Better Character Language Modeling Through Morphology

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Abstract

We incorporate morphological supervision into character language models (CLMs) via multitasking and show that this addition improves bits-per-character (BPC) performance across 24 languages, even when the morphology data and language modeling data are disjoint. Analyzing the CLMs shows that inflected words benefit more from explicitly modeling morphology than uninflected words, and that morphological supervision improves performance even as the amount of language modeling data grows. We then transfer morphological supervision across languages to improve language modeling performance in the low-resource setting.

1 Introduction

Character language models (CLMs) are distributions over sequences of characters (Sutskever et al., 2011), in contrast to traditional language models which are distributions over sequences of words. CLMs eliminate the need for a fixed word vocabulary, and modeling text at the character level gives the CLM access to subword information. These attributes suggest that CLMs can model regularities that exist within words, such as morphological inflection. However, even large language modeling (LM) corpora have sparse coverage of inflected forms for morphologically-rich languages, which has been shown to make word and character language modeling more difficult (Gerz et al., 2018b; Cotterell et al., 2018). Because to this, we hypothesize that accurately modeling morphology improves language modeling, but that it is difficult for CLMs to learn this from text alone.

Motivated by this hypothesis, we add morphology supervision to character language modeling and show that, across two benchmark datasets, multitasking morphology with CLMs improves bits-per-character (BPC) performance on twenty-four languages, even when the annotated morphology features and language modeling data do not overlap. We also show that models augmented by multitasking achieve better BPC improvements on inflected forms than on uninflected forms, and that increasing the amount of language modeling data does not diminish the gains from morphology. Furthermore, to augment morphology annotations in low-resource languages, we also transfer morphology information between pairs of high- and low-resource languages. In this cross-lingual setting, we see that morphology supervision from the high-resource language improves BPC performance on the low-resource language over both the low-resource multitask model and over adding language modeling data from the high-resource language alone.

2 Approach

Language Modeling Given a sequence of characters $\mathbf{c} = c_1, c_2, ..., c_n$, our character-level language models calculate the probability of **c** as

$$p(\mathbf{c}) = \prod_{i=1}^{|\mathbf{c}|} p(c_i | c_1, c_2, ..., c_{i-1}) \tag{1}$$

Each distribution is an LSTM (Hochreiter and Schmidhuber, 1997) trained such that at each time step t, the model takes in a character c_t and estimates the probability of the next character c_{t+1} as

$$p(c_{t+1} | c_{\leq t}) = g(\mathrm{LSTM}(\mathbf{w}_t, \mathbf{h}_{t-1})) \tag{2}$$

where $\mathbf{h}_{t-1}$ is the previous hidden state of the LSTM, $\mathbf{w}_t$ is the character embedding learned by the model for c_t, and g is a softmax over the character vocabulary space.

We calculate the loss function of our language model $\mathcal{L}_{\mathrm{LM}}$ as the negative log-likelihood of the

	CS		DE		EN		ES		FI		FR		RU	
	dev	test	dev	test	dev	test	dev	test	dev	test	dev	test	dev	test
HCLM	2.010	1.984	1.605	1.588	1.591	1.538	1.548	1.498	1.754	1.711	1.499	1.467	1.777	1.761
LM	2.013	1.972	1.557	1.538	1.543	1.488	1.571	1.505	1.725	1.699	1.357	1.305	1.745	1.724
MTL	**1.938**	**1.900**	**1.249**	**1.241**	**1.313**	**1.256**	**1.260**	**1.196**	**1.698**	**1.669**	**1.211**	**1.167**	**1.645**	**1.619**
Δ	0.075	0.072	0.308	0.297	0.230	0.232	0.311	0.309	0.027	0.030	0.146	0.138	0.100	0.105

Table 1: Results on Multilingual Wikipedia Corpus (MWC) in bits per character (BPC). Δ calculated improvement in BPC from the baseline LM to MTL. HCLM is the best model from Kawakami et al. (2017).

model on the character sequence **c**:

$$\mathcal{L}_{\text{LM}}(\mathbf{c}) = \text{NLL}(\mathbf{c}) = -\sum_{i=1}^{|\mathbf{c}|} \log p(c_i | c_{<i}) \quad (3)$$

We then evaluate the trained model's performance with bits-per-character (BPC):

$$\text{BPC}(\mathbf{c}) = -\frac{1}{|\mathbf{c}|} \sum_{i=1}^{|\mathbf{c}|} \log p(c_i | c_{<i}) \quad (4)$$

Multitask Learning To add morphology features as supervision, we use a multitask learning (MTL) objective (Collobert and Weston, 2008) that combines loss functions for predicting different morphological tags with the language modeling objective. Since morphological features are annotated at the word-level, we convert these annotations to the character level by placing each annotated word's tags as supervision on the first character (which we found to outperform supervising the last character in preliminary results).

This early placement allows the model to have access to the morphological features while decoding the rest of the characters in the word. Therefore, our morphology data $\mathbf{m} = m_1, m_2, ..., m_n$ is a sequence of labeled pairs in the form $m_i = (x, y)$ where x is a character and y is a set of morphology tags for that character. For example, "cats ran" would be given to our model as the sequence ('c', Number=Pl), ('a', -), ('t', -), ('s', -), (' ', -), ('r', Tense=Past), ('a', -), ('n', -).

We modify the model's loss function to

$$\mathcal{L}(\mathbf{c}, \mathbf{m}) = \mathcal{L}_{\text{LM}}(\mathbf{c}) + \delta \sum_{i=1}^{n} \mathcal{L}_i(\mathbf{m}) \quad (5)$$

where n is the number of morphological features we have annotated in a language, δ is a weighting parameter between the primary and auxiliary losses, $\mathcal{L}_{\text{LM}}$ is the original language modeling loss, and $\mathcal{L}_i$ are the additional losses for each morphological feature (e.g., tense, number, etc). Because we include a separate loss for each morphological feature, each feature is predicted independently.

3 Experimental Setup

Datasets We obtain morphological annotations for 24 languages (Table 2) from Universal Dependencies (UD; v.2.3), which consists of dependency parsing treebanks with morphology annotations on a large number of languages (Nivre et al., 2018). These languages were chosen based on the size of their treebanks (to ensure a sufficient amount of morphology annotations); we also exclude languages that do not have morphology features annotated in the treebank.

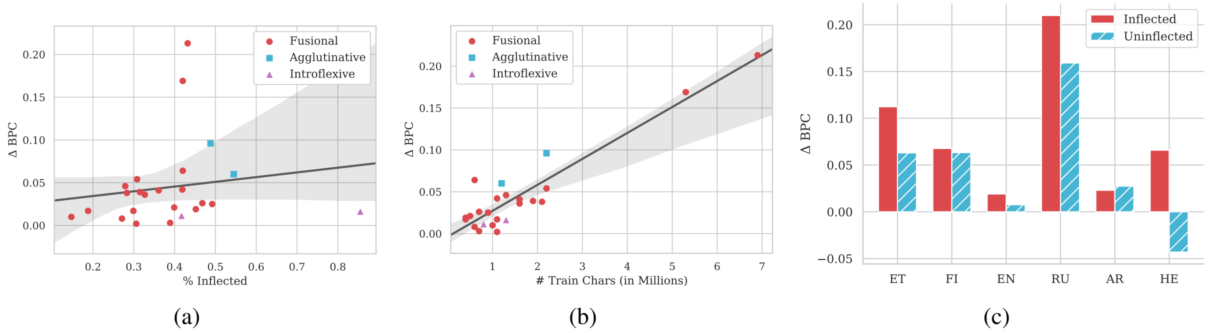
For language modeling supervision, we train two sets of models. One set is trained with the text from the UD treebanks; the other set of models is trained on the Multilingual Wikipedia Corpus (MWC) (Kawakami et al., 2017). This language modeling dataset consists of Wikipedia data across seven languages (Czech, German, English, Spanish, Finnish, French, and Russian).

Model architecture Our models each consist of a stacked LSTM with 1024 hidden dimensions and a character embedding layer of 512 dimensions. We include two hidden layers in the language models trained on UD, and three hidden layers in those trained on MWC. The parameters that integrate multitasking into the model (the layer at which we multitask morphology and the weighting we give the morphology losses, δ) are tuned individually for each language. Further hyperparameter and training details are given in the supplement.

4 Language Modeling Results

Distant MTL We first train CLMs where the language modeling data (from MWC) and morphology data (from UD) do not overlap (Table 1).[1]

[1] Since both of these datasets draw from Wikipedia, we verified that no sentences overlap between the MWC test set



(a)

(b)

(c)

Figure 1: Improvement of MTL over the LM baseline (a) over the inflection rate of each UD language, (b) over the quantity of training data for each UD language, and (c) for inflected and uninflected words in the UD dev set.

Lang	**ISO**	**%Infl**	**LM**	**MTL**	**Δ**
Bulgarian	BG	39%	1.890	1.887	0.003
Catalan	CA	31%	1.653	1.599	0.054
Czech	CS	43%	2.045	1.832	0.213
Danish	DA	30%	2.152	2.135	0.017
German	DE	33%	1.917	1.881	0.036
English	EN	15%	2.183	2.173	0.010
Spanish	ES	28%	1.801	1.763	0.038
Farsi	FA	27%	2.213	2.205	0.008
French	FR	32%	1.751	1.712	0.039
Hindi	HI	28%	1.819	1.773	0.046
Croatian	HR	49%	1.866	1.841	0.025
Italian	IT	36%	1.595	1.554	0.041
Latvian	LV	47%	2.243	2.217	0.026
Dutch	NL	19%	1.989	1.972	0.017
Polish	PL	42%	2.218	2.154	0.064
Portuguese	PT	31%	1.787	1.785	0.002
Romanian	RO	42%	1.840	1.798	0.042
Russian	RU	42%	1.993	1.824	0.169
Slovak	SK	45%	2.705	2.686	0.019
Ukranian	UK	40%	2.359	2.338	0.021
Estonian	ET	49%	2.089	1.993	0.096
Finnish	FI	55%	1.981	1.921	0.060
Arabic	AR	86%	1.724	1.708	0.016
Hebrew	HE	42%	2.293	2.282	0.011

Table 2: BPC results on the Universal Dependencies (UD) test set. %Infl is the inflection rate in each language. Languages are grouped by fusional, agglutinative, and introflexive typologies, respectively.

In this setting, we only train on the morphology features from UD and do not include this data as additional language modeling supervision. These models are trained on alternating batches from the two disjoint datasets. LM is a language modeling baseline with no multitask objective; MTL adds morphology supervision.

We find that for all seven languages, the MTL model outperforms our baseline trained only on MWC. Our model also outperforms the strongest model from Kawakami et al. (2017), HCLM-cache, which is a hierarchical language model with caching. Thus, adding morphology supervision to our character language models allows us to achieve lower BPCs than a more complicated LM architecture. Surprisingly, we see a larger gain on languages with more LM data (EN, DE, ES, FR) than those with less data (but are considered to be more morphologically rich, e.g., CS, DE, and RU); we explore this phenomenon more in Section 5.

Fully Supervised MTL We then train CLMs using UD for both langauge modeling and morphology supervision on more languages (Table 2). We again find that adding morphology supervision improves BPC. In general, we see smaller improvements between the LM and MTL models than under distant supervision, even though the UD LM data is fully annotated with morphology tags; this is likely due to the smaller training sets in UD (on average) than in MWC. On languages where the size of the two datasets are comparable, such as Russian and Czech, we see larger improvements on the fully supervised models than we do in the distant LM setting.

To investigate these results, we compare the rate of inflected words on the development set (which we use as a rough measure of morphological complexity of the language) in a language against BPC improvement by MTL model (Fig. 1(a)). The rate at which each language is inflected is given in Table 2. We unexpectedly find that how much a language benefits from morphology supervision is only weakly correlated with the inflection rate of the language (r=0.15). This is surprising, because one would expect that additional morphological supervision would help languages that encode more morphological features in the forms (i.e., with higher inflection rates).

We then examine the effect of training dataset

and the UD treebanks for each of the seven languages.

(a)

	% Train	# Chars	LM	MTL	Δ
CS	5%	0.31M	2.829	2.793	0.036
	10%	0.61M	2.625	2.581	0.044
	25%	1.5M	2.379	2.303	0.076
	50%	3.1M	2.191	2.120	0.071
	100%	6.1M	2.013	1.938	0.075
	MWC-LG	10.2M	1.835	1.729	0.106
RU	5%	0.47M	2.492	2.486	0.006
	10%	0.93M	2.305	2.283	0.022
	25%	2.3M	2.066	2.033	0.033
	50%	4.7M	1.935	1.898	0.037
	100%	9.3M	1.745	1.645	0.100
	MWC-LG	18.2M	1.554	1.377	0.177

(b)

	% Train	# Chars	BPC
CS	0%	(LM)	2.013
	5%	0.34M	2.040
	10%	0.69M	2.019
	25%	1.7M	2.000
	50%	3.4M	1.984
	100%	6.9M	**1.938**
RU	0%	(LM)	1.745
	5%	0.27M	1.758
	10%	0.53M	1.761
	25%	1.3M	1.673
	50%	2.7M	1.700
	100%	5.3M	**1.645**

(c)

LM data	Morph. data	BPC
SK	None	2.806
	SK	2.779
	CS	2.752
	CS+SK	2.777
CS+SK	None	2.668
	CS+SK	**2.446**
UK	None	2.369
	UK	2.348
	RU	2.348
	RU+UK	2.351
RU+UK	None	2.495
	RU+UK	**2.316**

Table 3: (a) BPC on MWC development set with varied amounts of LM training data from MWC. The last line is from training on MWC-large dataset, (b) BPC on MWC development set with varied amounts of supervised morphology data from UD train set (compared against the baseline LM), and (c) Cross-lingual transfer on UD, evaluated on low-resource language's development set: from Czech (CS; 6.9M characters in training set) to Slovak (SK; 0.4M) and from Russian (RU; 5.3M) to Ukrainian (UK; 0.5M)

size on BPC improvement between the LM and the multitasked model (Fig. 1(b)). We find that more training data (which adds both morphological and LM supervision) is strongly correlated with larger gains over the baseline LM (r=0.93). Therefore, it seems that any potential correlation between morphological complexity and the benefit of multitasking morphology is overwhelmed by differences in dataset size.

5 Analysis Experiments

Modeling Inflected Words We hypothesized that morphology supervision would be most beneficial to words whose form is dependent on their morphology, e.g. inflected words. To investigate this, we calculate BPC of our UD models on inflected and uninflected forms in the UD development set. We determine whether or not a word is inflected by comparing it to the (annotated) lemma given in the UD treebank. We find that on 16 of the 24 languages for which we train models on UD, the MTL model improves more on inflected words than uninflected words, and that the average delta between LM and MTL models is 31% greater for inflected words than uninflected. A comparison of the improvements in six of these languages are given in Fig. 1(c). We show results for the agglutinative (ET, FI) and introflexive (AR, HE) languages and pick two fusional languages (EN, RU) against which to compare.

Effect of Training Data One caveat to the observed gain from morphology is that the CLMs may capture this information if given more language modeling data, which is much cheaper to obtain than morphology annotations. To test this, we train CLMs on Czech (CS) and Russian (RU) on varied amounts of language modeling data from the MWC corpus (Table 2(a)). We find that for both RU and CS, increasing the amount of LM data does not eliminate the gains we see from multitasking with morphology. Instead, we see that increasing LM data leads to *larger* improvements in the MTL model. Even when we train the CLMs on twice as much LM data (obtained from a larger version of the MWC dataset, MWC-large), we continue to see large improvements via multitasking.

We then investigate how the amount of annotated morphology data affects performance on these models (Table 2(b)). We find that, as expected, increasing the amount of morphological data the language model is trained on improves BPC performance. For both Czech and Russian, the MTL models mulitasked with 25% or more of the annotated data still outperform the LM baseline, but MTL models trained on smaller subsets of the morphology data performed worse than the baseline. This is in line with our findings in Section 4 that the amount of annotated morphology data is closely tied with how much multitasking helps.

Cross-lingual Transfer In the previous section, we showed that the amount of training data (both for LM and for morphology) the CLM sees is crucial for better performance. Motivated by this, we extend our models to the cross-lingual setting, in which we use data from high-resource languages to improve performance on closely-related, low-resource ones. We train models on the (high, low) language pairs of (Russian, Ukrainian) and (Czech, Slovak) and transfer both LM and morphological supervision (Table 2(c)). We find the best performance for each low-resource language is achieved by using both the high-resource LM data and morphology annotations to augment the low-resource data. In Slovak (SK), this gives us a 0.333 BPC improvement over the MTL model on SK data alone, and in Ukranian (UK), we see a improvement of 0.032 in this setting over the MTL trained only on UK.

6 Related Work

Prior work has investigated to what degree neural models capture morphology when trained on language modeling (Vania and Lopez, 2017) and on machine translation (Belinkov et al., 2017; Bisazza and Tump, 2018). Other work has looked into how the architecture of language models can be improved for morphologically-rich languages (Gerz et al., 2018a). In particular, both Kawakami et al. (2017) and Mielke and Eisner (2019) proposed hybrid open-vocabulary LM architectures to deal with rare words in morphologically-rich languages on MWC.[2]

Another line of work has investigated the use of morphology to improve models trained on other NLP tasks. These approaches add morphology as an input to the model, either with gold labels on the LM dataset (Vania and Lopez, 2017) or by labeling the data with a pretrained morphological tagger (Botha and Blunsom, 2014; Matthews et al., 2018). This approach to adding morphology as input features to models has also been applied to dependency parsers (Vania et al., 2018) and semantic role labeling models (Şahin and Steedman, 2018). Unlike these approaches, however, our technique does not require the morphology data to overlap with the training data of the primary task or depend on automatically labeled features. More similarly to our work, Dalvi et al. (2017) find that incorporating morphological supervision into the decoder of an NMT system via multitasking improves performance by up to 0.58 BLEU points over the baseline for English-German, English-Czech, and German-English.

7 Conclusion

We incorporate morphological supervision into character language models via multitask learning and find that this addition improves BPC on 24 languages. Furthermore, we observe this gain even when the morphological annotations and language modeling data are disjoint, providing a simple way to improve language modelsing without requiring additional annotation efforts. Our analysis finds that the addition of morphology benefits inflected forms more than uninflected forms and that training our CLMs on additional language modeling data does not diminish these gains in BPC. Finally, we show that these gains can also be projected across closely related languages by sharing morphological annotations. We conclude that this multitasking approach helps the CLMs capture morphology better than the LM objective alone.

Acknowledgements

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program under Grant No. DGE-1762114. We thank Victor Zhong, Sewon Min, and the anonymous reviewers for their helpful comments.

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[2] Results comparing against Mielke and Eisner (2019) are given in the supplement, due to a different character vocabulary from Kawakami et al. (2017).

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A Appendix: Languages and Datasets

The languages we use from Universal Dependencies and details about their treebanks are given in Table 4. Most of the treebanks we used in this paper are manually annotated (and then possibly automatically converted to their current format), except for German, English, and French, which are automatically annotated. For models trained in the

			Num Chars		
Lang	**ISO**	**Treebank**	**Train**	**Dev**	**Test**
Bulgarian	BG	BTB	0.7M	90K	88K
Catalan	CA	AnCora	2.2M	0.3M	0.3M
Czech	CS	PDT	6.9M	0.9M	1.0M
Danish	DA	DDT	0.4M	56K	54K
German	DE	GSD	1.6M	75K	0.1M
English	EN	EWT	1.0M	0.1M	0.1M
Spanish	ES	GSD	2.1M	0.2M	65K
Farsi	FA	Seraji	0.6M	77K	78K
French	FR	GSD	1.9M	0.2M	52K
Hindi	HI	HDTB	1.3M	0.2M	0.2M
Croatian	HR	SET	0.9M	0.1M	0.1M
Italian	IT	ISDT	1.6M	67K	59K
Latvian	LV	LVTB	0.7M	0.1M	0.1M
Dutch	NL	Alpino	1.1M	65K	67K
Polish	PL	LFG	0.6M	74K	74K
Portuguese	PT	Bosque	1.1M	58K	55K
Romanian	RO	RRT	1.1M	98K	93K
Russian	RU	SynTagRus	5.3M	0.7M	0.7M
Slovak	SK	SNK	0.4M	76K	80K
Ukranian	UK	IU	0.5M	71K	98K
Estonian	ET	EDT	2.2M	0.2M	0.3M
Finnish	FI	TDT	1.2M	0.1M	0.2M
Arabic	AR	PADT	1.3M	0.2M	0.2M
Hebrew	HE	HTB	0.8M	63K	68K

Table 4: Dataset statistics for Universal Dependencies (UD; v.2.3). Languages are grouped by typology, from top to bottom: fusional, agglutinative, and introflexive

	Num Chars			
Lang	Vocab	Train	Dev	Test
CS	238	6.1M	0.4M	0.5M
DE	298	13.6M	1.2M	1.3M
EN	307	15.6M	1.5M	1.3M
ES	307	11.0M	1.0M	1.3M
FI	246	6.4M	0.7M	0.6M
FR	272	12.4M	1.3M	1.6M
RU	273	9.3M	1.0M	0.9M

Table 5: Dataset statistics for Multilingual Wikipedia Corpus (MWC). Vocabulary size is based on the character vocabulary given in (Kawakami et al., 2017).

fully-supervised MTL setting where UD is used for both LM and morphology supervision, we calculate the character vocabulary for each language by including any character that occurs more than 5 times in the training set of the language's UD treebank.

Dataset statistics for the Multilingual Wikipedia Corpus (MWC) are given in Table 5. When analyzing the effect of LM training dataset size on Czech and Russian, we also train models on the training portion of a larger version of the MWC corpus, MWC-large, which contains approximately twice as much training data as the standard MWC dataset. Specifically, MWC-large contains 10.2M training characters for Czech and 18.2M for Russian. There is no prior work that we know of that reports BPC on this larger dataset.

For models trained on the disjoint supervision setting, we use the character vocabulary provided for each language in the MWC dataset (see Kawakami et al. (2017) for preprocessing details). In cases where we use two sources of supervision for the model – LM supervision from MWC and morphology supervision from UD – we use the MWC character vocabulary for all inputs, so that BPC results across models are comparable. This only affects a small number of the character types (11 or fewer for each language) in the UD training data.

The character vocabulary provided in the MWC dataset and used for the distant supervision setting differs from the vocabulary calculated by including the characters that occur more than 25 times in the MWC training set.[3] Because of this, our distant supervision setting on MWC is not comparable with Mielke and Eisner (2019), which uses the second vocabulary setting. Therefore, we retrain our character LM baselines and multitasked models in this vocabulary setting (Table 6). We find that our LM and MTL models generally obtain slightly better performance on this setting, and we continue to see improvement from multitasking morphology over the character LM baseline.

B Appendix: Model Parameters and Training

To train all models presented in this paper, we use the Adam optimizer (Kingma and Ba, 2015) with an initial learning rate of 0.002 and clip the norm of the gradient to 5. We also apply a dropout of 0.5 to each layer. We train each model on sequences of 150 characters and use early stopping with a patience of 10. We only use the language modeling performance (BPC) on the development set for early stopping and hyperparameter selection (and do not consider the morphology losses). For the UD language models, we train models with two hidden layers for 150 epochs with a batch size of 10. The models trained on MWC contain three hidden layers and are trained for 250 epochs with a batch size of 32. All of our models are implemented in Pytorch.[4]

For each language, we individually tuned the level at which we multitask the morphology objectives and the weighting ratio between the primary and auxiliary losses δ. We consider multitasking the morphology objective at either the first or second hidden layer (as all of our models have two hidden layers), and tune for each language $\delta = \{0.01, 0.1, 0.5, 1, 1.5, 2\}$. The parameters chosen for each language and setting (fully supervised or distant MTL) are given in Table 7.

C Appendix: Additional Results

We provide the full set of results for our experiments in Section 5 on how well our CLMs model inflected forms versus uninflected forms across all 24 UD languages (Table 8).

[3] On English, this preprocessing difference decreases the character vocabulary size from 307 in the provided vocabulary to 167.

[4] https://pytorch.org/

	CS		DE		EN		ES		FI		FR		RU	
	dev	test	dev	test	dev	test	dev	test	dev	test	dev	test	dev	test
Mielke BPE	1.88	1.856	1.45	**1.414**	1.45	1.386	1.42	1.362	1.70	**1.652**	1.36	1.317	1.63	**1.598**
Mielke Full	1.95	1.928	1.51	1.465	1.45	1.387	1.42	1.363	1.79	1.751	1.36	1.319	1.74	1.709
LM	2.01	1.975	1.52	1.493	1.45	1.395	1.55	1.482	1.74	1.705	1.60	1.565	1.72	1.692
MTL	**1.81**	**1.771**	**1.43**	**1.414**	**1.32**	**1.262**	**1.33**	**1.268**	**1.69**	1.658	**1.15**	**1.104**	**1.62**	**1.596**

Table 6: Results on Multilingual Wikipedia Corpus (MWC) in bits per character (BPC), trained on the vocabulary from Mielke and Eisner (2019).

	Distant MTL		Fully-Supervised	
Lang	MTL layer	δ	MTL layer	δ
BG	-	-	2	1.0
CA	-	-	1	2.0
CS	2	1.5	2	1.5
DA	-	-	2	0.5
DE	2	2.0	1	1.0
EN	2	1.0	2	1.0
ES	2	1.0	1	1.5
FA	-	-	1	0.01
FR	3	1.0	1	2.0
HI	-	-	1	2.0
HR	-	-	2	1.0
IT	-	-	1	2.0
LV	-	-	2	1.0
NL	-	-	2	1.5
PL	-	-	2	1.0
PT	-	-	2	1.5
RO	-	-	2	0.5
RU	3	1.0	2	1.5
SK	-	-	2	2.0
UK	-	-	2	1.0
ET	-	-	2	2.0
FI	1	0.5	2	1.0
AR	-	-	2	0.5
HE	-	-	2	0.5

Table 7: Language specific parameters for multitasked models trained in the distant MTL setting and the fully-supervised MTL setting

Lang	%Infl	Word Type	LM	MTL	Δ
BG	39%	inflected	2.092	2.085	**0.008**
		uninflected	2.333	2.330	0.002
CA	31%	inflected	1.849	1.783	**0.066**
		uninflected	2.007	1.943	0.064
CS	43%	inflected	2.205	1.940	**0.265**
		uninflected	2.539	2.322	0.217
DA	30%	inflected	2.411	2.387	**0.024**
		uninflected	2.559	2.552	0.007
DE	33%	inflected	1.916	1.868	0.048
		uninflected	2.323	2.263	**0.060**
EN	15%	inflected	2.235	2.216	**0.019**
		uninflected	2.579	2.571	0.008
ES	28%	inflected	1.742	1.700	0.042
		uninflected	2.053	2.010	**0.043**
FA	27%	inflected	2.874	2.859	**0.016**
		uninflected	2.499	2.492	0.007
FR	32%	inflected	1.856	1.809	0.047
		uninflected	2.228	2.174	**0.054**
HI	28%	inflected	1.996	1.941	**0.053**
		uninflected	2.270	2.228	0.042
HR	49%	inflected	2.055	2.021	**0.035**
		uninflected	2.507	2.487	0.021
IT	36%	inflected	1.897	1.852	0.045
		uninflected	2.056	2.010	**0.046**
LV	47%	inflected	2.387	2.361	**0.027**
		uninflected	2.782	2.758	0.024
NL	19%	inflected	2.161	2.493	**0.030**
		uninflected	2.131	2.468	0.025
PL	42%	inflected	2.522	2.462	**0.060**
		uninflected	2.633	2.578	0.054
PT	31%	inflected	2.071	2.065	0.007
		uninflected	2.214	2.205	**0.009**
RO	42%	inflected	2.037	1.987	0.050
		uninflected	2.373	2.316	**0.057**
RU	42%	inflected	2.130	1.920	**0.210**
		uninflected	2.583	2.424	0.159
SK	45%	inflected	2.976	2.969	0.007
		uninflected	3.545	3.535	**0.010**
UK	40%	inflected	2.580	2.553	**0.027**
		uninflected	2.553	2.956	0.009
ET	49%	inflected	2.397	2.692	**0.112**
		uninflected	2.285	2.629	0.063
FI	55%	inflected	2.152	2.084	**0.068**
		uninflected	2.402	2.339	0.063
AR	86%	inflected	2.036	2.013	0.023
		uninflected	3.856	3.828	**0.027**
HE	42%	inflected	3.426	3.360	**0.066**
		uninflected	2.168	2.211	-0.043

Table 8: BPC performance on the UD development set on inflected versus uninflected words. Bold delta values for each language indicate whether than language improves more on inflected or uninflected words by when multitasking morphology is added.