.

First, the **factorized** approach (Dozat and Manning, 2017) uses two instances of biaffine classifiers. The first classifier (the "arc scorer") is responsible for predicting which (unlabeled) edges exist in the output structure. It predicts, for each token, a probability distribution over potential syntactic heads (i.e., all other tokens in the sentence). We then feed the log-probabilities to the Chu-Liu/Edmonds maximum spanning tree algorithm (Chu and Liu, 1965; Edmonds, 1967) and label the resulting tree using the label scorer. The second classifier (the "label scorer") then assigns dependency labels to edges predicted in the first step.

The **unfactorized** approach, proposed by Dozat and Manning (2018) for semantic graph parsing, uses only a single biaffine classifier (namely the label scorer). Non-existence of dependencies is encoded using simply another label ($\varnothing$). We adapt this approach to tree parsing by discarding the arc scorer and computing the edge weights for the Chu-Liu/Edmonds MST algorithm as $\log(1 - P(\varnothing))$ in order to extract a labeled dependency tree directly. To the best of our knowledge, this is the first time that the unfactorized architecture has been applied to the parsing of dependency tree structures.

3.3 Multi-Task Training

We study the effects of a multi-task training setup by implementing two approaches to training our parser: (a) **dep-only**, in which the model is trained only on syntactic dependencies; and (b) multi-task learning (**MTL**), in which the model additionally predicts universal part-of-speech tags (UPOS) and morphological features (UFeats). We follow Kondratyuk and Straka (2019) by learning different coefficients for the transformer layers for these tagging tasks (see Sec. 3.1) and then using a single-layer feed-forward neural network to extract logit vectors over the respective label vocabularies. By default, the loss for the entire system is computed as the sum of losses for the individual output modules (UPOS tagger, UFeats tagger, and dependency parser). However, we also add the option of scaling the loss of the individual output modules in order to prevent individual tasks from overwhelming the system as a whole (see Sec. 4.6).

4 Experiments

This section describes our experimental setup and reports the results of our experiments on pre-trained embeddings (Sec. 4.3), factorized vs. unfactorized parser architecture (Sec. 4.5), LSTM usage (Sec. 4.4), and multi-task training (Sec. 4.6).

4.1 Experimental Setup

Languages and treebanks. We select 12 languages, covering a diverse range of language families and writing systems, by applying linguistic criteria similar to those outlined by de Lhoneux et al. (2017). For each language, we select the largest available treebank from UD 2.6 for which token data is freely available. (The full list of treebanks can be found in Appendix A.2.) In all of our experiments, we use gold tokens and train language-specific models, testing on the test set of the respective treebank.

Evaluation metrics. We compute UAS and LAS using the official evaluation script for the CoNLL 2018 Shared Task.[2] UAS (Unlabeled Attachment Score) computes the fraction of tokens that have been assigned the correct syntactic head. LAS (Labeled Attachment Score) records the fraction of tokens that have been assigned the correct syntactic head with the correct edge label.

4.2 Implementation

Our parser is implemented in Python, using PyTorch (Paszke et al., 2019) and the Huggingface Transformers library (Wolf et al., 2019). Training is performed on a single nVidia Tesla V100 GPU.

Hyperparameters. We aim to obtain a simple yet high-performing hyperparameter configuration. We use the configuration of UDify, which is architecturally quite similar to STEPS, as a starting point and tune parameters on a small development set (consisting of English, Arabic, and Korean), aiming at a simplified setup that achieves good results across these diverse languages. In large part, our

[2] https://universaldependencies.org/conll18/conll18_ud_eval.py

settings correspond to UDify's values with the following differences. We use AdamW (Loshchilov and Hutter, 2019) instead of Adam; we perform neither label smoothing nor gradient clipping; we do not use differential learning rates. In addition, we do not train for a fixed number of epochs, but instead stop once performance on the validation set does not increase for 15 epochs, or after at most 24 hours. For model variants involving LSTMs, we tuned the hyperparameters involved in these layers in a second round of optimization consisting of 15 trials of random search on the English data. We then picked the two best-performing models and ran them on the other languages, finding that one of them performed best on all languages.

All of our final hyperparameter settings, as well as further details about the optimization procedure, can be found in Appendix A.3.

4.3 Impact of Pre-Trained Word Embeddings

We first evaluate how parsing performance differs when varying the underlying pre-trained language model. We here do not include an LSTM layer and perform only dependency parsing. Table 2 shows results for all 12 treebanks used in this study. UDPipe+ refers to the version of UDPipe enhanced with BERT and Flair embeddings proposed by Straka et al. (2019) and described in Sec. 2. UDify refers to the original system trained on all UD languages without treebank-specific fine-tuning. As multilingual training usually results in improved performance for low-resource languages at the cost of lowering scores for high-resource languages (Üstün et al., 2020), for meaningful comparison, we train $\text{UDify}_{\text{mono}}$ on single treebanks.

$\text{STEPS}_{\text{mBERT}}$ roughly corresponds to $\text{UDify}_{\text{mono}}$, and indeed the models overall perform similarly. We attribute differences to slightly different training setups. While UDify is trained for 80 epochs, STEPS employs early stopping after 15 epochs without improvement. Moreover, we did not disable multi-task learning for parallel UD feature prediction in $\text{UDify}_{\text{mono}}$, and this may be an explanation why $\text{STEPS}_{\text{mBERT}}$ does much better on Finnish, Czech and Russian, where morphological features may be harder to predict. (For a principled comparison of multi-task setups, see Sec. 4.6.) By contrast, UDPipe+ often outperforms UDify, $\text{UDify}_{\text{mono}}$, and $\text{STEPS}_{\text{mBERT}}$, which is likely due to the fact that it trains its own word embeddings in addition to mBERT and additionally makes use of character-level representations via GRUs.

Parsing accuracy of STEPS is very high across the board, with new state-of-the-art results being achieved on all languages except Japanese, often by considerable margins (>1.0 LAS). For most languages, the best results are achieved using $\text{STEPS}_{\text{XLM-R}}$, with $\text{STEPS}_{\text{langBERT}}$ coming in second. In contrast, using mBERT is not the best option on any treebank. In fact, the only languages for which mBERT achieves better results than langBERT in our experiments are Latvian and Hindi.[3] While using langBERT usually yields worse parsing accuracy than XLM-R, results are roughly on par for Arabic and English. We note that the language-specific models we chose for these treebanks (ArabicBERT-large and RoBERTa-large, respectively) are the only ones with a number of trainable parameters similar to XLM-R, while all others have a considerably smaller number of parameters (see Appendix A.1). This highlights the importance of model size in pre-trained word embeddings.

On Finnish and Latvian, $\text{STEPS}_{\text{XLM-R}}$ outperforms the previous state-of-the-art by very large margins (around 4.9 and 6.5 LAS, respectively). We assume that there are two main reasons for this. First, XLM-R is pre-trained on CommonCrawl data (Conneau et al., 2019; Wenzek et al., 2020) as opposed to Wikipedia dumps, which results not only in several orders of magnitude more training data (over 1 billion tokens for both languages), but also presumably more heterogenous data, which may provide better generalizations for the domains in our test data.[4] Second, XLM-R has a much larger vocabulary size than mBERT (250k vs. 100k), which means it may account better for the rich morphology of these languages. On average, a Finnish (Latvian) token is split up into 2.4 (2.1) word pieces when using mBERT, but only 1.9 (1.8) word pieces when using XLM-R.

4.4 Impact of LSTM Layer

In this section, we evaluate the performance of a system identical to $\text{STEPS}_{\text{XLM-R}}$ described above, but with 3 additional BiLSTM layers added on top

[3] In a similar study comparing mBERT- and langBERT-based parsers, Kanerva et al. (2020) also found Latvian to be one of the few languages for which mBERT outperformed the language-specific (WikiBERT) version. Both the Latvian and the Hindi Wikipedias are rather small, consisting of only 21M and 35M tokens, respectively (Pyysalo et al., 2020).

[4] Both fi-TDT and lv-LVTB contain, among others, "non-standard" data such as blog entries, legal texts, and spoken language (Haverinen et al., 2014; Pretkalniņa et al., 2018).

	ar PADT	cs PDT	de GSD	en EWT	fi TDT	hi HDTB	it ISDT	ja GSD	ko Kaist	lv LVTB	ru STR	zh GSD
UDPipe+	84.62	92.56	84.06	90.40	89.49	92.50	93.38	**94.27**	87.54	84.50	93.68	86.74
UDify[a]	82.88	92.88	83.59	88.50	82.03	91.46	93.69	92.08	84.52	85.09	93.13	83.75
$\text{UDify}_{\text{mono}}$	83.34	91.58	84.28	89.52	86.74	91.44	93.14	92.14	86.45	85.45	92.32	82.95
$\text{STEPS}_{\text{mBERT}}$	83.80	92.69	84.08	89.16	88.91	91.30	93.13	92.22	–	85.05	93.74	84.94
$\text{STEPS}_{\text{langBERT}}$	**86.60**	92.99	85.87	**91.98**	93.57	91.16	94.25	92.98	84.56	82.61	94.44	86.20
$\text{STEPS}_{\text{XLM-R}}$	86.55	**94.58**	**86.07**	91.91	**94.36**	**93.34**	**94.86**	94.10	**89.93**	**91.93**	**95.30**	**87.75**
$\text{STEPS}_{\text{XLM-R-LSTM}}$	86.41	94.52	**86.20**	91.58	93.92	93.28	94.57	94.01	89.91	91.61	95.27	86.96
$\text{STEPS}_{\text{XLM-R-unfact}}$	86.32	94.38	**86.19**	91.57	94.11	93.21	94.58	93.58	89.86	91.76	95.17	87.47

Table 2: Labeled Attachment Score (LAS) for **basic dependency parsing** varying input embeddings and architecture. Scores are averages of three runs. UDify results are for multilingual training without language-specific fine-tuning. In the upper part of the table, the top scores are bold-faced. Scores for $\text{STEPS}_{\text{XLM-R-LSTM}}$ and $\text{STEPS}_{\text{XLM-R-unfact}}$ are bold-faced if outperforming $\text{STEPS}_{\text{XLM-R}}$. Results for $\text{STEPS}_{\text{mBERT}}$ for Korean were not ready at time of the submission. For full results including UAS, see Appendix A.4.

of the language model ($\text{STEPS}_{\text{XLM-R-LSTM}}$ in Table 2). Changes in performance are generally small. With the exception of German, including LSTM layers actually decreases parsing accuracy. The LSTM model contains more trainable parameters and also makes use of differential learning rates, yet, we did not find any meaningful differences in convergence speed and training times. Hence, we conclude that when fine-tuning an underlying transformer-based language model, adding LSTM layers on top is not necessary.

4.5 Impact of Factorization

Dozat and Manning (2018) show that for semantic dependency graph parsing, a simplified parser architecture predicting edge presence and edge labels from the same scoring matrix achieves largely identical results compared to a model using two separate classifiers for arcs and labels. We here dive into the question whether such an unfactorized approach is also able to achieve competitive results in syntactic tree parsing. We do so by implementing a version of $\text{STEPS}_{\text{XLM-R}}$ that makes use of the unfactorized approach as descibed in Sec. 3.2.

Results of our experiments can be found in the row labeled $\text{STEPS}_{\text{XLM-R-unfact}}$ in Table 2. Overall, performance of the unfactorized approach is very close to the factorized version, but slightly lower. While this shows that the unfactorized approach is indeed viable for tree parsing, analysis of the training times reveals an increase by ca. 30 % on average when using the unfactorized model, indicating that the shared scorer takes a longer time to converge. (For details, see Appendix A.5.)

In light of these results, we propose to stick with the factorized version for syntactic tree parsing. At least in a research setting, shorter training times allow for a larger set of experiments and thus ultimately in using fewer resources. When applying the parser, differences in model size and parsing time are negligible.

4.6 Impact of Multi-Task Approach

Finally, we analyze how performance changes when predicting UPOS and UFeats in addition to dependencies. For these experiments, we use XLM-R as input embeddings and a factorized architecture. As shown in Table 3, $\text{STEPS}_{\text{MTL}}$ achieves very high accuracies for UPOS and UFeats, performing better or on par with the previous state of the art (UDPipe+). However, we find that compared to the dependency-only system, parsing accuracy drops considerably in the multi-task setting (up to over 1 LAS for Finnish).

During training of $\text{STEPS}_{\text{MTL}}$, accuracy on the validation set increased very rapidly for the tagging tasks and reached levels close to the final values after only a few epochs, while accuracy for the parsing task increased much slower. This suggests that the loss for the tagging tasks might overwhelm the system as a whole, causing the parser modules to underfit. We therefore also test $\text{STEPS}_{\text{MTLscale}}$, in which the loss for UPOS and UFeats is scaled down to 5% during training. $\text{STEPS}_{\text{MTLscale}}$ performs close to $\text{STEPS}_{\text{MTL}}$, even outperforming it in the case of Hindi. In turn, however, accuracy for UPOS and particularly UFeats drops considerably.

To sum up, our experiments indicate that multi-task setups as commonly employed in UD parsing have a non-neglilible effect on parsing performance. Hence, when comparing parser performance, it is crucial to take potential multi-task setups into ac-

Treebank	Model	UPOS	UFeats	UAS	LAS
Arabic (ar_padt)	UDPipe+	96.98	94.72	89.01	84.62
	$\text{STEPS}_{\text{dep-only}}$	–	–	**90.96**	**86.55**
	$\text{STEPS}_{\text{MTL}}$	**97.24**	**94.89**	90.34	86.01
	$\text{STEPS}_{\text{MTLscale}}$	96.47	87.74	90.80	86.41
Czech PDT (cs_pdt)	UDPipe+	99.34	97.67	94.43	92.56
	$\text{STEPS}_{\text{dep-only}}$	–	–	**95.89**	**94.58**
	$\text{STEPS}_{\text{MTL}}$	**99.41**	**98.06**	95.59	94.19
	$\text{STEPS}_{\text{MTLscale}}$	98.97	94.20	95.85	94.52
German (de_gsd)	UDPipe+	95.18	91.72	88.11	84.06
	$\text{STEPS}_{\text{dep-only}}$	–	–	**90.02**	**86.07**
	$\text{STEPS}_{\text{MTL}}$	**95.40**	**91.91**	89.53	85.46
	$\text{STEPS}_{\text{MTLscale}}$	94.65	83.33	89.74	85.80
English (en_ewt)	UDPipe+	97.59	97.82	92.50	90.40
	$\text{STEPS}_{\text{dep-only}}$	–	–	**93.90**	**91.91**
	$\text{STEPS}_{\text{MTL}}$	**97.84**	**98.02**	93.47	91.50
	$\text{STEPS}_{\text{MTLscale}}$	96.58	96.49	93.80	91.78
Finnish TDT (fi_tdt)	UDPipe+	97.57	95.80	91.66	89.49
	$\text{STEPS}_{\text{dep-only}}$	–	–	**95.69**	**94.36**
	$\text{STEPS}_{\text{MTL}}$	**98.52**	**96.75**	94.62	93.11
	$\text{STEPS}_{\text{MTLscale}}$	98.19	88.70	95.59	94.26
Hindi (hi_hdtb)	UDPipe+	97.58	94.24	95.56	92.50
	$\text{STEPS}_{\text{dep-only}}$	–	–	96.11	93.34
	$\text{STEPS}_{\text{MTL}}$	**98.09**	**94.49**	95.96	93.03
	$\text{STEPS}_{\text{MTLscale}}$	97.51	88.60	**96.18**	**93.39**
Italian (it_isdt)	UDPipe+	98.62	98.26	94.97	93.38
	$\text{STEPS}_{\text{dep-only}}$	–	–	**96.25**	**94.86**
	$\text{STEPS}_{\text{MTL}}$	**98.81**	**98.58**	95.80	94.36
	$\text{STEPS}_{\text{MTLscale}}$	98.43	94.28	96.09	94.69
Japanese (ja_gsd)	UDPipe+	**98.24**	**99.98**	95.55	**94.27**
	$\text{STEPS}_{\text{dep-only}}$	–	–	**95.62**	94.10
	$\text{STEPS}_{\text{MTL}}$	98.21	**99.98**	95.38	93.78
	$\text{STEPS}_{\text{MTLscale}}$	96.94	99.91	95.53	94.00
Korean (ko_kaist)	UDPipe+	95.77	**100.00**	89.35	87.54
	$\text{STEPS}_{\text{dep-only}}$	–	–	**91.71**	**89.93**
	$\text{STEPS}_{\text{MTL}}$	**96.41**	**100.00**	91.48	89.73
	$\text{STEPS}_{\text{MTLscale}}$	93.90	**100.00**	91.53	89.77
Latvian (lv_lvtb)	UDPipe+	96.11	93.30	88.05	84.50
	$\text{STEPS}_{\text{dep-only}}$	–	–	**94.32**	**91.93**
	$\text{STEPS}_{\text{MTL}}$	**97.73**	**94.79**	93.44	90.99
	$\text{STEPS}_{\text{MTLscale}}$	96.72	81.42	93.97	91.61
Russian (ru_syntagrus)	UDPipe+	99.23	97.97	94.92	93.68
	$\text{STEPS}_{\text{dep-only}}$	–	–	**96.32**	**95.30**
	$\text{STEPS}_{\text{MTL}}$	**99.27**	**98.34**	95.94	94.88
	$\text{STEPS}_{\text{MTLscale}}$	98.99	95.91	96.19	95.20
Chinese (zh_gsd)	UDPipe+	97.07	**99.58**	90.13	86.74
	$\text{STEPS}_{\text{dep-only}}$	–	–	**90.72**	**87.75**
	$\text{STEPS}_{\text{MTL}}$	**97.20**	99.50	89.70	86.86
	$\text{STEPS}_{\text{MTLscale}}$	95.21	98.53	90.31	87.39

Table 3: Results for **basic dependency parsing** vs. **parsing and feature prediction** (**multi-task**) for $\text{STEPS}_{\text{XLM-R}}$. Scorres are averages of three runs. For UPOS and UFeats, we report accuracy.

count. If the respective setups differ, ignoring them may result in misleading interpretations of parsing performance of model architectures (unless the variable of interest is the multi-task setup itself).

4.7 Summary

Our experimental findings can be summarized as follows: (a) Choice of pre-trained embeddings has the greatest impact on parser performance, with XLM-R yielding the best results in most cases; (b) adding LSTM layers is not necessary when working with a large fine-tuned language model; (c) a factorized parser architecture is preferable due to faster training; (d) when using a multi-task approach incorporating UPOS and UFeats prediction, there is a tradeoff between tagging and parsing accuracy, and conclusions regarding architecture should be drawn by comparing experiments performed in the same setting. Crucially, one of the simplest parsers in our evaluation ($\text{STEPS}_{\text{XLM-R}}$) achieves the best results overall, often surpassing more complex previous work by a wide margin.

5 Enhanced UD Parsing with STEPS

In order to determine whether our conclusions also hold for the related graph parsing task of Enhanced UD (Schuster and Manning, 2016), we run an additional batch of experiments on 7 treebanks from the IWPT 2020 Shared Task (Bouma et al., 2020).

Modifications to STEPS. We modify STEPS to generate dependency graphs using a factorized approach as proposed by Dozat and Manning (2018) for semantic dependency parsing, weighting the losses of the edge and label scorers:

$$\ell = \lambda_{edge}\ell_{edge} + \lambda_{label}\ell_{label}. \quad (5)$$

After tuning on English in a set of preliminary experiments, we set the hyperparameters λ_{edge} to 1.0 and λ_{label} to 0.05. For comparison, we also evaluate the unfactorized version of our parser.

While enhanced UD does not require output graphs to be trees, it imposes the constraint that every node must be reachable from the root. We use the heuristic proposed by Grünewald and Friedrich (2020) for graph post-processing, which greedily adds the highest-scoring edge from a node that is reachable from the root to a node that is unreachable from the root until the condition is fulfilled.

Furthermore, for certain relations such as *nmod* or *obl*, enhanced UD allows for the inclusion of lexical material (such as prepositions) in dependency

	Turku-NLP	Shanghai-Tech	STEPS$_{\text{XLM-R}}$ fact	unfact
ar-PADT	**77.83**	77.73	77.42	77.68
cs-PDT	88.17	**90.63**	89.49	89.43
en-EWT	86.14	86.30	87.11	**87.28**
fi-TDT	89.24	89.97	**91.53**	91.51
it-ISDT	91.54	91.49	92.35	**92.39**
lv-LVTB	84.94	87.64	**89.04**	88.95
ru-STR	90.69	92.31	93.68	**93.75**

Table 4: Results (ELAS) for **enhanced dependency parsing**. Scores are averages of three runs. For full results including EULAS, see Appendix A.6.

labels. To avoid data sparsity issues resulting from the increase in the number of dependency labels, we follow the label de- and re-lexicalization strategy proposed by Grünewald and Friedrich (2020), replacing lexical materials in labels with with placeholders such as *obl:[case]*. At prediction time, lexicalized parts of the labels can be retrieved from the respective child nodes in the graph. We apply this strategy for all languages in our study except Finnish and Russian (which do not have lexicalized labels) and Arabic (for which we additionally look up lemmas of the lexical material using a simple majority baseline method).

Experimental Results. We compare our results against **TurkuNLP**, a modified version of UDify which scored 1st in the official evaluation of the IWPT 2020 Shared Task, and **ShanghaiTech**, which scored 1st in the unofficial post-evaluation.

We evaluate in terms of ELAS (Enhanced LAS, i.e., F1 score over the set of enhanced dependencies in the system output and the gold standard) using the official evaluation script for the IWPT 2020 Shared Task[5] and report per-treebank results for TurkuNLP and ShanghaiTech as submitted.[6] To ensure comparability with previous work, we compute our results using raw text as input and using Stanza (Qi et al., 2020) for tokenization and sentence segmentation. Table 4 reports our results. Our parser achieves very high accuracy, outperforming TurkuNLP and ShanghaiTech on all evaluated languages except Arabic and Czech. Notably, the latter system also uses XLM-R embeddings, but with a more complex parser architecture.

Unlike in tree parsing, the unfactorized system actually outperforms the factorized system on a number of languages, with the largest margins on Arabic and English. Taken together, these results show that (a) our best approach is not only robust across languages, but also across (syntactic) parsing tasks, and (b) the unfactorized approach may be well-suited to graph parsing tasks, which is in line with the results of Dozat and Manning (2018).

[5] https://universaldependencies.org/iwpt20/iwpt20_xud_eval.py

[6] https://universaldependencies.org/iwpt20/Results.html

6 Discussion and Conclusion

In this paper, we have performed a detailed and principled analysis on a variety of decisions arising during dependency parser design. **What works?** We have identified an architecture based on fine-tuned XLM-R embeddings and factorized scoring that lead to new state-of-the-art performance for 11 out of 12 diverse language in our study on basic UD parsing, and for 5 out of 7 lanugages for enhanced UD parsing. **What doesn't?** Adding LSTM layers on top of the transformer leads to a decrease in accuracy in most cases. We have also shown that multi-task setups predicting UPOS and UFeats often degrade parsing performance. **What is really necessary?** For current state-of-the-art UD parsers, we recommend making sure that the pre-trained language model covers the intended domain well. In addition, keeping a factorized approach is a good idea for tree parsing, while in graph parsing, a single scorer module may suffice.

In this paper, we have addressed a high- to medium-resource scenario, assuming that we know the application language of a parser and thus training a single parser per language. Future work may address multilingual approaches such as the training setup used by UDify or the recently proposed UDapter (Üstün et al., 2020), which aims at boosting performance of low-resource languages while keeping performance of high-resource languages high. Furthermore, it would be interesting to see if our results about biaffine achitectures also hold for non-syntactic tasks that have recently been framed as dependency parsing tasks, such as Named Entity Recognition (Yu et al., 2020), negation scope detection (Kurtz et al., 2020) or Semantic Role Labeling (Shi et al., 2020).

To sum up, in this paper we have applied "Occam's razor" to graph-based dependency parsing. We believe that the insights from our study will foster further research on dependency parsing and on framing other tasks as dependency parsing, taking our simplified but robustly performing STEPS parser as a starting point.

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A Appendix

A.1 Listing of Transformer-based Language Models

Table 5 lists the transformer-based language models used in our experiments.

A.2 Listing of UD Treebanks

Table 6 lists the UD treebanks used in our experiments.

A.3 Hyperparameters

Table 7 lists the hyperparameters for the models used in our experiments.

Hyperparameters for training the transformer-based language models and the output modules (biaffine classifiers, taggers) were determined by starting out with UDify's configuration (Kondratyuk and Straka, 2019) and then evaluating by hand a number of modifications to it in ca. 40 overall runs on the English, Arabic, and Korean corpora used in our experiments. The modifications examined by us were

- Hidden size of the biaffine classifier (256 / 512 / 768 / 1024)
- Batch size (16 / 32)
- Base learning rate ($7e^{-6}$ to $5e^{-5}$)
- Early stopping patience (10 / 15 / 20 epochs)
- Learning rate schedule (constant LR / warmup only / cosine annealing / Noam)

For models involving LSTMs, we performed 15 trials of random search on the English data to tune the following hyperparameters (ranges given in parentheses):

- LSTM learning rate ($5e^{-4}$ to $1e^{-2}$)
- LSTM hidden size (256 to 512)
- LSTM dropout (0.0 to 0.5)
- Shared LSTM layers (0 to 3)
- Task-specific LSTM layers (0 to 2)
- Learning rate schedule (constant LR / Noam)

We picked the two best configurations (in terms of LAS) resulting from these trials and evaluated them on the other treebanks as well. The final hyperparameter configuration listed in Table 7 is the one that consistently achieved the best results on all evaluation sets. (The configuration only lists "number of layers", which refers to the number of *shared* layers. The best configuration does not include any task-specific LSTM layers.)

A.4 Full Results for Enhanced Dependency Parsing

Table 8 lists full results for basic UD parsing.

A.5 Factorization and Training Time

Table 9 lists the average training times in minutes for factorized and unfactorized models on the 12 treebanks evaluated by us. As can be seen, training unfactorized models takes longer in the majority of cases, and around 30 % on average. (However, this average is very likely an underestimation since training hits the 24-hour time limit imposed by us for both Czech and Russian.)

To see how this effect plays out in practice, consider Figure 2. Figure 2a shows a representative case: For Latvian, the plotted models (one factorized, one unfactorized) ultimately achieved roughly the same performance on the evaluation set (ca. 91.8 LAS), but the unfactorized model converges much slower than the factorized one, continuing to make very small incremental gains over the course of ca. 8 hours before reaching the termination criterion.

However, there are also exceptions to this general trend, as evidenced by Figure 2b. Here, the two plotted (German) models again achieved roughly the same evaluation accuracy (ca 86.2 LAS), but in this case, they converged roughly equally quickly. This demonstrates that while the longer training times for unfactorized model are a relatively consistent trend, they are not a hard rule.

A.6 Full Results for Enhanced Dependency Parsing

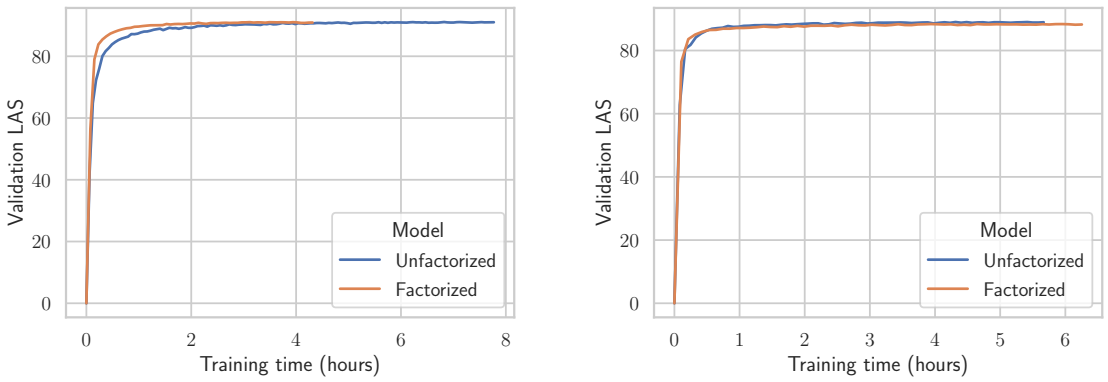
Table 10 lists full results for enhanced UD parsing.

Language	BERT model	Pre-training data	Citation	Model size
Arabic	ArabicBERT-large	Wikipedia, Webcrawl	Safaya et al. (2020)	335M
Chinese	Chinese BERT	Wikipedia	Devlin et al. (2019)	110M
Czech	Slavic-BERT	Wikipedia	Arkhipov et al. (2019)	110M
English	RoBERTa-large	Wikipedia, Books, News, Webcrawl	Liu et al. (2019)	355M
Finnish	FinBERT	News, Webcrawl	Virtanen et al. (2019)	110M
German	German BERT (dbmdz)	Wikipedia, Books, Subtitles, News, Webcrawl	github.com/dbmdz/berts	110M
Hindi	WikiBERT-Hindi	Wikipedia	Pyysalo et al. (2020)	110M
Italian	Italian BERT-XXL (dbmdz)	Wikipedia, Legal, Subtitles, Webcrawl	github.com/dbmdz/berts	110M
Japanese	WikiBERT-Japanese	Wikipedia	Pyysalo et al. (2020)	110M
Korean	KR-BERT	Wikipedia, News	Lee et al. (2020)	110M
Latvian	WikiBERT-Latvian	Wikipedia	Pyysalo et al. (2020)	110M
Russian	RuBERT	Wikipedia, News	Kuratov and Arkhipov (2019)	110M
Multilingual	mBERT	Wikipedia	Devlin et al. (2019)	110M
Multilingual	XLM-R	Webcrawl	Conneau et al. (2019)	550M

Table 5: Transformer-based language models used in our experiments.

Language	Treebank	Citation	#words
Arabic	PADT	Smrž et al. (2008)	282K
Chinese	GSD	github.com/UniversalDependencies/UD_Chinese-GSD/	123K
Czech	PDT	Bejček et al. (2012)	1509K
English	EWT	Silveira et al. (2014)	254K
Finnish	TDT	github.com/UniversalDependencies/UD_Finnish-TDT/	202K
German	GSD	McDonald et al. (2013)	292K
Hindi	HDTB	Bhat et al., Palmer et al. (2009)	351K
Italian	ISDT	github.com/UniversalDependencies/UD_Italian-ISDT/	298K
Japanese	GSD	github.com/UniversalDependencies/UD_Japanese-GSD/	192K
Korean	Kaist	Chun et al. (2018)	350K
Latvian	LVTB	github.com/UniversalDependencies/UD_Latvian-LVTB/	220K
Russian	SynTagRus	Droganova et al. (2018)	1107K

Table 6: UD treebanks used in our experiments.



(a) Latvian.

(b) German.

Figure 2: Learning curves (validation LAS as a function of training time) for two pairs of runs.

Transformer LM	
Token mask probability	0.15
Layer dropout	0.1
Hidden dropout	0.2
Attention dropout	0.2
Output dropout	0.5
Biaffine classifier	
Arc scorer dimension	768 or 1024[a]
Label scorer dimension	256 or 768/1024[b]
Dropout	0.33
LSTM	
Hidden size	330
Number of layers	3
Dropout	0.5
LSTM learning rate	$5e^{-4}$
Optimization	
Optimizer	AdamW
β_1, β_2	0.9, 0.999
Weight decay	0
Batch size	32
Base learning rate	$4e^{-5}$
LR schedule	Noam
LR warmup	1 epoch
λ_{edge}	1.00
λ_{label}	1.00 or 0.05[c]

Table 7: Hyperparameter values. [a]Identical to hidden size of the transformer encoder. [b]256 in factorized models, hidden size of transformer encoder in unfactorized models.

	ar-PADT		cs-PDT		de-GSD		en-EWT		fi-TDT		hi-HDTB	
	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS
UDPipe+	89.01	84.62	94.43	92.56	88.11	84.06	92.50	90.40	91.66	89.49	95.56	92.50
UDify[a]	87.72	82.88	94.73	92.88	87.81	83.59	90.96	88.50	86.42	82.03	95.13	91.46
$\text{UDify}_{\text{mono}}$	88.05	83.34	93.52	91.58	88.50	84.28	91.87	89.52	89.78	86.74	94.87	91.44
$\text{STEPS}_{\text{mBERT}}$	88.67	83.80	94.39	92.69	88.41	84.08	91.61	89.16	91.36	88.91	94.77	91.30
$\text{STEPS}_{\text{langBERT}}$	**90.97**	**86.60**	94.64	92.99	89.73	85.87	**93.94**	**91.98**	95.05	93.57	94.63	91.16
$\text{STEPS}_{\text{XLM-R}}$	90.96	86.55	**95.89**	**94.58**	**90.02**	**86.07**	93.90	91.91	**95.69**	**94.36**	**96.11**	**93.34**
$\text{STEPS}_{\text{XLM-R+LSTM}}$	90.94	86.41	95.87	94.52	**90.18**	**86.20**	93.60	91.58	95.42	93.92	96.10	93.28
$\text{STEPS}_{\text{XLM-R-unfact}}$	**90.99**	86.32	95.80	94.38	**90.12**	**86.19**	93.69	91.57	95.54	94.11	**96.22**	93.21

	it-ISDT		ja-GSD		ko-Kaist		lv-LVTB		ru-SynTagRus		zh-GSD	
	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS
UDPipe+	94.97	93.38	95.55	**94.27**	89.35	87.54	88.05	84.50	94.92	93.68	90.13	86.74
UDify	95.54	93.69	94.37	92.08	87.57	84.52	89.33	85.09	94.83	93.13	87.93	83.75
$\text{UDify}_{\text{mono}}$	94.82	93.14	94.15	92.14	88.69	86.45	88.91	85.45	93.90	92.32	86.71	82.95
$\text{STEPS}_{\text{mBERT}}$	94.90	93.13	94.10	92.22	–	–	88.82	85.05	95.08	93.74	88.08	84.94
$\text{STEPS}_{\text{langBERT}}$	95.71	94.25	94.78	92.98	86.90	84.56	86.85	82.61	95.62	94.44	89.09	86.20
$\text{STEPS}_{\text{XLM-R}}$	**96.25**	**94.86**	**95.62**	94.10	**91.71**	**89.93**	**94.32**	**91.93**	**96.32**	**95.30**	**90.72**	**87.75**
$\text{STEPS}_{\text{XLM-R+LSTM}}$	95.93	94.57	**95.62**	94.01	91.67	89.91	94.06	91.61	**96.32**	95.27	90.08	86.96
$\text{STEPS}_{\text{XLM-R-unfact}}$	96.01	94.58	95.43	93.58	**91.80**	89.86	94.29	91.76	96.30	95.17	90.46	87.47

Table 8: Unlabeled Attachment Score (UAS) and Labeled Attachment Score (LAS) for **basic dependency parsing** varying input embeddings and architecture. Scores are averages of three runs. UDify results are for multilingual training without language-specific fine-tuning. In the upper part of the table, the top scores are bold-faced. Scores for $\text{STEPS}_{\text{XLM-R+LSTM}}$ and $\text{STEPS}_{\text{XLM-R-unfact}}$ are bold-faced if outperforming $\text{STEPS}_{\text{XLM-R}}$. Results for $\text{STEPS}_{\text{mBERT}}$ for Korean were not ready at time of the submission.

Treebank	**Fact**	**Unfact**	**Unfact/Fact**
ar-PADT	**424.0**	888.7	209.6%
cs-PDT	**1352.2**	1440.0	106.5%
de-GSD	405.0	**400.0**	98.8%
en-EWT	**334.0**	570.7	170.9%
fi-TDT	**358.1**	534.6	149.3%
hi-HDTB	465.9	**407.9**	87.5%
it-ISDT	**477.8**	779.9	163.2%
ja-GSD	**353.7**	356.8	100.9%
ko-Kaist	**386.7**	426.2	110.2%
lv-LVTB	**319.9**	450.9	141.0%
ru-SynTagRus	**1440.0**	**1440.0**	100.0%
zh-GSD	**227.4**	287.9	126.6%
Avg.	**545.4**	665.3	130.4%

Table 9: Average training times (minutes) on the 12 treebanks evaluated by in our experiments.

	ar-PADT		cs-PDT		en-EWT		fi-TDT		it-ISDT		lv-LVTB		ru-SynTagRus	
	EULAS	ELAS	EULAS	ELAS	EULAS	ELAS	EULAS	ELAS	EULAS	ELAS	EULAS	ELAS	EULAS	ELAS
TurkuNLP	79.68	**77.83**	89.51	88.17	86.71	86.14	89.86	89.24	92.29	91.54	85.51	84.94	91.57	90.69
ShanghaiTech	79.91	77.73	**91.90**	**90.63**	86.95	86.30	90.93	89.97	92.17	91.49	88.19	87.64	92.73	92.31
$\text{STEPS}_{\text{XLM-R-fact}}$	79.73	77.42	91.30	89.49	87.49	87.11	**91.88**	**91.53**	93.03	92.35	**89.51**	**89.04**	93.98	93.68
$\text{STEPS}_{\text{XLM-R-unfact}}$	**80.14**	77.68	91.25	89.43	**87.66**	**87.28**	**91.88**	91.51	**93.11**	**92.39**	89.46	88.95	**94.08**	**93.75**

Table 10: Full results for **enhanced dependency parsing**.