



Figure 2: An example of extending a word-level parsing tree to a subword-level.

Table 7: Model parameters and training data where CC denotes CommonCrawl.

	UD-BERT	m-BERT	UD-XLM-R <sub>base</sub>	XLM-R <sub>base</sub>	UD-XLM-R <sub>large</sub>	XLM-R <sub>large</sub>
parameters	192.0M	177.9M	291.8M	278.0M	581.1M	559.9M
training data	UD+Wiki (373.16M)	Wiki (372.10M)	UD+CC (2502.26M)	CC (2501.20M)	UD+CC (2502.26M)	CC (2501.20M)

## A Appendix

### A.1 Extending Strategy for Parsing Treebanks

Denote a sentence as  $\hat{X} = [w_1, w_2, \dots, w_N]$  and its corresponding subword-level sentence as  $X = [[CLS], w_{11}, \dots, w_{1s_1}, w_{21}, \dots, w_{2s_2}, \dots, w_{N1}, \dots, w_{Ns_N}, [SEP]]$ . In the word-level parsing tree, for  $w_i \in \hat{X}$ , suppose the head of  $w_i$  is  $w_{h_i}$  and the dependency label is  $l_i$ . We design three strategies to extend the parsing tree from word level to subword level. All of them regard [CLS] as the ROOT ( $w_{01}$ ), and the header of [SEP] as [CLS], and the label as the padding label "\_".

- Set the head of all the subwords of  $w_i$  as  $w_{h_i1}$ , and the label as  $l_i$ .
- Set the head of  $w_{i1}$  as  $w_{h_i1}$  and the label as  $l_i$ , and set the head of  $w_{i2}, \dots, w_{is_i}$  as  $w_{i1}$  and label as a special label "APP".
- Set the head of  $w_{i1}$  as  $w_{h_i1}$  and the label as  $l_i$ , and set the head of  $w_{ij}$  as  $w_{i(j-1)}$  for  $j = 2, \dots, s_i$  and label as a special label "APP". As shown in Figure 2.

### A.2 Details of Experimental Data and Model Parameters

### A.3 Cross-lingual Results on UD Treebanks

Table 9 shows the zero-shot cross-lingual transfer experiments of our PrLM on the 22 languages of UD Treebanks. The findings from comparison reveal that our UD-BERT and UD-XLM-R have significantly improved the transfer effect of this parser in which the average improvement of UD-BERT and UD-XLM-R is 9.93/8.09, 8.86/8.32 UAS/LAS, respectively. This is due in large part to the usage of UD annotations in the language model pre-training, but it also demonstrates that our PrLM well learned UD parsing and encoded the structural information of the parse into the final representations.

### A.4 Monolingual Results on Low-resource Treebanks in UD

We select all treebanks in UD with training sets under 100 sentences to evaluate the performance of our model in low-resource languages. The results are shown in Table 10, where we compare our method with the baselines and the biaffine model without PrLM (w/o PrLM). It can be seen that the results on UD-BERT and UD-XLM-R all outperform their baseline. This shows that our method can partially solve the problem of poor performance of the multilingual PrLM in low-resource languages.

Table 8: Details of the selected languages in UD.

Language	Treebank	Sents
Bulgarian (bg)	BTB	8,907
Catalan (ca)	AnCora	13,123
Czech (cs)	PDT	102,993
Dutch (nl)	Alpino	18,058
English (en)	EWT	12,543
Estonian (et)	EDT	20,827
Finnish (fi)	TDT	12,217
French (fr)	GSD	14,554
German (de)	GSD	13,814
Hebrew (he)	HTB	5,241
Hindi (hi)	HDTB	13,304
Indonesian (id)	GSD	4,477
Italian (it)	ISDT	13,121
Korean (ko)	GSD	27,410
Latin (la)	PROIEL	15,906
Latvian (lv)	LVTB	5,424
Norwegian (no)	Bokmaal	29870
Polish (pl)	LFG	19,874
Romanian (ro)	RRT	8,043
Russian (ru)	SynTagRus	48,814
Slovak (sk)	SNK	8,483
Spanish (es)	AnCora	28,492

Table 9: The cross-lingual UAS/LAS results on 22 languages of UD Treebanks.

Cross-Transfer	en	bg	ca	cs	nl	et	fi	fr
m-BERT	92.52 / 91.29	83.80 / 72.77	79.60 / 69.00	73.95 / 61.23	77.76 / 69.02	73.11 / 50.90	75.71 / 54.96	83.18 / 70.76
<b>UD-BERT</b>	93.01 / 91.43	89.64 / 79.02	87.18 / 76.06	86.07 / 70.38	86.79 / 78.74	82.38 / 58.53	83.86 / 60.97	89.07 / 75.86
XLM-R <sub>large</sub>	93.10 / 91.32	88.67 / 77.91	85.00 / 73.71	77.80 / 65.12	82.10 / 72.79	78.66 / 57.67	80.97 / 60.63	88.27 / 74.71
<b>UD-XLM-R<sub>large</sub></b>	94.19 / 92.54	92.66 / 82.15	90.76 / 79.35	88.98 / 75.67	90.94 / 82.33	87.57 / 65.90	90.09 / 68.95	93.19 / 78.93
	en	de	he	hi	id	it	ko	la
m-BERT	92.52 / 91.29	76.54 / 66.00	73.48 / 47.26	43.77 / 29.83	57.06 / 47.82	87.41 / 80.93	36.97 / 23.44	52.39 / 36.42
<b>UD-BERT</b>	93.01 / 91.43	84.54 / 74.88	87.33 / 55.98	66.99 / 42.82	76.18 / 62.37	92.74 / 86.59	53.89 / 36.94	71.66 / 51.91
XLM-R <sub>large</sub>	93.10 / 91.32	81.65 / 71.34	73.86 / 48.66	48.08 / 31.66	60.57 / 51.32	91.02 / 84.31	40.64 / 25.50	60.95 / 42.44
<b>UD-XLM-R<sub>large</sub></b>	94.19 / 92.54	88.05 / 79.34	86.42 / 56.69	65.57 / 47.13	77.65 / 64.52	95.39 / 88.83	52.98 / 37.52	76.26 / 57.14
	en	lv	no	pl	ro	ru	sk	es
m-BERT	92.52 / 91.29	76.51 / 54.52	87.28 / 78.67	88.76 / 76.43	75.94 / 62.83	72.73 / 62.40	79.14 / 67.86	80.08 / 70.64
<b>UD-BERT</b>	93.01 / 91.43	83.07 / 60.94	90.41 / 82.22	92.97 / 81.26	87.50 / 72.59	85.80 / 72.58	88.69 / 74.83	85.93 / 76.15
XLM-R <sub>large</sub>	93.10 / 91.32	83.94 / 62.52	90.50 / 82.56	90.68 / 77.90	81.75 / 69.01	76.64 / 66.58	81.63 / 70.60	85.00 / 74.36
<b>UD-XLM-R<sub>large</sub></b>	94.19 / 92.54	91.21 / 69.64	94.14 / 86.37	95.48 / 83.91	91.28 / 77.80	91.29 / 80.64	92.02 / 80.56	90.37 / 79.78

Table 10: The monolingual UD parsing result (UAS/LAS) on treebanks with training set under 100 sentences: Kurmanji(kmr)-MG, Swedish\_Sign\_Language(swl)-SSLC, Livvi(olo)-KKPP, Kazakh(kk)-KTB, Buryat-BDT(bxr), Upper\_Sorbian(hsb)-UFAL.

All-FT	kmr-mg		swl-sslc		olo-kkpp		kk-ktb		bxr-bdt		hsb-ufal	
	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS	UAS	LAS
w/o PrLM	18.33	8.06	19.33	10.86	41.84	30.25	66.80	58.73	39.61	17.33	68.41	53.05
m-BERT	32.26	11.09	34.61	20.15	59.93	36.44	78.26	62.80	51.56	23.06	73.16	60.92
<b>UD-BERT</b>	38.80	17.01	39.82	23.50	64.48	41.71	81.13	65.56	55.68	26.29	75.33	62.94
XLM-R <sub>base</sub>	74.62	59.86	50.87	36.81	70.21	51.52	80.03	65.20	55.24	25.95	80.17	69.92
<b>UD-XLM-R<sub>base</sub></b>	78.55	62.92	55.88	42.00	75.97	54.33	81.74	66.79	59.37	29.40	83.25	72.88
XLM-R <sub>large</sub>	77.89	62.24	55.67	42.02	72.89	53.01	82.15	66.97	55.30	26.27	81.38	71.17
<b>UD-XLM-R<sub>large</sub></b>	81.62	64.10	58.26	43.72	76.08	56.41	85.69	70.98	60.40	30.92	85.12	74.16