

CompoundPiece: Evaluating and Improving Decompounding Performance of Language Models

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Abstract

While many languages possess processes of joining two or more words to create *compound* words, previous studies have been typically limited only to languages with excessively productive compound formation (e.g., German, Dutch) and there is no public dataset containing compound *and* non-compound words across a large number of languages. In this work, we systematically study *decompounding*, the task of splitting compound words into their constituents, at a wide scale. We first address the data gap by introducing a dataset of 255k compound and non-compound words across 56 diverse languages obtained from Wiktionary. We then use this dataset to evaluate an array of Large Language Models (LLMs) on the decompounding task. We find that LLMs perform poorly, especially on words which are tokenized unfavorably by subword tokenization. We thus introduce a novel methodology to train dedicated models for decompounding. The proposed two-stage procedure relies on a fully self-supervised objective in the first stage, while the second, supervised learning stage optionally fine-tunes the model on the annotated Wiktionary data. Our self-supervised models outperform the prior best unsupervised decompounding models by 13.9% accuracy on average. Our fine-tuned models outperform all prior (language-specific) decompounding tools. Furthermore, we use our models to leverage decompounding during the creation of a subword tokenizer, which we refer to as *CompoundPiece*. CompoundPiece tokenizes compound words more favorably on average, leading to improved performance on decompounding over an otherwise equivalent model using SentencePiece tokenization.

1 Introduction

Decompounding is the task of separating compound words into their single word constituents. Decompounding is used in user-facing tools such as dictionaries and morphological analyzers (Altinok,

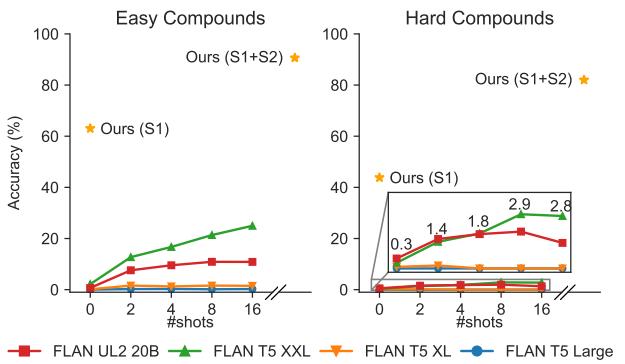


Figure 1: In-context learning performance of LLMs on compound segmentation vs. our method (§5).

	Constituents	Subwords
Hard Compound	wind surfing	wind surf ing
Easy Compound	spell binding	spell bind ing

Figure 2: Examples of easy and hard compounds w.r.t. the T5 tokenizer (also used by FLAN UL2 20B).

2018). Historically, it has also been widely used as a preprocessing step for other NLP tasks, e.g. for information retrieval (Monz and De Rijke, 2002; Braschler and Ripplinger, 2004), automatic speech recognition (Adda-Decker and Adda, 2000) and machine translation (Koehn and Knight, 2003).

Decompounding can come in two similar yet different task formats: (i) *compound segmentation* and (ii) *compound normalization* (Ziering and van der Plas, 2016). Compound segmentation is the task of segmenting a word into its compound constituents, while preserving its surface form (e.g. *bridesmaid* → *bride + maid*). Compound normalization is the task of recovering the base form of each compound constituent (e.g. *bridesmaid* → *bride + maid*).¹

Most prior work on decompounding has focused on the few languages with excessively productive

¹In morphological segmentation, segmentation and normalization are also referred to as surface-level segmentation and canonical segmentation, respectively (Cotterell et al., 2016).

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compound formation such as Finnish, German and Swedish (Koehn and Knight, 2003; Shapiro, 2016; Riedl and Biemann, 2016). However, compound words occur in a large, diverse number of languages (Vogel and Scalise, 2010). Yet, datasets which annotate compounds with their segmented or normalized form sparsely exist, even in languages with high compound usage. As the first contribution of this work, we aim to address this issue by introducing a dataset of 255k compound words and their normalized form as well as non-compound words covering 56 languages obtained from Wiktionary (www.wiktionary.org).

Using our dataset, we then find that large language models (LLMs), which typically rely on subword-based tokenization (Sennrich et al., 2016; Kudo and Richardson, 2018), struggle with decompounding, as illustrated in Figure 1. Performance is especially low for compounds where subword boundaries do not coincide with compound constituent boundaries; we term compounds with this property ‘hard’ compounds (Figure 2).

In order to create a more effective decompounding model, we then formulate compound segmentation and normalization as a sequence-to-sequence learning task (Sutskever et al., 2014) and train a byte-level ByT5 model (Xue et al., 2022) using a two-stage framework. In the first stage, we use a novel self-supervised hyphen-prediction objective to learn compound segmentation without any labeled data. In the second stage, we turn the model into a compound normalization model via supervised training on our Wiktionary data. In addition, we introduce a procedure to predict the segmentation of any compound word based on its normalized form, effectively making compound segmentation a subtask of normalization. Finally, we demonstrate that decompounding has real-world applications by investigating compound segmentation for language model tokenization. We apply compound segmentation as pretokenization during training of a SentencePiece tokenizer (Kudo and Richardson, 2018), which results in fewer hard compounds while incurring no extra cost during training and inference of the language model (i.e. the only extra cost occurs during creation of the tokenizer).

Our Stage 1 models outperform the best prior unsupervised models by 13.9% accuracy on average, while our (supervised) Stage 2 models outperform all prior language-specific decompounding tools. Furthermore, a model trained with a Com-

poundPiece tokenizer achieves a 5.5% improved performance on compound normalization over an otherwise equivalent SentencePiece model.

Contributions. **1)** We introduce a dataset for decompounding of 255k words across 56 languages obtained from Wiktionary. **2)** We show that a byte-level language model can efficiently decompose words via a two-stage training framework, whereas current subword-based LLMs fall short. **3)** We present a way to improve subword tokenization by performing compound segmentation during creation of the tokenizer. **4)** We make our code, models and dataset publicly available at github.com/bminixhofer/compoundpiece.

2 Related Work

Decompounding. Early work in decompounding used word frequency lists along with manually specified suffixes (e.g., a connective *-s-*) to segment and normalize German compounds (Langer, 1998; Koehn and Knight, 2003). Subsequently, multiple submissions to the Morpho Challenge in morphological segmentation (Kurimo et al., 2010) explicitly or implicitly made use of compound segmentation (Lignos, 2010; Virpioja et al., 2011). Later work replaced the fixed list of suffixes used in Koehn and Knight (2003) by learned morphological operations from parallel corpora (Macherey et al., 2011) or from pre-lemmatized corpora of non-compound words (Ziering and van der Plas, 2016). Another branch of work added more linguistic knowledge in the form of black- and white-lists to the paradigm of Koehn and Knight (2003), resulting in JWordSplitter² (German) and nl-splitter³ (Dutch); this has only been done for a couple of languages due to its knowledge-intensive nature. CharSplit (Tuggerer, 2016) achieves high performance for German by relying on the frequency of character n-grams appearing within the compound.

While the approaches above use (at most) light supervision, there exist supervised approaches which learn directly from an annotated corpus of compounds and their constituents, along with optional auxiliary signals (Biemann et al., 2008; Alfonseca et al., 2008). In contrast, SECOS (Riedl and Biemann, 2016) is a fully unsupervised and language-agnostic method achieving competitive performance by using word embeddings along with word frequencies for semantic compound segmen-

²github.com/danielnaber/jwordsplitter

³github.com/bminixhofer/ilps-nl-splitter

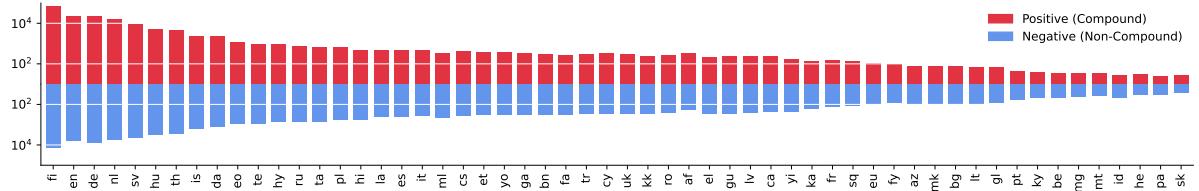


Figure 3: Number of positive and negative examples across languages in the Wiktionary dataset.

Word	Constituents	Language
هُنْيَا (<i>sibling</i>)	هُنْ (same) + نِيَا (ancestor)	Persian
akiratis (<i>horizon</i>)	akis (eye) + ratas (circle)	Lithuanian
шекара (<i>border</i>)	шек (limit) + апа (distance)	Kazakh
Abenteuer (<i>adventure</i>)	None	German
રોકડપ્રવાહ (<i>cashflow</i>)	રોકડ (cash) + પ્રવાહ (stream)	Gujarati

Figure 4: Example words in the Wiktionary dataset.

tation. Our method improves over SECOS in the unsupervised case and provides a unified alternative to prior language-specific decompositing tools via additional training on labelled data.

Relation to Morphological Segmentation. Decompositing can be seen as a special case of morphological segmentation (Batsuren et al., 2022a). However, a large amount of work in morphological segmentation focuses on derivational and inflectional morphology (Cotterell et al., 2016; Faruqui et al., 2016; Cotterell et al., 2018; McCarthy et al., 2019; Goldman et al., 2022), which is reflected by datasets such as UniMorph (Batsuren et al., 2022b) and MorphyNet (Batsuren et al., 2021) annotating inflectional and derivational affixes, but not compound constituents. The SIGMORPHON-2022 Shared Task (Batsuren et al., 2022a, SMST 2022) breaks this pattern by providing a dataset for segmentation into compound constituents in addition to inflectional and derivational affixes. We improve on the SMST 2022 dataset by broadening coverage from 9 to 56 languages, as well as handling negatives (i.e., non-compounds) more carefully (§3.1).

Decompositing Datasets. Besides the SMST 2022 dataset, datasets for decompositing include AuCoPro (van Zaanen et al., 2014) for Dutch and Afrikaans, and the GermaNet dataset for German (Henrich and Hinrichs, 2011). Although there is a significant amount of work studying compound

terms in languages with highly productive compound formation beyond German and Dutch, such as Finnish and Greek (Pollatsek et al., 2000; Lindén and Pirinen, 2009; Koliopoulou, 2014; Shapiro, 2016; Virkkunen et al., 2018), to the best of our knowledge there exist no public datasets for decompositing in these languages (and beyond).

Linguistically Informed Tokenization. Various studies have tried augmenting or replacing the ‘linguistically uninformed’ subword-tokenizers used in contemporary LMs (Devlin et al., 2019; Raffel et al., 2020, *inter alia*) such as SentencePiece (Kudo and Richardson, 2018) and BPE (Sennrich et al., 2016) with linguistic knowledge. Using manually constructed morphological analyzers before applying BPE (Pan et al., 2020) or after generation (Matthews et al., 2018) has led to improvements, but is limited by the availability (and quality) of morphological analyzers across many languages. Unsupervised morphological segmentation has not shown consistent improvements (Zhou, 2018; Salava and Lignos, 2021; Domingo et al., 2023); see Mielke et al. (2021) for additional discussion.

3 Methodology

3.1 Dataset Construction

We use words categorized as compound terms on Wiktionary to create a dataset for decompositing. The information on Wiktionary allows associating compound terms with their corresponding normalized constituents. Since Wiktionary only annotates the top-level split,⁴ we recursively split constituents into their smallest parts by checking if the top-level constituents are themselves compound words. Many prior decompositing tools do not evaluate performance on negative examples (i.e. non-compound words; Koehn and Knight, 2003; Riedl and Biemann, 2016; Tuggener, 2016) since most prior datasets do not contain any (Henrich

⁴For instance, highwayman is segmented into highway + man instead of high + way + man.

and Hinrichs, 2011; van Zaanen et al., 2014). It is not trivial to obtain negative examples from Wiktionary since a large amount of compound words are not categorized as such, leading to many false negatives. We solve this issue by using all normalized compound constituents as negative examples, since by definition the compound constituents can also appear on their own as non-compound words. Note that this way of obtaining negative examples is biased against words which never occur inside compounds; however, we found this to be a rather weak bias (Appendix E). We include every language with at least 100 words, leading to a dataset which covers 56 languages. The number of training examples is shown in Figure 3, example words in Figure 4. We select up to 1,000 words (but at most 50% of total words) in every language as evaluation data. See Appendix A for further details concerning the dataset.

3.2 Two-Stage Training

To overcome the problem of data scarcity in low-resource languages, we introduce a two-stage training procedure for creating dedicated decompounding models. In Stage 1, we train on the *self-supervised objective* of restoring hyphenation in words extracted from a large-scale Web corpus, leading to a self-supervised compound segmentation model. In Stage 2, we fine-tune the model on compounds and their normalized constituents from an annotated corpus in a *supervised fashion*, turning it into a compound normalization model.

Stage 1: Self-Supervised Compound Segmentation. This stage is motivated by the fact that hyphen characters can be seen as a *high-precision, low-recall indicator of compound constituent boundaries*, in the same way that newline characters are a high-precision, low-recall indicator of sentence boundaries (Minixhofer et al., 2023). We use this natural segmentation into compound constituents to create a compound segmentation model without requiring any labeled data. First, we obtain all words containing a hyphen plus an equivalent amount of non-hyphenated words from a corpus of unannotated text. Hyphens primarily have two uses: (1) as a compound boundary and (2) to indicate the word continues on the next line. We only want to retain hyphens when they function as compound boundaries, so we filter the instances of (2) by discarding all words where the hyphenated form of the word occurs $x \leq e^{-6}$ times less frequent

Input
Word x : akiratis (*horizon*)

Norm. constituents c : {akis (*eye*), ratas (*circle*)}
Find optimal segmentation

s_1	s_2	$\mathcal{L}(s_1, c_1)$	$\mathcal{L}(s_2, c_2)$	$C(s)$
a	kiratis	3	3	6
ak	iratis	2	2	4
aki	ratis	1	1	2
akir	atis	1	2	3
akira	tis	2	3	5
akirat	is	3	4	7
akirati	s	4	4	8

Output
Segmentation s^* : {aki, ratis}

Figure 5: Turning compound normalization into segmentation by minimizing edit distance (§3.3).

than the non-hyphenated form.⁵

We strip all words of hyphens and train a seq2seq LM to predict the original (hyphenated) form of each word. We introduce a logit bias b added to the logit of the token representing a hyphen to skew generation towards or away from hyphenation at inference time. Training on this data enables effective compound segmentation without relying on human annotations, as demonstrated later in §5.

Stage 2: Supervised Compound Normalization. In the second stage, we improve upon the Stage 1 model by additional training on labeled data, where the inputs are individual compounds, and the target is to predict the normalized constituents of each compound, separated by a hyphen. Training exclusively on compound normalization allows using data from the collected Wiktionary dataset, which contains compound terms along with their normalized constituents across many languages, but does not contain compound segmentation annotations.

3.3 Turning Normalization into Segmentation

Considering the scarcity of annotated compound segmentation data, it is infeasible to train a multilingual model directly on segmentation. Thus, we introduce a method to predict a segmentation given the normalized constituents. Let x be a word of length n . In addition, we have k normalized com-

⁵Consider for example the hyphen-as-compound-boundary in side-experiments and the hyphen-as-newline-indicator in experiments. $\frac{\#\text{experi-ments}}{\#\text{experiments}}$ will be considerably lower than $\frac{\#\text{side-experiments}}{\#\text{sideexperiments}}$. x was chosen from $\{e^{-4}, e^{-5}, e^{-6}, e^{-7}\}$ by manual inspection in preliminary experiments.

pound constituents $c = \{c_1, \dots, c_k\}$ (e.g. predicted by the Stage 2 model). Our aim is to find boundaries $r = \{r_0, \dots, r_k\}$, $r_0 = 0$, $r_k = n$ giving rise to the segmentation $s = \{\mathbf{x}[r_0 : r_1], \dots, \mathbf{x}[r_{k-1} : r_k]\}$. We approach this problem by minimizing the edit distance of each segment to its corresponding normalized constituent. This leads to an optimization problem where the cost $C(s)$ indicates the total edits needed to turn all segments into their corresponding normalized constituents:

$$C(s) = \sum_{i=1}^k \mathcal{L}(s_i, c_i).$$

Here, \mathcal{L} is an edit distance metric such as Levenshtein distance (Levenshtein et al., 1966). The optimal segmentation s^* is the segmentation with the minimal cost: $s^* = \arg \min_s C(s)$.

In case of ties, we prefer segmentations with higher edit cost for segments with lower indices due to the preference for languages in our training set for suffixation over prefixation (Hammarström, 2021).⁶ There is a total of $\binom{n}{k-1}$ possible segmentations, so solving the optimization problem via enumeration of all solutions is only feasible for short words (Figure 5). We introduce a more efficient search algorithm which is capable of quickly finding the optimal segmentation of long words by enumerating candidates in order of a lower bound on the edit distance in Appendix B. This method can be used to turn the normalization predictions of a model into segmentation. We also use it on the ground-truth normalization from Wiktionary, making it possible to approximate compound segmentation performance by comparing the segmentation corresponding to the ground-truth normalization to the segmentation produced by the model normalization predictions.

3.4 Reducing Hard Compounds

We define hard compounds relative to a particular tokenizer as compound words where the constituent boundaries do not coincide with token boundaries set by the tokenizer. More formally, a compound word made up of k constituents and l subwords is hard if the constituent boundaries $r = \{r_0, \dots, r_k\}$ are not a subset of the token boundaries $t = \{t_0, \dots, t_l\}$ i.e. $r \not\subset t$.

⁶E.g., given $\mathbf{x} = \text{bridesmaid}$, $c = \{\text{bride}, \text{maid}\}$, we prefer the segmentation $\{\text{brides}, \text{maid}\}$ over $\{\text{bride}, \text{smaid}\}$ although their cost is equal.

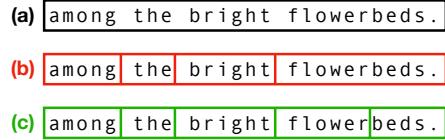


Figure 6: (a) no pretokenization, (b) pretokenization by splitting on whitespace, (c) our pretokenization.

We hypothesize that hard compounds may impair language model performance due to the non-trivial relation of subwords to the compound word. In contrast, in easy compounds the word is naturally decomposed into its constituents. The increased difficulty of hard compounds is apparent on the sequence-to-sequence compound segmentation task: for an easy compound, all tokens can be copied to the output (only the special separator tokens must be inserted). On the other hand, for hard compounds, the tokens change, requiring knowledge of the characters within each token.

Tokenizers where every possible constituent boundary is a token boundary trivially do not give rise to any hard compounds. This includes character-level (Clark et al., 2022; Tay et al., 2022b) as well as byte-level tokenizers (Xue et al., 2022). However, many contemporary language models use subword-based tokenizers to increase efficiency (Devlin et al., 2019; Raffel et al., 2020; Brown et al., 2020). We propose a modification to subword tokenization to reduce the number of hard compounds while keeping the efficiency advantages.

Subword tokenizers typically segment text into pre-tokens (e.g. by splitting on whitespace) before applying their subword tokenization algorithm (Mielke et al., 2021). We propose modifying pretokenization by applying compound segmentation in addition to splitting on whitespace. This modification is only done during creation of the tokenizer, thus incurring no additional cost once the tokenizer has been created. We refer to tokenizers created in this way as *CompoundPiece* tokenizers. The modified pretokenization tries to create more subwords which do not span compound constituent boundaries, thus decreasing the fraction of hard compounds (Figure 6). It aims to turn the dual-route model for computing the meaning of complex (compound) words proposed by Hofmann et al. (2021) into a single-route model which always computes the meaning of compounds from their constituent subwords, and never stores a compound word as a single subword.

4 Experimental Setup

4.1 Data

We obtain Stage 1 data by selecting all words containing a hyphen from a subset of the mC4 corpus (Xue et al., 2021) which results in $\sim 25M$ hyphenated words. As negative examples, we choose the n most common words from mC4 such that there is an equivalent amount of non-hyphenated and hyphenated words in every language. Regarding the Stage 2 data, see Section §3.1 before.

4.2 Training

We train a decompounding model using a two-stage framework (§3) covering 56 languages. We use ByT5 (Xue et al., 2022) as our main pretrained model and the main starting point since it directly ingests Unicode bytes instead of using subword tokenization, leading to zero hard compounds. We compare our approach against the subword-based T5 (Raffel et al., 2020), Flan-T5 (Chung et al., 2022) and mT5 (Xue et al., 2021) trained with the same two-stage framework. We use t5x (Roberts et al., 2022) for training with a batch size of 512 and a maximum sequence length of 64 tokens, otherwise matching T5 pretraining (Raffel et al., 2020). The setup is the same for Stage 1 and Stage 2.

4.3 Evaluation

Metric. We measure performance via averaged accuracy, i.e., the ratio of examples which are entirely correctly segmented or normalized.

Datasets. Besides our new Wiktionary evaluation subset, we use the established datasets for particular languages: GermaNet (Henrich and Hinrichs, 2011), AuCoPro for Dutch (van Zaanen et al., 2014) as well the subset containing compound-only words across 6 languages from the SIGMORPHON 2022 Shared Task (Batsuren et al., 2022a).⁷

Baselines. We use SECOS as the main unsupervised baseline, as well as CharSplit, JWS and nl-splitter as baselines using different amounts of supervision. For the SIGMORPHON 2022 Shared Task dataset, we compare against the task winner, DeepSPIN-3 (Peters and Martins, 2022).

⁷We do not include words containing derivational or inflectional affixes since the type of morpheme is not specified, so it is not possible to distinguish between derivational/inflectional affixes and compound constituents. We also do not include root words since we found from manual inspection that >10% of root words are mislabeled, likely due to the difficulty of obtaining negative examples from Wiktionary (§3.1).

Languages. For clarity of presentation, we present results on Danish, German, English, Spanish, Estonian, Greek, Persian, Finnish, Hungarian, Kazakh, Latvian, Dutch, Polish and Swedish as a linguistically diverse subset of languages with productive compound formation in the main paper. For the full evaluation across all languages, see Appendix C.

5 Results and Discussion

Main compound segmentation results are shown in Table 1. For the self-supervised models, we choose the logit bias $b = 3$ to bias generation towards hyphenated words.⁸ ByT5 outperforms subword-based models by a large margin with an absolute 8.9% improvement over the best subword-based model after Stage 1 training, and a 3.7% improvement after Stage 2 training. Comparing models not trained on any annotated data, the self-supervised ByT5 outperforms SECOS on 13 out of 14 languages, and by 13.9% on average.

We further compare against language-specific and supervised methods in Table 2. Our ByT5-based model outperforms all prior methods on every dataset. Since GermaNet tests compound *head* segmentation (i.e., even if a word contains multiple constituents, it is only split into a head and a modifier) we count an example as correctly segmented if either the first constituent matches the modifier or the last constituent matches the head.

Evaluating LLMs on Decompounding. We also evaluate in-context learning performance of multiple LLMs on compound segmentation. We use T5 models with 770M, 3B and 11B parameters (Raffel et al., 2020) as well as the UL2 model with 20B parameters (Tay et al., 2022a) since all of them use the same tokenizer, enabling performance comparisons on hard compounds across LLMs. We use the model versions fine-tuned on the Flan dataset collection (Chung et al., 2022), matching our prompt to the style of instructions in the Flan collection (Appendix D). Zero- to 16-shot results are shown in Figure 7. Although the LLMs perform non-trivially well on easy compounds, performance is close to zero (<3%) on hard compounds. Intriguingly, UL2 20B performs worse than Flan T5 XXL (11B), reversing the trend seen on other tasks (Tay et al., 2022a). All the LLMs perform considerably worse than our ByT5-based model; see Figure 1.

⁸Chosen among the set {0, 1, 2, 3, 4} to maximize performance on the English validation data.

		da	de	en	es	et	el	fa	fi	hu	kk	lv	nl	pl	sv	<i>Macro Avg.</i>	
P	S1	SECOS	30.0	66.5	41.2	29.0	23.4	5.3	1.4	53.1	38.8	5.0	13.9	46.8	22.2	32.2	29.2
		T5	55.3	56.1	85.9	69.8	29.0	0.0	0.0	31.6	48.6	16.9	29.6	44.9	36.1	53.1	39.8
		Flan-T5	58.4	58.5	89.1	71.0	37.0	0.0	0.0	33.0	53.4	17.6	41.7	44.8	40.3	56.5	42.9
		mT5	25.8	38.8	79.7	58.3	18.6	21.6	3.9	24.1	18.8	45.0	20.2	23.0	32.9	21.9	30.9
	S1+S2	ByT5	75.6	76.0	91.3	77.2	51.6	40.9	20.9	52.7	70.0	75.9	41.7	57.2	51.8	64.8	60.5
		T5	86.3	96.0	95.4	82.5	77.7	0.0	0.0	98.2	89.1	18.3	69.1	94.0	78.0	89.6	69.6
		Flan-T5	86.6	95.3	95.5	83.2	80.9	0.0	0.0	98.3	87.3	16.5	68.2	93.6	77.4	89.4	69.5
		mT5	87.1	94.1	95.4	82.3	83.2	73.1	62.1	97.1	90.4	86.7	76.7	93.4	84.1	90.0	85.4
N	S1	ByT5	92.2	96.6	97.8	87.1	92.6	86.1	76.6	98.8	97.2	91.7	84.8	97.5	91.2	94.3	91.7
		SECOS	96.1	86.6	93.8	97.4	98.6	99.7	100	88.2	95.5	100	100	94.1	96.9	97.3	96.0
		T5	88.5	91.8	91.7	88.7	82.3	100	100	82.2	93.8	74.0	87.4	83.7	90.6	91.8	89.0
		Flan-T5	88.5	92.1	91.3	89.9	82.3	100	100	82.9	91.6	72.9	87.0	87.0	90.4	92.4	89.2
	S1+S2	mT5	92.7	92.8	90.9	92.3	89.9	95.3	99.3	88.2	98.0	88.0	95.9	89.1	94.5	94.8	93.0
		ByT5	89.0	89.7	88.4	81.5	76.0	95.7	97.3	77.6	87.1	72.1	87.7	80.3	91.4	87.8	85.8
		T5	93.3	94.5	98.3	97.8	95.1	100	100	95.4	99.2	91.1	97.4	97.5	98.1	96.7	96.7
		Flan-T5	94.1	95.5	97.9	95.9	95.8	100	100	96.7	98.6	92.6	96.7	97.5	97.1	96.7	96.8
All	S1	mT5	93.8	96.2	99.2	97.4	97.9	96.3	98.7	94.1	98.6	96.9	98.1	96.7	97.9	97.3	97.1
		ByT5	95.2	96.2	98.3	98.8	97.9	97.3	97.3	95.4	99.7	99.2	98.9	97.9	99.0	97.6	97.8
		SECOS	53.5	72.4	53.9	63.2	56.0	60.9	52.2	58.4	59.0	50.7	61.0	58.1	57.8	53.6	57.9
		T5	67.1	66.5	87.3	79.3	52.1	59.0	51.5	39.3	64.7	44.4	61.2	54.2	62.1	65.8	61.0
	S1+S2	Flan-T5	69.1	68.3	89.6	80.5	56.6	59.0	51.5	40.6	67.0	44.2	66.5	54.9	64.2	68.3	62.9
		mT5	49.6	54.6	82.4	75.3	49.5	65.1	53.1	33.8	47.0	65.7	61.6	38.8	62.3	45.9	56.0
		ByT5	80.4	80.0	90.6	79.4	62.2	73.2	60.3	56.5	76.1	74.1	66.9	62.7	70.7	72.4	71.8
		T5	88.8	95.6	96.1	90.2	85.2	59.0	51.5	97.8	92.7	53.4	84.6	94.8	87.6	91.9	83.5
	S1+S2	Flan-T5	89.3	95.4	96.1	89.6	87.3	59.0	51.5	98.1	91.3	53.2	83.7	94.5	86.8	91.8	83.4
		mT5	89.5	94.7	96.3	89.8	89.6	86.8	80.9	96.6	93.3	91.6	88.4	94.2	90.7	92.4	91.1
		ByT5	93.3	96.5	97.9	92.9	94.9	92.7	87.3	98.3	98.1	95.3	92.5	97.6	94.9	95.4	94.8

Table 1: Accuracy on compounds (*Positives=P*), non-compound words (*Negatives=N*) and across all examples. We report scores of SECOS as baseline, as well as Stage 1 training only (S1) and Stage 1 plus Stage 2 training (S1+S2).

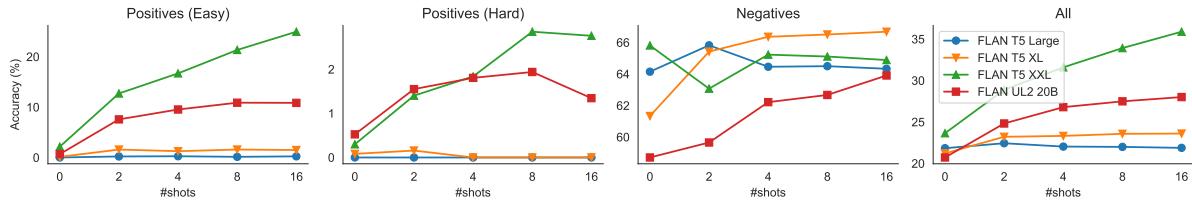


Figure 7: Few-shot in-context learning performance of LLMs on easy positives, hard positives, negatives and across all examples. Hard negatives are the same across all LLMs since they use the same tokenizer.

Reducing Hard Compounds via Compound-Piece. To evaluate our method of reducing the number of hard compounds in subword-based language models (§3.4), we train CompoundPiece models in two configurations: (i) multilingual tokenizers across all 56 languages and (ii) separate monolingual tokenizers for every language. For the multilingual tokenizers, we sample languages with $p(L) \propto |L|^\alpha$ where $p(L)$ is the probability of sampling text from a language L with $|L|$ texts as in prior work (Conneau et al., 2020). We use a subsample of 10M texts from the mC4 corpus (Xue et al., 2021) with $\alpha = 0.2$. The vocabulary size is 250k for the multilingual and 32k for the monolin-

gual tokenizers, following prior work (Rust et al., 2021; Conneau et al., 2020).

We use our fine-tuned ByT5 model for train-time pretokenization into compound constituents and SentencePiece (Kudo and Richardson, 2018) with Unigram LM (Kudo, 2018) as the subword tokenization applied after pretokenization. As a baseline, we train SentencePiece tokenizers with pretokenization into words (split by whitespace) on the same data. Table 3 shows the percentage of hard compounds for every tokenizer. CompoundPiece reduces the number of hard compounds from 27.1% → 9.7% on average in the monolingual case. In the multilingual case, there is a less marked

		Segmentation			Normalization		
		P	N	All	P	N	All
GermaNet	JWS	83.7	-	83.7	53.4	-	53.4
	CharSplit	95.1	-	95.1	-	-	-
	SECOS	83.6	-	83.6	-	-	-
	ByT5 (S1+S2)	97.9	-	97.9	79.6	-	79.6
Ours (de)	JWS	59.7	97.6	70.8	43.2	97.6	59.1
	CharSplit	84.7	29.5	68.6	-	-	-
	SECOS	66.5	86.6	72.4	-	-	-
	ByT5 (S1+S2)	96.6	96.2	96.5	89.8	96.2	91.7
AuCoPro-nl	nl-splitter	74.5	-	74.5	67.1	-	67.1
	SECOS	59.7	-	59.7	-	-	-
	ByT5 (S1+S2)	91.7	-	91.7	76.2	-	76.2
Ours (nl)	nl-splitter	61.2	96.7	69.7	47.0	91.2	57.6
	SECOS	46.8	94.1	58.1	-	-	-
	ByT5 (S1+S2)	97.5	97.9	97.6	87.8	97.9	90.2
SMST 2022	DeepSpin-3	88.6	-	88.6	87.3	-	87.3
	ByT5 (S1+S2)	92.5	-	92.5	88.6	-	88.6

Table 2: Comparison against supervised and rule-based baseline models. We use the subset of compound-only words from the Sigmorphon Shared Task (SMST) 2022 data which covers 7 languages (Batsuren et al., 2022a).

Language	Multilingual			Monolingual	
	SPM (mT5)	SPM	CPM	SPM	CPM
Danish	15.5	16.5	12.4	24.7	5.9
German	9.9	10.3	8.2	14.6	1.8
English	7.5	8.2	4.6	6.8	3.7
Spanish	29.0	24.9	18.7	14.2	10.3
Estonian	25.5	29.5	15.2	35.4	7.2
Greek	39.9	33.6	23.1	28.9	14.9
Persian	38.6	46.1	37.2	70.9	41.8
Finnish	25.1	25.1	20.3	10.3	5.1
Hungarian	13.8	17.1	10.1	26.1	3.7
Kazakh	14.4	13.7	9.0	28.4	4.0
Latvian	20.2	23.8	16.1	47.5	11.7
Dutch	12.8	15.4	10.2	17.2	3.3
Polish	45.7	42.5	33.1	33.6	17.0
Swedish	13.9	17.7	12.5	21.3	5.4
<i>Macro Avg.</i>	22.3	23.2	16.5	27.1	9.7

Table 3: Percentage of hard compounds after segmentation with different tokenizers. SPM (mT5) is the SentencePiece tokenizer used by mT5 (Xue et al., 2021). SentencePiece (SPM) and CompoundPiece (CPM) tokenizers are trained on text in all 56 languages (Multilingual) and for every language separately (Monolingual).

improvement of 23.2% → 16.5%. This may be because tokens from different languages interfere with the segmentation of any given word. We test this hypothesis by computing plausible token origins for tokens in the multilingual tokenizer. This is done by checking which monolingual tokenizers also contain the token in their vocabulary, and ordering the result by unigram token probability. Examples are shown in Table 4. Interference from

Word	Monolingual Segmentation		Multilingual Segmentation		Token Origin
	P	N	P	N	
tugboat	_tug, boat		_tu, gbo, at		_tu: es, sk, it gbo: yo, mg, fr at: id, hu, la
mindstate	_mind, state		_mindst, ate		_mindst: da ate: it, et, en
coatrack	_coat, rack		_coa, track		_coa: gl, ro track: hu, th, da

Table 4: Example compound words which are easy for the monolingual but hard for the multilingual CompoundPiece tokenizer. “_” indicates whitespace.

Language	Segmentation		Normalization	
	SPM-T5	CPM-T5	SPM-T5	CPM-T5
Danish	77.8		77.7	65.5
German	81.0		80.7	61.5
English	84.9		85.8	82.9
Spanish	75.2		74.7	50.1
Estonian	78.6		84.5	55.1
Greek	70.6		70.0	47.1
Persian	58.2		61.2	46.6
Finnish	72.8		74.1	59.0
Hungarian	76.2		76.9	73.3
Kazakh	72.9		75.7	59.0
Latvian	75.2		69.1	53.5
Dutch	78.2		80.7	60.9
Polish	65.8		65.6	42.6
Swedish	76.2		77.3	61.0
<i>Macro Avg.</i>	74.6		75.3	58.4
				63.9

Table 5: Accuracy of our multilingual T5 models trained with SentencePiece (SPM-T5) and CompoundPiece (CPM-T5) on segmentation and normalization.

	Segmentation			Normalization		
	P	N	All	P	N	All
ByT5 (S1)	50.8	82.5	66.6	28.5	82.5	55.2
- hyphen filtering	53.8	62.3	58.9	30.3	62.3	47.0
ByT5 (S1+S2)	80.9	98.0	89.8	58.2	97.8	78.5
- S1	79.3	97.3	88.6	56.8	97.1	77.4

Table 6: Ablation studies on not filtering hyphens-as-newline-indicator and on skipping Stage 1 training.

common tokens in other languages is likely the lead cause for the increased number of hard compounds in the multilingual tokenizers. It could potentially be solved by adjusting token probability based on the input language; we leave this to future work.

To more thoroughly evaluate our tokenization, we train multilingual T5 models using SentencePiece and CompoundPiece. We use the same sampling ratio ($\alpha = 0.2$) of mC4 as for creating the tokenizer, but instead use a subset of 500M texts. We match the architecture and the pretraining setup of the mT5-base model, but train for a total of

~65.5B tokens.⁹ We evaluate the model on the decompounding task. Results are shown in Table 5.

Ablation Studies. We quantify the impact of the most significant design choices of our model in Table 6. Although filtering hyphens-as-newline-indicator (§4.1) removes only 300k words (<1%) from the pretraining data, it increases performance on negatives by a large margin. Removing Stage 1 training (i.e., fine-tuning directly on the Wiktionary data instead) consistently decreases performance.

6 Conclusion

We systematically investigated word decompounding tasks of compound segmentation and normalization on a wide scale and in multilingual contexts. To this end, we introduced a dataset of 255k words including compounds and non-compounds across 56 languages from Wiktionary, which allowed us to evaluate performance of LLMs on decompounding. We found that current LLMs’ performance is limited due to hard compounds which arise when subword token boundaries do not coincide with compound constituent boundaries. We then introduced dedicated models for decompounding which use byte-level tokenization to entirely avoid hard compounds. Finally, we used our decompounding models to create novel CompoundPiece tokenizers, keeping the efficiency advantages of subword tokenization while strongly decreasing the amount of hard compounds; this increases the performance of CompoundPiece models over comparable SentencePiece models on the decompounding tasks.

Limitations

Although self-supervised training in Stage 1 allows for decompounding without any annotated training data, Stage 2 training is limited to languages with sufficient entries in Wiktionary: this excludes extremely low-resource languages. Furthermore, due to computational constraints we have not trained larger models using CompoundPiece tokenization; hence we are unable to report on its benefits at larger scales and on tasks besides decompounding.

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⁹This equates to $\frac{1}{16}$ of mT5’s ~1T tokens, chosen in line with our computational resources.

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References

- Martine Adda-Decker and Gilles Adda. 2000. Morphological decomposition for asr in german. In *Workshop on Phonetics and Phonology in ASR, Saarbrücken, Germany*, pages 129–143.
- Enrique Alfonseca, Slaven Bilac, and Stefan Pharies. 2008. **Decompounding query keywords from compounding languages.** In *Proceedings of ACL-08: HLT, Short Papers*, pages 253–256, Columbus, Ohio. Association for Computational Linguistics.
- Duygu Altinok. 2018. Demorphy, german language morphological analyzer. *arXiv preprint arXiv:1803.00902*.
- Khuyagbaatar Batsuren, Gábor Bella, Aryaman Arora, Viktor Martinovic, Kyle Gorman, Zdeněk Žabokrtský, Amarsanaa Ganbold, Šárka Dohnalová, Magda Ševčíková, Kateřina Pelegrinová, Fausto Giunchiglia, Ryan Cotterell, and Ekaterina Vylomova. 2022a. **The SIGMORPHON 2022 shared task on morpheme segmentation.** In *Proceedings of the 19th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, pages 103–116, Seattle, Washington. Association for Computational Linguistics.
- Khuyagbaatar Batsuren, Gábor Bella, and Fausto Giunchiglia. 2021. **MorphyNet: a large multilingual database of derivational and inflectional morphology.** In *Proceedings of the 18th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, pages 39–48, Online. Association for Computational Linguistics.
- Khuyagbaatar Batsuren, Omer Goldman, Salam Khalifa, Nizar Habash, Witold Kieraś, Gábor Bella, Brian Leonard, Garrett Nicolai, Kyle Gorman, Yustinus Ghanggo Ate, Maria Ryskina, Sabrina Mielke, Elena Budianskaya, Charbel El-Khaissi, Tiago Pimentel, Michael Gasser, William Abbott Lane, Mohit Raj, Matt Coler, Jaime Rafael Montoya Samame, Delio Siticonatzi Camaiteri, Esaú Zumaeta Rojas, Didier López Francis, Arturo Oncevay, Juan López Bautista, Gema Celeste Silva Villegas, Lucas Torroba Hennigen, Adam Ek, David Gurriel, Peter Dirix, Jean-Philippe Bernardy, Andrej Scherbakov, Aziyana Bayyr-ool, Antonios Anastasopoulos, Roberto Zariquiey, Karina Sheifer, Sofya Ganieva, Hilaria Cruz, Rítván Karahóga, Stella Markantonatou, George Pavlidis, Matvey Plugarov, Elena Klyachko, Ali Salehi, Candy Angulo, Jatayu Baxi, Andrew Krizhanovsky, Natalia

- Krizhanovskaya, Elizabeth Salesky, Clara Vania, Sar-dana Ivanova, Jennifer White, Rowan Hall Maud-slay, Josef Valvoda, Ran Zmigrod, Paula Czarnowska, Irene Nikkarinen, Aelita Salchak, Brijesh Bhatt, Christopher Straughn, Zoey Liu, Jonathan North Washington, Yuval Pinter, Duygu Ataman, Marcin Wolinski, Totok Suhardijanto, Anna Yablonskaya, Niklas Stoehr, Hossep Dolatian, Zahroh Nuriah, Shyam Ratan, Francis M. Tyers, Edoardo M. Ponti, Grant Aiton, Aryaman Arora, Richard J. Hatcher, Ritesh Kumar, Jeremiah Young, Daria Rodionova, Anastasia Yemelina, Taras Andrushko, Igor Marchenko, Polina Mashkovtseva, Alexandra Serova, Emily Prud’hommeaux, Maria Nepomniashchaya, Fausto Giunchiglia, Eleanor Chodroff, Mans Hulden, Miikka Silfverberg, Arya D. McCarthy, David Yarowsky, Ryan Cotterell, Reut Tsarfaty, and Ekaterina Vylomova. 2022b. **UniMorph 4.0: Universal Morphology**. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 840–855, Marseille, France. European Language Resources Association.
- Chris Biemann, Uwe Quasthoff, Gerhard Heyer, and Florian Holz. 2008. **ASV toolbox: a modular collection of language exploration tools**. In *Proceedings of the Sixth International Conference on Language Resources and Evaluation (LREC’08)*, Marrakech, Morocco. European Language Resources Association (ELRA).
- Martin Braschler and Bärbel Ripplinger. 2004. How effective is stemming and decompositing for german text retrieval? *Information Retrieval*, 7:291–316.
- Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. **Language models are few-shot learners**. In *Advances in Neural Information Processing Systems*, volume 33, pages 1877–1901. Curran Associates, Inc.
- Hyung Won Chung, Le Hou, Shayne Longpre, Barret Zoph, Yi Tay, William Fedus, Eric Li, Xuezhi Wang, Mostafa Dehghani, Siddhartha Brahma, et al. 2022. Scaling instruction-finetuned language models. *arXiv preprint arXiv:2210.11416*.
- Jonathan H. Clark, Dan Garrette, Iulia Turc, and John Wieting. 2022. **Canine: Pre-training an efficient tokenization-free encoder for language representation**. *Transactions of the Association for Computational Linguistics*, 10:73–91.
- Alexis Conneau, Kartikay Khandelwal, Naman Goyal, Vishrav Chaudhary, Guillaume Wenzek, Francisco Guzmán, Edouard 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, Online. Association for Computational Linguistics.
- Ryan Cotterell, Christo Kirov, John Sylak-Glassman, Géraldine Walther, Ekaterina Vylomova, Arya D. McCarthy, Katharina Kann, Sabrina J. Mielke, Garrett Nicolai, Miikka Silfverberg, David Yarowsky, Jason Eisner, and Mans Hulden. 2018. **The CoNLL-SIGMORPHON 2018 shared task: Universal morphological reinflection**. In *Proceedings of the CoNLL-SIGMORPHON 2018 Shared Task: Universal Morphological Reinforcement*, pages 1–27, Brussels. Association for Computational Linguistics.
- Ryan Cotterell, Tim Vieira, and Hinrich Schütze. 2016. **A joint model of orthography and morphological segmentation**. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 664–669, San Diego, California. Association for Computational Linguistics.
- 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.
- Miguel Domingo, Mercedes García-Martínez, Alexandre Helle, Francisco Casacuberta, and Manuel Heranz. 2023. How much does tokenization affect neural machine translation? In *Computational Linguistics and Intelligent Text Processing: 20th International Conference, CICLING 2019, La Rochelle, France, April 7–13, 2019, Revised Selected Papers, Part I*, pages 545–554. Springer.
- Manaal Faruqui, Yulia Tsvetkov, Graham Neubig, and Chris Dyer. 2016. **Morphological inflection generation using character sequence to sequence learning**. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 634–643, San Diego, California. Association for Computational Linguistics.
- Omer Goldman, David Guriel, and Reut Tsarfaty. 2022. **(un)solving morphological inflection: Lemma overlap artificially inflates models’ performance**. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers)*, pages 864–870, Dublin, Ireland. Association for Computational Linguistics.
- Harald Hammarström. 2021. **Measuring prefixation and suffixation in the languages of the world**. In

- Proceedings of the Third Workshop on Computational Typology and Multilingual NLP*, pages 81–89, Online. Association for Computational Linguistics.
- Yijie Han, Bhagirath Narahari, and H-A Choi. 1992. Mapping a chain task to chained processors. *Information Processing Letters*, 44(3):141–148.
- Verena Henrich and Erhard Hinrichs. 2011. Determining immediate constituents of compounds in GermaNet. In *Proceedings of the International Conference Recent Advances in Natural Language Processing 2011*, pages 420–426, Hissar, Bulgaria. Association for Computational Linguistics.
- Valentin Hofmann, Janet Pierrehumbert, and Hinrich Schütze. 2021. Superbizarre is not superb: Derivational morphology improves BERT’s interpretation of complex words. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3594–3608, Online. Association for Computational Linguistics.
- Philipp Koehn and Kevin Knight. 2003. Empirical methods for compound splitting. In *10th Conference of the European Chapter of the Association for Computational Linguistics*, Budapest, Hungary. Association for Computational Linguistics.
- Maria Koliopoulou. 2014. Issues of modern greek and german compounding: a contrastive approach. *Journal of Greek Linguistics*, 14(1):117–125.
- Taku Kudo. 2018. Subword regularization: Improving neural network translation models with multiple subword candidates. In *Proceedings of the 56th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 66–75, Melbourne, Australia. Association for Computational Linguistics.
- 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, Brussels, Belgium. Association for Computational Linguistics.
- Mikko Kurimo, Sami Virpioja, Ville Turunen, and Krista Lagus. 2010. Morpho challenge 2005-2010: Evaluations and results. In *Proceedings of the 11th Meeting of the ACL Special Interest Group on Computational Morphology and Phonology*, pages 87–95, Uppsala, Sweden. Association for Computational Linguistics.
- Stefan Langer. 1998. Zur morphologie und semantik von nominalkomposita. In *Tagungsband der 4. Konferenz zur Verarbeitung natürlicher Sprache (KONVENS)*, pages 83–97. Bonn.
- Vladimir I Levenshtein et al. 1966. Binary codes capable of correcting deletions, insertions, and reversals. In *Soviet physics doklady*, volume 10, pages 707–710. Soviet Union.
- Constantine Lignos. 2010. Learning from unseen data. In *Proceedings of the Morpho Challenge 2010 Workshop*, pages 35–38. Helsinki.
- Krister Lindén and Tommi Pirinen. 2009. Weighted finite-state morphological analysis of Finnish compounding with HFST-LEXC. In *Proceedings of the 17th Nordic Conference of Computational Linguistics (NODALIDA 2009)*, pages 89–95, Odense, Denmark. Northern European Association for Language Technology (NEALT).
- Klaus Macherey, Andrew Dai, David Talbot, Ashok Popat, and Franz Och. 2011. Language-independent compound splitting with morphological operations. In *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, pages 1395–1404, Portland, Oregon, USA. Association for Computational Linguistics.
- Fredrik Manne and Tor Sørevik. 1995. Optimal partitioning of sequences. *Journal of Algorithms*, 19(2):235–249.
- Austin Matthews, Graham Neubig, and Chris Dyer. 2018. Using morphological knowledge in open-vocabulary neural language models. In *Proceedings of the 2018 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long Papers)*, pages 1435–1445, New Orleans, Louisiana. Association for Computational Linguistics.
- Arya D. McCarthy, Ekaterina Vylomova, Shijie Wu, Chaitanya Malaviya, Lawrence Wolf-Sonkin, Garrett Nicolai, Christo Kirov, Miikka Silfverberg, Sabrina J. Mielke, Jeffrey Heinz, Ryan Cotterell, and Mans Hulden. 2019. The SIGMORPHON 2019 shared task: Morphological analysis in context and cross-lingual transfer for inflection. In *Proceedings of the 16th Workshop on Computational Research in Phonetics, Phonology, and Morphology*, pages 229–244, Florence, Italy. Association for Computational Linguistics.
- Sabrina J Mielke, Zaid Alyafeai, Elizabeth Salesky, Colin Raffel, Manan Dey, Matthias Gallé, Arun Raja, Chenglei Si, Wilson Y Lee, Benoît Sagot, et al. 2021. Between words and characters: A brief history of open-vocabulary modeling and tokenization in nlp. *arXiv preprint arXiv:2112.10508*.
- Benjamin Minixhofer, Jonas Pfeiffer, and Ivan Vulic. 2023. Where’s the point? self-supervised multilingual punctuation-agnostic sentence segmentation. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 7215–7235, Toronto, Canada. Association for Computational Linguistics.

- Christof Monz and Maarten De Rijke. 2002. Shallow morphological analysis in monolingual information retrieval for dutch, german, and italian. In *Evaluation of Cross-Language Information Retrieval Systems: Second Workshop of the Cross-Language Evaluation Forum, CLEF 2001 Darmstadt, Germany, September 3–4, 2001 Revised Papers*, pages 262–277. Springer.
- Yirong Pan, Xiao Li, Yating Yang, and Rui Dong. 2020. Morphological word segmentation on agglutinative languages for neural machine translation. *arXiv preprint arXiv:2001.01589*.
- Ben Peters and Andre F. T. Martins. 2022. [Beyond characters: Subword-level morpheme segmentation](#). In *Proceedings of the 19th SIGMORPHON Workshop on Computational Research in Phonetics, Phonology, and Morphology*, pages 131–138, Seattle, Washington. Association for Computational Linguistics.
- Alexander Pollatsek, Jukka Hyönä, and Raymond Bertram. 2000. The role of morphological constituents in reading finnish compound words. *Journal of Experimental Psychology: Human perception and performance*, 26(2):820.
- 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(140):1–67.
- Martin Riedl and Chris Biemann. 2016. [Unsupervised compound splitting with distributional semantics rivals supervised methods](#). In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 617–622, San Diego, California. Association for Computational Linguistics.
- Adam Roberts, Hyung Won Chung, Anselm Levskaya, Gaurav Mishra, James Bradbury, Daniel Andor, Sharan Narang, Brian Lester, Colin Gaffney, Afroz Mohiuddin, Curtis Hawthorne, Aitor Lewkowycz, Alex Salcianu, Marc van Zee, Jacob Austin, Sebastian Goodman, Livio Baldini Soares, Haitang Hu, Sasha Tsvyashchenko, Aakanksha Chowdhery, Jasmijn Bastings, Jannis Bulian, Xavier Garcia, Jianmo Ni, Andrew Chen, Kathleen Kenealy, Jonathan H. Clark, Stephan Lee, Dan Garrette, James Lee-Thorp, Colin Raffel, Noam Shazeer, Marvin Ritter, Maarten Bosma, Alexandre Passos, Jeremy Maitin-Shepard, Noah Fiedel, Mark Omernick, Brennan Saeta, Ryan Sepassi, Alexander Spiridonov, Joshua Newlan, and Andrea Gesmundo. 2022. [Scaling up models and data with t5x and seqio](#). *arXiv preprint arXiv:2203.17189*.
- Phillip Rust, Jonas Pfeiffer, Ivan Vulić, Sebastian Ruder, and Iryna Gurevych. 2021. [How good is your tokenizer? on the monolingual performance of multilingual language models](#). In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)*, pages 3118–3135, Online. Association for Computational Linguistics.
- Jonne Saleva and Constantine Lignos. 2021. [The effectiveness of morphology-aware segmentation in low-resource neural machine translation](#). In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Student Research Workshop*, pages 164–174, Online. Association for Computational Linguistics.
- Rico Sennrich, Barry Haddow, and Alexandra Birch. 2016. [Neural machine translation of rare words with subword units](#). In *Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 1715–1725, Berlin, Germany. Association for Computational Linguistics.
- Naomi Tachikawa Shapiro. 2016. [Splitting compounds with ngrams](#). In *Proceedings of COLING 2016, the 26th International Conference on Computational Linguistics: Technical Papers*, pages 630–640, Osaka, Japan. The COLING 2016 Organizing Committee.
- Robyn Speer. 2022. [rspeer/wordfreq: v3.0](#).
- Ilya Sutskever, Oriol Vinyals, and Quoc V Le. 2014. [Sequence to sequence learning with neural networks](#). In *Advances in Neural Information Processing Systems*, volume 27. Curran Associates, Inc.
- Yi Tay, Mostafa Dehghani, Vinh Q Tran, Xavier Garcia, Dara Bahri, Tal Schuster, Huaixiu Steven Zheng, Neil Houlsby, and Donald Metzler. 2022a. Unifying language learning paradigms. *arXiv preprint arXiv:2205.05131*.
- Yi Tay, Vinh Q. Tran, Sebastian Ruder, Jai Gupta, Hyung Won Chung, Dara Bahri, Zhen Qin, Simon Baumgartner, Cong Yu, and Donald Metzler. 2022b. [Charformer: Fast character transformers via gradient-based subword tokenization](#). In *International Conference on Learning Representations*.
- Don Tuggener. 2016. *Incremental coreference resolution for German*. Ph.D. thesis, University of Zurich.
- Menno van Zaanen, Gerhard van Huyssteen, Suzanne Aussems, Chris Emmery, and Roald Eiselen. 2014. [The development of Dutch and Afrikaans language resources for compound boundary analysis](#). In *Proceedings of the Ninth International Conference on Language Resources and Evaluation (LREC'14)*, pages 1056–1062, Reykjavik, Iceland. European Language Resources Association (ELRA).
- Päivi Johanna Virkkunen, Juraj Simko, Heini Henriikka Kallio, and Martti Tapani Vainio. 2018. Prosodic features of finnish compound words. In *Proceedings of the 9th International Conference on Speech Prosody 2018*. International Speech Communications Association.

Sami Virpioja, Ville T. Turunen, Sebastian Spiegler, Oskar Kohonen, and Mikko Kurimo. 2011. Empirical comparison of evaluation methods for unsupervised learning of morphology. *Traitement Automatique des Langues*, 52(2):45–90.

Irene Vogel and Sergio Scalise. 2010. Cross-disciplinary issues in compounding. *Cross-Disciplinary Issues in Compounding*, pages 1–390.

Linting Xue, Aditya Barua, Noah Constant, Rami Al-Rfou, Sharan Narang, Mihir Kale, Adam Roberts, and Colin Raffel. 2022. ByT5: Towards a token-free future with pre-trained byte-to-byte models. *Transactions of the Association for Computational Linguistics*, 10:291–306.

Linting Xue, Noah Constant, Adam Roberts, Mihir Kale, Rami Al-Rfou, Aditya Siddhant, Aditya Barua, and Colin Raffel. 2021. mT5: A massively multilingual pre-trained text-to-text transformer. In *Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 483–498, Online. Association for Computational Linguistics.

Giulio Zhou. 2018. *Morphological zero-shot neural machine translation*. Ph.D. thesis, Master’s thesis, University of Edinburgh.

Patrick Ziering and Lonneke van der Plas. 2016. Towards unsupervised and language-independent compound splitting using inflectional morphological transformations. In *Proceedings of the 2016 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 644–653, San Diego, California. Association for Computational Linguistics.

A Dataset Statistics

Statistics for the training and validation splits of the Wiktionary dataset are shown in Table 7.

B Efficient Segmentation Algorithm

Pseudocode of the brute-force algorithm to turn normalization into segmentation is shown in Algorithm 1. Since enumerating all possible segmentations is only feasible for short words (§3.3) we introduce a more efficient algorithm (Algorithm 2) where candidate segmentations are ordered such that segmentations with constituents closest in length to the corresponding normalized constituents appear first. Assuming insertions and deletions both have a cost of one (as is the case in standard Levenshtein distance), constituents are thus sorted in increasing order of a lower bound on edit distance. The procedure can stop once the lower bound on edit distance reaches the cost of the best solution found so far since by that point it is impossible for a better solution to be found.

Note that the normalization-to-segmentation problem is related to sequence partitioning (Manne and Sorevik, 1995; Han et al., 1992) where the aim is to find a partition of a sequence such that the maximum cost across partitions of some cost function is minimized. However, since our goal is to find the partitioning with the minimum aggregated cost, algorithms for conventional sequence partitioning are not applicable.

C Results for All Languages

Segmentation accuracy for all languages is shown in Tables 8-11.

D LLM Prompts

The prompt used for LLM evaluations (§5) is shown in Figure 8. The prompt was chosen among 10 prompts to maximize performance on Flan T5 Large. For 2- to 16-shot results, we provide 50% positive (compound) and 50% negative (non-compound) examples in a random order.

E Quantifying Negative Collection Bias

We conduct an experiment to measure the extent of the bias against words which do not occur inside compounds in our data collection methodology (§3.1). In particular, we quantify the bias against *long non-compound words*, which usually would not occur inside compounds. We took a

Zero-shot:

{word}

Hyphenate the above word.

Ans :

n-shot:

{example_0}

Hyphenate the above word.

Ans : {example_0_hyphenated}

...

{example_n}

Hyphenate the above word.

Ans : {example_n_hyphenated}

{word}

Hyphenate the above word.

Ans :

Figure 8: Prompts used to evaluate LLM in-context learning compound segmentation performance.

random sample of 500 words each from word frequency lists in English and German (Speer, 2022), manually removed compound words, and compared the length statistics of this (unbiased) sample of non-compounds to our non-compound dataset.

While words in our non-compound dataset are indeed shorter on average (6.0 vs. 6.7 chars for English, 6.7 vs. 7.1 chars for German), with less than one character length difference on average, there is only a weak length bias in data collection.

We also found qualitatively that our non-compound dataset contains a wide variety of words since compounding is typically a process that can occur for many different root words.

Data: Compound x , norm. constituents c .

Result: Optimal segmentation s^* .

$k \leftarrow \|c\|, n \leftarrow \|x\|$

$r_0 \leftarrow 0, r_n \leftarrow n$

best_cost $\leftarrow \infty$

```

for  $r_1, \dots, r_{n-1} \in \binom{[n]}{k-1}$  do
    Compute  $s, C(s)$  /* see §3.3 */
    if  $C(s) < \text{best\_cost}$  then
         $s^{\text{best}} \leftarrow s$ 
        best_cost  $\leftarrow C(s)$ 
    end
end

```

$s^* \leftarrow s^{\text{best}}$

Algorithm 1: Naïve brute-force segmentation.

Data: Compound x , norm. constituents c .

Result: Optimal segmentation s^* .

$k \leftarrow |c|, n \leftarrow |x|$

$r_0 \leftarrow 0, r_k \leftarrow n$

best_cost $\leftarrow \infty$

```

/*  $\Delta$  is the total difference in
   length of the normalized
   constituents to the word. */
 $\Delta = n - \sum_i |c_i|$ 
lower_bound  $\leftarrow |\Delta|$ 

```

```

while lower_bound  $<$  best_cost do
    offsets =  $\{x \mid |x| = k,$ 
     $\sum_i |x_i| = \text{lower\_bound},$ 
     $\sum_i x_i = \Delta\}$ 
    lower_bound  $\leftarrow$  lower_bound + 1
    for  $o_1, \dots, o_k \in \text{offsets}$  do
         $r_1, \dots, r_{k-1} =$ 
         $|c_1| + o_1, \dots, \sum_{i=1}^{n-1} |c_i| + o_i$ 
        Compute  $s, C(s)$  /* see §3.3 */
        if  $C(s) < \text{best\_cost}$  then
             $s^{\text{best}} \leftarrow s$ 
            best_cost  $\leftarrow C(s)$ 
        end
    end
end

```

$s^* \leftarrow s^{\text{best}}$

Algorithm 2: Segmentation by enumerating candidates in order of increased lower bound on edit distance.

Language	iso	#Positive	Training		Validation		Total
			#Negative	Total	#Positive	#Negative	
Afrikaans	af	326	193	519	322	197	519
Azerbaijani	az	78	97	175	85	89	174
Belarusian	be	32	47	79	40	38	78
Bulgarian	bg	71	89	160	68	92	160
Bengali	bn	301	334	635	304	331	635
Catalan	ca	220	218	438	219	218	437
Czech	cs	388	358	746	392	354	746
Welsh	cy	308	273	581	299	281	580
Danish	da	2145	1298	3443	644	356	1000
German	de	20743	7846	28589	708	292	1000
Greek	el	216	292	508	208	299	507
English	en	22896	6480	29376	759	241	1000
Esperanto	eo	1097	849	1946	559	441	1000
Spanish	es	433	401	834	417	417	834
Estonian	et	349	315	664	376	288	664
Basque	eu	102	98	200	98	101	199
Persian	fa	268	314	582	282	300	582
Finnish	fi	69948	13314	83262	848	152	1000
French	fr	149	135	284	135	148	283
Western Frisian	92	85	177	90	86	176	
Irish	ga	332	322	654	328	325	653
Galician	gl	70	79	149	80	69	149
Gujarati	gu	227	279	506	221	285	506
Hebrew	he	29	34	63	18	44	62
Hindi	hi	472	569	1041	478	522	1000
Hungarian	hu	5238	3162	8400	644	356	1000
Armenian	hy	872	745	1617	509	491	1000
Indonesian	id	26	45	71	32	38	70
Icelandic	is	2333	1603	3936	592	408	1000
Italian	it	452	352	804	437	366	803
Georgian	ka	137	156	293	149	143	292
Kazakh	kk	244	292	536	278	258	536
Kirghiz	ky	39	45	84	39	44	83
Latin	la	450	410	860	452	407	859
Lithuanian	lt	65	94	159	76	83	159
Latvian	lv	244	249	493	223	269	492
Malagasy	mg	35	42	77	32	45	77
Macedonian	mk	75	94	169	79	90	169
Malayalam	ml	318	435	753	331	421	752
Maltese	mt	35	36	71	36	35	71
Dutch	nl	15184	5258	20442	761	239	1000
Punjabi	pa	24	34	58	19	39	58
Polish	pl	628	556	1184	523	477	1000
Portuguese	pt	40	57	97	53	44	97
Romanian	ro	272	261	533	268	265	533
Russian	ru	753	718	1471	507	493	1000
Slovak	sk	26	28	54	25	29	54
Albanian	sq	124	113	237	109	127	236
Swedish	sv	8883	4172	13055	671	329	1000
Tamil	ta	656	710	1366	484	516	1000
Telugu	te	894	909	1803	507	493	1000
Thai	th	4287	2754	7041	614	386	1000
Turkish	tr	295	287	582	310	271	581
Ukrainian	uk	281	291	572	277	295	572
Yiddish	yi	162	218	380	176	203	379
Yoruba	yo	349	312	661	348	312	660
Total		164713	58757	223470	17539	13938	31477

Table 7: Statistics of the Wiktionary dataset.

			af	az	be	bg	bn	ca	cs	cy	da	de	el	en	eo	es	<i>Macro Avg.</i>
N	S1	SECOS	-	-	-	7.4	-	4.1	20.2	-	30.0	66.5	5.3	41.2	-	29.0	-
		T5	47.5	64.7	20.0	14.7	0.0	61.2	30.6	41.1	55.3	56.1	0.0	85.9	65.3	69.8	43.7
		FLAN T5	52.8	69.4	17.5	16.2	0.0	59.8	36.0	43.8	58.4	58.5	0.0	89.1	67.6	71.0	45.7
		mT5	22.7	34.1	20.0	10.3	14.5	50.7	28.8	36.5	25.8	38.8	21.6	79.7	44.0	58.3	34.7
	S1+S2	ByT5	64.9	70.6	45.0	29.4	34.5	68.5	48.2	49.8	75.6	76.0	40.9	91.3	82.3	77.2	61.0
		T5	83.9	75.3	22.5	35.3	0.0	70.8	68.9	60.2	86.3	96.0	0.0	95.4	78.7	82.5	61.1
		FLAN T5	84.8	74.1	22.5	33.8	0.0	75.3	67.3	59.5	86.6	95.3	0.0	95.5	77.6	83.2	61.1
		mT5	83.5	85.9	70.0	76.5	79.6	71.7	76.8	57.9	87.1	94.1	73.1	95.4	78.2	82.3	79.4
		ByT5	90.4	89.4	80.0	79.4	91.1	81.7	85.5	72.9	92.2	96.6	86.1	97.8	89.8	87.1	87.1
P	S1	SECOS	-	-	-	100	-	99.1	100	-	96.1	86.6	99.7	93.8	-	97.4	-
		T5	87.8	84.3	63.2	73.9	100	88.1	80.5	74.4	88.5	91.8	100	91.7	83.9	88.7	85.5
		FLAN T5	90.4	85.4	71.1	73.9	100	92.2	79.9	74.4	88.5	92.1	100	91.3	86.2	89.9	86.8
		mT5	95.4	91.0	81.6	93.5	95.8	93.6	96.3	82.9	92.7	92.8	95.3	90.9	90.2	92.3	91.7
	S1+S2	ByT5	87.8	86.5	57.9	72.8	93.1	84.9	87.9	70.5	89.0	89.7	95.7	88.4	76.6	81.5	83.0
		T5	91.9	97.8	94.7	96.7	100	97.2	94.6	93.6	93.3	94.5	100	98.3	97.7	97.8	96.3
		FLAN T5	90.9	96.6	94.7	95.7	100	95.4	93.5	96.1	94.1	95.5	100	97.9	97.3	95.9	96.0
		mT5	92.4	100	100	100	97.0	95.9	97.7	95.7	93.8	96.2	96.3	99.2	98.0	97.4	97.1
		ByT5	93.4	98.9	100	100	97.3	97.2	98.0	95.7	95.2	96.2	97.3	98.3	98.0	98.8	97.5
All	S1	SECOS	-	-	-	60.6	-	51.5	58.0	-	53.5	72.4	60.9	53.9	-	63.2	-
		T5	62.8	74.7	41.0	48.8	52.1	74.6	54.3	57.2	67.1	66.5	59.0	87.3	73.5	79.3	64.2
		FLAN T5	67.1	77.6	43.6	49.4	52.1	76.0	56.8	58.6	69.1	68.3	59.0	89.6	75.8	80.5	66.0
		mT5	50.3	63.2	50.0	58.1	56.9	72.1	60.9	59.0	49.6	54.6	65.1	82.4	64.4	75.3	61.6
	S1+S2	ByT5	73.6	78.7	51.3	54.4	65.0	76.7	67.0	59.8	80.4	80.0	73.2	90.6	79.8	79.4	72.1
		T5	86.9	86.8	57.7	70.6	52.1	84.0	81.1	76.4	88.8	95.6	59.0	96.1	87.1	90.2	79.5
		FLAN T5	87.1	85.6	57.7	69.4	52.1	85.4	79.8	77.2	89.3	95.4	59.0	96.1	86.3	89.6	79.3
		mT5	86.9	93.1	84.6	90.0	88.7	83.8	86.7	76.2	89.5	94.7	86.8	96.3	86.9	89.8	88.1
		ByT5	91.5	94.3	89.7	91.2	94.3	89.5	91.4	84.0	93.3	96.5	92.7	97.9	93.4	92.9	92.3

Table 8: Accuracy on languages af-es.

			et	eu	fa	fi	fr	ga	gl	gu	he	hi	hu	hy	id	<i>Macro Avg.</i>	
N	S1	SECOS	23.4	4.1	1.4	53.1	11.9	-	-	2.5	-	-	-	38.8	-	-	-
		T5	29.0	28.6	0.0	31.6	31.9	53.3	69.8	50.0	0.0	0.0	0.0	48.6	0.0	34.4	26.9
		FLAN T5	37.0	31.6	0.0	33.0	31.9	58.9	70.1	51.2	0.0	0.0	0.0	53.4	0.0	40.6	29.1
		mT5	18.6	18.4	3.9	24.1	21.5	24.4	59.8	38.8	59.3	22.2	39.7	18.8	4.3	12.5	26.2
	S1+S2	ByT5	51.6	42.9	20.9	52.7	44.4	52.2	76.8	52.5	79.6	38.9	66.5	70.0	10.2	50.0	50.7
		T5	77.7	38.8	0.0	98.2	48.1	84.4	83.2	65.0	0.0	0.0	0.0	89.1	0.0	46.9	45.1
		FLAN T5	80.9	41.8	0.0	98.3	49.6	86.7	81.4	60.0	0.0	0.0	0.0	87.3	0.0	46.9	45.2
		mT5	83.2	50.0	62.1	97.1	48.9	81.1	82.6	62.5	85.1	44.4	81.8	90.4	77.2	40.6	70.5
		ByT5	92.6	58.2	76.6	98.8	62.2	91.1	88.7	67.5	90.0	33.3	88.9	97.2	85.1	53.1	77.4
P	S1	SECOS	98.6	100	100	88.2	97.3	-	-	95.7	-	-	-	95.5	-	-	-
		T5	82.3	85.1	100	82.2	94.6	87.2	82.2	82.6	100	100	100	93.8	100	81.6	90.8
		FLAN T5	82.3	87.1	100	82.9	98.0	87.2	76.0	94.2	100	100	100	91.6	100	76.3	91.1
		mT5	89.9	89.1	99.3	88.2	95.3	90.7	88.3	95.7	97.9	97.7	99.4	98.0	97.6	78.9	93.3
	S1+S2	ByT5	76.0	71.3	97.3	77.6	91.9	88.4	77.8	71.0	94.7	95.5	98.3	87.1	92.5	57.9	84.1
		T5	95.1	98.0	100	95.4	97.3	100	98.8	95.7	100	100	100	99.2	100	100	98.5
		FLAN T5	95.8	96.0	100	96.7	97.3	100	97.5	95.7	100	100	100	98.6	100	100	98.4
		mT5	97.9	97.0	98.7	94.1	98.6	97.7	98.2	100	97.2	97.7	99.0	98.6	97.4	100	98.0
		ByT5	97.9	97.0	97.3	95.4	98.6	100	98.8	100	97.9	100	99.2	99.7	98.2	100	98.6
All	S1	SECOS	56.0	52.8	52.2	58.4	56.5	-	-	45.6	-	-	-	59.0	-	-	-
		T5	52.1	57.3	51.5	39.3	64.7	69.9	76.0	65.1	56.3	71.0	52.2	64.7	49.1	60.0	59.2
		FLAN T5	56.6	59.8	51.5	40.6	66.4	72.7	73.0	71.1	56.3	71.0	52.2	67.0	49.1	60.0	60.5
		mT5	49.5	54.3	53.1	33.8	60.1	56.8	74.0	65.1	81.0	75.8	70.9	47.0	50.1	48.6	58.6
	S1+S2	ByT5	62.2	57.3	60.3	56.5	69.3	69.9	77.3	61.1	88.1	79.0	83.1	76.1	50.6	54.3	67.5
		T5	85.2	68.8	51.5	97.8	73.9	92.0	91.0	79.2	56.3	71.0	52.2	92.7	49.1	75.7	74.0
		FLAN T5	87.3	69.3	51.5	98.1	74.6	93.2	89.4	76.5	56.3	71.0	52.2	91.3	49.1	75.7	74.0
		mT5	89.6	73.9	80.9	96.6	74.9	89.2	90.4	79.9	91.9	82.3	90.8	93.3	87.1	72.9	85.3
		ByT5	94.9	77.9	87.3	98.3	81.3	95.5	93.7	82.6	94.5	80.6	94.3	98.1	91.5	78.6	89.2

Table 9: Accuracy on languages et-id.

		is	it	ka	kk	ky	la	lt	lv	mg	mk	ml	mt	nl	pa	<i>Macro Avg.</i>
N	S1	SECOS	-	32.5	-	5.0	-	5.3	-	13.9	-	-	-	-	46.8	-
		T5	41.4	42.6	0.0	16.9	15.4	29.0	21.1	29.6	31.2	15.2	0.0	19.4	44.9	0.0
		FLAN T5	45.4	48.5	0.0	17.6	12.8	33.0	28.9	41.7	34.4	17.7	0.0	25.0	44.8	0.0
		mT5	26.4	26.8	21.5	45.0	30.8	21.9	11.8	20.2	25.0	24.1	18.4	25.0	23.0	42.1
	S1+S2	ByT5	65.9	56.1	61.7	75.9	64.1	33.6	25.0	41.7	37.5	36.7	33.5	27.8	57.2	68.4
		T5	78.7	68.6	0.0	18.3	23.1	59.3	65.8	69.1	53.1	49.4	0.0	41.7	94.0	0.0
		FLAN T5	78.7	68.9	0.0	16.5	17.9	61.7	63.2	68.2	40.6	49.4	0.0	41.7	93.6	0.0
		mT5	82.9	68.9	82.6	86.7	79.5	61.9	60.5	76.7	53.1	72.2	68.0	52.8	93.4	63.2
		ByT5	90.5	81.2	83.9	91.7	84.6	73.5	80.3	84.8	65.6	88.6	83.7	58.3	97.5	78.9
P	S1	SECOS	-	97.0	-	100	-	99.8	-	100	-	-	-	-	94.1	-
		T5	83.1	88.8	99.3	74.0	77.3	80.3	81.9	87.4	68.9	68.9	100	91.4	83.7	100
		FLAN T5	80.1	91.3	99.3	72.9	86.4	82.8	86.7	87.0	75.6	66.7	100	85.7	87.0	100
		mT5	90.0	92.1	97.2	88.0	95.5	84.5	85.5	95.9	84.4	90.0	96.9	97.1	89.1	100
	S1+S2	ByT5	82.1	83.6	88.8	72.1	86.4	56.0	71.1	87.7	57.8	85.6	72.7	94.3	80.3	100
		T5	96.1	96.4	100	91.1	97.7	94.8	92.8	97.4	88.9	93.3	100	94.3	97.5	100
		FLAN T5	95.6	96.2	99.3	92.6	97.7	95.6	95.2	96.7	91.1	93.3	100	97.1	97.5	100
		mT5	95.6	97.3	98.6	96.9	100	96.1	96.4	98.1	82.2	96.7	98.3	88.6	96.7	100
		ByT5	97.1	97.8	99.3	99.2	100	98.5	94.0	98.9	91.1	98.9	98.8	100	97.9	100
All	S1	SECOS	-	61.9	-	50.7	-	50.1	-	61.0	-	-	-	-	58.1	-
		T5	58.4	63.6	48.6	44.4	48.2	53.3	52.8	61.2	53.2	43.8	56.0	54.9	54.2	67.2
		FLAN T5	59.6	68.0	48.6	44.2	51.8	56.6	59.1	66.5	58.4	43.8	56.0	54.9	54.9	67.2
		mT5	52.3	56.5	58.6	65.7	65.1	51.6	50.3	61.6	59.7	59.2	62.4	60.6	38.8	81.0
	S1+S2	ByT5	72.5	68.6	75.0	74.1	75.9	44.2	49.1	66.9	49.4	62.7	55.5	60.6	62.7	89.7
		T5	85.8	81.3	49.0	53.4	62.7	76.1	79.9	84.6	74.0	72.8	56.0	67.6	94.8	67.2
		FLAN T5	85.6	81.3	48.6	53.2	60.2	77.8	79.9	83.7	70.1	72.8	56.0	69.0	94.5	67.2
		mT5	88.1	81.8	90.4	91.6	90.4	78.1	79.2	88.4	70.1	85.2	85.0	70.4	94.2	87.9
		ByT5	93.2	88.8	91.4	95.3	92.8	85.3	87.4	92.5	80.5	94.1	92.2	78.9	97.6	93.1
		90.2														

Table 10: Accuracy on languages is-pa.

		pl	pt	ro	ru	sk	sq	sv	ta	te	th	tr	uk	yi	yo	<i>Macro Avg.</i>
N	S1	SECOS	22.2	9.4	7.8	35.9	-	-	32.2	-	-	-	7.7	-	-	-
		T5	36.1	30.2	51.9	22.3	12.0	29.4	53.1	0.0	0.0	0.0	28.1	17.7	0.0	12.9
		FLAN T5	40.3	47.2	55.6	25.6	16.0	31.2	56.5	0.0	0.0	0.0	34.8	22.0	0.0	16.1
		mT5	32.9	20.8	47.8	15.8	16.0	22.9	21.9	19.6	40.2	9.3	15.2	13.0	36.4	10.9
	S1+S2	ByT5	51.8	45.3	61.2	31.0	36.0	34.9	64.8	46.1	61.7	27.0	32.6	35.7	50.6	18.7
		T5	78.0	49.1	63.8	50.3	48.0	52.3	89.6	0.0	0.0	0.0	67.4	37.5	0.0	19.0
		FLAN T5	77.4	49.1	64.9	50.1	60.0	45.9	89.4	0.0	0.0	0.0	66.1	36.1	0.0	19.0
		mT5	84.1	39.6	65.7	77.9	60.0	45.0	90.0	61.0	81.9	83.7	71.6	76.9	76.1	31.3
		ByT5	91.2	56.6	73.5	91.3	72.0	56.0	94.3	73.6	84.4	90.6	82.3	86.6	83.0	48.0
P	S1	SECOS	96.9	97.7	95.8	92.1	-	-	97.3	-	-	-	100	-	-	-
		T5	90.6	86.4	90.9	66.1	89.7	80.3	91.8	100	100	99.5	87.5	68.5	100	86.2
		FLAN T5	90.4	88.6	91.3	67.1	86.2	81.1	92.4	100	100	99.7	89.3	72.2	100	85.3
		mT5	94.5	81.8	94.7	83.6	96.6	96.1	94.8	94.4	97.9	94.8	87.1	99.5	92.9	93.4
	S1+S2	ByT5	91.4	79.5	86.8	67.3	86.2	83.5	87.8	63.2	95.7	89.6	81.2	72.2	92.1	85.6
		T5	98.1	97.7	95.8	95.9	96.6	93.7	96.7	99.8	100	100	95.6	97.3	100	93.9
		FLAN T5	97.1	97.7	97.7	95.9	96.6	95.3	96.7	100	100	96.3	98.6	100	97.1	
		mT5	97.9	97.7	95.8	98.6	100	99.2	97.3	94.6	97.8	98.5	99.7	97.0	97.8	
		ByT5	99.0	97.7	96.6	99.0	96.6	97.6	97.6	96.9	98.8	99.0	98.2	99.3	98.0	98.1
All	S1	SECOS	57.8	49.5	51.6	63.6	-	-	53.6	-	-	-	50.8	-	-	-
		T5	62.1	55.7	71.3	43.9	53.7	56.8	65.8	51.6	49.3	38.4	55.8	43.9	53.6	47.6
		FLAN T5	64.2	66.0	73.4	46.1	53.7	58.1	68.3	51.6	49.3	38.5	60.2	47.9	53.6	48.8
		mT5	62.3	48.5	71.1	49.2	59.3	62.3	45.9	58.2	68.9	43.5	52.3	51.2	70.2	49.7
	S1+S2	ByT5	70.7	60.8	73.9	48.9	63.0	61.0	72.4	54.9	78.5	51.2	55.2	54.5	72.8	50.3
		T5	87.6	71.1	79.7	72.8	74.1	74.6	91.9	51.5	49.3	38.6	80.6	68.4	53.6	54.4
		FLAN T5	86.8	71.1	81.2	72.7	79.6	72.5	91.8	51.6	49.3	38.6	80.2	68.4	53.6	55.9
		mT5	90.7	66.0	80.7	88.1	81.5	74.2	92.4	78.3	89.7	88.9	84.2	88.6	87.3	62.7
		ByT5	94.9	75.3	85.0	95.1	85.2	78.4	95.4	85.6	91.5	93.8	89.7	93.2	91.0	71.7
		87.5														

Table 11: Accuracy on languages pl-yo.