Language Contamination Helps Explain the Cross-lingual Capabilities of English Pretrained Models

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Abstract

English pretrained language models, which make up the backbone of many modern NLP systems, require huge amounts of unlabeled training data. These models are generally presented as being trained only on English text but have been found to transfer surprisingly well to other languages. We investigate this phenomenon and find that common English pretraining corpora actually contain significant amounts of non-English text: even when less than 1% of data is not English (well within the error rate of strong language classifiers), this leads to hundreds of millions of foreign language tokens in large-scale datasets. We then demonstrate that even these small percentages of non-English data facilitate cross-lingual transfer for models trained on them, with target language performance strongly correlated to the amount of in-language data seen during pretraining. In light of these findings, we argue that no model is truly monolingual when pretrained at scale, which should be considered when evaluating cross-lingual transfer.

1 Introduction

Pretrained language models have become an integral part of NLP systems. They come in two flavors: *monolingual*, where the model is trained on text from a single language, and *multilingual*, where the model is jointly trained on data from many different languages. Monolingual pretrained models are generally applied to tasks in the same language, whereas multilingual ones are used for cross-lingual tasks or transfer.

Recent work has claimed that monolingual pretrained models are also surprisingly good at transferring between languages, despite ostensibly having never seen the target language before (Gogoulou et al., 2021; Li et al., 2021, inter alia). However, because of the large scale of pretraining data and because many pretraining corpora are not publicly available, it is currently unknown how much foreign language data exists in monolingual pretraining corpora. In this paper, we show that (1) these data are almost certainly contaminated with very small percentages of text from other languages and that (2) cross-lingual transfer is possible from such data leakage in the pretraining corpus.

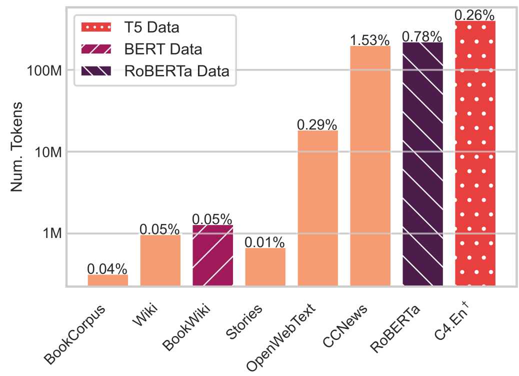

Figure 1: Estimated non-English data in English pretraining corpora (token count and total percentage); even small percentages lead to many tokens. C4.En (†) is estimated from the first 50M examples in the corpus.

More specifically, we quantify how *multilingual* English pretrained models are in two steps. First, we analyze common English pretraining corpora with a large-scale automatic evaluation to estimate their language composition, as well as a smaller-scale manual analysis. Second, we perform experiments across fifty languages on masked language modeling and part-of-speech (POS) tagging to measure how well the models trained on these pretraining corpora perform outside of English.

Our analysis finds that these corpora include very small percentages that amount to overall significant amounts of non-English text (Figure 1), particularly those derived from web-crawled data. Furthermore, the models trained on this data perform surprisingly well on other languages; this transfer is strongly correlated with the amount of target language data seen during pretraining. Notably, we find that the English T5 outperforms mBERT on POS tagging

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in multiple languages with no finetuning.

Overall, these results indicate that the considered models are actually multilingual and that their ability to transfer across languages is not zero-shot, despite what has been recently claimed. Given the effort required to fully remove all non-English data, we question whether it is practically possible to train truly monolingual models at scale.

Type	Num. of Lines in... Book	Wiki	Stories	OpenWeb	CCNews	C4
NE	156	129	99	175	193	169
	Ex: Moraliska argument utgår ifrån våra moraliska intuitioner att rätt och fel inte endast är förankrade i människors vilja. (OPENWEBTEXT)					
BiL	13	11	15	4	1	22
	Ex: The German blazon reads: "Von Silber über Schwarz geteilt..." (WIKI)					
Trans.	2	7	4	2	0	4
	Ex: Εκείνη δεν μπορούσε να πληρώσει [She couldn't pay.] (BOOKCORPUS)					
Ent.	1	28	5	1	0	1
	Ex: 2012 Playhouse Presents ウィルシリーズ1、エピソード1: "The Minor Character" (C4)					
En	26	22	55	12	6	3
	Ex: "Dere's buzzards circlin' ova dem trees." (BOOKCORPUS)					
XX	2	3	22	6	0	1
	Ex: M D I X O X I O O O = A (WIKI)					

Table 1: Results of the qualitative analysis of the non-English lines in various pretraining corpora. Type abbreviations are defined in Section 2.2.

2 Pretraining Data Composition

We first measure how much non-English text exists in commonly used English pretraining corpora with two analyses: an automatic language identification to estimate the amount of foreign language data in these corpora, and a manual qualitative analysis of the text classified as non-English.

We consider the following pretraining datasets: ENGLISH WIKIPEDIA (11.8GB); BOOKCORPUS (Zhu et al. 2015, 4.2GB); STORIES (Trinh and Le 2018, 31GB); OPENWEBTEXT (Gokaslan and Cohen 2019, 38GB), which is an open-source version of WEBTEXT (Radford et al., 2019); CC-NEWS (Liu et al. 2019, 76 GB); and C4.EN (Raffel et al. 2020, 305GB), as provided by Dodge et al. (2021). We use the versions of WIKIPEDIA, BOOKCORPUS, and CC-NEWS used to pretrain RoBERTa.

2.1 Automatic Evaluation of Language Composition

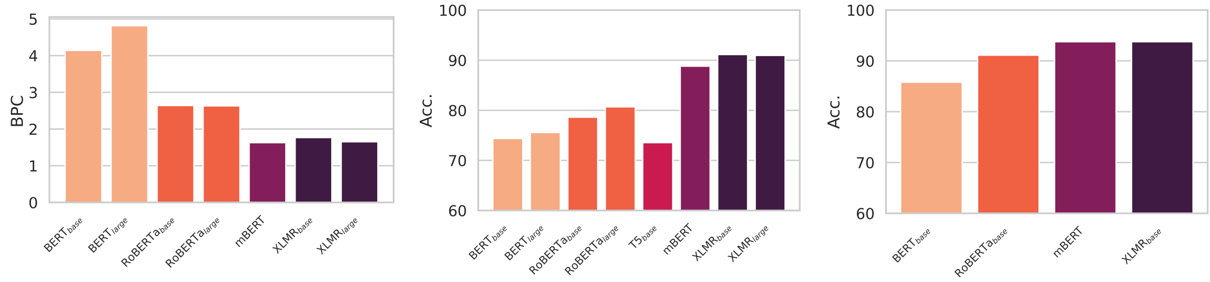
We use the FastText language identification model (Joulin et al., 2017) to label every line in each corpus and keep lines as non-English if they score above a set confidence threshold (0.6). Due to the large size of C4, we subsample the first 50M examples (or 14%); we classify the entirety of all other datasets. Since language detection is imperfect, particularly for low-resource languages (Caswell et al., 2021), we present the results of this analysis as an estimate of the non-English data in each dataset and perform a qualitative analysis of potential errors in the following section.

A summary of the language identification experiments is presented in Figure 1.[1] We see that every corpus contains notable quantities of non-English data, with our estimates ranging between 300k to 406M tokens. An obvious factor that affects the amount of non-English data in each corpus is the overall size of the dataset; however, even when controlling for size by looking at the percentage of non-English data, we still see that the smaller corpora (WIKIPEDIA, BOOKCORPUS, and STORIES) have relatively less non-English data.

Indeed, a major factor of language leakage is the method in which the data was collected: the datasets derived from web crawls contain higher percentages of non-English text (OPENWEBTEXT andCCNEWS). This is true even for C4, where the dataset was filtered with a classifier to exclude non-English text (Raffel et al., 2020). Since automatic methods for language identification are imperfect, the datasets with more manual filtering (such as WIKIPEDIA, which has human editors curating its content) are less prone to non-English data than those relying on classifiers. Due to these challenges, it is likely impossible to fully remove non-English text from a web-crawled dataset at scale.

We also see that non-English text makes up small percentages of the overall data, though this still leads to millions of tokens in large datasets. The largest individual languages after English only make up 0.01%, 0.15%, and 0.05% of the BERT, RoBERTa, and T5 training data, respectively. Multilingual pretraining work has shown that models generalize to new languages from varying amounts of data (Delvin, 2019; Lample and Conneau, 2019; Conneau et al., 2020); however, these approaches intentionally select data across languages, and most upsample low-resource languages during training. Without these considerations, it is an open question how well the models trained on these relatively small amounts of non-English data generalize.

[1] Full results of this evaluation are detailed in Appendix C.



(a) MLM (b) POS (probing) (c) POS (finetuned)

Figure 2: Average performance by each model across all languages for the task. Lower is better for BPC.

2.2 Qualitative Analysis of Non-English Texts

We also perform a closer analysis on a random subset (200 per corpus) of non-English lines predicted by the language classifier (Table 1). Each example is manually coded into one of six categories. The first set covers various kinds of foreign language data: **NE**, where the line contains only *non-English* language text; **BiL**, or *bilingual*, where the line contains both English and non-English text; **Trans.**, in which the English and non-English data that are *translations* of each other; and **Ent.**, where the line is primarily English but contains non-English *entities*. The last two codes pertain to errors made by the language classifier: **En.**, where the line only contains *English* text, and **XX**, which refers to lines that contain *no natural language*.

The majority of lines across datasets consist only of non-English text. The next most common type of non-English data is **BiL**; this contains many subtypes of data, such as codeswitching and foreign language dialogue within English text. These datasets also include parallel data at both the sentence- and word-level.[2] We note that all observed translations are between English and another language. Finally, some of the examples classified as non-English are actually English texts with non-English phrases.

Our analysis also shows that the language classifier performs worse on the non-web crawled data. For example, it misclassified a quarter of the sampled lines from STORIES as non-English when they in fact only contain English text; many of these lines stem from snippets of dialogue in the dataset. We generally observe that lines coded as **En** tend to be shorter than the correctly labeled lines and often contain non-standard English. The language classifier also struggles to handle noisy lines, for which it has no appropriate language label.

[2]e.g., "大学【だい・がく】– college", OPENWEBTEXT

3 Cross-lingual Transfer of English Pretrained Models

We now ask: how well do models pretrained on these putatively English corpora perform on non-English tasks? While the English data is more multilingual than previously thought, there are many differences between monolingual and multilingual pretraining; non-English data are often tokenized into more subword units[3] and are much less frequently observed during monolingual training.

We evaluate popular English pretrained models on tasks in more than 50 languages: (masked) language modeling, POS probing, and finetuned POS tagging. We compare the performance of monolingual BERT (Devlin et al., 2019), RoBERTa (Liu et al., 2019), and T5 (Raffel et al., 2020) against multilingual mBERT (Delvin, 2019) and XLM-R (Conneau et al., 2020). We report average performance across five runs with different random seeds for the POS evaluations. The full results and all languages can be found in Appendix D.

3.1 Non-English MLM Evaluation

We first measure the perplexity of English pretrained MLMs in other languages. We use Wiki-40B, a multilingual language modeling dataset that covers 41 languages (Guo et al., 2020). Following the Wiki-40B paper, we report bits per character (BPC) to allow comparison between models with different tokenizations of the text.

We find that both BERT models perform notably worse on modeling other languages; however, RoBERTa, reduces the gap with the multilingual models from 2.51 BPC to 0.87 BPC (Figure 2a). This finding is consistent with Tran (2020), who also found RoBERTa transfers well cross-lingually.

[3]For example, the Basque UD treebank requires on average 1.78, 2.59, and 2.66 tokens per word to be encoded by XLMR, RoBERTa, and BERT, respectively.

Task	Model	Corr. (ρ) with... lang. data ↑	en sim. ↓
MLM (BPC) ↓	BERT$_{base}$	-0.258	0.097
	BERT$_{lg}$	-0.258	0.118
	RoBERTa$_{base}$	-0.667**	0.326*
	RoBERTa$_{lg}$	-0.685**	0.345*
Frozen POS (Acc.) ↑	BERT$_{base}$	0.335*	-0.332*
	BERT$_{lg}$	0.314*	-0.375*
	RoBERTa$_{base}$	0.594**	-0.260
	RoBERTa$_{lg}$	0.674**	-0.304*
	T5$_{base}$	0.131	-0.271
Finetuned POS (Acc.) ↑	BERT$_{base}$	0.373*	-0.340*
	RoBERTa$_{base}$	0.507**	-0.292*

Table 2: Spearman correlations between task performance and (a) in-language data amounts in pretraining corpora (*lang. data*) and (b) language similarity with English (*en sim.*). $^{*}p < 0.05$ and $^{**}p < 0.001$.

3.2 POS Performance Across Languages

Next, we evaluate how well monolingual English models perform on non-English downstream tasks, using part-of-speech (POS) tagging as a case study.

Probing We first consider the performance of the encoders when probed for POS knowledge (Figure 2b).[4] Unsurprisingly, on average all of the English models underperform the multilingual models. Similar to MLM, we find that RoBERTa performs better than BERT when probed for POS features on other languages; surprisingly, it also strongly outperforms T5, despite C4 containing more absolute non-English data than the RoBERTa corpus.

This difference is likely due to two factors. First, in terms of relative percentages, RoBERTa is exposed to more non-English text than T5 (0.78% compared to only 0.22%). Secondly, RoBERTa's subword vocabulary is robust to unexpected inputs and does not substitute an UNK token any input tokens; in contrast, T5 and BERT have high rates of UNK tokens for some non-Latin languages (Appendix B).[5] However, for many high-resource languages the English models perform competitively, with T5 outperforming mBERT on German and Portuguese, among others.

Fine-tuning To test if the effects of foreign language data carry through after finetuning, we also finetune a subset of the models (BERT$_{base}$, RoBERTa$_{base}$, mBERT, XLMR$_{base}$) for non-English POS tagging (Figure 2c). After finetuning, the gap between the mono- and multilingual models is much smaller: RoBERTa only averages 2.65 points worse than XLM-R, compared to 12.5 points when probing.

[4]For T5, this means that we evaluate the output of the encoder and discard the decoder.

[5]*UNK tokens* refer to placeholder tokens used when the model receives an input not covered by its vocabulary.

3.3 Potential Reasons for Cross-lingual Generalization

We then investigate the correlation between potential transfer causes and model performance (Table 2). Specifically, we consider the quantity of target language data found in the model's pretraining corpus and the language similarity to English as potential causes of cross-lingual transfer.

We find that across tasks, RoBERTa task performance is most strongly correlated with the amount of target language data seen during pretraining. BERT and T5 task performance are less correlated with observed pretrained data, likely due to tokenization artifacts (Appendix B). Indeed, when we control for languages not written with Latin script on T5, the correlation between performance and the amount of target pretraining data increases to $\rho = 0.313$.

We also consider the effect of language similarity on task performance, which is often hypothesized to facilitate cross-lingual transfer. We use the syntactic distance of languages calculated by Malaviya et al. (2017); more similar languages score lower. However, we generally find that this is less correlated with performance than the quantity of target text, particularly for RoBERTa.

4 Discussion

In this paper, we demonstrate that English pretrained models are exposed to a considerable amount of non-English data during pretraining, particularly in the case of more recent models that are trained on larger corpora derived from web crawls. We also find that this non-English text acts as a significant source of signal for cross-lingual transfer.

Other recent work has focused on documenting the composition of pretraining corpora (Dodge et al., 2021; Gururangan et al., 2022). Caswell et al. (2021) manually audit a variety of multilingual datasets, finding data quality issues that are worse for low-resource languages and, similarly to our work, that texts for many languages are misclassified. In contrast, our focus is on the presence of foreign language data in primarily English corpora.

Prior work has also shown the ability of monolingual models to transfer to other languages across a wide range of tasks (Gogoulou et al., 2021; Li et al., 2021; Tran, 2020; Artetxe et al., 2020; Chi et al., 2020), but these works do not consider the effect of foreign language data leakage as a source of signal. Notably, de Souza et al. (2021) mention the presence of foreign language data in their corpora but assume the small amounts observed will not affect model performance. However, our findings demonstrate that the amount of foreign language data directly correlates with cross-lingual transfer.

An obvious follow-up to our findings would be to retrain the models with text that is verified to only contain English data; this would confirm the effect the leaked non-English data has on the models. We reiterate that the standard method for filtering these datasets, automatic language classifiers, is imperfect. This, and the infeasibility of manual filtering due to the scale of the data, means that controlling for the language the model is pretrained on is nearly impossible.

However, the presence of foreign language data in pretraining corpora is not inherently problematic. Models trained on these datasets perform exceedingly well on their target languages *and* generalize to other languages much better than expected. Rather, it is important to remember that these models are not performing zero-shot transfer when used in other languages, given the scale and data with which they were pretrained.

5 Limitations

Our work has a number of limitations. First, we measure the quantities of non-English data using a language classifier. The amounts of foreign language data we report are estimates for each dataset, as the classifier likely misclassified some examples. We manually audit the types of mistakes made by the language classifier in Section 2. Additionally, we evaluate downstream performance via POS tagging, and it is possible that the models would exhibit different behavior on other NLP tasks.

We also only consider the effect of foreign language contamination for English pretrained models. It is unclear to what extent this phenomenon affects monolingual models for other languages; however, since many of the resources evaluated in this work are also used to pretrain non-English monolingual models (e.g., Wikipedia), similar effects would likely be observed.

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References

Mikel Artetxe, Sebastian Ruder, and Dani Yogatama. 2020. On the cross-lingual transferability of monolingual representations. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 4623–4637.

Isaac Caswell, Julia Kreutzer, Lisa Wang, Ahsan Wahab, Daan van Esch, Nasanbayar Ulzii-Orshikh, Allahsera Tapo, Nishant Subramani, Artem Sokolov, Claytone Sikasote, et al. 2021. Quality at a glance: An audit of web-crawled multilingual datasets.

Zewen Chi, Li Dong, Furu Wei, Xianling Mao, and He-Yan Huang. 2020. Can monolingual pretrained models help cross-lingual classification? In *Proceedings of the 1st Conference of the Asia-Pacific Chapter of the Association for Computational Linguistics and the 10th International Joint Conference on Natural Language Processing*, pages 12–17.

Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Édouard Grave, Myle Ott, Luke Zettlemoyer, and Veselin Stoyanov. 2020. Unsupervised cross-lingual representation learning at scale. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 8440–8451.

Leandro Rodrigues de Souza, Rodrigo Nogueira, and Roberto Lotufo. 2021. On the ability of monolingual models to learn language-agnostic representations. *arXiv preprint arXiv:2109.01942*.

Jacob Delvin. 2019. Multilingual BERT Readme. `https://github.com/google-research/bert/blob/master/multilingual.md`.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. 2019. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, Minneapolis, Minnesota. Association for Computational Linguistics.

Jesse Dodge, Maarten Sap, Ana Marasović, William Agnew, Gabriel Ilharco, Dirk Groeneveld, Margaret Mitchell, and Matt Gardner. 2021. Documenting large webtext corpora: A case study on the colossal clean crawled corpus. In *Proceedings of the 2021*

Conference on Empirical Methods in Natural Language Processing (EMNLP).

Evangelia Gogoulou, Ariel Ekgren, Tim Isbister, and Magnus Sahlgren. 2021. Cross-lingual transfer of monolingual models. *arXiv preprint arXiv:2109.07348*.

Aaron Gokaslan and Vanya Cohen. 2019. Openwebtext corpus. http://Skylion007.github.io/OpenWebTextCorpus.

Mandy Guo, Zihang Dai, Denny Vrandečić, and Rami Al-Rfou. 2020. Wiki-40B: Multilingual language model dataset. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 2440–2452, Marseille, France. European Language Resources Association.

Suchin Gururangan, Dallas Card, Sarah K Drier, Emily K Gade, Leroy Z Wang, Zeyu Wang, Luke Zettlemoyer, and Noah A Smith. 2022. Whose language counts as high quality? measuring language ideologies in text data selection. *arXiv preprint arXiv:2201.10474*.

Armand Joulin, Édouard Grave, Piotr Bojanowski, and Tomáš Mikolov. 2017. Bag of tricks for efficient text classification. In *Proceedings of the 15th Conference of the European Chapter of the Association for Computational Linguistics: Volume 2, Short Papers*, pages 427–431.

Diederik P. Kingma and Jimmy Lei Ba. 2015. Adam: A method for stochastic optimization. In *Proceedings of 3rd International Conference of Learning Representations*.

Taku Kudo and John Richardson. 2018. Sentencepiece: A simple and language independent subword tokenizer and detokenizer for neural text processing. In *Proceedings of the 2018 Conference on Empirical Methods in Natural Language Processing: System Demonstrations*, pages 66–71.

Guillaume Lample and Alexis Conneau. 2019. Cross-lingual language model pretraining. *arXiv preprint arXiv:1901.07291*.

Zuchao Li, Kevin Parnow, Hai Zhao, Zhuosheng Zhang, Rui Wang, Masao Utiyama, and Eiichiro Sumita. 2021. Cross-lingual transferring of pre-trained contextualized language models. *arXiv preprint arXiv:2107.12627*.

Yinhan Liu, Myle Ott, Naman Goyal, Jingfei Du, Mandar Joshi, Danqi Chen, Omer Levy, Mike Lewis, Luke Zettlemoyer, and Veselin Stoyanov. 2019. Roberta: A robustly optimized bert pretraining approach. *arXiv preprint arXiv:1907.11692*.

Chaitanya Malaviya, Graham Neubig, and Patrick Littell. 2017. Learning language representations for typology prediction. In *Conference on Empirical Methods in Natural Language Processing (EMNLP)*, Copenhagen, Denmark.

Joakim Nivre, Marie-Catherine de Marneffe, Filip Ginter, Jan Hajic, Christopher D Manning, Sampo Pyysalo, Sebastian Schuster, Francis Tyers, and Daniel Zeman. 2020. Universal dependencies v2: An evergrowing multilingual treebank collection. In *Proceedings of the 12th Language Resources and Evaluation Conference*, pages 4034–4043.

Alec Radford, Jeffrey Wu, Rewon Child, David Luan, Dario Amodei, Ilya Sutskever, et al. 2019. Language models are unsupervised multitask learners. *OpenAI blog*, 1(8):9.

Colin Raffel, Noam Shazeer, Adam Roberts, Katherine Lee, Sharan Narang, Michael Matena, Yanqi Zhou, Wei Li, and Peter J Liu. 2020. Exploring the limits of transfer learning with a unified text-to-text transformer. *Journal of Machine Learning Research*, 21:1–67.

Ke Tran. 2020. From english to foreign languages: Transferring pre-trained language models. *arXiv preprint arXiv:2002.07306*.

Trieu H Trinh and Quoc V Le. 2018. A simple method for commonsense reasoning. *arXiv preprint arXiv:1806.02847*.

Thomas Wolf, Lysandre Debut, Victor Sanh, Julien Chaumond, Clement Delangue, Anthony Moi, Pierric Cistac, Tim Rault, R'emi Louf, Morgan Funtowicz, and Jamie Brew. 2019. Huggingface's transformers: State-of-the-art natural language processing. *ArXiv*, abs/1910.03771.

Yukun Zhu, Ryan Kiros, Rich Zemel, Ruslan Salakhutdinov, Raquel Urtasun, Antonio Torralba, and Sanja Fidler. 2015. Aligning books and movies: Towards story-like visual explanations by watching movies and reading books. In *Proceedings of the IEEE international conference on computer vision*, pages 19–27.

A Details of Transfer Experiments

For the language modeling experiments, we perform whole word masking on 15% of the words in the Wiki40B test set to calculate BPC. This experiment was zero-shot and required no further training of the models.

For the POS probing experiments, we train a linear classifier to predict POS from the final layer of each considered encoder; each probe therefore consists of a limited number of parameters $m * l$ where m is the output dimension of the encoder being probed (768 for base models and 1024 for large models) and l is the size of the label set (17 for POS tagging). For words that are tokenized into multiple subword units, we take the average representation of all tokens as the input to the classifier. When finetuning the model, we take the same setup as probing but unfreeze the encoder weights to allow them to update during training. The POS models are trained and evaluated on Universal Dependencies (UD) treebanks for each language (Nivre et al., 2020).

We use a batch size of 256 for the frozen experiments and batch sizes of 16 for the finetuned models; we used a learning rate of 0.001 for the probing task and 5e-6 for finetuning. Due to the large number of experiments, we did not tune these parameters. For both POS tagging experiments, we use an Adam optimizer (Kingma and Ba, 2015), and train each probe for 50 passes over the data (with early stopping on the validation set and a patience of 5). The pretrained models for all experiments are downloaded from Huggingface (Wolf et al., 2019).

Each of our models was trained on a single Nvidia V100 GPU: 16GB for the frozen models and 32GB for the finetuned ones. The frozen probes each took between <1 and 8 minutes to train, and the finetuned probes were trained for between 5 minutes and 7.5 hours (depending on the dataset size, which varies by language, and early stopping epoch).

B The Effect of Tokenization

A factor that varies across the considered models is how they tokenize the input text for different languages. Table 4 gives the number of subword tokens per (white-space separated) word in the validation split of Wiki40b (Guo et al., 2020), as well as the percentage of tokens that are unked out by the tokenizer. We see that in general, all of the models (including explicitly multilingual ones) require more subword tokens per word for languages other than English.[6] We can also see that T5 is more efficient at encoding French, German, and Romanian than the other monolingual models (without a high UNK rate), likely because the T5 tokenizer was explicitly trained on English data mixed with those languages (Raffel et al., 2020).

We also examine how many tokens are unked out by each tokenizer across languages. We see that BERT and T5 in particular have a high UNK rate ($> 10\%$) for many languages not written in Latin script. This is in part due to the different tokenization schemes used by the models: RoBERTa uses a byte-level BPE encoding (Radford et al., 2019), which produces no UNK tokens for Unicode text, whereas the tokenization methods used by BERT and T5 (SentencePiece, Kudo and Richardson (2018)) will unk out tokens not seen while training the tokenizer. Additionally, there are other potential decisions made during tokenization that could affect these UNK rates, including filtering on non-Latin tokens or learning the subword tokenizer on a subset of the training data.

High UNK rates in the tokenized text for a language affect performance on downstream tasks. With regards to evaluating BPC, high frequencies of UNK tokens in the data likely make the language modeling task artificially easy, leading to lower BPC scores. Because of this, we note the cases where a model UNKs out more than 10% of the considered data in the BPC results given in Table 5 with an asterisk (*). High UNK rates likely also lead to degraded performance on downstream tasks (including the considered POS tagging task in this work).

C Full Results of the Automatic Language Identity Analysis

We present a more complete set of results for the automatic language composition analysis (Section 2) in Table 3. We include every language that has 10,000 or more tokens in at least one of the considered corpora; we additionally report numbers for Basque and Frisian, as both languages are included in the experiments in Section 3.

D Full Results of Transfer Experiments

Full results for whole word MLM are given in Table 5; results for POS probing can be found in Table 6 and results for finetuned POS tagging are detailed in Table 7.

[6] We note that the number of subword tokens per "word" in Japanese is much larger than in other languages, as words in Japanese are not whitespace-separated.

ISO	Language	Number of Tokens							
		Wiki	Book	Stories	OpenWebText	CCNews	C4	BERT	RoBERTa
en	English	2.0B	802.4M	6.2B	6.4B	13.0B	17.8B	2.8B	28.3B
sq	Albanian	3.3K	0	195	8.8K	42.5M	14.4K	3.3K	42.5M
es	Spanish	112.8K	120.4K	150.6K	3.4M	36.6M	5.9M	233.2K	40.3M
de	German	176.2K	5.4K	104.8K	3.1M	34.4M	9.0M	181.5K	37.8M
ro	Romanian	19.6K	174	6.4K	1.4M	28.7M	164.0K	19.8K	30.2M
pt	Portugese	43.2K	760	44.2K	1.5M	10.0M	1.9M	44.0K	11.5M
it	Italian	102.9K	3.9K	46.1K	1.6M	9.2M	2.6M	106.7K	10.9M
fr	French	201.1K	88.1K	126.6K	2.5M	7.2M	6.0M	289.2K	10.1M
pl	Polish	56.2K	51	5.0K	239.9K	5.3M	686.9K	56.2K	5.6M
nl	Dutch	28.0K	1.0K	37.3K	254.7K	4.4M	1.7M	29.0K	4.8M
vi	Vietnamese	25.5K	98	2.8K	10.5K	3.5M	277.6K	25.6K	3.6M
tl	Tagalog	3.2K	3.7K	28.7K	124.3K	3.1M	312.1K	6.9K	3.3M
cs	Czech	8.8K	12	2.1K	152.7K	2.0M	295.0K	8.8K	2.1M
fi	Finnish	6.9K	119	4.7K	243.2K	1.7M	214.5K	7.0K	1.9M
no	Norwegian	9.5K	170	6.4K	204.3K	1.6M	300.5K	9.7K	1.8M
hu	Hungarian	8.9K	51	5.6K	32.5K	1.6M	194.2K	9.0K	1.7M
hi	Hindi	6.7K	0	520	32.2K	1.5M	328.0K	6.7K	1.6M
hr	Croatian	4.0K	0	482	313.2K	1.2M	30.8K	4.0K	1.5M
id	Indonesian	1.5K	100	12.9K	83.5K	1.3M	997.7K	1.6K	1.4M
ru	Russian	17.4K	606	3.9K	956.3K	64.8K	2.3M	18.0K	1.0M
sv	Swedish	11.1K	567	9.3K	784.9K	236.3K	743.5K	11.6K	1.0M
sr	Serbian	753	0	709	39.0K	976.2K	36.8K	753	1.0M
et	Estonian	2.8K	0	288	8.0K	817.1K	32.0K	2.8K	828.2K
tr	Turkish	6.3K	541	9.4K	131.4K	535.0K	401.9K	6.9K	682.6K
af	Afrikaans	852	0	2.7K	6.7K	584.1K	145.3K	852	594.3K
ku	Kurdish	185	0	0	6.7K	468.0K	3.5K	185	474.9K
da	Danish	3.1K	20	5.3K	249.8K	157.8K	271.1K	3.1K	415.9K
gl	Galican	101	0	309	637	317.5K	9.6K	101	318.6K
ja	Japanese	5.8K	3.4K	23.8K	188.7K	76.3K	3.0M	9.2K	298.1K
ca	Catalan	5.2K	99	418	28.2K	258.8K	108.3K	5.3K	292.8K
ar	Arabic	5.3K	0	665	154.2K	89.6K	601.7K	5.3K	249.7K
ko	Korean	3.2K	20	45	208.1K	8.0K	4.1M	3.3K	219.4K
el	Greek	15.2K	777	1.8K	123.8K	28.4K	288.7K	16.0K	169.9K
sl	Slovenian	262	0	250	102.1K	14.5K	46.8K	262	117.1K
is	Icelandic	1.5K	65.8K	758	10.4K	11.1K	114.7K	67.2K	89.5K
ga	Irish	1.2K	0	839	8.7K	77.9K	468.4K	1.2K	88.6K
uk	Ukranian	3.5K	10	232	63.4K	3.5K	232.1K	3.5K	70.7K
he	Hebrew	5.2K	0	4.6K	46.5K	9.6K	138.0K	5.2K	66.0K
lt	Lithuanian	3.4K	12	1.1K	2.8K	54.9K	56.8K	3.4K	62.2K
sk	Slovak	1.9K	0	76	16.2K	43.9K	64.7K	1.9K	62.0K
ms	Malay	896	29	1.4K	1.8K	45.9K	42.8K	925	50.0K
sw	Swahili	44	16	533	143	47.7K	5.9K	60	48.5K
eo	Esperanto	461	114	2.6K	34.9K	7.2K	37.2K	575	45.2K
zh	Chinese	4.1K	12	5.5K	30.8K	4.5K	410.2K	4.1K	44.8K
lv	Latvian	1.4K	0	367	4.0K	38.5K	47.0K	1.4K	44.3K
bn	Bengali	2.5K	24.8K	51	6.2K	10.1K	48.6K	27.3K	43.6K
fa	Persian	3.0K	0	261	28.2K	5.8K	668.9K	3.0K	37.2K
nn	Norysk	283	0	0	4.5K	32.5K	4.6K	283	37.2K
la	Latin	6.0K	641	3.8K	19.4K	4.7K	34.7K	6.6K	34.5K
az	Azerbaijani	2.0K	0	55	884	27.1K	12.9K	2.0K	30.0K
th	Thai	7.6K	0	592	15.1K	5.5K	131.8K	7.6K	28.7K
bg	Bulgarian	6.7K	20	284	18.7K	2.8K	96.7K	6.7K	28.5K
cy	Welsh	1.2K	84	440	18.5K	7.4K	59.5K	1.3K	27.6K
ilo	Iloko	19	0	16	628	18.8K	1.1K	19	19.5K
ur	Ukranian	5.0K	0	24	6.4K	7.0K	27.9K	5.0K	18.4K
ta	Tamil	5.4K	0	234	5.9K	5.8K	42.2K	5.4K	17.4K
mt	Maltese	177	0	0	371	13.9K	20.3K	177	14.5K
hy	Armenian	2.6K	0	0	7.5K	2.9K	21.5K	2.6K	13.0K
gd	Gaelic	198	0	52	874	8.8K	117.6K	198	10.0K
eu	Basque	99	5	1.8K	2.8K	2.4K	19.3K	104	7.0K
fy	Frisian	80	0	1.3K	1.5K	601	9.8K	80	3.4K
Total (Non-En)		983k	322k	682k	18.6M	201M	406M†	1.3M	222M

Table 3: Full results for the automatic language composition analysis of pretraining corpora presented in Section 2. The last two columns include the total data that BERT and RoBERTa were trained on, respectively; C4 contains the data T5 was trained on, and contains the estimates for the first 50M examples in the full C4 dataset; † represents the projected estimate for the full dataset.

ISO	Monolingual			Multilingual	
	BERT	RoBERTa	T5	mBERT	XLMR
ar	2.91 (0.60%)	3.11 (0.0%)	1.91 (**41.26%**)	1.95 (0.05%)	1.73 (9.8e-4%)
bg	3.03 (0.06%)	3.25 (0.0%)	2.88 (**17.83%**)	1.93 (0.67%)	1.72 (1.2e-3%)
ca	1.95 (0.01%)	1.83 (0.0%)	2.08 (1.23%)	1.55 (0.12%)	1.56 (4.6e-4%)
cs	2.64 (0.03%)	2.64 (0.0%)	2.85 (**10.30%**)	2.00 (0.22%)	1.86 (5.6e-4%)
da	2.19 (0.01%)	2.07 (0.0%)	2.42 (3.56%)	1.74 (0.14%)	1.63 (4.5e-4%)
de	2.21 (0.02%)	2.14 (0.0%)	1.85 (0.26%)	1.65 (0.37%)	1.67 (1.5e-3%)
el	2.74 (0.36%)	2.96 (0.0%)	1.82 (**40.30%**)	2.05 (0.05%)	1.73 (1.4e-3%)
en	1.38 (0.03%)	1.32 (0.0%)	1.44 (0.15%)	1.37 (0.22%)	1.42 (1.3e-3%)
es	1.76 (0.01%)	1.67 (0.0%)	1.88 (1.48%)	1.37 (0.11%)	1.37 (8.2e-4%)
et	3.02 (0.03%)	2.92 (0.0%)	3.35 (1.55%)	2.47 (0.33%)	2.21 (1.5e-3%)
fa	2.80 (1.12%)	3.34 (0.0%)	2.00 (**42.14%**)	1.70 (0.05%)	1.55 (6.1e-3%)
fi	3.18 (8.3e-3%)	3.06 (0.0%)	3.48 (0.13%)	2.45 (0.35%)	2.24 (9.9e-4%)
fr	1.90 (0.01%)	1.81 (0.0%)	1.78 (0.26%)	1.53 (0.43%)	1.57 (8.5e-4%)
he	2.82 (0.72%)	3.08 (0.0%)	1.97 (**40.30%**)	2.05 (0.06%)	1.89 (4.2e-4%)
hi	1.98 (**12.06%**)	2.84 (0.0%)	1.64 (**42.82%**)	1.64 (0.05%)	1.39 (1.3e-3%)
hr	2.38 (7.1e-3%)	2.27 (0.0%)	2.57 (3.71%)	1.85 (0.08%)	1.73 (1.1e-3%)
hu	2.78 (0.02%)	2.72 (0.0%)	3.00 (2.60%)	2.12 (0.28%)	1.93 (1.1e-3%)
id	2.34 (0.05%)	2.22 (0.0%)	2.54 (0.13%)	1.70 (0.12%)	1.59 (4.5e-3%)
it	1.92 (0.01%)	1.83 (0.0%)	2.05 (0.42%)	1.51 (0.10%)	1.52 (1.0e-3%)
ja	34.41 (**39.97%**)	47.67 (0.0%)	9.50 (**22.19%**)	35.22 (0.05%)	31.30 (0.03%)
ko	1.60 (**59.65%**)	4.78 (0.0%)	2.32 (**38.63%**)	2.65 (0.25%)	2.53 (0.03%)
lt	3.06 (0.80%)	3.12 (0.0%)	3.41 (8.78%)	2.48 (0.97%)	2.23 (7.7e-3%)
lv	2.89 (0.48%)	2.84 (0.0%)	3.13 (**12.52%**)	2.36 (0.30%)	2.06 (2.8e-3%)
ms	2.34 (0.03%)	2.21 (0.0%)	2.53 (0.10%)	1.71 (0.10%)	1.58 (1.9e-3%)
nl	2.18 (8.0e-3%)	2.04 (0.0%)	2.31 (0.21%)	1.64 (0.08%)	1.62 (4.6e-4%)
no	2.24 (0.03%)	2.10 (0.0%)	2.49 (3.01%)	1.74 (0.13%)	1.66 (2.0e-3%)
pl	2.60 (9.3e-3%)	2.60 (0.0%)	2.83 (6.50%)	1.96 (0.44%)	1.88 (7.2e-4%)
pt	1.86 (0.02%)	1.76 (0.0%)	2.01 (2.05%)	1.45 (0.11%)	1.43 (1.0-3%)
ro	2.03 (0.01%)	2.02 (0.0%)	1.73 (0.18%)	1.63 (0.25%)	1.54 (7.9e-4%)
ru	3.05 (0.02%)	3.25 (0.0%)	2.90 (**21.1%**)	1.92 (0.53%)	1.82 (2.1e-3%)
sk	2.86 (0.05%)	2.81 (0.0%)	3.14 (7.08%)	2.20 (0.19%)	2.00 (1.4e-3%)
sl	2.37 (9.7e-3%)	2.24 (0.0%)	2.53 (3.45%)	1.91 (0.06%)	1.73 (1.1e-3%)
sr	3.01 (0.71%)	3.33 (0.0%)	2.95 (**17.14%**)	1.95 (0.19%)	1.77 (4.8e-4%)
sv	2.57 (7.9e-3%)	2.40 (0.0%)	2.77 (2.08%)	1.90 (0.15%)	1.80 (8.5e-4%)
th	2.13 (**36.91%**)	11.79 (0.0%)	2.73 (**28.58%**)	8.34 (0.12%)	5.42 (1.6e-3%)
tl	2.14 (0.10%)	2.02 (0.0%)	2.44 (0.18%)	1.81 (0.12%)	1.70 (2.9e-3%)
tr	2.94 (0.01%)	2.87 (0.0%)	3.19 (7.36%)	2.13 (0.31%)	1.91 (2.0e-3%)
uk	3.36 (0.52%)	3.73 (0.0%)	3.23 (**24.12%**)	2.11 (0.54%)	1.94 (1.4e-3%)
vi	1.76 (1.44%)	1.95 (0.0%)	1.89 (**15.12%**)	1.19 (0.08%)	1.16 (3.2e-3%)

Table 4: The average number of subword tokens per white-spaced word (and the percentage of UNKed out tokens) in the Wiki40b validation set for each language. Cases where more than 10% of tokens are unked out are in bold.

ISO	Monolingual				Multilingual		
	BERT$_{ba}$	**BERT**$_{lg}$	**RoBERTa**$_{ba}$	**RoBERTa**$_{lg}$	**mBERT**	**XLMR**$_{ba}$	**XLMR**$_{lg}$
ar	6.214	9.331	3.319	3.899	1.849	1.871	1.691
bg	6.334	7.883	3.544	3.587	1.553	1.494	1.358
ca	3.382	3.565	1.834	1.640	1.108	1.477	1.329
cs	4.316	4.738	2.634	2.493	1.703	1.715	1.533
da	3.560	3.832	2.104	1.931	1.420	1.427	1.272
de	3.430	3.644	1.815	1.634	1.102	1.361	1.218
el	6.934	8.915	3.852	3.885	1.793	1.588	1.440
en	1.285	1.377	0.595	0.516	0.938	1.249	1.131
es	3.281	3.551	1.526	1.345	1.036	1.284	1.165
et	3.846	4.108	2.448	2.318	1.878	1.858	1.671
fa	5.813	8.501	3.614	4.113	1.723	1.567	1.418
fi	3.732	4.064	2.357	2.240	1.633	1.618	1.451
fr	3.213	3.439	1.586	1.414	1.038	1.434	1.305
he	6.490	9.074	3.530	3.831	1.817	1.976	1.739
hi	4.240*	5.503*	1.487	1.407	1.876	1.641	1.516
hr	3.972	4.298	2.267	2.109	1.563	1.644	1.484
hu	4.203	4.585	2.741	2.632	1.778	1.713	1.548
id	3.436	3.665	1.976	1.838	1.221	1.243	1.129
it	3.263	3.536	1.661	1.475	1.098	1.402	1.256
ja	1.840*	2.065*	5.481	6.775	2.082	6.827	8.016
ko	0.781*	0.846*	4.204	4.639	3.144	3.504	3.241
lt	3.953	4.271	2.746	2.633	1.840	1.789	1.604
lv	4.231	4.512	2.833	2.730	1.890	1.750	1.548
ms	3.461	3.698	2.010	1.886	1.280	1.365	1.257
nl	3.445	3.693	1.855	1.680	1.222	1.397	1.257
no	3.580	3.873	2.052	1.872	1.398	1.469	1.312
pl	4.020	4.505	2.506	2.365	1.495	1.604	1.437
pt	3.442	3.718	1.658	1.465	1.128	1.316	1.190
ro	3.641	3.929	1.950	1.772	1.402	1.435	1.286
ru	6.747	8.122	3.624	3.673	1.385	1.491	1.344
sk	4.263	4.628	2.714	2.594	1.804	1.753	1.594
sl	3.972	4.294	2.415	2.273	1.642	1.563	1.391
sr	6.081	7.216	3.610	3.661	1.772	1.783	1.681
sv	3.774	4.081	2.196	2.019	1.460	1.523	1.372
th	1.551*	1.689*	3.312	3.535	3.861	2.119	2.237
tl	3.250	3.458	1.763	1.623	1.616	1.713	1.572
tr	4.102	4.427	2.715	2.585	1.635	1.603	1.460
uk	6.542	7.912	3.763	3.823	1.566	1.635	1.488
vi	5.134	5.794	2.590	2.574	1.046	1.191	1.055

Table 5: Full results for the zero-shot BPC experiments in Section 3. Results noted with * correspond to cases of high UNK rates in the tokenization of the data (Section B).

ISO	Baselines		Monolingual					Multilingual		
	Maj. Label	**Word Maj.**	**BERT$_{ba}$**	**BERT$_{lg}$**	**Ro$_{ba}$**	**Ro$_{lg}$**	**T5-base**	**mBERT**	**XLMR$_{ba}$**	**XLMR$_{lg}$**
af	21.650	83.335	81.695	84.855	88.858	92.324	90.464	93.590	97.490	96.381
ar	33.297	90.148	79.595	79.994	78.939	79.242	43.182	93.724	95.659	95.533
bg	21.834	86.091	85.617	84.238	78.514	81.147	85.304	94.977	97.240	97.103
ca	17.868	90.984	93.208	93.432	94.333	94.545	95.863	97.610	98.222	98.202
cs	24.708	91.284	82.312	80.591	89.272	93.488	86.560	96.554	97.548	97.744
cy	31.099	73.587	69.625	72.641	69.171	70.309	76.220	81.713	76.690	77.215
da	18.606	77.841	81.137	81.485	85.308	91.057	86.832	91.901	96.757	96.087
de	17.784	81.992	86.663	88.306	91.266	93.074	92.878	92.022	94.851	94.020
el	21.148	81.128	79.996	79.110	66.604	76.795	37.050	92.509	95.435	95.371
en	16.999	82.920	93.803	92.903	94.785	94.418	96.286	93.666	95.366	95.342
es	17.734	90.734	89.639	92.860	97.652	93.171	97.222	97.699	98.418	98.497
et	26.462	78.486	74.987	78.524	74.460	81.150	79.287	91.891	90.717	91.143
eu	24.422	77.591	73.152	75.663	72.713	72.254	80.294	84.712	88.744	88.023
fa	33.521	91.916	78.545	78.202	67.668	66.767	46.485	93.025	96.310	96.597
fi	27.965	74.378	71.083	72.301	77.318	82.587	77.630	92.621	95.823	95.872
fr	18.749	89.584	90.960	90.197	93.690	95.278	96.612	95.963	95.837	95.813
fy	14.815	85.190	79.749	82.128	78.766	78.216	86.351	90.898	87.908	89.405
ga	29.122	81.512	72.470	77.009	76.983	79.169	82.430	87.097	91.493	92.583
gd	21.166	80.114	78.264	79.641	74.989	76.281	79.590	78.387	84.102	85.609
gl	22.969	86.294	87.727	89.058	92.638	93.176	93.647	92.559	95.145	95.548
he	23.601	85.491	75.040	75.393	69.930	70.160	45.758	93.206	96.403	94.864
hi	22.128	89.365	68.650	68.861	77.250	80.597	38.185	94.054	95.524	94.250
hr	24.182	83.533	80.408	82.370	92.955	94.742	87.784	96.164	98.011	98.313
hu	22.429	60.356	72.619	73.444	76.403	83.633	79.868	88.273	93.404	91.868
hy	24.995	68.931	50.956	52.033	58.560	58.792	44.142	89.001	90.403	93.937
id	21.642	81.278	4.151	4.151	79.539	81.664	4.151	4.151	4.151	4.151
is	17.286	90.407	80.969	84.217	79.792	82.154	84.121	91.414	97.459	97.778
it	19.920	89.758	89.497	91.317	93.991	95.521	94.715	96.662	97.454	96.854
ja	30.137	85.592	76.268	75.659	83.491	85.013	39.409	92.362	90.844	91.080
ko	30.011	67.715	48.090	47.683	67.852	70.745	47.288	76.359	80.372	80.704
la	21.355	94.888	91.416	94.079	92.133	92.489	95.928	95.008	98.250	97.548
lt	31.345	61.009	67.026	70.382	67.892	66.602	77.164	90.542	91.641	94.710
lv	27.108	79.198	71.889	77.190	72.061	74.857	81.630	87.627	93.565	92.775
mt	19.489	76.131	75.582	78.313	75.199	75.156	80.854	76.877	70.113	74.191
nl	16.799	81.878	79.448	84.540	90.126	92.816	89.207	94.356	95.920	95.990
pl	24.900	83.868	82.357	81.721	91.563	92.491	90.494	94.184	98.231	97.840
pt	18.117	83.517	85.594	86.801	91.591	92.114	95.120	94.066	96.981	94.810
ro	24.849	85.537	82.630	84.414	93.830	95.332	93.407	95.284	97.443	97.229
ru	23.843	88.593	84.258	85.526	82.713	86.811	88.812	95.299	96.943	94.714
sk	19.264	61.821	80.441	83.025	86.850	89.339	86.872	92.414	96.290	95.810
sl	21.289	77.815	82.459	80.959	88.357	88.176	87.189	96.388	97.953	98.144
sr	24.378	82.523	84.930	85.434	94.762	94.769	89.884	92.727	98.638	98.333
sv	17.579	78.993	71.818	79.061	78.523	88.662	83.226	92.826	96.246	95.350
ta	29.389	53.042	43.992	40.563	38.361	43.228	43.147	74.912	76.521	75.606
tr	36.494	82.343	78.115	73.015	67.656	67.340	80.830	88.633	91.392	89.939
uk	23.213	71.964	78.214	78.950	65.442	69.780	80.780	91.836	96.213	96.823
ur	23.564	85.736	68.112	68.819	69.202	67.458	34.116	88.954	91.170	92.341
vi	32.019	75.901	54.764	54.267	54.054	56.402	60.768	75.844	85.855	81.554
zh	27.478	78.696	49.462	51.400	64.537	67.238	44.479	87.363	88.565	85.921

Table 6: Full results for the frozen POS tagging experiments in Section 3.

ISO	Monolingual		Multilingual	
	BERT_{ba}	Ro_{ba}	mBERT	XLMR_{ba}
af	92.108	94.528	96.802	97.158
ar	92.896	93.417	96.151	96.673
bg	97.185	96.797	98.714	99.145
ca	98.058	98.264	98.813	98.845
cs	98.191	98.306	98.803	98.952
cy	82.152	72.484	92.109	84.927
da	93.134	93.872	97.037	97.556
de	93.285	93.554	95.178	95.189
el	92.725	90.452	96.735	96.897
en	96.496	97.186	96.431	97.082
es	97.841	98.459	98.828	98.781
et	95.142	95.244	96.547	97.402
eu	91.313	90.117	94.529	94.956
fa	94.477	94.113	97.193	97.609
fi	93.534	93.436	96.275	97.823
fr	96.970	97.112	97.845	98.102
fy	92.383	92.770	95.557	95.721
ga	91.263	91.164	93.293	94.334
gd	91.774	90.220	92.814	93.797
gl	94.261	95.565	95.130	96.892
he	91.373	90.847	96.242	97.035
hi	83.566	94.437	96.554	97.384
hr	95.955	96.687	98.061	98.293
hu	83.886	85.540	94.763	94.035
hy	53.953	86.965	92.985	93.829
id	4.151	91.635	4.151	4.151
is	96.583	96.489	97.899	98.404
it	96.521	97.297	98.172	98.334
ja	86.477	93.707	96.600	97.112
ko	47.783	91.514	94.941	95.464
la	98.386	98.633	99.399	99.199
lt	82.707	84.507	93.026	94.636
lv	93.252	93.710	95.744	96.908
mt	87.284	85.603	89.248	86.349
nl	93.974	94.861	96.669	96.969
pl	96.604	97.064	98.569	98.980
pt	95.420	96.572	97.526	97.611
ro	95.795	96.044	97.568	97.878
ru	97.310	97.103	98.306	98.568
sk	93.608	93.994	97.282	97.373
sl	95.233	95.776	98.157	98.798
sr	96.140	97.154	98.531	98.802
sv	90.737	92.805	96.242	97.080
ta	42.363	49.452	77.185	64.354
tr	92.390	92.320	94.667	94.946
uk	93.320	93.980	96.020	96.975
ur	84.556	84.432	92.622	93.251
vi	46.954	50.874	89.653	91.261
zh	55.811	84.877	95.022	95.972

Table 7: Full results for the finetuned POS tagging experiments in Section 3.